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ORIGINAL RESEARCH

Shapley value-based multi-objective data envelopment analysis application for assessing academic efficiency of university departments

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Abstract

This paper adopts a modified approach of data envelopment analysis (DEA) to measure the academic efficiency of university departments. In real-world case studies, conventional DEA models often identify too many decision-making units (DMUs) as efficient. This occurs when the number of DMUs under evaluation is not large enough compared to the total number of decision variables. To overcome this limitation and reduce the number of decision variables, multi-objective data envelopment analysis (MODEA) approach previously presented in the literature is applied. The MODEA approach applies Shapley value as a cooperative game to determine the appropriate weights and efficiency score of each category of inputs. To illustrate the performance of the adopted approach, a case study is conducted in a university in the Philippines. The input variables are academic staff, non-academic staff, classrooms, laboratories, research grants, and department expenditures, while the output variables are the number of graduates and publications. The results of the case study revealed that all DMUs are inefficient. DMUs with efficiency scores close to the ideal efficiency score may be emulated by other DMUs with least efficiency scores.

Keywords Academic efficiency · Data envelopment analysis · Multi-objective data envelopment analysis · University departments

List of symbols

q	Index of the qth category of inputs $(q = 1, \ldots, Q)$
i	Index of inputs $\left(i = 1, \ldots, m_q\right)$
j	Index of DMU $(j = 1, \ldots, n)$
r	Index of outputs $(r = 1, \ldots, s)$
n	Number of DMUs
m_q	Number of inputs in the qth category
s	Number of common outputs
x_{ij}	ith input for DMU_j
x_{ij}^q	ith input for DMU_j in the qth category of inputs
y_{rj}	rth output for DMU_j
v_i	Weight of the ith input
v_i^q	Weight of the ith input in the qth category of inputs
μ_r	Weight of the rth common output
K	Set of input categories in coalition
Ω	Set of input categories

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Introduction

Higher education institutions (HEIs) play an important role in preparing a country to be globally competitive through the skilled human capital resources it produces. With the proliferation of HEIs, most academic institutions are confronted with the issue on the deterioration of quality graduates (Conchada 2015). Also, HEIs have failed to meet the national expectations of quality education to match the labor requirements of a country and the world market (Bautista 2014). To assure that HEIs produce quality graduates, there is a need to constantly check itself against the standards set by a governing body and the latest demands of the labor market. This entails assessment on the educational resources to be conducted by accreditation bodies to HEIs such that its faculty, research, and facilities may be further developed (Conchada 2015). To carry this out, efficiency assessment on the utilization of educational resources must be done. This can help HEIs set strategic goals, allocate resources and budgets, and promote their institutions' accomplishments to potential faculty, funders, and students. More so, efficiency measurement in HEIs can be summed up as an investment in quality as it aids in accurate strategic decision-making whether to build on existing strength or develop new areas.

To measure efficiency, two basic methodologies can be used depending on the nature of efficiency under evaluation (i.e., economic or technical). In the case of HEIs, a non-parametric technique to evaluate relative efficiencies of a set of comparable decision-making units (DMUs) by mathematical programming is deemed appropriate to be implemented (Guccio et al. 2016). One non-parametric technique that is widely used in measuring technical efficiency is data envelopment analysis (DEA). It identifies the sources and level of inefficiency for each input and output (Cooper et al. 2007). DEA has been successfully applied in various fields such as: (a) evaluation of the relative technical efficiencies of academic departments of a university in Gaza, Egypt (Agha et al. 2011), (b) evaluation of the relative efficiency of public and private higher education institutions in Brazil (Zoghbi et al. 2013), (c) assessment of the performance levels of departments of a university in Turkey (Goksen et al. 2015), (d) assessment of the efficiency of agricultural farms in different regions of Turkey (Atici and Podinovski 2015), (e) estimation of the relative efficiency of local municipalities in traffic safety in Israel (Alper et al. 2015), (f) evaluation of the performance of the supply chain operations (Tajbakhsh et al. 2015), and (g) evaluation of electricity distribution companies under uncertainty about input/output data (Hafezalkotob et al. 2015). As an extension to the conventional DEA model, multiple objective-based models are further introduced. Some of which include (a) an interactive multi-objective linear programming (MOLP) procedure in selecting ideal output targets given the input level (Golany 1988), (b) a two-stage approach for solving DEA and multi-objective programming models in calculating efficiency scores (Li et al. 2009; Wang et al. 2014; Despotis et al. 2015), (c) a fuzzy multi-objective mathematical model for identifying and ranking of the candidate suppliers and finding the optimal number of parts and finished products in a reverse logistics network configuration (Moghaddam 2015), and (d) a multi-objective programming model as an alternative approach to solving network DEA (Kao et al. 2014).

The previously presented multi-objective DEA (MODEA) applications are not able to overcome the limitation of the conventional DEA which requires a number of decision variables that is lesser than the number of DMUs under evaluation (Cooper et al. 2007). As a result, DEA drops its discriminating ability, thereby, leading to a less accurate measure of efficiency. To address the limitation of the conventional DEA and compare DMUs more effectively regardless of the number of DMUs considered (i.e., DMUs can both be lesser than or greater than the decision variables), Rezaee (2015) introduced the use of Shapley value in MODEA. In this approach, it enables the use of a large set of decision variables when the number of DMUs evaluated is lesser than such variables. This is in direct contrast to the conventional DEA models that only allows a particular number of DMUs for a set of variables based on a predetermined guideline.

To take advantage of the strength of the Shapley-based MODEA model proposed by Rezaee (2015), this paper aims to apply this approach in a case study concerning an academic institution which, by nature, involves a wide array of decision variables that need to be considered to measure efficiency more accurately. In literature, the efficiency of academic institutions is mostly measured using the conventional DEA approach and none has made use of the MODEA approach despite its advantage of looking at the multi-objective characteristic of the problem. Thus, the gap that is advanced in this paper is the use of a large set of decision variables, i.e., inputs and outputs, in academic efficiency evaluation of a small number of university departments where the conventional DEA approach would result in low discriminating ability when such conditions are present. Furthermore, while Rezaee (2015) introduced the use of MODEA approach in evaluating power plants, this paper contributes by demonstrating the same approach in measuring the academic efficiency in university departments where the number of DMUs is sufficiently lesser than that of decision variables involved. The remainder of this paper is organized as follows: Sect. 2 presents the review of related literature with emphasis on how efficiency is characterized as well as outstanding

approaches used to measure efficiency and its other relevant applications in diverse fields. Section 3 provides a detailed flow on how the MODEA approach is implemented. An illustrative example is presented in Sect. 4 to validate the model based on MODEA approach with Shapely values and the discussion of results are shown in Sect. 5. The managerial implications and final remarks on the key results obtained are presented in Sect. 6.

Literature review

Efficiency is a systematic process that converts a set of inputs into a set of outputs. An input is a primary resource to produce an output while an output is the expected result. Any process, taking a set of inputs to produce certain outputs, can be viewed this way. In any organization, it is imperative to consider multiple inputs and multiple outputs. Coelli et al. (2005) suggest that efficiency reflects the ability of an organization to obtain maximum output from a given set of inputs. When an organization is able to maximize its output from a given set of inputs, it is said to be efficient (Rogers 1998).

Essentially, there are two main methodologies for measuring efficiency, that is, parametric methods and nonparametric methods. Parametric methods include thick frontier approach (TFA), stochastic frontier approach (SFA), and distribution free approach (DFA). These methods measure economic efficiency. Non-parametric methods include DEA and free disposal hull (FDH). These methods measure technical efficiency. Parametric methods are good in handling data with a certain level of uncertainty; however, it is not easy to be applied in a multiple-inputs-and-outputs situation. Moreover, these methods are not suited to measure the efficiency of a nonprofit organization since these methods usually involve market price. Cooper et al. (2007) have established DEA to measure the relative and technical efficiency of variables. It is a nonparametric method of measuring the efficiency with multiple inputs, multiple outputs, and no market prices. DEA uses linear programming to compute weights as the alternative to market prices. Linear programming computes the weights that maximize an objective function subject to the constraints identified. The data used for DEA are the observed inputs used and the actual outputs produced by the spending units.

Data envelopment analysis (DEA)

DEA is a mathematical programming model developed to evaluate the relative efficiency of homogeneous DMUs. According to Kuah et al. (2011), a DMU is an entity responsible for converting input(s) into output(s) and which performances are to be assessed. Farrell (1957) first used DEA to measure technical efficiency for a set of organizations, and this has been developed and extended by Charnes et al. (1978). The objective function in DEA is specified in terms of the overall output–input ratio. The constraints of this linear programming model are also output–input ratios pertaining to the DMUs. Suppose there are n DMUs, where each $\mathrm{DMU}_j (j = 1, \ldots, n)$ produces s outputs $(r = 1, \ldots, s)$ by utilizing m inputs $(i = 1, \ldots, m)$. According to these notations, DEA uses the following model for evaluating DMU_0's efficiency:

$$\begin{aligned} &\text{Maximize} \quad \frac{\sum_{r=1}^{s} \mu_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \\ &\text{Subject to} \quad \frac{\sum_{r=1}^{s} \mu_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad j = 1, \ldots, n \\ &v_i, \mu_r \geq \varepsilon, \quad i = 1, \ldots, m \quad r = 1, \ldots, s \end{aligned} \tag{1}$$

where μ_r and v_i are the weight of inputs and outputs, x_{ij} and y_{rj} are input and output variables, and $\varepsilon > 0$ is a non-Archimedean number that is smaller than any non-negative real number. The relative efficiency of DMUs is calculated by assigning 1 for efficient DMUs and less than 1 for inefficient DMUs.

Efficiency measurement with the use of DEA approach has been applied to several industries. Among the multi-faceted applications of DEA, the top-five industries addressed are banking, health care, agriculture and farm, transportation, and education. These industries practically adopt DEA for a variety of reasons, as Golany and Roll (1989) pointed out that it can be applied to identify sources of inefficiency, rank the DMUs, evaluate management, evaluate the effectiveness of programs or policies, and create a quantitative basis for reallocating resources. Another advantage of DEA is its ability to identify a set of corresponding efficient DMUs that can be referred as benchmarks for every inefficient DMU.

The application of DEA has been integrated with other mathematical approaches to further its ability to measure efficiency. For instance, Stackelberg approach is used in a mixed integer bi-level DEA model for bank branch performance evaluation (Shafiee et al. 2016). This approach involves a bi-level programming motivated by Von Stackelberg's game theory (1952) which aim is to obtain a solution that optimizes the objective functions of a leader and a follower. Another approach is that of a multilayer artificial neural network which has been applied to forecast the decision variables of each DMU for a specified period (Shokrollahpour et al. 2016). On the other hand, a slack-based measure of efficiency that involves constant inputs is used to calculate the perceived service quality index of the multiple-item service quality construct. DEA is further used to evaluate the service quality within a pre-determined

framework (Najafi et al. 2015). Another index, that is, Malmquist DEA-based productivity index is used to evaluate the changes in productivity in the technical efficiency and technology frontier (Abri and Mahmoudzadeh 2015). In another case, the efficiency scores obtained in DEA model is then applied to a mixed integer scenario-based stochastic programming model for a supplier selection problem (Zarindast et al. 2017). The objective functions include minimizing the total purchasing cost over the planning horizon and maximizing the rank of suppliers. A Nash bargaining game theory is integrated to DEA to tackle efficiency of suppliers in the presence of competition at the same time (Rezaee et al. 2017). The programming model focused on four objective functions defining total profit, defective rate, delivery delay rate, and efficiency in a competitive environment.

In the context of academic institutions, its efficiency is measured using DEA as shown in several studies in the literature. For instance, Kao et al. (2006) applied DEA to assess the relative efficiency of academic departments in a university in Taiwan by utilizing scarce resources in teaching students and producing research results. This study focused on the efficiency of resource utilization rather than academic performance. In another case, Tyagi et al. (2008) evaluated the performance efficiencies of 19 academic departments of a university in India using DEA approach. Sensitivity analysis is applied to test the robustness of the efficiency results. Similarly, academic departments of a university in Gaza are assessed by Agha et al. (2011) in terms of its technical efficiencies. Super-efficiency analysis is applied to efficient departments to determine the most efficient department. On the other hand, Goksen et al. (2015) determined the performance levels of 26 departments of a university in Turkey using DEA to reveal the main cause of its inefficiency. Academic colleges at a university in Iran are likewise assessed by Saniee Monfared and Safi (2013) using network DEA in comparison to the conventional DEA model.

Each of these previously presented studies differs in its scope, DMUs, and decision variables considered. The input and output variables for each study are shown in Table 1. Most of these studies used only the basic models of DEA which are based on Banker–Charnes–Cooper (BCC) and Charnes–Cooper–Rhodes (CCR) models except for Agha et al. (2011) who applied super-efficiency analysis in their study. In addition, these studies did not clearly answer the question as to which of the resources caused the DMUs' inefficiency.

Variable selection in university departments

The selection of decision variables is an important factor in DEA. One point to consider in using DEA is the relationship of the number of DMUs and the number of decision variables. According to Pedraja-Chaparro (1999), DEA drops its discriminative power and accuracy of measuring the efficiency of DMUs when the value of $n/(m+s)$, where n is the number of DMUs, m is the number of inputs, and s is the number of outputs, is too small. It is suggested that n should be greater than $3 \times (m+s)$ as a guideline for DEA (Banker et al. 1989; Friedman and Sinuany-Stern 1998; Cooper et al. 2007). According to Dyson et al. (2001), the number of DMUs must be at least $2 \times (m \times s)$ wherein if twice the product of the variables is equal to or lower than the number of DMUs, it indicates that the number of variables used is satisfactory for measuring efficiency through DEA.

Typically, the number of inputs and outputs and the DMUs determines how acceptable a discrimination exists between efficient and inefficient units. If DMUs are taken from an infinite set, DEA models can provide best estimations of production frontier. In other words, if there are lesser DMUs, the error of the production frontier estimation increases, and the possibility of domination for each DMU decreases due to other efficient DMUs. As a result, the number of efficient DMUs increases, however, some of which are not actually as efficient. When there is such a case, other post-optimality models may be applied to further rank DMUs (Ziari and Raissi 2016). These may include super-efficiency analysis (Anderson and Peterson 1993), Mehrabian-Alirezaee-Jahanshahloo (MAJ) model (Mehrabian et al. 1999), a nonlinear programming L_1-norm model (Jahanshahloo et al. 2004), and leave-one-out idea and L_∞-norm (Rezai Balf et al. 2012). It is, however, important to note that these models still require a large number of units under evaluation for it to be carried out. In practice, a large number of units are not always available. There are several inputs and outputs that decision-makers intend to use for evaluation but the number of DMUs is not sufficient (Rezaee 2015). One concrete example is that of university departments which is characterized by a wide range of variables (Berbegal and Sole 2012).

Variable reduction in DEA

To counteract with the limited distinction provided by DEA with many variables, previous findings have retained some variables originally planned for the analysis while

Table 1 Decision variables of previous studies of DEA applied in university departments

Year	Author	Input variables	Output variables
1990	Beasley	General expenditure	Undergraduates
		Equipment expenditure	Postgraduates on taught courses
		Research income	Postgraduates who are doing research
2003	Abbott et al.	Academic staff	Full-time students
		Non-academic staff	Postgraduate and undergraduate degrees enrolled
		Expenditure	Postgraduate degrees and undergraduate degrees conferred
		Non-current assets	
2006	Kao et al.	Personnel	Total credit hours
		Operating expenses	Publications
		Floor space	External grants
2008	Tyagi et al.	Academic staff	Total enrolled students
		Non-academic staff	Progress
		Department operating cost	Research index
2010	Halkos et al.	Academic staff	Academic research
		Auxiliary staff	Graduates
		Number of students	Publications
		Total income	
2010	Katharak et al.	Academic staff	Graduates
		Non-academic staff	Research income
		Actively registered students	
		Operating expenses	
2011	Agha et al.	Operating expenses	Graduates
		Credit hours	Promotions
		Training resources	Public service activities
2011	Kuah et al.	Academic staff	Graduates from taught courses
		Number of taught course students	Average graduates' results
		Average students' qualifications	Graduation rate
		University expenditures	Graduates' employment rate
		Research staffs	Graduates from research
		Average research staffs' qualifications	Publications
		Research students	Awards
		Research grants	Intellectual properties
2013	Kuhail	Full-time academic staff	Graduates
		Part-time academic staff	Promotions
		Academic staff salaries	Public service activities
		Training resources	
2013	Aziz et al.	Academic staff	Graduates
		Non-academic staff	Research grant received
		Yearly operating expenses	Academic publications
2015	Goksen et al.	Outdoor–indoor area of University	Publications
		Academic staff	Graduate students
		Administrative staff	

omitting other variables that are highly correlated with it. For instance, Zhu (1998) used principal component analysis (PCA) approach for aggregating multiple inputs and multiple outputs to evaluate the efficiency of DEA models. By means of aggregation, the number of variables of DMUs can be reduced using a joint application of DEA and

factor analysis as introduced by Nadimi et al. (2008). They also detected structure in the relationship between variables and applied joint DEA and factor analysis to form groups of variables that have a correlation with one another. Furthermore, only those that are considered as important variables from multiple inputs and multiple outputs can be selected using a stepwise regression data envelopment approach developed by Sharma et al. (2015). A null hypothesis is formulated to understand the importance of each variables using Kruskal–Wallis test. The Kruskal–Wallis is able to determine if all variables are of equal importance when it is present and when huge fluctuations in efficiency scores will be created in the absence of such variables. Similarly, an analysis of variance (ANOVA) is executed firstly to identify significant process parameters which then served as the basis for which the efficient frontiers using DEA are generated (Chen et al. 2013).

On the other hand, Jenkins and Anderson (2003) used a systematic statistical method in deciding which of the correlated variables identified can be omitted with least loss of information and which should be retained. The results of their study revealed that omitting variables that are highly correlated with one another and contain little additional information on the performance of departments can cause a major influence on the computed efficiency measures. Another approach is dealt by Alder and Yazhemsky (2010) which combined PCA and DEA to reduce the dimensionality of decision variables which consists of a large number of interrelated variables without much loss of information. The data compression is done by transforming the original data into a new set of variables which are uncorrelated with one another. A Monte Carlo simulation is further applied to generalize and compare two discrimination improving methods: (a) PCA applied to DEA, and (b) variable reduction based on partial covariance. The combination of PCA and DEA approach is also implemented by Omrani et al. (2015) in an integrated approach in assessing efficiency performance of electricity distribution companies.

These approaches entail some difficulties in target setting and evaluation goals because the original set of inputs and outputs are usually converted into new variables so that the latter variables are not of the same type as the former. It means that these new variables will not be appropriate for analysis and target setting (Rezaee 2015). The MODEA model is introduced to overcome the limitations of the conventional DEA models. In MODEA model, multiple objectives generate multiple frontiers. This approach, regardless of the number of DMUs, discriminates among the DMUs more effectively (Rezaee 2015).

Multi-objective data envelopment analysis (MODEA)

The MODEA model is based on the conventional DEA model given in (1) with the consideration of changing the variables to a non-fractional multi-objective model (Rezaee 2015). For simplicity, variables are denoted as $t_q = \left(\sum_{i=1}^{m_q} v_i^q x_{io}^q\right)^{-1}$, $v_i^q = t_q v_i^q$, and $\mu_r^q = t_q u_r$. As for the first objective, variables are given as $\mu_i^2 = \frac{t_2}{t_1}\mu_i^1$, $\mu_i^3 = \frac{t_3}{t_1}\mu_i^1, \ldots, \mu_i^Q = \frac{t_Q}{t_1}\mu_i^1$. By having, $\alpha_2 = \frac{t_2}{t_1}$, $\alpha_3 = \frac{t_3}{t_1}, \ldots, \alpha_Q = \frac{t_Q}{t_1}$ and $\mu_i = \mu_i^1$, then the conventional DEA model is converted to (2):

$$\begin{aligned}
&\text{Maximize}\left(\sum_{r=1}^{s}\mu_r y_{ro}, \alpha_2\sum_{r=1}^{s}\mu_r y_{ro}, \alpha_3\sum_{r=1}^{s}\mu_r y_{ro}, \ldots, \alpha_Q\sum_{r=1}^{s}\mu_r y_{ro}\right)\\
&\text{Subject to :}\\
&\sum_{r=1}^{s}\mu_r y_{rj} - \sum_{i=1}^{m_1} v_i^q x_{ij}^q \le 0 \quad j=1,\ldots,n, \quad q=2,\ldots,Q\\
&\sum_{i=1}^{m_q} v_i^q x_{ij}^q = 1 \quad j=1,\ldots,n, \quad q=1,\ldots,Q\\
&v_i^q, \mu_r > 0, \quad r=1,\ldots,s, \quad i=1,\ldots,m_q, \quad q=1,\ldots,Q
\end{aligned} \tag{2}$$

where α_q is the ratio of sum of weighted inputs in the first category to sum of weighted inputs in the qth category.

Several studies have made use of the MODEA model in various applications. For instance, Golany (1988) first presented a MODEA model which is designed as an interactive multi-objective linear programming (MOLP) procedure to select the preferred output targets given the input levels. Another variation of a MOLP problem is solved by Jahanshahloo et al. (2005) which consists of a one-stage algorithm for obtaining efficient solutions. On the other hand, Carrillo et al. (2016) presented a new method for ranking the evaluated DMUs according to its performance. This method uses common-weight DEA under a multi-objective optimization approach. Most studies apply a two-stage process wherein network DEA is

applied first to obtain the efficient solutions for a MOLP problem. With each iteration of the DEA model, one problem is solved and a new constraint is added.

On the other hand, Kao et al. (2014) proposed a multi-objective programming model as an alternative approach to solving network DEA. The divisional and overall efficiency of the organization is formulated as separate objective functions. The overall efficiency of DMUs is evaluated without neglecting the efficiencies of its sub-units. A network DEA approach is also presented by Despotis et al. (2015) in dealing with efficiency assessments in a two-stage process. This method uses multi-objective programming as its modeling framework. In another efficiency assessment problem, Mashayeki and Omrani (2015) presented a novel multi-objective model which aims to be used for effective portfolio selection. The model incorporates DEA cross-efficiency into Markowitz mean–variance model and deliberates return, risk, and efficiency of the portfolio. Then, Carayannis et al. (2016) presented a cohesive assessment and classification framework for national and regional innovation efficiency. The model proposed is based on DEA and is formulated as a multi-objective mathematical model to consider the objectives and constraints of the different stages of the innovation process.

Aside from the crisp MOLP model, the concept of the fuzzy set theory is also integrated such that various levels of uncertainty may be considered. In the study of Wu et al. (2010), they presented a fuzzy multi-objective programming model to select a reliable supplier in the presence of risk factors. A fuzzy dynamic multi-objective DEA model is presented by Jafarian-Moghaddam et al. (2011) in assessing the performance of railways as a numerical example to evaluate the results of the model. Then, Zhou et al. (2016) proposed a type-2 fuzzy multi-objective DEA model to evaluate sustainable supplier performance by combining effectiveness and efficiency and used the integrated productivity values to determine the sustainability of suppliers.

In real-life scenarios, the application of the MODEA approach as an evaluation tool is perceived to be interesting; however, it might be hampered due to the limitations of the conventional DEA in terms of the number of DMUs and its decision variables. Previously presented studies on MODEA are not also able to address this limitation, thus, the introduction of Shapley values in a MODEA approach (Rezaee 2015).

MODEA introduced by Rezaee (2015) uses multi-category of inputs and outputs to measure the technical efficiency of each DMUs. The approach applies Shapley value, a concept in a cooperative game theory, to determine the efficacies of each category. Shapley value index is an approach used to measure the power of coalitions in a cooperative game. It is calculated as the distribution of power among the categories in coalitions. The Shapley value measures a set of categories that are formed a coalition, according to its power. The approach starts with the classification of the inputs and outputs to different categories. Then, the efficacy of each category in coalitions is determined. In calculating the efficacy of each category, the impact of each category of a DMU is determined. Afterward, Shapley value is used as a criterion to determine the efficacy of the categories. The Shapley value helps to assign an appropriate weight to each objective function to obtain unique efficiency score. Lastly, technical efficiency scores of DMUs are calculated using Shapley values. With the use of MODEA, hierarchical efficiencies can be modeled flexible given that there might be different scenarios with decision variables not applicable to a general case (Carayannis et al. 2016).

The MODEA approach

This section describes how the MODEA approach based from Rezaee (2015) is carried out. The application of this methodology is motivated by the viability of this approach in the context of assessing the efficiency of university departments. In consideration of the very nature of university departments which involve a number of decision variables that is essentially greater than the number of DMUs, the implementation of the MODEA approach in this paper is also guaranteed to lead to more accurate results compared to that of the conventional DEA model:

Step 1: List possible coalitions. The list of coalitions of the categories is obtained by exhausting all possible sets from one category to n categories.

Step 2: Solve the efficacy of each category in coalitions. The objective efficacy degree (OED) of each coalition for $\mathrm{DMU}_j, \mathrm{OED}_j(K)$, denotes the marginal contribution of the coalition on the efficiency evaluation of DMU_j. The $\mathrm{OED}_j(K)$ is acquired using (3):

$$\mathrm{OED}_j(K) = \left|\frac{e_j(\Omega) - e_j\left(\frac{\Omega}{K}\right)}{e_j(\Omega)}\right|, \quad \forall K \subset \Omega \quad j = 1, \ldots, n \tag{3}$$

where the function $e_j(\Omega)$ is the optimal efficiency of DMU_j for the set of categories, and $e_j\left(\frac{\Omega}{K}\right)$ is the optimal efficiency of DMU_j for the set of categories excluding the coalition, K. While the OED for DMU_j if the qth category is excluded from K, $\mathrm{OED}_j\left(\frac{K}{\{q\}}\right)$, is acquired using (4):

$$\mathrm{OED}_j\left(\frac{K}{\{q\}}\right) = \left|\frac{e_j(\Omega) - e_j\left(\Omega \Big/ \left(\frac{K}{\{q\}}\right)\right)}{e_j(\Omega)}\right|, \quad \forall K \subset \Omega \quad j = 1, \ldots, n \tag{4}$$

The $e_j(\Omega)$, $e_j\left(\frac{\Omega}{K}\right)$, and $e_j\left(\Omega \Big/ \left(\frac{K}{\{q\}}\right)\right)$ is calculated as in (5):

$$\begin{aligned}
&\text{Maximize} \quad \frac{1}{|K|}\left(\sum_{q \in K} \alpha_q \sum_{r=1}^{s} \mu_r y_{r0}\right) \\
&\text{Subject to} \\
&\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m_1} v_i^1 x_{ij}^1 \le 0 \quad j = 1, \ldots, n \\
&\alpha_q \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m_q} v_i^q x_{ij}^q \le 0 \quad j = 1, \ldots, n \\
&\in K, q \ne 1 \\
&\sum_{i=1}^{m_q} v_i^q x_{ij}^q = 1 \quad j = 1, \ldots, n \quad q \in K \\
&v_i^q, \mu_r \ge \varepsilon \quad r = 1, \ldots, s \quad i = 1, \ldots, m_q \\
&\quad q \in K
\end{aligned} \tag{5}$$

where α_q is the ratio of the sum of inputs in the first category and the sum of inputs in the qth category. The worth of coalition K, $V(K)$, is obtained by (6):

$$V(K) = \sum_{j=1}^{n} OED_j(K) \tag{6}$$

while the worth of coalition K when the qth category is excluded from $V\left(\frac{K}{\{q\}}\right)$, is obtained through (7):

$$V\left(\frac{K}{\{q\}}\right) = \sum_{j=1}^{n} OED_j\left(\frac{K}{\{q\}}\right) \tag{7}$$

Step 3: Calculate the Shapley value. The efficacy of each category of inputs is taken by calculating the Shapley value, φ_q, using (8):

$$\varphi_q = \sum \frac{(|K| - 1)!(|\Omega| - |K|)!}{(|\Omega|)!}\left(V(K) - V\left(\frac{K}{\{q\}}\right)\right) \tag{8}$$

Step 4: Solve for the weights. After generating the Shapley values of each category, these values are applied in (9) to determine the weights, ω_q, of each category:

$$\omega_q = \frac{\varphi_q}{\sum_{q=1}^{Q} \varphi_q} \tag{9}$$

Step 5: Calculate the technical efficiency. The weights generated for each category are used in the model shown in (10) for measuring the technical efficiency of DMU_0, for instance:

$$\text{Maximize} \sum_{q=1}^{Q} \omega_q \lambda_q \tag{10}$$

Subject to

$$\lambda_1 \le \sum_{r=1}^{s} \mu_r y_{r1} \quad q = 1 \tag{11}$$

$$\lambda_q \le \alpha_q \sum_{r=1}^{s} \mu_r y_{r1} \quad q = 2, \ldots, Q \tag{12}$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m_1} v_i^1 x_{ij}^1 \le 0 \quad j = 1, \ldots, n \quad q = 1 \tag{13}$$

$$\alpha_q \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m_q} v_i^q x_{ij}^q \le 0 \quad j = 1, \ldots, n \quad q = 2, \ldots, Q \tag{14}$$

$$\sum_{i=1}^{m_q} v_i^q x_{ij}^q = 1 \quad j = 1, \ldots, n \quad q = 1, \ldots, Q \tag{15}$$

$$v_i^q, \mu_r, \lambda_q \ge \varepsilon \quad r = 1, \ldots, s \quad i = 1, \ldots, m_q \quad q = 1, \ldots, Q \tag{16}$$

where α_q is the ratio of the sum of inputs in the first category and the sum of inputs in the qth category. The objective function (10) measures the technical efficiency of DMU_1.

Constraint (11) ensures that the value for each of the category of inputs for DMU_1 is not greater than 1. Constraints (12) through (14) guarantee that the efficiency

score of each DMU is lesser than or equal to 1. In other words, these constraints are imposed to ensure that no DMUs and no category of inputs exceed the maximum efficiency level, which has been set equal to 1. Constraint (15) implies that the total value of the category of inputs of DMU_j is equal to 1. Constraint (16) ensures that each of the value of the input, category of inputs, and output variables, are strictly non-negative. This condition guarantees that the solution set in these variables are non-negative since the model cannot detect inefficiency when the values for the input and output variables are negative integers. The generated value for each DMU will determine whether the department is performing efficiently or not. If the efficiency score is equal to 1, it implies that the DMU is efficient, otherwise, it is inefficient. The results from the MODEA approach will also present the efficiency score of each of the category of inputs pertaining to a particular DMU.

Case study and analyses

In this section, an illustrative example is presented in order to show how the MODEA approach is applied in evaluating the efficiency of an academic institution in the Philippines for a particular academic year (note that to preserve the confidentiality of the case presented, the actual name of the university and its academic departments under a particular school is not divulged). A structured interview with the department chairperson is conducted to obtain relevant data relating to both input and output variables expended on the said department. Its results and findings are presented as follows.

Suppose that a university has six academic departments under a particular school. These departments (i.e., considered as DMUs) are, by nature, homogeneous since these use similar inputs and produce the same outputs. Additionally, these perform the same task and have similar objectives and goals. In selecting the decision variables, the category of inputs and outputs considered is in accordance with the views of the university's stakeholders in relation to its contribution to the overall efficiency of a department. The inputs are divided into three categories—human resource, facilities, and financial—while outputs are categorized as desirable factors (see Table 2).

Table 2 List of decision variables used to measure academic efficiency

Type	Category	Variables
Input	Human resource (HR)	Academic staff
		Non-academic staff
	Facilities (FA)	Classrooms
		Laboratories
	Financial (FI)	Research grants
		Department expenditure
Output	Desirable factors	Graduates
		Publications

Input variables

The academic staff is the main human resource utilized by every department that concentrates in both teaching and research activities. Their ranking is based on their expertise which is reflective of their highest educational attainment (i.e., doctorate degree, master's degree, and baccalaureate degree). For the purpose of proper aggregated measure composition of academic staff (Tzeremes and Halkos 2010), a pre-assigned weight is given to each rank. An academic staff who has a doctorate degree is assigned a weight of 0.60, while those who hold a master's degree is assigned a weight of 0.30. For an academic staff who is a baccalaureate degree holder, a weight of 0.10 is assigned. Another indicator for human resource is non-academic staff such as secretaries and working students. Every department has its own non-academic staff who does auxiliary errands to facilitate teaching and research activities. They also provide assistance to academic staff and student concerns.

Another input category is facilities used by academic staff and students to aid teaching and research activities. It includes classrooms and specialized laboratories.

The financial category is comprised of resources such as research grants and department expenditures which are utilized to produce a specific output. Research grants are awarded to academic staffs who apply for funding to conduct their research and have it submitted for publication. Department expenditures account for all teaching and research activities that aim to produce graduates.

Output variables

Two desirable outputs (i.e., graduates and publications) are targeted to be achieved by every department upon efficient utilization of all necessary input resources. Increasing the number of graduates at the end of every academic year reflects the quality of teaching performance rendered by the human resources available in each department. In terms of research activity, the increase in the number of publications is reflective of a department's research advancement. The forms of publication (i.e., dependent on its type) and authorship (i.e., dependent on author contribution) are pre-assigned with weights to properly aggregate the measure of publications (Tzeremes and Halkos 2010). In this illustrative example, journal articles and articles in conference proceedings are evident. Due to the fact that journal articles have undergone several strict, rigorous revisions according

to referees' suggestions and criticisms, it is assigned a higher weight compared to conference articles (Zobel 2000). A weight of 0.75 is given to journal articles while 0.25 is assigned to conference articles. For authorship merits, the weights depend on the extent of contribution each author has made. A higher weight, 0.75, is assigned to the main author while co-authors are given a weight of 0.25.

Case data and results

All succeeding computations are performed using Microsoft Excel© 2016 run in a Windows 8 64-bit operating software with Intel® Celeron® CPU 10170 at 1.60 GHz as its processor. To keep the confidentiality of data provided by the DMUs considered in this paper, all data used as decision variables in the MODEA model are normalized as listed in Table 3.

Following the steps in the MODEA approach presented in Sect. 3, three coalitions are listed under each category as shown in Table 4. Once the coalitions are known, the objective efficacy degree, $\mathrm{OED}_j(K)$, of each coalition are solved as in Table 5. Then, given in Table 6 are the efficacy of the category of inputs, its corresponding Shapley value, φ_q, and weights, ω_q. The efficacy of each category of inputs is taken by calculating the Shapley value. The Shapley value helps assign an appropriate weight to each of the category of inputs and obtain a unique efficiency score. These weights are used as coefficients of the objective function of the MODEA model.

Based on the calculated weights, it shows that the human resource category has the highest significance, followed by facilities, and financial category. The ranking of categories is in parallel with the results obtained by Rezaee (2015) in his study. The human resource (i.e., academic staff and non-academic staff) has the highest significance since it is recognized as the principal asset of a department that organizes the teaching and research activities for a specific course of a program. Its main task is to produce graduates by a combination of various resources which includes the facilities (Ferrari and Laureti 2005). The facilities category (i.e., classrooms and laboratories) has the second highest significance in recognition to the fact that this aids the human resource in its teaching and research activities (Agasisti and Dal Bianco 2009). Lastly, the financial category (i.e., research grants and department expenditures) garnered the lowest significance since it is dependent on the teaching and research activities organized by the human resource (Mantri 2006).

Table 4 Possible coalitions of each category

Category (q)	Coalition (K)
HR	(HR), (HR, FA), (HR, FI)
FA	(FA), (FA, HR), (FA, FI)
FI	(FI), (FI, HR), (FI, FA)

To proceed with the MODEA approach, an optimization model is developed in solving the efficiency score of each DMU. In solving for the efficiency score of each DMU involving its respective optimization models, Lingo for Windows Software version 16.0 is run on a Windows 8 64-bit operating software with Intel® Celeron® CPU 10170 at 1.60 GHz as its processor.

The results of the MODEA model for each DMU are shown in the column under the technical efficiency of Table 7. The efficiency score of each of the category of inputs is presented in the column under the efficiency using MODEA approach. Table 7 also provides the comparison of the efficiency score results using MODEA approach and the conventional DEA approach.

Discussion

The limitations of the conventional DEA models suggest that at least 24 university departments are needed to measure the efficiency score of the DMUs more accurately.

Table 3 Data collected for SOE departments' decision variables

DMU	Academic staff	Non-academic staff	Classrooms	Laboratories	Research grants	Department expenditures	Graduates	Publications
DMU 1	0.1234	0.2500	0.1667	0.1282	0.6667	0.0531	0.1055	0.1935
DMU 2	0.2468	0.1875	0.3333	0.1795	0.0000	0.2732	0.2612	0.0000
DMU 3	0.1646	0.0625	0.0952	0.2308	0.0000	0.1507	0.2401	0.0000
DMU 4	0.1709	0.1875	0.1905	0.2051	0.3333	0.0713	0.2111	0.0984
DMU 5	0.0949	0.1250	0.1429	0.1538	0.0000	0.1482	0.1293	0.0387
DMU 6	0.1994	0.1875	0.0714	0.1026	0.0000	0.3033	0.0528	0.6694

Table 5 Objective efficacy degree for three categories of inputs

Category (q)	Coalition (K)	DMU_1	DMU_2	DMU_3	DMU_4	DMU_5	DMU_6
HR	(HR)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.2618	0.6867	0.9066	0.7835	0.4436	0.6088
	$\mathrm{OED}_j(K)$	0.5483	0.5047	0.4589	0.1014	0.1841	0.0729
	(HR, FA)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.6218	0.5775	1.0000	1.0000	0.5690	1.0000
	$\mathrm{OED}_j(K)$	0.0731	0.2729	0.6092	0.4058	0.0467	0.5228
	(HR, FI)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.7560	0.7472	1.0000	0.7758	0.5033	1.0000
	$\mathrm{OED}_j(K)$	0.3046	0.6470	0.6092	0.0906	0.0743	0.5228
FA	(FA)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.9096	0.4639	0.6939	0.9285	0.6589	0.6443
	$\mathrm{OED}_j(K)$	0.5696	0.0226	0.1166	0.3053	0.2120	0.0189
	(FA, HR)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.6218	0.5775	1.0000	1.0000	0.5690	1.0000
	$\mathrm{OED}_j(K)$	0.0731	0.2729	0.6092	0.4058	0.0467	0.5228
	(FA, FI)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.8775	0.7255	1.0000	0.9643	1.0000	1.0000
	$\mathrm{OED}_j(K)$	0.5142	0.5992	0.6092	0.3555	0.8394	0.5228
FI	(FI)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.5603	0.5495	0.7384	0.6639	0.6667	0.8763
	$\mathrm{OED}_j(K)$	0.0332	0.2112	0.1883	0.0667	0.2262	0.3344
	(FI, HR)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.7560	0.7472	1.0000	0.7758	0.5033	1.0000
	$\mathrm{OED}_j(K)$	0.3046	0.6470	0.6092	0.0906	0.0743	0.9756
	(FI, FA)						
	$e_j(\Omega)$	0.5795	0.4537	0.6214	0.7114	0.5437	0.6567
	$e_j(\Omega/K)$	0.8775	0.7255	1.0000	0.9643	1.0000	1.0000
	$\mathrm{OED}_j(K)$	0.5142	0.5992	0.6092	0.3555	0.8394	0.5228

However, in the case study, only six university departments are evaluated. Hence, the results when using the conventional DEA models for this data set may be insufficient. The MODEA approach introduced by Rezaee (2015) is used to overcome this limitation. In Table 7, the efficiency scores of DMUs using DEA model and MODEA model are shown. The DMUs that garnered an efficiency score equal to 1.0000 are regarded as efficient, otherwise, it is not fully efficient.

In a comparison of results obtained using the conventional DEA model and MODEA model, it can be seen that there is a significant difference in the results. Based on the conventional DEA model, all DMUs are performing efficiently although not all category of inputs under each DMU is efficient. In contrary, results of the MODEA model reveal that no DMU is actually efficient. The fact that the number of DMUs considered is lesser than the number of decision variables makes the conventional DEA model give less discriminating ability thereby leading to a less accurate measure of efficiency. Correspondingly, the MODEA model showed a sufficient result compared to the conventional DEA model where clear discrimination among DMUs is made.

Table 6 Efficacy for three categories of inputs

Category (q)	Coalition (K)	$V(K)$	$V(K/\{q\})$	φ_q	ω_q
HR	(HR)	1.8703	0.0000	0.9357	0.3684
	(HR, FA)	1.9304	1.2450		
	(HR, FI)	2.2484	1.0601		
FA	(FA)	1.2450	0.0000	0.8217	0.3235
	(FA, HR)	1.9304	1.8703		
	(FA, FI)	3.4403	1.0601		
FI	(FI)	1.0601	0.0000	0.7823	0.3080
	(FI, HR)	2.2484	1.8703		
	(FI, FA)	3.4403	1.2450		

In reference to the results of the efficiency score of DMU*s* using the MODEA approach, DMU_4 has the highest efficiency followed by DMU_6, DMU_5, DMU_2, DMU_3, and DMU_1. As for the efficiency score on each category of inputs, it is remarkable that DMU_3 and DMU_6 have obtained an efficient score on HR and FA category, respectively. Even with such efficiency score on a particular category of inputs, it did not guarantee a high overall efficiency due to the fact that efficiency scores of other categories of input are taken into account as well. Table 7 also shows that DMU_2 has the lowest efficiency score as influenced by its very low efficiency score in FA category compared to other DMUs; it also scored second lowest in terms of efficiency in both HR and FI categories.

The inefficiency of DMUs can be traced back to how well input resources are utilized to produce desired outputs (Coelli et al. 2005). For DMU_1 and DMU_4, the main source of its inefficiency is FA category. While for DMU_2, DMU_3, DMU_5, and DMU_6, the main source of its inefficiency is FI category. Another contributory factor to the inefficiency of DMU_2 and DMU_3 is its failure to produce at least one publication for the evaluated academic year.

Conclusion

In measuring the efficiency, there may be instances when the number of DMUs under evaluation is lesser than the number of decision variables considered as such in an academic institution. When this is the case, the conventional DEA drops its discriminative power and accuracy in measuring the efficiency of DMUs. To address this limitation, this paper presents the MODEA approach using Shapley values that enable the use of a large set of decision variables and more accurately measure efficiency.

This approach has been implemented in an academic institution in the Philippines where six DMUs are evaluated given six inputs and two outputs. The conventional DEA approach has been likewise used to measure efficiency in the same case study. The results have proven that the MODEA approach is more accurate as it showed a more distinguished efficiency score of each DMU as compared to the conventional DEA approach which specified that all DMUs are efficient despite an inefficient score on all category of inputs. Furthermore, since the MODEA approach can also provide the sources of inefficiency, it is able to suggest which DMU should be emulated by an inefficient DMU for probable improvement on its overall efficiency. However, for this case, since no DMU is efficient, inefficient DMUs may refer to DMUs which has a higher efficiency score for benchmarking purposes.

In its realistic application, DMUs (i.e., university departments) considered in this case may further focus improvement efforts on decision variables from which a low efficiency score is obtained. Note that efficiency does not only involve inputs; it also requires maximization of outputs (Rogers 1998). Therefore, university departments should also look into the outputs produced given the set of inputs and carefully evaluate if they are able to maximize the outputs. Otherwise, there might be a possibility of underutilization of inputs.

Table 7 Efficiency scores of DMUs

Departments	Efficiency score computed from the conventional DEA			Efficiency using the conventional DEA model	Efficiency using the MODEA model	Efficiency score computed from the MODEA		
	HR	FA	FI			HR	FA	FI
DMU_1	1.0000	0.9851	1.0000	1.0000	0.5875	0.6755	0.4450	0.6179
DMU_2	0.6855	1.0000	0.6001	1.0000	0.4808	0.7255	0.3730	0.2703
DMU_3	1.0000	1.0000	1.0000	1.0000	0.6557	1.0000	0.4769	0.3873
DMU_4	0.7951	0.9035	1.0000	1.0000	0.7247	0.8710	0.4572	0.8063
DMU_5	0.6855	0.7073	0.5476	1.0000	0.5801	0.9410	0.3923	0.2991
DMU_6	1.0000	1.0000	1.0000	1.0000	0.6679	0.7527	1.0000	0.2174

For future work, other probable input and output variables (i.e., number of students and operating expenses) can be incorporated in the MODEA model to assess the performance of university departments. Additionally, data from the previous academic years can be looked into just so a direct comparison can be made, thus, serving as a basis for a probable point of improvement depending on which variable each DMU fell short for any given period. Another area that could be interestingly considered in the future is to incorporate uncertainty that may be present in data gathering of actual values of inputs and outputs. For instance, this may be made possible by introducing the fuzzy set theory in the context of the MODEA framework.

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