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Non-parametric Approach for Evaluating the Performance of Engineering Schools*

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The proposed Data Envelopment Analysis (DEA) model aims at creating a meaningful multiple criteria decision making platform for both national and international educators and educational administrators. The model compares the performance of each department in the School of Engineering at the University of Bridgeport with each other and with the School. In this regard, four independent DEA models are created, corresponding to the perspectives proposed by the Balanced Scorecard (BSC) approach. Data and case studies are provided to demonstrate the functionality of the proposed model.

Keywords: school of engineering; decision making; engineering education; data envelopment analysis

1. INTRODUCTION AND LITERATURE REVIEW

SCIENCE AND ENGINEERING are two disciplines that are highly receptive to the changes in demand for products and services. These disciplines can either be leading in nature, namely, they create the demand in the market (push) for new products and/or services, or they can adopt the changes caused by the varying market conditions (pull). Regardless of the reason, both science and engineering have the responsibility to be compatible with the emerging needs of the market. This fact is also true for the institutions awarding science and engineering degrees. Such higher education institutions also require continuous monitoring and evaluation in order to remain competitive in the educational arena.

Generally, educational institutions are evaluated for their (1) academic affairs and (2) administrative and financial operations. Academic affairs are monitored by outside authorities such as professional accrediting agencies, State Departments of Higher Education, and the regional accrediting bodies (e.g. NEASC), whereas outcome assessment for administrative and financial operations are handled by the Board of Trustees and the regional accrediting body. In addition, educational institutions also have internal assessment processes conducted to (1) ensure the ability to meet and/or exceed the national educational standards, (2) to be compatible with the mission and vision statements of the organization, and (3) to guarantee the continuous improvement of students, and academic and administrative personnel. This internal assessment process embodies a broad spectrum of performance criteria such as curriculum development and revision, contributions to the literature, ethnicity/gender profiles, budget allocation, and student and personnel development. Therefore, several factors that are tangible or intangible in nature have to be considered during internal reviews, thus creating a complex problem environment for the evaluators/decision makers.

This being the motivation, this work aims to provide a systematic mechanism and framework to evaluate the performance of academic departments in higher education. The innovation in the proposed approach stems from the fact that traditional academic evaluation or cyclical program review of departmental performance is typically centered on the view of the administrating entity or entities conducting the review, be that a Dean, Vice President, Provost, Chancellor, President, some permutation thereof, or a review committee. The review process in higher education is normally a function of a set of quantitative and possibly qualitative parameters or 'norms' that constitute, in the opinion of the reviewing entity, an appropriate set of assessment measures to evaluate departmental performance. In many instances in higher education, these relevant parameters or 'standards' are a function of the preferences of the entity performing the review. The devising of a global vision with multiple constituencies perspectives in the evaluation process often gets ignored or muddled in the process. Our proposed approach suggests a methodology that can be applied to an

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academic department residing within any global/international institution of higher education. It enables the systematic production of several perspectives and evaluation/assessment measures based on different constituency views, thus eliminating the traditional biases inherently present within a typical program performance review process that concentrates only on one or very few perspectives, such as financial, scholarly or other. The multiple viewpoints/constituency perspectives that our approach exemplifies and generates allows for a more global, fair and standardized evaluation tool: it provides the review process designers with the tools that enable the generation—from existing data—of different points of view/perspectives for evaluating programs based on the formulation of the quantitative parameters that are relevant to each point of view/constituency's interest.

In this regard, this paper proposes a Data Envelopment Analysis (DEA) model to compare each department in the School of Engineering at the University of Bridgeport with each other and with the School. Data and case studies are provided to demonstrate the functionality of the proposed model.

Data Envelopment Analysis (DEA) is a non-parametric approach that compares similar entities, i.e., decision making units (DMUs), against the 'best virtual decision making unit'. Owing to various advantages and ease of use, DEA has been employed extensively in various areas, such as health care, education, banking, manufacturing, and management.

One of the relevant studies is published by Deniz and Ersan [1]. There an integrated approach to the academic decision-support system design has been demonstrated that includes administrative and planning features as well as statistical analysis of performance features.

Johnson and Zhu [2], in their work, employed DEA to select the most promising candidates to fill an open faculty position. DEA has also been used extensively in the environmental arena. To this extent, Sarkis [3] proposed a two-stage methodology to integrate managerial preferences and environmentally conscious manufacturing (ECM) programs. Subsequently, Sarkis and Cordeiro [4] investigated the relationship between environmental and financial performance at the firm level. Furthermore, Talluri *et al.* [5] applied DEA and Goal Programming methods to a Value Chain Network (VCN), considering the cross efficiency evaluations of Decision Making Units (DMUs).

In the performance evaluation area, the literature offers several performance measurement frameworks including the Balanced Scorecard approach proposed by Kaplan and Norton [6] since there is considerable interest here in the role of strategic performance scorecards in assisting managers to develop competitive strategies. BSC, first proposed by Kaplan and Norton [7], allows the introduction of intangible performance measures and provides decision makers with the appropriate measurement criteria. This being the motivation, Johnson [2] applied the BSC approach for selecting and developing environmental performance indicators. Proposed balanced scorecard integrates environmental performance within the context of corporate strategic objectives. In the same area, Snow and Snow [8] proposed a Balanced Scorecard approach for evaluating the performance of organizations by including an additional perspective to conventional BSC.

Martinsons *et al.* [9] also developed a BSC that measures and evaluates information systems activities. Kloot and Martin [10] applied the BSC approach to measure the performance of local governmental activities. Olson and Slater [11] reported a BSC approach providing an insight into the performance evaluation requirements of the different strategy types and, as such, the associated requirements for their successful implementation. Sandstrom and Toivanen [12] proposed a performance analysis based on the BSC and connected product development and design to the management system of the company. Cheng *et al.* [13] presented a case that required students to identify the corporate objectives and critical success factors of the media and software division of a company and propose performance measures that should motivate employees to work towards these objectives. Lohman *et al.* [14] proposed a prototype performance measurement system that is a BSC adapted to the needs of Nike. Ravi *et al.* [15] proposed a combination of the BSC and analytic network process (ANP)-based approach model for the reverse logistics operations for EOL computers. In their study, various criteria, sub-criteria, and determinants for the selection of reverse logistics options are interrelated. The literature on Balanced Scorecard that deals with strategies and technologies for effectively managing businesses is quite vast. For further information regarding the development of the BSC approach and performance measurement metrics, please see Bontis *et al.* [16].

2. INTRODUCTION TO THE DATA ENVELOPMENT ANALYSIS APPROACH

Data Envelopment Analysis (DEA) is a non-parametric approach that compares similar entities, e.g., decision making units (DMUs), against the 'best virtual decision making unit.' DEA is usually modeled as a linear programming (LP) model providing relative efficiency scores for each DMU under consideration. The most appealing advantage of DEA is, unlike parametric approaches such as regression analysis (RA), that DEA optimizes each individual observation and does not require a single function that best suits all observations [17].

Furthermore, DEA, unlike parametric

approaches such as regression analysis (RA), optimizes on each individual observation and does not require a single function that best suits all observations [17]. Comparison of DEA and RA has been well studied in the literature. Even though there are some studies emphasizing the advantages of both (e.g., see Thanassoulis [18]), there are various studies in the literature reporting the DEA as a more advantageous technique.

For instance, Banker *et al.* [19] compared estimates of technical efficiencies of individual hospitals, obtained from the econometric modeling of the translog cost function, and the application of DEA and reported that DEA estimates were highly related to the capacity utilization.

Bowlin *et al.* [20] compared DEA and RA with a set of fifteen hypothetical hospitals and reported that DEA outperformed RA with its ability to identify the sources of inefficiencies by underlining the resources that are used in excess in inefficient hospitals. In addition, the authors claimed that DEA also performed better in estimating and returning scale characterizations. Sarkis [21] compared DEA and conventional multiple criteria decision making (MCDM) tools in terms of efficiency and concluded that DEA appeared to perform well as a discrete alternative MCDM tool. Reinhard *et al.* [22] compared Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) to compare the calculation of efficiency.

DEA algorithms can be classified into two categories according to the 'orientation' of the model: *Input-oriented* DEA models concentrate on reducing the amount of input by keeping the output constant while *Output-oriented* DEA models focus on maximizing the amount of output with the constant amount of input. In DEA modeling, inputs are considered as the items that are subject to minimization, whereas outputs are the items that are 'more is better' in nature, i.e., the items that are subject to minimization.

Further classification of DEA models is concerned with the 'optimality scale' criterion. That is, DEA models can work under the assumption of Constant Returns to Scale (CRS), or non-constant returns to scale, i.e., Increasing Returns to Scale (IRS), 'Decreasing Returns to Scale (DRS)', and 'Variable Returns to Scale (VRS)', implying that not all DMUs are functioning at a optimality scale. VRS was initially introduced by Banker *et al.* [23] as an extension of the CRS DEA model. In this paper, we employ an output oriented CRS DEA model.

A basic DEA model allows the introduction of multiple inputs and multiple outputs and obtains an 'efficiency score' of each DMU with the conventional output/input ratio analysis. Defining basic efficiency as the ratio of weighted sum of outputs to the weighted sum of inputs, the relative efficiency score of a test DMU p can be obtained by solving the following DEA ratio model (CCR) proposed by Charnes *et al.* [24]:

$$\begin{aligned} max \quad & \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \\ s.t. \quad & \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \leq 1 \quad \forall \text{ DMUs } i \\ & v_k, u_j \geq 0 \qquad \forall\, k,j. \end{aligned} \tag{1}$$

where $k = 1$ to s, $j = 1$ to m, $i = 1$ to n, and

y_{ki} = amount of output k produced by DMU i,
x_{ji} = amount of input j produced by DMU i,
v_k = weight given to output k,
u_j = weight given to input j.

Equation (1) can be easily converted into a linear program as in Equation (2). We refer the reader to the study by Charnes *et al.* [17] for further explanation of the model.

$$\begin{aligned} max \quad & \sum_{k=1}^{s} v_k y_{kp} \\ s.t. \quad & \sum_{j=1}^{m} u_j x_{jp} = 1 \\ & \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \quad \forall \text{ DMUs } i \\ & v_k, u_j \geq 0 \qquad \forall\, k,j, \end{aligned} \tag{2}$$

where the $\sum_{j=1}^{m} u_j x_{jp} = 1$ constraint sets an upper bound of 1 for the relative efficiency score.

In the CCR model provided in Equation (2), evaluating the efficiency of n DMUs correspond to a set of n LP problems. Using duality, the dual of the CRS model can be represented as in Equation (3):

$$\begin{aligned} min \quad & \theta \\ s.t. \quad & \sum_{i=1}^{n} \lambda_i x_{ji} - \theta x_{jp} \leq 0 \quad \forall \text{ Inputs } j \\ & \sum_{i=1}^{n} \lambda_i y_{ki} - y_{kp} \geq 0 \quad \forall \text{ Outputs } k \\ & \lambda_i \geq 0 \qquad \forall \text{ DMUs } i. \end{aligned} \tag{3}$$

Equation 3 above is the dual of the basic input-oriented CCR model assuming constant returns to scale for all the inputs and outputs. Using Talluri's notation [25], the dual of a basic output-oriented CRS model can be written as follows:

$$\begin{aligned} max \quad & \phi \\ s.t. \quad & x_{jp} - \sum_{i} \lambda_i x_{ji} \geq 0 \qquad \forall \text{ Inputs } j \\ & -\phi y_{kp} + \sum_{i} \lambda_i y_{ki} \geq 0 \quad \forall \text{ Outputs } k \\ & \lambda_i \geq 0 \qquad \forall \text{ DMUs } i. \end{aligned} \tag{4}$$

In the case where the assumption that not all DMUs are functioning at an optimality scale, Equation (4) could be converted into a VRS model by including the constraint $\sum_i \lambda_i \geq 0$ to the set of technological constraints.

The result of the model, Φ is the relative efficiency score of each DMU. The inverse of the variable Φ ($1/\Phi$) provides the technical efficiency value (*TE*) for each DMU. Here, given that the technical efficiency value is equal to one ($TE = 1$), DMU p is considered efficient for its selected weights. Hence, DMU p lies on the optimal frontier and is not dominated by any other DMU. With similar reasoning, if the technical efficiency value is less than one ($TE < 1$), then DMU p is not on the optimal frontier and there exists at least one efficient DMU in the population.

The following demonstrates the application of the CRS DEA model to the evaluation process for the School of Engineering.

3. APPLYING DATA ENVELOPMENT ANALYSIS TO THE SCHOOL OF ENGINEERING DEPARTMENTAL REVIEW PROCESS

At the graduate level, the School of Engineering has a total of four departments each offering a Master of Science degree, namely, Computer Science and Engineering (CPSE), Electrical Engineering (EE), Mechanical Engineering (ME), and Technology Management (TM), in addition to the doctorate degree offered by the Department of Computer Science and Engineering. At present, evaluations and recommendations regarding faculty members are conducted by the department chairs, whereas financial and administrative decisions are handled by the Dean's Office. However, these decisions are mostly made on a need-basis and do not involve a detailed comparative analysis among various departments, potentially leading to a gap between the overall institutional goals and objectives and the departmental activities.

The goal of the generation of multiple analysis perspectives and multiple views of looking at the same department not only serves to 'compare' departments, but allows the review process designers to allow for different constituencies to look at the performance of a department (or more) from a particular perspective that is relevant to their own interests and needs without having to sort through a significant set of parameters to get an 'overall' perspective, which is not a realistic aspiration as different entities/constituencies typically care about performance criteria in different ways and in different areas of interest. For example, the financial perspective is typically very different from the scholarly perspective, student perspective, faculty perspective, alumni perspective, media perspective, growth potential perspective, etc.

Therefore, to bring the monitoring and evaluation processes to a level where more meaningful data will be available to the decision makers, this paper proposes a DEA model to rank the efficiency of each department from different aspects.

One of the most commonly used approaches to evaluate business operations is called the Balanced Scorecard (BSC). Used as a new strategic management system, the scorecard addresses a serious deficiency in traditional management systems: their inability to link a company's long-term strategy with its short-term actions [7].

This approach was first introduced by Kaplan and Norton [7] in the early 1990s. Since then, the concept has been widely used in business as a tool for implementing a business strategy and has become the focus of many research endeavors. BSC combines both financial and non-financial performance indicators in a single report and aims to provide managers with richer and more relevant information about activities they are managing than is provided by financial measures alone.

Kaplan and Norton [26] proposed that the number of measures on a balanced scorecard should also be constrained in number and clustered into four groups, namely, *customer perspective*, *internal business processes perspective*, *financial perspective* and *learning and growth perspective*. The BSC approach intends to keep score of a set of items that maintain a balance 'between short- and long-term objectives, between financial and non-financial measures, between lagging and leading indicators, and between internal and external performance perspectives' [27].

Customer perspective concentrates on accomplishing the mission statement while providing value to the customers.

Internal business processes perspective concentrates on meeting the demands of customers and investors while achieving productivity and efficiency in the work flows.

Financial perspective concentrates on achieving financial success while providing value to the investors.

Learning and growth perspective concentrates on obtaining continuous improvement via innovation and learning while achieving the objectives included in the mission statement.

The proposed DEA model in this study aims at comparing the departments in the School of Engineering with each other and with the School of Engineering using four DEA models each corresponding to one of the perspectives imposed by the BSC. To achieve this, the data for the departments are collected via the DEA models to evaluate the relative efficiency of each DMU (departments and the School), and is employed with a total of 12 performance criteria and four perspectives.

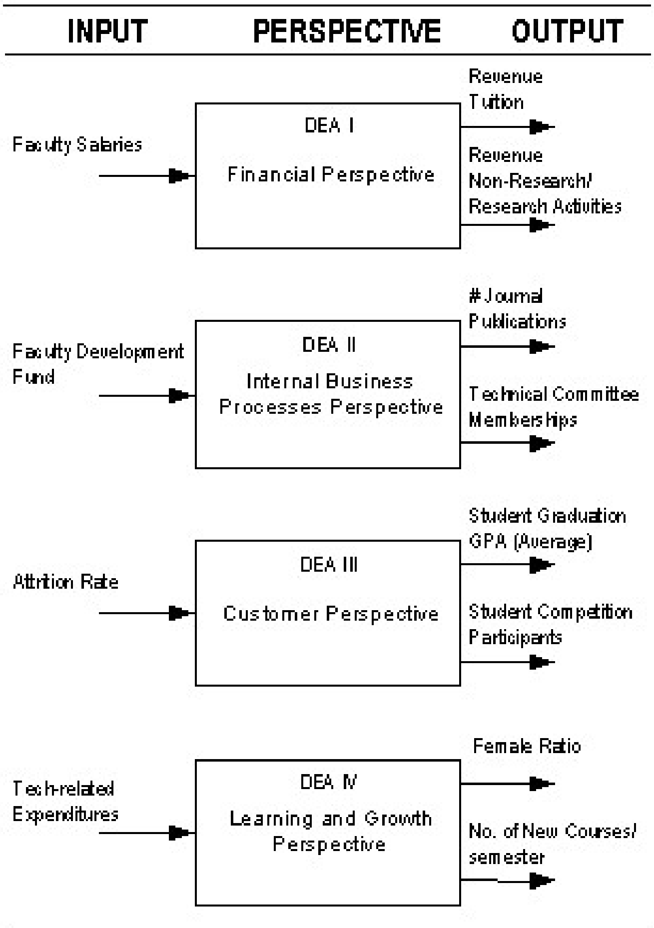

Fig. 1. Simplified schematic diagram of the proposed DEA models (Set a).

3.1 DEA Model I for the Evaluation Process

In DEA modeling, inputs are generally considered as the items that are subject to minimization whereas outputs are the items that need to be maximized. In our model, the departments and the School of Engineering correspond to decision-making units in the DEA model, while departmental data correspond to criteria in the DEA model, dependent on the definition of the indicators (inputs or outputs in the DEA model). Figure 1 lists the proposed DEA models and related input and output variables that are fed into the four DEA models.

In the figure, the variable *Female Ratio* is calculated as the sum of female faculty and female student percentages. The sum is then divided by two to get a normalized value representing the female contribution to the School activities. The related data set is provided in Table 1.

Table 1. Initial data for the D EA model

Input/Output variables	**SOE**	**CPSE**	**EE**	**TCMG**	**ME**	**Ph.D. CPSE**
No. of journal publications/year	38	12	6	8	3	9
Revenue from research/non-research	\$8.2m	\$5.1m	\$0.7m	0	\$1.1m	\$1.3m
Student enrollment	1170	300	350	303	195	22
No. of faculty members (full time faculty)	23	5.5	6	5	4	2.5
Revenue from tuition and fees	\$13.7m	\$3.51m	\$4.1m	\$3.55m	\$2.28m	\$0.26m
Faculty salaries (current average, all)	\$74k	\$85k	\$68k	\$70k	\$64k	\$88k
Students graduation GPA (average)	3.35	3.4	3.25	3.35	3.3	3.85*
Technical committee memberships	37	12	6	5	2	12
Student competition participants	76	18	20	16	10	12
Women faculty	5	1	1	2	1	0
Women students	150	40	45	38	25	2
Attrition rate (max retention)	4%	4%	4%	4%	4%	0%
Faculty professional development funding	\$140k	\$40k	\$40k	\$30k	\$20k	\$10k
Tech-related expenditures (s/w, h/w, etc.)	\$5.3m	\$2.75m	\$1.2m	\$0.05m	\$0.9m	\$0.4m
No. of new courses/semester	15	3	3	3	4	2

* Estimated value.

Table 2. Relative efficiency score and rank of each DM

Financial perspective			Internal business processes perspective		
Rank	DMU	Score	Rank	DMU	Score
1	CPSE	1.000	1	PhD_CPSE	1.000
1	EE	1.000	2	CPSE	0.333
1	TCMG	1.000	3	SOE	0.302
4	ME	0.959	4	TCMG	0.296
5	SOE	0.891	5	EE	0.167
6	PhD_CPSE	0.542	5	ME	0.167
Customer perspective			**Learning and growth perspective**		
Rank	**DMU**	**Score**	**Rank**	**DMU**	**Score**
1	PhD_CPSE	1.0000	1	TCMG	1.000
2	CPSE	0.0022	2	PhD_CPSE	0.083
3	SOE	0.0021	3	ME	0.074
3	TCMG	0.0021	4	SOE	0.047
5	ME	0.0021	5	EE	0.042
6	EE	0.0021	6	CPSE	0.018

Using this data set, the output-oriented DEA model is run for each department in the sample using DEA-Solver-PRO 5.0. DEA-Solver-PRO is a DEA software designed on the basis of the textbook by Cooper *et al.* [28] to solve and analyze DEA models. After the runs are completed for independent DEA models, the technical efficiency (*TE*) is calculated as the reciprocal of each model outcome (TE = 1/) for each department. The results of the model are presented in Table 2.

According to the DEA results depicted in Table 2, the Department of Computer Science and Engineering has the highest financial score along with the Departments of Electrical Engineering and Technology Management whereas the Ph.D. program is the most efficient in terms of internal business processes. Furthermore, the Ph.D. program is efficient in terms of customer perspective whereas the master's degree program in Technology Management is the leader in terms of learning and growth perspective (Figure 2).

3.2 DEA Model I for the Evaluation Process

In order to analyze and improve the proposed approach further, an additional set of four DEA models for the four perspectives (namely, *financial, internal business processes, customer, and learning and growth*) are built and run.

Figure 3 depicts the proposed DEA models (DEA model b) and related input and output variables.

Here, DEA model I embodies Total Revenue from research/non-research activities per faculty and staff member, and Total Revenue from tuition per faculty and staff member as output variables whereas Faculty and Staff salaries constitute the input variable. DEA model II includes Faculty Development per faculty as its input variable while Journal and Conference Publications per faculty and Technical Committee Memberships, Session, Conference and Workshop Chairpersonships, Journal and Book Editorial Duties per faculty are the output variables. DEA model III

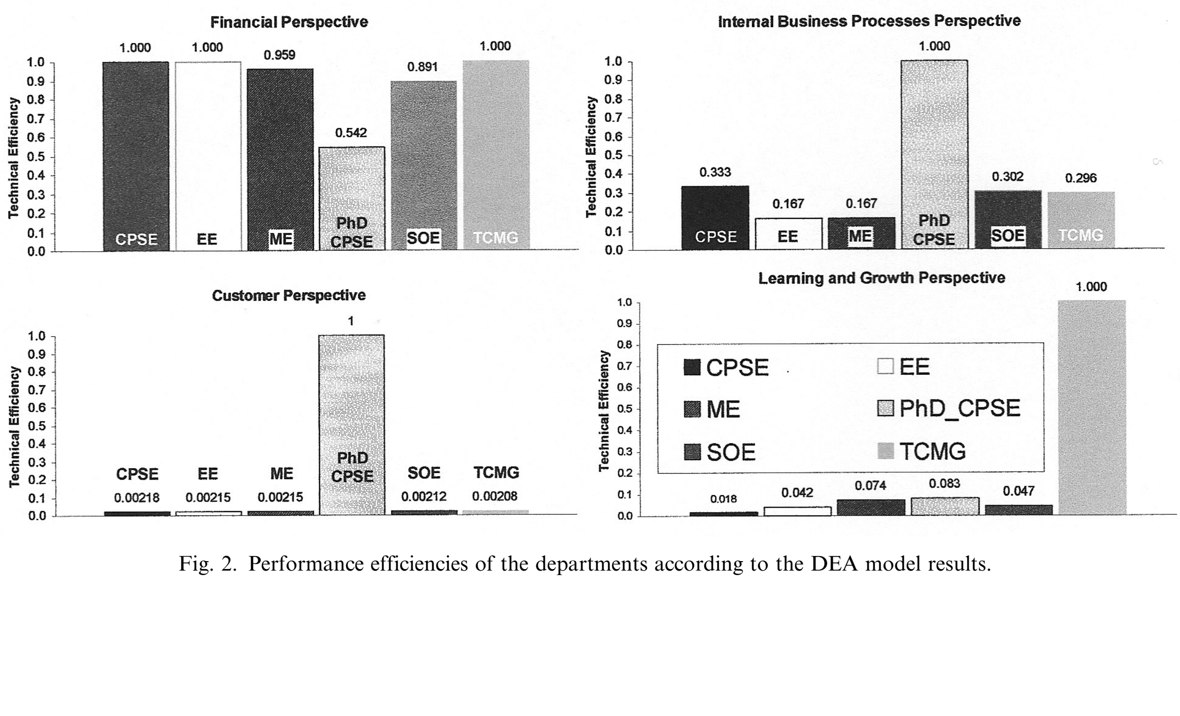

Fig. 2. Performance efficiencies of the departments according to the DEA model results.

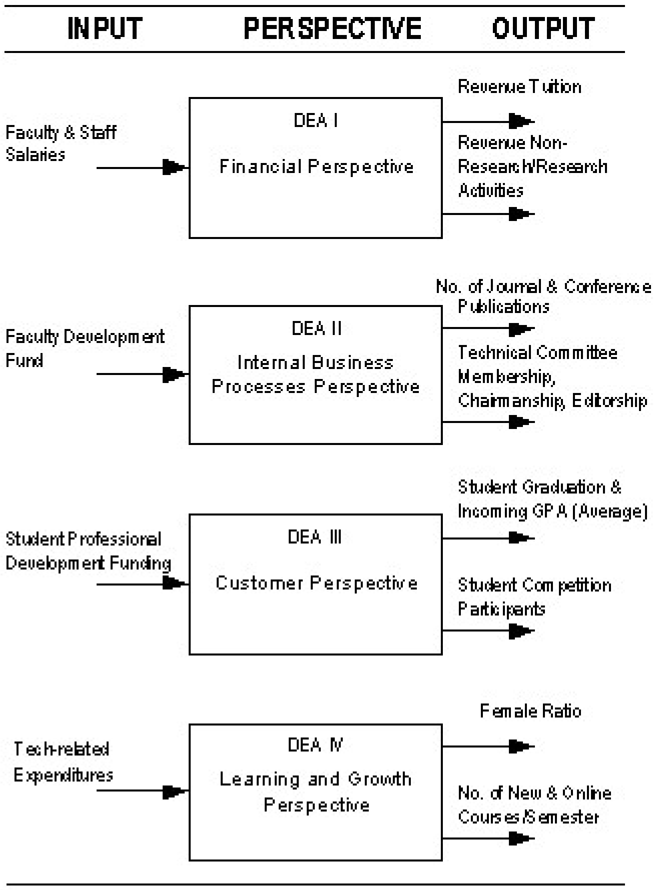

Fig. 3. Simplified schematic diagram of the proposed DEA models (Set b).

includes the average of incoming and graduation GPA of the student body as one of the output variables. Competition Participation per student is another output for this model whereas Student Professional Development Funding per student (thousand) becomes the input variable. Finally, the Number of New and Online Courses per semester per faculty member and the Female Ratio (identical to DEA model a) are the two output variables for the DEA model IV, and the Tech-Related Expenditure (software, hardware, etc.) per department.

Using these input and output variables, each output-oriented DEA model is run for all departments in the sample. The results of the model are presented in Table 3.

Table 3. Relative efficiency score and rank of each DMU

Financial perspective			**Internal business processes perspective**		
Rank	**DMU**	**Score**	**Rank**	**DMU**	**Score**
1	CPSE	1.00	1	PhD_CPSE	1.00
1	EE	1.00	2	CPSE	0.28
3	TCMG	0.99	3	SOE	0.27
4	SOE	0.87	4	TCMG	0.20
5	ME	0.79	5	EE	0.18
6	PhD_CPSE	0.58	6	ME	0.14
Customer perspective			**Learning and growth perspective**		
Rank	**DMU**	**Score**	**Rank**	**DMU**	**Score**
1	ME	1.00	1	TCMG	1.00
2	TCMG	0.80	2	SOE	0.07
3	EE	0.67	3	PhD_CPSE	0.06
4	SOE	0.56	4	CPSE	0.05
5	PhD_CPSE	0.48	5	ME	0.04
6	CPSE	0.36	6	EE	0.02

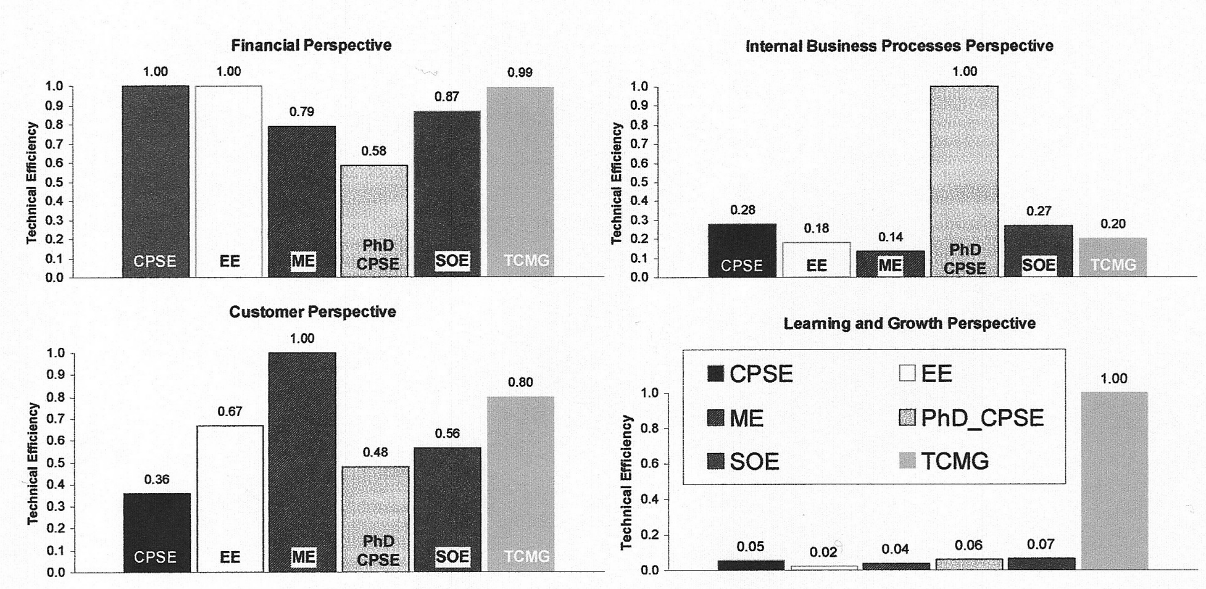

Fig. 4. Performance efficiencies of the departments according to the DEA model (Set b) results.

According to the DEA results depicted in Table 3, now the Department of Computer Science and Engineering has the highest financial score along with the Departments of Electrical Engineering. Compared with DEA Set a, Technology Management is no longer among the efficient departments even though it still has a significantly high technical efficiency score, 99%. The Ph.D. program is once again the most efficient in terms of internal business processes. Furthermore, the M.S. in Mechanical Engineering program is efficient in terms of customer perspective. This is most likely caused by the low student professional development funding per student. The master's degree program in Technology Management is the leader in terms of learning and growth perspective (Figure 4).

4. CONCLUSIONS AND FUTURE RESEARCH

In this study, an implementation of an output-oriented DEA model is described and applied to the School of Engineering at the University of Bridgeport to provide a comparative analysis.

The proposed approach considered the creation of a meaningful decision making platform for both national and international educators and educational administrators since they are encouraged to employ the formulation in devising appropriate multiple criteria for designing program reviews for their various departments. They also have to perform, in parallel, the review to serve a wide set of constituencies/audiences depending on their interest areas, and not only one entity/perspective. Here, the comparison base could be with internal departments or departments external to the institution, as long as the data are available for other entities with which the comparison is to be made. However, one advantage for external comparisons that our approach provides is that the 'full' data do not need to be available for an external entity in order to be used as a comparison base. As so long as the data are available for a particular perspective, that perspective—at least—can be compared among several internal or external departments.

Furthermore, the types of decisions/improvements to be made are to be based on the different perspectives under consideration. Despite the fact the some of the perspectives will yield results that are undesirable for some departments; it will still be inevitable that these same departments would/could receive very complimentary results using another analysis perspective. The input and output parameters for a DEA model that yields undesirable BSC perspective results are to be looked at by the respective department and attempts to increase or decrease these input or output parameters, based on the desired outcome, are to be conducted in order to rectify the efficiency issue.

In addition, having the Balanced Scorecard performance indicators used in the modeling structure provides a basis for further improvements. Hence, in the future, goals for each perspective can be determined and can be associated with related objectives. Furthermore, the number of perspectives can also be increased leading to a tailored Balanced Scorecard, given that the existing structure doesn't allow a thorough assessment.

On another note, the model structure is limited to a single DEA model for each perspective with a total of three input/output variables. This is mainly because of the mathematical restrictions of the DEA model, since it is commonly accepted that the number of DMUs has to be at least 2 to 5 times the total number of input/output variables used in the model. This limitation can be easily handled by introducing multiple DEA models for each perspective.

As with every data dependent approach, the accuracy and completeness of the data set is another issue that needs to be taken into consideration. For instance, since the program was started only three years ago, 'graduation GPA' and 'student employment percentage after graduation' are estimated due to the lack of students who obtained a Ph.D. degree from the School. In future, the above enhancements will be considered to create a more comprehensive assessment structure for the School of Engineering.

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