# A Hybrid Approach to Evaluate the Performance of Engineering Schools

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## ABSTRACT

Science and engineering (S&E) are two disciplines that are highly receptive to the changes in demand for products and services. These disciplines can either be leading in nature, viz., they create the demand in the market (push) for new products and/or services, or 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 to be able to remain competitive in the educational arena. Generally, educational institutions are evaluated for their (i) 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 (i.e., 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, 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 and 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 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.

**Keywords:** School of Engineering, Decision Making, Engineering Education, Data Envelopment Analysis.

## 1. Introduction and literature review

This paper proposes a Data Envelopment Analysis (DEA) model to compare 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.

The paper is organized as follows: A literature review regarding applications of Data Envelopment Analysis (DEA) and the Balanced Scorecard (BSC) approach are provided next. A mathematical introduction to Data Envelopment Analysis is provided in section 2 and case study data and modeling are provided in Section 3. The paper concludes with considerations regarding future enhancements and discussion.

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". Due to various advantages and ease in its 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 Johnson and Zhu[1]. In their work, the authors employed DEA to select the most promising candidates to fill an open faculty position. DEA has also been utilized extensively in the environmental arena. To this extent, Sarkis[2] proposed a two-stage methodology to integrate managerial preferences and environmentally conscious manufacturing (ECM) programs. Subsequently, Sarkis and Cordeiro[3] investigated the relationship between environmental and financial performance at the firm level. Furthermore, Talluri *et al*.[4] 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 [5] since there is considerable interest here in the role of strategic performance scorecards in assisting managers develop competitive strategies. BSC, first proposed by Kaplan and Norton[6], allows the introduction of intangible performance measures and provides decision makers with the appropriate measurement criteria. This being the motivation, Johnson[7] 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. To provide 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, i.e., 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), DEA optimizes each individual observation and does not require a single function that suits best for all observations[17].

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.*[18] 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.*[19]:

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

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.

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

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 Eq. (3):

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

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[20], the dual of a basic output-oriented CRS model can be written as follows:

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

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, $\Phi$ is the relative efficiency score of each DMU. The inverse of the variable $\Phi$ ($1/\Phi$) provides the technical efficiency value ($TE$) for each DMU. Here, given 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, viz., 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.

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[6].

This approach was first introduced by Kaplan and Norton [6] 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 [21] proposed that the number of measures on a balanced scorecard should also be constrained in number, and clustered into four groups viz., *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" [22].

*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.

### 4.1 DEA model 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 model.

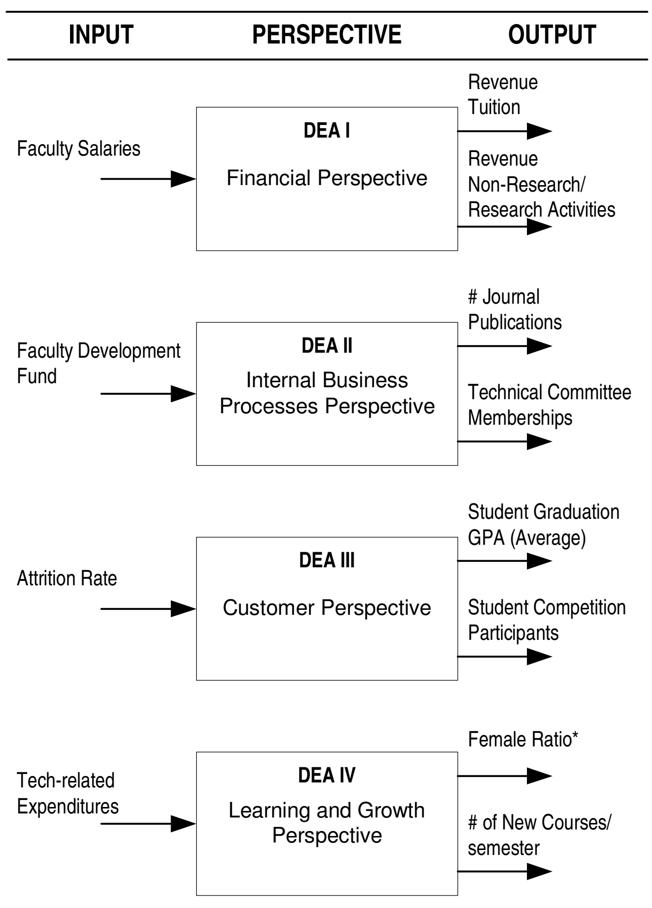


**Figure 1.** Simplified schematic diagram of the proposed DEA models.

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 DEA model

| Input/Output Variables | SOE | CPSE | EE | TCMG | ME | Ph.D. CPSE |
|---|---|---|---|---|---|---|
| # 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 |
| # 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 |
| # of New Courses/semester | 15 | 3 | 3 | 3 | 4 | 2 |

* Estimated value

Using this data, 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.[23] 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 ($TE = 1/\Phi$) for each department The results of the model are presented in Table 2.

**Table 2.** Relative efficiency score and rank of each DMU.

| 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 |

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).

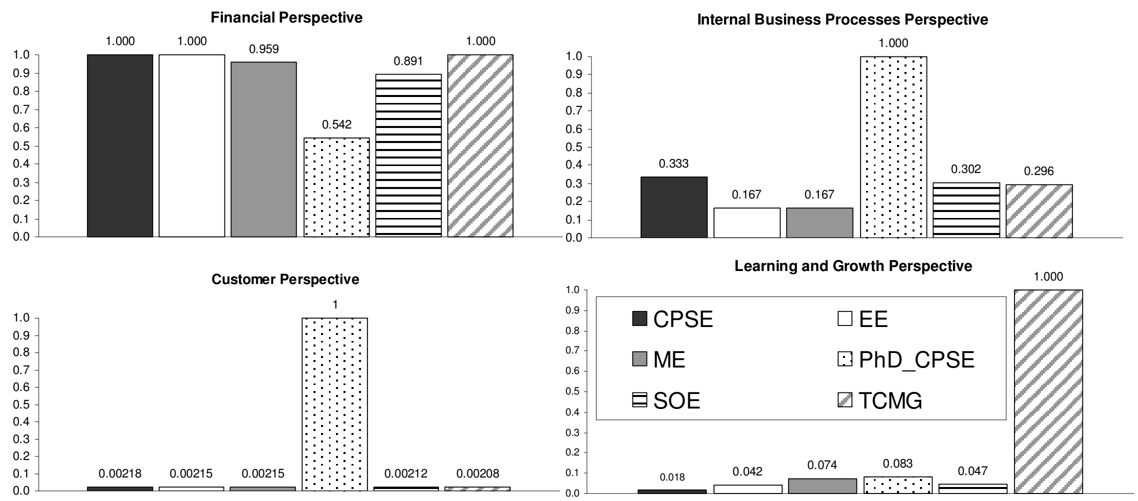


**Figure 2.** Performance efficiencies of the departments according to the DEA model results.

## 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. 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.

In addition, 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 of 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 3 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 the future, the above enhancements will be considered to create a more comprehensive assessment structure for the School of Engineering.

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