AC 2007-3122: EVALUATING THE EFFICIENCY OF CANDIDATES FOR GRADUATE STUDY VIA DATA ENVELOPMENT ANALYSIS

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Evaluating the Efficiency of Candidates for Graduate Study via Data Envelopment Analysis

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ABSTRACT

In this paper, we present a DEA approach to measure the relative efficiency of applicants to the graduate programs in engineering. The proposed performance criteria are determined depending on the current evaluation criteria in the School of Engineering at the University of Bridgeport. The steps and implementation of the proposed methodology are explained with the help of a numerical example for the Fall 2004 semester.

Keywords: Graduate Enrollment, Engineering, Decision Making, Engineering Education, Data Envelopment Analysis.

1. Introduction

Today, the global demand for U.S. graduate engineering programs is increasing rapidly, causing the application evaluation process to be a very cumbersome and time consuming task. Furthermore, most evaluation processes are handled by a variety of admission committee members depending on different preference criteria, leading to a less objective, and non-standardized decision making process. One efficient way to lessen the subjectivity and to develop a more uniformed decision making process is to utilize a common tool that provides rapid and objective efficiency scores for the applicants.

Data envelopment analysis (DEA) is a widely applied linear programming-based technique to evaluate the efficiency of a set of decision-making units. DEA was first developed by Charnes *et al.*[1] in 1978 and since then has mostly been used for benchmarking and for performance evaluation purposes.

This paper presents a DEA approach to measure the relative efficiency of applicants to the graduate programs in engineering. The proposed performance criteria are determined depending on the current evaluation criteria in the School of Engineering at the University of Bridgeport. Steps and implementation of the proposed methodology are explained with the help of a numerical example for the Fall 2004 semester.

The paper is organized as follows: A brief list of previous studies is given in the next section. Section 3 provides a summary of the data envelopment analysis approach. The Problem description and a case study are the focus of Section 4. Conclusions and thoughts for future research are provided in Section 5.

2. Literature review

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 these 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 most relevant studies is published by Johnson and Zhu [2]. In their work, the authors employed DEA to select the most promising candidates to fill an open faculty position. In this regard, authors proposed a DEA aided recruiting process that (1) determines the performance levels of the ‘‘best’’ candidates relative to other applicants; (2) evaluates the degree of excellence of ‘‘best’’ candidates’ performance; (3) forms consistent tradeoff information on multiple recruiting criteria among search committee members, and, then, (4) clusters the applicants.

DEA also found a large variety of applications in the environmental arena. To this extend, Sarkis [3] proposed a two-stage methodology to integrate managerial preferences and environmentally conscious manufacturing (ECM) programs. Consequently, 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).

Methods other than DEA have also been utilized to study the efficiency of application and admission processes. Moore [6] built an operational two-stage expert system to examine the admission decision process for applicants to an MBA program, and predict the degree completion potential for those actually admitted. A similar study is also published by Nilsson [7] to investigate if there are any differences in the predictive relationships between the scores of the Graduate Record Examination (GRE) and the graduate grade point average, and the scores of the Graduate Management Admission Test (GMAT) and the graduate grade point average. Landrim *et al.* [8] constructed a value tree diagram for fifty-five graduate institutions offering the Ph.D. degree in psychology. The authors used this diagram to indicate the relative weight of admission factors used in the decision making process.

3. 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”. Usually modeled as a linear programming (LP) model, the method provides relative efficiency score for each decision making unit under consideration.

The most appealing advantage of DEA is, unlike parametric approaches like regression analysis (RA), DEA optimizes on each individual observation and does not require a single function that suits best to all observations (Charnes *et al.*[9]). Comparison of DEA and RA has been well studied in the literature. Even though there are some studies emphasizing the advantages of both (*i.e.*, see

Thanassoulis[10]), it is more commonly accepted in the literature that DEA is more advantageous in comparing decision making units.

Banker *et al.* [11] compared estimates of technical efficiencies of individual hospitals obtained from the econometric modeling of the translog cost function, and the application of DEA. The authors reported that DEA estimates were highly related to the capacity utilization, where as translog estimates did not provide such relationship.

Bowlin *et al.* [12] compared DEA and RA using 15 hypothetical hospitals and concluded that DEA outperformed RA by being able to identify the sources of inefficiencies by underlining the resources that are used in excess in inefficient hospitals. Furthermore, the authors stated that DEA also performed better in estimating and returning scale characterizations. Furthermore, Sarkis [13] 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. In addition, DEA is also able to accommodate multiple inputs and multiple outputs, allowing these variables to be included in the model with different units of measurement.

DEA algorithms can be classified into two categories, *input*- and *output-oriented* DEA models, according to the "orientation" of the model. *Input-oriented* DEA models concentrate on reducing the amount of input by keeping the output constant. *Output-oriented* DEA models on the other hand, focus on maximizing the amount of output with the same amount of input. In DEA modeling, inputs are considered as the items that are subject to minimization, whereas, outputs are the items that are subject to minimization.

Another classification of DEA models can be given depending on the "optimality scale" criterion. Here, 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*.[14] as an extension of the CRS DEA model. In this paper, we employ an output oriented CRS DEA model. Further explanation regarding the CRS model follows.

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*.[1]:

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

Where,
$k = 1$ to s,
$j = 1$ to m,
$i = 1$ to n,
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 converted into a linear program as in Equation (2). We refer the reader to the study by Charnes *et al.*[9] for further explanation of the model.

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

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):

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

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

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

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

The result of the model, Φ is the relative efficiency score of each DMU. Inverse of the variable Φ ($1/\Phi$) 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 of the applicants for graduate engineering programs.

4. Applying data envelopment analysis to the application review process

Currently, there is no automated technique to evaluate the candidates for admission to the graduate programs of the School of Engineering at the University of Bridgeport. At present, evaluation and selection decisions are being handled by discipline-related faculty members. Even though the human involvement increases the reliability of the evaluation and selection processes, the rapidly increasing number of applications to the graduate engineering programs has caused this approach to be very time consuming and less consistent.

To accelerate and standardize the evaluation procedure, the Office of Admissions and School of Engineering administration decided to initiate the implementation of a prototype for a software tool to automatically rank and select candidates to the graduate program in Computer Science; since a significantly high number of applications is submitted to this program every semester.

The proposed DEA model in this study aims at (i) accepting students (a) with efficiency scores equal or higher than a predetermined technical efficiency value or (b) up to a given number, (ii) comparing the accepted students with the DEA model results, and, (iii) preparing a base to observe the students' future success to evaluate the performance criteria fed into the model.

To achieve these objectives, the data for all 107 applicants (n = 107) for the Masters of Science (M.S.) in Computer Science program in the School of Engineering for Fall 2004 semester is collected. According to the office of admissions records, the acceptance rate of the Computer Science graduate program for the Fall 2004 semester is approximately 34 percent, with 36 accepted, and 71 rejected students.

Following data collection, a DEA model to evaluate the relative efficiency of each candidate is employed with six performance criteria, viz., the Bachelors of Science (B.S.) GPA, TOEFL and GRE Quantitative (-Q) scores, number of years of work experience, number of undergraduate semesters till B.S. degree completion, and the number of below-B grades in math-related and technical courses in the B.S. degree transcript.

4.1 DEA model for the evaluation process

Figure 1 shows the current admission process to the graduate programs in engineering at the University of Bridgeport, along with the proposed method.

Here, following the retrieval of the complete application materials, related data is entered into the applications database. The office of admissions then sends each applicant a confirmation e-mail with an assigned UB identification number confirming that the application has been received.

Subsequently, the applications are filtered by the office of admissions depending on basic application criteria, filtering out unqualified applicants. These applicants are then notified regarding the result of their applications.

Remaining applications which meet the basic requirements are then sent to the relevant Faculty for decision making.

The information provided by this study enables users to identify the best candidates for the graduate engineering program. In the following sections, we illustrate how the evaluation process can be enhanced using the DEA approach introduced earlier.

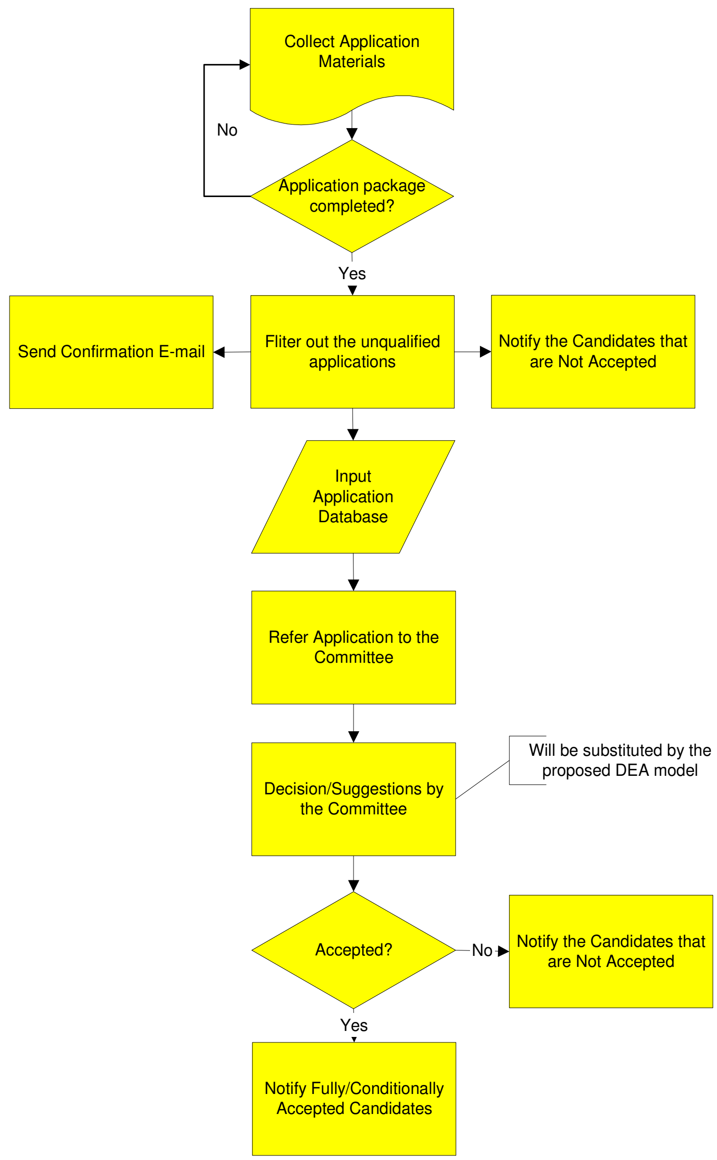

Figure 1. Simplified schematic diagram of the application evaluation and decision making process.

4.2 DEA model to evaluate the efficiency of candidates for graduate study

In our model, the applications to the graduate program correspond to decision-making units in DEA, while *selected* application data correspond to criteria in DEA, dependent on the definition of the indicators (inputs or outputs in the DEA model).

In total, 107 decision-making units and six criteria are introduced. These criteria include two inputs and four outputs. Input criteria consist of e_1, and e_2, whereas output criteria include, e_3, e_4, e_5, and, e_6, where,

e_1 = number of below-B grades in math-related/technical courses in the BS transcript of the applicant,
e_2 = number semesters that the applicant spent to complete the BS degree,
e_3 = BS GPA of the applicant,
e_4 = TOEFL score of the applicant,
e_5 = GRE-Q score of the applicant,
e_6 = number of years of work experience of the applicant.

The first input introduced to the model is the number of below-B grades in math-related/technical courses in the B.S. transcript (e_1). Following the notation of the first DEA model, the first input formulation for each DMU i (x_{1i}) can be written as follows:

$$x_{1i} = e_{1i} \qquad \forall \text{ DMUs } i. \qquad (5)$$

The second input introduced to the model is the number of semesters spent to complete the B.S. degree, (e_2). Hence, the second input formulation for each DMU i (x_{2i}) can be written as follows:

$$x_{2i} = e_{2i} \qquad \forall \text{ DMUs } i. \qquad (6)$$

The output variables in the proposed DEA model are selected as, the B.S. GPA of the applicant (e_3), the TOEFL score of the applicant (e_4), the GRE-Q score of the applicant (e_5), and the number of years of previous work experience (e_6) of the applicant.

Therefore, with similar reasoning, equations (7), (8), (9), and (10) can be expressed mathematically as follows:

$$y_{1i} = e_{3i} \qquad \forall \text{ DMUs } i. \qquad (7)$$
$$y_{2i} = e_{4i} \qquad \forall \text{ DMUs } i. \qquad (8)$$
$$y_{3i} = e_{5i} \qquad \forall \text{ DMUs } i. \qquad (9)$$
$$y_{4i} = e_{6i} \qquad \forall \text{ DMUs } i. \qquad (10)$$

This completes the formulation of the DEA model. Selected application data for a total of 107 candidates are provided in Table 1.

Table 1. Initial data for the DEA model

DMU #	e_1	e_2	e_3	e_4	e_5	e_6	DMU #	e_1	e_2	e_3	e_4	e_5	e_6	DMU #	e_1	e_2	e_3	e_4	e_5	e_6.
1	13	8	2.87	597	720	0	37	18	8	2.75	637	700	1	73	11	8	3.20	507	770	0
2	26	8	2.77	563	620	0	38	13	10	2.82	593	780	2	74	0	8	2.37	507	750	0
3	19	8	3.00	597	780	0	39	16	8	3.14	473	690	0	75	5	6	3.14	490	750	0
4	9	6	2.90	560	640	4	40	23	10	2.94	473	530	0	76	0	8	3.98	553	800	0
5	32	12	2.34	613	650	0	41	5	8	3.35	620	720	0	77	18	8	2.92	677	790	1
6	39	8	1.71	563	630	0	42	15	8	2.82	637	660	0	78	20	10	2.97	633	780	0
7	20	8	3.09	567	590	0	43	15	10	2.85	610	770	0	79	8	8	3.10	563	660	2
8	22	8	2.95	473	650	0	44	10	8	3.07	637	780	0	80	2	8	3.56	593	800	0
9	16	8	3.07	627	570	0	45	19	8	2.61	620	720	0	81	23	8	2.98	523	660	2
10	6	8	3.50	560	710	0	46	0	6	2.10	473	690	0	82	15	8	3.24	563	700	0
11	26	10	2.19	610	620	0	47	18	8	3.13	603	720	0	83	0	6	3.77	597	600	0
12	20	8	2.98	567	520	0	48	16	8	3.04	573	720	0	84	6	8	3.41	593	660	0
13	23	8	2.94	610	750	0	49	13	8	3.24	473	630	0	85	1	8	3.85	600	770	0
14	24	10	2.63	537	740	0	50	20	8	2.70	670	710	0	86	11	8	3.33	550	570	0
15	21	8	2.81	587	750	0	51	8	8	3.33	567	750	0	87	1	8	3.68	480	640	2.5
16	15	8	2.68	543	690	1	52	20	8	2.30	567	590	0	88	0	6	4.00	603	660	0
17	15	8	3.20	550	690	0	53	23	8	2.79	547	690	0	89	1	8	3.92	643	800	0
18	11	8	2.95	650	770	0	54	20	8	2.44	473	690	0	90	0	8	3.65	567	590	0
19	20	8	2.60	637	690	0	55	17	8	2.74	593	710	0	91	9	8	3.37	627	710	0
20	34	10	2.52	593	680	0	56	33	8	1.70	647	710	0	92	17	8	3.11	560	610	0
21	21	8	2.69	620	620	0	57	17	8	2.78	500	720	0	93	12	8	3.32	610	730	0
22	18	8	2.90	560	710	0	58	20	8	2.93	530	770	1	94	6	6	3.68	507	750	2
23	24	8	2.87	560	690	0	59	16	8	3.13	560	650	0	95	0	6	3.40	507	750	5
24	4	6	2.84	473	690	0	60	8	8	3.40	587	690	1	96	12	8	3.24	577	730	0
25	24	8	2.98	527	440	0	61	17	8	3.12	633	550	0	97	9	8	3.04	583	580	0
26	19	8	3.08	650	720	0	62	36	8	2.18	627	750	0	98	0	8	2.97	560	760	0
27	29	8	2.40	483	340	0	63	18	8	2.97	587	760	0	99	14	8	3.03	550	730	0
28	26	10	2.70	567	680	0	64	3	6	3.00	587	570	2	100	7	8	3.34	560	640	0
29	9	8	3.20	530	730	0	65	12	8	2.94	677	750	0	101	9	8	3.34	550	620	0
30	11	8	3.43	550	140	0	66	23	8	2.84	537	380	0	102	11	8	3.07	647	630	0
31	12	10	2.90	637	770	0	67	11	8	3.04	587	670	0	103	7	8	3.52	563	670	0
32	16	8	3.24	577	590	0	68	13	8	2.37	577	680	0	104	1	6	3.38	653	760	7
33	17	8	3.17	560	650	0	69	21	8	2.78	537	550	0	105	3	8	3.67	560	610	0
34	22	8	3.03	620	710	0	70	19	8	3.10	597	740	0	106	2	6	3.50	507	750	8
35	34	10	2.50	563	760	0	71	13	8	3.04	620	730	0	107	0	8	3.44	587	770	0
36	14	10	2.90	553	640	0	72	8	8	3.22	477	640	0	*Ave.*	14.29	8.04	3.02	572.80	677.10	0.39

Using this data, the output-oriented DEA model is run for each applicant 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.[16] to solve and analyze DEA models.

After the runs are completed for all 107 candidates, the technical efficiency (*TE*) is calculated as the reciprocal of each model outcome ($TE = 1/\Phi$) for each candidate.

The results of the model are presented in Table 2 in descending order of *TE* values.

Table 2. Relative efficiency score and rank of each candidate

Rank	DMU	*TE*	Rank	DMU	*TE*	Rank	DMU	*TE*
1	106	1	35	37	0.7316	73	67	0.6743
1	104	1	38	70	0.7303	74	97	0.6711
1	95	1	39	91	0.7283	75	68	0.6711
1	94	1	40	61	0.7270	76	30	0.6698
1	88	1	41	93	0.7243	77	33	0.6662
6	83	0.9901	42	41	0.7237	78	101	0.6655
7	75	0.9868	43	10	0.7233	79	79	0.6652
8	46	0.9250	44	29	0.7204	80	86	0.6633
9	24	0.9079	44	99	0.7204	81	59	0.6626
10	64	0.8989	44	96	0.7204	82	7	0.6614
11	4	0.8577	44	71	0.7204	83	92	0.6570
12	76	0.8315	48	9	0.7201	84	12	0.6542
13	89	0.8226	49	87	0.7193	85	72	0.6536
14	107	0.8081	50	21	0.7121	86	81	0.6526
15	85	0.7986	50	45	0.7121	87	52	0.6512
16	80	0.7895	50	34	0.7121	88	49	0.6500
17	98	0.7865	53	1	0.7105	89	2	0.6466
18	77	0.7796	53	48	0.7105	89	6	0.6466
19	65	0.7776	53	47	0.7105	91	8	0.6431
20	3	0.7697	53	57	0.7105	92	25	0.6218
20	44	0.7697	57	60	0.7091	93	66	0.6207
22	50	0.7695	58	103	0.7067	94	69	0.6168
23	18	0.7599	59	90	0.7052	95	38	0.6158
23	73	0.7599	60	84	0.7033	95	78	0.6158
23	58	0.7599	61	22	0.7007	97	43	0.6079
26	74	0.7500	61	55	0.7007	97	31	0.6079
26	63	0.7500	63	82	0.6962	99	35	0.6000
28	26	0.7466	64	105	0.6936	100	14	0.5842
29	102	0.7431	65	17	0.6861	101	11	0.5605
29	56	0.7431	66	39	0.6830	102	27	0.5547
31	13	0.7401	67	53	0.6809	103	20	0.5449
31	15	0.7401	67	16	0.6809	104	28	0.5368
31	62	0.7401	67	23	0.6809	105	36	0.5101
31	51	0.7401	67	54	0.6809	106	5	0.4694
35	19	0.7316	71	32	0.6793	107	40	0.4614
35	42	0.7316	72	100	0.6764	***Ave.***		0.7179

According to the DEA results depicted in Table 2, Candidates 106, 104, 95, 94, and 88 are efficient in terms of their pre-application academic performances with technical efficiency (*TE*) values equal to 1. All other applicants have a potential to increase the relative efficiency of academic performances by 1 minus the *T*E value. For instance, the efficiency of candidate 42 could be increased by 26.84%. The two lowest technical efficiency values are calculated for Candidates 40 and 5 with 46.14% and 46.94%, respectively.

These low values are most probably driven by the number of below-B grades in math-related/technical courses in the BS transcript and the GRE-Q scores of the applicants.
The average efficiency for the sample is 71.79%. Figure 2 represents the average efficiency and the *TE* values for the 107 candidates in the population. As illustrated by Figure 2, 58 candidates fall below the average efficiency value.

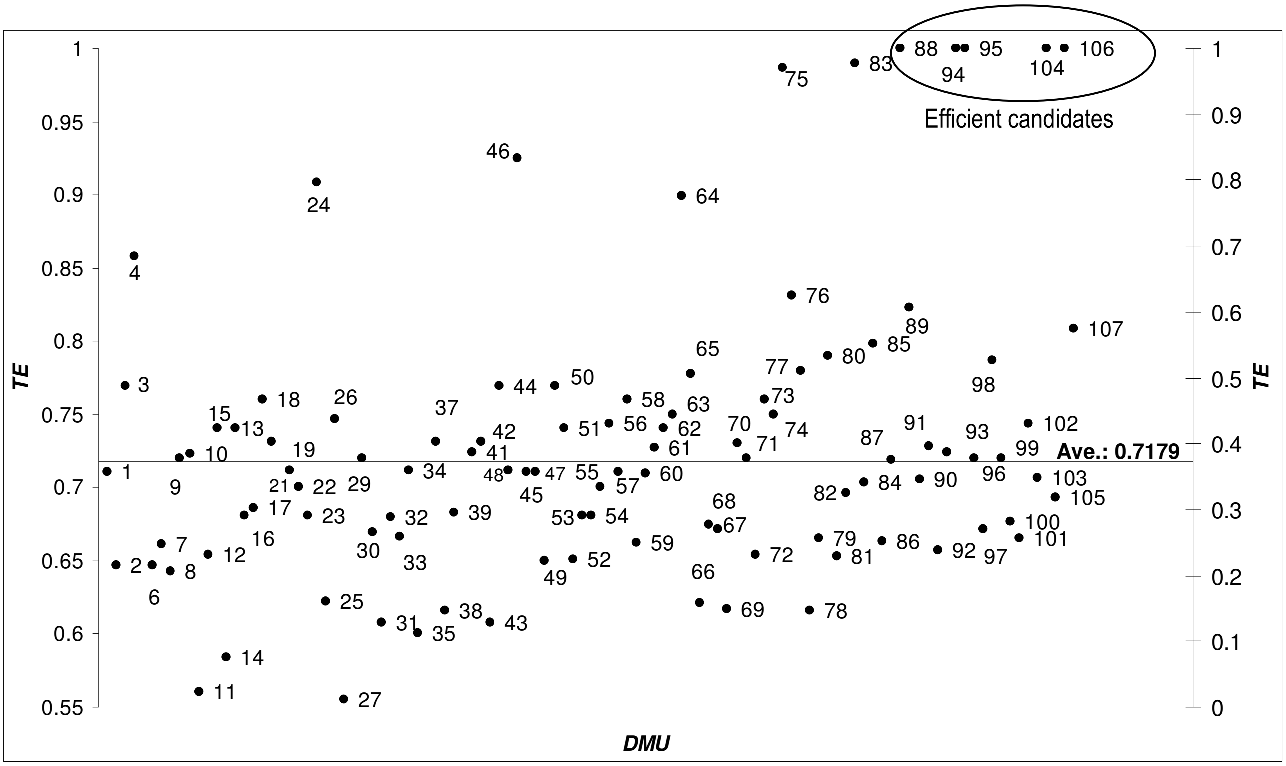

Figure 2. Performance efficiencies of 107 candidates according to the DEA model results.

As we analyze the results further, we can easily observe that all of efficient candidates have completed their B.S. degrees in the identical number of semesters (6). In addition, the efficient candidates are characterized by either significantly high GPAs, GRE-Q scores, years of work experience, significantly low numbers of below-B grades in math-related/technical courses, or a combination of these criteria.

With this in mind, depending on the importance of each criterion, the input data can be normalized and weighed according to the decision maker preferences, so that the more important criterion would provide competitive advantage to the candidate.

In summary, we can conclude that the results indicated that the DEA model functions properly and provides meaningful and fair comparative results for the applicants to the graduate program. Further discussion and considerations for the future research is provided next.

5. Conclusions and future research

In this study, an implementation of an output-oriented DEA model is considered and applied to a sample of 107 candidates to the Computer Science M.S. program at the University of Bridgeport to determine the relative efficiency score of applicants based on their credentials. The model provides a basis to conduct a fast and reliable automated application evaluation process.

In reality, candidates 71-107, provided in Table 1, constitute the manually-accepted students set, where as the remaining candidates were rejected. As one can easily observe from Table 2, there is a significant difference between the results of applying the two methods. This is most likely caused by (i) the inconsistency of the manual evaluation process and/or (ii) the presence of factors that are not included in the model; for example: the ranking of the university providing the B.S. degree, the B.S. major, the strength of the recommendation letters, etc. Therefore, in order to minimize this difference between the real/manual experience and strengthen the proposed model, the DEA model needs to be modified to include appropriate additional criterion, which is one focus of our future research.

In the future, we plan to apply the same methodology to various graduate program applications in several fields to observe the applicants' relative efficiencies. These results will then be compared to the manually-accepted candidate sets. The significant differences will be analyzed and the evaluation criteria will be modified according to the feedback obtained from this comparative study. Following the modification of the model, alternate results will be fed to the model in order to evaluate the future performance of each graduate school to determine the efficiency of the model and the selection criteria. Future performance will be further analyzed to seek a correlation between the students' performance in the graduate programs after admission and to compare the existing evaluation results, towards the eventual implementation of an automated graduate application admission system.

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