An Aggregated Metric for Evaluating Plant Performance: Implications for Performance Improvement and Resource Reallocation

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Abstract

Performance metrics are currently receiving significant importance in both practitioner and academic circles. However, both researchers and managers have tended to view metrics individually and in very simplistic form without considering the interrelationships among various metrics and how they impact the performance of a system under consideration. This paper fills this gap by proposing a methodology for generating an aggregated metric of performance by effectively considering a variety of metrics that has important implications on performance improvement and resource reallocation. We test our models on a case with six globally located production plants of a medium sized manufacturer of specialty chemicals. The contributions of this research are three-fold: an aggregated performance metric that assists in internal benchmarking and performance improvement is suggested, the impact of technology transfer on plant performance is investigated, and a decision tool for assisting managers in plant shutdown and resource reallocation options is developed. Thus, our research assists in both strategic and operational decisions for improving the performance of individual plants and overall system performance.

1. Introduction

Performance metrics are critical for understanding and managing any business operation, manufacturing or otherwise since they

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provide an effective means for controlling and evaluating performance, reporting performance, communicating, identifying opportunities for improvement, and framing expectations (Melnyk 1999). As the adage goes «one cannot manage what one cannot measure». Thus, the evaluation and utilization of multiple performance metrics has been extensively promoted in most of the performance measurement literature from areas such as operations, engineering, and cost accounting (for example see, Kaplan and Norton, 1996; Nanni et al., 1992; Adams et al., 1995). It is also contested that these metrics may need to incorporate various performance characteristics that are both strategic and operational in nature. However, an issue in simultaneously considering multiple performance metrics is that managers may not be able to easily aggregate these measures in evaluating performance and thereby indulge in various strategic and operational decisions that assist in continuous process improvement efforts. Also, researchers and managers have tended to view metrics individually and in very simplistic form without considering the interrelationships among various metrics and how they impact the performance of an entire supply chain (Melnyk 1999). This paper fills this gap by proposing a methodology for generating an aggregated metric of performance by effectively considering a variety of metrics that has important implications on performance improvement and resource reallocation. We test our models on a case with six globally located production plants of a medium sized manufacturer of specialty chemicals (Flaherty 1985; 1992). The contributions of this research are three-fold: an aggregated performance metric that assists in internal benchmarking and performance improvement is suggested, the impact of technology transfer on plant performance is investigated, and a decision tool for assisting managers in plant shutdown and resource reallocation options is developed. Thus, our research assists in both strategic and operational decisions for improving the performance of individual plants and overall system performance.

The rest of the paper is organized as follows. The next section reviews some of the relevant literature in performance evaluation and benchmarking. The case company profile is subsequently discussed, and the results are presented. Finally, conclusions and extensions are addressed. The DEA models utilized in this paper are discussed in Appendix I.

2. Performance Evaluation and Benchmarking

A number of reviews on the practice, requirements design and development of performance measurement systems exist, for example, see Adams, et al. (1995), Lockamy & Cox (1994), Neely et al. (1995). Kueng (2000) points out two important characteristics for performance measures that we seek to address here:

– Performance is multidimensional. As performance has many contributing factors, it cannot be gathered and assessed by a single indicator.
– Performance indicators are not independent. Most performance indicators stand in a relationship with one another. For the most part, the type of relationship is either conflicting or complementary; independence is the exception rather than the rule.

Several techniques have been proposed in the literature for performance evaluation at various levels of decision making. At the strategic level of analysis, performance metrics range from standard financial measures such as return on assets or investment (ROA and ROI) to stock market returns. One of the most popular evaluation techniques at the strategic level of performance is Kaplan and Norton's (1996) Balanced Scorecard approach. This approach is a strategic management instrument that supplements traditional financial measures with three additional perspectives: the customer, the internal business process, and the learning and growth perspective. It is meant to be a tool for describing an organization's overall performance across a number of measures on a regular basis and is focused on corporations or organizational units such as strategic business units, but not on business processes. It involves business processes only as far as their impact on customer satisfaction and in achieving an organization's financial objectives.

At a more tactical level, many tools and techniques have been proposed in the literature for performance evaluation and benchmarking. Camp (1995) shows that the focus has been on the presentation of data in some graphical form. The presentation graphics are relatively easy to understood and capable of depicting the performance across multiple metrics simultaneously, but the analyst is still left with the arduous task of integrating these elements in a meaningful and useful manner. Some of the more popular techniques include the *spider* or *radar* diagram and the *Z* chart for gap analysis. Another approach is the use of the analytic hierarchy process (AHP) maturity matrix (Eyrich, 1991), which utilizes a weighted scoring technique in the analysis of various benchmarks and provides a single score using perceptual values as set forth by decision-makers. Statistical methods that include regression and various descriptive statistics have also been utilized for performance evaluation and benchmarking purposes (Blumberg, 1994; Schefczyk, 1993). However, even with the strong theoretical foundation of statistical tools such as multiple regression, its limitation lies primarily in the numbers of simultaneous inputs (independent variables) and outputs (dependent variables) to consider and that it measures a correlation or central tendency, but not best practice. As far as the use of simple ratios go, Athanassopoulos and Ballantine (1995) have argued that the use of ratio analysis in itself is insufficient for assessing performance, and that more advanced tools like data envelopment analysis (DEA) should be used to complement ratio analysis. It is for these reasons that multi-factor non-parametric tools such as DEA, which overcome the aforementioned limitations, have started to receive significant importance in the area of performance evaluation and benchmarking (Collier and Storbeck, 1993; Bell and Morey, 1995; Banker and Mainderatta, 1988; Barr and Seiford, 1994; Athanassopoulos and Ballantine, 1995). However, some of the traditional DEA models utilized in this area have certain limitations, which are addressed in detail in the methodology section of the paper. Other tactical level performance evaluation methods that consider multiple metrics from a quantitative modeling focus can be found in Bititici et al. (2001), Ghalayini, et al. (1997), Sabri and Beamon (2000), Sarkis and Talluri (1996), Suwigno et al. (2000), and Talluri and Sarkis

(2002). While these methods are effective in their own way, they do not address issues relating to process improvement and resource reallocation in a detailed manner.

3. Company Profile

The case company operates with six manufacturing plants located around the world. The parent manufacturing facility is located in Gary, Indiana. It has the design capacity to manufacture prototype samples for customers. Because of this, much of the new product research occurred at the Gary plant. Two other plants located in North America are in Mexico and Canada. In Western Europe a plant is located in Frankfurt. Two other plants are located in Venezuela and Sunchem, which are in Latin America and Pacific region, respectively.

Many executives within top management felt that the Gary plant had fallen behind some of the other company's plants in terms of efficiency, costs, and technical expertise. In order to further study the productivity and evaluate the different plants, a study was requested by the company's executives. The study that was performed was limited to one chemical product called Release-Ease. Release-Ease is a plastic molding compound that easily released from metal holder after compression molding. The study collected information on several critical performance variables, but the performance evaluation methods used failed to consider all the measures simultaneously. Thus, these methods did not allow for an accurate portrayal of the plant productivity and efficiencies. The data and information regarding the case company are taken from Flaherty (1985; 1992).

4. Performance Evaluation

4.1. Aggregated Performance Metric

In this analysis, we consider cost and average number of workers (W) as inputs, and volume (VOL) and utilization (UTL) as outputs for the DEA model. Cost components considered include material, overhead, and operating costs. Volume is the annual production volume, and utilization is the ratio of production volume to design capacity.

The plant data and DEA results are shown in Table 1. Mexico, Venezuela, and Frankfurt plants have achieved a relative efficiency score of 1, and are considered efficient. Canada, Gary, and Sunchem plants are inefficient with relative efficiency scores of 0.901, 0.898, and 0.699, respectively. These results indicate that Canada, Gary, and Sunchem plants must either increase their output levels for their current levels of inputs, or decrease their input levels in maintaining their current levels of output. It is also evident from Table 1 that Mexico did not put any weight on cost (u_1=0), and emphasized all the weight on the other three measures. This phenomenon of emphasizing importance on certain factors alone is referred to as unrestricted weight flexibility in DEA. The weighting scheme of other plants is depicted in this table as well.

TABLE 1
Manufacturing Plant Data, Efficiency Scores, and Weights

Plant	Cost ($/100 lb)	Avg. W (#)	VOL (millions of lbs)	UTL (%)	Eff	u_1	u_2	v_1	v_2
Mexico	92.63	44.4	17.2	78.18	1.000	0	0.022523	0.044776	0.00294
Canada	93.25	27.7	2.6	70.27	0.901	0.009571	0.003882	0	0.012816
Venezuela	112.31	23.9	4.1	91.11	1.000	0.008196	0.003325	0	0.010976
Frankfurt	73.34	86.1	38.0	80.85	1.000	0	0.011614	0.026316	0
Gary	89.15	58.3	14.0	75.68	0.898	0.008865	0.003596	0	0.011872
Sunchem	149.24	31.0	4.0	80.00	0.699	0	0.032258	0.05633	0.005927

In order to identify the best overall performer, we utilized formulation (2) to identify the input and outputs weights, which are used in the evaluation of the CEM shown in Table 2. For example, the value in the first row and second column, 0.518, indicates how well Canada is performing with respect to the optimal weights or strengths of Mexico. In general, a DMU with a high column mean score is considered as a good overall performer.

TABLE 2

Cross-Efficiency Matrix for Applichem Data

Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem
Mexico	1.000	0.518	0.839	1.000	0.647	0.593
Canada	0.946	0.901	1.000	1.000	0.898	0.662
Venezuela	0.462	0.665	1.000	0.246	0.340	0.677
Frankfurt	0.358	0.054	0.070	1.000	0.303	0.052
Gary	0.946	0.900	0.999	1.000	0.898	0.662
Sunchem	0.989	0.631	1.000	0.929	0.651	0.699
Mean	0.784	0.611	0.818	0.863	0.623	0.557

Based on the CEM scores, the performance ranking of the plants is: Frankfurt (0.863), Venezuela (0.818), Mexico (0.784), Gary (0.623), Canada (0.611), and Sunchem (0.557) in that order. Frankfurt plant is evaluated to be the best overall performer with a mean score of 0.863.

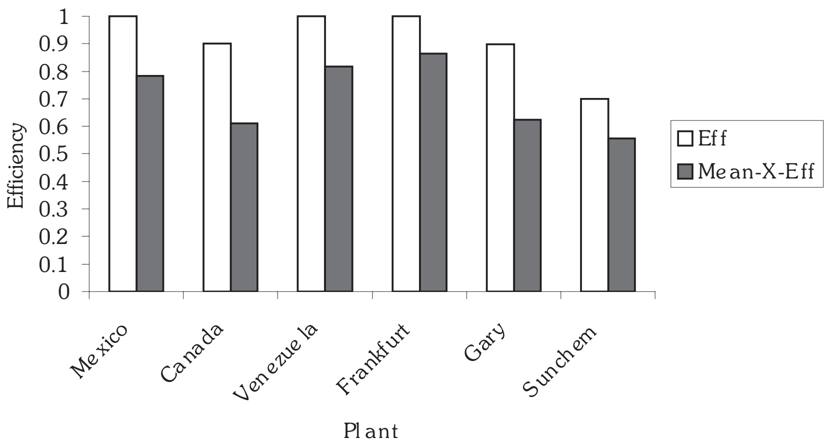

Fig. 1: Simple and Mean-Cross Efficiencies of Alternate Plants

It is interesting to note that Canada, which achieved a high relative efficiency score of 0.901 from ratio DEA analysis, is in fact a poor overall performer with a mean score of only 0.611 ranked next to last. Figure 1 compares the ratio DEA efficiencies (EFF) and mean cross-efficiency scores (M-X EFF) of the six plants.

4.2. Identification of Internal Benchmarks

We have utilized expression (3) in developing benchmarks for inefficient units. From Table 3, it is evident that Canada, which is inefficient, must use Venezuela and Frankfurt plants as benchmarks for improvement. Based on the λ values, we can conclude that a hypothetical combination plant with 68.22% (λ_3) of all Venezuela's inputs (outputs) and 10.03% of all Frankfurt's inputs (outputs) has utilized only 90.01% of Canada's current input levels in producing no less of any output. Thus, in DEA sense there is scope for improving Canada's performance. DEA acts as a diagnostic tool in the identification of benchmarks for improvement. In terms of actually improving the operations of the Canada plant management must identify the policies and procedures utilized in these two benchmark plants, and make necessary changes accordingly in the operations of Canada. Similarly, Gary must use Venezuela and Frankfurt as benchmarks, and Sunchem should utilize Mexico and Venezuela as possible benchmarks for improvement. It is evident from this analysis that Frankfurt and Venezuela are effective benchmarks for the inefficient plants. This result is in harmony with our earlier cross-efficiency analysis that identified Frankfurt and Venezuela to be the best overall performers with mean cross-efficiency scores of 0.863 and 0.818, respectively.

One of the limitations of the above traditional DEA benchmarking analysis is that each of the inefficient units must benchmark against a linear combination of efficient units. However, in practice such combination does not really exist. In order to overcome this problem, we develop a set of more appropriate benchmarks based on performance correlations of various plants. The correlations between the column scores of the CEM provide us with information on how each of the plants are evaluated by their peers, which can be considered as a measure of similarity between plants. Benchmarks for a plant can be selected by identifying a superior performing plant with the highest positive correlation, which is a more lucid approach than some of the clustering methods suggested by Doyle and Green (1994).

TABLE 3

Benchmarks for Inefficient Plants

DMU	Plant	Efficiency	Benchmarks	Lambda Values
1	Mexico	1.000	None*	
2	Canada	0.901	DMUs 3, 4	λ_3=0.6822, λ_4=0.1003
3	Venezuela	1.000	None*	
4	Frankfurt	1.000	None*	
5	Gary	0.898	DMUs 3, 4	λ_3=0.3858, λ_4=0.5012
6	Sunchem	0.699	DMUs 1, 3	λ_1=0.0292, λ_4=0.8529

None indicates that the DMUs are efficient*

TABLE 4

Revised Benchmarking Results

Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem
Mexico	1.000	0.651	0.664	0.515	0.866	0.677
Canada	0.651	1.000	0.916	-0.089	0.791	0.889
Venezuela	0.664	0.916	1.000	-0.266	0.610	0.998
Frankfurt	0.515	-0.089	-0.266	1.000	0.538	-0.264
Gary	0.866	0.791	0.610	0.538	1.000	0.588
Sunchem	0.677	0.889	0.998	-0.264	0.588	1.000

Based on the results from Table 4, Mexico, Canada, and Sunchem plants need to utilize Venezuela as the primary benchmark for improvement, and Gary must use Mexico as benchmark. The added value in this analysis is that some of the plants that are inefficient from a traditional DEA sense (for example, Mexico) can further improve by selecting appropriate benchmarks, which is not possible from Table 3 analysis. Also, it is interesting to note that while Frankfurt received the highest cross-efficiency score, it is not considered to be an appropriate benchmark for other plants due to weak and negative correlations. This is an important insight in the selection of appropriate benchmarks.

4.3. Technology Transfer

In this section, we illustrate the effect of the technology transfer on the efficiency scores of the manufacturing plants. Table 5 presents the raw material usage for each of the plants (lbs/hundred pounds of Release-Ease). Every plant uses four material types: A, B, C, and D in the production of Release-Ease, although in different mix ratios. By technology we imply the material mix utilized by the plants. We performed technology transfer by adopting the most cost efficient material mix for every plant. For example, Table 6 depicts the technology transfer options for the Mexico plant. The costs are computed by utilizing the material cost in Mexico, and the alternative mix ratios at each of the plants. If Mexico adopts the material mix usage from Venezuela and keeps all other costs the same then this will result in a decrease in cost of (92.63-90.16) dollars. The best scenario for Mexico is \$87.97 (per hundred pounds of release-ease) by the adoption of Frankfurt material mix usage. Similarly, we have calculated the best mix scenarios for all the other plants. The resulting costs are shown in Table 7. The DEA computations are conducted with this new cost structure, and the resulting efficiency scores are depicted in Table 7. The efficiency scores remained same for all the plants except Gary. In fact Gary's relative efficiency increased from 0.898 to 0.958.

This analysis indicates that Gary can improve its efficiency score by altering the material mix ratio through technology transfer. Although in this analysis we have assumed the outputs to be the same before and after technology transfer, it may not be the case in actual managerial practice. But this analysis illustrates the situation in which management can utilize these decision models to perform such an evaluation, which aids in performance improvement.

TABLE 5

Raw Material Usage by Plants

Material	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem
A	20.04	19.53	19.27	18.90	20.75	19.14
B	51.21	51.15	50.60	47.82	53.8	48.23
C	55.97	50.96	52.00	50.28	53.6	49.49
D	26.40	26.09	26.00	24.21	28.77	25.07

TABLE 6

Alternate Technology Transfer Scenarios for Mexico

Scenario	1	2	3	4	5	6
Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem
Cost ($)	92.63	90.38	90.16	87.97	94.15	88.37

TABLE 7

Efficiency Scores After Technology Transfer

DMU	Cost	W	VOL	UTL	Eff
Mexico	87.97	44.4	17.2	78.18	1.000
Canada	90.66	27.7	2.6	70.27	0.901
Venezuela	109.07	23.9	4.1	91.11	1.000
Frankfurt	73.34	86.1	38.0	80.85	1.000
Gary	80.95	58.3	14.0	75.68	0.958
Sunchem	148.9	31.0	4.0	80.00	0.699

4.4. Evaluating Plant Shutdown Options

In this section, we evaluate the effect of alternate plant shutdowns on the system efficiency of Applichem. Table 8 provides the capacities, demands, and production & transportation costs associated with the six plants. For example, the entry in the cell corresponding to Canada (row) and Mexico (column), which is

\$104.25 (per hundred pounds of release-ease), indicates the production and transportation costs associated with shipping one hundred pounds of Release-Ease from Canada to Mexico. The original solution with all plants operating is shown in Table 9 and the corresponding generic linear program is shown in Appendix II. The total cost associated with this solution is \$6,805.99 (in tens of thousands of dollars). We utilized the transportation model to identify the minimum costs associated with alternate plant shutdowns by eliminating each of the six plants in succession. These costs are represented in Table 10. All data used in these computations is obtained from Applichem (Flaherty 1985; 1992). For example, \$7,011.66 (in tens of thousands of dollars) is the production and transportation cost after closing down Mexico.

In order to evaluate the system efficiency, we computed the values of the system performance variables associated with closing each of the plants, they are: average workers (Avg. W), average volume (Avg. VOL), average utilization (Avg. UTL), short-term demand loss (STD), and long-term demand loss (LTD). For example, average workers from closing Mexico are obtained by evaluating the mean number of workers from the remaining five plants. The same logic is utilized in obtaining average volume and average utilization. The short-term demand loss and long-term demand loss are directly computed from the transportation model. STD denotes the demand that is immediately lost if the specified plant is closed down, and LTD represents the demand that Applichem loses in the long term because of the absence of production in the specified region. All this data is depicted in Table 10. In DEA, large value of an output is preferred to small. For this reason we have performed a linear scale transformation on STD and LTD by subtracting all the values from the largest value. The scaled data utilized in DEA computations is shown in Table 11.

TABLE 8
Transportation Data

Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem	Capacity (millions of lbs)
Mexico	$92.63	104.03	99.63	103.63	103.63	106.63	22
Canada	104.25	93.25	102.25	104.75	99.25	106.25	3.7
Venezuela	119.31	122.31	112.31	125.31	122.71	126.61	4.5
Frankfurt	83.34	84.84	85.84	73.34	84.54	86.64	47
Gary	99.15	95.15	100.15	99.15	89.15	89.15	18.5
Sunchem	163.24	162.24	161.74	163.44	162.24	149.24	5
Demand (millions of lbs)	3	2.6	16	20	26.4	11.9	

TABLE 9
Transportation Solution with All Plants Operating

Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem	Capacity
Mexico	3		8.8				22
Canada		2.6					3.7
Venezuela							4.5
Frankfurt			7.2	20	19.8		47
Gary					6.6	11.9	18.5
Sunchem							5
Demand	3	2.6	16	20	26.4	11.9	

TABLE 10
Plant Shutdown Data

Plant	Cost ($0000)	Avg. W	Avg. VOL	Avg. UTL	STD	LTD
Mexico	7011.66	45.40	12.54	79.58	1.2	3.0
Canada	6819.09	48.74	15.46	81.16	0.0	2.6
Venezuela	6805.10	49.50	15.16	76.99	0.0	16.0
Frankfurt	5453.35	37.06	8.38	79.05	26.2	20.0
Gary	7229.53	42.62	13.18	80.08	0.0	26.4
Sunchem	6805.10	48.08	15.18	79.22	0.0	11.9

TABLE 11

Scaled Plant Shutdown Data

Plant	Cost ($0000)	Avg. W	Avg. VOL	Avg. UTL	STD	LTD
Mexico	7011.66	45.40	12.54	79.58	25.0	23.4
Canada	6819.09	48.74	15.46	81.16	26.2	23.8
Venezuela	6805.10	49.50	15.16	76.99	26.2	10.4
Frankfurt	5453.35	37.06	8.38	79.05	0.0	6.4
Gary	7229.53	42.62	13.18	80.08	26.2	0.0
Sunchem	6805.10	48.08	15.18	79.22	26.2	14.5

TABLE 12

CEM for Alternate Plant Shutdowns

Plant	Mexico	Canada	Venezuela	Frankfurt	Gary	Sunchem
Mexico	1.000	0.947	0.408	0.335	0.000	0.585
Canada	0.956	1.000	0.438	0.336	0.000	0.610
Venezuela	0.926	0.998	1.000	0.000	0.941	1.000
Frankfurt	0.783	0.821	0.781	1.000	0.764	0.803
Gary	0.896	0.874	0.861	0.000	1.000	0.886
Sunchem	0.926	0.998	1.000	0.000	0.941	1.000
Mean	0.915	0.940	0.748	0.279	0.608	0.814

We have utilized DEA to evaluate the relative efficiencies of these six plant shutdown options. All the six scenarios were efficient with a relative efficiency score of 1. Since DEA could not effectively discriminate between the options, we have used the CEM evaluated from expression (2) weights to identify the optimal shutdown option. The corresponding CEM is shown in Table 12. Based on the CEM, the system efficiency is least affected by closing Canada. This is because the mean system efficiency without Canada is 0.94. The next possible shutdown option is Mexico without which the system efficiency is 0.915. But it is advantageous not to close a large plant such as Mexico because of economies of scale. It is evident that the efficiency will be adversely affected by closing down Frankfurt, which if closed will result in a score of 0.279. Management can also consider closing Canada (0.940) and

Sunchem (0.814) combination, which would result in a total cost of \$6,819.086 (in tens of thousands of dollars). This analysis provides management with possible plant shutdown options. Once the shutdown decisions are made, if any, then the resources at those locations can be reallocated to further improve the performance of the remaining plants.

5. Conclusions and Extensions

In this paper we illustrate the use of DEA for productivity analysis of manufacturing plants as applied to a medium sized manufacturer of specialty chemicals. DEA allows for the inclusion of multiple inputs and outputs and thus provides for a more complete analysis of systems under consideration. It overcomes the limitations of traditional ratios that are often used by managers in productivity analysis. The primary limitation of such ratios is that they do not simultaneously take into consideration all the performance measures. We demonstrated the advantage of cross-efficiency analysis in DEA, which improves the discriminatory power of the analysis and ranks DMUs. We evaluated the performance of the plants, and provided effective internal benchmarks for inefficient plants to use as a source for improvement. We have also analyzed technology transfer and alternate plant shutdown options, and provided recommendations.

Appendix I: Multi-Factor Efficiency Models

DEA considers multiple input and output measures in determining relative efficiency scores of decision making units. Efficiency is defined as a ratio of sum of weights outputs to sum of weighted inputs. DEA has been utilized extensively for comparing the relative efficiencies of schools, hospitals, bank branches, and other profit and not-for profit organizations (Charnes et al., 1994).

The relative efficiency of a unit p is obtained by solving the following linear program (shown as expression (1)) proposed by Charnes et al. (1978).

Expression (1):

$$\max \sum_{k=1}^{s} v_k y_{kp}$$
$$\text{s.t.} \sum_{j=1}^{m} u_j x_{jp} = 1, \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \ \forall i,$$
$$v_k, u_j \geq 0 \ \forall k, j$$

where: p is the unit being evaluated, s represents the number of outputs, m represents the number of inputs, n is the number of units, y_{ki} is the amount of output k produced by unit i,x_{ji} is the amount of input j used by unit i,v_k is the weight assigned to output k, and u_j is the weight assigned to input j.

Expression (1) is a linear program that is solved n times in evaluating the relative efficiencies of all the units. Each unit selects input and output weights that maximize its efficiency score under the constraints that the efficiency scores of all units with respect to these weights remain below a value of 1. A relative efficiency score of 1 indicates that the unit under consideration is ratio efficient, whereas a score less than 1 indicates that it is ratio inefficient. For more details on the model development, see Charnes et al. (1978).

It is well known in DEA literature that expression (1) used in evaluating the efficiencies has certain limitations. The efficiency score obtained from this model is referred to as simple efficiency or simple radial efficiency. In the determination of simple radial efficiency, formulation (1) allows for unrestricted factor weights (v_k and u_j). Thus, a DMU can achieve a high relative efficiency score by being involved in an unreasonable weighting scheme (Dyson & Thannassoulis, 1988; Wong and Beasley, 1990). These DMUs heavily weigh few favorable measures and completely ignore other inputs and outputs. Such DMUs are niche members and are not good overall performers. To overcome this limitation cross-efficiencies can be specified in the DEA model.

Sexton et al. [1986] introduced the concept of cross-efficiency evaluations in DEA. In their work, a Cross-Efficiency Matrix (CEM), which provides information on the performance of a particular DMU with the optimal DEA weights of other DMUs, was introduced. In the CEM, the element in i^{th} row and j^{th} column represents the efficiency of DMU j with the optimal weights of DMU i. A DMU, which is a good overall performer, should have several high cross-efficiencies along its column. On the other hand, a poorly performing DMU should have several low values. The column means can be computed to effectively differentiate between good and poor performers (Boussofiane et. al, 1991).

A problem with CEM is that input and output weights identified in formulation (1) may not be unique. Thus, a DMU's evaluation of other DMUs may depend on the first of many alternate optimal solutions reached. This ambiguity can be resolved by using formulations proposed by Doyle and Green (1994). These formulations are categorized into aggressive and benevolent types. The aggressive formulation attempts to obtain weights far away from other DMUs' optima, while the benevolent formulation obtains weights that tend to converge toward other DMUs' optima. Thus, the aggressive formulation always attempts to find optimal weights that make the target DMU the best that it can be and others the worst. In the case of the benevolent formulation, optimal weights obtained make both the target DMU and all other DMUs as good as possible. In situations where relative dominance among the DMUs is to be analyzed, the aggressive formulation is more appropriate. Sometimes an average of aggressive and benevolent formulations can be used. For more information on the applicability of these formulations, see Doyle and Green (1994).

These formulations not only maximize the ratio of weighted output to weighted input of a DMU, but they also minimize (aggressive) or maximize (benevolent) the sum of all other DMUs' efficiencies in some sense. The only difficulty in considering the latter goal is that the sum of efficiencies is non-linear. A surrogate approach proposed by Doyle and Green (1994) is to minimize the efficiency of the composite DMU constructed from other n-1 DMUs. Doyle and Green's aggressive formulation, which we utilize in this study, is shown as expression (2).

Expression (2):

$$\min \sum_{k=1}^{s} \left\{ v_k \sum_{i \neq p} y_{ki} \right\}$$

$$\text{s.t.} \sum_{j=1}^{m} \left\{ u_j \sum_{i \neq p} x_{ji} \right\} = 1, \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \ \forall i \neq p, \sum_{k=1}^{s} v_k y_{kp} - \theta_{pp} \sum_{j=1}^{m} u_j x_{jp} = 0,$$

$$v_k, u_j \geq 0 \ \forall k, j$$

where θ_{pp} is the simple efficiency of DMU p obtained from expression (1).

DEA identifies effective benchmarks for improving the performance of inefficient units. The inefficient units can use one or more efficient units as a benchmark for improvement. These benchmarks can be identified from the dual formulation of (1) as expression (3). Where λ's represent the dual multipliers, which indicate the benchmarks that inefficient units must utilize in order to become efficient.

Expression (3):

$$\min \theta$$

$$\text{s.t.} \sum_{i=1}^{n} \lambda_i x_{ji} - \theta x_{jp} \leq 0 \ \forall j, \sum_{i=1}^{n} \lambda_i y_{ki} - y_{kp} \geq 0 \ \forall k$$

$$\lambda_i \geq 0 \ \forall i$$

Appendix II: Transportation Model

The following model, shown as expression (4), minimizes the total cost of transportation from sources to destinations by meeting the demand and capacity constraints.

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij}$$

$$\text{s.t.} \sum_{i=1}^{n} x_{ij} = D_j \ \forall j, \sum_{j=1}^{m} x_{ij} \leq K_i \ \forall i$$

$$x_{ij} \geq 0$$

where: c_{ij} represents the transportation cost associated in shipping one unit from source i to destination j;x_{ij} represents the number of units being shipped from source i to destination j;D_j represents the demand at destination j;K_i represents the capacity at source i.

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