The Comparison of Data Envelopment Analysis (DEA) and Financial Analysis Results in a Production Simulation Game

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Abstract: Production and service systems are generally evaluated based on financial information. The financial approach looks for opportunities to boost profits in two main ways: by decreasing operating costs and/or by increasing production quantity. Consequently, the cost of operation is evaluated and cost reduction possibilities are explored with proper cost analysis methods. Scoring methods extend the frontiers of performance evaluation by also employing non-financial information, although these methods generally contain several subjective elements. Data Envelopment Analysis (DEA) aims to integrate several performance measures into an aggregate output measure and several resource usage characteristics into an aggregate input measure. Based on the inputs applied and on the outputs generated, an efficiency score is calculated using linear programming. The objective of this paper is to illustrate the differences between performance evaluations, based on financial information, versus the DEA results. The results of a production simulation game are used to show how a DEA based performance evaluation can be carried out. The additional information provided by DEA may help to identify the causes of inefficient operation and to explore ways of improving efficiency.

Keywords: Data envelopment analysis (DEA); Performance evaluation; Production management; Simulation games; Linear programming

1 Introduction

Evaluating the performance of production systems is one of the most important tasks for managers. Performance evaluation is especially complicated when several conflicting evaluation criteria must be considered at the same time. Profit, for example, is one of the major objectives of a production system. High customer satisfaction favorably influences profit in the long term. Spending on customer satisfaction improvement may, however, decrease profit in the short term. It is difficult to evaluate these two conflicting criteria at any particular point in time. This is because the integration of the value of profit and the measure of customer satisfaction into a single score is subjective. Many other similar evaluation issues arise, in practice.

A specific example of performance evaluation is the analysis of the results of business simulation games used in management education and training programs. Simulation games are especially popular in the field of production and operations management. The beer game has been used for many years to study the bullwhip effect in supply chains, and a range of other logistic and/or manufacturing related games are in common use (see for example, Sterman, 1989; Ammar and Wright, 1999; Holweg and Bicheno, 2002; Battini et al., 2009). In the case of simulation games, the evaluation of the performance of the participating teams (or individuals) must be completed using special evaluation criteria related to the learning process which occurs during the game (Voss, 2015).

Generally, when evaluating the performance of systems on the basis of several evaluation criteria, scoring methods are employed. Scoring methods transform performance data into a common scale and an aggregate score is calculated with subjective weights. Data envelopment analysis (DEA) is a special type of scoring method. In DEA, weights are determined by means of linear programming (LP). Hence, the subjective judgment of the decision maker is eliminated when the efficiency scores are calculated. Data envelopment analysis evaluates the performance of decision making units (DMU) based on the outputs provided and on the inputs used by the DMUs. Thus, DEA determines the relative efficiency of DMUs based on the observed input and output values. A single efficiency score is calculated, and improvement policies are explored for non-efficient DMUs. Many DEA models exist in the literature, which aim to capture different real life operation and decision making environments (Cooper, Seiford and Tone, 2007).

The objective of this paper is to show how a slack-based DEA model can be used to analyze the performance of student teams in a production simulation game. The paper compares the financial results and the DEA efficiency scores of the participating teams. A correlation of the two results is analyzed and the differences are explained. The additional information provided by the DEA results are illustrated with several examples.

The structure of the paper is as follows. In Section 2, relevant literature related to DEA in financial analysis is reviewed. In Section 3, the main DEA concept and the basic models related to the presented research are reviewed. Section 4 introduces the objective and the basic conditions of the production simulation game used in the study. Section 5 compares and explains the financial and DEA results obtained. Finally, in Section 6, some general conclusions are drawn and further research possibilities are suggested.

2 Literature Review Related to the Application of DEA for Financial Evaluation

The three major sources of financial analysis are generally the Income Statement, the Balance Sheet, and the Statement of Cash Flow. When the characteristics of some economic sectors are analyzed or the performance of companies, are compared, financial ratios, using data of these three sources, are calculated. Sometimes simple ratios are used, such as return on assets or return on investment, but sophisticated systems of ratios are also found in practice (Harrison and Rouse, 2016).

The application of ratios is very widespread and accepted by practitioners, but there are also several criticisms (see for example Smith, 1990; Thanassoulis, Boussofiane and Dyson, 1999 or Harrison and Rouse, 2016). First, those ratios consider only two dimensions of operation, namely those which are described by the numerator and those by the denominator. It is possible to aggregate several ratios to incorporate more dimensions of the analyzed problem, but in this case the weights used for aggregation are subjective. Second, ratios generally provide an indication of efficiency problems, but a further analysis is required to trace the causes of inefficiencies. Both problems can be solved using DEA, which calculates an aggregate measure of efficiency and provides information about efficiency improvement possibilities.

Smith (1990) was one of the first to suggest the application of DEA to evaluate Financial Statements. He studied the efficiency of 47 pharmaceutical firms using average equity, average debt as inputs, and earnings available for shareholders, interest payments and tax payments as outputs, taken from their accounting system. The efficiency scores, calculated with an input oriented variable return to scale model, were compared with the return on capital ratios.

The efficiency of bank branches, belonging to a Turkish bank, were analyzed by Oral and Yolalan (1990). They applied two DEA models, one for analyzing profitability using financial information and one for analyzing service efficiency using operational information. They showed that DEA is not only complementary to the traditionally used financial ratio analysis, but also a useful tool for operations management decision making.

A similar study was conducted by Bowlin (1999), who compared the efficiency of the defense and non-defense related segments of the defense industry. Accounting information of 18 randomly sampled firms was used for the analysis of the trends of efficiency change between 1983 and 1992. The trends indicated by DEA were very similar to the trends indicated by some classic financial ratios.

Thanassoulis, Boussofiane and Dyson (1996) analyzed the perinatal care system in the United Kingdom. The efficiency of 189 units providing perinatal care was calculated with a radial model applying five inputs and five outputs, and the results were contrasted with several officially used performance indicators. In this case not traditional financial ratios, but official performance indicators of the District Health Authorities were used for comparison.

These four examples are among the first published cases which intended to use accounting information for DEA. Since then, several papers were published with the objective of highlighting the possibilities of DEA for financial evaluation. (for example, Ferro, Kim and Raab, 2003; Fenyves, Tarnoczi and Zsidó, 2015; Ederer, 2015; or Hosseinzadeh et al., 2016).

The general conclusion of these applications is that if inputs and outputs are carefully selected, then DEA results generally do not contradict financial results, and furthermore, DEA provides direct information for improvement possibilities. Two problems, however, must be considered when DEA is applied for the comparison of financial performance of different organizations.

The first problem is the violation of homogeneity assumption (Dyson et al., 2001). When DEA is applied, it is important that DMUs undertake similar activities, produce comparable products and/or services, apply a common set of inputs and use similar technology. This assumption is partly overlooked in the previously mentioned cases. The pharmaceutical companies, analyzed by Smith (1990), do not produce identical products. In the defense industry analysis, even the separation of defense and non-defense segments of the activity is ambiguous, according to the author (Bowlin, 1999). The prenatal care units analyzed by Thanassoulis, Boussofiane and Dyson (1996) do not provide exactly the same services, and finally the services offered by the bank branches may also differ (Oral and Yolalan, 1990).

The second problem is related to the application of DEA results. In the previously mentioned cases the information of DEA concerning improvement possibilities are not generally traced back directly to the analyzed units. Only Oral and Yolalan (1990) mentioned that DEA can also serve as a bank management tool if the results are used for decision making related to future operation.

The main novelty of this paper is that in the presented application these two problems are solved. All participating teams in the production simulation game produce the same products, use the same inputs, and apply the same production technology. Only marketing, financial and operation decisions are different. Consequently, homogeneity assumption is perfectly satisfied. The results of DEA are used for performance evaluation of the students, that is, the results and improvement possibilities are directly traced back to the decision makers.

3 Basic Concepts and Models of DEA

Charnes, Cooper and Rhodes (1978) suggested a linear programming model for the comparison of Decision Making Units (DMUs) using relative efficiency measures. Based on the model they suggested, relative efficiency analysis, or data envelopment analysis (DEA), became an important research area and a useful tool for performance evaluation. Several applications of DEA models are reported in the literature in both the service and the production sectors (Doyle and Green, 1991; Panayotis, 1992; Sherman and Ladino, 1995). A frequently applied area of DEA is higher education. Johnes (2006) compared more than 100 higher educational institutions in England using a nested DEA model. Sinuany-Stern, Mehrez and Barboy (1994) analyzed the relative efficiency of several departments within the same university.

The model suggested by Charnes, Cooper and Rhodes (1978) can be explained by an intuitive analogy taken from engineering. According to the law of energy conservation while energy can be transformed from one form into another, energy cannot be created. In power plants, for example, it is not possible to produce more energy than the energy content of the fuel used, or, to expressed differently, the technical efficiency of a power station is always lower than 1. Applying this engineering analogy to the area of performance evaluation in operations management, it can be stated that the measure of output is always smaller than the measure of input. In the best possible case, the ratio of output measure and input measure is equal to 1. The output and input measures are calculated as weighted outputs and weighted inputs, and the best possible weight values are sought for a reference DMU *R*. Let us assume that *J* number of DMUs are evaluated, when *K* different outputs are observed and *I* different inputs are used. Notations applied in this paper are listed in Table 1. If y_{kj} (k=1,…,K; j=1,…,J) are the observed output values of output k, and x_{ij} (i=1,…,I; j=1,…,J) are the observed input values of input i for DMU j, while v_k (k=1,…,K) and u_i (i=1,…,I) denote the output and input weights, then the linear programming formulation for finding the most favorable weights for DMU *R* is as follows:

$$\begin{aligned}
&Max\left(\sum_{k=1}^{K} v_k y_{kR} / \sum_{i=1}^{I} u_i x_{iR}\right) \\
&\sum_{k=1}^{K} v_k y_{kj} / \sum_{i=1}^{I} u_i x_{ij} \le 1 \qquad j = 1,\dots,J \\
&u_i, v_k \ge 0 \qquad i = 1,\dots,I; \quad k = 1,\dots,K.
\end{aligned} \tag{1}$$

If problem (1) is transformed in order to eliminate the ratio of variables, and the weighted input is fixed (equal to 1) in order to obtain a unique solution for LP problem (1), then the primal version of the input oriented, constant return to scale (CRS) model is obtained, that is:

$$
\begin{aligned}
& Max\left(\sum_{k=1}^{K} v_k y_{kR}\right) \\
& \sum_{i=1}^{I} u_i x_{iR} = 1 \\
& \sum_{k=1}^{K} v_k y_{kj} - \sum_{i=1}^{I} u_i x_{ij} \le 0 \qquad j = 1,\ldots,J \\
& u_i, v_k \ge 0 \qquad i = 1,\ldots,I; \quad k = 1,\ldots,K
\end{aligned} \tag{2}
$$

The dual version of problem (2), however, has more practical relevance and leads to another interpretation of DEA. According to the dual interpretation, any linear combination of the observed output and input values leads to a new and feasible DMU, which may exist in practice. The production possibility set is determined by all possible linear combinations of the observed outputs and inputs. If λ_j (j=1,…,J) are the coefficients of the linear combination of output and input values, then the production possibility set of DMU R can be defined as follows,

$$
\begin{aligned}
& y_{kR} \le \sum_{j=1}^{J} y_{kj}\lambda_j \qquad k = 1,\ldots,K \\
& x_{iR} \ge \sum_{j=1}^{J} x_{ij}\lambda_j \qquad i = 1,\ldots,I
\end{aligned} \tag{3}
$$

If we consider the λ_j (j=1,…,J) coefficients as variables, and a proper objective function is used to get an optimal combination of the output and input values, then the distance of any existing DMU from the optimal DMUs can be the basis of the efficiency score. The dual version of the input oriented CRS model assumes that all inputs must be decreased to the same proportion (θ), and efficiency is given by the smallest value of this proportion. Consequently, the smallest amount of input necessary to produce the observed output must be determined. The corresponding dual LP model is as follows:

$$
\begin{aligned}
& Min(\theta) \\
& \sum_{j=1}^{J} \lambda_j y_{kj} \ge y_{kR} \qquad k = 1,\ldots,K \\
& \sum_{j=1}^{J} \lambda_j x_{ij} \le \theta x_{iR} \qquad i = 1,\ldots,I \\
& \lambda_j \ge 0 \qquad j = 1,\ldots,J
\end{aligned} \tag{4}
$$

Models (2), (3), and (4) are based on a radial measure of efficiency, where all inputs are decreased proportionally by the same ratio. The slack based model (SBM) proposed by Tone (2001) uses the difference of the observed values and the best possible linear combination of inputs and outputs. The difference between the actual value and the best possible value is called slack. All possible slack values of DMU *R* can be determined if (3) is completed with slack variables. In (5), s_k^+ indicates the degree to which output *k* can be increased and s_i^- indicates the degree to which input *i* can be decreased, thus:

$$\begin{aligned} s_k^+ &= \sum_{j=1}^{J} \lambda_j y_{kj} - y_{kR} \qquad k = 1,\dots,K \\ s_i^- &= x_{iR} - \sum_{j=1}^{J} \lambda_j x_{ij} \qquad i = 1,\dots,I \end{aligned} \tag{5}$$

The slack values express the distance of a DMU from the best possible DMU. Based on the slack values the following efficiency measure can be used,

$$\mu_R = \frac{1 - \sum_{i=1}^{I} w_i^- s_i^- / x_{iR}}{1 + \sum_{k=1}^{K} w_k^+ s_k^+ / y_{kR}} \tag{6}$$

The slack-based measure of efficiency proposed by Tone (2001) can take any value between 0 and 1, and it is based on the weighted average of the normalized input and output slacks. Depending on the orientation of the analysis, either the nominator or the denominator can be ignored in the objective function. The input-oriented approach applied in this paper uses the following objective function:

$$Min\left(1 - \sum_{i=1}^{I} w_i^- s_i^- / x_{iR}\right) \tag{7}$$

In Section 4, an input oriented, slack-based DEA model, using objective function (7) and production possibility set (5), is applied to evaluate the results of student teams in a production simulation game. Since all DMUs in the game start with the same initial conditions, and considerable size differences cannot be achieved during the game, a constant return to scale (CRS) model is appropriate.

Table 1
Notation

Indices:		
j	-	index of decision making units (DMUs), j=1, …, J
i	-	index of inputs, i=1, … I
k	-	index of outputs, k=1, …, K
R	-	index of the reference DMU
Parameters:		
J	-	number of DMUs
I	-	number of inputs
K	-	number of outputs
x_{ij}	-	quantity of input i of DMU j
y_{kj}	-	quantity of output k of DMU j
w_i^-	-	weight of input slack i
w_k^+	-	weight of output slack k
Variables:		
u_i	-	weight of input i
v_k	-	weight of output k
λ_j	-	dual variable of DMU j
θ	-	radial efficiency score
μ_R	-	slack based measure efficiency score of DMU R
s_i^-	-	vector containing the input surplus values of each DMU
s_k^+	-	vector containing the output shortage values of each DMU

4 Introduction of the Simulation Game Applied in the Experiment

The production simulation game applied in this paper was developed by EcoSim Ltd. to support education and training in the field of production management. This simulation game is used in a module entitled *Decision Making in Production and Service Systems*, on the Production and Operations Management Master's degree program at the Budapest University of Technology and Economics. The objective of the game is to simulate production management decision making in a car engine manufacturing factory. The factory produces three different car engines for five different markets. Each market has its own demand characteristics. The car engines are assembled from parts on assembly lines operated by workers. Decisions must be made by each student team for the next production period (year) in the following areas:

– *The production quantities of the three car engines*. Forecasts must be prepared of expected demand based on the known demand of several previous periods. The expected demand, the available production capacity and the final product inventory information are used to determine the production quantities for the next year.

– Prices and payment conditions. Demand can be stimulated by changes to the selling price and by offering favorable payment conditions. Decisions must be made on the purchase price in the next production period and on the payment delay percentages offered to customers.

– *Quantities of parts to be ordered*. The order quantities of the various parts groups must be determined based on the planned production quantities, on the bill-of-material of the car engines and on inventory and financial information.

– *Number of workers, number of shifts, and quantity of overtime*. Production quantity is determined by the machine capacity and by the number of workers. In the short term, capacity can be changed by hiring or firing workers and by changing the number of production shifts, or by applying overtime. Decisions must be taken about the number of the workforce, about the number of shifts and about the quantity of overtime in the next production period.

– *Investments in the production line and in space*. In the long term, production capacity can be increased by investing in new production lines and in making more space available for production and for inventory. Decisions must be made in each production period about the number of new production line installations and about the number of square meters of space extensions.

– *Launch of efficiency improvement projects*. It is possible to launch projects which may improve production conditions. The predefined projects have different effects and different launch and maintenance costs. Decisions must be made on which projects to launch in a production period.

– *Application for loans*. Three different types of loan are available for financing the operation of the factory. Each type of loan has different conditions. Decisions must be made about the amount used of each loan type and about the repayment of earlier loans.

After the decisions are submitted, the simulation program generates the results of the current production period. The results are summarized in two reports:

– *Production report*. The production report summarizes the decisions made by the student teams for the current production period and the current state of the production system. The quantity of engines produced and sold, the quantity of parts used and the engine and part inventories at the end of the production period are given in details. The number of workers, machine capacities, number of production lines, and space, available for the next production period are also listed.

– *Financial report*. The financial report contains the balance sheet, the revenue report and the cash flow report valid at the end of the current production period.

When students evaluate the production and financial reports, and take decision on the next production period they need to apply their knowledge of several study areas taught on the Master's program. Awareness of marketing methods is required to estimate the behavior of customers when prices and payment conditions changes. A familiarity with forecasting models is needed to evaluate future demand possibilities. Inventory control and materials requirement planning techniques must be used to determine and control the inflow of raw materials and parts. Capacity planning techniques are needed to determine the workforce level, the number of assembly lines operating and the amount of space required. Cash flow analysis methods are required to evaluate the potential effects of efficiency improvement projects. Finally, managerial accounting and corporate finance knowledge is needed to properly understand balance sheets, cash flow reports and revenue reports.

At the end of the seventh production period the student teams are evaluated. This evaluation is very difficult even if only the financial situation of the plants is considered. Furthermore, purely financial analysis can be misleading. Some of the possible traps of narrow minded financial evaluation include:

– Short term success may not necessarily lead to long term success. The plant may make large profits in the first seven periods, but if production resources (production lines, production space, improvement projects) do not support production increases in the future financial performance may later decrease.

– A group may follow a cautious strategy. They may decide on a low production quantity, financed solely by their own financial sources. In these cases small profits and slow but steady growth can characterize the plant.

– Long term strategic thinking may provide unfavorable financial results in the short run. Heavy investments can be made at the beginning using loans in order to secure capacity for future growth. If all this is paired with a demand- stimulating marketing policy and with efficiency-improvement projects, profit will be low at the beginning, but steep growth can be expected in the future.

5 Comparison of Financial and DEA Results

Financial data (revenue and profit) are provided by the simulation game automatically in the output report at the end of each production period. The efficiency scores are determined with an SBM, input oriented, constant return to scale DEA model using an objective function (7) and a production possibility set (5). Cumulated output and input data are applied to evaluate the overall efficiency of operation over the course of seven production periods. Four inputs are used, which represent the four main resource groups used for production (workers, machines, material and money). The cumulated number of workers, the cumulated number of machine hours, the cumulated sum of money spent on raw materials and the cumulated value of credits represent the resources used in the production process, and the corresponding values are taken from the production and financial reports. The cumulated revenue is used as a single output of the DEA model. Comparison of the financial results and the DEA results is based on a comparison of the cumulated profit and of the SBM efficiency scores of each team.

The results of the simulation game are summarized in Table 2. Column (2) of the table lists the revenue of the student teams while column (5) shows the ranking of the teams based on revenue. Column (3) shows the net profit value of the teams and column (6) shows the ranking of teams based on net profit. Finally, column (4) shows the SBM efficiency score of each team and column (7) shows the ranking of teams based on SBM efficiency scores.

Intuitively, it may be assumed that if high revenue is paired with good financial and production decisions then the profit and the efficiency score will also be high. Consequently, a team with a good profit rank will also have a good efficiency rank. A rank correlation analysis shows that the Spearman rho value is equal to 0.588 with a p-value equal to 0.008. This result indicates a strong correlation between efficiency scores and profit. Tied ranks of efficiency scores are substituted with rank averages in the calculation of the Spearman rho value (Iman and Conover, 1989).

Relatively high differences in ranks, however, not necessarily express very different results. Figures 1, 2 and 3 show the revenue, net profit and SBM efficiency scores of the teams in decreasing order and in the form of column diagrams. Figure 1 shows that there are very small differences among the revenues of the first 9 teams. Figure 2, however indicates, that teams with similar levels of revenue may have very different operations, as illustrated by the much wider spread of profit values. The spread of efficiency values is less marked, and several teams have identical or very similar efficiency scores. Similar efficiency scores, however, may be attained with very different operations, as indicated by the slack values in Table 3. The slack values of the optimal solution of the SBM DEA model can be used to explore operational shortcomings and possibilities for improvement.

Detailed analysis of the net profit ranks and efficiency ranks shows that high profit ranks do not always correlate with high efficiency ranks. Figure 4 shows the net profit ranks, revenue ranks and SMB efficiency ranks in a column diagram. Teams are ordered in increasing order of profit rank. It can be seen that in many cases that if revenue is high but it is not paired with efficient operation then profit is low, and the efficiency score is also low (see, for example Team 3, 5 and 16). Sometimes, however, low revenue and low profit co-occur with high SBM efficiency, showing a modest but efficient operation (see for example Team 14). Some typical cases are presented below to illustrate the additional insight provided by DEA results.

Table 2
Result of the simulation game

Team (1)	Revenue (WCU) (2)	Net profit (WCU) (3)	SBM Efficiency (4)	Rank Revenue (5)	Rank Net profit (6)	Rank Efficiency (7)
1	10,661,696	176,318	0.9907	13	18	8
2	10,577,446	1,148,395	0.9902	14	11	9
3	12,033,234	991,530	0.9784	8	12	13
4	12,061,476	1,538,008	0.9816	7	6	12
5	11,637,708	793,093	0.9653	10	14	17
6	12,101,500	1,800,132	0.9948	4	4	6
7	12,075,614	1,936,412	**1.0000**	6	3	1
8	10,232,003	1,370,187	0.9923	15	9	7
9	10,145,111	346,178	0.9771	16	17	15
10	12,213,420	2,048,193	**1.0000**	2	2	1
11	11,341,162	1,609,319	0.9875	12	5	10
12	10,102,317	120,912	0.9388	17	19	19
13	12,336,201	2,130,817	**1.0000**	1	1	1
14	9,633,311	726,334	0.9962	18	15	5
15	12,211,651	1,353,441	**1.0000**	3	10	1
16	12,099,778	1,511,871	0.9780	5	7	14
17	11,608,198	855,236	0.9823	11	13	11
18	12,012,255	1,479,598	0.9756	9	8	16
19	8,029,665	507,042	0.9649	19	16	18

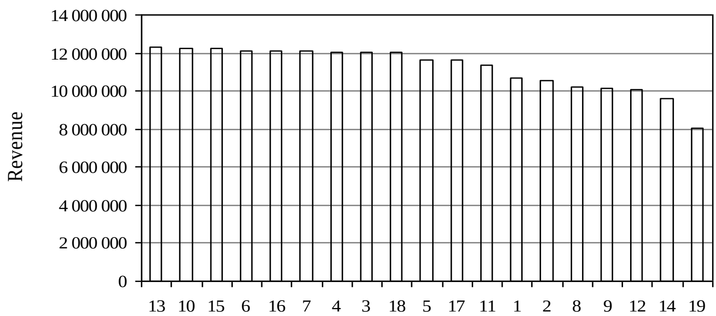

Figure 1
Revenue of team in decreasing order

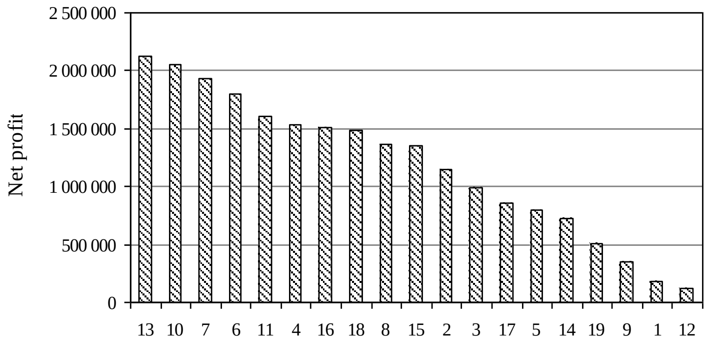

Figure 2
Net profit of team in decreasing order

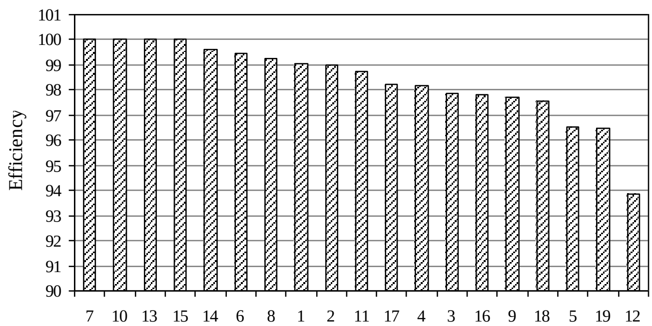

Figure 3
SBM score of teams in decreasing order

Team (1)	Revenue (2)	Workers (3)	Capacity (4)	Raw material (5)	Debt (6)
1	0	0	0	1.25	1.44
2	0	0	0.37	0.31	0.22
3	0	0	0	0.54	1.27
4	0	1.97	0.46	0	0
5	0	0.15	0	0.55	0
6	0	0	0	0.03	0
7	0	0	0	0	0
8	0	1.23	0.17	0	0
9	0	2.35	0	0.86	0.62
10	0	0	0	0	0

11	0	0.77	0.59	0	0
12	0	1.43	0	0.48	0.62
13	0	0	0	0	0
14	0	0.16	0	0.41	0
15	0	0	0	0	0
16	0	1.01	0.5	0	0
17	0	0	0	0.84	0.19
18	0	0.55	0.33	0	0
19	0	1.32	0.48	0	1.09

Table 3
Optimal slack values of the SBM DEA model (scaled data)

The best results were obtained by Team 13. This team is ranked first by all criteria. Three other teams were also efficient (Teams 7, 10, 15), but they have very different revenue and profit results. Consequently, a different operation policy may lead to different financial results, but still result in efficient operations. Based on net profit and on efficiency, Team 12 is ranked last.

Team 7 is ranked 6th in terms of revenue, but 3rd by profit. This shows that despite its relatively low revenue this team operated efficiently, which is reflected in the efficiency score. Team 14 had similar results, with low revenue and profit paired with relatively high efficiency. In this case, however, efficiency problems can be seen. Based on the slack values found in Table 3, the number of workers could be decreased and better inventory management would be required to improve the efficiency of this low revenue production.

Team 16 is ranked 5th by revenue, but the differences in revenue are insignificant for the first 9 teams, as seen in Figure 1. In terms of net profit, this team is ranked 7th and the differences in profit between the best teams is significant, as seen in Table 2. Consequently, operational shortcomings may be suspected, and indeed this is indicated by the relatively low efficiency score (rank 14). Similar results can also be observed for Team 3. Despite the similarity in results of Teams 3 and 16, they were quite different in operational terms, as indicated by the slack values in Table 3. Team 3 used excessive amounts of raw materials and ran up high levels of debt. Team 16 employed too many workers, and had excess machine capacity. Team 3's problem might be solved by improving inventory and financial management, while in the case of team 16, better capacity management may improve performance.

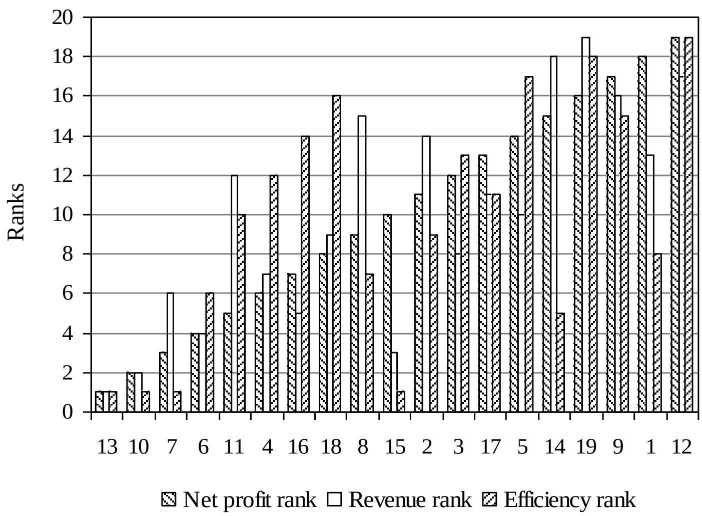

Figure 4

Comparison of the ranking of teams

Finally, an interesting case is Team 15, which is among the best with respect to revenue. This team is efficient according to the SBM score, even though its profit is relatively low (ranked 10th). In this case efficiency and profit does not correlate. This situation can be explained partly by the different marketing policy of Team 15. This team charged higher selling prices than the other teams and produced slightly smaller quantities. The joint effect of higher selling price and smaller quantity resulted in high total revenue (ranked 3rd). In this case the inefficient use of inputs had greater consequences for profit, than for SBM efficiency because the negative consequences of increasing selling prices are not considered by the DEA model. In the long run, selling price increases, may unfavorably affect market demand. This is not, however, reflected in the SBM efficiency score.

Conclusions

This paper compared different evaluation possibilities for a production simulation game. The first type of evaluation is based on financial data provided in form of traditional financial reports (balance sheet, revenue and cash-flow reports). The second type of the evaluation is made with the help of a slack based DEA model. Both results are based on the same basic principle, contrasting revenue with the resources used. Financial analysis takes profit as its major indicator, which is calculated as the difference between revenue and the cost of all resources used for operation. In DEA an efficiency score is calculated, which is the ratio of weighted outputs and weighted inputs. Since only one output is used in this paper, the efficiency score expresses the ratio of revenue and the weighted sum of the major resources used for operation. Roughly speaking, first we take the difference between the revenue and the cost of resources and second, we take the ratio of the revenue and the resources used. Consequently, the major results of the two analyses should be similar. This is partly borne out by rank correlation analysis, which showed that profit ranks and efficiency ranks exhibited a strong correlation.

The major difference between performance evaluation based on financial data and DEA is that DEA considers only inputs which can be influenced by the decision maker, and intentionally incorporates them into the analysis. In contrast, profit related results include all the costs of operation. This difference has two major consequences:

− DEA based performance evaluation better expresses the shortcomings of operation caused by improper management decisions, since not all costs (only discretionary costs) are involved in the analysis. Ways to improve can thus easily be discovered.

− An assessment of profit includes all the costs of operation, while the inputs used in DEA are decided upon by the decision maker, which involves a subjective judgment in the calculation of the results. The advantage of this is that efficiency scores can better express the priorities of the decision maker. On the other hand, some important inputs are ignored, which may distort the result. Consequently, the selection of which inputs to employ in DEA must be very carefully considered.

Similar considerations can be made about the outputs. Financial based evaluation concentrates only on revenue, while DEA can incorporate several non-financial results of operation, such as quality indicators, customer satisfaction, speed of delivery etc. Consequently, DEA can provide a much more detailed picture of the results of operation and ways to improve.

Apart from the evaluation of results, one of the key objectives of performance evaluation is to explore ways to improve operation. Several techniques are used in financial analysis to explore avenues for improvement (see, for example, variance analysis in standard costing, or activity based costing). In DEA, however, the slack values directly show operational shortcomings and the areas of improvements.

This paper presented a special example of performance evaluation based on financial data and on the results of data envelopment analysis. Comparing the performance of student teams in a production simulation game provided information not only about the result of the game, but also about the learning process. A detailed analysis of the learning characteristics of student teams with DEA is presented by Koltai et al. (2013).

The main contribution of the results presented in this paper can be summarized as follows. The evaluation of the results of business simulation games with DEA is a new area of application. If the traditional financial information is the output of the simulation game then an ideal environment is found for the comparison of financial results and DEA efficiency scores. First, all participating teams in the production simulation game produce the same products, use the same inputs, and apply the same production technology. Only marketing, financial and operation decisions are different. Consequently, *homogeneity assumption* is perfectly satisfied. Second, the results used for performance evaluation of the students, that is, the results and improvement possibilities are *directly traced back* to the decision makers.

In future work, the DEA-based performance evaluation presented in this paper can be extended to consider several other characteristics of operations. Non-financial outputs can easily be incorporated, the orientation of the analysis (input oriented, output oriented) can be changed, and the dynamic characteristics of the results can be analyzed with network DEA models. As a consequence of the development of DEA in the last decades, several important elements of real life operation can be easily considered. Consequently, applying DEA instead of, or in parallel with, financial analysis, is a challenging possibility for performance evaluation optimization.

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