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An Exploration on the Use of Data Envelopment Analysis for Product Line Selection

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Abstract. We define product line (or mix) selection problem as selecting a subset of potential product variants that can simultaneously minimize product proliferation and maintain market coverage. Selecting the most efficient product mix is a complex problem, which requires analyses of multiple criteria. This paper proposes a method based on Data Envelopment Analysis (DEA) for product line selection. Data Envelopment Analysis (DEA) is a linear programming based technique commonly used for measuring the relative performance of a group of decision making units with multiple inputs and outputs. Although DEA has been proved to be an effective evaluation tool in many fields, it has not been applied to solve the product line selection problem. In this study, we construct a five-step method that systematically adopts DEA to solve a product line selection problem. We then apply the proposed method to an existing line of staplers to provide quantitative evidence for managers to generate desirable decisions to maximize the company profits while also fulfilling market demands.

Keywords: Product Line Selection, Data Envelopment Analysis.

1. INTRODUCTION

Designing product families in place of single products is an approach many companies have taken to reduce product development and production costs, and to diversify their product offerings (Simpson *et al.*, 2005). A key strategy in creating product families is to identify products that can be produced effectively from a single platform, while maintaining the competitiveness of the product line. As more manufacturing companies consolidate their product lines, there is an increasing need for more systematic and consistent approaches to help them do so. Recently, Thevenot *et al.* (2006, 2007) developed a method based on multi-attribute utility theory (MAUT) for product line selection. MAUT involves a single decision-maker who chooses among a number of alternatives on the basis of two or more criteria or attributes. The decision-maker seeks to maximize a utility function that depends on these attributes. Most companies usually face large scale decision problems with numerous alternatives and criteria for product line selection problems. For this situation, using MAUT is time consuming. In addition, decision making process may involve a group of decision-makers. In such a situation, the MAUT application becomes very complex.

For the reasons indicated above, a method which can easily work on large scale multi-criteria problems and by several decision-makers is needed. Accordingly, we propose to use Data Envelopment Analysis (DEA), a widely used multi-criteria decision making method. Although there have been several studies that used DEA mostly for project evaluations, it has not been applied to product line selection problems. Accordingly, we fill this void in the literature. The remaining sections of the paper are as follows: Section 2 introduces the related literature review. Section 3 provides details for the product line selection problem based on an industrial case. Section 4 describes the proposed method, while Section 5 demonstrates its application and related results. Finally, Section 6 provides conclusions and recommendations for future work.

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2. LITERATURE REVIEW

Data Envelopment Analysis (DEA), developed by Charnes *et al*. (1978), is a linear programming based technique. DEA is commonly used to measure the relative productivity efficiency among a group of decision making units (DMUs) by forming an efficient frontier. Given a set of DMUs, the efficiency value (θ) is measured using the relative distance projection toward the frontier.θis usually regarded as the efficiency or the productivity index. The most efficient DMUs locate on the frontier withθ= 1, while the inefficient ones fall beyond the frontier with θ <1.θvalues range from 0 to 1.

There are a variety of models, which result from different ways in measuring the projection. For example, CCR (**C**harnes, **C**ooper, **R**hodes) model (Charnes *et al*., 1978) and BCC (**B**anker, **C**harnes, **C**ooper) model (Banker *et al*., 1984) measure the projection to the frontier, while the additive model (ADD) measures the largest sum of the horizontal and vertical distances toward the frontier (Cooper *et al*., 2000).

In comparison to other multi-criteria decision making (MCDM) methods, DEA has two major advantages. First, it works with multi-dimensional problems with multiple input and output indices (variables). This feature makes DEA an advantageous performance evaluation tool widely adopted in various fields. Second, DEA avoids the difficulty of deciding for potentially unequal weights for the criteria. In MCDM problems, the allocation of weights (to show the varying importance levels for criteria) is generally controversial. DEA uses the weight for each input and output that will let each DMU reach its maximum possible efficiency value (Charnes *et al*., 1994).

There are two possible orientations of DEA models: (1) the input oriented model, and (2) the output oriented model. For the input oriented model, the performance is improved by using the inputs while we try to do the improvement by adjusting the outputs for the output oriented model. The two basic DEA models are the CCR model and the BCC model. The two models differ in the appearance of their frontiers. The CCR model is the initial DEA model developed by Charnes *et al*. (1978). CCR is based on the assumption of constant return to scale (CRS). The BCC model is introduced by Banker *et al*. (1984). The BCC model considers variable return to scale (VRS). Due to the CRS feature, the CCR model forms the frontier under the most productive scale. Each DMU compares its performance to the most productive scale and receive an absolute efficiency value. Thus, the CCR model provides a global view for all the DMUs with a consistent standard for comparison. The efficiency obtained by the CCR model is generally regarded as the productive efficiency. Different from the CCR model, the BCC model with VRS feature has its frontier spanned by the convex hull of the existing DMUs (Cooper *et al*., 2000). In comparison to the CCR model, DMUs can obtain better efficiency scores under the BCC model because of the more conservative frontier. To distinguish from the CCR efficiency, the BCC efficiency is generally taken as the technical efficiency.

DEA has been applied to various areas as a tool for evaluating performance. For example, in the engineering design area, Miyashita *et al*. (2002) constructed a supervisor system that used DEA to solve a collaborative design problem, Paradi *et al*. (2002) used DEA to analyze the performance of engineering design teams at Bell Canada, and Farris *et al*. (2006) adopted DEA as a project evaluation tool to analyze projects from two different engineering design processes. Although DEA has been used in the engineering design domain, it has not been used for solving the product line selection problems. The complexity of the product line selection problem is rooted in making a selection that will impact many operational outcomes of a company (e.g., manufacturing cost, inventory levels, profit, market coverage and consumer satisfaction). In this study, we apply DEA to this problem in order to aid design decision-makers.

3. PROBLEM DEFINITION

In the paper, we utilize data pertaining to a product family previously introduced in (Thevenot *et al*., 2006) (see Table 1). The problem introduced was the following: a company produces three different types of staplers (numbered 1, 2, 3 in the *Product Mix* column in Table 1). Business leaders in the company would like to add a new model to their product line to increase the market coverage (numbered 4 in the *Product Mix* column in Table 1). However, introducing a new product is a complex decision as it impacts many operational issues and their outcomes (e.g., costs, inventory levels, etc.). The goal in this problem is to decide which product mix would result in high profits while minimizing product proliferation and maintaining competitive market coverage. *Note that this case study is based on real data from the company, but the strategy analyzed is only an illustrative example for proving our methodology and will not be implemented.*

Table 1. Data from previous research (adapted from Thevenot *et al*. (2006, 2007).

Product Mix	PCI (%)	Profit ($)	Market Coverage (%)
1 2 3 4	36.5	$45,543,018	80
1 2 3	40.7	$36,280,518	70
1 2 4	40.7	$26,389,514	60
2 3 4	43.1	$48,793,824	80
1 3 4	43.1	$39,817,768	80
1 2	59.2	$17,127,014	50
1 3	42.9	$30,555,268	70
1 4	42.9	$20,664,264	60
2 3	42.9	$39,531,324	70
2 4	42.9	$29,640,320	0.6
3 4	63.3	$28,416,004	0.3

We want to use the DEA technique as an approach to assist the company in selecting the most efficient product family given two conflicting points of view -- from the view of the manufacturer and the customer. The available data set includes 11 different product family combinations along with their corresponding product line commonality values (PCI), market coverage (MC), and profit information. The data set is provided in Table 1. The PCI, introduced by Kota *et al.* (2000), measures the product line commonality from several dimensions. It evaluates if component size/shapes, materials/manufacturing processes, and assembly processes are identical for the non-unique components across the products of a family. PCI values range from 0 to 100. A higher PCI value represents more commonality among the non-unique components of the product family. The profit and market coverage represent the possible results that the choice of the certain product family alternative could bring.

From a manufacturing point of view, along with the high profit and wide market coverage, the company might prefer to produce a product family with high product commonality. High commonality in products would reduce the complexity in manufacturing processes, and also reduce the production costs. On the other hand, high commonality would cause products to be less unique. From a consumer point of view, a reduction in product variety may lessen customer interest for purchasing. Accordingly, making the product line selection decision is a trade-off situation, which may lead to losing customers or increasing costs and production complexity. In this study, we first show the decision choices for the two viewpoints. Then, we propose a method to derive a compromising solution.

4. METHODOLOGY

In this section, we explain our method for using DEA to assist in product line selection. The method consists of five steps, which are briefly explained below. The overall flow of the decision process is provided in Figure 1.

4.1 Data collection

For each component of the different product family alternatives, all pertaining information on potential variables (e.g., costs, revenues etc.) should be collected and recorded. For example, calculating the PCI would require detailed information about all the components, processes, materials, etc. The quality of the collected data will in part determine the quality of the eventual decision.

4.2 Identify model indices (variables)

The main question to answer at this stage is "What are the main indices that could directly affect the decision?" One word of caution is that the set of indices should be limited in size, and accordingly, only the main factors which significantly affect the decision should be included in the set. Too many indices will cause the result of losing discriminatory power (Paradi *et al.*, 2002). The recommended maximum number of input and output indices for DEA is equal to one-half the number of DMUs (Dyson *et al.*, 2001).

4.3 Model selection

According to the property of the indices and the decision purpose, we can select the most appropriate DEA model as our approach. Model types might change based on the calculation of the projection (CCR, ADD), or problem/variable characteristics (such as input-oriented or output oriented models) may dictate the selection of the model. Steps 2 and 3 of the method should be treated very carefully as the property of the indices would have strong influence on the model to be used.

4.4 Run the DEA model

There are several software packages for DEA calculations such as Frontier Analyst, DEAFrontier, etc. In

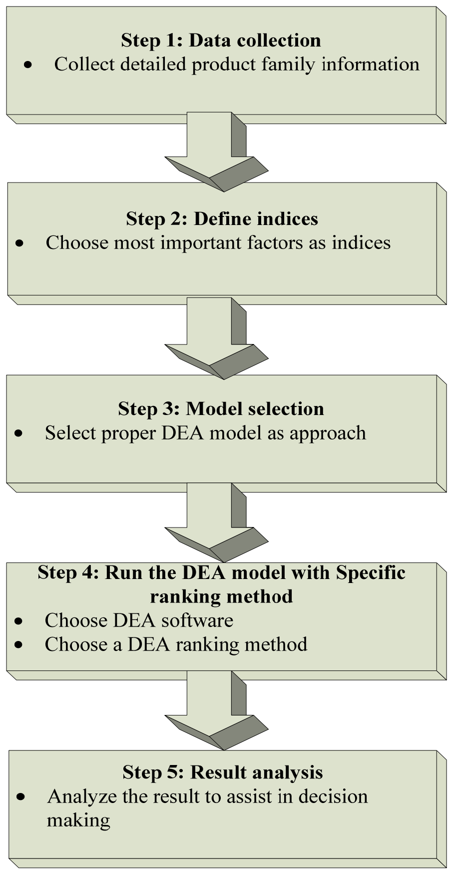

Figure 1. The decision process for product line selection using DEA.

addition, a generic software could be programmed to complete the calculations. For example, in this study, we used Excel VBA.

4.5 Result analysis

When a tie is present in the results, a ranking of the results with a specific DEA ranking method such as cross-efficiency method, or the Andersen-Petersen method might be necessary. This ranking will break the ties. During the analysis of the results, special attention should be directed to the meaning of the model parameters such as θ, η, μ etc., to obtain the most appropriate result.

5. APPLICATION, RESULTS and DISCUSSION

In this section, we apply the above presented five step method to the stapler company product line selection problem explained in Section 3. As provided in Table 1, we have collected data related to the problem at hand (Step 1). The overall data set contains information on PCI, profit, and market coverage for varying product mixes. In Table 1, each product mix is represented with a collection of integers each representing a product variant (e.g., 23 would mean product mix involves product 2 and product 3). All indices available are used in the DEA (Step 2).

In Step 3 we make model decisions. Regardless of the point of view we take, our ultimate goal is to find the product mix with the best performance in profit and market coverage given the PCI values. Thus, output oriented DEA model with two outputs, profit and market coverage along with the only input, PCI, is selected as our model. Notice that choosing the most efficient product family is our objective, and accordingly the performance measure in determining the overall efficiency in a global view from the 11 product family alternatives is important to us. Therefore, we decide to use the CCR output oriented model with constant return to scale (CRS) property as our approach. The CCR output oriented model is given in Eq. (1):

$$
\begin{aligned}
&Min \quad \eta_k = \frac{\sum_{i=1}^{m} v_i x_{ik}}{\sum_{r=1}^{s} u_r y_{rk}} \\
&s.t. \quad \frac{\sum_{i=1}^{m} v_i x_{ij}}{\sum_{r=1}^{s} u_r y_{rj}} \le 1, \quad j = 1, \cdots, n, \\
&\qquad v_i \ge \varepsilon > 0, \quad i = 1, \cdots, m, \\
&\qquad \mu_r \ge \varepsilon > 0, \quad r = 1, \cdots, s.
\end{aligned} \tag{1}
$$

From Eq. (1), η_k is the efficiency value of the k^{th} DMU, and $\eta_k = 1/\theta_k$. x_{ik} and y_{rk} represent the input and output indices of the k^{th} DMU. v_i and u_r are the weights, which are generated automatically during the computation process.

The dual linear programming model is shown in Eq. (2):

$$
\begin{aligned}
&\max \quad \eta_k \\
&s.t \quad x_k - \sum_{j=1}^{n} x_{ij}\mu_j \ge 0 \quad (i = 1,\ 2, \cdots m) \\
&\qquad \sum_{j=1}^{n} y_{rj}\mu_j \ge \eta y_{rk} \quad (r = 1,\ 2, \cdots, s) \\
&\qquad \mu_j \ge 0 \quad (j = 1,\ 2, \cdots, n)
\end{aligned} \tag{2}
$$

Since η is increasing from 1 and that is difficult to distinguish the degree of difference, we represent the score by 1/η as θ for easiness in comparison. The DEA

Table 2. The DEA results from manufacturer's view.

Product Mix	100-PCI	Profit (dollar)	Market Coverage (100%)	DEA Score	Cross Efficiency	Ranking
1234	63.5	45543018	0.8	0.896063	0.885209	3
123	59.3	36280518	0.7	0.839587	0.816654	6
124	59.3	26389514	0.6	0.719646	0.683155	10
234	**56.9**	**48793824**	**0.8**	**1**	**1**	**1**
134	56.9	39817768	0.8	1	0.966553	2
12	40.8	17127014	0.5	0.87163	0.802155	7
13	57.1	30555268	0.7	0.871935	0.826859	5
14	57.1	20664264	0.6	0.747373	0.688218	9
23	57.1	39531324	0.7	0.871935	0.860189	4
24	57.1	29640320	0.6	0.747373	0.721548	8
34	36.7	28416004	0.3	0.90291	0.639859	11

Table 3. The DEA results from customer's view.

Product Mix	PCI	Profit (Dollar)	Market Coverage (100%)	DEA Score	Cross Efficiency	Ranking
1234	**36.5**	**45543018**	**0.8**	**1**	**1**	**1**
123	40.7	36280518	0.7	0.784705	0.765535	4
124	40.7	26389514	0.6	0.672604	0.630889	7
234	43.1	48793824	0.8	0.907316	0.863354	2
134	43.1	39817768	0.8	0.846868	0.817833	3
12	59.2	17127014	0.5	0.385346	0.343487	10
13	42.9	30555268	0.7	0.744464	0.697107	6
14	42.9	20664264	0.6	0.638112	0.569365	9
23	42.9	39531324	0.7	0.744464	0.74284	5
24	42.9	29640320	0.6	0.638112	0.615098	8
34	63.3	28416004	0.3	0.359774	0.25538	11

scores of the 11 product family alternatives based on two conflicting points of view (manufacturer's, and consumer's) are shown Tables 2 and Tables 3.

Owing to different points of view, we use two different input indices: 100-PCI and PCI. For manufacturer's view, we set the 100-PCI as the input, thus a higher PCI value will result in a smaller input. For consumer's view, since a lower PCI value represents the higher distinctness among the members of the product family, setting the PCI as the input will assign higher efficiency to the most distinctive product family alternative.

The data set obtained by using the output-oriented CCR model is shown in Tables 2 and 3. DEA might involve the problem of having multiple DMUs tie with same scores, as in Table 2 (i.e., product family alternative 234 and 134 are both efficient with the same score while DMUs 14 and 24 are less efficient and have equal scores). Accordingly, distinguishing DMUs in a detailed ranking might be important for users in the process of decision making. There are many studies discussing various ranking methods used to rank DEA results. For this study, the cross efficiency ranking method is selected to rank all the product family alternatives.

The cross-efficiency matrix was first developed by Sexton *et al*. (1986). For each DMU, this ranking method calculates the efficiency scores as a product of n and the best weights of each DMU, as in the Eq. (3) (Adler *et al*., 2002). It then forms a $n \times n$ matrix, called the cross-efficiency matrix, which is shown in Eq. (4). In the cross-efficiency method, each element's value ranges from 0 to 1, and the diagonal represents the original DEA score. The cross-efficiency score of each DMU is obtained by averaging the sum of each row in the cross-efficiency matrix, which is shown in Eq. (5). When a cross-efficiency method is adopted, the most efficient DMU might get a score lower than 1. If a DMU gets a cross-efficiency score with 1, it indicates that this DMU dominates all the others in performance.

$$h_{kj} = \frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}} \quad k = 1, \cdots, n \quad j = 1, \cdots, n \tag{3}$$

$$\begin{matrix} h_{11} & h_{12} & \bullet\ \bullet & h_{1n} \\ h_{21} & h_{22} & \bullet\ \bullet & h_{2n} \\ \bullet & & & \bullet \\ \bullet & & & \bullet \\ h_{n1} & h_{n2} & \bullet\ \bullet & h_{nn} \end{matrix} \tag{4}$$

$$\bar{h}_k = \frac{\sum_{j=1}^{n} h_{kj}}{n} \quad k = 1, \cdots, n \tag{5}$$

In Step 5 an analysis of the results is recommended. The cross-efficiency scores and the ranking are shown in the last two columns of Tables 2 and 3. For manufacturer's view, product family alternative (234) is our best choice. However, for the consumer's view, the results indicate product mix 1234 to be the recommended choice. Since Table 2 and Table 3 are from two conflicting points of view, the corresponding ranking orders still cannot facilitate us to make a final decision. Accordingly, we introduce a compromise viewpoint to assist the decision-makers in choosing the best product family alternative.

In this compromise solution, we consider the two different points of view to have equal importance with a 0.5 value for each weight. Accordingly, we transfer the PCI values to the compromise PCI using Eq. (6). We first transfer the PCI to the absolute distance from the average PCI, and then rescale the absolute distance by adding another average PCI. For this viewpoint, we assume that the average PCI is the more reasonable value for both

Table 4. The DEA results for the compromise viewpoint.

Product Mix	45.3+ |45.3-PCI|	Profit ($)	Market Coverage 100%	DEA Score	Cross Efficiency	Ranking
1234	54.1	45543018	0.8	0.878003697	0.867368149	3
123	49.9	36280518	0.7	0.832915832	0.81016487	6
124	49.9	26389514	0.6	0.713927856	0.677727331	9
234	**47.5**	**48793824**	**0.8**	**1**	**1**	**1**
134	47.5	39817768	0.8	1	0.966552935	2
12	59.2	17127014	0.5	0.501478041	0.461506823	10
13	47.7	30555268	0.7	0.871331237	0.826286679	5
14	47.7	20664264	0.6	0.746855346	0.687740909	8
23	47.7	39531324	0.7	0.871331237	0.859593504	4
24	47.7	29640320	0.6	0.746855346	0.721047734	7
34	63.3	28416004	0.3	0.90291	0.309690568	11

manufacturer and consumer to compromise. Thus, we use the compromise PCI to substitute PCI and rerun the DEA model along with the cross-efficiency ranking. The results of this run are shown in Table 4. We see in the table that the product mix that has product variants 2, 3 and 4 is recommended.

$$Compromise\ PCI = Avg\ PCI + \left|Avg\ PCI - PCI\right| \quad (6)$$

Further, the resultant rankings of the three different points of view (manufacturer's, consumer's, and compromise) are compared to the ranking achieved using MAUT in Thevenot *et al.* (2007) in Table 5. As a measure of comparison for the rankings, Spearman's ''footrule'' (Spearman, 1904) is used, which is calculated as provided in Eq. (7). In Eq. (7), R_i and Q_i represent the ranks for n items in a set. This statistic measures disagreement in rankings, and it takes on its minimum value (0) if and only if $R_i = Q_i$ for i = 1, ⋯, n. In general, a smaller value represents a smaller disagreement between rankings.

$$F = \sum_{i=1}^{n} \left|R_i - Q_i\right| \quad (7)$$

In Table 5, three Spearman's footrule statistics revealing the disagreement between all three DEA-based rankings introduced in this paper and the MAUT-based ranking (from Thevenot *et al.* (2007)) are provided as 14, 12 and 10 for the manufacturer's, consumer's and the compromise point of view, respectively. Accordingly, the disagreement between the ranking achieved using the compromise view and MAUT is smaller than the others. Further, first seven ranks in both rankings are at most one ranking step apart (i.e., if the rank is 2 in one ranking, it is 3 in the other); and three of the first seven ranks are the

Table 5. The comparison of ranking results from the three different views and MAUT.

Product Family	Ranking under Manufacturer's view (R1)		Ranking under Consumer's view (R2)		Ranking under Compromise view (R3)		Ranking under MAUT (R4) (Henri *et al.*)
	Rank	|R1-R4|	Rank	|R2-R4|	Rank	|R3-R4|	Rank
1234	3	1	1	1	3	1	2
123	6	1	4	1	6	1	5
124	10	1	7	2	9	0	9
234	1	0	2	1	1	0	1
134	2	1	3	0	2	1	3
12	7	3	10	0	10	0	10
13	5	1	6	0	5	1	6
14	9	2	9	2	8	3	11
23	4	0	5	1	4	0	4
24	8	1	8	1	7	0	7
34	11	3	11	3	11	3	8
		Σ(|R1-R4|) = 14		Σ(|R2-R4|) = 12		Σ(|R3-R4|) = 10	

same, including 1, 4, and 7. Therefore, we conclude that the compromise view offered is an acceptable method in selecting a product line, where the decision-makers would like to avoid complexity of MAUT calculations and exploit advantages of DEA.

6. CONCLUSIONS and RECOMMENDATIONS FOR FUTURE WORK

In the paper, a decision making methodology, which involves DEA, is proposed for product line selection problems. The inherent advantages of DEA (e.g., avoiding subjective decision making regarding the weights of decision variables, and allowing treatment of multiple input and output variables) make it a suitable tool. The application presented above shows these advantages. However, upon a close review of the application one can also observe that the way in which decision variables are introduced to the model impacts the recommended product mix for varying market conditions. For example, when the company is the market leader a manufacturer's point of view might be adopted, while there is intense competition in the market place a consumer's point of view might be adopted. However, neither of these points of view may be valid in the long run given the volatility in market conditions. Accordingly, compromise solutions should be generated to fit the changing market conditions. In the paper, we provide one example of a compromise solution, which has a smaller Spearman's footrule (F) statistic in comparison to using only manufacturer's, or consumer's point of view. However, we recommend further research in the area to incorporate the dynamic nature of such decisions to account for market volatility.

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