

On The Applicability of Data Envelopment Analysis for Multiple Attribute Decision Making in the Context of Information Systems Appraisals

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ABSTRACT

This article elaborates on the applicability of basic and extended data envelopment analysis (DEA) models for various information system (IS) decision use-cases including illustrative examples from an enterprise resource planning (ERP) software investment appraisal. The usage of data envelopment analysis models and their extensions for IS decisions remains limited. This omission seems critical in particular for two reasons. First, organizational studies have shown that in practice business management fails to appreciate the portfolio of investment appraisal techniques available. Second, DEA based methodologies, especially new extensions, promise valuable insights to support the complex IS decision problem. The results indicate DEA applicability in a number of use-cases, e.g. for structural analysis of system alternatives or validation of ranking outcomes.

Keywords: Decision support, information systems evaluation, data envelopment analysis, multi attribute decision making

INTRODUCTION

Information Technology (IT) infrastructure capabilities are widely recognized as being important to firm competitiveness (Broadbent et al., 1990; Closs et al., 1997; McKenney, 1995). Information Systems (IS) are the central component of IT infrastructures. In this sense, IS investments add value to the firms' (IT) infrastructure capability and can be viewed as an important strategic infrastructure decision. Focused resource commitments on developing information technology capabilities can positively impact economic and quality related organizational performance (Daugherty et al., 2005). We like to stress the term focused, which places the problem of making the right investment decision in particular IS evaluation into the center of attention. The literature reports extensively on diverse problems associated with IS evaluation (Irani, 2002). The problems can be derived from the difficulty of understanding the complex factors involved in IS decision making such as scope and impact of the decision, or the concept of value and its multi-dimensional facets. In addition to the complex problem domain, research reported that the introduced evaluation methodologies do not meet the requirements of business management (Parker and Benson, 1989). Furthermore, a high rate of IT/IS failure was reported to be partly attributable to a lack of solid but easy to use management techniques especially for evaluating, and thereafter controlling IT investments (Hochstrasser and Griffiths, 1991). More recent organizational studies have shown that business management still fails to appreciate the available portfolio of IS related investment appraisal techniques (Bernroider and Stix, 2001; Farbey et al., 1992; Farbey et al., 1993). For the mentioned and other reasons, business management seems to perceive appraisal methodologies apart from standard financial techniques for driving IS evaluation as inappropriate. Thus, more methodical elaborations in the field of IS investment appraisals with a focus on practicability are needed. This article seeks to contribute to methodical elaborations in the field by analyzing the applicability of approaches based on or derived from data envelopment analysis (DEA) from the perspective of multiple attribute decision making (MADM). This setting can be justified due to the following reasons. IS decisions have the propensity to operate under multiple, often conflicting criteria. The decision space is discrete, meaning that a limited number of alternatives and attributes need to be assessed. This is the typical setting in which the discipline of MADM is grounded. The MADM approach to support IS decision making has been widely accepted and analyzed for many

years. The deployment of DEA as a discrete alternative multiple attribute decision making technique is a relatively new development, in particular in terms of IS decisions. DEA can be seen as a promising new candidate for supporting the appraisal and selection of IS-investments. Basic and some extended DEA models were evaluated in the context of MADM. Extensions of DEA target some of the weaknesses of the basic approach while at the same time preserve DEA specific strengths (Adler et. al, 2002). Little attention has so far been paid to the wider applicability especially of extended DEA based models to IS-investment appraisals. This article seeks to increase the awareness of DEA based MADM to the professional and scientific community by critically assessing such approaches and their applicability with respect to the contextual characterization given above. Consequently, the questions asked can be formulated as follows:

- Which basic and extended DEA models can support MADM based IS investment appraisals?
- What are the use-cases of these DEA methodologies?

The questions are primarily addressed by a basic theoretical overview of the most relevant topics in the field. However, short practical demonstrations extracted from a real life scenario to identify and demonstrate issues with adequate DEA based models will be given. To improve readability and keep the article balanced, in-depth methodical elaborations were omitted and background information on the given IS decision example were kept short. Due to the pervasive nature of IS systems, our results should be of interest for a wide range of professional and scholarly communities (from software engineering to accounting), apart from the IS field. The paper is organized as follows. The next section provides the conceptual background comprising MADM and DEA. This is followed by an elaboration of DEA models in the light of MADM based IS decision support. The section concludes with a summary of potential use-cases identified for IS investment appraisals, which were forwarded into an illustration of DEA approaches in the context of an enterprise resource planning (ERP) software decision. Finally, the article provides conclusions and directions for further research.

CONCEPTUAL BACKGROUND

Multi attribute decision making (MADM)

Multi attribute decision making (MADM) approaches help the decision maker in undertaking preference decisions over a finite set of available alternatives or courses of action characterized by multiple, potentially conflicting attributes (Yoon and Hwang, 1995). In the first step of MADM approaches the relevant attributes and alternatives need to be determined. In the next step the alternatives and the corresponding attributes have to be attached with numerical measures reflecting their relative importance (utility). Consequently, the decision problem is usually expressed by a matrix, where columns contain the attributes considered, the rows denote the competing alternatives and the cross field shows the numerical values for each pair of attribute/alternative. As a third step, the MADM problem needs to be examined or solved by one of the many methods available. Solving the MADM problem can imply the aggregation of utilities into an overall evaluation for each alternative leading to a final ranking. The availability of a wide selection of methods to solve MADM problems generates the paradox that the selection of a MADM method for a given problem has led to a MADM problem itself (Triantaphyllou, 2000).

For MADM based IS appraisals, a popular method to practitioners due to its simplicity and intuitive understanding is the simple additive weighting (SAW) technique. The overall suitability of each alternative is thereby calculated by averaging the score of each alternative with respect to every attribute with the corresponding importance weighting. A critical issue of this approach is the correct choice of the weights. These must be assigned by the decision maker or a decision committee and are often very subjective measures.

Decisions based on the principles of MADM often arise in the IS-world, e.g. the evaluation of enterprise resource planning solutions is often supported by a MADM based methodology. Basically, costs and profitability can be incorporated as one of the issues that should be taken into account. Especially in IS evaluations it is often not desirable to incorporate these aspects into the same model, especially due to necessary scale transformations and the loss of currency based values. Thus, they are often looked at in another evaluation, after a ranking of alternatives is achieved. In practice, standard and modified discounted cash flow methods are applied, either exclusively or in conjunction with a MADM based evaluation.

Data envelopment analysis (DEA)

Data envelopment analysis (DEA) was traditionally applied to assess the relative efficiency among different organizational decision making units (DMUs) such as governmental organizations (Bowlin, 1986), bank branches (Boufounou, 1995) or universities (Abbott and Doucouliagos, 2003). Due to its simple structure and intuitive base-idea it has spread through the last decades in different domains and a large amount of variations and adaptations to the model have been introduced. The basic idea is that the weights already mentioned in the SAW approach above are chosen by an optimization procedure and not by the decision maker. Weights are assigned optimally for every input and output attribute. This makes the approach more robust against human interference. The original DEA model by Charnes, Cooper and Rhodes (Charnes et al. 1978), referred to as CCR-model, optimizes the fractional output per input (efficiency measure) defined by multiple inputs and outputs. It can be translated into the following linear program (LP):

$$h_k = \max_{u,v} \sum_{r=1}^s u_r y_{rk} \quad (1)$$

subject to

$$\begin{aligned} \sum_{i=1}^m v_i x_{ij} - \sum_{r=1}^s u_r y_{rj} &\geq 0 \quad \text{for } j = 1, \dots, n \\ \sum_{i=1}^m v_i x_{ik} &= 1 \\ u_i, v_j &\geq 0 \quad \text{for all } i, j \end{aligned} \quad (2)$$

Subject to this optimization problem are the input and output weights v and u . These are optimally selected for each alternative. The efficiency measure defined by multiple inputs x_i and outputs y_i is used to assess n different DMUs without the need to know their production function. Each DMU is defined with m input attribute values represented through the $m \times n$ matrix X and s output attributes values stored in the $s \times n$ matrix Y . This non-parametric approach optimizes one LP per DMU (selected by parameter k) yielding optimal weights with respect to the chosen inputs and outputs for every DMU. The vectors v and u are the weight vectors for input- and output-attributes, respectively and are the decision variables of the LP. Consequently, the optimized relative efficiency rating calculated by DEA is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. Through solving the LP, each DMU is free to choose its optimal weights in order to make itself look best. Constraint (2) ensures that the efficiency (weighted output per weighted input) can not exceed 1. This is enforced for the one DMU under consideration as well as for all other DMUs using the same weight vectors. All DMUs which are able to achieve 100% efficiency form a Pareto frontier, which form an envelope of all alternatives. Each alternative is either part of the envelop or has an efficiency below 100%. The latter one is called an inefficient DMU and means that there exist no combination of weights under which not at least on competing DMU is already 100% efficient. For a complete introduction into DEA see e.g. (Cooper et al., 2000; Thanassoulis, 2001) and for an up to date scheme for classifying the DEA literature we refer to (Gattoufi et al., 2004). While the CCR model works with constant returns to scale, a second basic DEA model, named BCC (Banker et al., 1984) is based on variable returns to scale. If an increase in a DMU input does not produce a proportional change in its outputs, then the DMU exhibits variable returns to scale. According to (Lovell and Pastor, 1999) an output-oriented CCR model with a single constant input coincides with the corresponding BCC model.

DEA BASED MADM FOR IS DECISION SUPPORT

Starting with the basic DEA model this section briefly outlines DEA based methodologies and discusses their potentials to support IS investment appraisals. The section concludes with a list of identified use-cases.

The basic DEA-model

The basic CCR-DEA model was defined in the previous section. For the calculating process the basic DEA approach needs no further information from the decision maker regarding the weighting of attributes. This feature of requiring little information from decision makers and analysts is seen as the main relative advantage of DEA in comparison with classic MADM methods (Sarkis, 2000). Solving the DEA model yields the DEA-efficiency scores as well as benefit- and cost related weighting schemes for every alternative. Before stepping into an in-depth evaluation of IS alternatives, usually a short list containing the most promising solutions is required. This screening process can be supported by setting up the CCR-model with cost attributes as input variables or with one single input attribute set to one, and benefit attributes as output variables. As mentioned earlier, using the basic CCR-model with a large number of attributes results almost always in 100% efficient DMUs. For short listing purposes, the decision maker draws on quite a number of alternatives measured by a limited number of attributes. Therefore screening via identifying inefficient alternatives can be attempted with the CCR-model. The CCR-model could also indicate shortcomings of alternatives in comparison to the data envelope via analysis of the slacks.

Extended and/or modified DEA models

The efficiency scores of the CCR model basically group the alternatives into two sets, those that are 100% efficient and define the data envelope and those that are inefficient. In most cases the ranking of the inefficient DMUs is unique but the efficient ones are indistinguishable. If the decision maker is interested in a more differential view, DEA extensions can be applied that improve the discrimination among (efficient) alternatives. Other enhancements do not seek explicitly to enhance the discrimination power, instead they focus on the structural insights that can be gained from the calculated individual weighting schemes. One of the most popular extensions to improve the discrimination of alternatives is the (ranking) RCCR model also known as super-efficiency ranking techniques proposed by Anderson and Peterson (Anderson and Peterson, 1993). It is a simple, but very helpful variation of the CCR model for ranking the various alternatives. The new formulation (respectively modification of the LP constraints) allows the currently maximized DMU k to be greater than 1 and thus to pierce through the envelope. This means that the efficiency of the current DMU is only limited by the achievement a 100% efficiency of one the remaining DMUs (using the same weights). So it can happen that the other DMUs construct the envelope and the DMU under consideration is above this envelope, i.e. is super-efficient. This is achieved by removing the k -th constraint in (2) leading to

$$\sum_{i=1}^m v_i x_{ij} - \sum_{r=1}^s u_r y_{rj} \geq 0 \quad \text{for } j = 1, \dots, n; \quad j \neq k. \quad (3)$$

This results in a more discriminating set of scores suitable for ranking purposes. Strictly viewed, there no longer exists a data envelope in the original sense. A review of several ranking methods in the data envelopment analysis context is provided by (Adler et al., 2002). Alternative ways to improve ranking in the DEA context comprise the evaluation of a cross-efficiency matrix (Baker und Talluri, 1997; Sexton et al., 1986), benchmarking analysis (Torgersen et al., 1996), multivariate statistical techniques (Sinuany-Stern et al., 1998), and methods based on proportional measures of inefficiency (Bardhana et al., 1996).

The use of preference information

So far the models have minimized the need for prior knowledge. In the context of MADM there are often situations where additional information is available or where the decision maker is willing to make assumptions that lead to the introduction or modification of conditions in the LP. Preference information can be very useful to further increase the discriminatory power of the DEA models as well as to new applications of DEA. To improve discrimination, the most common approach is to impose weight restrictions, i.e. an imposition of conditions other than nonnegativity on the components of the vectors v and u . Well known approaches are the Assurance Region

Model (ARM) developed by (Thompson et al., 1986) and the cone-ratio developed by (Charnes et al., 1990). In this manner, the decision-makers could e.g. specify which benefit or cost attributes lend greater importance to the model solution. Besides moderating the discrimination issue and supporting group decisions, new applications that incorporate preference information target comparative structural analysis. The structural information that can be gained from the weight vectors of each alternative leads to the possibility of analyzing the relative shortcomings and surpluses in terms of specific attributes of (in)efficient alternatives. By selectively adding preference information and changing the number of attributes in the DEA model, further structural insights can be gained: E.g. the identification of decisive attributes, respectively an analysis of the contribution of a specific attribute (set) for calculating a CCR efficiency value (Bernroider and Stix, 2004). Preference information can also be used to incorporate validation into the IS decision making process. If the decision maker applies a MADM method, e.g. SAW, he implicitly assumes that he works with an adequate approximation, gained through experience, exploration, simulation, etc. of the true optimal weighting profile (Yeh, 2003). Thus, upper and lower bounds for the elements of the weight vector can be defined leading to a feasible region within which the decision maker expects the true weighting vector. To validate, respectively question the ranking outcome of the applied MADM method, this feasible region can be used as assurance region in an ARM. Subsequently, if the model produces a ranking outcome that differs from the classic MADM based solution, one or more alternatives were able to improve their ranking with a weighting vector available within the feasible region. This procedure may help in validating different decision approaches with the use of DEA. Validation is a big issue and of great importance for risk management in IS investment appraisals.

Combined approaches

DEA can be seen as valuable method enrichment in a multi-staged or multi-methodical decision making approach. Authors have shown how to combine DEA with classic MADM techniques: DEA screening followed by MADM (Khouja, 1995), multi-staged approaches that utilize an Analytical Hierarchical Process (AHP) together with DEA (Sinuany-Stern et al., 2000; Yang and Kuo, 2003), and a methodology that combines the commonly used SAW technique with the benefits of the DEA (Bernroider and Stix, 2005). Since the discrimination of alternatives especially through the basic CCR approach is limited, researcher have suggested to use DEA to screen, respectively limit the number of alternatives, for further evaluation by other MADM techniques, e.g. for technology selection problems in the area of manufacturing (Khouja, 1995). A new field of application for decision making exploits the classical usage of DEA as an ex-post methodology in the sense that it can be used to validate rankings and assumptions made by traditional MADM techniques such as SAW. Despite the significant development in MADM related research, the validity of the calculated ranking remains an unresolved issue. There are no objective measures that a decision maker can assess to which the outcome of the chosen MADM method can be compared. To avoid or limit drawbacks from individual approaches the decision maker can invoke several ranking mechanism including DEA based models, then compute an average or median rank based on the models employed as suggested in (Friedmann and Sinuany-Stern, 1998). The recently introduced profile distance method (PDM), also incorporating distances, is characterized by an automated multi-phased procedure to optimally incorporate structural aspects and constraints (Bernroider and Stix, 2005). It utilizes the concept of organizational fit, i.e. by exploring the distance based on attribute weights to a desired product or company profile. It seeks to improve ranking, and to identify decisive selection criteria. The desired weighting profile can be gained from a previously undertaken MADM approach. The attribute weights are obtained from calculating the underlying modified DEA-based optimization problem allowing the decision maker to fade between the DEA and the SAW approach. The variation of the model results in optimizing (4) instead of (1).

$$h_k = \max_{u,v} \sum_{r=1}^s u_r y_{rk} - \alpha f(u, w) \quad (4)$$

Here f is a metric measuring the distance from the variable u to a given desired profile-vector w and α controls the impact of the given profile. Setting $\alpha = 0$ results in the original DEA and for $\alpha \rightarrow \infty$ the model changes to SAW, using w as the fixed weight vector. The choice of α gives the responsible decision maker the opportunity to fade between solutions. Thus this model does not produce only one ranking but offers the decision maker several rankings depending on α , the importance of the desired weight profile.

Identified use-cases

To summarize, the following major use-cases of MADM based DEA models in the context of IS decisions were mentioned: Screening of alternatives, ranking of alternatives, group decision support, analysis of structure and organizational fit of alternatives, and validation of ranking outcomes. The following section seeks to provide more insights in terms of these potentials by demonstrating their application for specific IS investment appraisals.

DISCUSSIONS ON APPLICABILITY WITH ILLUSTRATIONS

We consider the given DEA models in terms of their applicability in MADM for the needs in IS evaluation and decision making by the example of enterprise resource planning (ERP) software. ERP systems are comprehensive packaged IS comprising several configurable modules that integrate core business activities (finance, human resources, manufacturing and logistics) into one single environment based on an integrated, shared database. ERP evaluation and selection is usually complicated by the following organizational and contextual characterization:

- the challenge of strategic alignment and organizational fit (Hong and Kim 2002; Jordan and Tricker, 1995),
- limited knowledge of decision making methodologies available (Bernroider and Koch, 2001),
- different interests from various stakeholder including business
- management leading to a group decisional context (Pan, 2005; Irani, 2002),
- a large number of evaluation attributes covering a wide and complex
- application domain (Irani, 2002)
- as well as high costs and considerable organizational impact resulting in high
- associated risks (Renkema and Berghout, 1997).

For the following illustrations we draw on an ERP investment project faced by Primagaz, the Austrian subsidiary of an international wholesaler of liquid and gaseous fuels and related products (SHV Holdings N.V.). In accordance to the above declared characterization, the following key issues of their ERP project were evident:

The strategic position was considered for determining the fundamental decision objectives,

- MADM with SAW was applied, but no other methodical aid, e.g., to evaluate the level of organizational fit.
- A decision committee was in place with key users from all functional departments which also agreed on weights and utility values.
- 73 pre-selected attributes were defined covering (1) controlling and reporting, (2) accounting, (3) logistics, (4) purchasing, (5) needs of local divisions, (6) services and engineering, (7) sales, and (8) business management.
- The high costs and associated risks were acknowledged by business management.

The weighted utility scores for the three pre selected ERP solutions (we will refer to them as *A*, *B* and *C*) resulted in the numbers 253, 288 and 252 respectively. These results strongly indicated alternative B as best solution, followed by two equally good systems. The difficulty of interpreting the scores was evident, and further structural insights limited. For a more detailed consideration of the illustrative example and its background we want to refer to (Bernroider and Stix, 2004).

Screening and Ranking

All considered competitors in the example achieved 100% efficiency using the basic CCR-model, which is not surprising and a very often discussed problem in the context with basic DEA models. This is because our example situation is characterized by a large set of attributes together with a small set of IS alternatives. This gives the optimization problem (1) too much freedom in choosing the weight vectors. So all alternatives are able to choose their optimal weights in a way to become 100% efficient. Therefore the decision maker needed to look beyond basic DEA to discriminate between these alternatives, even for a screening application. We applied the super efficiency RCCR-model to rank the alternatives according to their internal representation. The application of this model resulted in a clear ranking $B \succ A \succ C$ with super-efficiencies of 148%, 136% and 104% respectively. These results improved the original ranking outcome supplied by SAW by indicating the inferiority of alternative *C*, which was not much more efficient in the RCCR-model compared to the CCR-model. As another approach we incorporated preference information resulting in an ARM model to reflect the following constraints commonly shared by stakeholders on weight vectors in MADM: No weights were allowed to be zero and no attribute was allowed to be more than two times as important as any other (Yeh, 2003). With these strong limitations even the

CCR-model was able to rank the alternatives as $B \succ A \succ C$ with 100%, 98% and 92% efficiencies respectively. It should be noted, however, that imposing such strong constraints must be taken into account before and during the compilation process of the respective attributes. In this study these restrictions were not considered beforehand. In the class of combined approaches, the PDM can also be used for ranking purposes. Since it is discussed later we refer to section "Structural analysis and organizational fit".

Group decision support

The feature of supporting group decisions draws on the ARM. It covers a very important and delicate issue in IS-decision problems due to the many heterogenous stakeholders involved (e.g. top-management, users or members of the IT service staff). The ARM-DEA model can take into account the various views of evaluators by including upper and lower bounds as the assurance region constraints for input and output weights in the underlying LP (Cooper et al., 2000). Through this feature the decision committee only needs to agree upon the "flexibility" of the attributes' weights to present themselves in the DEA model. The experience and estimation of importance of every evaluator is found in the model, and no one is set better. Per definition, the resulting weighting vectors always lie within the groups feasible region (Bernroider and Stix, 2003). As DEA is based on an efficiency ratio, the magnitude of weights in constraints compared among each other has to be expressed in ratios as well. If a person prefers to think in weights as a percentage of importance, summing up to 100%, these numbers can be easily transformed into rational descriptions. It is easier for humans to provide the relative importance of two attributes rather than defining all weights at once. This statement is in line with the basic motivation for the AHP mentioned earlier. Following this recommendation, each member of the decision committee would need to define its preference with respect to every pair of attributes. Concerning our illustration, this could be achieved hierarchically by giving the relative importance of pairs of attributes within the 8 main functional-subclasses followed by an assessment of the relative importance in pairs for the subclasses themselves. A complete comparison scheme would become too exhaustive. The 73 attributes result in 2628 possible pairs of attributes whereas hierarchic ordering requires only 368 comparisons. Additional, the relative preference of attributes belonging to very different subclasses can be difficult to assess. The effort can further be limited by only estimating the relative importance for the main-subclasses resulting in 28 assessments or 73 weights without pair-wise consideration could be established. Because of the source of inconsistencies in scale, we do not recommend the latter one. Once the relative weights have been estimated (or calculated from linear ones) by all group members, a feasible region can be derived. Since DEA constitutes an optimization program, other than in SAW, weights do not have to be fixed to e.g. the mean of the group-weight vector. Instead the feasible region for the weight vector variable can be constraint to lie between e.g. the minimum and the maximum estimates given by the respective group members. Thereby, DEA helps to find optimal weights within given boundaries, set by the group members. Instead of minimum and maximum, any other quantile can be used, in order to compensate for outliers. A more restrictive method would be to let the members define minimum and maximum weights of their own and then set the maximum of all minima to be the lower bound and the minimum of all maxima to be the upper bound for each weight. This method ensures, that everyone's opinion is reflected in the final result, so nobody has reasons to object to the final weight vector. The drawback of this approach lies, however, in the double effort and the more complicated procedure in weight estimation, as well as in the possibility to overrule the optimization system by a single person through setting the minimum and maximum weights equal or very close together. Through the mixture of the presented methods, several social-political circumstances can be addressed through modification of the feasible region. In some sub-classes, where the expertise lies within a sub-group of the decision committee, only those estimates can be used in a maxi-min and mini-max fashion. Several relative weights can even be fixed to a value assigned by the final decision maker or another single committee authority. The importance of several members and their estimation, however, can not be adjusted in the basic-DEA concept. These restraints arise from the linear form of the model, since each solution is attained at the boundary of the feasible region.

Structural analysis and organizational fit

The structural analysis advances a step further focusing on the shape of the different competing products. To illustrate the applicability for this context, we refer to the profile distance method (PDM) mentioned earlier. As a precondition for method application a desired profile has to be defined. In our illustration the desired weight profile of the 8 main sub-classes was assigned by the decision committee as shown in figure 1. Here the importance of the respective attributes are expressed relative to the importance of the first attribute. This profile describes e.g. that the company want the importance of sub-class three (logistics) to be half as important as subclass one (controlling and reporting). This profile could also reflect a future strategic orientation against which the alternatives need be evaluated.

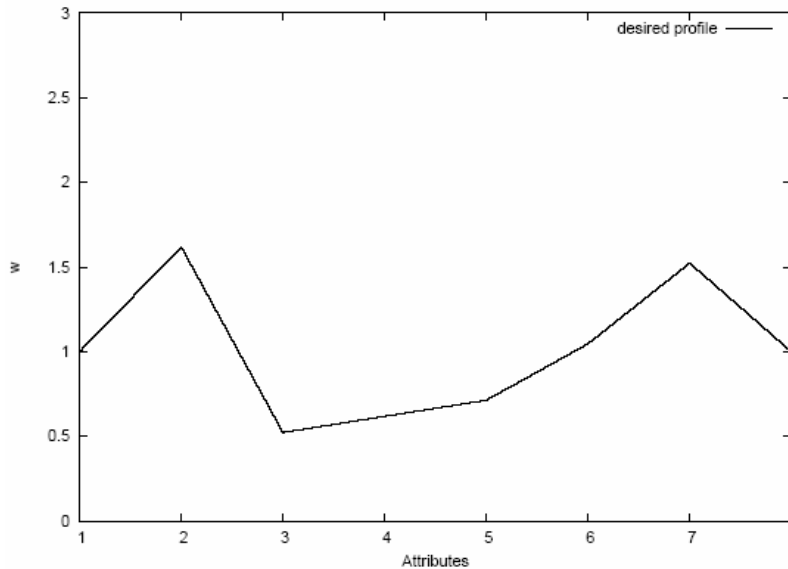


Figure 1: Desired Profile Over 8 Main Sub-Classes.

On the one hand the respective alternatives should fit well to the strategic profile. On the other hand, the evaluating company still gives each DMU (via the DEA-idea) the possibility to present themselves in their best possible light. Table 1 shows the different outcomes depending on the variable α used in the model. The dimension of α was chosen in the experiment by increasing α from 0 until the weight profile of any alternative changed. This was done until all the distances of all alternatives became 0. All changes are documented in Table 1 and the number where the change with increasing α appeared is in bold typeface. The absolute dimension of α itself has no interpretation.

α	A	B	C
0.0000000	502 (100%)	386 (100%)	472 (100%)
0.0000002	328 (100%)	386 (100%)	472 (100%)
0.0000003	256 (100%)	386 (100%)	472 (100%)
0.0000004	256 (100%)	386 (100%)	454 (100%)
0.0000005	153 (100%)	0 (100%)	449 (100%)
0.0000007	153 (100%)	0 (100%)	443 (100%)
0.3408758	153 (100%)	0 (100%)	0 (88%)
0.7910204	0 (88%)	0 (100%)	0 (88%)

Table 1. Distance Measures and Efficiencies. Bold Figures Mark Points of Change.

The entries in the columns show for each DMU the corresponding distance and the DEA efficiency of the chosen profile given α . Figures in bold indicate changes for that specific transition-level. The small magnitude of α is due to the model-data and does not imply un-/importance.

Alternative *A* can be seen to be preferable for α in $[0.0000002; 0.0000005)$, whereas alternative *B* is dominant in all other cases. Alternative *A* can approximate the desired profile earlier than its two competitors, however, only up to a certain amount. Alternative *C*, however, never exceeds the two others. The table also reveals, that α had to be risen by an order of magnitude to force alternative *A* and *C* into the desired profile, at which point they were no longer DEA efficient. This shows that the decision maker that although alternative *A* and *C* seem to be equally good using a conventional SAW method (see above), alternative *A* is able to adapt to the company's desired strategic profile whereas alternative *C* is not. When restricting the basic DEA model through α a little, alternative *A* becomes short also competitive to alternative *B*. Experimenting with the level of α can show the decision maker, that alternative *B* is the most robust one (it is in all times 100% efficient and has a small distance to the desired profile). This helps to justify a decision and is a basic consideration for validation issues which are discussed next.

VALIDATION

As a first step to illustrate a validation issue, the mentioned ARM is used. In the general IS context, the basic CCR model produces only 100% efficient alternatives (within the short-list). Due to the flexibility of the optimization process, it has the propensity to assign unrealistic weighting schemes for each alternative. The results are attribute weights equal to zero, or relative attribute weights of 1:100 and more. In a real world setting, these assignments can be assumed as invalid. Bounding the relative weights e.g. within 1:10 down to 1:3 shows the stability of the respective DMU rankings. We have applied confinements to validate ranking outcomes of the RCCR-model. Regarding the alternatives *B, A, C* we obtain for restricting to 1:10 and to 1:3 the ranking outcomes 126%, 119%, 100%, and 117%, 102%, 95% respectively. It can be seen, that the ranking is consistent compared to the original outcome. Thus, the results seem to be valid, at least within the context of this decision model. This approach can be seen as a kind of sensitivity analysis but more as a technique to validate, if attributes are chosen and evaluated properly. As a second step, the ranking outcome can be validated against the unknown true weighting vector. As a precondition, an assurance region needs to be specified that contains the unknown vector. The assurance region can be defined around a weighting vector interpreted as an estimation of the true weighting vector. In our example, again the pre-defined weights of the SAW method can be used. The size of the fixed feasible region around the expert estimation determines the flexibility of the underlying DEA-based optimization. We chose this flexibility to be 50% up and down of the estimated optimal weight vector. Within this region only alternative *B* was able to stay 100% efficient, whereas the other two alternatives only gained 93%. This can be interpreted that an optimal assignment for alternative *A* and *C* can not be found inside the region, where we assume the true optimum lies. Here again, due to the linearity of the model, only vectors on the boundary of the assurance region will be found. Another possible approach can be the usage of the PDM as already described in the previous section. Due to the fact, that the distance function f can be non-linear, solutions may be obtained also in the interior of the region where the true weight vector was estimated. The drawback is a more complex optimization model.

CONCLUSIONS AND FURTHER RESEARCH

The goal of this article was to analyze the applicability of DEA in the light of MADM based IS decision support by assessing the research questions stated in the introduction. The theoretical elaborations of DEA comprising the original CCR model, extensions and modifications, the use of preference information, as well as combined approaches indicated that DEA can support a number of important use-cases in IS investment appraisals. In this context academic literature has predominantly considered screening and ranking of alternatives as well as the support of group decisions especially based on the CCR model or minor variants with and without incorporating preference information. In particular in terms of the mentioned extended and modified models, all areas of application should be forwarded into more empirical grounded research. This article provides a short illustration of the applicability of specific DEA-models for use-cases mentioned. The IS-context is provided by an ERP software decision example: A group decision had to be found with the challenge of strategic alignment and organizational fit based on a large number of evaluation attributes covering the entire organization for a small number of alternatives. Due to the associated risks, the company chose a MADM based approach (SAW) to support and justify their investment decision. A practical discussion of the applicability of DEA in the light of a real case enterprise resource planning software decision showed that all identified use-cases can be met by an appropriate DEA based methodology. We would like to stress that in the illustration, DEA applicability was dependent on the type of model

used. Due to the nature of DEA -- the freedom of each alternative to show his best representation by choosing an individual weighting scheme in the underlying LP --, the application of the basic model resulted in 100% efficiencies with no or limited discrimination power. Only the application of RCCR or other extended methods with or without the usage of preference information provided a clear ranking of alternatives. Besides the ranking issue, extended DEA contributed structural insights of the underlying decision problems and helped the decision maker to easily parameterize different scenarios of the problem space. In this sense, DEA can help to assess the fit between the organizational needs and the target systems' characteristics prior to its adoption which is regarded as critical especially for implementation success. As a precondition, a (iterative) value-focused approach to identify decision making attributes needs to be implemented, which was indeed observed in the analyzed example. An interesting application of DEA is to provide information on the validity of suggestions offered through a classic MADM decision support tool. The validity of ranking outcomes remains an unresolved issue in MADM. In DEA no comparison with precise assignments of the unknown objective measures is needed. As this example shows, DEA variants in MADM preserved DEA specific strengths. Practice calls for simple, user-friendly and communicative techniques for dealing with complex decision settings. This article showed that DEA based methodologies, especially approaches that combine DEA with a simple classic MADM method such as SAW, can be valuable decision aids. They can help to comprehend the full spectrum of decision making attributes as a whole, i.e. the profiles of the alternatives under evaluation, or to validate classic MADM outcomes. In order to be accepted by business management, however, the relevant DEA models would need to be implemented as easy-to-use decision support systems, which provide automated procedures as well as comprehensible outputs, e.g. graphical representations of product profiles. At the present stage DEA models and their derivatives provide a tool set more suitable for experts in optimizational research community. As we have seen, DEA can play a more important role in MADM based IS decisions. In particular, we hope that further research explores the applicability of DEA and its variants for specific requirements of IS investment appraisals. More empirical grounded research, technical articles considering model enhancements and easy to use decision tools can eventually help practitioners facing the complex nevertheless important task of appropriately assessing IS investments.

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