The Profile Distance Method: Towards More Intuitive Multiple Criteria Decision Making in Information Systems

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Abstract. This paper seeks to improve usability and semantics of complex decision support based on multiple criteria and data envelopment analysis using the profile distance method. We recognize the need of decision making practice for more intuitive and understandable decision support in complex and comprehensive settings by proposing three areas for improvement. We suggest a more meaningful indicator of organizational fit, an advanced and dynamic multi-dimensional visualization, and embed support for weight estimation with pairwise comparisons into the method. The methodological advancements are shortly illustrated for an Information System selection problem.

1 Introduction

This paper proposes an augmentation of the profile distance method (PDM) originally proposed by Bernroider and Stix [1] to allow a more intuitive application of the method to increase its appeal to decision makers in practice. While decision making and investment appraisal techniques have received a lot of attention in the last decade, research reports an inability of management to holistically evaluate the implications of adopting a new technology in particular referring to Information Systems [2]. The absence of intuitive approaches and suitable implementations thereof to help the decision maker (DM) fully understand the underlying decision problem in all dimensions remains an open problem. Decision support systems (DSS) are often constructed and therefore understood as black box machines that calculate an output (e.g. a ranking or an efficiency score) based on some input information given by the DM. The methods and techniques used are often mathematically challenging in particular in selection problems based on multiple criteria. Thus, "the average DM" is not anywhere near fully understanding or comprehending the methods applied to adequately interpret results. This results in common mistakes and an underutilisation of potential benefits in applying methods. The Profile Distance Method (PDM)

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itself constitutes one of the possible optimization based methods that a DSS can adopt. In contrary to many other optimization models the PDM actively encourages the DM to acquire a deeper understanding of the multi-dimensional structure of the decision problem, comparing the optimal individual profiles of each considered alternative (calculated by means of DEA based optimization) with a given desired weight profile (gained by using a utility model). The DM is thereby given a way not only to engage comparative analysis of alternatives but also to better understand the organizational fit considering all given dimensions. As the original authors mention, one essential issue is how well the method is embedded in a decision support system and what kind of access level in particular in terms of visualization is offered to the DM [1].

This paper intends to advance the PDM and its application in three ways, by (i) introducing a more intuitive understanding of the profile distance indicator, (ii) enabling the DM to graphically design the decision problem instead of formulating it on a text-based entry only and (iii) complementing left out parts of the decision process with a pairwise-comparison based desired weight profile (DWP) definition process.

Referring to (i), in order to implement a more intuitive indicator reflecting the information held as profile distance, we take a detailed look at the composition of the profile distance value and its interpretation. By focusing on user-oriented aspects, we translate the profile distance from a mathematical term to a meaningful indicator for the DM. This is achieved by defining an upper boundary for the profile distance value (a worst performing alternative) and normalizing all other alternatives thereby. We compare the possible alternatives, demonstrate the improved model using showcases and validate the increase in intuitivity and usability.

With regard to (ii), a second major improvement in practicability is proposed by implementing an interactive graphical interface. Based on a prototype implementation [3], a more advanced concept lets the user model the decision problem interactively with support of the tool. We argue that thereby the user can get into more direct contact with the problem and can test different scenarios to explore organizational fit of the alternatives. Additionally, the DM gets a deeper understanding of the indicators provided by the PDM to support the decision making process.

Thirdly (iii), we augment the existing PDM process by adding support for the definition of the desired weight profile (DWP) by making use of pairwise comparison concepts from the Analytical Hierarchy Process [4]. We thereby follow a three staged process including identification, analysis and implementation. Attention of many existing models and methods was placed on the analysis stage in particular regarding the PDM. We add functionality by using a pairwise technique for the definition of the desired state. In addition, the net of transitive dependencies created by the aforementioned technique is integrated in the analysis part, where the PDM model is augmented to react properly on input changes in advanced phases of the process.

The remainder of this article is outlined as follows. In the course of the next section we briefly present the Profile Distance Method and its foundations. Subsequently, we elaborate on the meaning of the profile distance and introduce the new indicator. In Sect. 4 an interactive graphical tool for decision modeling is introduced. Section 5 covers the pairwise-comparison process for tool-supported weight profile definition. Section 6 discusses and summarizes the findings and concludes with further research issues to be addressed.

2 The Profile Distance Method

The profile distance method (PDM) is a multiple attributive decision making method proposed by Bernroider and Stix [1] based on a linear optimization model. While the method was successfully implemented and tested for Information Systems (IS) selection problems, usability and visualization were identified as main targets for further development [3]. The linear optimization model of the PDM is grounded on the original Data Envelopment Model (DEA) model referred to as CCR-model proposed by Charnes, Cooper and Rhodes [5] mapping a fractional linear measure of efficiency into a linear programming (LP) format. It reflects a non-parametric approach optimizing a linear programme per decision making unit (DMU) yielding weights for both the chosen input and outputs, and a relative efficiency rating given by the sum of its weighted output levels to the sum of its weighted input levels. For a complete introduction into DEA see e.g. [6].

A review paper due to the recent 30 year anniversary of the popular method by Cook and Seiford [7] suggests connections into general multiple criteria decision models (MCDM) as an area for future DEA developments [7], which is in essence what the PDM seeks to achieve. The PDM links into a general MCDM framework termed utility ranking models (URMs), i.e., into an additive value model, which is concerned with selecting the best alternative among a finite set of possible choices based on multiple attributes reflected by partial utility functions [8]. Viewed in isolation, both, the DEA and URM approaches, have a number of problems in decision making practice. For example, the pure DEA approach achieves no clear cut ranking naturally evident in settings with many attributes and a few alternatives. On the other side, the URM creates super utility values based on biased estimations of weights that cannot easily be interpreted or justified. The idea of the PDM is to mitigate those and other problems by combining merits of both approaches. The mathematical representation of the PDM is an optimisation model and can be given as follows:

$$h_k = \max_{u,v} \sum_{r=1}^{s} u_r y_{rk} - \alpha \sum_{i=1}^{s} d_i (u_i - w_i u_1) \tag{1}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \quad \text{for } j = 1, \ldots, n$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$
$$\alpha d_i(u_i - w_i u_1) \geq 0 \quad \text{for } i = 1, \ldots, s$$
$$u_i, v_j \geq 0 \quad \text{for all } i, j$$

According to DEA, we have n alternatives each with m benefit attributes represented through the $m \times n$ matrix X and s cost attributes stored in the $s \times n$ matrix Y. The vectors v and u are the DEA multipliers or weight vectors for benefit- and cost-attributes, respectively. We have for each DMU a different LP which can lead to a different optimal solution. The parameter k selects the alternative for which the optimization should be performed. In contrast to DEA, the objective function (1) of PDM includes a penalty function, which measures the distance from a given desired weight profile given by the URM. It therefore accepts that the given weight profile is just an approximation of the true and ideal profile but seeks to penalise system alternatives depending on the distance of their DEA multipliers to the approximation. The function f measures the absolute distances between the weight vector u and the desired profile w. The fade-factor α controls the tradeoff level of DEA ($\alpha = 0$) and URM ($\alpha \to \infty$), which allows the user to fade between both techniques, thereby exploring the organizational fit of the current alternative under evaluation. For more details on the metric used to measure distances and its implementation we refer to the original publication [1].

3 Improving the Profile Distance Indicator

The profile distance is one of the main benefits of the PDM and allows insights into the structure of the decision problem. It helps comparing the alternatives with each other and the desired profile. In the course of our research, we expand the benefits of the profile distance by normalizing its value within a lower and upper bound. We can thereby raise the intuitive understanding of the indicator and the PDM as a whole.

3.1 Mathematical Interpretation

As follows from Sect. 2, the profile distance f represents the sum of all distances between the relative weights of a given profile (desired weight vector) and the relative optimized weight vector of an alternative, calculated by means of DEA-like optimization. Using the fade factor α to force the optimized weights of an alternative closer to the desired profile, the profile distance decreases monotone with increasing α. The fade factor α is bound by the DEA optimization of each alternative in the case $\alpha = 0$. Its upper boundary is dependent on the underlying alternative, being reached at the point the profile distance f reaches zero. Moreover, the profile distance f boundaries are defined by zero as the lower bound and a data dependent upper bound given by DEA optimization.

3.2 Semantic Improvements

From the decision makers perspective the profile distance may be hard to interpret in its original composure. Furthermore, while the profile distance reflects suitability for a single option only, the DM is likely to be interested in relative performances between competing alternatives. We are therefore augmenting the model with problem specific boundaries for the profile distance, enhancing the meaning with an overlap rate of the alternatives' profile with the desired profile. This is achieved by defining an upper boundary for the profile distance, viz. a worst competing alternative. In the following we will present a case that demonstrates a way of creating such a boundary, using the worst competing alternative as upper bound.

We are using empirical data drawn from an enterprise resource planning selection problem comprising 3 possible alternatives (DMUs) with 8 output criteria each. The desired weight profile (DWP) has been assessed by the responsible decision makers and domain experts. Table 1 shows weights per alternative for each of the eight criteria resulting from a PDM optimization with an initial setting of $\alpha = 0$, thereby gaining full DEA compliance. The table contains the optimized weights for each DMU (rows) for each criterion (columns). The leftmost column (depicting the values for criterion 1) is always 1 since all values are normalized with the first value according to the recommendations of the PDM. The rightmost column shows the numerical value of the profile distance indicator.

Table 1. Relative weight vectors and profile distance

	Crit. 1	**Crit. 2**	**Crit. 3**	**Crit. 4**	**Crit. 5**	**Crit. 6**	**Crit. 7**	**Crit. 8**	**Profile distance**
DWP	1	1,619	0,523	0,619	0,714	1,047	1,523	1	0
DMU 1	1	1	10	1	1	1	1	1	0,384
DMU 2	1	1	1	1	1	1	1	10	0,356
DMU 3	1	1	7,551	1	1	8,967	10	1	0,464

In order to define an upper bound for a normalization of the profile distance value, the worst competing real DMU is taken into account. That is, the alternative with the highest profile distance value when optimizing under pure DEA conditions ($\alpha = 0$). As Table 1 shows, the highest profile distance is reached by DMU3 with a value of 0.464. Due to the monotone decrease of the profile distance with increasing α, this value can be considered as the largest under all possible circumstances. We argue that it is more intuitive for the DM to be presented an overlap rate rather than a distance measure, so we are transforming the profile distance values according to the following procedure. The division by the largest existent number (0.464) results in relative deviations, denoting DMU3 as the worst performer with a value of 1. Flipping the results by calculating (1 - deviation) allows us to interpret the outcome as overlap rate with the desired profile, thus stating that DMU3 has a relative overlap rate of 0 per cent, whereas DMU2 has a rate of 23 per cent and so forth. The results of this transformation are shown in Table 2.

Table 2. Transforming the profile distance into a structural overlap measure

	Profile distance	Deviation	Overlap rate
DMU 1	0,384	0,827	0,173
DMU 2	0,356	0,767	0,233
DMU 3	0,464	1	0

4 Interactive Visualizations with Radar Plots

Multiple research efforts have shown that visual approaches are particularly helpful in the area of MCDM, to communicate a clear picture of the likely complex decision problem [9,10]. With regard to PDM a previous implementation and empirical test of the method showed that satisfaction and acceptability can be substantially improved when providing graphical representations of the decision problem [3]. Although only static visualizations were used in this test, a significant number of respondents valued those features "very high" in terms of usefulness and practical convenience. Consequently, we were aiming at further improving visual support by adding an active visual decision modelling component to a PDM software tool and explored different techniques therefore. Choosing an effective graphical depiction for a decision problem is, however, not an easy task. That is particularly true in the area of MCDM, where multiple interdependent criteria and weights form a complex net of influences.

In a previous attempt to visualize the decision process using the PDM a bar chart was used to outline the weights of the desired profile in comparison with all DMUs. While this type of diagram gives a good overview of the weights for the alternatives for a specific attribute, it lacks the ability to integrate both the profile distance indicator as well as overall efficiency into the visualization. Consequently, it is not possible to include insights into the structural overlap with the desired profile. For this reason we decided to use a radar plot diagram to visualize the performance of the alternatives, additionally allowing the decision maker to interact with the graphical representation.

The radar plot chart is an integrated visualization of the criteria of the decision problem, showing not only weights and structural composition but also depicting the efficiency by means of surface area. The DM can easily change the desired profile by interacting with the radar plot in a drag and drop manner. The connected attribute weights are calculated accordingly in time so the user can actually get in touch with the decision problem more intuitively.

In the following we present an example scenario for the usage of radar plot within the PDM. Figure 1 displays settings drawn from the same data used in Sect. 3, comprising 3 DMUs with 8 output variables each. The desired weight profile is drawn in a bold water mark style, enabling the decision maker to easily compare the structure of the alternatives against it. While both DMU 2 and DMU 3 comply with the weight structure defined by the DM (full structural overlap), the larger surface area of DMU 2 indicates its better performance in overall efficiency. When forcing both affected alternatives into this condition, DMU 2 objectively outperforms DMU 3.

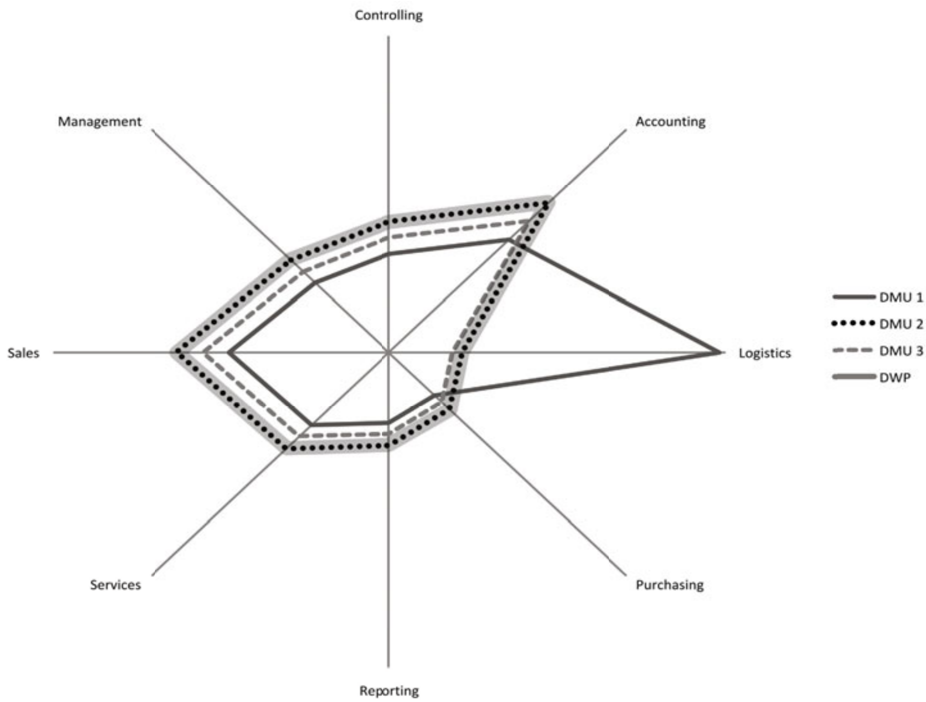

Fig. 1. Radar plot visualization ($\alpha = 0.42$)

5 Incorporation of Pairwise Comparisons

Using pairwise comparisons as an instrument of comparative judgement has been addressed by scientific research in various fields in particular by psychology and decision making theory. Pairwise comparisons have been applied to multitudinous scientific fields (e.g. voting systems, social choice or MCDM [11]). The underlying problem of estimating a weight vector has been an active area of research for a long time(e.g. [12]). A prominent application in decision support embodying pairwise comparisons and the eigenvector has been developed by T. Saaty, called the Analytic Hierachical Process (AHP) [13]. Pairwise comparisons ultimately lead to a structure of the problem situation and a clear ranking of the decision makers preferences [14].

Referring back to phase one of PDM, the DM has to define a desired weight profile (DWP) that is to be compared to the performance of the alternatives. Since the issue of having a sound desired weight profile is of critical importance to the whole decision making process we are addressing this problem by preconcatenating a pairwise comparison methodology to the PDM. In many utility ranking based decision making approaches, it is left to the decision makers' discretion how to estimate the weighting vector needed for value aggregation. We suggest to estimate the desired weights from pairwise comparison matrices and refer to the standard approach in the AHP based on the eigenvector method. The DM is requested to define n influencing criteria in the beginning of the process to allow the construction of a $n \times n$ square matrix A. A is defined to be a positive reciprocal matrix and has to follow the rules of transivity (2) and reciprocity (3) to be consistent, for i, j and k being alternatives of the matrix:

$$a_{ij} = a_{ik} \cdot a_{kj} \tag{2}$$

$$a_{ij} = \frac{1}{a_{ji}} \tag{3}$$

As discussed in previous research the generation of a completely consistent pairwise comparison matrix is only realistic in very small matrices and does not necessarily reflect the real choice of the DM [15]. Many weight derivation methods account for this problem using one of the concepts of pertubation theory or distance minimization. Saaty proposes the principal eigenvector (EV) to be used for weight derivation to allow for slight inconsistences in matrices to be reflected in the weight vector (see [16] for detailed information).

Here after establishing the $n \times n$ square matrix A the principal diagonal holds the comparisons for the criteria with itself (all elements equal 1). All entries under the principal diagonal are subject to reciprocity. A fully consistent matrix allows $n - 1$ elements to be chosen by the DM, whereas all others are calculated by means of transivity. Since we do not force the DM into having a fully consistent matrix we allow comparisons for each pair of criteria, simultaneously filling the rest of the matrix according to transivity rules. The DM can change this elements at any time, possibly generating inconsistencies. The matrix is needed to have a consistency rate lower than 0.1 in order to function properly with the eigenvector [13]. Using a multiplicative matrix with a 1 to 9 range value results very likely in an inconsistent matrix.

The EV is then derived using a heuristic approach, namely squaring the matrix with itself and then calculating and normalizing row sums. This procedure is repeated until the difference between the calculations no longer excesses a given criterion. The result is the EV, which represents the input for the PDM to be used as a desired weight profile.

6 Conclusions and Future Work

This research paper extends existing research into multiple criteria decision making and data envelopment analysis referring to the profile distance method [1] and to its initial implementation [3]. We recognized the problem of decision making practice with meaningful applications of rather complex decision making methods and suggest three potential improvements of the PDM which were shortly illustrated for an Information System selection problem.

With the ambition in mind to provide a more complete approach to MCDM we augmented the original PDM methodology by giving support for estimating a sound desired weight profile. The idea of pairwise comparisons was extensively exploited in AHP based evaluations not only in the area of Information Systems. For practicability, our implementation of PDM with computer software accounts for the quality of comparison matrices to support the decision maker in creating comparison matrices with inconsistences that remain in certain boundaries.

Our second area of improvement demonstrated an interactive graphical interface based on a radar chart, which can include an additional dimension reflecting distances or overlap measures. We argue that thereby the users conceive additional information and get in more direct contact with the underlying model and its optimization results. A main feature is that the user can explore the problem and test different scenarios to explore organizational fit of the alternatives intuitively and directly. Thereby, the DM is expected to get a deeper understanding of the indicators provided by the PDM to support the decision making process.

We also proposed to replace or complement the main indicator of distance with a new overlap measure, that seems to be more intuitive and meaningful in its semantic representation. As possible drawback we see that a real worst upper bound to normalize the profile distance value could tempt the DM to prematurely dismiss this DMU from further analysis. To abate this setting a virtual worst DMU can be used instead. We can thus retain the benefits of setting the profile distance indicator of the alternatives into relation with each other, thereby making the measure better understandable while at the same time mitigating pre-mature exclusion of alternatives. The concept of adding artificial DMUs to a set of real DMUs is a common technique in the area of DEA research. Various different approaches make use of artificial DMUs, mostly due to the lack of discrimination power in the original DEA approach [17]. The investigation on how to generate a virtual DMU that represents the greatest profile distance for the PDM is a matter of ongoing research.

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