AN APPROACH FOR EXTENDING PROMETHEE TO REFLECT CHOICE BEHAVIOUR OF THE DECISION MAKER

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Multiple Criteria Decision Making, choice behaviour, PROMETHEE

Abstract

In this study, an approach based on PROMETHEE is developed to correctly reflect the choice behavior of the decision maker that is not explained by the utility theory. The prospect theory argues that losses have higher impact than gains. We integrate the prospect theory into PROMETHEE through defining new preference functions. The proposed approach is behaviorally realistic and tolerates some degree of intransitivities in the preferences of the decision maker. For determining the criteria weights, we utilize pairwise comparison method of Analytic Hierarchy Process. Performance of the approach is demonstrated on a university ranking problem.

PROMETHEE'NİN KARAR VERİCİNİN SEÇİM DAVRANIŞINI YANSITACAK ŞEKİLDE GENİŞLETİLMESİ İÇİN BİR YAKLAŞIM

Anahtar Kelimeler

Çok kriterli karar verme, seçim davranışı, PROMETHEE

Öz

Bu çalışmada, karar vericinin fayda teorisi ile açıklanamayan seçim davranışını doğru bir şekilde yansıtabilmek için PROMETHEE yöntemini temel alan bir yaklaşım geliştirilmiştir. Seçim davranışı teorisi, zararların kazançlardan daha yüksek etkisinin olduğunu ileri sürmektedir. Bu teori PROMETHEE yöntemine yeni tercih fonksiyonları tanımlamak suretiyle entegre edilmiştir. Önerilen yaklaşım, davranışsal olarak gerçekçi ve karar vericinin tercihlerinde oluşabilecek geçişsiz değerlendirmelere izin veren bir yöntemdir. Kriter ağırlıklarının belirlenmesinde Analitik Hiyerarşi Süreci yaklaşımındaki ikili karşılaştırma metodu kullanılmıştır. Önerilen yaklaşımın etkinliği bir üniversite sıralama problem üzerinde gösterilmiştir.

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1. Introduction

Discrete multi-criteria decision making (MCDM) problems such as R&D project selection, construction site selection, supplier ranking, inventory classification, loan applications sorting into risk categories are encountered very often within organizations. For decades various methodologies have been developed to systematically solve such problems. Analytical Hierarchy Process (AHP) (Saaty, 1990) is one of the most popular techniques used by the researchers and practitioners. It is a pairwise comparison technique, which can model complex problems in a unidirectional hierarchical structure. AHP provides a framework for determining criteria weights/values. Outranking based approaches are less restrictive and require less information from the decision maker than utility based approaches. They do not assume that preference structure of the decision maker can be described with a certain functional form. They only try to find enough information to state that one alternative is at least as good as another. Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) is a class of outranking methods developed by Brans, Vincke, and Mareschal (1986). PROMETHEE I provides a partial preorder, PROMETHEE II gives a complete preorder of the alternatives. For simplifying the decision making process, an approach based on AHP and PROMETHEE is integrated with the prospect theory in this study. In literature there are studies that employ AHP and PROMETHEE together. Babic and Plazibat (1998) and Wang and Yang (2007) combine AHP and PROMETHEE II to form a hybrid method to rank alternatives. They used AHP to determine the weights of the criteria and to understand the structure of the problem whereas PROMETHEE II for the final ranking. Adem, Alıcıoğlu and Dağdeviren (2019) integrate fuzzy AHP and PROMETHEE to evaluate the performance of the dealers by considering organizational performance criteria.

Choice behavior of the decision maker is another issue that is addressed in this study. Keeney and Raiffa (1976) use Multi-Attribute Utility Theory (MAUT) to model the choice behavior of the decision maker for each criterion and evaluate the overall utility of each alternative for the decision maker by either additive or multiplicative utility function. The alternatives are then ranked according to the final utilities. However, Kahneman and Tversky (1979) argue that MAUT fails to reflect the actual choice behavior of the decision maker and develop a new theory called Prospect theory, stating that the outcomes are expressed as positive or negative deviations (gains or losses) from a reference alternative or aspiration level and losses have higher impact than gains. Although value functions differ among individuals, Kahneman and Tversky (1979) propose that they are commonly S-shaped: concave above the reference point, and convex below it. Preference functions are commonly assumed steeper for losses than that of gains to represent that the displeasure from a specific amount of loss is greater than the pleasure brought by the same amount of gain. Currim and Sarin (1989) show that prospect theory "outperforms" utility theory for paradoxical choices.

Although researches, experiments and empirical studies show that prospect theory better models the choice behavior, there are few studies in literature that integrate it into MCDM methods. Though it was originally developed for single criterion problems, the ideas have been extended to MCDM problems as well by Korhonen, Moskowitz and Wallenius (1990). They conducted an experimental study to observe the choice behavior and their results were persistent with prospect theory. Salminen (1994) also incorporates prospect theory to MCDM. In his study, piecewise linear marginal value functions are assumed to approximate the S-shaped value functions of prospect theory. Gomes and Lima (1992a, 1992b) develop TODIM (an acronym in Portuguese for Interactive and Multicriteria Decision Making) method to evaluate each alternative by establishing a multiattribute value function based on prospect theory. Gomes and Gonzalez (2012) generalize TODIM method towards cumulative prospect theory. Lahdelma and Salminen (2009) incorporate difference functions of prospect theory into stochastic multicriteria acceptability analysis (SMAA). Wang, Li and Zhang (2012) define a new score function based on prospect value function and developed a fuzzy multi-criteria decision-making approach based on the prospect score function. The only study that integrates PROMETHEE and prospect theory is conducted by Lerche and Geldermann (2016). They define an artificial reference alternative to be benchmarked against real alternatives and modify the preference functions of PROMETHEE using smaller threshold values in order to incorporate loss aversion elements of prospect theory into PROMETHEE. However, this attempt is limited in the fact that prospect theory is not incorporated in all pairwise comparisons and comparison of alternatives with an artificial alternative might be difficult. Krol, Ksiezak, Kubinska and Rozakis (2018) apply PROMETHEE and Lerche and Geldermann's (2016)'s method to a real life problem and conclude that Lerche and Geldermann's (2016) method gives more realistic results than PROMETHEE.

In this study, we develop a ranking method based on PROMETHEE II to capture the choice behavior of the decision maker. The proposed approach does not require any artificial reference alternative as in Lerche and Geldermann's (2016) method. Gain and loss in the context of prospect theory is considered explicitly in each pairwise comparison. In the proposed methodology, besides the classical preference functions of PROMETHEE methods, functions representing the choice behavior of the decision maker are developed. Thus, the proposed approach is behaviorally realistic and tolerates some degree of intransitivities in the preferences of the decision maker. Also, PROMETHEE method does not suggest any specific technique to specify the weights of the criteria, which have a crucial influence towards the final ranking. For the determination of the criteria weights, AHP is used.

Organization of the paper is as follows: In section 2, the proposed methodology is described. In section 3, the proposed approach is used for ranking top universities around the world according to six criteria. In the final section, concluding remarks are given.

2. An Approach to Choice Behavior

We propose a hybrid methodology based on AHP and PROMETHEE. We also incorporate the prospect theory in order to correctly reflect the choice behavior of the decision maker. We provide the flowchart of the proposed approach in Figure 1.

2.1. Determination of the Criteria Weights

AHP is used for the determination of the weights of the criteria. The question posed to the decision maker during the pairwise comparisons is as follows:

"Which criterion is more important with respect to the main goal and how much?"

In this technique the decision maker conducts ½(n-1)(n-2) pairwise comparisons, where n is the total number of criteria, and the eigenvector corresponding to the highest eigenvalue yields the weights for criteria.

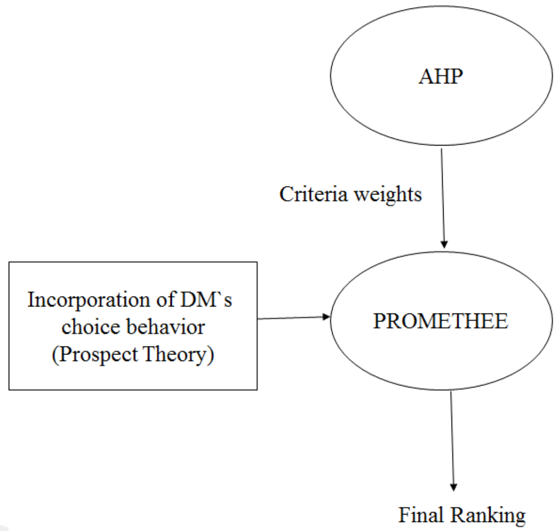


Figure 1. Flowchart of the Proposed Approach

2.2. Evaluation of the Alternatives

After the determination of the weights of the criteria, alternatives are ranked with PROMETHEE II method. Like the weight determination stage, this part also requires interaction with the decision maker to understand his/her perception of each criterion one by one. At this stage, the proposed methodology tries to obtain three important aspects of the problem:

1. For a specific criterion, does the decision maker have a preference function that is parallel to choice theory?
2. For a specific criterion, which preference function among the presented types, best suits and represents nature of that criterion?
3. What are the values of the parameters, which are specific for the type of the preference function determined?

In the beginning, the decision maker is asked the following question for each criterion:

"Considering the criterion under consideration, minimum how many unit(s) of gain can satisfy you upon one unit of loss?" The answer determines the *gain/loss* ratio.

If the answer is "one", the six basic types of preference functions defined in Brans et al. (1986) (I, II, .., VI) are used. These functions and the parameters required for each function are summarized in Figure 2. Let $f_n(a_i)$ be the evaluation of alternative a_i on criterion n and d be the difference between criterion values of alternatives a_i and a_j, i.e., $d = f_n(a_i)- f_n(a_j)$. Function P_n represents the decision maker's preference of a_i over a_j on criterion n if $d \geq 0$, i.e., $P_n(d) = P_n(a_i, a_j)$, otherwise $P_n(d) = P_n(a_j, a_i)$. Parameter q is indifference threshold, parameter p is preference threshold and parameter σ is an intermediate value between p and q. What is significant here is that these functions are symmetrical with respect to the vertical axis.

If the answer is "more than one" which is consistent with prospect theory, two new preference functions, VII and VIII, are proposed to model the choice behavior of the decision maker for the criterion under consideration. These two preference functions are illustrated in Figure 3. Symmetrical property of the previous set of functions does not exist in those new set of functions. Note that prospect theory argues that the answer cannot be "less than 1".

Preference function VII is a variation of the preference function V, criterion with linear preference and indifference area, proposed by Brans et al. (1986). Preference function VIII is based on exponential function. The most significant difference of the two is that one is linear; the other is concave, whereas both have an indifference threshold, which are specified by defining the corresponding indifference threshold value. Linear function represents constant marginal rate of substitution, concave function represents the diminishing marginal rate of substitution. If the contribution of a small difference of the criterion values beyond the indifference threshold is significant, then it would be more appropriate for the decision maker to choose the preference function VIII (exponential function) because this function has a steeper slope just after the indifference threshold. Let t be $(\text{gain/loss})^{-1}$ (to be defined by the decision maker), q be indifference threshold (to be defined by the decision maker) and p be the maximum absolute difference among the criterion values. Difference between the values of alternatives for criterion n is to be $d = f_n(a_i)- f_n(a_j)$.

Preference Function VII:

If a_j is reference alternative (that is alternative under consideration) and d has **loss** property,

$$P_n(a_i, a_j) = P_{nL}(d) \tag{1}$$

$$d \leq q \Rightarrow P_{nL}(d) = 0 \tag{2}$$

$$d > q \Rightarrow P_{nL}(d) = \frac{(d-q)}{p-q} \tag{3}$$

Else if a_i is reference alternative and d has **gain** property,

$$P_n(a_i, a_j) = P_{nG}(d) \tag{4}$$

$$d \leq q \Rightarrow P_{nG}(d) = t \cdot P_{nL}(d) = 0 \tag{5}$$

$$d > q \Rightarrow P_{nG}(d) = t \cdot P_{nL}(d) = t \cdot \frac{(d-q)}{p-q} \tag{6}$$

Preference Function VIII:

If a_j is reference alternative and d has **loss** property,

$$P_n(a_i, a_j) = P_{nL}(d) \tag{7}$$

$$d \leq q \Rightarrow P_{nL}(d) = 0 \tag{8}$$

$$d > q \Rightarrow P_{nL}(d) = 1 - e^{-\lambda(d-q)} \tag{9}$$

where

$$\lambda = \frac{\ln(\varepsilon)}{p-q} \text{ and } \varepsilon = 0.01$$

Else if a_i is reference alternative and d has **gain** property,

$$P_n(a_i, a_j) = P_{nG}(d) \tag{10}$$

$$d \leq q \Rightarrow P_{nG}(d) = t \cdot P_{nL}(d) = 0 \tag{11}$$

$$d > q \Rightarrow P_{nG}(d) = t \cdot P_{nL}(d) = t - t \cdot e^{-\lambda(d-q)} \tag{12}$$

where

$$\lambda = \frac{\ln(\varepsilon/t)}{p-q} \text{ and } \varepsilon = 0.01$$

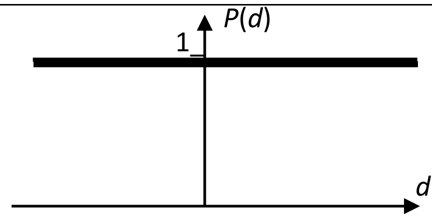
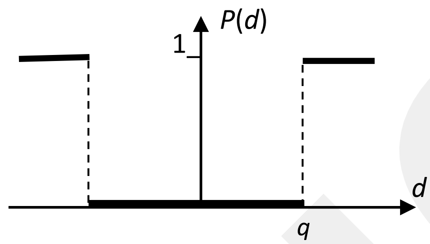
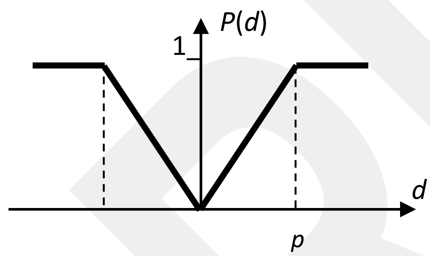
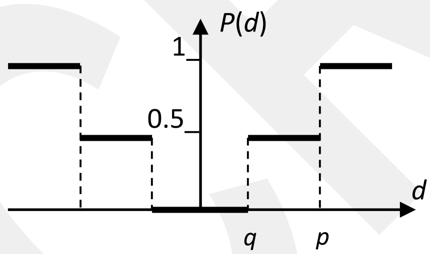
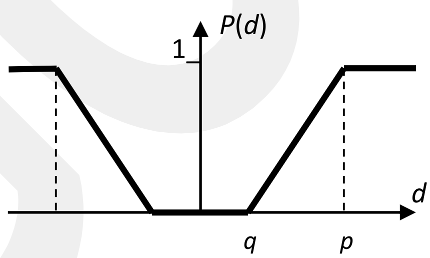
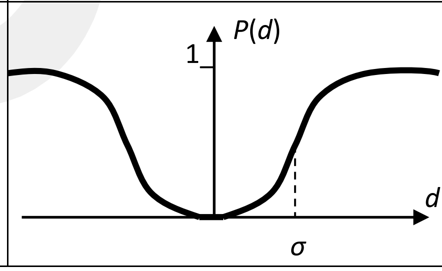
I. Usual Criterion		Parameters to be defined: –
II. Quasi-Criterion		Parameters to be defined: q
III. Criterion with Linear Preference		Parameters to be defined: p
IV. Level Criterion		Parameters to be defined: q , p
V. Criterion with Linear Preference and Indifference Area		Parameters to be defined: q , p
VI. Gaussian Criterion		Parameters to be defined: σ

Figure 2. Preference Functions (Brans et al., 1986)

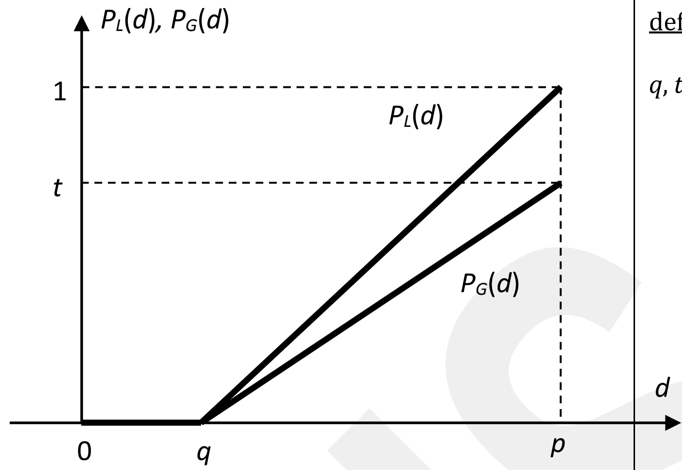
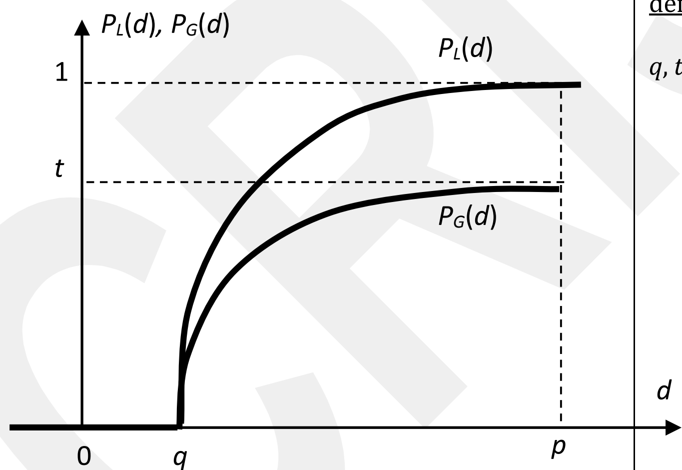
VII. **Linear Criterion**	 	Parameters to be defined: q, t
VIII. Exponential Criterion	 	Parameters to be defined: q, t

Figure 3. New Preference Functions. Here p is the maximum absolute difference among the criterion values

After the decision maker's decision on all the preference functions and the corresponding parameters for each criterion, PROMETHEE II method is applied for the complete ranking. In the methodology developed, the crucial part of the PROMETHEE II application is the incorporation of the choice behavior of the decision maker. The overall preference index of an alternative pair is calculated as follows:

$$\pi(a_i, a_j) = \sum_n P_n(a_i, a_j) \cdot w_n \tag{13}$$

where $P_n(a_i, a_j)$ is the preference function associated to the criterion n and w_n is the weight of the criterion n.

If *gain/loss* > 1, $P_n(a_i, a_j)$ yields different results, when either a_i or a_j is set as the reference alternative, respectively. That is because if $f_n(a_i) - f_n(a_j)$ is positive, when a_i is set as the reference alternative, it has "*gain*" property and whereas if a_j is set as the reference alternative, it has "*loss*" property and according to Preference functions VII and VIII gains have less impact than losses on outranking degree.

In the methodology developed, each alternative in the pair is set as the reference alternative separately. Hence for every alternative pair, two different preference indices are calculated and finally two separate preference index tables (Π_1 and Π_2) are obtained as shown in Tables 1 and 2, respectively.

The "*leaving flow*" value may be interpreted as the overall dominance of the reference alternative on others and it is calculated by summing the preference indices that flow from the reference alternative to the others. It is the total flow from one alternative to the rest. Therefore, the reference alternative is the alternative under consideration (row element), and Π_1 table is used for calculating the "*leaving flow*" values as follows:

$$\phi^+(a_i) = \sum_j \pi_1(a_i, a_j) \quad \forall a_i \in K \qquad \text{(*Leaving Flow*)} \tag{14}$$

where $\pi_1(a_i, a_j) = \sum_n P_n(a_i, a_j) \cdot w_n$ and $P_n(a_i, a_j) = P_{nG}(a_i, a_j)$.

Table 1
Preference Indices Table (Π_1) and Calculation of Leaving Flows (First Elements of the Alternative Pairs are the Reference Alternatives)

Π_1	a_1	a_2	$\cdots$	a_j	$\cdots$	a_k	$\phi^+(a_i)$
a_1	$\pi_1(a_1,a_1)$	$\pi_1(a_1,a_2)$	$\cdots$	$\pi_1(a_1,a_j)$	$\cdots$	$\pi_1(a_1,a_k)$	$\sum_j \pi_1(a_1,a_j)$
a_2	$\pi_1(a_2,a_1)$	$\pi_1(a_2,a_2)$	$\cdots$	$\pi_1(a_2,a_j)$	$\cdots$	$\pi_1(a_2,a_k)$	$\sum_j \pi_1(a_2,a_j)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
a_i	$\pi_1(a_i,a_1)$	$\pi_1(a_i,a_2)$	$\cdots$	$\pi_1(a_i,a_j)$	$\cdots$	$\pi_1(a_i,a_k)$	$\sum_j \pi_1(a_i,a_j)$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
a_k	$\pi_1(a_k,a_1)$	$\pi_1(a_k,a_2)$	$\cdots$	$\pi_1(a_k,a_j)$	$\cdots$	$\pi_1(a_k,a_k)$	$\sum_j \pi_1(a_k,a_j)$

Table 2
Preference Indices Table (Π_2) and Calculation of Entering Flows (Second Elements of the Alternative Pairs are the Reference Alternatives)

Π_2	a_1	a_2	$\cdots$	a_j	$\cdots$	a_k
a_1	$\pi_2(a_1,a_1)$	$\pi_2(a_1,a_2)$	$\cdots$	$\pi_2(a_1,a_j)$	$\cdots$	$\pi_2(a_1,a_k)$
a_2	$\pi_2(a_2,a_1)$	$\pi_2(a_2,a_2)$	$\cdots$	$\pi_2(a_2,a_j)$	$\cdots$	$\pi_2(a_2,a_k)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
a_i	$\pi_2(a_i,a_1)$	$\pi_2(a_i,a_2)$	$\cdots$	$\pi_2(a_i,a_j)$	$\cdots$	$\pi_2(a_i,a_k)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
a_k	$\pi_2(a_k,a_1)$	$\pi_2(a_k,a_2)$	$\cdots$	$\pi_2(a_k,a_j)$	$\cdots$	$\pi_2(a_k,a_k)$
$\phi^-(a_j)$	$\sum_i \pi_2(a_i,a_1)$	$\sum_i \pi_2(a_i,a_2)$	$\cdots$	$\sum_i \pi_2(a_i,a_j)$	$\cdots$	$\sum_i \pi_2(a_i,a_k)$

The "*entering flow*" value may be interpreted as the overall dominance of the other alternatives on the reference alternative and it is calculated by summing the preference indices that flow to that alternative from the rest. It is the total flow to one alternative from others. Therefore, the alternative under consideration is not the reference alternative, but the others (column elements) are, and Π_2 table is used for calculating the "*entering flow*" values as follows:

$$\phi^-(a_j) = \sum_i \pi_2(a_i,a_j) \qquad \forall a_j \in K$$ (*Entering Flow*) (15)

where $\pi_2(a_i,a_j) = \sum_n P_n(a_i,a_j) \cdot w_n$ and $P_n(a_i,a_j) = P_{nL}(a_i,a_j)$.

Two different preference index tables are obtained for the calculation of flow values. In the first one (Π_1), the first elements in the alternative pairs (row elements) are set as the reference alternatives, i.e. the criteria value differences have "gain" property, whereas in the second table (Π_2), the second elements in the alternative pairs (the column elements) are set as the reference alternatives, i.e. the criteria value differences have "loss" property. The "net flow" values are calculated using the "leaving flow" and the "entering flow" values and the final ranking of the alternatives are obtained.

If in the beginning of the problem, all the answers to the "*gain/loss*" ratio question is given as "1" by the decision maker, the two preference indices tables become equal ($\Pi_1 = \Pi_2$), and the problem turns out to be an ordinary PROMETHEE II application.

3. An Application: Ranking Universities

The developed methodology is applied to the problem of ranking top 101 universities around the world according to six criteria. The problem data is obtained from the ranking study performed in the Institute of Higher Education, Shanghai Jiao Tong University (ARWU, 2006).

The universities are ranked by several indicators of academic or research performance, including alumni and staff winning Nobel Prizes and Fields Medals, highly cited researchers, articles published in Nature and Science, articles indexed in major citation indices, and the per capita academic performance of an institution. The data used is provided in Appendix 1. In the ranking study of Shanghai Jiao Tong University, for each criterion, the highest scoring institution is assigned a score of 100, and other institutions are calculated as a percentage of the top score. All institutions are ranked according to their overall scores. This ranking is known as Academic Ranking of World Universities or Shanghai Ranking (ARWU, 2006). In literature, there are criticisms about Shanghai Ranking. Billaut et al. (2010) criticize the weights of the criteria and the aggregation method used. They argue that weights are not defined as scaling constants that are linked to the normalization of the criteria. They also emphasize that weighted sum method is used to aggregate criteria which is incapable of handling tradeoffs between criteria and unsupported efficient solutions. In this study, these problems are tackled with the proposed preference functions. They normalize criterion values which enable weights to be used as scaling constants. Also preference functions are useful in handling tradeoffs and unsupported efficient solutions. The criteria definitions and the weights utilized in Shanghai Ranking are summarized in Table 3.

PROMETHEE and the proposed method are also applied to the same data. Interested readers are referred to Ishizaka and Nemery (2013) for detailed steps of the PROMETHEE algorithm. The proposed algorithm differs from PROMETHEE only in calculating the value of introduced preference functions. The weights given in Table 3 and preference functions and the corresponding parameters given in Table 4 are used.

Table 3
Criteria Definitions & Weights of the Original Study

Criteria	**Definition**	**Code**	**Weight**
Quality of Education	Alumni of an institution winning Nobel Prizes and Fields Medals	Alumni	0.10
Quality of Faculty	Staff of an institution winning Nobel Prizes and Fields Medals	Award	0.20
	Highly cited researchers in 21 broad subject categories	HiCi	0.20
Research Output	Articles published in Nature and Science	N&S	0.20
	Articles in Science Citation Index-expanded, Social Science Citation Index	SCI	0.20
Size of Institution	Academic performance with respect to the size of an institution	Size	0.10

Table 4
Preference Functions and the Parameters

	PROMETHEE		The Proposed Method		
Criteria	Preference Func.	Parameters	Gain/Loss	Preference Func.	Parameters
Alumni	V	q=4, p=100	2	VII	q=4
Awards	V	q=3, p=100	1.5	VII	q=3
HiCi	III	p=6	1	III	p=6
N&S	V	q=2, p=6	1	V	q=2, p=6
SCI	V	q=3, p=75.9	1.5	VIII	q=3
Size	III	p=6	1	III	p=6

Shanghai Ranking and the final ranking obtained by PROMETHEE and the proposed method are given in Appendix 2. The most obvious outcome of the study is that rankings of the PROMETHEE and the proposed method have substantial deviations from the original study. Ranks of the universities change 6.75 with PROMETHEE and 7.54 with the proposed method on the average per university. Between PROMETHEE and the proposed method, the average rank difference is 1.90 and maximum difference is 15. This shows that change in the ranks of the universities is approximately 2 on the average per university and maximum difference is quite large when choice theory is incorporated into PROMETHEE. Note that we assume that choice behavior of decision maker follows the prospect theory in three out of six criteria. Rank deviation are presented in Table 5. Results show that the kind of approach and the assumptions are very much determining towards the solution in multiple criteria problems. Thus, failing to incorporate the choice behavior of the decision maker, when there is an underlying difference in gain and loss perception may lead to substantial differences in the final rankings. Depending on the data for a ranking problem, the effect may be larger.

Table 5
Comparison of the Rankings

	Shanghai-PROMETHEE	Shanghai-The Proposed Method	PROMETHEE-The Proposed Method
Average of the rank deviations	6.75	7.54	1.90
Standard deviation of the rank deviations	6.83	7.11	2.33
Maximum rank deviation	34	30	15
Number of alternatives whose rank changed at least 6 places	43	48	5

4. Conclusion

In this study, a methodology aiming to rank the alternatives in a discrete MCDM problem is proposed. It is developed based on well-known outranking method PROMETHEE II. New preference functions that incorporate the choice behavior of the decision maker into PROMETHEE are developed. The important feature of the methodology developed is that it can model the choice behavior of the decision maker with a simple interaction by asking a single question for each criterion during the construction of the problem.

Two different sets of preference functions are used. The first set is composed of conventional functions suggested with PROMETHEE by Brans et al (1986). In the second set, there are two new preference functions that incorporate the choice behavior of the decision maker (Kahneman and Tversky, 1979). The preference function is steeper for losses than for gains in the new preference functions.

The proposed extension is limited to the conventional PROMETHEE preference function of type V. Additional work to integrate the prospect theory into the remaining conventional preference functions would be a future contribution to this study.

The proposed method is also limited to a single decision maker. It may also be extended by introducing the group decision making techniques since within organizations, important decisions are made by a board of executives instead of a single decision maker.

Conflict of interest

The authors declare no conflict of interest.

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APPENDIX 1. PROBLEM DATA (6 CRITERIA, 101 ALTERNATIVES)

Table A.1 Criteria values for the alternatives

Institution	Country	Score on Alumni	Score on Award	Score on HiCi	Score on N&S	Score on SCI	Score on Size	Total Score
Harvard Univ	USA	100	100	100	100	100	73.6	100
Univ Cambridge	UK	96.3	91.5	53.8	59.5	67.1	66.5	72.6
Stanford Univ	USA	39.7	70.7	88.4	70	71.4	65.3	72.5
Univ California - Berkeley	USA	70.6	74.5	70.5	72.2	71.9	53.1	72.1
Massachusetts Inst Tech (MIT)	USA	72.9	80.6	66.6	66.4	62.2	53.6	69.7
California Inst Tech	USA	57.1	69.1	59.1	64.5	50.1	100	66
Columbia Univ	USA	78.2	59.4	56	53.6	69.8	45.8	61.8
Princeton Univ	USA	61.1	75.3	59.6	43.5	47.3	58	58.6
Univ Chicago	USA	72.9	80.2	49.9	43.7	54.1	41.8	58.6
Univ Oxford	UK	62	57.9	48	54.3	66	46	57.6
Yale Univ	USA	50.3	43.6	59.1	56.6	63	49.3	55.9
Cornell Univ	USA	44.9	51.3	56	48.4	65.2	40.1	54.1
Univ California - San Diego	USA	17.1	34	59.6	54.8	65.6	47.1	50.5
Univ California - Los Angeles	USA	26.4	32.1	57.6	47.5	77.3	34.9	50.4
Univ Pennsylvania	USA	34.2	34.4	57	41.7	73.6	40	50.1
Univ Wisconsin - Madison	USA	41.5	35.5	53.3	45.1	68.3	29.3	48.8
Univ Washington - Seattle	USA	27.7	31.8	53.3	47.6	75.5	27.8	48.5
Univ California - San Francisco	USA	0	36.8	55.5	54.8	61.1	48.2	47.7
Tokyo Univ	Japan	34.8	14.1	41.4	51.5	85.5	35.2	46.7
Johns Hopkins Univ	USA	49.5	27.8	40.7	52.2	68.8	25.3	46.6
Univ Michigan - Ann Arbor	USA	41.5	0	61.5	41.6	76.9	31.2	44.5
Kyoto Univ	Japan	38.3	33.4	36.9	36.2	72.4	31.7	43.9
Imperial Coll London	UK	20.1	37.4	40	39.7	64.2	40.2	43.4
Univ Toronto	Canada	27.1	19.3	38.5	36.5	78.3	44.8	42.8
Univ Illinois - Urbana Champaign	USA	40.1	36.6	45.5	33.6	57.7	26.3	42.5
Univ Coll London	UK	29.6	32.2	38.5	43.2	60	33.4	42.2
Swiss Fed Inst Tech - Zurich	Switzerland	38.8	36.3	35.3	39.9	43.5	52.6	41.2
Washington Univ - St. Louis	USA	24.2	26	37.7	45.6	55.3	40.4	40.4
New York Univ	USA	36.8	24.5	42.8	34	54	26.4	38.4
Rockefeller Univ	USA	21.8	58.6	28.8	44.8	24.1	38.4	38.3
Duke Univ	USA	20.1	0	48	45.4	62.4	40.3	38.2
Univ Minnesota - Twin Cities	USA	34.8	0	50.4	34.1	69.7	24.3	37.8
Northwestern Univ	USA	21	18.9	44.9	33.6	57.1	36.7	37.6
Univ Colorado - Boulder	USA	16	30.8	40	37	46.4	30.1	36.4
Univ California - Santa Barbara	USA	0	35.3	42.1	37	43.7	35.7	36.1
Univ British Columbia	Canada	20.1	18.9	31.7	31.9	62.1	36.6	35.5
Univ Maryland - Coll Park	USA	25	20	40	32.7	53.8	26.4	35.4
Univ Texas Southwestern Med Center	USA	23.4	33.2	31.7	38.1	39.8	33.5	35.2
Univ Texas - Austin	USA	21	16.7	48	28.3	55.4	21.8	34.9
Univ Utrecht	Netherlands	29.6	20.9	28.8	27.5	57.3	26.9	33.4

Table A.1 Criteria Values For The Alternatives (Continued)

Institution	Country	Score on Alumni	Score on Award	Score on HiCi	Score on N&S	Score on SCI	Score on Size	Total Score
Vanderbilt Univ	USA	12.1	29.6	32.6	24.7	50.6	36.2	33.2
Pennsylvania State Univ - Univ Park	USA	13.5	0	44.9	37.7	58	23.8	32.7
Univ California - Davis	USA	0	0	47.4	33.3	63.3	30.1	32.7
Univ California - Irvine	USA	0	29.4	35.3	28.9	49	32.4	32.6
Univ Paris 06	France	34.4	23.5	23.1	24.9	52.9	32.5	32.4
Rutgers State Univ - New Brunswick	USA	14.8	20	38.5	32.7	46.5	24.6	32.3
Univ Southern California	USA	0	26.8	37.7	24.1	54	26.6	32
Karolinska Inst Stockholm	Sweden	29.6	27.3	33.5	18	48.7	25.6	31.9
Univ Pittsburgh - Pittsburgh	USA	24.2	0	40	24	65	28.6	31.9
Univ Manchester	UK	26.4	18.9	24.3	24.9	58.7	28.7	31.7
Univ Munich	Germany	35.8	22.9	15.4	28	52.9	32.2	31.5
Univ Edinburgh	UK	21.8	16.7	25.5	35.4	49.3	30.3	31.4
Univ Florida	USA	21.8	0	36.1	25.1	65.6	26.7	31
Australian Natl Univ	Australia	17.1	12.6	37.7	30.1	44.4	32.8	30.8
Tech Univ Munich	Germany	41.5	23.6	24.3	19.5	46.2	30.7	30.8
Carnegie Mellon Univ	USA	33.7	32.8	32.6	12.7	37.5	31.8	30.5
Univ Copenhagen	Denmark	29.6	24.2	23.1	24.8	46.4	30	30.5
Univ Zurich	Switzerland	12.1	26.8	21.8	29.7	47.9	31.4	30.4
Univ North Carolina - Chapel Hill	USA	12.1	0	37.7	29.3	60.3	27.9	30.3
Hebrew Univ Jerusalem	Israel	32	20	25.5	25.2	44.7	29.5	30
Osaka Univ	Japan	12.1	0	25.5	30.7	67	29.9	29.6
McGill Univ	Canada	27.7	0	30.8	22.4	59.7	33.5	29.5
Univ Bristol	UK	10.5	17.9	29.8	26.3	47.8	33.2	29.5
Univ Paris 11	France	32	33.5	13.3	20.8	44.7	29.7	29.4
Uppsala Univ	Sweden	25	32.2	13.3	24.6	49.3	21.5	29.3
Ohio State Univ - Columbus	USA	17.1	0	40.7	20.6	61.3	19.7	29

Table A.1 Criteria Values For The Alternatives (Continued)

Institution	Country	Score on Alumni	Score on Award	Score on HiCi	Score on N&S	Score on SCI	Score on Size	Total Score
Univ Heidelberg	Germany	19.1	27.2	18.8	21.5	49.5	29.5	29
Univ Oslo	Norway	25	33.4	18.8	17.7	42.7	28.5	28.6
Univ Sheffield	UK	22.6	14.1	23.1	29.2	45.8	30.2	28.5
Case Western Reserve Univ	USA	39.2	11.5	21.8	22	43.9	33.6	27.9
Moscow State Univ	Russia	49.5	34.2	0	5.6	54.3	33.4	27.9
Univ Leiden	Netherlands	24.2	15.5	28.8	18.9	46	28.5	27.8
Purdue Univ - West Lafayette	USA	18.2	16.7	27.7	20.7	50.6	19.9	27.7
Univ Helsinki	Finland	18.2	17.9	20.4	19.2	53.4	29.2	27.6
Univ Rochester	USA	32	8.9	26.6	21.6	43.3	35.6	27.6
Tohoku Univ	Japan	18.2	0	20.4	22.6	65.9	29.2	27.2
Univ Arizona	USA	0	0	28.8	36.7	54	25.6	27.2
Univ Melbourne	Australia	14.8	14.1	23.1	18.1	54.8	25.2	26.7
Univ Nottingham	UK	14.8	20	23.1	18.3	45	27.6	26.2
Michigan State Univ	USA	12.1	0	37.7	22.7	51.2	18.6	26.1
Boston Univ	USA	14.8	0	31.7	26.7	51.6	17.8	25.9
Univ Basel	Switzerland	25	17.1	20.4	22.4	36.2	35.4	25.9
King's Coll London	UK	16	23.1	20.4	16.7	43.9	26.7	25.8
Stockholm Univ	Sweden	28.4	29.6	15.4	18.5	36.9	19.7	25.6
Brown Univ	USA	0	13.6	28.8	26.7	40.5	28.4	25.4
Univ Goettingen	Germany	37.3	20	15.4	15.9	40.8	26	25.4
Rice Univ	USA	21	21.9	23.1	22	30.4	30.4	25.3
Texas A&M Univ - Coll Station	USA	0	0	31.7	24.4	55.7	20.8	25.1
Tokyo Inst Tech	Japan	16	0	23.1	23.3	51.2	32.5	25
Lund Univ	Sweden	28.4	0	24.3	20.2	52.2	18.8	24.7
McMaster Univ	Canada	16	18.9	21.8	14.2	44.6	25.6	24.7

Table A.1 Criteria Values For The Alternatives (Continued)

Institution	Country	Score on Alumni	Score on Award	Score on HiCi	Score on N&S	Score on SCI	Score on Size	Total Score
Univ Birmingham	UK	24.2	10.9	21.8	15.2	46.6	27.6	24.7
Univ Freiburg	Germany	24.2	20.9	17.2	18.4	38.8	24.4	24.6
Univ Utah	USA	0	0	30.8	28.6	47.1	25.3	24.5
Univ Iowa	USA	0	0	33.5	22.4	51.6	21.8	24.3
Univ Strasbourg 1	France	28.4	22.5	18.8	16.7	33.6	23.6	24.2
Indiana Univ Bloomington	USA	13.5	17.9	24.3	18.9	40.7	17.8	24.1
Nagoya Univ	Japan	0	14.1	15.4	21.6	52.9	25.8	24
Ecole Normale Super Paris	France	46.1	24.5	13.3	14.8	27.3	24.1	23.6
Arizona State Univ - Tempe	USA	0	14.1	21.8	27	42.6	18.1	23.5
Univ Roma - La Sapienza	Italy	16	15.5	10.9	19.4	53.3	14.8	23.5
	Mean	27.4	25.1	35.3	32.4	54.3	32.9	36.4
	Median	24.2	20.9	32.6	28.3	52.9	30	31.5
	Maximum	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Minimum	0.0	0.0	0.0	5.6	24.1	14.8	23.5

APPENDIX 2. RANKINGS FOR THE TOP 101 UNIVERSITIES AROUND THE WORLD

Table A.2 Rankings obtained

Institution	Shanghai	PROMETHEE	The Proposed Method
Harvard Univ	1	1	1
Univ Cambridge	2	3	5
Stanford Univ	3	5	3
Univ California – Berkeley	4	2	2
Massachusetts Inst Tech (MIT)	5	4	4
California Inst Tech	6	6	6
Columbia Univ	7	7	7
Princeton Univ	8	8	13
Univ Chicago	8	11	16
Univ Oxford	10	10	10
Yale Univ	11	9	8
Cornell Univ	12	12	11
Univ California - San Diego	13	13	9
Univ California - Los Angeles	14	15	14
Univ Pennsylvania	15	16	15
Univ Wisconsin – Madison	16	18	19
Univ Washington – Seattle	17	19	21
Univ California - San Francisco	18	14	12
Tokyo Univ	19	17	17
Johns Hopkins Univ	20	24	24
Univ Michigan - Ann Arbor	21	20	18
Kyoto Univ	22	29	29
Imperial Coll London	23	22	22
Univ Toronto	24	23	25
Univ Illinois - Urbana Champaign	25	31	31
Univ Coll London	26	26	26
Swiss Fed Inst Tech – Zurich	27	27	28
Washington Univ - St. Louis	28	25	23
New York Univ	29	36	34
Rockefeller Univ	30	32	41
Duke Univ	31	21	20
Univ Minnesota - Twin Cities	32	33	33
Northwestern Univ	33	28	27
Univ Colorado – Boulder	34	34	35
Univ California - Santa Barbara	35	30	30
Univ British Columbia	36	38	37
Univ Maryland - Coll Park	37	40	38
Univ Texas Southwestern Med Center	38	37	39
Univ Texas – Austin	39	42	40

Table A.2 Rankings Obtained (Continued)

Institution	Shanghai	PROMETHEE	The Proposed Method
Univ Utrecht	40	54	56
Vanderbilt Univ	41	46	47
Pennsylvania State Univ - Univ Park	42	39	36
Univ California – Davis	42	35	32
Univ California – Irvine	44	43	43
Univ Paris 06	45	57	59
Rutgers State Univ - New Brunswick	46	44	44
Univ Southern California	47	49	52
Karolinska Inst Stockholm	48	67	70
Univ Pittsburgh – Pittsburgh	48	47	46
Univ Manchester	50	61	63
Univ Munich	51	65	65
Univ Edinburgh	52	48	48
Univ Florida	53	51	49
Australian Natl Univ	54	41	42
Tech Univ Munich	54	72	75
Carnegie Mellon Univ	56	69	77
Univ Copenhagen	56	66	68
Univ Zurich	58	56	58
Univ North Carolina - Chapel Hill	59	45	45
Hebrew Univ Jerusalem	60	59	50
Osaka Univ	61	53	53
McGill Univ	62	55	57
Univ Bristol	62	50	55
Univ Paris 11	64	83	86
Uppsala Univ	65	86	87
Ohio State Univ – Columbus	66	63	62
Univ Heidelberg	66	80	79
Univ Oslo	68	88	89
Univ Sheffield	69	58	61
Case Western Reserve Univ	70	71	73
Moscow State Univ	70	89	91
Univ Leiden	72	75	60
Purdue Univ - West Lafayette	73	81	80
Univ Helsinki	74	82	81
Univ Rochester	74	64	54
Tohoku Univ	76	78	76
Univ Arizona	76	52	51
Univ Melbourne	78	87	84

Table A.2 Rankings Obtained (Continued)

Institution	Shanghai	PROMETHEE	The Proposed Method
Univ Nottingham	79	85	85
Michigan State Univ	80	68	67
Boston Univ	81	70	69
Univ Basel	81	76	78
King's Coll London	83	92	93
Stockholm Univ	84	100	100
Brown Univ	85	62	66
Univ Goettingen	85	98	97
Rice Univ	87	79	82
Texas A&M Univ - Coll Station	88	74	72
Tokyo Inst Tech	89	73	71
Lund Univ	90	90	88
McMaster Univ	90	96	95
Univ Birmingham	90	91	92
Univ Freiburg	93	97	96
Univ Utah	94	60	64
Univ Iowa	95	77	74
Univ Strasbourg 1	96	99	99
Indiana Univ – Bloomington	97	94	94
Nagoya Univ	98	93	90
Ecole Normale Super Paris	99	101	101
Arizona State Univ – Tempe	100	84	83
Univ Roma - La Sapienza	100	95	98