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A robust LINMAP for EFQM self assessment

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A B S T R A C T

During the past two decades, there have been tremendous efforts on developing efficient business excellence models to improve the quality of organizations. A typical business excellence model proposes several alternatives with different budget and the primary objective is to use the best ones. In this paper, we present a robust LINMAP method for measuring the relative importance of various alternatives in an EFQM self assessment. The presented robust model is capable of handling uncertainty as part of the problem formulation. The proposed model of this paper is implemented for a case-study of energy sector in Iran with various alternatives. The orderings of the alternatives are measured using data from multiple experts through applying the proposed model of this paper.

1. Introduction

Multi-attribute decision making (MADM) problem is an important type of multi-criteria decision making (MCDM) problem which is a common issue for most real-world decision making situations. MADM problems can be divided into different categories depending on the criteria defined. We may have the choice to consult with decision maker (DM) or we may prefer to make the final decision solely based on some existing data. Technique for order preference by similarity to ideal solution (TOPSIS) is one of the well known methods introduced by Hwang and Yoon (1981). TOPSIS orders alternatives based on some positive and negative criteria with the primary assumption that all the input data are available in advance. In TOPSIS, decision matrix and weight vector are given as crisp values. The positive ideal solution (PIS) and the negative ideal solution (NIS) are generated from the decision matrix directly and the best compromise alternative is then defined as the one that has the

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shortest distance to the PIS and the farthest from the NIS. The other model is the linear programming technique for multidimensional analysis of preference (LINMAP) developed by Srinivasan and Shocker (1973). TOPSIS and LINMAP are two well-known MADM methods which are similar to some extends but they require different types of information. The LINMAP is based on pair-wise comparisons of alternatives given by the decision maker and generates the best compromise alternative as the solution that has the shortest distance to the PIS. In LINMAP, all decision data are known precisely or given as crisp values. However, under many conditions, crisp data are inadequate or insufficient to model real-world decision problems. Indeed, human judgments on preference information are vague or fuzzy in nature and the information could be under uncertainty.

There are different methods to handle uncertainty on data for MCDM problems such as implementing fuzzy programming, stochastic and robust optimization. Zadeh (1965) is believed to be the first who introduced the concept of fuzzy logic. The method can be more useful when we have no historical information and the information comes from DM's prejudgment. The idea of integrating fuzzy logic into MCDM problems has been widely used during the past two decades. Chen and Tan (1994) developed a theoretical approach to handle vague values in the context of fuzzy programming for MCDM problems. Hong and Choi (2000) developed multi-criteria fuzzy decision making problems based on vague set theory. Chen (2000) presented a comprehensive approach to use fuzzy numbers for TOPSIS. Fisher (2003) implemented fuzzy numbers for an application of decision making on air pollution. Li et al. (2007) presented various multi-criteria fuzzy decision making approaches based on intuitionist fuzzy sets. Actually, there are tremendous cases where we can find the applications of fuzzy logic on MCDM problem (e.g. Carlsson & Fuller, 2000; Delgado et al., 1992; Li & Yang, 2004; Li, 2005a; Li, 2005b).

The other method of handling the uncertainty is to use the recent advances of robust optimization on handling uncertainty on decision making problem. Consider a mathematical programming problem which could be modeled in form of linear programming. Traditional sensitivity analysis could be used when some of the input parameters are not precisely. However, consider a case where all input data are subject to uncertainty. In this case, we may not be able to use old fashion analysis to cope with uncertainty. One of the primary questions on handling the uncertainty is the amount of cost we spend to reduce the uncertainty. There are different methods developed to maintain a less conservative solution while the uncertainty is kept at the pre-defined level.

Soyster (1973) was known as a pioneer to introduce robust optimization but his method was too conservative. Ben-Tal and Nemirovski (2000) introduced a new less conservative concept of robust optimization. His method uses the idea of cone programming to handle uncertainty on linear programming. Therefore a regular linear programming problem is formulated as nonlinear programming which makes it intractable among many practitioners. Bertsimas and Sim (2003) introduced a more popular robust optimization where the structure of the original problem is maintained in robust form. The method is almost as conservative as the method introduced by Bertsimas and Sim.

Both methods have been widely used for different MCDM problems. Sadjadi and Omrani (2008, 2009) used these robust techniques for data envelopment analysis. Gharakhani et al. (2010) used the robust optimization for a multi-objective reliability problem. In this paper, we present a new robust optimization technique for the implementation of LINMAP for an MCDM problem. The proposed model of this paper is applied for a real-world case study and the results are discussed in details. This paper is organized as follows. We first present LINAMP model for multidimensional analysis of preferences in section 2. Section 3 presents the robust form of LINMAP and the implementation of the proposed robust LINMAP is given in section 5. Finally, concluding remarks are given in the last section to summarize the contribution of the paper.

2. LINMAP

Consider m alternatives composed of n attributes are represented as m points in the n-dimensional space. A DM is assumed to have his ideal point which denotes the most preferred alternative location. Once the location of the ideal solution is determined, we can choose an alternative which has the shortest distance from the ideal solution. Given two alternatives, a DM is presumed to prefer an alternative which is closer to his ideal point. Then the weighted Euclidean distance d_i, of the A_i from the ideal point is given by the following:

$$d_i = [\sum_{j=1}^{n} w_j (x_{ij} - x_j^*)^2]^{1/2} , \qquad i = 1,2,\dots,m \tag{1}$$

where x_j^* is the ideal point value for j_{th} attribute.

$$s_i = d_i^2 = \sum_{j=1}^{n} w_j (x_{ij} - x_j^*)^2 . \qquad i = 1,2,\dots,m \tag{2}$$

Let $\Omega = \{(k,l)\}$ denote a set of ordered pairs (k,l) where k designates the preferred alternative on a forced choice basis resulted from a pair wise comparison involving k and l. Normally but not necessarily Ω has $m(m-1)/2$ elements and for every ordered pair $(k,l) \epsilon \Omega$, the solution $(w, x*)$ could be consistent with the weighted distance model whenever the following holds,

$$s_{l} \geq s_k . \tag{3}$$

Now the problem is to determine the solution $(w, x*)$ for which the above condition of (3) are violated as minimally as possible with the given decision matrix and Ω. For the pair (k,l), if $s_l \geq s_k$, the condition (3) is satisfied and there is no error associated with the solution. On the other hand if $s_l < s_k$, then $(s_k - s_l)$ denotes the error extent to which the condition is violated. In general, if we define

$$(s_l - s_k)^- = \begin{cases} 0 , & if\ s_l \geq s_k \\ s_k - s_l , & if\ s_l < s_k \end{cases} , (s_l - s_k)^- = max \{0, (s_k - s_l)\} \tag{4}$$

then $(s_l - s_k)^-$ denotes the error for the pair (k, l) $\epsilon\Omega$. We obtain

$$B = \text{poorness of fit} = \sum_{(k,l)\epsilon\Omega} (s_l - s_k)^- . \tag{5}$$

By definition, $(s_l - s_k)^-$ is nonnegative and obviously B is also nonnegative. Our problem is to find a solution (w, x^*) for which B is minimal.

Let us define goodness of fit G, similar to B, such that

$$G = \sum_{(k,l)\epsilon\Omega} (s_l - s_k)^+ , \tag{6}$$

where:

$$(s_{l-}s_k)^+ = \begin{cases} s_{l-}s_k, & if\ s_{l\geq}s_k \\ 0, & if\ s_{l<}s_k \end{cases} \tag{7}$$

We then add the following condition, using the definition of G, in minimizing B, where $G > B$ or equivalently $G - B = h$, where h is an arbitrary positive number. It directly follows that $(s_{l-}s_k)^+ - (s_{l-}s_k)^- = (s_{l-}s_k)$. Furthermore, h can be extended as $\sum_{(k,l)\epsilon\Omega}\ (s_{l-}s_k)$.

Thus (w, x^*) can be obtained by solving the constrained optimization problem of the following form,

$$\min B = \sum_{(k,l)\epsilon\Omega} max\,\{0, (s_{k-}s_l)\}$$

subject to (8)

$$\sum_{(k,l)\epsilon\Omega}\ (s_{l-}s_k)\ = \text{h}$$

or equivalently:

$$\min \sum_{(k,l)\epsilon\Omega}\ z_{kl}$$

subject to

$$(s_{l-}s_k) + z_{kl}\ \geq 0, \qquad for\ (k,l)\ \epsilon\ \Omega \tag{9}$$

$$\sum_{(k,l)\epsilon\Omega}\ (s_{l-}s_k) = \text{h},$$

$$z_{kl} \geq 0, \qquad for\ (k,l)\ \epsilon\Omega$$

Finally we can make the LP formulation of (7) through (9) ready to solve by substituting s_l and s_k to obtain:

$$(s_{l-}s_k)\ = \sum_{j=1}^{n} w_j \left(x_{lj} - x_j^*\right)^2 - \sum_{j=1}^{n} w_j \left(x_{kj} - x_j^*\right)^2 = \sum_{j=1}^{n} w_j \left({x_{lj}}^2 - {x_{kj}}^2\right) \quad - 2\sum_{j=1}^{n} w_j\, x_j^* \left(x_{lj} - x_{kj}\right). \tag{10}$$

Since x_j^* is an unknown constant, $w_j x_j^*$ is replaced by v_j .Therefore the proposed LP model is as follows:

$$\min \sum_{(k,l)\in\Omega} z_{kl}$$

subject to

$$\sum_{j=1}^{n} w_j\,({x_{lj}}^2 - {x_{kj}}^2) \quad - 2\sum_{j=1}^{n} v_j\,(x_{lj} - x_{kj}) +\ z_{kl}\ \geq\ 0\ , \qquad \text{for (k, l)} \in \Omega \tag{11}$$

$$\sum_{j=1}^{n} w_j \quad \sum_{(k,l)\in\Omega}({x_{lj}}^2 - {x_{kj}}^2) - 2\sum_{j=1}^{n} v_j\ \sum_{(k,l)\in\Omega} \in (x_{lj} - x_{kj}) = \text{h}$$

$$w_j \geq 0,\ z_{kl} \geq 0 \quad \text{for } (k,l)\ \in\ \Omega,\ v_j \in URS \ \text{ j=1,2,…,n.}$$

There are the following cases with model (11):

I) If $w_j^* > 0$, then $x_j^* = v_j^*/w_j^*$

II) If $w_j^* = 0$ and $v_j^* = 0$, define $x_j^* = 0$,

III) If $w_j^* = 0$ and $v_j^* > 0$, then $x_j^* = +\infty$,

IV) If $w_j^* = 0$ and $v_j^* < 0$, then $x_j^* = -\infty$,

then the square distance from the x^* is defined as below:

$$s_i = \sum_{j'} w_{j'}^* (x_{ij'} - x_{j'}^*)^2 - 2\sum_{j"} v_{j"}^* x_{ij"}, \qquad i = 1,2,\dots,m$$

$$j' = \{j | w_j^* \geq 0\} \tag{12}$$

$$j" = \{j | w_j^* = 0 \ and \ v_j^* \neq 0\}$$

3. Robust LINMAP

Robust optimization is an approach to cope with parameter uncertainty. Consider a given linear programming problem of the following form:

$$\max \ C^t X$$

subject to (13)

$$\tilde{A}X \leq b,$$

$$L \leq X \leq \mathrm{U}.$$

Based on Bertsimas and Sim's work assume that data uncertainty only affects the elements in matrix A and suppose there are only j_i coefficient subject to uncertainty in a particular row i and each entry a_{ij}, $j \in J_i$ is modeled as a symmetric random variable $\tilde{a}_{ij}$ that only takes value in interval $[\hat{a}_{ij} - \delta_{ij}, +\hat{a}_{ij} + \delta_{ij}]$; in which $\hat{a}_{ij}$ and δ_{ij} is the nominal value and maximum deviation of element a_{ij}, respectively. Bertsimas and Sim show that under mentioned assumptions the constraints of robust counterpart of model (13) can be rewritten as follows:

$$\sum_j \hat{a}_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \leq b_i, \forall i$$

$$z_i + p_{ij} \geq \delta_{ij} y_j, \qquad \forall i, j \in J_i$$

$$-y_j \leq x_j \leq y_j, \qquad \forall j \tag{14}$$

$$l_j \leq x_j \leq u_j, \qquad \forall j$$

$$p_{ij} \geq 0,\ y_j \geq 0, z_i \geq 0 \qquad \forall i, j \in J_i$$

Applying the idea of robust optimization proposed by Bertsimas and Sim to LINMAP model presented by Eq. (11) yields the robust counterpart as follows,

$$\max \quad -\textstyle\sum_{(k,l)\epsilon\Omega} z$$

subject to

$$-\textstyle\sum_j w_j (x_{lj}^2 - x_{kj}^2)) + 2\sum_j v_j (x_{lj} - x_{kj}) - z_{kl} + \psi_{kl}\gamma + \sum_j (P_{klj} + Q_{klj}) \leq 0 \quad for\ (k,l)\ \epsilon\ \Omega$$

$$\psi_{kl} + P_{klj} \geq \Delta_1(X_{lj}2 - X_{kj}2)Y_j \qquad \forall(k,l,j) \in \Omega'$$

$$\psi_{kl} + Q_{klj} \geq \Delta_2(X_{lj} - X_{kj})\varphi_j \qquad \forall(k,l,j) \in \Omega' \tag{15}$$

$$-Y_j \leq W_j \leq Y_j, \qquad \forall\ j = 1,..,n,$$

$$-\varphi_j \leq V_j \leq \varphi_j, \qquad \forall\ j = 1,..,n,$$

$$\sum_j w_j \sum_{kl\epsilon\Omega}(x_{lj}^2 - x_{kj}^2) - 2\sum_j v_j \sum_{kl\epsilon\Omega}\left(x_{lj} - x_{kj}\right) = h,$$

$$w_j, \psi_{kl}, z_{kl} \geq 0 \quad \text{for } (k,l) \in \Omega,\ v_j \in URS \qquad j=1,2,\ldots,n.$$

In order to solve robust LINMAP model we assume 10% perturbation in parameters i.e. $\Delta = 0.1$. We also assume $\gamma = 1.5$ which represent 0.95% guarantee in holding the constraints. Finally the parameter $h = 1$ as suggested by the model.

4. Case study

In order to illustrate the implementation of the proposed model we consider a real-world case study in this section from a popular business excellence model known as European foundation of quality management (EFQM). The method is used as a framework for self assessment where an organization could study the effects of various alternatives on the success of a particular business. According to EFQM methodology, there are normally nine criteria associated with any firm and the method provides a balance among all these criteria using cause and effect relationships. When we compare the effects of different alternatives, we may choose to adopt the implementation of LINMAP to measure the relative performance of each choice. Since there are uncertainties associated with possible DM preferences, robust LINMAP could be adopted to solve the resulted problem.

4.1. Case study

MAPNA GROUP is a conglomeration of parent company and its 29 subsidiaries engaged in development and implementation of power, oil & gas, railway transportation and other industrial projects under EPC & IP schemes as well as manufacturing relative equipment. The company was estabilished in 1992 and it has constructed over 60 projects valuing € 17 billion, among them power projects cover more than 52,000MW, having a share of 86% of the country's total grid capacity. The company has been successful on executing several exclusive projects with the focus of energy sector. The company uses EFQM self assessment using three criteria of time, cost and maturity of the organization. There are eight alternatives involved with this study which are summarized in Table 1.

Table 1
The summary of eight alternatives for the assessment

Alternative number	Description	Alternative number	Description
A_1	360 degree assessment	A_5	Risk management
A_2	Strategic planning	A_6	Management information system
A_3	Employee performance	A_7	Six Sigma
A_4	Management assessment	A_8	Customer evaluation

There are eight projects defined for all alternatives defined in Table 1. The time and the cost associated with each project are summarized in Table 2. The costs and time are in terms of ten million rials and months, respectively.

Table 2
The cost and the time associated with eight items

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Cost	6	14	4	9	8	10	4	12
Time	6	10	5	6	10	10	5	10

The decision matrix D is also given in the following form:

$$D = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \end{array} \begin{bmatrix} 6 & 6 & 0.7 \\ 14 & 10 & 1 \\ 4 & 5 & 0.3 \\ 9 & 6 & 0.7 \\ 8 & 10 & 0.9 \\ 10 & 10 & 0.5 \\ 4 & 5 & 0.5 \\ 12 & 10 & 0.9 \end{bmatrix}$$

In our study, three DM are requested to relatively compare three criteria which are summarized as follows,

$$\Omega_1 = \{(A_2, A_1), (A_2, A_3), (A_2, A_4), (A_3, A_7), (A_6, A_1), (A_5, A_8), (A_5, A_2), (A_3, A_8), (A_7, A_1)\}$$

$$\Omega_2 = \{(A_2, A_1), (A_8, A_3), (A_2, A_6), (A_2, A_7), (A_7, A_6), (A_2, A_8), (A_8, A_7), (A_7, A_5)\}$$

$$\Omega_3 = \{(A_1, A_2), (A_5, A_1), (A_2, A_3), (A_2, A_7), (A_2, A_8), (A_7, A_6), (A_8, A_6), (A_6, A_3), (A_7, A_3), (A_8, A_4)\}$$

The implementation of the regular LINMAP yields the following weights for DM_1 to DM_3.

Table 3
Different weights for three decision makers using regular LINMAP

	DM_1	DM_2	DM_3
w_1	0.0000	0.0000	0.0000
w_2	0.0000	0.0000	0.0000
w_3	0.0000	0.0000	0.0000
v_1	0.0000	0.0015	-0.0167
v_2	0.0455	-0.0303	0.0083
v_3	-0.3247	0.3636	0.3333

Based on the information of Table 3 we find the relative distance for each alternative. Column two, three and four of Table 4 summarizes the distances associated with decision maker 1, 2 and 3, respectively. The last column of Table 4 is the absolute geometric average for three decision makers.

Table 4
The relative distance and geometric average absolute distance using regular LINMAP

	DM_1	DM_2	DM_3	Average
A_1	-0.09	-0.16	-0.37	0.176
A_2	-0.26	-0.16	-0.37	0.250
A_3	-0.26	0.07	-0.15	0.141
A_4	-0.09	-0.17	-0.27	0.161
A_5	-0.32	-0.07	-0.50	0.228
A_6	-0.58	0.21	-0.17	0.274
A_7	-0.13	-0.07	-0.28	0.139
A_8	-0.32	-0.08	-0.37	0.216

From the results of Table 4 we understand that alternative 6, management information system, has the highest priority and alternative seven which is the implementation of Six Sigma comes in the last priority. The orders of priorities for all alternatives are as follows,

$A_7 < A_3 < A_4 < A_1 < A_8 < A_5 < A_2 < A_6$.

We have implemented the proposed robust LINMAP for the case study of this paper and the optimal weights for all alternatives in robust problem formulation is summarized in Table 5.

Table 5
Different weights for three decision makers using robust LINMAP

	DM_1	DM_2	DM_3
w1	0.0000	0.0000	0.0012
w2	0.0000	0.0000	0.0009
w3	0.0000	0.0000	0.1874
v1	0.0000	0.0176	0.0000
v2	0.4876	-0.0228	0.0000
v3	-0.3247	0.0882	0.5013

Again, we have determined the optimal distances for all eight alternatives and the absolute geometric average for eight alternatives are given in the last column of Table 6.

In this case, we can observe that the second alternative A_2, comes first in terms of priority. Alternative four comes as the second one and the other alternatives of A_1, A_3, A_6, A_5, A_8 and A_7 come in the descending order of priorities. In other word, strategic planning may help this unit reach its objectives when there is uncertainty associated with DM's criteria. Also, in the event of uncertainty, customer evaluation plays an important role on the success of a business unit.

Table 6
The relative distance and geometric average absolute distance using robust LINMAP

	DM1	DM2	DM3	Average
A1	-5.40	-0.06	0.81	0.643
A2	-9.10	-0.21	0.86	1.185
A3	-4.68	0.03	1.10	0.561
A4	-5.40	-0.17	0.86	0.919
A5	-9.17	0.02	0.76	0.477
A6	-9.43	0.02	1.10	0.547
A7	-4.55	0.00	0.93	0.162
A8	-9.17	0.00	0.86	0.199

5. Conclusion

In this paper, we have presented a robust LINMAP method for measuring the relative importance of different alternatives in an EFQM self assessment. The proposed model of this paper has been implemented for a case study of energy sector in Iran. There were eight alternatives defined for the success of the case study and three DM has been questioned for the relative importance of these alternatives. The orderings of these eight alternatives have been measured using the regular and robust LINMAP approach. The preliminary results indicate that the proposed model of this paper could be easily used for different industries.

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