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Multidimensional Compromise Optimization for Development Ranking of the Gulf Cooperation Council Countries and Turkey

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***Abstract*—**In this research, a multidimensional compromise optimization method is proposed for multidimensional decision making analysis in the development ranking of the Gulf Cooperation Council Countries and Turkey. The proposed approach presents ranking solutions resulting from different multicriteria decision analyses, which yield different ranking orders for the same ranking problem, consisting of a set of alternatives in terms of numerous competing criteria when they are applied with the same numerical data. The multiobjective optimization decision making problem is considered in three sequential steps. In the first step, five different criteria related to the development ranking are gathered from the research field. In the second step, identified evaluation criteria are, objectively, weighted using standard deviation procedure. In the third step, a country selection problem is illustrated with a numerical example as an application of the proposed multidimensional compromise optimization model. Finally, multidimensional compromise optimization approach is applied to rank the Gulf Cooperation Council Countries and Turkey.

***Keywords*—**Standard deviation, performance evaluation, multicriteria decision making, multidimensional compromise optimization, vector normalization, multicriteria decision making, multicriteria analysis, multidimensional decision analysis.

I. Introduction

MULTICRITERIA DECISION MAKING (MCDM) analysis is used to making optimal decisions in the presence of multiple usually conflicting criteria for MCDM problems in real life situations. A typical MCDM problem involves a number of alternatives to be assessed and a number of criteria to evaluate the alternatives for multidimensional compromise optimization of complex systems [1], [2]. MCDM methods use different normalizations and aggregating functions for ranking. In multidimensional compromise optimization data normalization is used to eliminate the units of criterion functions.The multidimensional compromise optimization method determines the compromise ranking and the compromise solution obtained with the given weights of criteria. The multidimensional compromise optimization method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria, whilst introducing the multicriteria ranking index based on the particular measure of ‘‘closeness” to the ‘‘ideal” solution, which originated from the multicriteria compromise programming method. The multidimensional compromise optimization method of compromise ranking determines a quantitative solution, providing a maximum ‘‘group utility’’ for the ‘‘majority’’ and a minimum of an individual regret for the ‘‘opponent’’ [25], [26], [32]. The multidimensional compromise optimization method also determines a solution with the shortest distance to the ideal solution and the greatest distance from the negative ideal solution [24].

The MCDM analysis is usually carried out in the presence of multiple incommensurable and conflicting decision criteria, different units of measurement values among the criteria, and the presence of quite different alternatives [3]. Therefore, the alternatives in MCDM problem have performance values for all criteria and based on these quantitative values; the alternatives can be assessed and ranked for selection problem in consideration [4], [5]. These computational MCDM methods are widely considered to be significant potential models for analyzing complex system problems due to their inherent ability to rank different alternatives on various criteria for possible selection of the optimal alternative(s) [6], [7]. The MCDM methods are divided into three categories to bring the MCDM methods together according to some similarities: (i) multiattribute methods; (ii) outranking methods; (iii) interactive methods [8], [9]. On the other hand, MCDM methods are classified: (i) unique synthesis criterion method, eliminating any incomparability; (ii) outranking synthesis method, accepting incomparability; (iii) interactive local judgment method, with trial-error interaction [1], [10].

Basically, there are three sequential steps in operating any MCDM method involving numerical analysis of alternatives; determination of the relevant criteria and alternatives, attaching numerical values to the relative importance or priority to critical criteria, and impact of the alternatives on the decision criteria, and processing the numerical values to determine a ranking of each alternative for a compromise solution [2], [11]. Hence, multidimensional MCDM methods are able to improve the quality of decisions by making the decision making process more explicit, rational and efficient for multicriteria compromise optimization analysis. On the other hand, an interesting problem with MCDM methods which rank a set of alternatives in terms of numerous competing criteria is that often different MCDM methods may yield different rank orders when they are applied with the same numerical data [12], [13]. A great deal of effort has been made regarding the multicriteria compromise optimization in ranking problems [18]-[27]. However, a generalized quantitative evaluation model based on multicriteria decision making is still lacking in multiobjective optimization decision making (MODM) problems [1]-[17].

From strategic decision making perspective, determining the most important factors of development ranking is crucial and helps decision makers to focus on factors with the highest weight and identify the best policy to improve the sustainable development strategy [12]. Therefore, a multicriteria decision making approach is essential in order to evaluate the relative importance of these factors on alternatives. Consequently, this research proposes a model that hybridizes the standard deviation procedure and the multidimensional compromise optimization method in order to provide an objective evaluation model that prioritizes the objective weights of development ranking problem. The intended research contributions are: (i) to determine and evaluate the most relevant criteria for development ranking; (ii) to apply a hybrid multicriteria decision model based on standard deviation and multidimensional compromise optimization methodology; (iii) to present results of different MODM analyses that reflects the effects of different criteria on qualitative and quantitative characteristics of the ranking of the alternatives.

Organization of the rest of the paper is as follows: Section II describes the standard deviation approach as an objective weighting procedure in the MCDM models, Section III reviews the MCDM methods, Section IV explains the multidimensional compromise optimization method and vector normalization, and Section V compares the empirical results of a country selection and development ranking problem obtained with the standard deviation-multidimensional compromise optimization model, and Section VI concludes with closing remarks.

II. Standard Deviation Method

Standard deviation procedure is proposed for determining the objective weights of the importance of the attributes. Standard deviation is an objective weighting method in which objective weights are derived from MODM dataset. Weight extraction from MODM datasets is one of the most challenging processes in MCDM models, and standard deviation determines objective criteria weights. Standard deviation is an objective weighting method that assigns an objective weight to each criterion using standard deviations [29]. The deviation of a dataset carries an important information, and it is suitable for comparing the criteria weights after normalizing the MODM dataset.

$$R = [r_{ij}]_{nxm} = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1m} \\ r_{21} & \cdots & r_{2j} & \cdots & r_{2m} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ r_{n1} & \cdots & r_{nj} & \cdots & r_{nm} \end{bmatrix} \tag{1}$$

$$i \in \{1,2,...,m\} \ \ j \in \{1,2,...,n\}$$

where r_{ij} is the performance value of i^{th} alternative on j^{th} criterion, m is the number of alternatives, and n is the number of criteria. Then, the deviation of the j^{th} criterion of i^{th} alternative:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(r_{ij} - \overline{r}_j)^2}{m}} \tag{2}$$

where σ_j is a standard deviation of the data corresponding to the j^{th} attribute. $\overline{r}_j$ is the mean or average value of r_{ij}. The objective weight of the j^{th} attribute can be obtained from the ratio of σ_j to the total deviation of the normalized dataset:

$$\omega_j = \frac{\sigma_j}{\sum_{j=1}^{n}\sigma_j} \tag{3}$$

where ω_j is the objective weight of the j^{th} criterion that the standard deviation assigns. The standard deviation concept of determining the objective weights of the attributes is comparatively simpler than the entropy method.

III. Multidimensional Decision Making

In this paper, standard deviation and multidimensional compromise optimization, are chosen to deal with the problem of selecting a country with optimal development indices. The multidimensional compromise optimization method reflects a different approach to solving a given discrete MCDM problem of choosing the optimal among several preselected alternatives. The multidimensional compromise optimization method requires the preselection of a countable number of alternatives and the use of a countable number of quantifiable conflicting and incommensurable performance criteria [14], [15].

The evaluation attributes may indicate benefits and costs to a decision maker for an MCDM problem. A larger outcome always means a greater preference for a benefit or less preference for a cost criterion. Hence, after inter- and intra-comparison of the alternatives with respect to a given set of performance attributes, implicit/explicit trade-offs are established and used to rank the alternatives. The problem of ranking countries' development grades is considered as a multicriteria decision making analysis problem. A multicriteria optimization decision analysis procedure, dealing with the various aspects of finding optimum decisions in problems with multiple decision alternatives and conflicting objectives (criteria), recently, has been applied in various fields of technology, economics, mathematics, and computics [16].

In general, in multiobjective optimization, there is no single best solution for MCDM problem in consideration. Therefore, it is common to directly or indirectly search for a set of Pareto efficient solutions, and apply set oriented search procedures for multiobjective optimization analysis [28]. Also, there is an alternative multicriteria optimization approach, which is the construction of ranking and scoring methods that aggregate objectives, which normally yields a particularly efficient solution on the Pareto front. Moreover, in multicriteria decision analysis, the evaluation of multivariate data and trade-offs are discussed, and solution models that can support human decision makers in complex environments [17].

Many MCDM complex problems ranging from production scheduling to online performance evaluation involve selection procedure by ranking alternatives for supporting human decision makers in complex environments [15]. Multicriteria decision analysis has many applications in decision science, performance science, engineering, and related fields for determining the optimal choice by selecting, classifying or ranking multiple alternatives [15], [16]. There are various MCDM models, applicable to economics, business and related fields, from production to finance, and each has a different capability for determining the best alternative to a set of possible solutions [18].

The configuration of an MCDM model for a decision problem is based upon an abstract language where subjective judgment, intuition, experience, and preference are at the forefront. The main advantage of MCDM models stems from the fact that criteria values of alternatives melt in the same pot for a holistic evaluation, and typically, these models do not require criteria selection or statistical significance tests. The multidimensional compromise optimization method is an MCDM ranking model that converts quantitative ratings of the alternatives into quantitative ranking expressions [19].

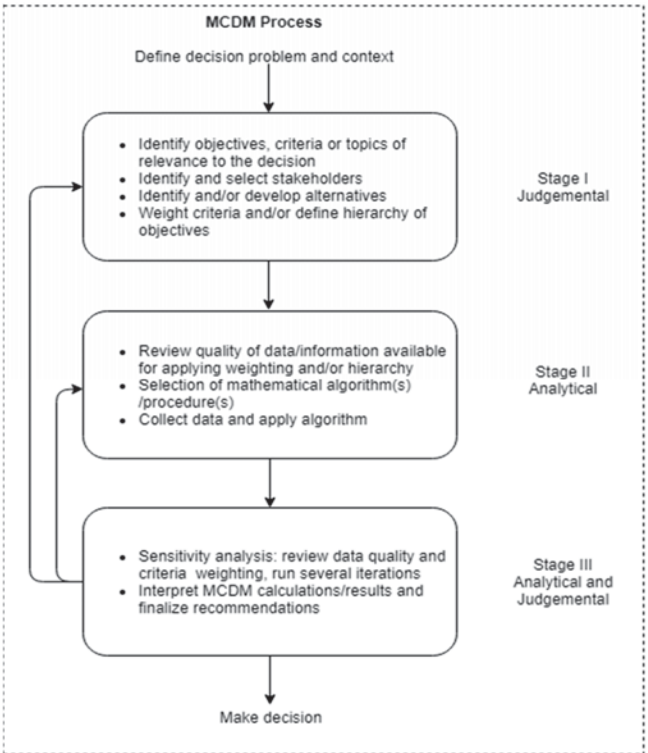

Fig. 1 The overall process of MCDM models

A quantitative MCDM method of multidimensional compromise optimization is proposed to determine the relative rankings of alternatives. The structure of the multidimensional compromise optimization model includes the interacting goal, criteria, and the alternatives. This paper presents an objective ranking method, which embeds vector normalization and standard deviation into multidimensional compromise optimization. The method of standard deviation - multidimensional compromise optimization computes criteria weights from the MCDM dataset itself, eliminates the issue of consistency due to subjective judgments, and yet continues to benefit from the strength of MCDM analysis process.

IV. Multidimensional Compromise Optimization

In decision making problems, decision making for MCDM problem is the process of selecting a possible direction of action from all of the available alternatives in the presence of conflicting criteria. On the other hand, the multiplicity of criteria for ranking the alternatives is pervasive, and the decision maker wants to obtain more than one objective or goal in selecting the route of action while satisfying the constraints identified by environment, processes, and resources [20]. The multidimensional compromise optimization method is proposed to solve MCDM problems with conflicting and incommensurable criteria, considering that compromising is acceptable for conflict resolution when the decision maker wants a multidimensional compromise solution that is the nearest to the ideal, and the alternatives are quantitatively evaluated according to identified criteria. The multidimensional compromise optimization approach emphasis on ranking and selecting from a set of alternatives in the presence of conflicting criteria, and proposing compromise solution for MODM problem [21].

The solution of MCDM problems usually starts with a given reference point, and the MCDM problems can then be solved by positioning the alternatives or decisions which are the nearest to the reference point. Therefore, the MCDM problem becomes measuring the distance to the reference point. Goal programming measures this distance by using the weighted sum of absolute distances from given goals. The global criteria method measures this distance by using Minkowski's L_p metric. The L_p metric defines the distance between two points, f_{ij} and f_{ij}^{+} (the reference point), in n-dimensional space as:

$$L_p = \left\{ \sum_{j=1}^{n} (f_{ij}^{+} - f_{ij})^{p} \right\}^{1/p} \quad p \geq 1 \tag{4}$$

where L_p the distance (p=1,2,…,∞) is operationally significant, when p increases, distance L_p decreases, $L_1 \geq L_2 \geq ... \geq L_\infty$. Specifically, p = 1, L_1 (the Manhattan distance) implies an equal weights for all these deviations and is called, for p=2, L_2 (the Euclidean distance) implies that the deviations are weighted proportionately with the largest deviation having the largest weight. Ultimately, while p = ∞, L_∞ (the Tchebycheff) implies the largest deviation completely dominates the distance determination.

$$L_{\infty} = \max_{j}\left\{| f_{ij}^{+} - f_{ij} |\right\} \quad (5)$$

Distances L_1 (the Manhattan distance) and L_2 (the Euclidean distance) are the longest and the shortest distances in the geometrical sense; L_{∞} (the Tchebycheff) is the shortest distance in the numerical sense. Especially, considering the incommensurability nature of objectives or criteria, the distance family is then normalized to remove the effects of the incommensurability by using the reference point [18]-[27]. The distance family then becomes

$$L_p = \left\{ \sum_{j=1}^{n} \left[\frac{(f_{ij}^{+} - f_{ij})}{f_{ij}^{+}} \right]^{p} \right\}^{1/p} \quad 1 \le p \le \infty \quad (6)$$

The amount of L_p decreases when parameter p increases.The technique for order of preference by similarity to ideal solution [24] is proposed to solve multiple attribute decision making (MADM) problems by using the concept of optimum multidimensional compromise solution, and later the concept is further extended for MADM problems, and developed for solving multiple objective decision making (MODM) problems [18]. Thus, using the normalized distance family with the ideal solution being the reference point, the MODM problem becomes solving the following auxiliary problem of aggregating function:

$$\min_{x \in X} L_p^{i} = \left\{ \sum_{j=1}^{n} \left[\omega_j \frac{(f_{ij}^{+} - f_{ij})}{f_{ij}^{+} - f_{ij}^{-}} \right]^{p} \right\}^{1/p}$$

$$\min_{x \in X} L_p^{i} = \left\{ \sum_{j=1}^{n} \left[\omega_j \frac{(f_{ij}^{+}(x^{+}) - f_{ij}(x)}{f_{ij}^{+}(x^{+}) - f_{ij}^{-}(x^{-})} \right]^{p} \right\}^{1/p} \quad 1 \le p \le \infty \quad (7)$$

$$L_p^{i} = \left\{ \sum_{j=1}^{n} \left[\omega_j \frac{(f_{ij}^{+} - f_{ij})}{f_{ij}^{+} - f_{ij}^{-}} \right]^{p} \right\}^{1/p} \quad p \ge 1$$

$$i \in \{1, 2, ..., m\} \ \ j \in \{1, 2, ..., n\}$$

where the distance family is normalized using positive ideal solution (f_{ij}^{+}) and negative ideal solution (f_{ij}^{-}) and p = 1, 2 ,…,∞. The value chosen for p reflects the way of achieving a multidimensional compromise solution by minimizing the weighted sum of the deviations of criteria from their respective reference points (ideal solution) [20]-[24].

The measure L_p^{i} represents the distance of the alternative A_i to the ideal solution, ω_j is the weight of j^{th} objective, f_{ij}^{+} is the best (positive ideal solution) value of corresponding j^{th} criterion, and f_{ij}^{-} is the worst (negative ideal solution) value of corresponding j^{th} criterion. With the concept of optimal compromise solution, the best alternative or decisions of technique for order of preference by similarity to ideal solution method are those that have the shortest distance from the positive ideal solution as well as have the farthest distance from the negative ideal solution [24]. This multidimensional compromise method assumes that each criterion takes either monotonically increasing or monotonically decreasing utility, the larger the criteria outcome, the greater the preference for beneficial attributes and the less the preference for non beneficial attributes. The multidimensional compromise solution is proposed as a ranking method for decision problems with a predefined decision matrix. The multidimensional compromise solution procedure for ranking alternatives consists of the following main steps:

1. Determine the goal or objective of the problem and identify the relevant decision criteria and alternatives. Construct the decision matrix using all available information on alternatives and criteria. Each row of the decision matrix is allocated to one alternative and each column to one criterion. Therefore, an element x_{ij} of the decision matrix gives the value of j^{th} criterion in original non normalized form and unit for i^{th} alternative.
2. Compute the normalized decision matrix. The normalized value r_{ij} is computed using vector normalization method.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \text{ for beneficial criteria} \quad (8)$$

$$r_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \text{ for non beneficial criteria} \quad (9)$$

3. Compute the weighted normalized decision matrix u_{ij} by multiplying each element of the column of the matrix r_{ij} with its associated weight ω_j.The weighted normalized value u_{ij} is computed.

$$u_{ij} = \omega_j r_{ij}$$

$$U_i = \sum_{j=1}^{n} u_{ij} = \sum_{j=1}^{n} \omega_j r_{ij}$$

(10)

$$\sum_{j=1}^{n} \omega_j = 1,$$

$$i \in \{1, 2, ..., m\} \ \ j \in \{1, 2, ..., n\}$$

where ω_j is the weight of j^{th} objective.

4. Determine the positive ideal and negative ideal solution.

$$A^{+} = u_j^{+} = \left\{u_1^{+},...,u_m^{+}\right\} = \left\{\max_i u_{ij} \mid j \in J),(\min_i u_{ij} \mid j \in J')\right\} \quad (11)$$

$$A^{-} = u_j^{-} = \left\{u_1^{-},...,u_m^{-}\right\} = \left\{\min_i u_{ij} \mid j \in J),(\max_i u_{ij} \mid j \in J')\right\} \quad (12)$$

where J is associated with benefit criteria, and J' is associated with non beneficial criteria.

5. Compute the separation measures of each alternative from the positive ideal and the negative ideal solutions, using the n dimensional Euclidean geometric distance. The separation of each alternative from the positive ideal solution is given.

$$d_i^{+} = \left[\sum_{j=1}^{n}(u_{ij} - u_j^{+})^2\right]^{1/2} \quad (13)$$

Similarly, the separation from the negative ideal solution is given.

$$d_i^{-} = \left[\sum_{j=1}^{n}(u_{ij} - u_j^{-})^2\right]^{1/2} \quad (14)$$

6. Compute the relative closeness coefficient to the positive ideal solution of each alternative. The relative closeness of the alternative A_i with respect to the positive ideal solution d^{+} is defined.

$$P_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}, \quad 0 \le P_i \le 1 \quad (15)$$

where P_i is the overall performance score for i^{th} alternative. Alternatives, based on the decreasing values of closeness coefficient, are ranked from most valuable to worst using the preference order of alternatives. The best alternative, having highest closeness coefficient P_i is selected.

7. A linear aggregating function Z_i based on the d_i^{+} and d_i^{-} distances is aslo proposed:

$$Z_i = \alpha d_i^{-} + (1-\alpha)(1-d_i^{+}) \quad (16)$$

where α is a coefficient that describes the decision maker's decision strategy (aggressive or conservative). The higher α reflects the more conservative the decision maker.

8. Based on the overall performance scores (U_i, P_i, Z_i) the alternatives are ranked in descending order.

V. Empirical Results

A. Constructing the Decision Matrix

In this paper, a compromise approach is presented to decision support that applies MCDM methods based on reference points. The MCDM problems start with a decision/evaluation matrix exhibiting the performance of different alternatives with respect to various criteria. A country selection problem is investigated by the MCO method, and the results are compared with characteristics of the MCDM methods. In order to demonstrate the applicability and potentiality of the multidimensional compromise optimization method in solving multiobjective decision making problems in sustainable economic growth and development environment, the following quantitative illustrative example is considered. The MCDM dataset of the country selection and ranking problem, for multicriteria decision making in the development ranking of GCC Countries and Turkey, consists of seven alternatives and five identified criteria as given in the decision matrix.

In Table I, Gulf Cooperation Countries (Saudi Arabia, Kuwait, UAE, Qatar, Bahrain, Oman) [30], and Turkey in the rows of the decision matrix are evaluated according to five criteria in the columns of the decision matrix. In this present research work, five attributes for ranking the countries are considered in the decision matrix. Dataset for five criteria was retrieved from world bank database and other related sources [31] for the years 2015-2016; and these criteria respectively measure Human Development Index (C1), Global Competitiveness Report (C2), Knowledge Economic Index (C2), Global Innovation Index (C4), and Global Entrepreneurship Index (C5). All criteria other than Global Competitiveness Report (C2) are considered benefit criteria for ranking the alternatives. Standard deviation method is applied to calculate the normalized weights of the criteria. The multidimensional compromise optimization approach is used to determine the most suitable alternative from the obtained values. Table I presents the decision matrix considered in the selection problem.

B. Normalizing the Decision Matrix

The decision matrix in MCDM consideration first requires being normalized so that it becomes dimensionless and all of its elements are comparable. In Table II, application of the proposed methodology starts with the vector normalization as given in (8)-(9).

TABLE I
DECISION MATRIX OF THE COUNTRY SELECTION PROBLEM

Country	C1	C2	C3	C4	C5
Optimization	max	min	max	max	max
Saudi Arabia	0,85	29	5,96	37,80	47,16
Kuwait	0,80	38	5,33	33,60	42,47
UAE	0,84	16	6,94	39,40	43,6
Qatar	0,86	18	5,84	37,50	57,95
Bahrain	0,82	48	6,90	35,50	44,68
Oman	0,80	66	6,14	32,20	43,60
Turkey	0,77	55	5,16	39	43,69
f_j^{+}	0,86	16	6,94	39,4	57,95
f_j^{-}	0,77	66	5,16	32,2	42,47

The objective weights of criteria are obtained using standard deviation equations (1)-(3) and shown in Table II. The objective weights of identified criteria are computed using standard deviation and shown in Table II.

TABLE II
NORMALIZED DECISION MATRIX

Country	C1	C2	C3	C4	C5
Optimization	max	min	max	max	max
Saudi Arabia	0,148	0,893	0,141	0,148	0,146
Kuwait	0,139	0,852	0,123	0,131	0,127
UAE	0,147	0,944	0,161	0,154	0,131
Qatar	0,176	0,933	0,162	0,174	0,200
Bahrain	0,197	0,809	0,227	0,199	0,192
Oman	0,229	0,678	0,259	0,225	0,232
Turkey	0,256	0,609	0,289	0,351	0,302
σ_j	0,002	0,014	0,003	0,005	0,003
ω_j	0,063	0,514	0,126	0,174	0,123

C. Weighted Normalized Decision Matrix

The normalized decision matrix is weighted using (10) and shown in Table III. The determination of a set of ideal (A_i^+) and negative ideal (A_i^-) solutions are indicated using (11) and (12) as shown in Table III.

TABLE III
WEIGHTED NORMALIZED DECISION MATRIX

Country	C1	C2	C3	C4	C5	
Optimization	max	min	max	max	max	U_i
Weights ω_j	0,063	0,514	0,126	0,174	0,123	
Saudi Arabia	0,009	0,459	0,018	0,026	0,018	0,530
Kuwait	0,009	0,438	0,016	0,023	0,016	0,501
UAE	0,009	0,485	0,020	0,027	0,016	0,558
Qatar	0,011	0,480	0,020	0,030	0,025	0,566
Bahrain	0,012	0,416	0,029	0,035	0,024	0,515
Oman	0,014	0,349	0,033	0,039	0,029	0,463
Turkey	0,016	0,313	0,036	0,061	0,037	0,464
u_j^+	0,016	0,485	0,036	0,061	0,037	
u_j^-	0,009	0,313	0,016	0,023	0,016	

D. Computing the Separation Measures

The positive ideal solutions (PIS) d_i^+ and negative ideal solutions (NIS) d_i^- are computed by (13) and (14), and shown in Table IV respectively.

E. Computing the Multidimensional Compromise Solutions

In point of fact, in the multidimensional compromise solutions, the evaluation of alternatives according to distances from positive ideal and negative ideal points represents two significant decision attitudes: the distance from positive ideal can be regarded as encouraging aggressive decisions, in which the decision maker tries to approach the best as closely as possible; the distance from negative ideal is conservative, as the decision maker tries to maximize distance to the worst in the Pareto set [34].

Consequently, similar to compromise solution by MCDM methods (regarding α as the weight of the ‘‘majority of criteria’’ strategy, [25], [35], a relative weight for conservative (as opposed to aggressive) decision making can be introduced to aggregate the two distances in multidimensional compromise solution [24]. For instance, the compromise aggregation function (16) uses α as the weight of the conservative decision strategy. Afterwards, conventional aggregation in the multidimensional compromise solution can be regarded as aggregation under a specific value of α . Subsequently, in connection with the country raking problem, the classical aggregation function, (15) is used for integration of distances from positive ideal and negative ideal points, for comparison purposes. The multidimensional compromise solution is stable within a decision making process, which could be the strategy of maximum group utility (when $\alpha > 0.5$ is needed), or ‘‘by consensus’’ $\alpha \approx 0.5$, or ‘‘with veto’’ ($\alpha < 0.5$). Here, α is introduced as the weight of decision making strategy of maximum group utility, here $\alpha = 0.5$. The multidimensional compromise solutions (Z_i) are computed using (13), (14), and (16) with decision strategy α , and final rankings are shown in Table IV.

F. Overall Performances of the Alternatives

The performances of the alternatives (U_i, P_i, Z_i) for MCDM compromise optimization problem are computed using (13)-(16) and shown in Table IV.

TABLE IV
COMPUTING THE MULTIDIMENSIONAL COMPROMISE SOLUTIONS

Alternative	U_i	Rank	d_i^+	d_i^-	P_i	Rank	Z_i	Rank
Saudi Arabia	0,530	3	0,106	0,154	0,592	3	0,524	3
Kuwait	0,501	5	0,135	0,125	0,481	5	0,495	5
UAE	0,558	2	0,078	0,182	0,700	2	0,552	2
Qatar	0,566	1	0,070	0,190	0,731	1	0,560	1
Bahrain	0,515	4	0,121	0,140	0,537	4	0,510	4
Oman	0,463	7	0,173	0,087	0,336	7	0,457	7
Turkey	0,464	6	0,172	0,088	0,338	6	0,458	6

In Table IV, the final ranking results of the multidimensional compromise optimization method are listed to reflect different ranking characteristics of the multicriteria decision making procedure. The standard deviation standard deviation based multidimensional compromise optimization method is, objectively, considered for multidimensional compromise optimization for country ranking problem. The objective ranking of country performance values is very useful in operational and strategic management situations. The considered standard deviation based multidimensional compromise optimization method is quite capable in solving real time country selection decision making problems and the rankings of the country alternatives. It is observed that the vector normalization procedure is the most preferred choice to normalize the criteria values in the decision matrices [33].

VI. CONCLUSION AND DISCUSSION

In this paper, to demonstrate the computational flexibility and applicability of multidimensional compromise method, the selection problem of the development ranking of the Gulf

Cooperation Council Countries and Turkey is considered, Therefore an efficient MCDM method is proposed to solve the country selection problem and select the best country through a multiple criteria decision making process. In this research, an MDCM approach, multidimensional compromise optimization is implemented to deal with conflicting criteria and a suitable country is selected successfully. The outranking order of countries and rating of countries can easily be determined by using this method. In multicriteria decision making problems, making the right optimal selection amongst alternatives is an important factor for multicriteria optimization analysis. A country selection problem that ranks sustainable developing indices using multicriteria compromise optimization analysis is quite essential for global sustainable development ranking. Thus, when selecting a developed country from a set of potential prospective states in the present, several criteria and alternatives should be taken into consideration in the course of multicriteria analysis. In this paper, in a country selection problem with five criteria that are effective in country selection among developed countries, standard deviation and multidimensional compromise optimization are used together for multicriteria optimization analysis problem.

The multidimensional compromise optimization technique was applied to optimally select the country process parameters that produced the ranking with the optimum properties. However, standard deviation was used to determine the weights allocated to each value of the development indices utilized in the course of running the multidimensional compromise optimization process. This multiobjective optimization model utilizes a ranking method for the development parameters selection process. In accordance with the findings of the research, Qatar is found to be the best optimum performing country according to the evaluation based on the criteria with the proposed multidimensional compromise optimization method. Nevertheless, it should be considered that the results can change if different criteria are used for MCDM country selection problem. Although MCDM plays a significant critical role in many complex real time problems, it is also hard to accept an MCDM method as being accurate all the time for the solution of multiobjective optimization problems. Consequently, it is less likely that the ranking similarities, irregularities, and differences among the applied MCDM methods will take place in multicriteria compromise optimization problems when the considered alternatives are very prominent from each other. Finally, the proposed multidimensional compromise optimization method is considered flexible systematic approach which can be applied to different types of decision making problems.

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