A Novel Integrated AHP-TOPSIS Model to Deal with Big Data in Group Decision Making

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Abstract

This study presents an approach for ranking the alternative solutions based on ideal values of criteria. For this purpose, a group multi criteria decision making (GMCDM) model is presented with combination of Analytical Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methods. The proposed model is capable of finding optimal solution for high-dimensional problems with simple and manual calculations. In the first stage, decision making matrix and weight vector of criteria are calculated using AHP, and in the second stage, the alternatives are ranked according to the least distances from ideal values of criteria. The model contributes to the literature by considering intangible and tangible criteria, handling opinions of multiple decision makers, solving problems with many alternatives and criteria in a short time frame, and applying source limitations as spotted to be one of the limitations of decision makers. A numerical example is presented to analyze proposed approach's effectiveness. Findings illustrate that proposed algorithm is flexible against different criteria and is capable to reach similar solutions in comparison with other MCDM methods in a short timeframe and a simplistic approach.

Keywords Group Multi Criteria Decision Making (GMCDM); Analytical Hierarchy Process (AHP); Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS);

1. Introduction

The growth of competition in today's business requires successful firms to improve the quality and the quantity of the provided services or products continuously. These improvements require extensive decision makings which include selection of one decision from various alternatives based on different criteria and constraints. The decisions, regardless of their size and time frame, should be managed and handled carefully. According to a recent study, even small decisions and small decision changes can have cascaded impacts on the whole system, causing significant deficiencies (Vahdat, Griffin et al. 2018, Shahraki and Noorossana 2014). In many cases, the final decisions are long-term policies of the companies and may have vital effects on the future of their businesses. Hence, it is important to find methods that reduce the risk of decision making.

In the last decades, many researchers have strived to mastermind systematic methods for making risk-free decisions, or decisions with the least affiliated risks and until now, many of these methods have been used in various industries and impacted the decision making process. For instance, (Firouzabadi, Henson et al. 2008) have introduced a model that is applicable to both tangible and intangible criteria, aggregates the views of multiple decision makers, and finally, uses linear programming to rank the alternatives. Another example is (Vahdat and Vahdatzad 2017) that introduces a two-stage stochastic model for long-term and medium-term risk-free decisions in supply chains with the focus of product returns. In addition, (Shahraki and Yadav 2015) propose an approach to find the optimal system configuration for risk-averse decision making that maximizes the mean of system reliability and minimizes the system reliability variance caused by uncertainty in the components reliability. However, these models, similar to many other methods in the literature, are not computationally tractable, known to be NP-hard, and as the number of parameters engaged in the problem increases, number of possible solutions also increases exponentially, hence, reaching the optimal solution becomes almost impossible. In this study, we focus on removing computationally intractable limitations with introducing a new model that reaches the same results within a short timeframe. In addition, the proposed approach can find optimal solution of problems with many alternatives and criteria and can be programmed easily on a computer spreadsheet.

There are several studies that provide a summary of Multi Criteria Decision Making (MCDM) methods, see (Tzeng and Huang 2011). Most of the earlier decision making methods are only concerned with addressing quantitative benefits, while neglecting the qualitative benefits, which makes these approaches ineffective for long term decisions of companies (Parsaei and Wilhelm 1989). An illustration is (Noble 1990) in which the proposed model only provides economic analysis with considering long time decisions and quantifiable aspects. In order to reflect qualitative benefits into the modeling, two main problems always exist. First, qualitative criteria are usually intangible and unrecognizable. Second, there are difficulties in transforming qualitative criteria into quantitative values, because numerical values are needed for systematic decision making. An example of using quantifiable and non-quantifiable decisions is shown in (Ordoobadi and Mulvaney 2001) where author used traditional economic methods in order to justify Advanced Manufacturing Technologies (AMTs). If the offered plan from economic model is not completely justifiable, instead, the qualitative benefits will be used.

Two MCDM methods, namely Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) are among most common methods used by decision makers. In the following a brief overview, advantageous, and disadvantageous of each method is further discussed.

AHP is a MCDM method that has been widely used owing to its simplicity and ability to transform qualitative data to quantifiable information (Saaty 2008). A wealth of research exist that have used AHP to rank alternatives (Parsaei and Wilhelm 1989, Soni, Parsaei et al. 1990, Borenstein and Baptista Betencourt 2005, Bayazit, Karpak et al. 2006, Ahn 2017, Krejčí, Pavlačka et al. 2017, Jing, Jie et al. 2018). The ability in transforming the qualitative information has motivated the use of AHP in conjunction with other decision science and operation management models. In fact, the combination of AHP with other methods have shown a great benefit in making more effective decisions. Troxler and Blank (1989) compare and evaluate the alternatives where several tangible and intangible operatives exist in the model, such as sufficiency toward strategic planning, capability, performance, and productivity. Zavadskas and Antucheviciene (2007) used multiple criteria sustainability approach to evaluate urban buildings for the building's regeneration alternatives with respect to economical, environmental and social impacts. Another example is (Hoffman, Schniederjans et al. 2004), in which the authors combine the business strategic management concepts with goal programming for the selection of a company manager.

While the literature advocates the wide use of AHP, in previous studies, such as those noted, many authors could only benefit from AHP for single decision making while group decision making are widely neglected. Yang and Chen (2006) use AHP and Grey theory to select supplier, still with only one decision maker. Schniederjans and Garvin (1997), and (Badri 2001) combined AHP and Zero-One Goal Programming (ZOGP), but authors have not used relative weights that are gained in pairwise comparisons for intangible criteria coefficients and general weights of alternatives for making objective function. Firouzabadi, Henson et al. (2008) have improved the method proposed by (Schniederjans and Garvin 1997, Badri 2001) by using individual models that are made for different viewpoints of decision makers, and if the solution of models were different from each other, they will be aggregated to reach a single solution. This model is further explored in Section 2.

TOPSIS is another widely utilized MCDM method in different industries and decision making processes (Rudnik and Kacprzak 2017, Sun, Miao et al. 2017, Chen, Shen et al. 2018). TOPSIS selects the optimal solution based on two distant functions from ideal and counter ideal solutions. The optimal solution should have the shortest distance from the Positive Ideal Solution (PIS) and the largest distance from the negative Ideal Solution (NIS)(Chen, Lin et al. 2006). In this technique, after calculating distance of each alternative from PIS and NIS, a closeness coefficient is defined for each one, and alternatives will be ranked based on their corresponding closeness values. Some research studies have expanded TOPSIS model with use of linguistic variables (Wei 2010).

The combination of MCDM methods have shown promising results with robust solutions in many problems. Shyur (2006) and (Shyur and Shih 2006) use a hybrid TOPSIS and Analytical Network Process (ANP) model for salesperson selection and cost evaluation respectively. Işıklar and Büyüközkan (2007) provided a hybrid model using AHP and TOPSIS to select mobile line. Torfi, Farahani et al. (2010) applied fuzzy AHP to determine relative weights of criteria and fuzzy TOPSIS to rank the alternatives. Yu, Guo et al. (2011) propose to use crisp AHP and fuzzy TOPSIS to set factory and electronic business.

According to the brief description provided for different methods of decision making, all of these methods seek to achieve a more appropriate model with the least risk by removing the disadvantages of the other methods, such as neglecting the intangible criteria and utilizing different viewpoints, if available. Vahdat, Griffin et al. (2017) indicated that not always the best decision is intuitively available, but most of the times, the best decision may be a counter-intuitive combination of multiple decisions that provide the best outcome. In a continuum of improving previous methods, in this research, we further improved the authentic ZOGP model provided by (Firouzabadi, Henson et al. 2008). For this purpose, our proposed model dispelled the necessity to solve mathematical programming model using software or computer packages. The proposed model approximates the decision making problem in polynomial time by using an algorithm, presented in section 3. As mentioned earlier, the ZOGP (Firouzabadi, Henson et al. 2008) model is NP-hard and by increasing the number of parameters and problem constraints, the method cannot find the optimal solution.

The rest of this study is organized as follows: In section 2, the linear programming model by (Firouzabadi, Henson et al. 2008) is introduced. In section 3, a group multi criteria decision making approach is proposed for ranking alternatives. In order to illustrate proposed approach and better understanding of its operation, a numerical example is presented in section 4. In the final section, we concluded this research with remarks and future research directions.

2. Mathematical Model: Zero-One Goal Programming Model

Zero One Goal Programming (ZOGP) models are an extension of linear programming that handle conflicting objectives. Each of the conflicting objectives has a given target value to be achieved. Unwanted deviations from this set of target values are then minimized in an achievement function. A ZOGP model is provided by (Firouzabadi, Henson et al. 2008) for solving a multi criteria decision making problem. The model solved in Lindo, an operations research software packages, is constructed as follows:

$$\text{Min } \sum_{i=1}^{I} w_{hi}^{g}\, d_{hi}^{+/-} \quad (h = 1,2,\dots) \tag{1}$$

subject to :

$$\sum_{i=1}^{K} w_{hki}^{\text{NORM}}\, x_k - d_{hi}^{+} + d_{hi}^{-} = b_{hi} \quad (i = 1,2,\dots,)$$

$$\sum_{i=1}^{K} w_{hki}^{\text{AHP}}\, x_k - d_{hi'}^{+} + d_{hi'}^{-} = b_{hi'} \quad (i' \neq i)$$

$$\sum_{i=1}^{K} x_k = 1$$

$$\forall x_k \epsilon (0,1); \quad \forall d_{hi}^{+/-} \geq 0; \quad \forall d_{hi'}^{+/-} \geq 0$$

Where:

K	number of alternatives
x_k	binary selection variable of kth alternative (1 = selection, 0 = otherwise)

w_{hi}^{g} global weight of *i*th sub-criterion in the penultimate level of *h*th hierarchy

$d_{hi}^{+/-}$ deviation variables for sub-criteria of the *h*th hierarchy that can be desirable or undesirable

w_{hki}^{NORM} *i*th AHP weight of tangible sub-criteria for the *h*th hierarchy with regard to the *k*th alternative

w_{hki}^{AHP} *i*th weight of intangible sub-criteria for the *h*th hierarchy with regard to the *k*th alternative

b_{hi} target value of *i*th tangible sub-criterion of the *h*th hierarchy

$b_{hi'}$ target value of *i´*th intangible sub-criterion of the *h*th hierarchy

It should be noted that target values can be determined both via use of alternatives coefficient (performance of alternatives with respect to each criterion) and experts' opinions. In this model, the alternative with the least undesirable deviation of determinate target values gets selected. Now, if the model has different solutions for individual viewpoints, it can aggregate objective functions with desired weights to reach the single solution. We can refer to utilize intangible criteria beside tangible criteria, to use ideas of several viewpoints and spotted limitations of decision makers as some of the advantages of this model.

3. Proposed Solution Methodology

The model provided in (Firouzabadi, Henson et al. 2008) is based on the scale measuring of relative distance of alternatives from target value of each criterion. Then, it would select an alternative which is closer to the target point than other alternatives. This is a similar reasoning concept that it has already being used in the TOPSIS technique with a slight difference. In TOPSIS model, not only the proximity attribute to ideal point impacts the final selection, but also does the distance attribute of the anti-ideal point. Using desired target values for criteria is the major distinction between the introduced method with TOPSIS. However, after normalizing the ideal values in TOPSIS, there exist the largest value in positive criteria and the smallest value in negative criteria. This feature can increase the flexibility and sensitivity analysis of the model for different target values, and it also gives more authority to decision maker in use of the model.

In addition to above cases, it should be noted that to reach the optimal solution in (Firouzabadi, Henson et al. 2008) model, the linear programming should be solved with a software; otherwise, the optimal solution cannot be obtained which can be a limitation of this model. Also, the difficulty of problem solving will increase with increase in the number of alternatives and constraints (criteria) in zero-one programming, so this problem is NP-hard and with considering complexity of it in these conditions, solving the model will take a long time by operations research software, like Lindo; and it will not be able to find the solution of problem after crossing a stage.

In this study, we intend to present an approach to solve a GMCDM problem with large dimensions without said limitations. With the following proposed approach, we will be able to reach the optimal solution easily without use of any linear programming software and solution of mathematical programming. Other advantages of proposed approach are the ability of coding on computer spreadsheet and using views of several decision makers.

The steps of implementing proposed approach are following:

1. First, a pairwise comparison matrix is formed for each criterion according to AHP, then the relative weight of alternatives will calculate with respect to each criterion after ensuring the acceptability of inconsistency ratio of each matrix. Gained weights in each criterion make one of the columns of decision matrix *D*. In matrix *D*, element of f_{ij} shows the performance rating of alternative A_i with respect to criterion F_j. The elements of this matrix are normalized because they are calculated via AHP technique. With pairwise comparison of each of the criteria, weight wj is calculated which is the importance of each criterion to reach vector W. Note that for the tangible criteria, it is enough to normalize data, and the pairwise comparisons matrix need not be established.

$$W = (w_1, w_2, \dots, w_j, \dots, w_n) \tag{2}$$

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccccc} F_1 & F_2 & \cdots & F_i & \cdots & Fn \end{array} \\ \begin{bmatrix} f_{11} & f_{21} & \cdots & f_{i1} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2i} & \cdots & f_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ii} & \cdots & f_{in} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mi} & \cdots & f_{mn} \end{bmatrix} \end{array}$$

2. To calculate weighted normalized matrix, weight of each criterion is multiplied by its column in matrix D to construct V (= [v_{ij}]).

$$v_{ij} = w_j \times f_{ij}\ , i = 1,2, \dots, m;\ j = 1,2, \dots, n \tag{3}$$

3. Now, ideal point of decision maker has to be determined and form the vector E. In this vector, the element e_j represents the ideal value of criterion F_j which has set between zero and one, similar to the element of decision matrix. Note that this value can be identical with or different from the elements of column j in matrix D.

$$\begin{array}{c} \\ E = \end{array} \begin{array}{ccccccc} & F_1 & F_2 & \dots & F_j & \dots & F_n & \\ (& e_1 & e_2 & \cdots & e_j & \dots & e_n &) \end{array} \tag{4}$$

4. To compare the performance of each alternative with ideal point, the vector E has to be weighted:

$$x_j = w_j \times e_j;\ j = 1,2, \dots, n \tag{5}$$

5. Negative deviation of each alternative with respect to ideal value of each criterion is calculated. If B and C are equal with benefit and cost criteria respectively, give:

$$\begin{cases} d_{ij} = x_j - v_{ij} & x_j \geq v_{ij} \\ 0 & x_j < v_{ij} \end{cases} ; j \in B \tag{6}$$

And

$$\begin{cases} d_{ij} = v_{ij} - x_j & v_{ij} \geq x_j \\ 0 & v_{ij} < x_j \end{cases} ; j \in C \tag{7}$$

6. Negative Euclidean distance of each alternative with respect to ideal point is calculated. Then alternatives are ranked in descending order of Negative Euclidean distances calculated using Eq. (8). As shown in step 5, use of Negative term for Euclidean distance is due to if in a criterion, alternative performance is better than ideal value of that criterion then we will consider the distance value 0 and only the undesirable distance will be spotted.

$$D_i = \sqrt{\sum_{j=1}^{n} d_{ij}^2}\ ; i = 1,2, \dots, m \tag{8}$$

7. The five above steps have to operate for all of decision makers. If reached solutions from decision makers are different with each other, then they are aggregated in the following sequence, and get a unique solution. At the first step, the number of criteria or columns of decision matrix is added to the number of total criteria of all decision makers; that is the decision matrices of decision makers with the number of same rows or alternatives locate by each other and operate as a unit matrix. The weight of each criterion is calculated using Eq. (9) and in all of relations modified weight of $w_j^{'}$ is used instead of w_j. w_j^c represents the weight of cth decision makers. In the step 3, the number of elements of vector E must add to the number of total criteria of all of decision makers. To reach the final single solution, other algorithm steps are repeated without any changes.

$$w_j^{'} = w_j^c \times w_j\ ; j = 1,2, \dots, n \tag{9}$$

4. Numerical example and Comparison

Following example is extracted from (Firouzabadi, Henson et al. 2008). This example is about one of the Iranian vehicle manufacturing companies. This company wants to purchase a foreign vehicle technology among the alternatives of Fiat, Honda, Hyundai, Toyota, and Volkswagen according to viewpoints of its managers and customers. Criteria of customers' viewpoint include 13 criteria of Comfort, Elegance, Type, Dimension and shape, Modern equipment, Price, Fuel consumption, Repairing costs, Easy to sell second hand, Safety, Durability, Horsepower and Easy to repair which represented with C1, C2, …, C17 respectively. also criteria of manager viewpoint include 17 criteria of Net profit, Added-value, Price of technology, Export possibility, National market share, International market share, Manufacturing technology, Accessible to know-how, Flexibility, Quality of technology, National supports, International supports, National make ability, Governments supports, Customer's style, National trust and Suitability with consumption pattern which represented with M_1, M_2, …, M_{17} respectively. For compression and reason of similarity, we only investigate customers' viewpoint.

Step 1. Normalized decision matrix and weight vector of criteria for decision maker (the customers in this example) are presented in Table 1. All of the results of this matrix are none scaled and they set between 0 and 1.

Table 1. Normalized decision matrix and weight vector of criteria

	Fiat	Honda	Hyundai	Toyota	Volkswagen	weight
C_1	0.066	0.274	0.085	0.369	0.207	0.054
C_2	0.081	0.276	0.099	0.375	0.168	0.035
C_3	0.073	0.255	0.089	0.382	0.201	0.038
C_4	0.078	0.241	0.103	0.346	0.232	0.031
C_5	0.080	0.269	0.118	0.349	0.183	0.033
C_6	0.181	0.217	0.168	0.193	0.241	0.143
C_7	0.141	0.201	0.217	0.193	0.248	0.073
C_8	0.129	0.262	0.189	0.187	0.233	0.129
C_9	0.092	0.235	0.114	0.360	0.199	0.128
C_{10}	0.081	0.254	0.084	0.328	0.253	0.128
C_{11}	0.087	0.217	0.074	0.303	0.319	0.099
C_{12}	0.102	0.213	0.195	0.190	0.300	0.044
C_{13}	0.127	0.201	0.177	0.327	0.168	0.063

Inconsistency ratio in all of pairwise comparative tables are acceptable. $C_{6,}$ C_7 and C_{12} are tangible criteria in Table 1, and columns as to them gained via normalized. $C_{6,}$ C_7 and C_8 are cost criteria and other criteria are benefit.

Step 2. Calculate the weighted normalized matrix *V* by Eq. (3), as Table 2.

Table 2. Weighted Normalized decision matrix

	Fiat	Honda	Hyundai	Toyota	Volkswagen
C_1	0.0036	0.0148	0.0046	0.0199	0.0112
C_2	0.0028	0.0097	0.0035	0.0131	0.0059
C_3	0.0028	0.0097	0.0034	0.0145	0.0076
C_4	0.0024	0.0075	0.0032	0.0107	0.0072
C_5	0.0026	0.0089	0.0039	0.0115	0.0060
C_6	0.0259	0.0310	0.0240	0.0276	0.0345
C_7	0.0103	0.0147	0.0158	0.0141	0.0181
C_8	0.0166	0.0338	0.0244	0.0241	0.0301
C_9	0.0118	0.0339	0.0146	0.0461	0.0255
C_{10}	0.0104	0.0325	0.0108	0.0420	0.0324
C_{11}	0.0086	0.0215	0.0073	0.0300	0.0316
C_{12}	0.0045	0.0094	0.0086	0.0300	0.0132
C_{13}	0.0080	0.0127	0.0112	0.0206	0.0125

Step 3. The ideal vector of the customer's viewpoint is shown as

$$E = (0.369\ \ 0.375\ \ 0.382\ \ 0.346\ \ 0.349\ \ 0.145\ \ 0.172\ \ 0.129\ \ 0.360\ \ 0.328\ \ 0.319\ \ 0.173\ \ 0.327)$$

Here, ideal of criteria C_6, C_7 and C_{12} are different from alternatives performance in these criteria. Stated criteria are tangible. However, using the best coefficient of each criterion, that is the largest coefficient in benefit criteria and the smallest coefficient in cost criteria, is simpler and desirable for intangible criteria.

Step 4. Calculate weighted ideal vector as vector *X*.

$$X = (0.0199\ \ 0.0131\ \ 0.0145\ \ 0.0107\ \ 0.0115\ \ 0.0207\ \ 0.0126\ \ 0.0116\ \ 0.0461\ \ 0.0420\ \ 0.0316\ \ 0.0076\ \ 0.0206)$$

Step 5. Using Eq. (5) and (6) calculate negative deviation of alternatives for benefit and cost criteria respectively as Table 3.
In Table 3, because of calculating negative deviations, if in a criterion, the performance rating of an alternative is better than ideal value of the criterion, the deviation value will be zero.

Table 3. Negative deviations from criteria ideal values

	Fiat	Honda	Hyundai	Toyota	Volkswagen
C_1	0.0164	0.0051	0.0153	0	0.0087
C_2	0.0103	0.0035	0.0097	0	0.0072
C_3	0.0117	0.0048	0.0111	0	0.0069
C_4	0.0083	0.0033	0.0075	0	0.0035
C_5	0.0089	0.0026	0.0076	0	0.0055
C_6	0.0051	0.0103	0.0033	0.0069	0.0137
C_7	0	0.0021	0.0033	0.0015	0.0055
C_8	0	0.0172	0.0077	0.0075	0.0134
C_9	0.0343	0.0122	0.0315	0	0.0206
C_{10}	0.0316	0.0095	0.0312	0	0.0096
C_{11}	0.0230	0.0101	0.0243	0.0016	0
C_{12}	0.0031	0	0	0	0
C13	0.0126	0.0079	0.0095	0	0.0081

Step 6. Calculate measure of negative Euclidean distance of each alternative of ideal point by Eq. (8). Table 4 presents the total performance of each alternative from customers' viewpoint with respect to ideal point of decision maker. Column *f* in Table 4 expresses objective function value of (Firouzabadi, Henson et al. 2008) model and it is presented in order to better comparison.

Table 4. Negative Euclidean distance from the ideal point (customers' viewpoint)

Rank	Alternative	*D*	*f*
1	Toyota	0.0104	0.0175
2	Honda	0.0298	0.0924
3	Volkswagen	0.0347	0.1048
4	Hyundai	0.0574	0.1620
5	Fiat	0.0597	0.1653

It is shown that reached ranking does not have any difference with solution of (Firouzabadi, Henson et al. 2008). But in the proposed method, the software need not be used, and the number of alternatives and criteria can be increased a lot. According to the results of Table 4, Toyota and Fiat is determined as the best alternative and the worst alternative, respectively. Results of ranking from managers' viewpoints can be seen in Table 5 that as the customers' viewpoint does not have any differences with reached results by (Firouzabadi, Henson et al. 2008) model. Also, results as to aggregate two viewpoints of customers and managers (decision makers) with assumption of the identical weights are presented in Table 6 that Toyota is preferred to other alternatives.

Table 5. Negative Euclidean distance from the ideal point (managers' viewpoint)

Rank	Alternative	*D*	*f*
1	Volkswagen	0.0278	0.0711
2	Toyota	0.0292	0.0744
3	Hyundai	0.0349	0.0899
4	Honda	0.0394	0.1097
5	Fiat	0.0547	0.1806

Table 6. Negative Euclidean distance from the ideal point (aggregated viewpoint with the identical weights)

Rank	Alternative	*D*	*f*
1	Toyota	0.0155	0.0459
2	Volkswagen	0.0222	0.0879
3	Honda	0.0247	0.1010
4	Hyundai	0.0336	0.1260
5	Fiat	0.0405	0.1730

If aggregated problem is solved again, of course with unequal weights in viewpoints of managers and customers, then for changing the solution of problem, the importance weight of managers against customers should change to 0.97 versus 0.03, and 0.79 versus 0.21, in (Firouzabadi, Henson et al. 2008) model and proposed approach, respectively. On the other hand, if the importance weight of customers vs. managers is spotted inconsiderable, then results will change that it is opposite of customer satisfaction. Also, with changing the criteria weight, effect of each criterion can be analyzed in decision making.

5. Conclusions

In this research, a Group Multi Criteria Decision Making (GMCDM) model is presented that (1) spots viewpoints of decision makers, and (2) can be applied to consider intangible criteria with tangible criteria in decision making by quantitative operation. This approach can enter the decision makers' targets and limitations like budget via different criteria with various weights into the model. In the proposed approach of this study, criteria weight and alternatives performance with respect to them are calculated by AHP model. The proposed approach is based on the concept that the chosen alternative has less undesirable deviation from the given ideal point. To help the explanation and better understanding of the proposed approach, the case study of (Firouzabadi, Henson et al. 2008) is presented and the results of proposed approach is compared with introduced linear programming model by (Firouzabadi, Henson et al. 2008). The example highlights the important specification of the proposed approach which approximates the final solution and scales well without using a software, which makes it suitable in large scale group decision making problems. Also, this method has better function in problems consisting of many alternatives and criteria, because the (Firouzabadi, Henson et al. 2008) model is a zero and one linear programming, so it is NP-hard, and with increasing problem parameters, the difficulty of solving the problem is increased. In these conditions, using the operations research software is not efficient.

The case study reveals that the final evaluation index of alternatives presents not only a ranking but also the assessment status and useful information of all alternatives. All above subjects show that this approach is useful for solving the GMCDM problems and can be applied to other management decision problems.

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