A New Decision Model Based on the Common Set of Weights DEA and Liner Goal Programming

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Abstract: Data envelopment analysis (DEA) has a wide application in measuring the relative efficiency of identical units with the same inputs and outputs. There are weaknesses in the classical models. One of the weaknesses is poor judgment and ranking among efficient decision making units, and another weakness is that the number of decision making units must greater than a certain limit. This model will not be valid when decision making units are relatively low. Also the most important weakness of classical model is changing weight of inputs and outputs that it makes the efficiency of decision units measured with different weight. Researchers believed that calculation with different weights for the same indexes in the set of homogeneous decision units is not logical. The important problem is how all decision units with a weight measured and simultaneously their efficiency is optimized. So, in this paper a model presented that all decision units measured with a weight and simultaneously efficiency of decision making units is optimized.

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1. Introduction

Data envelopment analysis (DEA) has a wide application in measuring the relative efficiency of identical units with the same inputs and outputs that is offered by Charnes et al at 1978 [1]. Nowadays, DEA is one of the most fast growing fields at science management and operation research and it use to evaluate the efficiency of organization [2]. However, there are some issues in using these techniques. One of the weaknesses of these methods is that the number of evaluated units related to number of variables input and output. Also, when the number of organizational units is less than certain measure then differentiation power of basic models of DEA is reduced [2]. Hence, in some research full ranking of Anderson and Peterson and crossover efficiency are used and [4 &5]. Some of researches to purpose reducing the number of variables try to increase differentiation power of DEA. In this condition, reducing the number of variables for using at DEA model should have the lowest effect on differentiation of efficient and inefficient units. Therefore, in some research, partial covariance matrix for eliminating variables that have correlation together is used [3]. In another study, instead of outputs or inputs that are imported into the DEA model, principal component analysis was used and the principal components of input and output are replaced by principal variables [6]. For solving this problem, combining DEA with multi-objective programming and goal programming is offered. For example, Zhu (1996) presented Multi-objective non-radial DEA model that it is possible to regard comments and concerns of decision makers [7]. Joro et al (1998) and Halme et al (1999) compared the structure of DEA model and multi-objective models; they found that DEA is a multi-objective model [8&9]. Li and Reeves [10] proposed a multi-criteria DEA model, in which they try to improve the distribution weights of input and output parameter. Chiang and Tzeng [11] and Yu et al [12] also offered multi-objective DEA model. Chen (2005) presented multi-objective model that it was possible to define constraints based on arbitrary criteria of decision makers [13]. Wong et al [14] and Yang et al (2008) compared the structure of the DEA model and multi-objective models and the conclusion reached that the two models are similar and the one complementary to another [14,15]. They had provided multi-objective DEA model based on constraints of DEA model [14&15]. The basic DEA models with a focus on each decision making units, calculate separate weights for input and output and using the rate of weighted sum inputs to outputs, efficiency is calculated. Some researchers believe the calculation different weights for the same indexes in set of homogeneous decision-making units are not reasonable; therefore, they decided for solving the problems. The idea of common weight for the first time introduced by Cook et al and was completed by Roll et al [16 & 17]. Then, researchers have attempted for gaining common weight and creation changes in the basic model. Jahanshahloo et al (2005) used a multi-objective model in a form of maximum and solve common weight [18]. Kao and Hung [19] pointed out that the DEA method is perfectly flexible in determining the weights of decision-making units on the basis of common threatens; therefore, They presented an agreement approach for calculating common weight in the framework of DEA. This method used weights in the standard model as an ideal weight and search of variables common weight vector that it has the minimum distance with ideal weight. Accordingly, some efficient weight is obtained as the compromise solution that in comparison with other methods is unique [19]. Makui et al (2008) using the goal programming model has gained common weights [20]. Another set of methods ranking is based on limiting weights. If for input and output weights we consider upper and lower bounds so that achieved the changes. In CSW, weights with the amount minimum are obtained [21]. This paper presents a model for calculating common weights of decision making units. Therefore, this article seeks to solve the above problems and for solving problems, Common Set of Weight (CSW) of the DEA has combined the goal programming. This paper is structured as follow. In the second part of this paper a short overview of the data envelopment analysis and programming model with multiple objectives is presented. In the third part, the principle of mathematics and logic of propose method have been discussed and in the fourth section an example show the power of the model and its results have been evaluated. Finally, conclusion is presented.

2. Background

2.1-Goal Programming

The aim of a linear programming model is to optimize the objective function. In models with multiple objectives, decision maker looking for to optimize multiple objective functions simultaneously. The concept of multi-objective functions first introduced by Kuhn and Tucker and then a lot of research was done on developing decision making models with multiple objectives [22, 23]. A multi-objective decision-making method is a goal programming that the first was created in 1960 by Charnes and Cooper [24]. The goal programming is the first technique of multiple objectives function that has relatively wide acceptance for use in various areas of decision-making in industry and services. Essentially linear goal programming problem is a linear programming problem that seeks to achieve more than one goal. The goal programming presented as follows:

$$\text{Min } Z. = \sum_{k=1}^{g} \sum_{i=1}^{m} P_k (d_i^- + d_i^+)$$

St:

$$\sum_{j=1}^{n} C_{ij} X_j + d_i^- - d_i^+ = b_i \qquad (i=1,\dots\dots m)$$

$$\sum_{j=1}^{n} a_{rj} X_j \le b'_r \qquad (r=0,1,\dots\dots s)$$

$$X_j,\ d_i^+,\ d_i^- \ge 0 \qquad (i = 1,\dots\dots m), (j = 1,\dots\dots n)$$

Model (1)

X_j Indicate variables of decision model that the model can be use any non-negative number. $\bar{d_i}, \overset{+}{d_i}$ shows variable deviations from the ideal of positive and negative i. b_i states the right hand sight number. p_k specifies the priority of k goals. a_{rj} provides technical coefficients of model. C_{ij} represents the coefficient of the variables decision j in the ideal i. b'_r is right hand sight number of functional limitations. This model has n decision variables, m ideal, k priority, and s functional constraints.

2.2 The Data Envelopment Analysis

DEA proposed by Charnes et al [1] (Charnes –Cooper–Rhodes (CCR) model) and developed by Banker et al (1984) (Banker– Charnes –Cooper (BCC) model) is an approach for evaluating the efficiencies of DMUs. The CCR model measures the efficiency of DMU_o relative to a set of peer DMUs:

$$\text{Max}Z_o \ \sum_{r=1}^{s} U_r Y_{ro} \Big/ \sum_{i=1}^{m} V_i X_{io} \ ,$$

Model (2)

$$\text{st}:$$

$$\sum_{r=1}^{s} U_r Y_{rj} \Big/ \sum_{i=1}^{m} V_i X_{ij} \le 1, \qquad (j = 1,2,...,n),$$

$$U_r, V_i \ \ge 0 \ , \qquad (r = 1,2,....,s), (i = 1,2,...,m).$$

Where there is a set of n peer DMUs, $DMU_j \{j = 1,2,..., n\}$,which produce multiple outputs $Y_{rj}(r = 1,2,...,s)$ by utilizing multiple inputs $X_{ij}(i = 1,2,...,m)$. DMUo Is the DMU under consideration? U_r is the weight given to output r and V_i is the weight given to input i. e is a positive non-Archimedean infinitesimal. DMUo Is said to be efficient $E_o = 1$ if no other DMU or combination of DMUs can produce more than DMU_o on at least one output without producing less in some other output or requiring more of at least one input. The linear programming equivalent of (2) is as follows:

$$\text{Max } Z_o = \sum_{r=1}^{s} u_r y_{ro} \ ,$$

$$\text{St}:$$

$$\sum_{i=1}^{m} v_i x_{io} = 1,$$

Model (3)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i \le 0, \qquad (j = 1,2,....., n),$$

$$u_r, v_i \ge 0, \qquad (r = 1,2,...., s), (i = 1,2,..., m).$$

2.3 GP-DEA Model

Classical model of DEA, model (3) can be presented as a DEA model with the objective of minimizing the deviation variables and as a goal programming model. This model is presented as follow:

$$\text{Min} = d_o,$$

$$\text{St}:$$

$$\sum_{i=1}^{m} v_i x_{io} = 1,$$

Model (4)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i + d_j = 0, \qquad (j = 1,2,.....,n),$$

$$u_r, v_i, d_j \ge 0, \qquad (r = 1,2,....,s), (i = 1,2,...,m), (j = 1,2,.....,n).$$

In addition to usual linear programming variables other variables as "deviation variable from the ideal" is defined. These variables represents the difference between the determined ideal and earned value that "d" deviation variable for under investigation unit and "d_j" deviation variable for unit j (that appears in inequality constraint j). This model is efficient when z =1 or d = 0. If the evaluated unit is not efficient, efficiency scores are equal z = 1-d. Here the above model is the same model of classical DEA. The amount of "d" in the range of [0 ,1) implies inefficiency. Therefore, it can be said that the classical model to minimize the efficiency of under review unit [10, 25]. In 1986, Sexton used total deviations of deviation variables as a function in the DEA model. This model is called MinSum and the general form of this model is presented as follows:

$$\text{Min} = \sum_{j=1}^{n} d_j,$$

$$\text{St}:$$

$$\sum_{i=1}^{m} v_i x_{io} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i + d_j = 0, \quad (j = 1,2,\ldots, n),$$

$$u_r, v_i, d_j \geq 0, \quad (r = 1,2,\ldots, s), (i = 1,2,\ldots, m), (j = 1,2,\ldots, n).$$

Model (5)

Value efficiency for j is obtained from ($Z. = 1 - dj$) [10, 25].

3. Proposed method

As mentioned, one of the problems of classic models, to obtain a separate set of weights for different DMU which makes do not define accurate comparison between units of economic decisions. One way to resolve this proposed problem is ranking method using a common set of weights (CSW). Lotfi et al [26] due to the fact that the feasible regions of all problems are the same, presented a model as follow:

$$\text{Max}Z_o \left\{ \frac{\sum_{r=1}^{s} U_r Y_{r1}}{\sum_{i=1}^{m} V_i X_{i1}}, \ldots, \frac{\sum_{r=1}^{s} U_r Y_{rn}}{\sum_{i=1}^{m} V_i X_{in}} \right\}$$

$$\text{st}:$$

$$\sum_{r=1}^{s} U_r Y_{rj} \Big/ \sum_{i=1}^{m} V_i X_{ij} \leq 1, \quad (j = 1,2,\ldots,n),$$

$$U_r, V_i \geq \varepsilon, \quad (r = 1,2,\ldots,s), (i = 1,2,\ldots,m).$$

Model (6)

In these models, units are not evaluating in the best condition and for any single, one model cannot be solved. In this model, the fractional multi-objective programming model converts to a different nonlinear programming and then is resolved. But in this paper, a method based on goal programming and data envelopment analysis is presented to multi-objective fractional programming model becomes converting to a linear goal programming model. The new model is presented as follow:

$$Min = W1\left(\sum_{j=1}^{n} d_j\right) + W2\left(\sum_{j=1}^{n} d'_j\right),$$

$$St:$$

$$\sum_{i=1}^{m} v_i x_{ij} + d_j = 1, \quad (j = 1,2,\ldots, n),$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i + d'_j = 0, \quad (j = 1,2,\ldots, n),$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} v_i \leq 0, \quad (j = 1,2,\ldots, n),$$

$$u_r \geq \varepsilon, \quad (r = 1,2,\ldots, s),$$

$$v_i \geq \varepsilon, \quad (i = 1,2,\ldots, m),$$

$$d_j, d'_j \geq 0, \quad (j = 1,2,\ldots, n).$$

Model (7)

The Parameters of W_1 and W_2 determine the priority of objectives and d_j and d'_j are deviation variables. As you know, ε is the smallest value of non-Archimedean in DEA literature. After obtaining the optimal weights by model (7), put them in the below formula and then obtain the efficiency of decision making units.

$$E_j = \frac{\sum_{r=1}^{s} U^*_r Y_{rj}}{\sum_{i=1}^{m} V^*_i X_{ij}}, \qquad j = 1,\dots,n.$$

4. Numerical Example

To evaluate the proposed model and its application, a numerical example is investigated. For this purpose, we provide an example of Kao and Hung (2005) has been used. These examples want to measure the efficiency of Seventeen planting areas with four inputs and three outputs. Primary data is presented in Table 1 [19]:

Table 1: The primary data

DMU (District)	Budget (dollars)	Initial stocking (m^3)	Labor (person)	Land (ha)	Main product (m^3)	Soil conservation (m^3)	Recreation (visits)
DMU_1	51.62	11.23	49.22	33.52	40.49	14.89	3166.71
DMU_2	85.78	123.98	55.13	108.46	43.51	173.93	6.45
DMU_3	66.65	104.18	257.09	13.65	139.74	115.96	0
DMU_4	27.87	107.6	14	146.43	25.47	131.79	0
DMU_5	51.28	117.51	32.07	84.5	46.2	144.99	0
DMU_6	36.05	193.32	59.52	8.23	46.88	190.77	822.92
DMU_7	25.83	105.8	9.51	227.2	19.4	120.09	0
DMU_8	123.02	82.44	87.35	98.8	43.33	125.84	404.69
DMU_9	61.95	99.77	33	86.37	45.43	79.6	1252.62
DMU_{10}	80.33	104.65	53.3	79.06	27.28	132.49	42.67
DMU_{11}	205.92	183.49	144.16	59.66	14.09	196.29	16.15
DMU_{12}	82.09	104.94	46.51	127.28	44.87	108.53	0
DMU_{13}	202.21	187.74	149.39	93.65	44.97	184.77	0
DMU_{14}	67.55	82.83	44.37	60.85	26.04	85	23.95
DMU_{15}	72.6	132.73	44.67	173.48	5.55	135.65	24.13
DMU_{16}	84.83	104.28	159.12	171.11	11.53	110.22	49.09
DMU_{17}	71.77	88.16	69.19	123.14	44.83	74.54	6.14

This example is solved by using the original CCR model and the weights assigned to inputs and outputs are provided in Table 2. Accordingly, each of decision making unit assigned different weights for inputs and outputs. For example, the Sixteenth decision-making units for increasing efficiency, four of seven criteria are assigned zero weight that it cannot be acceptable. As can be seen in the last column of Table 2, the value efficiency of nine unit of seventeen is equal one and power distinction is very low.

Table 2: The results of CCR model

DMU	V_1	V_2	V_3	V_4	U_1	U_2	U_3	Efficiency
DMU_1	0.015424	0.002655	0.001996	0.002259	0.011060	0.002615	0.000162	1.000000
DMU_2	0.000778	0.005438	0.003312	0.000705	0.001146	0.005461	0.000051	1.000000
DMU_3	0.008343	0.001436	0.001080	0.001222	0.005982	0.001414	0.000088	1.000000
DMU_4	0.027310	0.000203	0.013697	0.000173	0.038228	0.000200	0.000012	1.000000
DMU_5	0.012915	0.000563	0.007817	0.000247	0.020748	0.000286	0.000018	1.000000
DMU_6	0.014839	0.000110	0.007442	0.000094	0.020771	0.000109	0.000007	1.000000
DMU_7	0.000778	0.000829	0.076979	0.000705	0.046495	0.000816	0.000051	1.000000
DMU_8	0.000324	0.009942	0.001275	0.000294	0.000478	0.007714	0.000021	1.000000
DMU_9	0.001549	0.001650	0.018730	0.001404	0.016386	0.001625	0.000101	1.000000
DMU_{10}	0	0.006771	0.000271	0.003503	0	0.007097	0	0.940277
DMU_{11}	0	0.004543	0.000182	0.002351	0	0.004762	0	0.934635
DMU_{12}	0	0.007689	0.004153	0	0.005155	0.005507	0	0.829028
DMU_{13}	0	0.004129	0.000166	0.002137	0	0.004328	0	0.799690
DMU_{14}	0	0.007685	0.002716	0.003992	0.004783	0.007632	0	0.773269
DMU_{15}	0	0.006462	0.003186	0	0	0.005614	0.000046	0.762683
DMU_{16}	0.001041	0.008742	0	0	0	0.006745	0	0.743471
DMU_{17}	0.005829	0.001824	0.006083	0	0.015331	0.000000	0	0.687298

For solving the mentioned problems, proposed model (models 7) is used and the results are presented in Table 3. Values of the relative efficiency of decision making units and ranking based on CCR model and proposed method are presented in Table 4. With comparing original CCR model, the result of model has more discriminate power between decision making units. Based on the result of model, nine decision making units are efficient. In the proposed model for different values of W_1 and W_2, there are only four or two decision making units. Accordingly, instead of nine units are rated one, in the proposed model for different values of W_1 and W_2, four or two units are rated one. Moreover, as you can see in Table 3, the proposed model for all criteria decision maker units are assigned a non-zero weight.

Table 3: The results of proposed model

W_1	W_2	V_1	V_2	V_3	V_4	U_1	U_2	U_3
0.5	0.5	0.00001000	0.00419498	0.00013523	0.00203109	0.00001000	0.00430141	0.00001829
0.3	0.7	0.00001000	0.00419498	0.00013523	0.00203109	0.00001000	0.00430141	0.00001829
0.7	0.3	0.00001000	0.00394561	0.00011832	0.00255797	0.00001000	0.00410191	0.00001000
0.8	0.2	0.00001000	0.00394561	0.00011832	0.00255797	0.00001000	0.00410191	0.00001000

Table 4: The Results of CCR model

DMU	CCR	Rank	Efficiency	Rank
DMU_1	1.000000	1	1.000000	1
DMU_2	1.000000	1	1.000000	1
DMU_3	1.000000	1	1.000000	1
DMU_4	1.000000	1	0.755214	11
DMU_5	1.000000	1	0.932324	7
DMU_6	1.000000	1	1.000000	1
DMU_7	1.000000	1	0.569839	16
DMU_8	1.000000	1	0.981371	5
DMU_9	1.000000	1	0.610567	14
DMU_{10}	0.940277	10	0.939687	6
DMU_{11}	0.934635	11	0.925801	8
DMU_{12}	0.829028	12	0.662014	12
DMU_{13}	0.799690	13	0.795222	9
DMU_{14}	0.773269	14	0.766778	10
DMU_{15}	0.762683	15	0.637593	13
DMU_{16}	0.743471	16	0.588482	15
DMU_{17}	0.687298	17	0.509813	17

Besides the above, it is possible for the proposed model to make sensitivity analysis and with changing W_1 and W_2 values, different values will increase. As can be seen in Table 5, for $W_1 = 0.8$ and $W_2 = 0.2$, the distinction values will maximize and only DMU_3 and DMU_6 are efficient.

Table 5 : Sensitivity analysis for proposed model and ranking

	W_1=0.5,W_2=0.5		W_1=0.3,W_2=0.7		W_1=0.7,W_2=0.3		W_1=0.8,W_2=0.2	
DMU	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank
DMU_1	1.000000	1	1.000000	1	0.682952	10	0.682952	10
DMU_2	1.000000	1	1.000000	1	0.922416	3	0.922416	3
DMU_3	1.000000	1	1.000000	1	1.000000	1	1.000000	1
DMU_4	0.755214	11	0.755214	11	0.675174	11	0.675174	11
DMU_5	0.932324	7	0.932324	7	0.870040	7	0.870040	7
DMU_6	1.000000	1	1.000000	1	1.000000	1	1.000000	1
DMU_7	0.569839	16	0.569839	16	0.492792	16	0.492792	16
DMU_8	0.981371	5	0.981371	5	0.883128	5	0.883128	5
DMU_9	0.610567	14	0.610567	14	0.548356	14	0.548356	14
DMU_{10}	0.939687	6	0.939687	6	0.874505	6	0.874505	6
DMU_{11}	0.925801	8	0.925801	8	0.899255	4	0.899255	4
DMU_{12}	0.662014	12	0.662014	12	0.597394	12	0.597394	12
DMU_{13}	0.795222	9	0.795222	9	0.758360	8	0.758360	8
DMU_{14}	0.766778	10	0.766778	10	0.714921	9	0.714921	9
DMU_{15}	0.637593	13	0.637593	13	0.571894	13	0.571894	13
DMU_{16}	0.588482	15	0.588482	15	0.521074	15	0.521074	15
DMU_{17}	0.509813	17	0.509813	17	0.455931	17	0.455931	17

5. Concluding Remarks

DEA is one of the useful methods for evaluating and benchmarking relative efficiency of a set of homogenous decision making units with inputs and outputs that are identical. In this method for increasing strength of distinguish between efficient and inefficient units, the number of inputs and outputs must be proportionate with units that are evaluated. In final evaluation ignoring this principle cause to that a large number of functional units differentiate between these units is not correctly. In this paper, a method for ranking efficient units using a common weight is presented. In this paper, first we apply a linear programming model for all units to obtain weight vector; then, using the common weight vector, efficiency units are obtained.

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