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A Common Weight Data Envelopment Analysis Approach for Material Selection

S. A. Torabi*, I. Shokr

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran.

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ABSTRACT

Material selection is one of the major challenges in manufacturing systems. The improper selection may lead to failure in the production processes and result in customer dissatisfaction and cost inefficiency. Every material has different properties which should be considered as major criteria during the material selection. Selection criteria could be quantitative or qualitative. Quantifying the performance of qualitative criteria is an inevitable issue in the multi criteria decision making (MCDM) problems. In this paper, a common weight data envelopment analysis (CWDEA) model is applied for the material selection problem which accounts for both quantitative and qualitative criteria in an effective manner. Through a numerical example borrowed from the literature, it is shown that CWDEA is not able to produce a full ranking vector in this case. Accordingly, the problem is solved under different normalization methods and the resulting ranking vectors are then aggregated by the linear assignment method to generate a final full ranking vector.

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1. INTRODUCTION

Choosing the appropriate set of material required for production processes from a large group of alternatives is a challenging issue in the presence of different qualitative and/or quantitative properties of material. Selecting the most suitable material is of vital importance in the initial stage of process design/redesign in the product life cycle [1, 2]. Material properties could include physical, magnetic, mechanical, chemical and manufacturing properties along with cost, availability, cultural aspects, etc. [3]. Low-quality products, failure in manufacturing processes, extra costs and so on are examples of unwanted outcomes originating from improper material selection. The importance of selecting the best set of materials is to achieve the best production conditions according to conflicting criteria and requirements. Most of the multi-criteria decision making (MCDM) methods like TOPSIS and data envelopment analysis (DEA) could be preferred for use in this context because of their simplicity and ease of applicability. Almost, majority of MCDM techniques consist of generating alternatives, considering attributes (i.e. criteria) and assessment of alternatives according to the weights of criteria. MCDM techniques assist decision makers in selecting the best alternative in the presence of several qualitative and/or quantitative criteria. Selecting the most suitable material among a set of alternatives is a multi-attribute decision making (MADM) problem. Several methods have been proposed to solve the material selection problem so far and each of them has its own advantages and deficiencies. Usually, there are various alternatives with several criteria which should be considered in the material selection process. Criteria may be of quantitative or qualitative type, and in conflict with one another. Also, criteria could be grouped into beneficial and non-beneficial classes. Those criteria for which a higher performance value is more desirable are called beneficial, such as fatigue limit as a physical characteristic of some material. On the other hand, those for which a lower performance value is more favorable are called non-beneficial criteria such as cost, risk, etc. Majority of decision making problems involve a mixture of beneficial and non-

*Corresponding Author's Email: satorabi@ut.ac.ir (S. A. Torabi)

beneficial criteria. Accordingly, criteria should be consistent with each other and may have positive and/or negative effects on the decision process when deciding to solve these problems. It is suggested to transform the non-beneficial criteria into beneficial form with inversing the values of non-beneficial criteria [4]. Besides, some normalization methods can be applied to avoid any scaling problem while making all criteria as beneficial ones.

As mentioned before, MCDM approaches are commonly used in material selection problems. Jee and kang [5] utilized TOPSIS method to find the best material in flywheel. Shanian and Savadago [6] used TOPSIS to rank candidate materials in the problem of metallic bipolar plates for polymer electrolyte fuel cell. They used Ordinary and Block TOPSIS to improve efficiency of their proposed procedure. Rao and Davim [3] presented a procedure which is a combination of TOPSIS and AHP method and is able to consider infinite number of quantitative and qualitative attributes. Analytic Network Process (ANP) enables the decision maker to have feedbacks and investigate interactions between criteria and alternatives. Also, fuzzy AHP (FAHP) could be helpful when available data are imprcise as Kaboli et al. implemented FAHP for location problems [7]. Also, Mousavi et al. [8] proposed a MCDM approach with interval numbers which could be helpful when facing uncertainties. Their approach is based on decision tree (DT) and TOPISIS techniques. Jahan et al. [9] proposed a new normalization method and extended TOPSIS method. The presented normalization method is able to address both beneficial and non-beneficial criteria, and target values of criteria along with capability of overcoming difficulties in some cases where the current version of TOPSIS is deficient in selecting the best alternative. Jahan et al. [10] provided a new version of VIKOR for solving the problem by developing a novel normalization method and considering the target value of criteria. This new version of VIKOR method promotes the exactness of material selection especially in biomedical problems related to human subjects. Tavakkoli-Moghadam et al. [11] states that combination of AHP and VIKOR gives more power to decision makers which helps to more exploit implicit and explicit information. Chatterjee et al. [12] utilized ELECTRE and VIKOR as outranking and compromising methods, respectively, where the flywheel and the sailing-boat mast are investigated in the form of a hollow cylinder [13] problem. ELECTRE III is employed to solve the gear material selection problem by Milani and Shanian [14] by considering uncertainty and incomplete data, designer's preference and criteria trade-off. Also, Shanian and Savadogo [15] used ELECTRE IV as a non-compensatory solution in the bi-polar plates for polymer electrolyte membrane fuel cell. A new approach of material selection is proposed based on PROMETHEE method by Jiao et al. [16] and they claim that PROMETHEE performs better than ELECTRE in material selection and uses more candidate information. The major advantage of the proposed method is that it is not necessary for using normalization procedures. Different normalization procedures can produce different results. Chan and Tong [17] applied Grey Rational Analysis for material selection problem. They provided a new methodology and considered environmental factors besides technical and economic factors. Milani et al. [18] investigated the material selection problem based on ANP concept. They assigned different weighting factors to clusters and studied their impacts on final results. Final ranking may vary due to considering inner and outer dependencies between criteria and alternatives. So, a case study is provided to show the different results obtained by ANP and AHP methods. Milani et al. [19] evaluated different normalization techniques and their effects on final rankings in material selection problems. Entropy and TOPSIS are employed to rank candidate materials for producing gear for power transmission. Chatterjee and Chakraborty [20] employed four preference MCDM methods for solving the gear problem: PROMTHEE II, complex proportional assessment of alternatives with gray relations, operational competitiveness rating analysis and ORESTE.

Chatterjee et al. [21] developed two new MCDM methods for material selection involving: complex proportional assessment (COPRAS) and evaluation of mixed data (EVAMIX) and compared the results of these two methods with those of previous methods. Preference Selection Index (PSI) is employed as a new method in decision making by Maniya and Bhatt [22] to solve the material selection problem. Mayyas et al. [23] applied Quality Function Deployment (QFD) as a tool for gathering customer needs in a vehicular structure problem. Then, the AHP approach is used to select the best material in order to meet customer needs. Also, Cavallini et al. [24] tried to use QFD to identify customer needs, integrate them into products or services, and implemented VIKOR to find the most suitable material according to the QFD results. Yang and Ju[25] presented a novel fuzzy MADM method with uncertain linguistic information. Liu et al. [26] presented a hybrid MCDM model including the DEMATEL, ANP and VIKOR for solving the material selection problem. Liu et al. [27] proposed an interval 2-tuple linguistiv VIKOR for the situation where data are uncertain or incomplete. Peng and Xiao [28] proposed a mixed MADM method including the PROMETHEE and ANP for selecting the proper material. They utilized ANP to find weights of criteria, and then PROMETHEE to obtain alternative rankings. Anojkumar et al. [29] applied four MCDM methods (i.e. fuzzy AHP-TOPSIS, fuzzy AHP-VIFKOR, fuzzy AHP-ELECTRE, and fuzzy

AHP-PROMTHEE) on the material selection problem and compared their performance and applicability**.**

Jahan et al. [30] proposed the linear assignment method by considering different criteria for materials. The proposed method is also applicable when both quantitative and qualitative properties and attributes are considered. Implementing this linear program results in better performance in comparison with other MCDM methods such as VIKOR, ELECTRE, etc. Another advantage of the proposed model is that it does not need to normalize criteria performances. Athawale et al. [31] used Utility Additive Method (UTA) to solve material selection problem in flywheel and sail-boat problems. They used UTA in order to make an approximation of non-linear additive function by linear programming **.**

Since the first studies on material selection problems, various MCDM approaches have been developed to find the most appropriate material. However, they are not accurate enough especially in dealing with qualitative criteria. Past methods often use linguistic approaches like Likert scale on qualitative criteria to transform them into quantitative values. In the Likert scale, a number from one (1) to nine (9) is allocated to qualitative performances in a way that the nine (9) is assigned to the best performance and one (1) to the worst. In this paper, a well-used test problem in the literature (i.e. the flywheel problem [5]) is solved with more attention to qualitative criteria. The common weight DEA (CWDEA) model proposed by Hatefi et al. [32] that is originated from DEA model [33], is adopted here which is able to calculate weights of criteria in an objective and precise way especially in the presence of both quantitative and qualitative criteria. Requiring less information to be asked from expert is another advantage of this method. The model is implemented to provide a reliable ranking for the material selection problem. The results are compared with those of previous works and effects of different normalization methods on the final results are also investigated.

2. PROPOSED MADM TECHNIQUE

Data Envelopment Analysis (DEA) is a linear programming method which evaluates the relative efficiency of some homogeneous Decision Making Units (DMU). DEA is easy to understand and quite simple in computations. Moreover, less information is required in order to calculate the DMUs efficiencies.

Ramahatan [4] proposed a weighted linear optimization model to obtain the efficiency for each DMU. The Ramahatan's model [4] measures the efficiency of each DMU in the range of [0, 1]. A higher value for objective function represents a better performance. So, the efficiency value 1 is assigned to the best DMU according to the considered criteria. The model is presented below:

$$Max\sum_{j=1}^{M1} v_{ij}\, y_{ij} \tag{1}$$

$$\sum_{j=1}^{M1} v_{ij}\, y_{nj} \le 1 \qquad n = 1,\ldots,N \tag{2}$$

$$v_{ij} \ge 0 \qquad j = 1,2,\ldots,M1 \tag{3}$$

It is assumed that there are M1 quantitative criteria. y_{ij} is the performance of ith DMU, when jth criterion is under consideration and vij denotes the weight of jth criterion with respect to DMU i. This model should be solved for each DMU separately. The values obtained for objective function indicate the DMUs efficiencies. Hatefi et al. [32] modified the previous model by assuming that there are also M2 qualitative criteria and solved the ABC classification problem to validate their proposed model. The modified linear optimization DEA model proposed by Hatefi et al. [32] is as follows:

$$Max\sum_{j=1}^{M1} v_{ij}\, y_{ij} + \sum_{r=1}^{M2}\sum_{l=1}^{L} w_{rl}^{j}\, y_{rl}(i) \tag{4}$$

$$\sum_{j=1}^{M1} v_{ij}\, y_{nj} + \sum_{r=1}^{M2}\sum_{l=1}^{L} w_{rl}^{j}\, y_{rl}(n) \le 1 \qquad n = 1,\ldots,N \tag{5}$$

$$w_{rl}^{j} - w_{r(l+1)}^{j} \ge \epsilon \qquad r = 1,2,\ldots,M2 \quad l = 1,2,\ldots,L-1 \tag{6}$$

$$w_{rL}^{j} \ge \epsilon \qquad r = 1,2,\ldots,M2 \tag{7}$$

$$v_{ij} \ge \epsilon \qquad j = 1,2,\ldots,M1 \tag{8}$$

$y_{rl(n)}$ is defined as follows:

$$y_{rl}(n) = \begin{cases} 1 & \text{if item } n \text{ is rated in the } l\text{th level in respect to the } r\text{th criterion} \\ 0 & \text{otherwise} \end{cases}$$

It is assumed that qualitative criteria can be categorized into L levels. For example, suppose that cost, the first qualitative criterion, is categorized into the three levels: low, medium and high. Then, L is equal to 3. In addition, suppose that the cost performance with respect to item 5 is medium, then y11(5)=0, y12(5)=1 and y13(5)=0. Also, denotes the weight of r-th criterion at l-th level when i-th item is under evaluation. Equations (3) and (4) represent the allowable set of weights for qualitative criterion. Parameter ε is introduced as discrimination parameter which is considered as a lower bound for weights of all criteria . Finding the appropriate value for ε by considering the most powerful discrimination and maintaining feasibility of the model is important. Hatefi et al. [32] suggested using ε_{max} instead of ε so that the model finds the most powerful discrimination in ranking DMUs. They proposed the following formulas:

$$\varepsilon_{max} = min\left\{\frac{1}{\psi_n}, n = 1,2,\ldots,m\right\} \tag{9}$$

$$\psi_n = \sum_{j=1}^{M1} y_{nj} + \sum_{r=1}^{M2} \left(L - I_{nr} + 1\right) \tag{10}$$

where Ψ_n should be calculated for each DMU. I_{nr} denotes the place of r-th qualitative criterion performance for item n. Thus, $y_{rl(n)}=1$according to the above definition. It is noteworthy that CWDEA method [32] is able to calculate the weights of criteria in parallel to finding the ranking vector of alternatives by solving the linear programming model (4)-(8) in an objective manner where there is no need to judgmental opinions of experts. Notably, CWDEA finds the most suitable weights for all criteria fully objectively by solving the linear model (4)-(8). This is one of the main advantages of CWDEA as it is a simple in use and also computationally efficient approach in deriving the weights of criteria and the ranking vector of alternatives concurrently by solving N linear programming models.

To avoid any scaling problem, it is also suggested to normalize the quantitative performance measures before solving the model. In this regard, Janan and Edwards [34] reviewed the different normalization methods and investigated their applicability on material selection problems. It is worth mentioning that different normalization method may lead to different results in multi criteria decision making procedures. In this paper, different normalization methods and their effects on the final results are investigated while applying the DEA model proposed by Hatefi et al. [32]. Here, the following normalization methods are considered (see Table 1).

3. THE APPLIED AGGREGATION METHOD

The linear assignment method proposed by Jahan et al. [30] has been applied in this paper to aggregate the results produced by different normalization methods for obtaining the final ranking vector. Jahan et al. [30] used this method to aggregate the different results obtained by MADM methods. The linear assignment method consists of the following steps: Step 1- Determine the importance weight of each method that is favorable to be aggregated. In this paper, all normalization methods are assumed to have equal weights of 0.25.

Step 2- Calculate the weighted number of times a rank k is allocated to each alternative by considering the n attributes. It results in the matrix f where element f_{ij} indicates the contribution of ith alternative assigned the jth overall rank. It should be mentioned that tied ranking is not acceptable. In the tied situations, the solution is using the weights of attributes as follows (see Table 2) [30]. As can be seen from Table 2, the first and second alternatives are allocated to the first rank. So, as Table 3 shows, the attribute X_j with the weight w_j is divided into two attributes each of which has the weight $\frac{w_j}{2}$ (see Table 3).

TABLE 1. Normalization methods

Equation	Method No.
$R_{ij} = \dfrac{y_{ij} - min_{i=1,2,\ldots,N}\left\{y_{ij}\right\}}{max_{i=1,2,\ldots,N}\left\{y_{ij}\right\} - min_{i=1,2,\ldots,N}\left\{y_{ij}\right\}}$ for $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,M1$	#1
beneficial criterion: $R_{ij} = \dfrac{y_{ij}}{\max\left(y_{ij}\right)}$ for $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,M1$; non-beneficial criterion: $R_{ij} = \dfrac{\min\left(y_{ij}\right)}{y_{ij}}$ for $i = 1,2,\ldots,m$ and $1,2,\ldots,M1$	#2
$R_{ij} = \dfrac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^2}}$ for $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,M1$	#3
$R_{ij} = \dfrac{y_{ij}}{\sum_{i=1}^{m} y_{ij}^2}$ for $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,M1$	#4

TABLE 2. Tie ranking

Rank	$X_j(w_j)$
1	A1,A2
2	
3	A3

TABLE 3. Resolving tie ranking

Rank	$X_{j1}(\frac{w_j}{2})$	$X_{j2}(\frac{w_j}{2})$
1	A1	A2
2	A2	A1
3	A3	A3

Step 3- Solve the following linear programming to assign the appropriate rank to each material:

$$\max \sum_{i=1}^{m}\sum_{k=1}^{m} f_{ij} N_{ij} \tag{11}$$

$$\sum_{j=1}^{m} N_{ij} = 1 \qquad i = 1,2,3,\ldots,m \tag{12}$$

$$\sum_{i=1}^{m} N_{ij} = 1 \qquad j = 1,2,3,\ldots,m \tag{13}$$

$$N_{ij} \in \{0,1\} \qquad i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,m \tag{14}$$

N_{ij} is the decision variable. The N_{ij}=1 signifies that the jth rank is assigned to the ith alternative.

Equation (11) ensures that the maximum value of assigning DMUs to ranks is achieved. Equations (12) and (13) assure that each DMU must be allocated to only one rank and vice versa. Equations (14) define N_{ij} variables as binary variables.

It is also noted that Jahan. et al. [35] have presented another aggregation method which is so similar to the linear assignment method [30] applied in this paper and one can utilize it as well.

Figure 1 depicts the steps of the proposed methodology in a flowchart.

4. NUMERICAL EXAMPLE

To show the application of common weight DEA model [32] in material selection problem by considering both quantitative and qualitative criteria, a flywheel material selection problem borrowed from the literature has been studied. This example is one of the well-applied test problems in the material selection literature as the results of previous competing methods are available on this example. This is why we are using it for our comparative studies. Jee and Kang [5] performed a material selection problem including ten alternatives and four criteria (Table 4): fatigue limit (σ_{limit}/ρ), fracture toughness (KIC/ρ), price per mass and the fragment ability. Flywheel is a device for storing the kinetic energy in automobiles, urban subway trains, wind power generators, etc. Athawale et al. [31] illustrated criteria. Higher values for the fatigue limit criterion mean better performance of material and increase the opportunity of the candidate material to be selected as the best choice. Hence, the fatigue limit criterion is a beneficial one. Fracture toughness (KIC/ρ) is the performance measure for failure prior to brittle fracture, and consequently is a beneficial criterion, as well. Price per unit mass is a non-beneficial criterion for which the decision maker prefers lower values. The fourth criterion (fragmentability) signifies that if a flywheel breaks into small pieces, the hazard should be much reduced.According to the previous section, quantitative criteria presented Table 4 should be normalized. In all normalization methods except Norm No.2, Non-beneficial criteria like price/mass should be transformed into beneficial ones and then normalized using the normalization methods introduced previously. For instance, the normalized data for the flywheel problem using Norm No.1 formulation is as Table 5.The model for each alternative is provided and solved by the Hatefi et al. model [32]. The efficiencies of each DMU using different normalization methods are indicated in Table 6.It can be concluded that the DEA model proposed by Hatefi et al. [32] is not capable of obtaining a full ranking when using the normalization methods No. 1 and No. 4. However, it is crucial to obtain a full ranking vector. For this purpose, the first example is solved by other normalization methods introduced in section 2. Then, the linear assignment method [30] is applied to aggregate the ranking vectors to obtain the final and full ranking vector. To apply linear assignment method, the weights of results obtained by different normalization methods are assumed to be equal. Thus, the weight of each result produced by each normalization method is equal to 0.25. Eventually, the final ranking vector is compared with final ranking vectors provided in the literature as Table 7.In addition, the graphical objective value for each material using different normalization methods is shown in Figure 2.

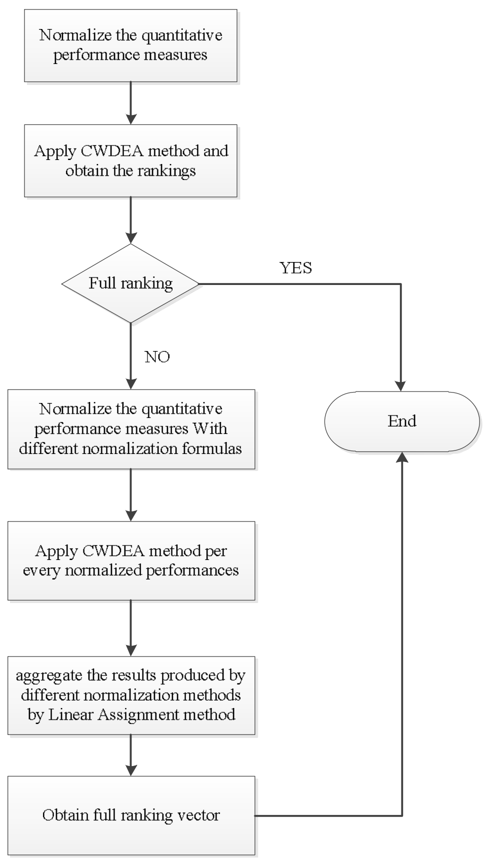

Figure 1. Flowchart of the proposed methodology

TABLE 4. Flywheel material selection problem

Alternatives	Name	σ_{limit}/ρ	KIC/ρ	Price/Mass	Fragmentability
M1	300 M	100	8.61	4200	Poor
M2	2024-T3	49.65	13.47	2100	Poor
M3	7050-T73651	78.01	12.55	2100	Poor
M4	Ti-6Al-4V	108.8826	10	500	Poor
M5	E glass-epoxy FRP	70	10	2735	Excellent
M6	S glass-epoxy FRP	165	25	4095	Excellent
M7	Carbon-epoxy FRP	440.25	22.01	35470	Fairly good
M8	Kevlar 29-epoxy FRP	242.86	28.57	11000	Fairly good
M9	Kevlar 49-epoxy FRP	616.44	34.25	25000	Fairly good
M10	Boron-epoxy FRP	500	23	315000	Good

TABLE 5. Normalized data under first normalization method

σlimit/ρ (Normalized)	KIC/ρ (Normalized)	$\frac{1}{price}$	$\frac{1}{price}$(Normalized)	Fragmentability
0.08883361	0.00000000	0.00023810	0.11764706	Poor
0.00000000	0.18954758	0.00047619	0.23688394	Poor
0.05003617	0.15366615	0.00047619	0.23688394	Poor
0.10450537	0.05421217	0.00200000	1.00000000	Poor
0.03590395	0.05421217	0.00036563	0.18151618	Excellent
0.20351453	0.63923557	0.00024420	0.12070441	Excellent
0.68914413	0.52262090	0.00002819	0.01252901	Fairly good
0.34088463	0.77847114	0.00009091	0.04393699	Fairly good
1.00000000	1.00000000	0.00004000	0.01844197	Fairly good
0.79456236	0.56123245	0.00000317	0.00000000	Good

TABLE 6. Efficiencies when different normalization method are applied

Alternatives	The CWDEA linear programming method			
	Method No.1	Method No.2	Method No.3	Method No.4
M1	0.2402699	0.2993656	0.2881920	0.1211235
M2	0.2604782	0.3343817	0.3165893	0.2398931
M3	0.2870555	0.3381212	0.3198128	0.2398927
M4	0.4301561	0.4821860	0.4686355	1
M5	0.8624233	0.8962148	0.9416813	1
M6	1	1	1	0.9394364
M7	0.8401554	0.8537456	0.8151971	0.8293348
M8	0.8295986	0.8347357	0.7S994671	0.8606222
M9	1	0.9805305	0.8954803	0.8352317
M10	0.6686926	0.6805568	0.6148430	0.8145044

TABLE 7. Comparative results with previous methods

	Comparison of rankings			
	CWDEA model	Jee and Kang [5]	Chatterjee et l. [12]	khabbaz et al. [7]
	Linear Assignment method[30]			
Rank 1	M6	M9	M9	M9
Rank 2	M9	M8	M7	M8
Rank 3	M5	M6	M6	M6
Rank 4	M7	M7	M8	M7
Rank 5	M8	M1	M10	M1
Rank 6	M10	M4	M4	M4
Rank 7	M4	M3	M5	M3
Rank 8	M3	M5	M3	M5
Rank 9	M2	M2	M2	M2
Rank 10	M1	M10	M1	M10

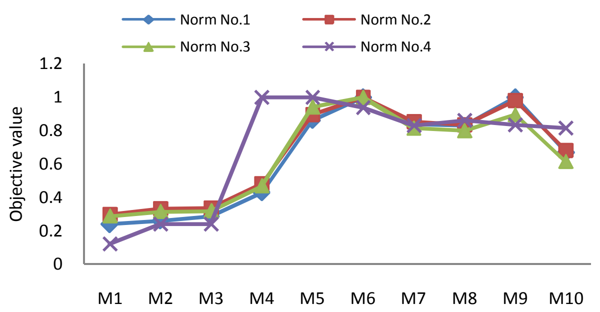

Figure 2. Comparison of objective values under different normalization methods

5. DISCUSSION

The flywheel example contains both qualitative and quantitative criteria. For measuring the DMU performances, qualitative criteria should be quantified first. One of the common methods to quantify the qualitative criteria is the Likert spectrum which scores linguistic expressions in the numeric scale of 1 to 9. While the applied CWDEA in this paper does not need any quantification of qualitative criteria as it computes their scores by the mathematical model. Thus, the main superiority of CWDEA method is treating the qualitative criteria in a more precise manner than the Likert scale.

Also, the previous methods included in Table 7use the Likert scale which is not as precise as the CWDEA method when quantifying the qualitative criteria. Therefore, it is expected to obtain different rankings with other MADM methods. For instance, M9 is ranked first when using the first normalization technique, which shows the applied CWDEA method is compatible with past techniques' results. However, when the problem is solved with other normalization techniques, different rankings are obtained in which M9 does not always occupy the first rank. So, we aggregated the results produced by different normalization methods to obtain the final ranking vector by which M6 is known as the first rank.

6. CONCLUSION

Material selection is a challenging issue in manufacturing organizations especially in the product design process. Choosing the appropriate material from a large group of alternatives in the presence of different properties, advantages and disadvantages for each alternative makes the decision making process a difficult task especially when considering qualitative criteria. Majority of the previous researchers have dealt with the material selection problems by using the Likert scale to transform qualitative criteria performances into the quantitative equivalents. Nevertheless, the importance of quantifying the qualitative performance measures is well recognized in the decision-making processes. In this paper, the common weight DEA (CWDEA) model proposed by Hatefi et al. [32] is applied to the material selection problem while accounting for both quantitative and qualitative criteria. The DEA model applied in this paper performs more accurately than the previous MADM methods in evaluating the efficiency of each DMU, especially in the presence of qualitative criteria [32]. For constructing the DEA model, performance measures should be normalized for each criterion to avoid scaling problem. A numerical example selected from the literature, (i.e. the flywheel material selection [5])is used to test the efficiency and effectiveness of the proposed model. Rankings are obtained by solving the DEA models, but some normalization methods are not able to produce full ranking vectors. Hence, CWDEA models are solved again by other normalization methods introduced in section (2) and the results of different normalization methods are aggregated using the Linear Assignment method [30] to obtain a full ranking vector for each example. Comparative results with previous models demonstrate the applicability and usefulness of the proposed approach in the context of material selection.

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A Common Weight Data Envelopment Analysis Approach for Material Selection

S. A. Torabi, I. Shokr

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

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چکیده

انتخاب مواد اولیه مناسب یکی از مسائل چالش برانگیز در سیستم‌های تولیدی است. انتخاب نامناسب مواد اولیه می‌تواند باعث شکست در فرآیندهای تولیدی شده و تبعاتی همچون هزینه بر بودن تولید و نارضایتی مصرف کنندگان را به همراه داشته باشد. هر یک از مواد اولیه خصوصیات مختلفی دارند که باید در هنگام انتخاب بهترین ماده اولیه مد نظر قرار گیرند. برخی از این معیارها کیفی و برخی دیگرکمی هستند. تعیین معادل کمی مناسب برای معیارهای کیفی همواره از چالش‌های اصلی در به کارگیری فنون تصمیم‌گیری چند معیاره بوده است. در این مقاله از یک روش تحلیل پوششی داده‌ها با اوزان یکسان با در نظر گرفتن هم‌زمان معیارهای کیفی و کمی در مسئله انتخاب مواد اولیه مناسب استفاده شده است. همچنین از طریق یک مثال عددی نشان داده شده است که این روش همواره قادر به ارائه رتبه‌بندی کاملی از گزینه‌ها نیست. لذا برای غلبه بر این مشکل، مسئله با استفاده از روش‌های نرمال‌سازی مختلف توسط روش مذکور حل شده و در انتها با استفاده از یک روش ادغام‌سازی مبتنی بر برنامه‌ریزی خطی،یک رتبه‌بندی کامل به دست آمده است..

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