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Aggregating the results of benevolent and aggressive models by the CRITIC method for ranking of decision-making units: A case study on seven biomass fuel briquettes generated from agricultural waste

Narong Wichapa[a*], Porntep Khokhajaikiat[b] and Kumpanat Chaiphet[c]

[a]*Department of Industrial Engineering, Faculty of Engineering and Industrial Technology, Kalasin University, Kalasin, 46000, Thailand*
[b]*Department of Industrial Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen, 40002, Thailand*
[c]*Department of Mechanical Engineering, Faculty of Engineering and Industrial Technology, Kalasin University, Kalasin, 46000, Thailand*

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A B S T R A C T

The ranking of decision-making units (DMUs) is one of the main issues in data envelopment analysis (DEA). Hence, many different ranking models have been proposed. However, each of these ranking models may produce different ranking results for similar problems. Therefore, it is wise to try different ranking models and aggregate the results of each ranking model that provides more reliable results in solving the ranking problems. In this paper, a novel ranking method (Aggregating the results of aggressive and benevolent models) based on the CRITIC method is proposed. To prove the applicability of the proposed ranking method, it is examined in three numerical examples, six nursing homes, fourteen international passenger airlines and seven biomass materials for processing into fuel briquettes. First, benevolent and aggressive models were used to calculate the efficiency rating for each DMU. As a result, the decision matrix was generated. In the decision matrix, the results of benevolent and aggressive models were viewed as criteria and DMUs were viewed as alternatives. Then, the weights of each criterion were generated by the CRITIC method. Finally, each DMU was ranked. In a comparative analysis, the proposed method can lead to achieving a more reliable decision than the method which is based on a stand-alone method.

1. Introduction

Thailand is one of the agricultural countries in Southeast Asia having a large amount of agricultural residues left over, at around 80 million tons per year, such as coconut shells, sugarcane bagasse, cassava rhizomes, coconut husks, sawdust, rice husks, coffee husks and soda weed (Promdee et al., 2017). These biodegradable wastes can be processed into a massive amount of energy and raw materials. Moreover, biomass energy is an environmentally friendly energy resource, and it can be processed directly into fuel briquettes for cooking. Thus, the idea of using the agricultural wastes for processing into fuel briquettes is one of most attractive way to solve the country's energy shortage. However, the decision-making process for selecting suitable biomass materials from agricultural wastes for processing into fuel briquettes is a complicated problem, because of the multiple conflicting criteria/properties in the decision-making process, which is hard to implement because there are multiple properties to consider simultaneously. This is a multiple attribute decision-making problem (MADM problem) in which each material must be measured and ranked for the most effective resource utilization. Data Envelopment Analysis (DEA) is a mathematical programming model (non-parametric approach) for measuring a group of relative efficiency scores of Decision Making Units (DMUs) with multiple inputs and outputs (Hosseinzadeh Lotfi et al., 2013; Omid & Zegordi, 2015; Wichapa & Khokhajaikiat, 2019). The DEA approach was described by Farrel (1957), but a mathematical model for measuring relative efficiency was originally developed by Charnes, Cooper and Rhodes (1979) and

* Corresponding author.
E-mail address: narong.wi@ksu.ac.th (N. Wichapa)

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other forms of DEA models have been improved by other researchers (Banker, Charnes, & Cooper, 1984; Cooper, Seiford, & Tone, 2007). The main objective of DEA is to generate the optimal weights for each DMU to maximize the ratio of the sum of weighted outputs to the sum of weighted inputs, in order to evaluate the efficiency scores of each DMU for identifying the DMUs as being efficient or inefficient (Lu & Liu, 2016; J. Wu, Chu, Sun, Zhu, & Liang, 2016). Over the past four decades, DEA has been widely applied in various fields such as manufacturing, banking, hospitals and education (Kuah, Wong, & Behrouzi, 2010; Lesik et al., 2020; Liu, Lu, & Lu, 2016; Mardani, Zavadskas, Streimikiene, Jusoh, & Khoshnoudi, 2017), which has proven that DEA is a valuable and capable method for evaluating performance in various fields. However, one of the main drawbacks of DEA is that efficient DMUs cannot be ranked, because the efficiencies of each efficient DMU have the same value (Efficiency score =1), so other ranking methods should be considered in solving such problems. To overcome the inability of DEA in ranking a set of efficient DMUs, many researchers (Andersen & Petersen, 1993; Cook, Roll, & Kazakov, 1990; Li & Reeves, 1999; Sueyoshi, 1999) have proposed various ranking methods. However, one of the most popular methodologies is the cross-efficiency evaluation method, first proposed by Sexton et al. (1986), which is an extension of DEA based on the cross efficiency concept. In an application of the cross-efficiency evaluation method, the efficiency scores of each DMU are evaluated through self-assessment and peer assessment, a set of weights for each DMU in the traditional DEA model determined, resulting in n weight sets. Then, each DMU is calculated using the n weight sets to obtain n efficiency values. The cross-efficiency score of each DMU is the average of the n efficiency values. Finally, all DMUs can be ranked by the average of cross-efficiency scores. However, there still exist some drawbacks in many cases, for example the drawback of this method is that the weights are not unique, which cannot clearly provide the results to help decision makers to improve their performance (Si & Ma, 2019; Wu, Sun, Zha, & Liang, 2011). To solve the above problems, Sexton et al. (1986) recommended using a secondary-goal model in the Cross-efficiency evaluation method. Inspired by this idea, Doyle and Green (1994) have proposed a secondary-goal model, aggressive (minimal) and benevolent (maximal) models, to deal with multiple DEA solutions. Based on the secondary-goal model, many researchers (Liang, Wu, Cook, & Zhu, 2008b; Wang & Chin, 2010b) offered secondary-goal models. There are often suggestions that we would like to rank all DMUs using aggressive (minimal) and benevolent (maximal) models. A question arises: which one is more appropriate? It is possible that the rankings of DMUs obtained by aggressive and benevolent models may not be the same. Each of the ranking models has different views which we would like not to ignore. Hence, it is wise to try different ranking models and aggregate the results of the aggressive and benevolent models for ranking all DMUs.

CRiteria Importance Through Intercriteria Correlation (CRITIC method), which was originally developed by Diakoulaki et al. (1995), has been widely accepted as an effective weighting method for determining the objective weights of each criterion in the decision matrix of multi-criteria decision making problems (MCDM problems). It can be used to aggregate the results of many models for ranking all DMUs, as well as Shannon's entropy. There are many applications of the CRITIC method for determining objective weights for criteria in decision making processes, as shown in the literature (Bellver, Cervelló, & García, 2011; Diakoulaki et al., 1995; Keshavarz Ghorabaee, Amiri, Zavadskas, & Antucheviciene, 2018; Vujicic, Papic, & Blagojević, 2017), which has proven that the CRITIC method is a valuable and capable method for determining the objective weights of criteria in the decision matrix of MADM problems. These are the major reasons why the aggressive and benevolent models based on the CRITIC method are selected as a suitable method for ranking all DMUs in this paper. To this end, this paper provides a hybrid approach (Aggressive and benevolent models) which is based on the CRITIC method for ranking all DMUs. The proposed method provides more reliable results in solving the ranking problem because aggregating the cross-efficiency results of the aggressive and benevolent models provides a more realistic ranking compared with using any of the ranking models individually. The calculation steps of this research are as follows. In the first step DMUs are categorized by aggressive and benevolent criteria and in the following the CRITIC method is employed to calculate the weight of each criterion. Finally, the ranking is obtained by multiplying the criteria weight and the cross-efficiency values. Billions of tons of agricultural residue are generated each year in the developing and developed countries. This volume of biodegradable wastes can be converted to an enormous amount of energy and raw materials. Agricultural biomass waste converted to energy can substantially displace fossil fuel, reduce emissions of greenhouse gases and provide renewable energy to people in developing countries, which still lack access to electricity. As raw materials, biomass wastes have attractive potentials for large-scale industries and community-level enterprises. Thailand, as a developing country depends heavily on wood fuel as a source of energy, contributing about 72% of the primary energy supply followed by crude oil and hydroelectricity in that order . The associated harmful environmental, health and social effects with the use of traditional biomass like firewood and fossil fuel has enhanced the growing interest in the search for alternate cleaner source of energy globally.

The rest of this research is organized as follows. Literature review, Methodology and Application examples are presented in Sections 2, 3 and 4 respectively. Finally, Section 5 is the Conclusion.

2. Literature review

DEA has been studied for over forty years. Even though it is old, applications of many forms of DEA models to various problems are becoming more attractive. DEA is a classic model for evaluating the efficiency score of DMUs with multiple input and output variables, originating from Farrel (1957). However, it is formally accepted by all researchers that Charnes, Cooper, and Rhodes's mathematical model (Charnes et al., 1979) is the most significant historic origin of DEA. Later, other forms of DEA models were developed by other researchers (Banker et al., 1984; Cooper et al., 2007). The CCR model by Charnes et al. (1979) together with the BCC model by Banker et al. (1984) are the most popular models of evaluating efficiency score among a group of DMUs. The right choice of a CCR or BCC is often, if not always, a hard decision. Hence, one DEA model that is often suggested for problem solving is the CCR model, which has been widely used in many fields (Lovell & Pastor, 1999; Niu, Zhang, Zhang, Zhang, & Yang, 2020; C.-K. Wei, Chen, Li, & Tsai, 2011), which proves that the CCR model is a valuable and capable method for evaluating performance of DMUs in various fields. It is well known that the main drawback of the DEA is its inability to rank multiple efficient DMUs. To solve the ranking problem, Sexton et al. (1986) proposed the cross efficiency evaluation to overcome the shortcomings of self-evaluation in the CCR-DEA model; it provides a full ranking for all DMUs. Because of this main advantage, the cross-efficiency evaluation method has been widely applied in various fields (Dotoli, Epicoco, Falagario, & Sciancalepore, 2016; Yang & Wei, 2019). However, the cross-efficiency evaluation method still has some disadvantages requiring further improvement. For example, the drawback of this method is that the weights are not unique, which cannot clearly provide the results to help decision makers to improve their performance (Si & Ma, 2019; J. Wu et al., 2011). Inspired by the idea of Sexton et al. (1986), two well-known models based on benevolent and aggressive models have been developed by Doyle & Green (1994). A neutral DEA model has been proposed by Wang & Chin (2010a) for overcoming the difficulty of the choice between the aggressive and benevolent models, and also providing a full ranking for all the DMUs. A game cross-efficiency model has been presented by Liang et al. (2008a) to get a reasonable cross-efficiency value. Besides the ranking methods, another way to solve the ranking problem is to integrate the results of multiple ranking methods for evaluating all the DMUs. For example, ranking methods based on Shannon entropy have been widely used for solving the ranking problems of all DMUs as shown in the literature (Hosseinzadeh, Eshlaghy, & Shafiee, 2012; Lu & Liu, 2016; Shirouyehzad, Lotfi, & Reza, 2013; Song & Liu, 2018). Likewise, the ranking methods based on the Grey Relational Analysis (GRA) have been proposed by many researchers (Kumar & Singh, 2020; Tosun, 2006). In recent years, various ranking methods based on the CRITIC method have been widely applied in various fields (Abdel-Basset & Mohamed, 2020; H.-W. Wu, Zhen, & Zhang, 2020). In addition, there are the ranking methods combined with the MADM methods, instead of the average scores of cross-efficiency evaluation. For instance, Wu et al. (2013) presented a combined DEA cross-efficiency evaluation and TOPSIS and used it to rank all the DMUs. Rakhshan et al. (2017) proposed a new ranking method based on TOPSIS and DEA to rank efficient DMUs. The CRITIC method, proposed by Diakoulaki et al. (1995), is one of the weighting methods which determine weights for each criterion in the decision matrix of MADM problems. It uses correlation analysis of all pairs of criteria to find out the objective weights of criteria. In the CRITIC method, the decision matrix is generated and the standard deviation of each criterion and the correlation coefficients of all pairs of criteria are employed to determine the weights of each criterion (Rostamzadeh, Ghorabaee, Govindan, Esmaeili, & Nobar, 2018). In recent years, the CRITIC method has been used extensively for determining the objective weights of criteria together with MADM methods as shown in the literature. Rostamzadeh et al. (2018) developed a conceptual framework for sustainable supply chain risk management using the CRITIC method and fuzzy TOPSIS. Tuş and Aytaç Adalı (2019) proposed a combined CRITIC-WASPAS method for solving the software selection problem. Wei et al. (2020) proposed a combined GRA-CRITIC method for location planning of electric vehicle charging stations. Zhao et al. (2020) proposed an improved Prospect theory and the Copula-CRITIC method to measure the construction schedule robustness. The association of weights in MADM problems is a crucial stage of the whole decision-making process. In many situations, decision makers may not be able to clearly determine the subjective preferences for varieties of criteria. In addition, the CRITIC method has been accepted as an effective tool to determine weights for criteria in decision-making problems, as shown in the above literature. These are therefore the important reasons for choosing the CRITIC method for determining the weights of each quantitative criterion in this paper.

3. Methodology

When measuring and ranking all DMUs, the evaluation process should have an approach that provides more reliable results in solving the ranking problems, and the approach must be able to solve the problem effectively. Thus, this section presents a novel aggregated method for ranking all DMUs. Details of the proposed ranking method are demonstrated in Fig. 1.

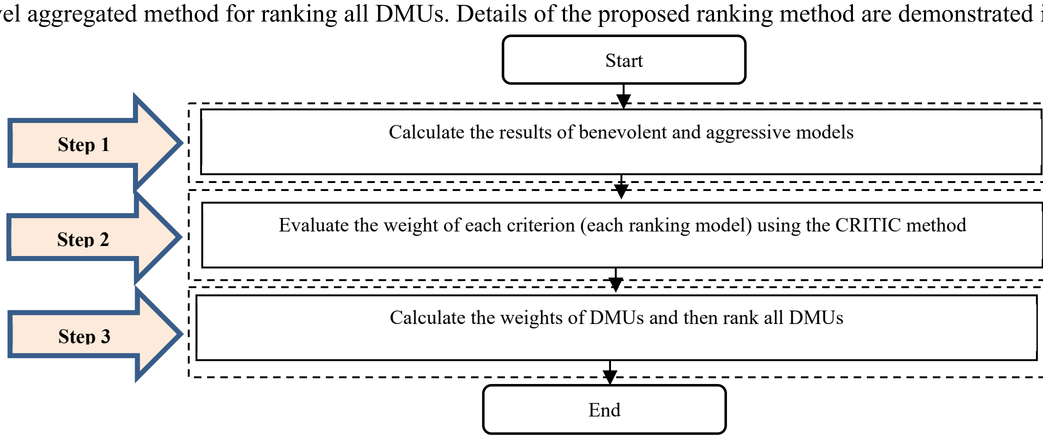

Fig. 1. Diagram for the proposed ranking method

3.1 Calculate the results of benevolent and aggressive models

Let there be a set of n DMUs, where DMU$_j$ (j = 1, 2, 3, . . . , n) uses m different inputs to produces s different outputs which can be denoted as x_{ij} = (1, 2, 3, . . . , m) and y_{rj} = (1, 2, 3, . . . , s) respectively. μ_{rd} and ω_{id} are weight of outputs and weight of inputs respectively. For any evaluated DMU$_d$ ($1 \le d \le n$), the efficiency score E_{dd} can be calculated by the CCR model as follows:

$$\max \sum_{r=1}^{s} \mu_{rd} \cdot Y_{rd} = E_{dd}$$

subject to:

$$\begin{aligned} &\sum_{r=1}^{s} \mu_{rd} \cdot Y_{rj} - \sum_{i=1}^{m} \omega_{id} \cdot X_{ij} \le 0, \quad \forall j,\ j = 1,2,3,\dots,n \\ &\sum_{i=1}^{m} \omega_{id} \cdot X_{ij} = 1 \\ &\omega_{id} \ge 0, \quad \forall i, \quad i = 1,2,3,\dots,m \\ &\mu_{rd} \ge 0, \quad \forall r, \quad r = 1,2,3,\dots,s \end{aligned} \tag{1}$$

For each DMU$_d$ (d = 1, 2, 3, . . . , n), a group of optimal weights can be obtained by solving
the CCR model in Equation (1). In the CCR model, each DMU is self-evaluated and termed efficient if and only if the optimal objective function is equal to 1. The cross-efficiency of each DMU$_j$ using the weights of DMU$_d$, namely E_{dj}, can be defined as follows:

$$E_{dj} = \frac{\sum_{r=1}^{s} \mu_{rd} \cdot Y_{rd}}{\sum_{i=1}^{m} \omega_{id} \cdot X_{id}}, \quad d,j = 1,2,3,\dots, n \tag{2}$$

The cross-efficiency matrix (CEM) can be generated using Equation (2).

Then the average cross-efficiency score (ACE score) of each DMU$_j$ is defined as follows:

$$\bar{E}_j = \frac{1}{n} \sum_{d=1}^{n} E_{dj}, \quad j = 1,2,3,\dots,n, \quad d,j = 1,2,3,\dots, n \tag{3}$$

The optimal weights of each DMU$_j$ obtained from the CCR model in Eq. (1) are usually not unique. Consequently, E_{dj} defined in Eq. (2) is generated arbitrarily. To overcome this drawback, the well-known aggressive and benevolent models were proposed by Doyle and Green (1994) to identify the optimal weights of each DMU$_j$. The benevolent and aggressive models are

$$\max \sum_{r=1}^{s} \mu_{rd} \sum_{j=1, j \ne d}^{n} Y_{rj}$$

subject to:

$$\begin{aligned} &\sum_{i=1}^{m} \omega_{id} \sum_{j=1, j \ne d}^{n} X_{ij} = 1 \\ &\sum_{r=1}^{s} \mu_{rd} \cdot Y_{rj} - E_{dd} \cdot \sum_{i=1}^{m} \omega_{id} \cdot X_{ij} = 0, \quad \forall j, j \ne d,\ j = 1,2,3,\dots,n \\ &\sum_{r=1}^{s} \mu_{rd} \cdot Y_{rj} - \sum_{i=1}^{m} \omega_{id} \cdot X_{ij} \le 0, \quad \forall j,\ j \ne d,\ j = 1,2,3,\dots,n \\ &\omega_{id} \ge 0, \quad \forall i, \quad i = 1,2,3,\dots,m \\ &\mu_{rd} \ge 0, \quad \forall r, \quad r = 1,2,3,\dots,s \quad \text{and} \end{aligned} \tag{4}$$

$$Min \sum_{r=1}^{s} \mu_{rd} \sum_{j=1, j \ne d}^{n} Y_{rj} \tag{5}$$

subject to the same constraints as in Model (4)

Model/Eq. (4) represents the benevolent strategy for cross efficiency evaluation, which aims to maximize the cross efficiency of the integrated unit consisting of the other DMUs while maintaining the self-evaluation efficiency of a particular DMU under evaluation, whereas Model/Eq. (5) is known as the aggressive strategy which minimizes the cross efficiency of the integrated unit. The two models optimize the input and output weights in two different views. As a result, there is no guarantee that both the models can lead to the same ranking orders and are incapable of providing the decision makers with a definite decision conclusion. Thus, the idea of aggregating the results of the well-known DEA models for ranking DMU*s* is an interesting solution approach for solving the ranking problem.

3.2 Evaluate the weights of each criterion using the CRITIC method

There are three calculation steps to evaluate the weights of each criterion using the CRITIC method. Details of each calculation step are as follows.

3.2.1 Generate the decision matrix

The decision matrix will be generated using the results of benevolent and aggressive models in Section 3.1. Details are shown in Table 1.

Table 1
The decision matrix (X) of each method

	Criteria	
Alternatives/DMU*s*	**Benevolent (C_1)**	**Aggressive (C_2)**
1	x_{11}	x_{12}
2	x_{21}	x_{22}
3	x_{31}	x_{32}
…	…	…
n	x_{n1}	x_{n2}

As in Table 1, consider a decision matrix (X), $X = \left[x_{ij}\right]_{n\times m}$, where x_{ij} is the efficiency score of alternative i with respect to criterion j, n and m are the numbers of alternatives and the number of criteria respectively.

3.2.2 Normalize the decision matrix

The normalized decision matrix will be generated using Eq. (6)

$$\chi_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{6}$$

where $x_j^{\max} = \max(x_{ij}, j = 1, 2, 3, ..., n)$ and $x_j^{\min} = \min(x_{ij}, j = 1, 2, 3, ..., n)$.

3.2.3 Calculate the weights of each criterion

While calculating the weights of each criterion j, the standard deviation of each criterion j (σ_j) and correlation between the criterion i and criterion j (r_{ij}) can be computed using Excel 2010. In this regard, the weight of the criterion j (w_j) is obtained as:

$$w_j = \frac{C_j}{\sum_{j=1}^{m} C_j}, \tag{7}$$

where C_j is the quantity of information contained in criterion j determined as:

$$C_j = \sigma_j \sum_{i=1}^{n} (1 - r_{ij}) \tag{8}$$

3.3 Calculate the weights of DMUs and rank all DMUs

The weight of each DMU$_i$ is obtained by multiplying the CRITIC weight value by the corresponding decision matrix using Eq. (9).

$$\theta_i = \sum_{j=1}^{m} (w_j \cdot x_{ij}), \qquad \forall i,\ i = 1, 2, 3, \ldots, n \tag{9}$$

where θ_i is the integrated weight of each DMU$_i$. After obtaining the results of θ_i using Equation (9), it can be concluded that a higher value means that the DMUs ranking is higher.

4. Numerical examples

This section uses the proposed ranking method to evaluate three numerical examples. The first is six nursing homes (Sexton et al., 1986), the second fourteen international passenger airlines (Tofallis, 1997a), and the third is a case study on seven biomass fuel briquettes generated from agricultural waste. Details of calculation steps of the proposed methodology are shown in Sections 4.1, 4.2 and 4.3 respectively.

4.1. Efficiency evaluation of six nursing homes

As shown in Table 2, the six nursing homes, proposed by Sexton et al. (Sexton et al., 1986), has two inputs (x_1 and x_2) and two outputs (y_1 and y_2).

StHr (x_1): staff hours per day, including nurses, physicians, etc.
Supp (x_2): supplies per day, measured in thousands of dollars.
MCPD (y_1): total Medicare-plus Medicaid-reimbursed patient days.
PPPD (y_2): total privately paid patient days.

Table 2
Data set of six nursing homes

	Inputs		Outputs	
DMU$_s$	***StHr (x_1)***	***Supp (x_2)***	***MCPD (y_1)***	***PPPD (y_2)***
A	1.50	0.20	1.40	0.35
B	4.00	0.70	1.40	2.10
C	3.20	1.20	4.20	1.05
D	5.20	2.00	2.80	4.20
E	3.50	1.20	1.90	2.5
F	3.20	0.70	1.40	1.5

Step 1: Calculate the results of benevolent and aggressive models for six nursing homes.

Consider a DEA efficiency evaluation problem with six nursing homes, each DMU with two inputs and two outputs as in Table 2. The benevolent ((Eq. (4)) and aggressive ((Eq. (5)) models were coded using LINGO software (as shown in Appendix 1). As a result, we can obtain the decision matrix of six nursing homes listed in Table 3.

Table 3
Decision matrix of six nursing homes

	Criteria	
Alternatives/DMU*s*	**Benevolent (*C1*)**	**Aggressive (*C2*)**
A	1.0000	0.7639
B	0.9773	0.7004
C	0.8580	0.6428
D	1.0000	0.7184
E	0.9758	0.6956
F	0.8570	0.6081
$x_j^{\max}$	**1.0000**	**0.7639**
$x_j^{\min}$	**0.8570**	**0.6081**

Step 2: Evaluate the criteria weights for six nursing homes using the CRITIC method.

Consider the decision matrix of six nursing homes in Table 3, DMUs are viewed as alternatives, and the results of benevolent and aggressive models are viewed as criteria. After that, the decision matrix of six nursing homes was normalized using Eq. (6). Then, σ_j was calculated using the function "=STDEVA (xxx:xxx)" in Excel 2010. As a result, we can obtain the normalized decision matrix listed in Table 4.

Table 4
Normalized decision matrix of six nursing homes

Alternatives/DMUs	Criteria	
	Benevolent (C_1)	Aggressive (C_2)
A (1)	1.0000	1.0000
B (2)	0.8416	0.5925
C (3)	0.0068	0.2230
D (4)	1.0000	0.7079
E (5)	0.8311	0.5617
F (6)	0.0000	0.0000
σ_j	**0.4780**	**0.3553**

After obtaining the normalized decision matrix, the next step is to calculate the correlation between criterion *i* and criterion *j* (r_{ij}) using the function "=CORREL(xx:xx,xx:xx)" in Excel 2010. As a result, we can obtain the correlation matrix listed in Table 5.

Table 5
Correlation matrix (r_{ij} matrix) for six nursing homes

	Benevolent	Aggressive
Benevolent	1.0000	0.9220
Aggressive	0.9220	1.0000

After obtaining the correlation matrix, the weight of the criterion j (w_j) was obtained using Eq. (7) and Eq. (8). C_j was computed using Eq. (8), For example, $C_1 = \sigma_1 \sum_{i=1}^{2}(1-r_{i1}) = 0.4780((1-1)+(1-0.9220)) = 0.4780(0.0000+0.0780) = 0.0373$. Likewise, the value C_2 was obtained from the same calculation as the C_1 value. Finally, w_1 *and* w_2 are shown in Table 6.

Table 6
Criteria weights for six nursing homes using the CRITIC method

	Benevolent	Aggressive
Benevolent	0.0000	0.0780
Aggressive	0.0780	0.0000
$\sum_{i=1}^{n}(1-r_{ij})$	0.0780	0.0780
σ_j	0.4780	0.3553
C_j	**0.0373**	**0.0277**
w_j	**0.5737**	**0.4263**

Step 3: Calculate the weights of DMUs and then rank all DMUs

After obtaining the w_j of all criteria, θ_i can be obtained using Equation (9). Based on values of each θ_i , the ranking of each DMU$_i$ is as shown in Table 7. Finally, the correlation of each method (r_s) was tested using Spearman's rank correlation. Details of r_s values are shown in Table 8.

Table 7
The ranking of DMUs for six nursing homes

DMUs	CCR	Rank	Benevolent	Rank	Aggressive	Rank	Proposed method	Rank
A (1)	1.0000	1	1.0000	1	0.7639	1	0.8993	1
B (2)	1.0000	1	0.9773	3	0.7004	3	0.8593	3
C (3)	1.0000	1	0.8580	5	0.6428	5	0.7662	5
D (4)	1.0000	1	1.0000	1	0.7184	2	0.8799	2
E (5)	0.9775	5	0.9758	4	0.6956	4	0.8564	4
F (6)	0.8675	6	0.8570	6	0.6081	6	0.7509	6

Table 8
The correlation test for six nursing homes

	CCR	Benevolent	Aggressive	Proposed Method
CCR	1.000	0.686	0.676	0.676
Benevolent	0.686	1.000	0.986	0.986
Aggressive	0.676	0.986	1.000	1.000

Proposed method	0.676	0.986	1.000	1.000

As seen in Table 7, the CCR model using Eq. (1) identifies DMU_1 through DMU_4 as efficient DMUs, while it cannot discriminate among efficient DMUs. To solve this problem, we use the proposed method to evaluate these six DMUs. Finally, the efficiency rating and ranking were obtained as in Table 7. The proposed method assesses that $DMU_1 > DMU_4 > DMU_2 > DMU_5$ $DMU_3 > DMU_6$. The aggressive model and proposed method agree that DMU_1 is the best DMU and DMU_6 is the worst DMU. Whereas, benevolent model cannot agree that DMU_1 is the best DMU because it cannot discriminate among DMU_1 and DMU_4 (DMU_1 and DMU_4 are same cross-efficiency value). As seen in Table 8, after the Spearman correlation test, the Spearman's rank correlation coefficients for proposed method and CCR efficiency value, benevolent efficiency value and aggressive efficiency value are calculated as $r_s = 0.676$, 0.986 and 1.000 respectively. This is a guarantee that the proposed method is more reliable.

4.2 Efficiency evaluation of fourteen international passenger airlines

As shown in Table 9, the data set of fourteen international passenger airlines, proposed by Tofallis (Tofallis, 1997b), has three inputs (x_1, x_2 and x_3) and two outputs (y_1 and y_2).

x_1: aircraft capacity in ton kilometers.
x_2: operating cost.
x_3: non-flight assets such as reservation systems, facilities and current assets.
y_1: passenger kilometers.
y_2: non-passenger revenue.

Table 9
Data set of fourteen international passenger airlines

	Inputs			Outputs	
DMU_s	x_1	x_2	x_3	y_1	y_2
1	5723	3239	2003	26677	697
2	5895	4225	4557	3081	539
3	24099	9560	6267	124055	1266
4	13565	7499	3213	64734	1563
5	5183	1880	783	23604	513
6	19080	8032	3272	95011	572
7	4603	3457	2360	22112	969
8	12097	6779	6474	52363	2001
9	6587	3341	3581	26504	1297
10	5654	1878	1916	19277	972
11	12559	8098	3310	41925	3398
12	5728	2481	2254	27754	982
13	4715	1792	2485	31332	543
14	22793	9874	4145	122528	1404

Step 1: Calculate the results of benevolent and aggressive models for fourteen international passenger airlines.

Consider the data set of fourteen international passenger airlines, benevolent and aggressive models using LINGO software (Details are shown in Appendix 2). As a result, we can obtain the decision matrix of fourteen international passenger airlines listed in Table 10.

Table 10
Decision matrix of fourteen international passenger airlines

	Criteria	
Alternatives/DMU_s	Benevolent (C_1)	Aggressive (C_2)
1	0.7543	0.5990
2	0.1894	0.1652
3	0.7678	0.6226
4	0.8222	0.6734
5	0.8912	0.7983
6	0.7554	0.6385
7	0.8214	0.6478
8	0.7242	0.5855
9	0.7590	0.6309
10	0.7803	0.6813
11	0.9193	0.7742
12	0.8850	0.7314
13	0.9190	0.7503
14	0.8659	0.7316

$x_j^{\max}$	**0.9193**	**0.7983**
$x_j^{\min}$	**0.1894**	**0.1652**

Step 2: Evaluate the criteria weights for fourteen international passenger airlines using the CRITIC method.

Considering the decision matrix of fourteen international passenger airlines in Table 10, the calculation steps are the same as Step 2 of Section 4.1. As a result, the normalized decision matrix was generated as shown in Table 11. Finally, the weights of each criterion were determined using the CRITIC method as listed in Table 12.

Table 11
Normalized decision matrix of fourteen international passenger airlines

	Criteria	
Alternatives/DMU$_s$	**Benevolent (C_1)**	**Aggressive (C_2)**
1	0.7740	0.6851
2	0.0000	0.0000
3	0.7924	0.7225
4	0.8669	0.8026
5	0.9614	1.0000
6	0.7754	0.7475
7	0.8659	0.7623
8	0.7326	0.6638
9	0.7804	0.7355
10	0.8095	0.8152
11	1.0000	0.9619
12	0.9530	0.8943
13	0.9995	0.9242
14	0.9269	0.8946
σ_j	**0.2481**	**0.2419**

Table 12
Criteria weights for fourteen international passenger airlines using the CRITIC method

	Benevolent	**Aggressive**
Benevolent	0.0000	0.0126
Aggressive	0.0126	0.0000
$\sum_{i=1}^{n}(1-r_{ij})$	0.0126	0.0126
σ_i	0.2481	0.2419
C_j	0.0031	0.0030
w_j	**0.5063**	**0.4937**

Step 3: Calculate the weights of DMUs and then rank all DMUs for fourteen international passenger airlines

After obtaining the w_j of all criteria, θ_i can be obtained using the same Step 3 of Section 4.1. The results are shown in Table 13. Finally, r_s was tested using Spearman's rank correlation as listed in Table 14.

Table 13
The ranking of DMUs for fourteen international passenger airlines

	CCR	**Rank**	**Benevolent**	**Rank**	**Aggressive**	**Rank**	**Proposed method**	**Rank**
1	0.8684	12	0.7543	12	0.5990	12	0.6776	12
2	0.3379	14	0.1894	14	0.1652	14	0.1775	14
3	0.9475	11	0.7678	9	0.6226	11	0.6961	10
4	0.9581	9	0.8222	6	0.6734	7	0.7487	6
5	1.0000	1	0.8912	3	0.7983	1	0.8453	2
6	0.9766	8	0.7554	11	0.6385	9	0.6977	9
7	1.0000	1	0.8214	7	0.6478	8	0.7357	7
8	0.8588	13	0.7242	13	0.5855	13	0.6557	13
9	0.9477	10	0.7590	10	0.6309	10	0.6958	11
10	1.0000	1	0.7803	8	0.6813	6	0.7314	8
11	1.0000	1	0.9193	1	0.7742	2	0.8477	1
12	1.0000	1	0.8850	4	0.7314	5	0.8092	4
13	1.0000	1	0.9190	2	0.7503	3	0.8357	3
14	1.0000	1	0.8659	5	0.7316	4	0.7996	5

As seen in Table 13, the CCR model using Eq. (1) identifies DMU_5, DMU_7 and DMU_{10} through DMU_{14} as efficient DMUs, which it cannot discriminate amongst. To solve this problem, we use the proposed method to evaluate all DMUs. Finally, the efficiency rating and ranking were obtained as in Table 13. The proposed method and benevolent model agree that DMU_{11} is the best DMU. Whereas, the aggressive model indicates that DMU_5 is the best DMU. All of the methods agree that DMU_2 is the worst DMU. As seen in Table 8, after the Spearman correlation test, the Spearman's rank correlation coefficients for the proposed method and the CCR efficiency value, benevolent efficiency value and aggressive efficiency value are calculated as r_s = 0.880, 0.982 and 0.974 respectively. This is a guarantee that the proposed method is highly reliable.

Table 14
The correlation test for fourteen international passenger airlines

	CCR	**Benevolent**	**Aggressive**	**Proposed method**
CCR	1.000	0.857	0.908	0.880
Benevolent	0.857	1.000	0.952	0.982
Aggressive	0.908	0.952	1.000	0.974
Proposed method	0.880	0.982	0.974	1.000

4.3 Application to seven biomass fuel briquettes generated from agricultural waste

Thailand is one of the agricultural countries in Southeast Asia having a large amount of agricultural waste which could be used for fuel briquettes. Therefore, the idea of using the agricultural wastes for manufacturing into fuel briquettes is a very attractive issue. The moisture content (analyzed following the ASTM D3173), ash content (analyzed following the ASTM D3174), heating value (analyzed following the ASTM D5865) and fixed carbon (analyzed following the ASTM D3172) are important properties of fuel briquettes for cooking. These properties can be viewed as inputs and outputs in DEA, and each material type of fuel briquettes can be viewed as a DMU. Selecting the suitable agricultural wastes for manufacturing into fuel briquettes is a complicated problem because of the multiple conflicting criteria/properties in the decision-making process, which is hard to implement. Therefore, the proposed ranking method based on DEA was used to select the suitable materials for the most effective resource utilization. As shown in Table 15, the seven biomass fuel briquettes have two inputs (x_1 and x_2) and two outputs (y_1 and y_2).

x_1 : moisture content (%).
x_2 : ash content (%).
y_1 : heating value (kcal/kg).
y_2 : fixed carbon (%).
DMU_1: Bagasse.
DMU_2: Incense reed.
DMU_3: Water hyacinth.
DMU_4: Rice husk.
DMU_5: Coconut shell.
DMU_6: Sawdust.
DMU_7: Sensitive plant.

Table 15
Data set of seven biomass fuel briquettes

	Inputs		**Outputs**	
DMUs	x_1	x_2	y_1	y_2
1	6.4	8.81	4,462	17.66
2	6.15	24.61	3,251	14.50
3	6.74	25.67	3,146	14.75
4	7.5	21.01	3,886	17.3
5	6.9	3.4	6,761	72.7
6	4.45	1.45	4,876	27.4
7	10.2	3.87	4,376	24.77

Step 1: Calculate the results of benevolent and aggressive models for seven biomass fuel briquettes.

Considering the data set of seven biomass fuel briquettes, the benevolent and aggressive models were coded using LINGO software (Details are shown in Appendix 3). As a result, we can obtain the decision matrix of seven biomass fuel briquettes listed in Table 16.

Table 16
Decision matrix of seven biomass fuel briquettes

	Criteria	
Alternatives/DMUs	**Benevolent (C_1)**	**Aggressive (C_2)**
1	0.6372	0.4935
2	0.4852	0.3580
3	0.4293	0.3170
4	0.4756	0.3549
5	0.9476	0.8892
6	1.0000	0.9834
7	0.3978	0.3749

Alternatives/DMUs	Criteria	
	Benevolent (C_1)	Aggressive (C_2)
$x_j^{\max}$	**1.0000**	**0.9834**
$x_j^{\min}$	**0.3978**	**0.3170**

Step 2: Evaluate the criteria weights for seven biomass fuel briquettes using the CRITIC method.

Based on the same calculation procedure as the Step 2 of the Section 4.1 and Section 4.2, w_1 and w_2 were obtained as shown in Table 17.

Table 17
Criteria weights for seven biomass fuel briquettes using the CRITIC method

	Benevolent	Aggressive
Benevolent	0.0000	0.0141
Aggressive	0.0141	0.0000
$\sum_{i=1}^{n}(1-r_{ij})$	0.0141	0.0141
σ_j	0.4161	0.4178
C_j	0.0059	0.0059
w_j	0.4990	0.5010

Step 3: Calculate the weights of DMUs and then rank all DMUs for the seven biomass fuel briquettes

After obtaining the w_j of all criteria, θ_i values were obtained using Eq. (9). Based on the values of each θ_i , the ranking of each DMU$_i$ was shown in Table 18. Finally, the correlation of each method (r_s) was tested using Spearman's rank correlation. Details of r_s values are shown in Table 19.

As seen in Table 18, the CCR model using Equation (1) identifies DMU$_5$ through DMU$_6$ as efficient DMUs, which it cannot discriminate between. To solve this problem, we use the proposed method to evaluate these DMUs. Finally, the efficiency rating and ranking were obtained. The proposed method assesses that DMU$_6$> DMU$_5$ > DMU$_1$ > DMU$_2$> DMU$_4$ > DMU$_7$ > DMU$_3$. The benevolent, aggressive and proposed models agree that DMU$_6$ is the best DMU. Whereas, CCR model cannot agree that DMU$_6$ is the best DMU because it cannot discriminate among DMU$_5$ and DMU$_6$ (DMU$_5$ and DMU$_6$ are same cross-efficiency value).

Table 18
The ranking of DMUs for seven biomass fuel briquettes

DMUs	CCR	Rank	Benevolent	Rank	Aggressive	Rank	Proposed method	Rank
1	0.6463	3	0.6372	3	0.4935	3	0.5652	3
2	0.4900	4	0.4852	4	0.3580	5	0.4215	4
3	0.4327	6	0.4293	6	0.3170	7	0.3730	7
4	0.4803	5	0.4756	5	0.3549	6	0.4151	5
5	1.0000	1	0.9476	2	0.8892	2	0.9184	2
6	1.0000	1	1.0000	1	0.9834	1	0.9917	1
7	0.3980	7	0.3978	7	0.3749	4	0.3864	6

Table 19
The correlation test for seven biomass fuel briquettes

	CCR	Benevolent	Aggressive	Proposed method
CCR	1.000	0.991	0.775	0.955
Benevolent	0.991	1.000	0.786	0.964
Aggressive	0.775	0.786	1.000	0.893
Proposed method	0.955	0.964	0.893	1.000

As seen in Table 19, after the Spearman correlation test, the Spearman's rank correlation coefficients for the proposed method and CCR efficiency value, benevolent efficiency value and aggressive efficiency value are calculated as r_s = 0.955, 0.964 and 0.893 respectively. In a comparative analysis, it is believed that the proposed ranking method should be more valuable and applicable than stand-alone ranking methods.

5. Conclusions

This paper presents a novel aggregated method to solve the ranking problems, under multiple inputs, multiple outputs and multiple DMUs. The proposed method was tested with three numerical examples (The six nursing homes, fourteen international passenger airlines and seven biomass fuel briquettes). We first utilized benevolent and aggressive models to evaluate the efficiency rating of DMUs. The results of each model were used to generate a decision matrix. In the decision matrix, the results of benevolent and aggressive models were viewed as criteria and DMUs were viewed as alternatives. Secondly, the weights of each criterion were generated by the CRITIC method. Finally, each DMU was evaluated and ranked. The proposed method is useful and applicable to rank DMUs, which differ from other stand-alone ranking models. We believe that the proposed ranking method can be used to tackle other ranking problems in real-world situations.

For future research, the limitations of this paper lie in that only three numerical examples were studied. Application of the proposed ranking method should be tested with more cases of ranking problems in real-world situations to enhance the validity of the research output further.

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References

Abdel-Basset, M., & Mohamed, R. (2020). A novel plithogenic TOPSIS- CRITIC model for sustainable supply chain risk management. *Journal of Cleaner Production, 247*, 119586. doi: https://doi.org/10.1016/j.jclepro.2019.119586

Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science, 39*(10), 1261-1264.. doi: 10.1287/mnsc.39.10.1261

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science, 30*(9), 1078-1092.

Bellver, A. J., Cervelló Royo, R. E., & García García, F. (2011). Spanish savings banks and their future transformation into private capital banks.determining their value by a multicriteria valuation methodology. *European Journal of Economics, Finance and Administrative Sciences*, *35*, 155-164.

Charnes, A. W., Cooper, W. W., & Rhodes, E. (1979). Measuring The Efficiency of Decision Making Units. *European Journal of Operational Research, 2*, 429-444. doi: 10.1016/0377-2217(78)90138-8

Cook, W. D., Roll, Y., & Kazakov, A. (1990). A dea model for measuring the relative eeficiency of highway maintenance patrols. *INFOR: Information Systems and Operational Research, 28*(2), 113-124.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Alternative Dea Models. *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, 87-130..

Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers & Operations Research, 22*(7), 763-770. doi: https://doi.org/10.1016/0305-0548(94)00059-H

Dotoli, M., Epicoco, N., Falagario, M., & Sciancalepore, F. (2016). A stochastic cross-efficiency data envelopment analysis approach for supplier selection under uncertainty. *International Transactions in Operational Research, 23*(4), 725-748.. doi: 10.1111/itor.12155

Doyle, J., & Green, R. (1994). Efficiency and cross-efficiency in DEA: Derivations, meanings and uses. *Journal of the Operational Research Society, 45*(5), 567-578.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*(3), 253-290. doi: 10.2307/2343100

Hosseinzadeh, F., Eshlaghy, A., & Shafiee, M. (2012). *Providers Ranking Using Data Envelopment Analysis Model, Cross Efficiency and Shannon Entropy*. *Applied Mathematical Sciences, 6*(4), 153-161.

Hosseinzadeh Lotfi, F., Jahanshahloo, G. R., Khodabakhshi, M., Rostamy-Malkhlifeh, M., Moghaddas, Z., & Vaez-Ghasemi, M. (2013). A review of ranking models in data envelopment analysis. *Journal of Applied Mathematics, 2013*, 20. doi: 10.1155/2013/492421

Keshavarz Ghorabaee, M. K., Amiri, M., Zavadskas, E. K., & Antucheviciene, J. (2018). A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations. *Archives of Civil and Mechanical Engineering, 18*, 32-49. doi: https://doi.org/10.1016/j.acme.2017.04.011

Kuah, C., Wong, K., & Behrouzi, F. (2010). A review on Data Envelopment Analysis (DEA). *Asia International Conference on Modelling & Simulation, 0*, 168-173. doi: 10.1109/AMS.2010.45

Kumar, V., & Singh, H. (2020). Parametric optimization of rotary ultrasonic drilling using grey relational analysis. *materials today: Proceedings, 22*, 2676-2695. doi: https://doi.org/10.1016/j.matpr.2020.03.399

Lesik, I., Bobrovska, N., Bilichenko, O., Dranus, L., Lykhach, V., Dranus, V., ... & Nazarenko, I. (2020). Assessment of management efficiency and infrastructure development of Ukraine. *Management Science Letters*, 3071-3080. doi: 10.5267/j.msl.2020.5.016

Li, Xiao-Bai, & Reeves, Gary R. (1999). A multiple criteria approach to data envelopment analysis. *European Journal of Operational Research, 115*(3), 507-517. doi: https://doi.org/10.1016/S0377-2217(98)00130-1

Liang, L., Wu, J., Cook, W. D., & Zhu, J. (2008). Alternative secondary goals in DEA cross-efficiency evaluation. *International Journal of Production Economics, 113*(2), 1025-1030. doi: https://doi.org/10.1016/j.ijpe.2007.12.006

Liang, L., Wu, J., Cook, W. D., & Zhu, J. (2008). The DEA game cross-efficiency model and its Nash equilibrium. *Operations research, 56*(5), 1278-1288. doi: 10.1287/opre.1070.0487

Liu, J. S., Lu, L.Y. Y., & Lu, W.-M. (2016). Research fronts in data envelopment analysis. *Omega, 58*, 33-45. doi: https://doi.org/10.1016/j.omega.2015.04.004

Lovell, C. A. K., & Pastor, J. T. (1999). Radial DEA models without inputs or without outputs. *European Journal of Operational Research, 118*(1), 46-51. doi: https://doi.org/10.1016/S0377-2217(98)00338-5

Lu, T., & Liu, S.-T. (2016). Ranking DMUs by comparing DEA cross-efficiency intervals using entropy measures. *Entropy, 18*, 452. doi: 10.3390/e18120452

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., & Khoshnoudi, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews, 70*, 1298-1322. doi: https://doi.org/10.1016/j.rser.2016.12.030

Niu, T., Zhang, L., Zhang, B., Zhang, B., & Yang, B. (2020). Scientific research efficiency evaluation model based on DEA and its application analysis—take Shanghai as an example. *In Recent Trends in Decision Science and Management* (pp. 55-70). Springer, Singapore.

Omid, A., & Zegordi, S. (2015). Integrated AHP and network DEA for assessing the efficiency of Iranian handmade carpet industry. *Decision Science Letters, 4*(4), 477-486. doi: 10.5267/j.dsl.2015.6.002

Promdee, K., Chanvidhwatanakit, J., Satitkune, S., Boonmee, C., Kawichai, T., Jarernprasert, S., & Vitidsant, T. (2017). Characterization of carbon materials and differences from activated carbon particle (ACP) and coal briquettes product (CBP) derived from coconut shell via rotary kiln. *Renewable and Sustainable Energy Reviews, 75*, 1175-1186.

Rakhshan, S.A. (2017). Efficiency ranking of decision making units in data envelopment analysis by using TOPSIS-DEA method. *Journal of the Operational Research Society, 68*(8), 906-918.

Rostamzadeh, R., Ghorabaee, M. K., Govindan, K., Esmaeili, A., & Nobar, H. B. K. (2018). Evaluation of sustainable supply chain risk management using an integrated fuzzy TOPSIS-CRITIC approach. *Journal of Cleaner Production, 175*, 651-669. doi: https://doi.org/10.1016/j.jclepro.2017.12.071

Sexton, T. R., Silkman, R. H., & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. *New Directions for Program Evaluation, 1986*(32), 73-105. doi: 10.1002/ev.1441

Shirouyehzad, H., Lotfi, F. H., & Dabestani, R. (2013). Aggregating the results of ranking models in data envelopment analysis by Shannon's entropy: a case study in hotel industry. *International Journal of Modelling in Operations Management, 3*(2), 149-163. doi: 10.1504/IJMOM.2013.055970

Si, Qin, & Ma, Zhanxin. (2019). DEA cross-efficiency ranking method based on grey correlation degree and relative entropy. *Entropy, 21*(10), 966.

Song, L., & Liu, F. (2018). An improvement in DEA cross-efficiency aggregation based on the Shannon entropy. *International Transactions in Operational Research, 25*(2), 705-714. doi: 10.1111/itor.12361

Sueyoshi, T. (1999). DEA non-parametric ranking test and index measurement: slack-adjusted DEA and an application to Japanese agriculture cooperatives. *Omega, 27*(3), 315-326. doi: https://doi.org/10.1016/S0305-0483(98)00057-7

Tofallis, C. (1997a). Input efficiency profiling: An application to airlines. *Computers & OR, 24*, 253-258. doi: 10.1016/S0305-0548(96)00067-6

Tofallis, C. (1997b). Input efficiency profiling: An application to airlines. *Computers & Operations Research, 24*(3), 253-258. doi: https://doi.org/10.1016/S0305-0548(96)00067-6

Tosun, N. (2006). Determination of optimum parameters for multi-performance characteristics in drilling by using grey relational analysis. *The International Journal of Advanced Manufacturing Technology, 28*(5), 450-455. doi: 10.1007/s00170-004-2386-y

Tuş, A., & Aytaç Adalı, E. (2019). The new combination with CRITIC and WASPAS methods for the time and attendance software selection problem. *OPSEARCH, 56*(2), 528-538. doi: 10.1007/s12597-019-00371-6

Vujicic, M., Papic, M., & Blagojević, M. (2017). Comparative analysis of objective techniques for criteria weighing in two MCDM methods on example of an air conditioner selection. *Tehnika, 72*, 422-429. doi: 10.5937/tehnika1703422V

Wang, Y.-M., & Chin, K.-S. (2010a). A neutral DEA model for cross-efficiency evaluation and its extension. *Expert Systems with Applications, 37*(5), 3666-3675. doi: https://doi.org/10.1016/j.eswa.2009.10.024

Wang, Y.-M., & Chin, K.-S. (2010b). Some alternative models for DEA cross-efficiency evaluation. *International Journal of Production Economics, 128*(1), 332-338. doi: https://doi.org/10.1016/j.ijpe.2010.07.032

Wei, C.-K., Chen, L.-C., Li, R.-K., & Tsai, C.-H. (2011). Exploration of efficiency underestimation of CCR model: Based on medical sectors with DEA-R model. *Expert Systems with Applications, 38*(4), 3155-3160. doi: https://doi.org/10.1016/j.eswa.2010.08.108

Wei, G., Lei, F., Lin, R., Wang, R., Wei, Y., Wu, J., & Wei, C. (2020). Algorithms for probabilistic uncertain linguistic multiple attribute group decision making based on the GRA and CRITIC method: application to location planning of electric vehicle charging stations. *Economic Research-Ekonomska Istraživanja, 33*(1), 828-846. doi: 10.1080/1331677X.2020.1734851

Wichapa, N., & Khokhajaikiat, P. (2019). A novel holistic approach for solving the multi-criteria transshipment problem for infectious waste management. *Decision Science Letters, 8*, 441-454.

Wu, Hua-Wen, Zhen, Jin, & Zhang, Jing. (2020). Urban rail transit operation safety evaluation based on an improved CRITIC method and cloud model. *Journal of Rail Transport Planning & Management*, 100206. doi: https://doi.org/10.1016/j.jrtpm.2020.100206

Wu, J., Chu, J., Sun, J., Zhu, Q., & Liang, Liang. (2016). Extended secondary goal models for weights selection in DEA cross-efficiency evaluation. *Computers & Industrial Engineering, 93*, 143-151.

Wu, J., Sun, J., Song, M., & Liang, L. (2013). A ranking method for DMUs with interval data based on dea cross-efficiency evaluation and TOPSIS. *Journal of Systems Science and Systems Engineering, 22*. doi: 10.1007/s11518-013-5216-7

Wu, J., Sun, J., Zha, Yang, & L., Liang, L. (2011). Ranking approach of cross-efficiency based on improved TOPSIS technique. *Journal of Systems Engineering and Electronics, 22*(4), 604-608.

Yang, Z., & Wei, X. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross-efficiency DEA. *Journal of Cleaner Production, 209*, 439-450. doi: https://doi.org/10.1016/j.jclepro.2018.10.271

Zhao, M, Wang, X, Yu, J., Xue, L., & Yang, S. (2020). A construction schedule robustness measure based on improved prospect theory and the Copula-CRITIC method. *Applied Sciences, 10*(6), 2013.