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Interval Efficiency Assessment in Network Structure Based on Cross – Efficiency

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Abstract

As we know, in evaluating of DMUs some of them might be efficient, so ranking of them have a high significant. One of the ranking methods is cross-efficiency. Cross efficiency evaluation in data envelopment analysis (DEA) is a commonly used skill for ranking decision making units (DMUs). Since, many studies ignore the intra-organizational communication and consider DMUs as a black box. For significant of this subject, we applied cross-efficiency for network DMUs. However, In view of the fact that precise input and output data may not always be available in real world due to the existence of uncertainty, we have developed the model with interval data. the existing classical interval DEA method is not able to rank the DMUs, but can only classify them as efficient or inefficient , so this paper improve that. The proposed method can be used for each network that includes DMUs with two stages in production process. However, this paper is the first study that examined cross efficiency of DMUs in structure framework with interval data. the new approach enables us to ranking of first stage for n DMU and second stages of them. DMUs with the best rank can be used as benchmark for improving efficiency of other DMUs. Finally, We present Illustrate example with two steps for proposed model that can be develop for more than two steps.

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Introduction

Data envelopment analysis (DEA) is a linear and non-parametric programming technique for measuring the relative efficiency of decision making units (DMUs) with multiple inputs and multiple outputs[31]. The efficiency score of a DMU is describe as the maximum of the ratio of its weighted sum of outputs to its weighted sum of inputs and it cannot be greater than 1 any DMU. A DMU is efficient if its efficiency score is equal to 1, otherwise it is inefficient. Usually, efficient DMUs are assessed to perform better than inefficient DMUs Since its institution [32], various DEA models were suggested by other scholars. One of the most popular models is the cross-efficiency method, found by Sexton et al. (1986). It was developed as a DEA extension, and could be used to rank efficient DMUs by using cross-efficiency scores which were related to all DMUs. When cross-efficiency method is used, optimal weights computed by the DEA model are generally not unique, making cross-efficiency scores generated arbitrarily [23]. This set of weights may possibly develop some DMUs' ranks, while worsen those of the others, which might reduce the usefulness of cross-efficiency. To overcome this problem, Doyle & Green (1994) proposed two different types of models: aggressive and benevolent formulations, which represent two diametrically across from strategies. The idea of the aggressive or benevolent model is to recognize optimal weights that can not only maximize the efficiency of the DMU under evaluation but also maximize or minimize the average efficiency of other DMUs[11]. Liang et al. (2008) suggested a series of secondary objective functions to extend Doyle and Green's models. Each secondary objective function represents a kind of efficiency evaluation criterion, according to which the efficiency scores are compared from multiple different angles[29]. Wang & Chin (2010) proposed a neutral DEA model for cross- efficiency evaluation. They belief that in evaluation of the DMU should cover whether the weights could be as favorable as possible to itself, rather than how aggressive or benevolent the weights are to the others [6]. However, neither the traditional DEA model nor the cross-efficiency methods can directly handle interval data. Some theoretical research of DEA with interval data has been presented in the literature, for instance, Despotis & Smirlis (2002) and Jahanshahloo et al. (2004) suggested some new models in earlier research. These models can only classify the DMUs, but fail to rank them. In this study, A new approach is developed to address the issue of ranking all the DMUs.

The new approach, cross-efficiency method applied for two stages DMUs with interval data. So, 1)we consider lower bound in first stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one , also, 2)we consider upper bound in first stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one. Now, Calculate the average of two above numbers. The smaller average have a better rank, so rank the first stage of DMUs. Similarly as above, we rank the second stage of DMUs.

The rest of the paper is organized as follows. Section 2introduces the literature review of interval DEA models and cross efficiency. Section 3presents the new model for the cross-efficiency evaluation method with interval data for tow stage DMUs. Illustrative example for proposed method are presented in section 4. Conclusions and further remarks are given in Section 5.

Material and methods

Data envelopment analysis (DEA), originally proposed by Charnes, Cooper, and Rhodes (1978), is a non-parametric programming method for evaluating the efficiency of a group of homogenous decision making units (DMUs) with multiple inputs and multiple outputs [1, 2, 3, 4, 5] The main idea of DEA is to generate a set of optimal weights for each DMU in a set of DMUs to maximize the ratio of its sum of weighted outputs to its sum of weighted inputs while keeping all the DMU ratios at most 1. This maximum ratio is defined as the efficiency of the DMU under evaluation [6, 7].For its effectiveness in identifying the best-practice frontier and ranking the DMUs, DEA has been widely applied in benchmarking and efficiency evaluation of schools [8], hospitals [9], bank branches [10],and so on. However, the traditional self-evaluated DEA models with total weight flexibility may evaluate many DMUs as DEA efficient and cannot make any further distinction among these efficient DMUs. Therefore, one of the main shortfalls of the traditional DEA model (CCR or BCC model) is its inability to discriminate among DMUs that are all deemed efficient [6].

To improve the power of DEA in discriminating the efficient DMUs, Sexton, Silk man, and Hogan (1986) incorporated the concept of peer evaluation into DEA, and proposed the cross-efficiency evaluation method. In cross-efficiency evaluation, each DMU gets a self-evaluated efficiency obtained by its own most favorable weights and n-1 peer-evaluated efficiencies obtained using the other DMUs' most favorable weights. Then, all these efficiencies are aggregated into a final efficiency for the DMU under evaluation. There are at least three principal advantages of the cross-efficiency evaluation. Firstly, it almost always ranks the DMUs in a unique order [11].Secondly, it eliminates unrealistic weight schemes without incorporating weight restrictions [12]. Finally, it effectively distinguishes good and poor performers among the DMUs[13].Due to these advantages, cross-efficiency evaluation has been extensively applied in performance evaluation of nursing homes [14], preference ranking and project selection [15], selection of flexible manufacturing systems [16], judging suitable computer numerical control machines [17 , determining the efficient operators and measuring the labor assignment in cellular manufacturing systems [18], performance ranking of countries in the Olympic Games [19], supplier selection in public procurement [20], portfolio selection in the Korean stock market [21], energy efficiency evaluation for airlines [22], and so on.

In spite of its advantages and wide applications, there are still some shortcomings in DEA cross-efficiency evaluation. For example, the non-uniqueness of the DEA optimal weights may reduce the usefulness of cross-efficiency evaluation[14]. Specifically, the optimal weights generated from the traditional models (CCR or BCC model) are generally not unique. Thus, the cross-efficiency scores for the DMUs are somewhat arbitrarily generated [23]. To solve this problem, Sexton, Silk man, and Hogan (1986) suggested incorporating secondary goals into cross-efficiency evaluation. Based on this idea, many secondary goal models have been proposed [14]. For example, Jahanshahloo, Hosseinzadeh Lofti, Yafari, and Maddahi (2011) used selecting symmetric weights asa secondary goal in cross-efficiency evaluation [24]. Wu, Sun, Zha, and Liang (2011) and Contreras (2012) proposed weights selecting models in which the secondary goal is to optimize the ranking position of the DMU under evaluation[25, 26]. Lim (2012) proposed models using the minimization (or maximization) of the best (or worst) cross efficiencies of peer DMUs as the secondary goal [27]. Maddahi, Jahanshahloo, Hosseinzadeh Lotfi, and Ebrahimnejad (2014) suggested optimizing proportional weights as a secondary goal in DEA cross-efficiency evaluation[28]. Among the secondary goal models, the most commonly used are the benevolent and aggressive models [11] The main idea of the benevolent(aggressive) model is to select for each DMU a set of optimal weights that makes the other DMUs' cross efficiencies as large (small) as possible while keeping its own efficiency at its predetermined optimal level (CCR efficiency). Liang, Wu, Cook, and Zhu (2008) extended the model of Doyle and Green (1994) by introducing various secondary objective functions. Each new secondary objective function represents an efficiency evaluation criterion and can be applied in different practical case scenarios [29]. They also proposed alternative secondary goal models, but they replaced the target efficiency of each DMU from the ideal point 1 to CCR efficiency.

Another main drawback of cross-efficiency evaluation is that the generated average cross-efficiency scores for the DMUs are not Pareto optimal [25], which means it may be difficult to get all the DMUs to accept these cross-efficiency evaluation results. To overcome this drawback, some scholars have eliminated the average assumption for determining the ultimate cross-efficiency scores by using a common weights evaluation method. For example, Wu, Liang, and Yang (2009) considered the DMUs as players in a cooperative game, in which the characteristic function values of coalitions are defined to compute the Shapley value of each DMU, and the common weights associated with the imputation of the Shapley values are used to determine the ultimate cross-efficiencies scores [30].

Interval DEA Models

Assume there are n DMUs with two stages to be evaluated. Each DMU produces s outputs using min puts. Input i and output r for DMU$_j$ are denoted as x_{ij} and y_{rj} , respectively. The input and output data x_{ij} and y_{rj} are not assumed to be exactly obtained because of uncertainty. Only their bounded interval $[x_{ij}^l, x_{ij}^u]$ and $[y_{rj}^l, y_{rj}^u]$ with $x_{ij}^l > 0$ and $y_{rj}^l > 0$, are known. In order to measure the efficiencies of the DMUs with uncertain inputs and outputs data, Despotis & Smirlis (2002) proposed a pair of linear problem models to generate the lower and upper bounds of the efficiency for each DMU. However, Wang & Yang (2005) pointed out that the efficiencies calculated by the models in Despotis & Smirlis (2002) are lack of the comparability. Because different production frontiers have been adopted in the process of efficiency measurement. In order to deal with such an uncertain situation, the CCR-DEA model can be defined as:

$$\max E_{dd} = \frac{\sum_{r=1}^{s} \mu_{rd}[y_{rd}^{l}, y_{rd}^{u}]}{\sum_{i=1}^{m} \omega_{id}[x_{id}^{l}, x_{id}^{u}]}$$
$$s.t \quad \frac{\sum_{r=1}^{s} \mu_{rd}[y_{rj}^{l}, y_{rj}^{u}]}{\sum_{i=1}^{m} \omega_{id}[x_{ij}^{l}, x_{ij}^{u}]} \le 1, \; j = 1,\dots,n \qquad (1)$$
$$\omega_{id}, \mu_{rd} \ge \varepsilon \quad \forall id, rd$$

In order to calculate the lower and upper bound of the efficiency of DMUd , Wang et al.(2005) proposed the following two linear formulations to generate the bounded interval $[E_{dd}^{l}, E_{dd}^{u}]$.

$$\max E_{dd}^{l} = \sum_{r=1}^{s} \mu_{rd} y_{rd}^{l}$$
$$s.t \quad \sum_{i=1}^{m} \omega_{id} x_{ij}^{l} - \sum_{r=1}^{s} \mu_{rd} y_{rj}^{u} \ge 0 \qquad j = 1,\dots,n \qquad (2)$$
$$\sum_{i=1}^{m} \omega_{id} x_{id}^{u} = 1$$
$$\omega_{id}, \mu_{rd} \ge \varepsilon \quad \forall id, rd$$

In the above two models, DMU_d is the DMU under evaluation, w_{id} and μ_{rd} are the weights assigned to the inputs and outputs respectively. E_{dd}^{l} is the lower efficiency for DMU_d, E_{dd}^{u} is the upper efficiency. ε is the non-Archimedean infinitesimal. Considering model (3) and (4), it is clear that $E_{dd}^{l} \le E_{dd}^{u}$ DMUd , can be considered as DEA efficient if its best possible upper efficiency $E_{dd}^{u*} = 1$, or it is inefficient if $E_{dd}^{u*} < 1$:

$$\max E_{dd}^{u} = \sum_{r=1}^{s} \mu_{rd} y_{rd}^{u}$$
$$s.t \quad \sum_{i=1}^{m} \omega_{id} x_{ij}^{l} - \sum_{r=1}^{s} \mu_{rd} y_{rj}^{u} \ge 0 \qquad j = 1,\dots,n \qquad (3)$$
$$\sum_{i=1}^{m} \omega_{id} x_{id}^{l} = 1$$
$$\omega_{id}, \mu_{rd} \ge \varepsilon \quad \forall id, rd$$

Cross-efficiency Evaluation Method with Interval Data

In fact, the DMU under evaluation heavily weighs the inputs and outputs of a few favorable DMUs and ignores those of the others in order to maximize its own efficiency ratio. Moreover, optimal weights calculated with the models (2)and (3) are generally not unique. The different calculation software may produce different optimal weights, making the generated cross-efficiency scores arbitrary. Therefore, an interval cross-efficiency evaluation method is used to overcome this shortcoming. The cross-efficiency method in DEA uses peer evaluation instead of self-evaluation. It can define the cross-efficiency scores of DMUs on their interval (Wang & Yang 2005).

In the traditional cross-efficiency method, some choice of weights may lead to a lower cross-efficiency for some DMUs or a higher cross-efficiency for the others. So we introduce a secondary objective function to reduce the ambiguity. Model (4) can calculate the low cross-efficiency values for interval data.

$$
\begin{aligned}
\max \; & \sum_{r=1}^{s} \mu_{rd} y_{rj}^{l} \\
s.t \quad & \sum_{i=1}^{m} \omega_{id} x_{ij}^{l} - \sum_{r=1}^{s} \mu_{rd} y_{rj}^{u} \geq 0 \qquad j = 1,\dots,n \\
& \sum_{i=1}^{m} \omega_{id} x_{ij}^{u} = 1 \\
& E_{dd}^{l} \times \sum_{i=1}^{m} \omega_{id} x_{id}^{u} - \sum_{r=1}^{s} \mu_{rd} y_{rd}^{l} = 0 \\
& \omega_{id}, \mu_{rd} \geq \varepsilon \qquad \forall id, rd
\end{aligned} \tag{4}
$$

Similarly, the large cross-efficiency values of interval data can be computed with model (5).

$$
\begin{aligned}
\max \; & \sum_{r=1}^{s} \mu_{rd} y_{rj}^{u} \\
s.t \quad & \sum_{i=1}^{m} \omega_{id} x_{ij}^{l} - \sum_{r=1}^{s} \mu_{rd} y_{rj}^{u} \geq 0 \qquad j = 1,\dots,n \\
& \sum_{i=1}^{m} \omega_{id} x_{ij}^{l} = 1 \\
& E_{dd}^{u} \times \sum_{i=1}^{m} \omega_{id} x_{id}^{l} - \sum_{r=1}^{s} \mu_{rd} y_{rd}^{u} = 0 \\
& \omega_{id}, \mu_{rd} \geq \varepsilon \qquad \forall id, rd
\end{aligned} \tag{5}
$$

After all cross-efficiency values are computed, an efficiency matrix (CEM) can be constructed as shown in Table 1.For each column, $[E_{dj}^{l}, E_{dj}^{u}]$ represents the lower and upper limits of the cross-efficiency scores of DMUj by using the weights that DMU_d (j=1,…,n) has chosen. The elements on the main diagonal are the limits obtained through self-evaluation which can be calculated by using models (2) and (3).

Table 1. A generalized cross-efficiency matrix (CEM)

Rating	Rated DMU_j				
DMU_d	1	2	3	…	n
1	$[E_{11}^{l}, E_{11}^{u}]$	$[E_{12}^{l}, E_{12}^{u}]$	$[E_{13}^{l}, E_{13}^{u}]$	…	$[E_{1n}^{l}, E_{1n}^{u}]$
2	$[E_{21}^{l}, E_{21}^{u}]$	$[E_{22}^{l}, E_{22}^{u}]$	$[E_{23}^{l}, E_{23}^{u}]$	…	$[E_{2n}^{l}, E_{2n}^{u}]$
3	$[E_{31}^{l}, E_{31}^{u}]$	$[E_{32}^{l}, E_{32}^{u}]$	$[E_{33}^{l}, E_{33}^{u}]$	…	$[E_{3n}^{l}, E_{3n}^{u}]$
.	.	.	.		.
.	.	.	.	…	.
.	.	.	.		.
N	$[E_{n1}^{l}, E_{n1}^{u}]$	$[E_{n2}^{l}, E_{n2}^{u}]$	$[E_{n3}^{l}, E_{n3}^{u}]$	…	$[E_{nn}^{l}, E_{nn}^{u}]$

Results

Proposed model has shown in figure 1., according to it, cross-efficiency method applied for two stages DMUs with interval data. So, 1)we consider lower bound in first stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one , also, 2)we consider upper bound in first stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one. Now, calculate the average of two above numbers. The smaller average has a better rank, so rank the first stage of DMUs.

Similarly as above, for second stage of DMUs 1)we consider lower bound in second stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one , also, 2)we consider upper bound in second stage of whole DMUs , Forming Crossover n*n table and then Compute the average elements of each row for DMU and then calculate distance of it from one. Now, Calculate the average of two above numbers. The smaller average have a better rank, so rank the second stage of DMUs.

This approach can be used to comparison of DMUs with two stages. The proposed model Provide a solution to increase the efficiency of each DMU and Improving each stage of every DMU with the best performance available among DMUs in that stage. In other words, our model is a benchmark to DMUs with two stages. In order to prove the effectiveness of the proposed approach, numerical examples are illustrated finally. We considered n DMUs with two stages and interval data. Then calculated cross efficiency for lower and upper bounds of first stages separately, and for lower and upper bounds of second stages. Finally, the new approach enables us to ranking of first stage for n DMU and second stages of them. DMUs with the best rank can be used as benchmark for improving efficiency of other DMUs.

The proposed method can be used for each network that include DMUs with two stages in production process. However, this paper is the first study that examined cross efficiency of DMUs in structure framework with interval data.

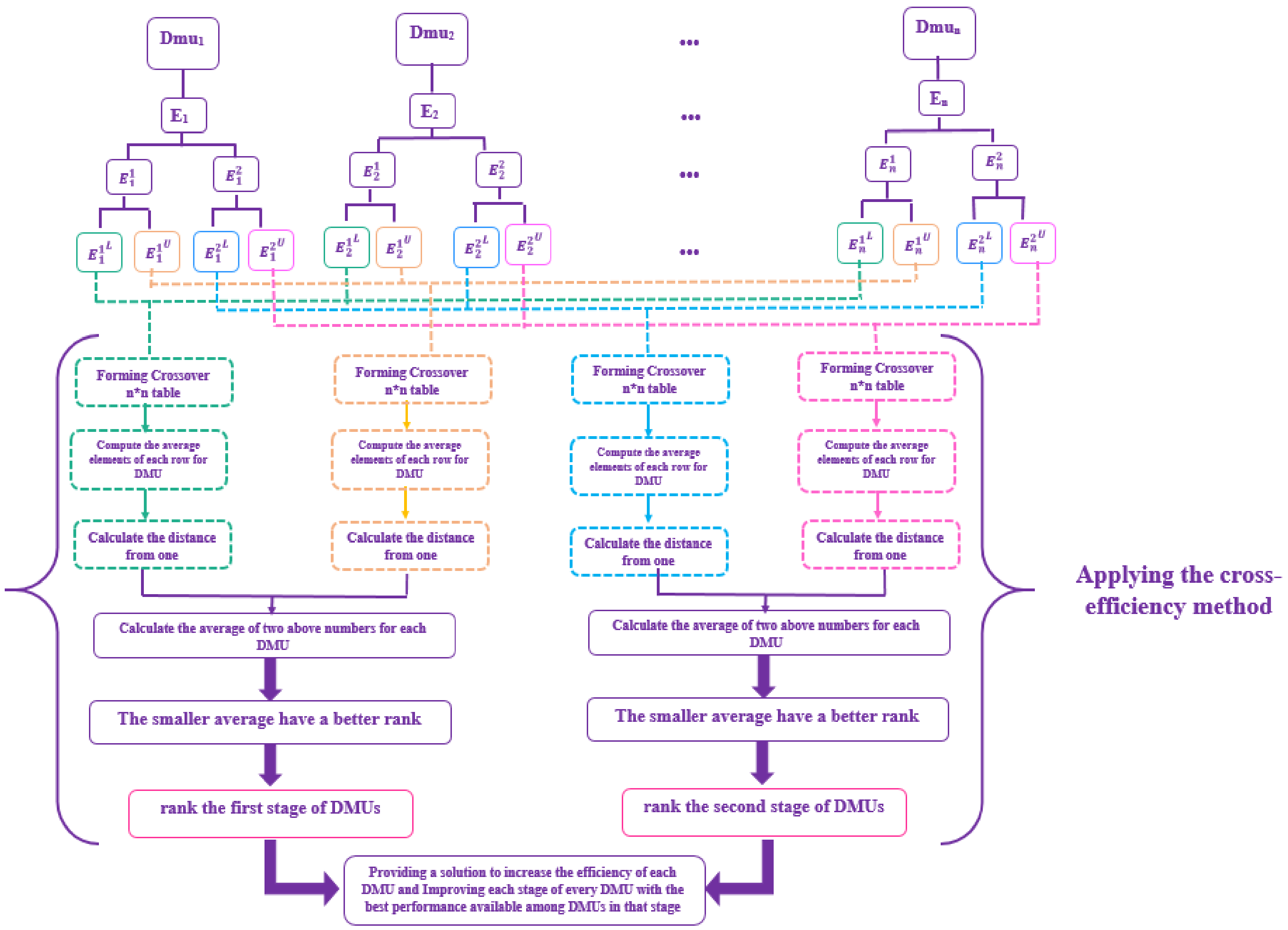

Fig 1. Proposed Method

Discussion

Assume there are n DMUs with two stages to be evaluated. Each DMU produces s outputs using min puts. Input r and output k for DMUj are denoted as x_{ri} and y_{ki} , respectively. The input and output data x_{ri} and y_{ki} are not assumed to be exactly obtained because of uncertainty. Only their bounded interval $x_{ri} = \left[x_{ri}{}^{l}, x_{ri}{}^{u} \right]$, r=1,…,m and $y_{ki} = \left[y_{ki}{}^{l}, y_{ki}{}^{u} \right]$, k=1,…,s with $x_{ri}^{l} > 0$ and $y_{ki}^{l} > 0$, are known.

Efficiency score of DMUs is interval and have lower and upper bound.

Table 2. and table 3. shows lower and upper bound of each DMUs with two stages, respectively.

Table 2. Lower bound of first and second stage for DMUs

		I1	I2	O1	O2
First stage	DMU1	4	5	2	3
	DMU2	7	6	1	2
	DMU3	3	1	7	1
Second stage	DMU1	2	5	3	8
	DMU2	1	2	1	2
	DMU3	7	5	7	1

Table 3. upper bound of first and second stage for DMUs

		I1	I2	O1	O2
First stage	DMU1	6	6	4	6
	DMU2	8	9	3	4
	DMU3	4	4	9	2
Second stage	DMU1	5	6	5	9
	DMU2	3	4	3	3
	DMU3	9	6	8	4

First, we calculate CCR input oriented model for lower and upper bounds of first and second stage for DMUs. Results bring to table 4. and then table 5. And table 6. shows computing cross-efficiency for lower and upper bounds of DMUs with two stages, respectively.

Table 4. CCR input oriented model for lower and upper bounds of first and second stage for DMUs

		CCR_{Lower}	CCR_{Upper}
First stage	DMU1	0.128788	0.311355
	DMU2	0.055556	0.174699
	DMU3	0.514706	1
Second stage	DMU1	0.333333	0.625
	DMU2	0.125	0.75
	DMU3	0.243056	0.353982

Table 5.cross-efficiency for lower bounds of first stage for DMUs

	First stage			
First stage		DMU1	DMU2	DMU3
	DMU1	-	0.32	0.166667
	DMU2	0.083333	-	0.164835
	DMU3	0.113032	0.2	-

Table 6.cross-efficiency for lower bounds of second stage for DMUs

	Second stage			
		DMU1	DMU2	DMU3
Second stage	DMU1	-	0.083333	0.243056
	DMU2	0.15	-	0.243056
	DMU3	0.15	0.083333	-

Table 7.cross-efficiency for upper bounds of first and second stage for DMUs

	First stage			
		DMU1	DMU2	DMU3
First stage	DMU1	-	1	1
	DMU2	1	-	0.810811
	DMU3	0.34	1	-

Table 8.cross-efficiency for upper bounds of second stage for DMUs

	second stage			
		DMU1	DMU2	DMU3
Second stage	DMU1	-	0.75	0.353982
	DMU2	0.625	-	0.353982
	DMU3	0.625	0.75	-

For ranking of DMUs we Compute the average elements of lower bound and upper bound for each DMUs and then calculate distance of them from one. Now, Calculate the average of two numbers for each DMUs in first stage and then second stage. The smaller average have a better rank in each stage between all DMUs, so rank DMUs. The results are shown in table 9.

Table 9. Ranking of DMUs for first and second stages

		A L	A U	1-A L	1-A U	A
First stage	DMU1	0.151074	0.158601	0.848926	0.841399	0.845162
	DMU2	0.151153	0.158689	0.848847	0.841311	0.845079
	DMU3	0.160068	0.168594	0.839932	0.831406	0.835669
second stage	DMU1	0.169408	0.178971	0.830592	0.821029	0.82581
	DMU2	0.155241	0.163231	0.844759	0.836769	0.840764
	DMU3	0.151074	0.158601	0.848926	0.841399	0.845162

Conclusions

In many practical examples, the outputs and inputs of DMUs are not known exactly, for example, given as intervals. However, the existing classical interval DEA method is not able to rank the DMUs, but can only classify them as efficient or inefficient. In view of the drawbacks, we put forward our approach. Then new model is proposed. This approach can be used to comparison of DMUs with two stages. The proposed model Provide a solution to increase the efficiency of each DMU and Improving each stage of every DMU with the best performance available among DMUs in that stage. In other words, our model is a benchmark to DMUs with two stages. In order to prove the effectiveness of the proposed approach, numerical examples are illustrated finally. We considered n DMUs with two stages and interval data. Then calculated cross efficiency for lower and upper bounds of first stages separately, and for lower and upper bounds of second stages. Finally, the new approach enables us to ranking of first stage for n DMU and second stages of them. DMUs with the best rank can be used as benchmark for improving efficiency of other DMUs. Through the example, we can conclude that the proposed method is convenient to solve multiple attribute problems with interval data. It can make full use of the original data information, and provide complete and fair results for all DMUs. The method in this paper can be further expanded in the future.

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