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Determination of Right/Left return to Scale in Two-Stage Processes Based on Dual Simplex

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Abstract

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As a non-parametric method of relative efficient measurement of a group of decision making units (DMU_s) , Data Envelopment Analysis (DEA) is one of the most important tools in efficiency computation. One of the main concerns dealt with in DEA is dealing with return to scale in two-stage processes in which, produced outputs of the first stage inputs are used as inputs for the second stage. The outputs of the first stage are considered as the intermediate products. Therefore, the second stage uses these intermediate products for producing the outputs of the same stage. Based on this construction, the total process can be analyzed for efficiency production from two sub-processes. In this paper, a new model is proposed that eliminates the defections of the previous models and is used to determine the right and left return to scale in two-stage processes of decision making units.

Keywords: Efficiency, Two-stage processes, Return to scale.

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1. Introduction

Nowadays, units' calculation and comparison are one of the most important fields in economy that act cooperatively in the same field. Charnes et al. [1] have proposed a practical model to calculate and compare the efficiency of decision making that could calculate the efficiency of the units with various inputs and outputs. During 1970s, the field has attracted many attention and been developed to a great extent and different models have been proposed by experts in different areas. One of those areas is multi-stage decision making units. For example, Charnes et al. [2] faced a problem similar to a two-stage decision making, in which two-stage method must be used for army employment. Later on, Schinnar et al. [3], Sexton and Lewise [4], Chen and Zhu [5], and Liang et al. [6] applied two-stage DEA in mental health care, baseball, information technology, and evaluation the performance of supply chain, respectively. So far, various scientists have studied this field. For instance, Izadikhah and Saen [7], Kalhor and Kazemi matin [8]. Kao and Hwang [9] have proposed a different model by which the efficiency of the whole systems is decomposed into the efficiency of two systems. This model has been proposed based on the assumption of return to scale. Chen et al. [10] have proposed a model similar to Kao and Hwang [9], in which constant return to scale and variable return to scale were studied. Later, Chen et al. [11] and Kao and Hwang in [12] developed their proposed models.

Despotis et al. [13] proposed a new definition of system efficiency in twostage process. It was based on weak link in supply chain, maximum flow algorithm, and minimal cut theorem for networks. Hatami-Marbini et al. [14] and Alirezaee et al. [15] introduced new approaches in return to scale in data envelopment analysis.

In this paper, it is purposed to introduce a new model for two-stage DEA. Considering both the importance of return to scale and the defects of the other mentioned proposed models in two-stage DEA, return to scale of two-stage model is discussed by the use of right and left return to scale that was studied by Golany and Yu [16] and Hadjicostas and Soteriou [17]. This study is done using the proposals of Zarepisheh and Soleimanidamaneh [18]. Other parts of this paper are as follows. Section 2 is devoted to literature review of two-stage processes. The organization of the paper is in the following way. Our recommended model is presented in section 3. In the section 4, return to scale in two-stage DEA is calculated with the proposed model. Finally, a numerical example is solved in section 5 and the section 6 is devoted to conclusions.

2. Review

Consider n decision making units that each $DMU_j (j \in J = \{1, ..., n\})$ generates the q outputs of $z_{pj}(p = 1, ..., q)$ using m inputs of x_{ij} ($i = 1, ..., m$) and then the obtained q outputs would be the inputs for generating s outputs of y_{ri} ($r = 1, ..., s$). Hwang and Kao [19] have used two-stage DEA of Seiford and Zhu [20] to measure the total efficiency as well as the efficiency of the first and the second stage. Also, they have introduced the efficiency of the first and the second stage by assuming constant return to scale as follows:

$$
E_o^1 = \max \sum_{p=1}^{q} w_p z_{po} / \sum_{i=1}^{m} v_i x_{io}
$$

s.t.
$$
\sum_{p=1}^{q} w_p z_{pj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,
$$

j = 1, ..., n,

$$
w_p, v_i \ge \varepsilon, p = 1, ..., q; i = 1, ..., m,
$$
 (1)

And the efficiency score of the second stage has been introduced as follows: E_o^2 = max $\sum_{r=1}^{s} u_r y_{ro} / \sum_{p=1}^{q} w_p z_{po}$ $\sqrt{\Sigma_{\rm p=1}^{\rm q}}$ s. t. $\sum_{r=1}^{s} u_r y_{rj} / \sum_{p=1}^{q} w_p z_{pj}$ $\sqrt{\Sigma_{\rm p=1}^{\rm q} w_{\rm p} z_{\rm pj}} \leq 1$,

$$
j = 1, ..., n,
$$

\n
$$
u_r, w_p \ge \varepsilon, r = 1, ..., s; \ p = 1, ..., q.
$$
\n(2)

In which, ε was a small non-Archimedean number and w_n , v_i and u_r were weight of inputs, intermediate products and outputs, respectively. The efficiency of each stage in models (1) and (2) were calculated independently. Kao and Hwang [9] have proposed their new model as a relational model by using intermediate products and assuming constant return to scale and the equality of weights in intermediate products of data envelopment. The overall efficiency score of the relational model was calculated as follows:

$$
E_o = \max \sum_{r=1}^{S} u_r y_{ro} / \sum_{i=1}^{m} v_i x_{io}
$$

s.t. $\sum_{r=1}^{S} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \le 1$,
 $j = 1, ..., n$,
 $\sum_{p=1}^{q} w_p z_{pj} / \sum_{i=1}^{m} v_i x_{ij} \le 1$,
 $j = 1, ..., n$,
 $\sum_{r=1}^{S} u_r y_{rj} / \sum_{p=1}^{q} w_p z_{pj} \le 1$, $j = 1, ..., n$,
 $u_r, v_i \le v_p \ge \varepsilon$, $r = 1, ..., s$;
 $i = 1, ..., m$; $p = 1, ..., q$.

The set of limitations in model (3) were in fact the set of limitations of models (1) and (2).

So, the overall efficiency was $E_o = E_o^1 \times$ E_0^2 . Indeed, in their relational model, the overall efficiency score was the multiplication of the first and the second stages. But, as multiplication of two numbers between 0 and 1 leads to a smaller one, the result was not a true representation of efficiency score. Moreover, in Hwang and Kao independent model [19], two models are independently solved and this is not logical for the decision making units with a common decision maker. As the proposed model by Kao and Hwang [9] was in the form of constant return to scale, Chen et al. [10] introduced their model in form of constant return to scale and variable return to scale. Considering

the complex computation of this model and the large number of variables and constants, calculating the return to scale of decision making units is a difficult task. In the next section, a new model is proposed that is less complex.

3. Proposed model

According to what mentioned above, a new model is proposed here to calculate the efficiency of decision making units with different stages. Similar to the dependent model introduced by Kao Hwang [9], in this model, intermediate production is considered equal without taking the roles of the inputs and outputs into account and is entered into the model as one intermediate production. In this paper it is tried to calculate the efficiency of each stage simultaneously by considering the roles of the input and the output. The envelopment form of the model based on the output oriented is as follows:

max
$$
\alpha
$$

\ns.t. $\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io}, i = 1, ..., m,$
\n $\sum_{j=1}^{n} \lambda_j z_{pj} \ge \alpha z_{po}, p = 1, ..., q,$
\n $\sum_{j=1}^{n} \lambda_j = 1,$
\n $\sum_{j=1}^{n} \mu_j z_{pj} \le z_{po},$
\n $p = 1, ..., q,$
\n $\sum_{j=1}^{n} \mu_j y_{rj} \ge \alpha y_{ro}, r = 1, ..., s,$
\n $\sum_{j=1}^{n} \mu_j = 1,$
\n $\lambda_j \ge 0, \mu_j \ge 0, j = 1, ..., n.$

Considering the corresponding variables of t_p , u_r , w_p and v_i with constraints of model (4), the dual model is presented as follows:

Min
$$
\sum_{i=1}^{m} v_i x_{io} + \sum_{p=1}^{q} w_p z_{po} + \hat{u} + \bar{u}
$$

\n*S.t.* $\sum_{i=1}^{m} v_i x_{ij} - \sum_{p=1}^{q} w_p z_{pj} + \hat{u} \ge 0$,
\n*j* = 1, ..., *n*,
\n $\sum_{p=1}^{q} t_p z_{pj} - \sum_{r=1}^{s} u_r y_{rj} - \bar{u} \ge 0$,
\n*j* = 1, ..., *n*,
\n $\sum_{p=1}^{q} w_p z_{po} + \sum_{r=1}^{s} u_r y_{ro} = 1$,
\n $u_r \ge 0, v_i \ge 0, w_p \ge 0, t_p \ge 0$,

 $r = 1, ..., s$, $i = 1, ..., m$, $p = 1, ..., q$.

4. Return to scale in two- stage DEA

In this section, it is tried to develop the proposed model using the presented suggestions by Zarepisheh and Soleimanidamaneh [18].

In this model,

$$
X_j = (x_{1j}, x_{2j}, ..., x_{mj}), Z_j
$$

= (z_{1j}, z_{2j}, ..., z_{qj}), and Y_j
= (y_{1j}, y_{2j}, ..., y_{sj})

are defined as the vectors of input, intermediate and output of DMU_j , respectively. Also,

$$
X = [x_1, x_2, ..., x_n], Z
$$

= [z₁, z₂, ..., z_n], and Y
= [y₁, y₂, ..., y_n]

are $m \times n$, $q \times n$, and $s \times n$ matrices of inputs, intermediate productions and outputs, respectively. According to the proposed model, production possibility is defined as follows:

Where, o and e are two vectors with zero and one component, respectively. Based on the proposed model, the efficiency of the decision making unit, like DMU_0 in output oriented, is evaluated as follows:

Definition 1. DMU_0 is defined as the technical efficient unit in output oriented if $\alpha^* = 1$ (where '*' shows optimality). For the inefficient units, according to Banker et al. [21], they can be used in RTS evaluation by being projected in the efficient frontier. Here, the projection points are defined as follows:

$$
\hat{X}_o = X_o
$$
, $\hat{Z}_o = \alpha^* Z_o$, $\hat{Y}_o = \alpha^* Y_o$

As a result, in order to determine constant return to scale, (X_o, Z_o, Y_o) must be replaced by $(\hat{X}_0, \hat{Z}_0, \hat{Y}_0)$; therefore, to determine RTS of the proposed model, the following limits can be used (see Hadjicostas, Soteriou [17]).

$$
\rho_0^+ = \lim_{\beta \to 1^+} \frac{\alpha(\beta) - 1}{\beta - 1},
$$

\n
$$
\rho_0^- = \lim_{\beta \to 1^-} \frac{\alpha(\beta) - 1}{\beta - 1}
$$
\n(6)

The function $\alpha(\beta)$ corresponding to DMU_o is

 $\alpha(\beta) = \max{\{\alpha | (\beta X_o, \alpha Z_o, \alpha Y_o) \in T_v\}}$ } (7)

Notification 1. According to model (4) and α definition, $\alpha(\beta)$ can be supposed as the optimal value of model (4) in which βX_o is placed in input as a substitution of X_o . By accepting this issue and model (7), it is clear that if $\beta = 1$, the researcher wants to solve model (4) for vectors of the inputs and outputs (X_o, Z_o, Y_o) . Therefore, considering the projection points $(\hat{X}_0, \hat{Z}_0, \hat{Y}_0)$ and the fact that α is optimal for model (4) along with $(X_o, \alpha Z_o, \alpha Y_o)$ vector has been projected on the efficient frontier, it can be concluded that $\alpha(1) = 1$.

Assumption 1. As mentioned in Hadjicostas and Soteriou [17], $\eta \in$ $[0,1), \gamma \ge 0$ exists such that $(\eta X_o, \gamma Z_o, \gamma Y_o) \in T_{\nu}$.

It means that reduction of input s with the same relation from DMU_0 in T_v is possible.

Lemma 1. If $\alpha(1) = 1, \rho_o^+$ exists and is finite.

Proof: To prove the following assumption, there is: Assumption 1: convexity $if (x, y) \in T, (x', y') \in T, \implies (\lambda x + \lambda y)$ $(1 - \lambda)x', \lambda y + (1 - \lambda)y' \in T$

Assumption 2: Monotonicity $if (x, y) \in T, x' \geq x, 0_s \leq y' \leq y$ $for (x', y') \in R^m \times R^s \implies (x', y') \in T$

Assumption 3: Inclusion of observations $n \in N^+$ exists and n , DMU_s are exist too such that for each $j = 1, ..., n$ the observation of $(x_j, y_j) \in T$ are related to DMU_j .

Assumption 4: Minimum extrapolation If a set preserves the possibility of T' production of assumptions 1, 2, and 3 (for n observations $((x_j, y_j) \cdot j = 1, ..., n)$), then $T \subseteq T'$. Now, if 3 and 4 are appointed, ρ_o^+ exists and is finite.

Lemma 2: If $\alpha(1) = 1$ and assumption 1 is determined, ρ_{o}^- exists and is finite.

Proof: If $\alpha(1) = 1$ and assumption 1 is determined, the following limits exist and are finite.

$$
\rho_o^+ = \lim_{\beta \to 1^+} \frac{\alpha(\beta) - 1}{\beta - 1}, \rho_o^- = \lim_{\beta \to 1^-} \frac{\alpha(\beta) - 1}{\beta - 1}
$$

Here, assumption 1 is determined. The proposed model is convex because it is the products of two conceive sets.

Definition 2: RTS in DMU_o is increasing from right (constant, decreasing) if $\rho_0^+ > 1 (= 1, < 1)$ and is decreasing if $\rho_0^- > 1 (= 1, 0.1).$

If assumption 1 is not determined, it means that reduction with the same proportion of DMU_0 inputs in T_v is impossible. In this situation, \ddot{DMU}_o contraction cannot be discussed and, consequently, RTS cannot be defined for left.

Now, in order to calculate ρ_o^+ and ρ୭ ିaccording to Hadjicostas and Soteriou [17], we can act as follows.

First model (4) must be solved. Then, ρ_o^+ and ρ_0^- can be calculated after the linear program model has been solved.

$$
\rho_o^+ = 1 - \alpha^*
$$

\n
$$
\alpha^* = \max \hat{u} + \bar{u}
$$

\n*S. t.*
$$
\sum_{i=1}^m v_i x_{ij} - \sum_{p=1}^q w_p z_{pj} + \hat{u} \ge 0,
$$

\n*j* = 1, ..., *n*,
\n
$$
\sum_{p=1}^q t_p z_{pj} - \sum_{r=1}^s u_r y_{rj} - \bar{u} \ge 0,
$$

\n*j* = 1, ..., *n*,
\n
$$
\sum_{p=1}^q w_p \hat{z}_{po} + \sum_{r=1}^s u_r \hat{y}_{ro} = 1,
$$

\n
$$
\hat{u} + \bar{u} + \sum_{i=1}^m v_i \hat{x}_{io} + \sum_{p=1}^q w_p \hat{z}_{po} = 1,
$$

\n
$$
\hat{u} \ge 0, \bar{u} \ge 0.
$$
 (8)

And
$$
\rho_0^- = 1 - \beta^*
$$
 is defined as follows:
\n $\beta^* = Min \quad \hat{u} + \bar{u}$
\n*S. t.* $\sum_{i=1}^m v_i x_{ij} - \sum_{p=1}^q w_p z_{pj} + \hat{u} \ge 0$,
\n*j* = 1, ..., *n*,
\n $\sum_{p=1}^q t_p z_{pj} - \sum_{r=1}^s u_r y_{rj} - \bar{u} \ge 0$,
\n*j* = 1, ..., *n*,
\n $\sum_{p=1}^q w_p \hat{z}_{po} + \sum_{r=1}^s u_r \hat{y}_{ro} = 1$,
\n $\hat{u} + \bar{u} + \sum_{i=1}^m v_i \hat{x}_{io} + \sum_{p=1}^q w_p \hat{z}_{po} = 1$,
\n $\hat{u} \ge 0, \bar{u} \ge 0$.

 \hat{x}_0 , \hat{z}_0 , and \hat{y}_0 were introduced before.

Theorem 1: If $\alpha(1) = 1$ and matrix B is an optimal base for model (4) as:

$$
\begin{pmatrix} x_0 \\ Z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 1 \end{pmatrix}, B^{-1} \begin{pmatrix} x_0 \\ Z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 0 \end{pmatrix} \ge 0, (10)
$$

$$
\text{So,}\rho_{\text{o}}^{+} = C_{\text{B}}\text{B}^{-1} \begin{pmatrix} x_{0} \\ Z_{\text{o}} \\ 0_{q \times 1} \\ 0 \\ 0 \end{pmatrix} \text{ in that } C_{\text{B}}
$$

shows the target function coefficient vector corresponding to basis B in model (4) .

Proof: Put

$$
\bar{b} = B^{-1}\left(\begin{array}{c} x_o \\ Z_o \\ 0_{s\times 1} \\ 0_{q\times 1} \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0\end{array}\right),
$$

$$
\hat{b} = B^{-1}\left(\begin{array}{c} x_o \\ 0_{s\times 1} \\ 0_{q\times 1} \\ 0_{q\times 1} \\ 0 \\ 0 \\ 0\end{array}\right),
$$

Define
$$
\overline{\delta} = \infty
$$
 if $\hat{b} \ge 0$; otherwise,
\n $\overline{\delta} = \min \left\{ \frac{-\overline{b}_i}{\hat{b}_i} : i \in \{1, ..., m + s + 1\}, \hat{b}_i < 0 \right\}$

Because $(\bar{b}, \hat{b}) \ge 0$, we have $\bar{\delta} > 0, \bar{b} + \hat{c}$ $\delta \hat{b} \geq 0$.

For each
$$
\delta \in (0, \delta)
$$
 and
\n
$$
B^{-1} \begin{pmatrix}\n(1 + \delta)x_0 \\
(1 + \delta)Z_0 \\
0_{s \times 1} \\
0_{q \times 1} \\
1\n\end{pmatrix} \ge 0,
$$

for each $\delta \in (0, \overline{\delta})$, it means that B is an optimal basis for model (4) that corresponds to $((1 + \delta)x_0, (1 + \delta)Z_0, Y_0)$. Optimality of basis is separated from RHS vector and, as a result, B is the optimal basis for model (4) that is corresponding to $((1 + \delta)x_0, (1 +$ δ)Z₀, Y₀). Put $\beta = 1 + \delta$, $\overline{\beta} = 1 + \overline{\delta}$. According to notification 1, for $\beta \in$ $(1, \overline{\beta})$, it is concluded that

$$
\alpha(\beta) = C_B B^{-1} \begin{pmatrix} \beta x_0 \\ \beta Z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 1 \end{pmatrix}.
$$

The equality of $\alpha(1) = 1$ leads to $C_B B^{-1}$ λ \overline{a} I $\check{\mathbf{x}}_0$ Z_0 $0_{\rm sx1}$ $0_{q\times 1}$ 1 $1 \frac{7}{1}$ ⎟ ⎟ ⎞ $= 1$, so: $\alpha(\beta) = C_B B^{-1}$ ⎝ \parallel I $(1 + \beta - 1)x_0$ $(1 + \beta - 1)Z_0$ $0_{s\times 1}$ $0_{q\times 1}$ 1 $1 /$ $\overline{}$ ⎞ $=\mathcal{C}_{\mathrm{B}}\mathrm{B}^{-1}$ λ \lfloor I x_0 Z_0 $0_{s\times 1}$ $0_{q\times 1}$ 1 $1 \frac{7}{1}$ $\overline{}$ ⎞ + $(\beta - 1)C_B B^{-1}$ $\left(\begin{array}{cc} 0 \end{array} \right)$ I x_0 Z_0 $0_{s\times 1}$ $0_{q\times 1}$ 0 ⎟ ⎟ ⎞ ⇒ $\alpha(\beta) = 1 + (\beta - 1)C_B B^{-1}$ ⎝ ⎜ ⎜ I x_0 Z_0 $0_{s\times 1}$ $0_{q\times 1}$ 0 0 / ⎟ ⎟ ⎞ $\Rightarrow \frac{\alpha(\beta)-1}{\beta-1}$ $\frac{(\beta)-1}{\beta-1} = C_B B^{-1}$ λ \overline{a} I x_0 Z_0 $0_{s\times 1}$ $0_{q\times 1}$ 0 0 / $\overline{}$ ⎞ .For each $\beta \in (1, \overline{\beta}) \Rightarrow$ $\rho_o^+ = C_B B^{-1}$ λ I x_0 Z_0 $0_{\rm sx1}$ $0_{q\times 1}$ 0 0 / $\frac{1}{2}$ ⎞

Theorem 2: if $\alpha(1) = 1$ and matrix B is an optimal basis for model (4) as

$$
\begin{pmatrix}\n\mathbf{B}^{-1}\begin{pmatrix}\nX_0 \\
\mathbf{B}^{-1} \\
\mathbf{
$$

Proof: The proof of this theorem is similar to the previous one. In this case, it

should be
$$
\hat{b} = B^{-1} \begin{pmatrix} -x_0 \\ -z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 0 \\ 0 \end{pmatrix}
$$
.

Figure 1 shows the different stages of the proposed method for obtaining left and right return to scale (RTS).

Figure 1: The algorithm to obtain left and right RTS based on the proposed model

5. Numerical Example

5.1 Example 1

Table 1 shows the data of 24 branches of none-life insurance company of Taiwan from Hwang and Kao [19]. The inputs of the first process are operation and insurance costs. On the other hand, the outputs of the first process that are intermediate production are direct written premiums and reinsurance premiums that are the inputs of the second stage. Finally, the outputs of the second stage are underwriting profit and investment profit. Table 2, shows the amount of the

efficiency of Hwang and Kao [19], independent model Kao and Hwang [9] dependent model, and the proposed model. In Kao and Hwang [9] dependent model, none of units are efficient. In the independent model, on the other hand, some of the units are efficient, while none of sub-processes are efficient. As it can be seen in the proposed model, most of the units are efficient and the inefficient units have similar efficiency, that leads to a better outcome compared to independent and dependent models.

branches of none-life Company.													
DMU	Suggestion two-stage model	Relational two-stage model	Independent two-stage model										
1		0.699	0.984										
$\overline{\mathbf{c}}$		0.625	1.000										
$\overline{3}$		0.960	0.988										
$\overline{\mathcal{L}}$	0.7243	0.304	0.488										
5		0.767	1.000										
6	0.9753	0.390	0.594										
$\overline{7}$	0.8032	0.277	0.470										
8	0.8404	0.275	0.415										
9		0.223	0.327										
10	0.8616	0.46	0.781										
11	0.7580	0.164	0.283										
12		0.760	1.00										
13	0.8873	0.208	0.353										
14	0.7246	0.289	0.470										
15		0.614	0.979										
16	0.9099	0.320	0.472										
17		0.360	0.635										
18		0.259	0.427										
19		0.411	0.822										
20		0.547	0.935										
21	0.8950	0.20	0.333										
22		0.590	1.000										
23	0.9855	0.420	0.599										
24		0.135	0.257										

E. Alipour Chavari, et al. / IJDEA Vol.7, No.2, (2019), 1-14 **Table 2: The amount of the efficiency of independent, dependent, and proposed models for 24**

5-2 Example 2

To investigate the proposed method for left/right return to scale, we use the following illustrative example:

Suppose that we have one input, one intermediate measure, and one output (m=s=q=1). Data is given in Table 3.

First, we consider the DMU_A as the under evaluation unit. The corresponding model (4) to this DMU is as follows and optimal solution of this problem is shown in table of (4):

 $max z = \alpha$ s.t. $2\lambda_1 + 3\lambda_2 + 4\lambda_3 + 5\lambda_4 \leq 2$, $2\lambda_1 + 4\lambda_2 + 3\lambda_3 + 5\lambda_4 \geq 2\alpha$ $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$, $2\mu_1 + 4\mu_2 + 3\mu_3 + 5\mu_4 \leq 2$, $2\mu_1 + 5\mu_2 + 3\mu_3 + 5\mu_4 \geq 2\alpha$, $\mu_1 + \mu_2 + \mu_3 + \mu_4 = 1$, $\mu_j \geq 0$, $\lambda_j \geq 0$, $j = 1, ..., 4$, α is free.

DMU		

Table 3: Input, output, and intermediate data

	\mathcal{A}_{1}	ハっ	Λz	\mathcal{A}_4	A	Λς	Λ_{6}	μ_1	μ_2	μ_3	μ_4	μ_{5}	μ_{6}	RHS	SRHS
Z	0	0	0	0	θ	0	$\boldsymbol{0}$	0	$\boldsymbol{0}$	1/4	$\frac{3}{4}$	3/4	1/2		3/2
\mathcal{A}_4	0	0				2/3	1/3	$\boldsymbol{0}$	$\boldsymbol{0}$	$-1/6$	$-1/2$	$-1/2$	$-1/3$	0	1/3
α	$\boldsymbol{0}$	0	0	θ		0	θ	$\boldsymbol{0}$	θ	1/4	$\frac{3}{4}$	3/4	1/2		3/2
λ_1		0		0		1/3	2/3	$\boldsymbol{0}$	$\boldsymbol{0}$	$-1/3$	-1	- 1	$-2/3$		$-4/3$
μ_2	0	0	0	0		0	0	$\boldsymbol{0}$		1/2	3/2	1/2			
Λ_{2}	0		- 1	0	θ	- 1	- 1	$\boldsymbol{0}$	θ	1/2	3/2	3/2			
μ_1	0	0	0	0		0	θ		0	1/2	$-1/2$	$-1/2$			- 1

Table 4: Optimal Simplex table from solving model (4) for DMU_4

Table 4 is the latest simplex Table and in the other words, is simplex optimal table in solving model (4) for DMU_A . Considering Table 4, and the latest right column, we obtain ρ_0^+ from Eq. 10 and the following formula:

$$
\rho_0^+ = C_B B^{-1} \begin{pmatrix} x_0 \\ Z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 0 \end{pmatrix}
$$

Also, to obtain ρ_0^- using Eq. 11, the last column of Table 4 is multiplied by (-1).

.

And
$$
\rho_0^- = C_B B^{-1} \begin{pmatrix} -x_0 \\ -Z_0 \\ 0_{s \times 1} \\ 0_{q \times 1} \\ 1 \end{pmatrix}
$$

will be resulted.

Notice that λ_5 , λ_6 , μ_5 and μ_6 are the covariants of 1, 2, 3, 4 and 5 limitations in Table (4). λ_7 and μ_7 are the artificial variables of equal constrains. In table (4) it can be seen that, if we consider RHS and SRHS columns, we have condition (10) and we have $\rho^+ = 3/2$. Also, in order to calculate ρ^- , we consider table (4), multiplying SRHS in(-1), the result would be table (5). In this table, it can be seen that the corresponding lines to λ_4 , μ_2 and λ_2 are orderly (0,-1/3), (0,-1) and (0,-1) and we don't have the condition (11) therefore, it is not possible to apply the dual simplex.

Now we consider the DMU_c . Table (6) shows the obtained optimal table of the model (4), which corresponds to this DMU.

Table 5: Multiplication the SRHS in Table 4 by -1 to obtain ρ^-

	\mathcal{A}_{1}	ハっ	\mathcal{L}_2	Λ_4	A	∕ις	π_{6}	μ_1	μ_2	μ_3	μ_4	μ_{5}	μ_{6}	RHS	SRHS
Z	0	0	0	0	θ		0	0	0	1/4	3/4	3/4	1/2		3/2
Λ_4	0	0				2/3	1/3	0	0	$-1/6$	$-1/2$	$-1/2$	$-1/3$		$-1/3$
А	0	0	0	0		θ	0	0	θ	1/4	3/4	3/4	1/2		$-3/2$
n_1		0		0		/3	2/3	0	0	$-1/3$	- 1	- 1	$-2/3$		4/3
μ_2	0	0	0	0			0	0		1/2	3/2	1/2			$\overline{}$
Λ	$\overline{0}$		- 1	0	θ	- 1	- 1	0	θ	1/2	3/2	3/2			$\overline{}$
μ_1	θ	0	0				0		0	/2	$-1/2$	$-1/2$			

	Table 6: Optimal Simplex table from solving model (4) for DMU_c														
	Λ_1	Λ	\mathcal{L}_2	Λ_4	α	Λς	n ₆	μ_{1}	μ_{2}	μ_3	μ_4	μ_{5}	μ_{6}	RHS	SRHS
7						θ	1/3			1/6	1/2	1/2	/3	7/6	
Λ_4	0		3/2	3/2					0	$-1/4$	$-3/4$	3/4	$-1/2$	11/4	
A			0			0	1/3		0	1/6	1/2	1/2	1/3	7/6	
\mathcal{A}_1			1/2	$-1/2$		θ	0			$-1/4$	$-3/4$	3/4	$-1/2$	7/4	
μ_2	0					θ				1/2	3/2	1/2	$^{(1)}$	1/2	
んっ			1/2	3/2		θ				1/4	3/4	3/4	$\sqrt{2}$	3/4	
μ_1										$\frac{1}{2}$	$-1/2$	רו $-1/$		1/2	

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Table 7: Multiplication the SRHS in Table 6 by -1 to obtain ρ^-

	rapic 7. Manupheation the SKITS in Table 0 by -1 to obtain p														
	\mathcal{L}_1	ハっ	\mathcal{L}_3	Λ_4	α	\mathcal{A}_{5}	Λ_{6}	μ_1	μ_{2}	μ_3	μ_4	μ5	μ_{6}	RHS	SRHS
Z	θ	0	0		θ	0	1/3	0	0	1/6	1/2	1/2	1/3	7/6	
\mathcal{A}_4	0		3/2	3/2	θ		0	0	0	$-1/4$	$-3/4$	3/4	$-1/2$	11/4	
A	0	0	0			0	1/3	0	0	1/6	1/2	1/2	1/3	7/6	-2
\mathcal{L}_1		0	1/2	$-1/2$	θ	0	θ	0	0	$-1/4$	$-3/4$	3/4	$-1/2$	7/4	-3
μ_2	θ	0	0		0	0	θ	0		1/2	3/2	1/2	0	1/2	-2
λ_2	0		1/2	3/2	θ	0	θ	0	0	1/4	3/4	3/4	1/2	3/4	-3
μ_1	0		0		0	θ				1/2	$-1/2$	$-1/2$	θ	1/2	$+2$

It is obvious that, considering RHS and SRHS columns, we have the condition (10) and also $\rho^+ = 2$. To obtain the ρ^- , we consider the table (6). Multiplying to (-1) we try to have the condition (11). The result is the table (7) with result $\rho^{\dagger} = 2$.

6- Conclusion

In this paper, different methods have been shown for measuring efficiency and return to scale in two-stage processes.

So far, many methods for efficiency evaluation and network return to scale have been proposed, each contains pros and cons. One of the problems in determining network return to scale is the feasibility of the proposed method. For example, the proposed method by Golany and Yu, [16] is not always feasible, but our approach is always feasible for all DMUs under evaluation.

In addition, in many other network approaches, two independent models are considered to evaluate the efficiency of network processes. Such as, independent model of Kao and Hwang [9] which two independent models will result in two independent efficiency frontiers. Indeed, we can hardly find a common approach for return to scale of units between these two frontiers. Although Kao and Hwang [9] evaluated the whole process efficiency, their model was only considered in constant return to scale condition. Kao and Hwang [9] have computed

efficiency in an overall process, but their model was only true assuming constant return to scale. Chen et al. [10] have proposed their models under constant and variable return to scale, but their model can be used only for determining efficiency and falls short to compute return to scale class. As addressed earlier, measuring return to scale in two-stage processes is not an easy task due to the unknown possible space for generating in the PPS. Therefore, in this paper we tried

to measure left and right return to scale in two-stage processes by proposing a new model and also applying suggested algorithm by Zarepisheh, Soleimanidamaneh, [18]. While the proposed method is with high computational complexity, considering theorems and examples, it can be accomplished with acceptable results. Moreover due to the proposed model, the joint border problem of the two stages has been solved.

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