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Evaluating efficiency and ranking of suppliers using non-radial super-efficiency data envelopment analysis with uncontrollable factors

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ABSTRACT

Supply chain management (SCM) has been received much attention from academics and corporates. Effective and sustainable SCM require proper efficiency evaluation of suppliers. Such evaluation can be performed using data envelopment analysis (DEA). Classical DEA models presume all inputs and outputs are under the control of suppliers' management, as well as the models cannot provide a complete ranking of efficient and inefficient suppliers. However, in SCM and other real-managerial problems, some inputs and/or outputs may be uncontrollable (outside management control). Thus, this paper proposes a super efficiency of slacks-based measure (SE-SBM) approach that can handle uncontrollable factors. The proposed approach can distinguish between efficient and inefficient suppliers and identify their rankings. The discriminating power of the proposed approach is due to it concurrently deals with input excesses and output shortfalls to improve inefficient suppliers, as well as input savings and output surpluses of efficient suppliers to maintain their efficient status.

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1. Introduction

Supply chain management (SCM) is the management of a network of technologies, firms, workers, information, activities and resources transferring services and/or products from original suppliers to customers [1]. The main aims of SCM are to fulfil demand, facilitate financial success and increase customer satistification by efficiently organizing and managing business activities from suppliers to customers [2]. These activities may include raw material possession, product manufacturing and distribution, customers service, and product reprocessing and disposal [3]. Successful SCM has been proven as a very effective mechanism for providing high-quality levels of services and products to customers with the least cost [4]. Developing such SCM can, however, be influenced by many factors, such as resource availability and management [5], skills [6] and supplier selection. Supplier selection is, thus, one of the crucial factors in managing effective and efficient SCM [7,8] and the most serious issue facing SCM. A recent trend of SCM is delivering of products or goods from suppliers to customers via an electronic arrangement [9].

Supplier selection refers to the process where a firm identifies, evaluates and contracts with suppliers. Its main objective is to minimize purchasing risk, maximize buyer values and enhance a long-term

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relationship between suppliers and buyers [10,11]. Proper selection of suppliers is one of the most crucial decisions [12] enabling companies to produce and deliver products or services to their customers with cost-effective and within a specified timeline. Besides, supplier selection plays an important role in disaster operations management (DOM), that ensure effective procurement of relief supplies [13]. To better select suppliers, including the review and evaluation of suppliers [14], many quantitative methods have been introduced. However, the existence of these various methods may confuse decision makers, while identifying and choosing the best supplier selection method. Since there exist many criteria in supplier selection, decision makers commonly use multi-criteria decision making (MCDM) as an effective tool to holistically evaluate suppliers [2]. One of the most vital methods for evaluating suppliers is a non-parametric approach of data envelopment analysis (DEA) [15].

DEA is a decision making technique measuring the efficiency of homogeneous organizations – called DMUs – based on a linear programming theory. An organization utilizes inputs to produce outputs. The ratio of the weighted outputs to the weighted inputs can then be used to measure the organization's efficiency relative to other homogenous organizations [16]. Such efficiency score measurement, considering both multiple inputs and outputs, is an essential feature of DEA. Standard DEA models, however, cannot rank efficient DMUs appropriately. This issue has been solved by a radial super efficiency model, proposed by Andersen and Petersen [17]. Their model discriminates and ranks high performing DMUs whose returns to scale is constant (CRS) – a proportionate increase in inputs will result in a proportionate increase in outputs. Due to the slacks of input savings (i.e. the maximum expansions in inputs) and the slacks of output surpluses (i.e. the maximum reductions in outputs) cannot be identified simultaneously by the radial models, the models may suffer from the infeasibility issue in either orientation (i.e. input or output-oriented)[1] under some cases of variable returns to scale (VRS) [21,22].

To rectify the infeasibility issue, Tone [23] developed a non-radial slacks-based measure of super efficiency (SE-SBM) approach. The approach simultaneously deals with input savings and output surpluses at different rates to rank efficient and inefficient DMUs under VRS and CRS technologies [24] . Various DEA studies have been performed based on Tone's [23] SE-SBM approach. These include the studies of Du et al. [25], Fang et al. [26], Hussain et al. [27], Johnes and Tone [28], Kasim et al. [29], and Taleb et al. [30]. All of the mentioned efficiency studies, however, treated all inputs and outputs as controllable (discretionary).

In many settings of real-world applications, some factors of inputs and/or outputs cannot normally be controlled by their DMUs' management (i.e. uncontrollable or non-discretionary factors). A radial model considered non-discretionary inputs was initially prepared by Charnes et al. [31]. Several radial DEA models (i.e. input or output-oriented) have been introduced by many scholars and researchers, such as, Banker and Morey [32], Izadikhah and Farzipoor Saen [15], Tsai et al. [33] and Wu et al. [34]. However, all of these studies were carried out under the concepts of radial models. Since radial models ignore slacks of inputs and outputs in calculating efficiency scores, the models cannot reflect all inefficiency of inefficient DMUs [35]. To address this issue, Farzipoor Sean [36] developed a new formula of SBM model can concurrently deal with discretionary and non-discretionary inputs and outputs. Based on the Farzipoor Sean's model, various non-radial models dealing with non-discretionary factors have been introduced, such as Esmaeili [37], Hua et al. [38], and Rashidi et al. [39]. All of these studies, however, could not rank high performing DMUs in the context of uncontrollable inputs and/or outputs.

To fill the gap in the literature, the objective of this research is to propose a methodology that integrates uncontrollable factors of inputs and outputs into Tone's [23] SE-SBM approach, via utilizing the study introduced in Esmaeili [37]. The uncontrollable factors are integrated into their relevant input and output constraints of Tone's [23] approach. The proposed approach's optimal solution is obtained by transforming its nonlinear program to a linear program. Since the proposed approach deals with uncontrollable inputs and outputs eliminating unrealistic assumption of the discretionary factors, it can provide accurate efficiency measures, helping decision makers distinguish between inefficient and efficient DMUs and improve the inefficient DMUs, as well as identify their ranks efficiently.

Utilizing the efficiency measures, effective strategies and policies can be planned to improve the performance of the DMUs. The applicability of the proposed approach is examined by evaluating and ranking the efficiency of the data set of 18 suppliers involving uncontrollable input. This is the first time that uncontrollable factors of inputs and outputs have been incorporated into Tone's [23] SE-SBM approach. Thus, the proposed approach provides a comprehensive evaluation and ranking of suppliers in the presence of uncontrollable factors.

To the best of authors' knowledge, there has not been any reference attempted to incorporate uncontrollable inputs and outputs into the SE-SBM approach of Tone [23] to evaluate the sustainability of SCM. Consequently, the contributions of this research are as below:

- To realize the peer assessment of supplier selection instead of the self assessment, an SE-SBM approach in DEA considers uncontrollable inputs and outputs is proposed.
- The proposed approach guarantees the feasibility condition in the existence of uncontrollable factors regarding the CRS and VRS technologies, which deem the prominent merit of the proposed super efficiency approach.
- The results of this research contribute to the body of knowledge in the SCM-DEA literature by illustrating the proposed approach, using a real data set retrieved from the literature.
- This research compares the efficiency measures of the proposed approach with those of Tone's [23] SE-SBM approach, and outline the potential limitations inherent in eliminating uncontrollable inputs and outputs.

This paper proceeds as follows. A review of relevant literature serving the background of the proposed approach is considered in Section 2. The methodology of the proposed approach is illustrated in Section 3. By using the data set of 18 suppliers retrieved from the literature, the practicability of the proposed approach is examined in Section 4. Academic and managerial implications are considered in Section 5. Finally, some conclusions and directions for future research are provided in Section 6.

2. Background

There are two types of super efficiency measures in DEA: radial and non-radial. The first radial super efficiency model was invented by Andersen and Petersen [17]. Their model ranks efficient and inefficient DMUs under CRS or VRS assumption. For each efficient DMU obtained from a radial model, the super efficiency score is identified by excluding the assessed efficient DMU_o from its reference set of the considered model. The super efficiency score is then revealed by the radial distance between the efficient DMU_o and its efficient frontier, formed by the remaining efficient DMUs [21]. For each excluded efficient DMU_o, the input savings (i.e. proportional increases in inputs) or output surpluses (i.e. proportional decreases in outputs) should be calculated [24,40]. In the context of evaluating and selecting suppliers, Wu and Blackhurst [8] introduced a super efficiency model based on the radial measure to enhance the discriminating power of classical DEA models in suppliers' evaluation and ranking. Jahanshahloo et al. [41] proposed a new super efficiency model for ranking extreme-efficient, non-extreme-efficient, and inefficient suppliers. Based on the model of Andersen and Petersen [17], many efficiency studies evaluating and selecting suppliers have been conducted (e.g. [42–44]). However, an issue of infeasibility may raise under some cases of VRS since radial models cannot simultaneously consider the slacks of input savings and output surpluses.

To remedy the infeasibility issue, a novel non-radial super efficiency of slacks-based measure (SE-SBM) approach was invented by Tone [23]. Its essential concepts are based on that of the model of Andersen and Petersen [17]. The Tone's SE-SBM approach simultaneously identifies the maximum expansions in inputs and (the maximum reductions in outputs) for each efficient DMU by adding (subtracting) the slack of input saving (the slack of output surplus) to (from) their relevant constraints of the excluded efficient DMU_o [25]. By doing this, the feasibility condition under CRS and VRS assumptions is satisfied [24,30] . In the approach of Tone [23], the super efficiency score of

an efficient DMU is obtained by measuring the non-radial distance between the efficient production frontier and the excluded efficient DMU_o [35,45]. By identifying the minimum non-radial distance, input savings and output surpluses of the efficient $DMU_o$are identified [26]. Large non-radial distance leads to a high score of super efficiency, while small non-radial distance judges that the super efficiency score to be small. However, all of the mentioned studies did not consider SE-SBM to evaluate supplier selection. Additionally, these models assume that all inputs and outputs are discretionary – controllable. This conflicts with many real-life managerial problems, including supplier selection.

In real-life problems, some inputs and/or outputs of many organizations are outside of their management's control since they are subject to non-discretionary factors. To obtain accurate efficiency measures, any reduction in non-discretionary inputs or augmentation in non-discretionary outputs should be prohibited by their relevant constraints. Consequently, the objective function has to only deal with discretionary inputs and outputs. The incorporation of uncontrollable factors into radial and non-radial models was first laid out by Charnes and Cooper [46] and Charnes et al. [47]. Based on these studies, many DEA studies dealing with non-discretionary factors have been carried out. These include the studies introduced in Agasisti [48], Banker and Morey [32], Cook and Seiford [49], Muñiz et al. [50], Nigam et al. [51], Patel and Pande [52] and Ruggiero [53]. To evaluate suppliers with a non-discretionary situation of inputs and/or outputs of radial models, Farzipoor Saen [54], Noorizadeh et al. [55], and Noorizadeh et al. [56] introduced an integrated methodology using radial models with uncontrollable inputs and/or outputs. All of these studies were, however, carried out under an orientation DEA model (i.e. input-or output-oriented). In addition, they did not rank efficient and inefficient suppliers.

Lotfi et al. [57] introduced a super efficiency model of input-oriented DEA dealing with non-discretionary inputs. However, the model suffers from the infeasibility issue under VRS assumption. In the light of the infeasibility issue, an alternative approach of SE-SBM considering non-discretionary inputs and outputs was proposed by Taleb, Ramli, Khalid [58]. Their approach was based on two approaches – the approach of Fang et al. [26] developed an alternative SE-SBM and the approach introduced by Farzipoor Sean [36] in terms of SBM and non-discretionary factors. However, their approach considers that some outputs are not completely discretionary. To deal with inputs and outputs as completely discretionary or non-discretionary, Esmaeili [37] proposed the non-discretionary inputs into Tone's [59] SBM model. To evaluate suppliers, Mahdiloo et al. [60] developed a new SBM model in dual-role factor. However, their model did not consider the super efficiency situation of efficient suppliers. To the best of authors' knowledge, no studies have considered SE-SBM with non-discretionary factors to evaluate suppliers based on Tone's [23] approach. The key DEA studies introduced in the literature considering radial and non-radial models for supplier selection are summarized in Table 1.

Position of this paper: Uncontrollable inputs and outputs have been incorporated into the novel non-radial SE-SBM approach of Tone [23] to enhance its ability to deal and evaluate real-life applications. Incorporating these factors into the existing approach for classifying efficient and inefficient suppliers, as well as ranking them regarding their efficiency is the main objective of this research.

3. Proposed methodology for suppliers ranking

The SE-SBM approach of Tone [23] can directly deal with input excesses and output shortfalls, as well as input savings and output surpluses at different rates, via a procedure includes two stages. In stage-I, the SBM model is applied to effectively classify efficient and inefficient DMUs. In stage-II, the efficient DMUs are discriminated and ranked, using the super efficiency of SBM model. However, all inputs and outputs of the approach are expected to be controllable by their managements. The models should, thus, be integrated with uncontrollable factors to support various situations of real-life applications. To do that, assume that there are n DMUs needing to be assessed, indexed by $j = 1, \frac{1}{4}\frac{1}{4}, n$. Each DMU consumes inputs to produce outputs. The inputs and outputs can be classified into four factors: $x^D \in \mathbb{R}_+^m$, $x^{ND} \in \mathbb{R}_+^z$, $y^D \in \mathbb{R}_+^{s_1}$, $y^{ND} \in \mathbb{R}_+^{s_2}$. In this case, x^D is a discretionary input, x^{ND} is

Table 1. A brief overview in the DEA literature of supplier selection.

Researcher(s)	Strengths	Limitations
Farzipoor Saen [54]	Proposed an output-oriented model with non-discretionary outputs for selecting technology suppliers from supplier's perspective of 12 nuclear power plants	• The model did not consider suppliers' ranking using the super efficiency approach • The model did not simultaneously consider the non-discretionary inputs and outputs
Izadikhah and Farzipoor Saen [15]	Developed a DEA model based on a modification of context dependent for suppliers ranking	• Their model did not consider non-discretionary factors • Suppliers ranking did not carry out for the case of a non-radial super efficiency approach
Mahdiloo et al. [60]	Proposed an SBM model in the presence of dual-role factor to assess supplier selection of 12 suppliers	• The non-discretionary factors for standard inputs-outputs (non-dual role factors) did not take into consideration
Mahdiloo et al. [18]	• Proposed a multiplier DEA model decomposing efficiency measures into technical efficiency, environment, and eco-efficiency for green supplier selection of Hyundai Steel Company • The proposed model is less computationally intensive than those in literature since it used linear goal programming to integrate technical efficiency, environment, and eco-efficiency	• Their model did not provide a complete measure for ranking suppliers • Did not consider effect of non-discretionary factors on efficiency evaluation
Noorizadeh et al. [56]	Proposed a cross-efficiency model with non-discretionary inputs for ranking suppliers	• Their model was proposed in a multiplier DEA formula. Thus, discretionary output surpluses of efficient suppliers cannot be identified • The model did not provide a complete ranking of suppliers
Noorizadeh et al. [61]	Proposed a multiplier DEA model considering dual-role factor, non-discretionary, and weight restrictions for selecting suppliers	• The model did not provide a comprehensive evaluation since it proposed under a multiplier formula • It did not consider ranking of suppliers
Noorizadeh et al. [62]	Proposed a radial super efficiency model considering uncontrollable inputs and undesirable outputs for evaluating the data set of 18 suppliers	• The model was proposed in terms of radial measures

Source: As described above.

a non-discretionary input, y^D is discretionary output, and y^{ND} is a non-discretionary output. The matrices of these factors are defined as follows:

$$X^D = [x_1^D, \ldots, x_n^D] \in \mathbb{R}_+^{m\times n},\ X^{ND} = [x_1^{ND}, \ldots, x_n^{ND}] \in \mathbb{R}_+^{z\times n},$$
$$Y^D = [y_1^D, \ldots, y_n^D] \in \mathbb{R}_+^{s_1\times n},\ Y^{ND} = [y_1^{ND}, \ldots, y_n^{ND}] \in \mathbb{R}_+^{s_2\times n}$$

We assume that discretionary and non-discretionary inputs, as well as discretionary and non-discretionary outputs are positive data (*i.e.*, $X^D > 0,\ X^{ND} > 0,\ Y^D > 0,\ Y^{ND} > 0$).

The notations applied in the proposed approach can be summarized as follows:

x_{ij}^D: the ith discretionary input for DMU_o

x_{bj}^{ND}: the bth non-discretionary input for DMU_o

y_{rj}^D: the rth discretionary output for DMU_o

y_{uj}^{ND}: the uth non-discretionary output for DMU_o

i: index of discretionary inputs

m: number of discretionary inputs
b: index of non-discretionary inputs
z: number of non-discretionary inputs
r: index of discretionary outputs
s_1: number of discretionary outputs
u: index of non-discretionary outputs
s_2: number of non-discretionary outputs
n: number of assessed DMUs
o: index of a specific DMU being evaluated

Based on the theoretical concepts of Tone's [59] SBM model, as well as the SBM model with non-discretionary factors introduced in Esmaeili [37], the production possibility set (PPS) spanned by all evaluated DMUs in the existence of non-discretionary inputs and outputs regarding the VRS assumption is described in formula (1).

$$\mathrm{P}^{\text{SBM - ND}} = \left\{ (X^D,\ X^{ND},\ Y^D,\ Y^{ND}) \,\middle|\, x^D \geq \sum_{j=1}^{n} X_j^D \lambda_j,\ x^{ND} = \sum_{j=1}^{n} X_j^{ND} \lambda_j, \right.$$
$$\left. y^D \leq \sum_{j=1}^{n} Y_j^D \lambda_j,\ y^{ND} = \sum_{j=1}^{n} Y_j^{ND} \lambda_j,\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0 \right\} \tag{1}$$

where $\lambda_j, j = 1, \frac{1}{4}\frac{1}{4}, n$ are non-negative intensity variables, serving to construct the convex combinations of data set.

Using PPS defined in (1), a new version of SBM model dealing with non-discretionary factors for assessing DMU$_o$ (x_o^D, x_o^{ND}, y_o^D, y_o^{ND}) is proposed as follows:

[SBM-ND model]

$$\min\ \rho_o = \frac{1 - \frac{1}{m}\left(\sum_{i=1}^{m} \frac{s_i^-}{x_{io}^D}\right)}{1 + \frac{1}{s_1}\left(\sum_{r=1}^{s_1} \frac{s_r^+}{y_{ro}^D}\right)} \tag{2}$$

s.t.

$$\sum_{j=1}^{n} x_{ij}^D \lambda_j = x_{io}^D - s_i^-, \quad i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} x_{bj}^{ND} \lambda_j = x_{bo}^{ND} - s_b^-, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1}^{n} y_{rj}^D \lambda_j = y_{ro}^D + s_r^+, \qquad r = 1, \ldots, s_1,$$

$$\sum_{j=1}^{n} y_{uj}^{ND} \lambda_j = y_{uo}^{ND} + s_u^+, \qquad u = 1, \ldots, s_2,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0,\ s_i^- \geq 0,\ s_b^- \geq 0,\ s_r^+ \geq 0,\ s_u^+ \geq 0,$$

$$x_{io}^D,\ x_{bo}^{ND},\ y_{ro}^D,\ y_{uo}^{ND} \in \mathbb{R}_+^{m+z+s_1+s_2}.$$

The non-radial slacks s_i^- and s_r^+ denote input excesses and output shortfalls of the discretionary inputs and outputs, respectively. Conversely, the uncontrollable factors of inputs and outputs should be kept at their fixed levels. Therefore, the SBM-ND model disallows any decrease and increase in the levels of non-discretionary inputs and outputs. The non-discretionary input and output slack variables are omitted from the objective function of model (2) because they are outside the control of DMUs' management. Due to model (2) proposed in the existence of non-discretionary inputs and outputs making their amounts are fixed, an issue of infeasibility may raise in some cases of VRS assumption. To remedy the infeasibility issue, the slacks of uncontrollable inputs and outputs are imposed into their corresponding constraints of model (2). Up to this point, improved SBM-ND model (2) can discriminate between efficient and inefficient DMUs in terms of uncontrollable factors. To obtain the optimal solution to model (2), its nonlinear program should be converted into a linear program, using the transformation of Charnes and Cooper [63] (see also [45], p.345; [64]). By using a positive scalar variable v (> 0), model (2) can be transformed into the program, as defined in model (3).

$$\min \ \tau_o = v - \frac{1}{m}\left(\sum_{i=1}^{m}\frac{vs_i^-}{x_{io}^D}\right) \tag{3}$$

s.t.

$$v + \frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{vs_r^+}{y_{ro}^D}\right) = 1,$$

$$\sum_{j=1}^{n} x_{ij}^D\lambda_j = x_{io}^D - s_i^-, \quad i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} x_{bj}^{ND}\lambda_j = x_{bo}^{ND} - s_b^-, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1}^{n} y_{rj}^D\lambda_j = y_{ro}^D + s_r^+, \qquad r = 1, \ldots, s_1,$$

$$\sum_{j=1}^{n} y_{uj}^{ND}\lambda_j = y_{uo}^{ND} + s_u^+, \qquad u = 1, \ldots, s_2,$$

$$\sum_{j=1}^{n}\lambda_j = 1,$$

$$\lambda_j \geq 0,\ s_i^- \geq 0,\ s_b^- \geq 0,\ s_r^+ \geq 0,\ s_u^+ \geq 0,\ v > 0.$$

We assume that $S_i^- = vs_i^-$, $S_b^- = vs_b^-$, $S_r^+ = vs_r^+$, $S_u^+ = vs_u^+$, $\Gamma_j = v\lambda_j$. Then, the nonlinear program of model (3) is transformed to the following linear program in S_i^-, S_b^-, S_r^+, S_u^+, *and* Γ_j, as presented in model (4).

$$\min \ \tau_o = v - \frac{1}{m}\left(\sum_{i=1}^{m}\frac{S_i^-}{x_{io}^D}\right) \tag{4}$$

s.t.

$$v + \frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{S_r^+}{y_{ro}^D}\right) = 1,$$

$$\sum_{j=1}^{n} x_{ij}^{D}\Gamma_j = \nu x_{io}^{D} - S_i^-, \quad i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} x_{bj}^{ND}\Gamma_j = \nu x_{bo}^{ND} - S_b^-, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1}^{n} y_{rj}^{D}\Gamma_j = \nu y_{ro}^{D} + S_r^+, \quad r = 1, \ldots, s_1,$$

$$\sum_{j=1}^{n} y_{uj}^{ND}\Gamma_j = \nu y_{uo}^{ND} + S_u^+, \quad u = 1, \ldots, s_2,$$

$$\sum_{j=1}^{n} \Gamma_j = \nu,$$

$$\Gamma_j \geq 0,\ S_i^- \geq 0,\ S_b^- \geq 0,\ S_r^+ \geq 0,\ S_u^+ \geq 0,\ \nu > 0.$$

Note that $\nu\ (> 0)$ by virtue of the first constraint. It provides an indicator that the transformation is reversible. Thus, the optimal solution of model (4) be τ_o^*, ν^*, Γ_j^*, S_i^{-*}, S_b^{-*}, S_r^{+*}, S_u^{+*}. Hence, the optimal solution of model (2) is defined by

$$\rho_o^* = \tau_o^*,\ \lambda_j^* = \Gamma_j^*/\nu,\ s_i^{-*} = S_i^{-*}/\nu,\ s_b^{-*} = S_b^{-*}/\nu,\ s_r^{+*} = S_r^{+*}/\nu,\ s_u^{+*} = S_u^{+*}/\nu.$$

It is noteworthy that slacks values of non-discretionary inputs and outputs resulting from the optimal solution of model (4) have to ignored. The ignorance is due to that these slacks have integrated into model (2) to keep its feasibility condition solely, as mentioned above.

Definition 3.1: DMU_o is said to be fully efficient in SBM-ND model (2) if and only if its efficiency score is equal to one ($\rho_o^* = 1$). This condition is equivalent to all slack values of discretionary input excesses and output shortfalls are zero (i.e. $s_i^{-*} = s_r^{+*} = 0$). In other cases, where all or some of these slacks have positive values, DMU_o is inefficient.

However, in many situations of performance evaluation, high performing DMUs have the status of full-efficient, whose values are denoted by one. To discriminate and rank the efficient DMUs, it is necessary to analyse factors that influence their efficiency. To obtain precise efficiency values, this paper proposes non-discretionary factors of inputs and outputs into Tone's [23] super efficiency of SBM model. In order to define a new super efficiency model corresponding to model (2), a new PPS of the super efficiency model considering non-discretionary factors is described in (5), by excluding efficient $\mathrm{DMU}_o$from its reference set of model (2) (*i.e.*, $j \neq o$).

$$\mathrm{P}^{SE-SBM-ND} = \left\{ \begin{array}{l} (X^D,\ X^{ND},\ Y^D,\ Y^{ND}) \Big| x^D \geq \sum_{j=1,j\neq o}^{n} X_j^D\lambda_j,\ x^{ND} = \sum_{j=1,j\neq o}^{n} X_j^{ND}\lambda_j, \\ \quad y^D \leq \sum_{j=1,j\neq o}^{n} Y_j^D\lambda_j, \\ y^{ND} = \sum_{j=1,j\neq o}^{n} Y_j^{ND}\lambda_j, \sum_{j=1,j\neq o}^{n} \lambda_j = 1,\ \lambda_j \geq 0, j \neq o \end{array} \right\} \quad (5)$$

The intensity variable λ has defined in (1).
The proposed SE-SBM model for assessing DMU_o (x_o^D, x_o^{ND}, y_o^D, y_o^{ND}) is as follows:
[SE-SBM-ND model]

$$\min \delta_o = \frac{1 + \frac{1}{m}\left(\sum_{i=1}^{m} \frac{k_i^-}{x_{io}^D}\right)}{1 - \frac{1}{s_1}\left(\sum_{r=1}^{s_1} \frac{k_r^+}{y_{ro}^D}\right)} \quad (6)$$

s.t.

$$\sum_{j=1,j\neq o}^{n} x_{ij}^{D}\lambda_j \leq x_{io}^{D} + k_i^{-}, \quad i = 1, \ldots, m,$$

$$\sum_{j=1,j\neq o}^{n} x_{bj}^{ND}\lambda_j \leq x_{bo}^{ND} + k_b^{-}, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1,j\neq o}^{n} y_{rj}^{D}\lambda_j \geq y_{ro}^{D} - k_r^{+}, \qquad r = 1, \ldots, s_1,$$

$$\sum_{j=1,j\neq o}^{n} y_{uj}^{ND}\lambda_j \geq y_{uo}^{ND} - k_u^{+}, \qquad u = 1, \ldots, s_2,$$

$$\sum_{j=1,j\neq o}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0,\ k_i^{-} \geq 0,\ k_b^{-} \geq 0,\ k_r^{+} \geq 0,\ k_u^{+} \geq 0,\ k_r^{+} \leq y_{ro}^{D},$$

$$x_{io}^{D}, x_{bo}^{ND}, y_{ro}^{D}, y_{uo}^{ND} \in \mathbb{R}_{+}^{m+z+s_1+s_2}.$$

Model (6) calculates the projection of the excluded efficient DMU_o by minimizing its discretionary input savings (k_i^{-}) and discretionary output surpluses (k_r^{+}). The discretionary inputs and discretionary outputs are considered in the model's objective function since objective's value only relies on the discretionary factors. To ensure that the value of the objective function is positive, $k_r^{+} \leq y_{ro}^{D}$ should be satisfied. The procedure of model (6) in calculating super efficiency score is the same of that proposed by Tone [23]. The only difference is that model (6) imposes a condition of discretionary and non-discretionary data. Consequently, the condition classifies the constraints of model (6) into two categories: discretionary and non-discretionary inputs and outputs. In model (6), the efficient DMU_o should be excluded from the reference set of SBM-ND model (2). This exclusion aims to ensure that each efficient DMU_o resulting from model (2) has the ability to move (i.e. project) itself on a new super-efficient frontier, formed by the super-efficient units.

The minimum non-radial distance from the efficient DMU_o to a situated point on the super-efficient frontier is identified by adding (subtracting) discretionary input savings (discretionary output surpluses) to (from) their relevant constraints. In contrast, model (6) should prohibit any increase and decrease in the levels of the non-discretionary inputs and outputs. However, the slacks of non-discretionary inputs (non-discretionary outputs) are added (subtracted) to (from) their relevant input (output) constraints to avoid the infeasibility issue. The aim of considering the non-discretionary input and output constraints in the performance evaluation of the proposed approach is to ensure fair comparisons [65]. Note that model (6) is particularly useful when the number of considered DMUs is small compared with the total number of considered inputs and outputs, which may lead to many efficient DMUs needing to rank their performance.

The transformation procedure applied on SBM-ND model (2) can be followed to obtain the optimal solution to model (6). Thus, model (6) is transformed to the program, using a positive scalar variable v (> 0), as introduced in model (7).

$$\min \eta_o = v + \frac{1}{m}\left(\sum_{i=1}^{m} \frac{vk_i^{-}}{x_{io}^{D}}\right) \tag{7}$$

s.t.

$$v - \frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{vk_{ro}^{+}}{y_{ro}^{D}}\right) = 1,$$

$$\sum_{j=1,j\neq o}^{n} x_{ij}^{D}\lambda_j \leq x_{io}^{D} + k_i^{-}, \qquad i = 1, \ldots, m,$$

$$\sum_{j=1,j\neq o}^{n} x_{bj}^{ND}\lambda_j \leq x_{b}^{ND} + k_b^{-}, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1,j\neq o}^{n} y_{rj}^{D}\lambda_j \geq y_{ro}^{D} - k_r^{+}, \qquad r = 1, \ldots, s_1,$$

$$\sum_{j=1,j\neq o}^{n} y_{uj}^{ND}\lambda_j \geq y_{uo}^{ND} - k_u^{+}, \qquad u = 1, \ldots, s_2,$$

$$\sum_{j=1,j\neq o}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0,\ k_i^{-} \geq 0,\ k_b^{-} \geq 0,\ k_r^{+} \geq 0,\ k_u^{+} \geq 0,\ v > 0.$$

We assume that $K_i^{-} = vk_i^{-}$, $K_b^{-} = vk_b^{-}$, $K_r^{+} = vk_r^{+}$, $K_u^{+} = vk_u^{+}$, $\Gamma_j = v\lambda_j$. Then, the nonlinear program of model (7) is transformed to the following linear program in K_i^{-}, K_b^{-}, K_r^{+}, K_u^{+}, *and* Γ_j, as introduced in model (8).

$$\min \eta_o = v + \frac{1}{m}\left(\sum_{i=1}^{m}\frac{K_i^{-}}{x_{io}^{D}}\right) \tag{8}$$

s.t.

$$v - \frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{K_{ro}^{+}}{y_{ro}^{D}}\right) = 1,$$

$$\sum_{j=1,j\neq o}^{n} x_{ij}^{D}\Gamma_j \leq vx_{io}^{D} + K_i^{-}, \qquad i = 1, \ldots, m,$$

$$\sum_{j=1,j\neq o}^{n} x_{bj}^{ND}\Gamma_j \leq vx_{b}^{ND} + K_b^{-}, \qquad b = 1, \ldots, z,$$

$$\sum_{j=1,j\neq o}^{n} y_{rj}^{D}\Gamma_j \geq vy_{ro}^{D} - K_r^{+}, \qquad r = 1, \ldots, s_1,$$

$$\sum_{j=1,j\neq o}^{n} y_{uj}^{ND}\Gamma_j \geq vy_{uo}^{ND} - K_u^{+}, \qquad u = 1, \ldots, s_2,$$

$$\sum_{j=1,j\neq o}^{n} \Gamma_j = v,$$

$$\Gamma_j \geq 0,\ K_i^- \geq 0,\ K_b^- \geq 0,\ K_r^+ \geq 0,\ K_u^+ \geq 0,\ \nu > 0.$$

Let the optimal solution of model (8) be $\eta_o^*,\ \nu^*,\ \Gamma_j^*,\ K_i^{-*},\ K_b^{-*}, K_r^{+*},\ K_u^{+*}$. Thus, the optimal solution of the nonlinear program in model (6) is defined by $\delta_o^* = \eta_o^*,\ \lambda_j^* = \Gamma_j^*/\nu,\ k_i^{-*} = K_i^{-*}/\nu,\ k_b^{-*} = K_b^{-*}/\nu,\ k_r^{+*} = K_r^{+*}/\nu,\ k_u^{+*} = K_u^{+*}/\nu$.

Definition 3.2: The status of the excluded efficient DMU_o from the reference set of SBM-ND model (2) is super efficiency in terms of SE-SBM-ND model (6), where the obtained efficiency score is greater than one (i.e. $\delta_o^* > 1$). This condition is satisfied in case that some or all values of discretionary input savings and/or output surpluses are positive. In other cases, where the resulting efficiency score is equal to one (i.e., $\delta_o^* = 1$), the excluded DMU_o is inefficient since its exclusion has no effect on the original PPS, leading to all discretionary input savings and outputs surpluses are zero values.

4. Case application

To test the applicability and usefulness of SBM-ND model (2) and SE-SBM-ND model (4), this paper utilized the data set of 18 suppliers, involving discretionary and non-discretionary inputs, as well as discretionary outputs. The data set were retrieved from a study introduced by Farzipoor Saen [12]. Each supplier, whose efficiency needs to be discriminated and ranked, was considered as an independent DMU. Each DMU consumes three inputs to produce three outputs. The discretionary inputs are the total cost of shipment (x_1^D) (in \$1000) and supplier reputation (x_2^D), while the non-discretionary input is delivery distance (x_3^{ND}) (in kilometre). The discretionary outputs are the number of shipments arrived on time (y_1^D), the number of bills received from suppliers without errors (y_2^D) and the number of supplied parts (y_3^D). Using the inputs and outputs, the resulting efficiency measures of models (2) and (4) are presented in the following subsections. Figure 1 exhibits the scenarios of evaluating and ranking supplier selection, using the proposed approach.

4.1. SBM-ND efficiency measures

In order to report and discuss the efficiency measures resulting from the proposed approach, a two-stage procedure should be run. In the first stage, the linear program of SBM-ND in model (4) is coded and run, using the Lingo software to distinguish between inefficient and efficient suppliers. The efficiency measures, including efficiency scores and slacks of discretionary input excesses and/or discretionary output shortfalls resulting from the first stage are exhibited in Table 2.

The efficiency scores of efficient and inefficient suppliers, as well as discretionary input and discretionary output slacks calculated by the linear program in model (4) are presented in columns #2 to #7 of Table 2. The slack of non-discretionary input of delivery distance did not present in Table 2 since its level is uncontrollable by management. The efficiency score of each efficient supplier is equal to one, this is equivalent to all of its discretionary input excess and output shortfall slacks are equal to zero (see Definition 3.1). The zero values of discretionary input and discretionary output slacks state that all of efficient suppliers takes place on the efficient production frontier, formed by the full-efficient suppliers. Consequently, the full-efficient status has only been achieved by nine suppliers. Conversely, since some or all values of discretionary input excess and/or discretionary output shortfall slacks are positive, the efficiency score of each inefficient supplier is less than one (see Definition 3.1). The positive slack values of discretionary input excesses (discretionary output shortfalls) reveal the maximum input (output) amount that can be subtracted (added) from (to) their relevant inputs (outputs) to decrease (increase) their levels. For instance, the input excesses and output shortfalls of inefficient supplier #11 are related to all of discretionary inputs and outputs by 37, 14, 18, 70 and 18, respectively. This shows that the efficiency of supplier #11 can be improved and transformed to

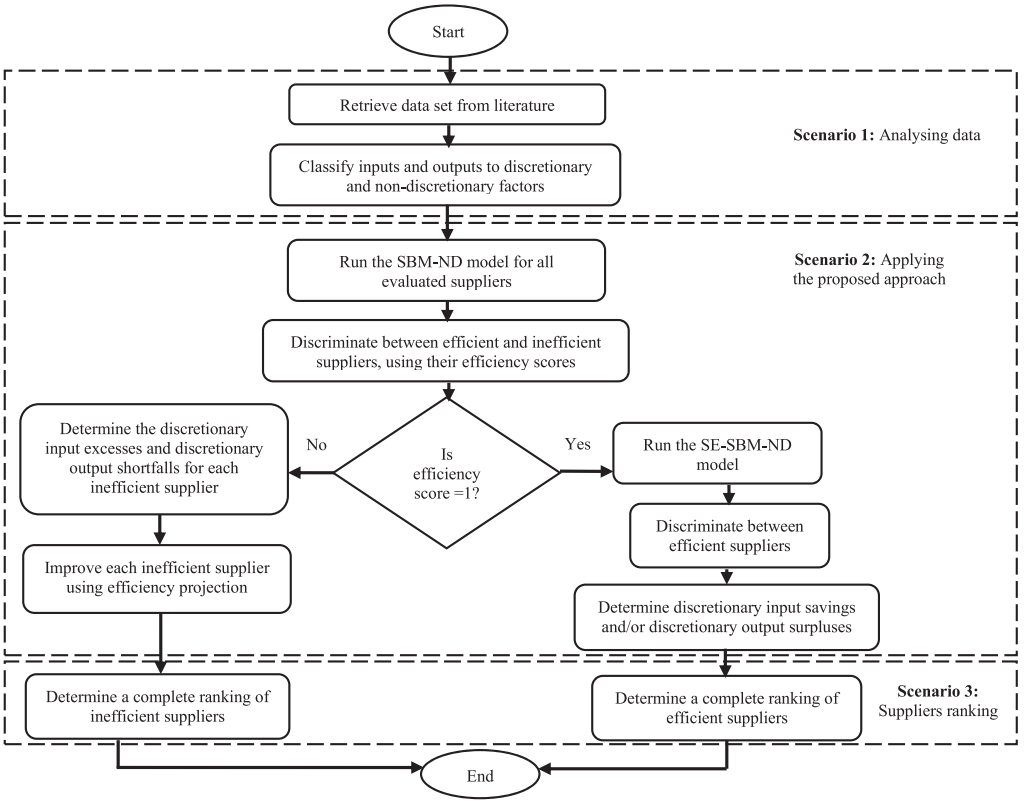


Figure 1. Scenarios of ranking suppliers using the proposed approach.

efficient supplier if its discretionary inputs are decreased by 37, and 14, while its discretionary outputs should be increased by 18, 70 and 18, respectively. These processes can be carried out, using the efficiency projection for each inefficient DMU.

The efficiency projection of the non-radial SBM model aims to decrease (increase) discretionary inputs (discretionary outputs) disproportionally, which is deemed the salient merit of the non-radial SBM model over radial models. However, if all or some values of the discretionary input excess slacks and/or discretionary output shortfall slacks of an inefficient supplier are increased more than their current amounts, leading to over decrease (increase) in their corresponding discretionary inputs (discretionary outputs), then status of the inefficient supplier remains inefficient. For instance, if some or all values of input excesses and/or output shortfalls of supplier #11 have increased more than their current amounts listed in Table 2, leading to extra decreasing in inputs and/or increasing in outputs. Thus, the efficiency of supplier #11 cannot be improved, and its status remains inefficient. Observe that all inefficient suppliers have input excesses in the total cost of shipment and supplier reputation, as well as output shortfall in the supplied parts. This reflects that these three factors have a significant role that causing the inefficiency status of all the inefficient suppliers.

4.2. SE-SBM-ND efficiency measures

Based on the results obtained from model (4), high performing suppliers have to distinguished and ranked. Therefore, the linear program of SE-SBM-ND in model (8) is coded and run, using the Lingo software, at the second stage. The resulting efficiency measures are tabulated in Table 3.

Table 2. Efficiency measures of the SBM-ND model.

		Input excesses			Output shortfalls	
Supplier	Efficiency score	Total cost of shipment s_1^-	Supplier reputation s_2^-	Number of shipments s_1^+	Number of bills s_2^+	Number of supplied parts s_3^+
1	0.1217	4.9821	3.0178	4.7321	79.2851	26.1071
2	0.3923	19.2142	7.9285	0	42.1428	13.2142
3	1	0	0	0	0	0
4	1	0	0	0	0	0
5	1	0	0	0	0	0
6	1	0	0	0	0	0
7	0.0581	22.5	5.6666	0	110.5	26.3333
8	0.4369	80.8214	8.8928	0	28.2142	1.3214
9	0.3751	75.8571	6.7142	0	28.5714	9.8571
10	1	0	0	0	0	0
11	0.24027	37	14	18	70	18
12	1	0	0	0	0	0
13	0.4099	32.8250	13.1750	24.3750	0	10.0500
14	0.3829	85	16	9	45	32
15	1	0	0	0	0	0
16	0.0616	85	16	9	45	32
17	1	0	0	0	0	0
18	1	0	0	0	0	0

Table 3. Efficiency measures of the SE-SBM-ND model.

			Input savings			Output surpluses	
Supplier	Super efficiency score	Rank	Total cost of shipment k_1^-	Supplier reputation k_2^-	Number of shipments k_1^+	Number of bills k_2^+	Number of supplied parts k_3^+
1	0.1217	16	0	0	0	0	0
2	0.3923	12	0	0	0	0	0
3	1.0879	4	0	0	22	28.50	0
4	1.1647	2	59.2941	0	0	0	0
5	1.0116	8	0	0	7.0582	0	0
6	1.0582	6	4.1780		3.2602	21.1369	0
7	0.0581	18	0	0	0	0	0
8	0.4369	10	0	0	0	0	0
9	0.3751	14	0	0	0	0	0
10	1.1357	3	0	0	0	0	19
11	0.2402	15	0	0	0	0	0
12	1.0033	9	0	0	0	2	0
13	0.4099	11	0	0	0	0	0
14	0.3829	13	0	0	0	0	0
15	1.0595	5	0	0	0.2000	31	0
16	0.0616	17	0	0	0	0	0
17	1.5937	1	0	1	0	0	6
18	1.0334	7	14.4480	0	0	0	0

Regarding the proposed SE-SBM-ND in model (6), the efficiency score of each inefficient supplier is equal to one, while it is greater than one for each efficient supplier, which deems the salient merit of the SE-SBM approach. The efficient status has been achieved by nine suppliers (i.e, DMUs #3, #4, #5, #6, #10, #12, #15, #17, and #18), out of the total 18 evaluated suppliers. According to Definition 3.2, for each super-efficient supplier, all or some of its slack values of discretionary input savings and/or discretionary output surpluses are positive. The positive values of discretionary input savings reveal the maximum amounts of inputs that can be added to the current levels of their relevant inputs of the efficient supplier to identify the maximum amounts of discretionary inputs. By contrast, the

positive values of discretionary output surpluses reveal the maximum amounts of outputs that can be subtracted from the current level of their relevant outputs of the efficient supplier to identify the minimum amounts of discretionary outputs.

The purpose of identifying the maximum amounts of discretionary inputs and the minimum amounts of discretionary outputs is to confirm that each efficient supplier which excluded from its reference set of SBM-ND can project on the super-efficient frontier to achieve the super efficiency status. For instance, the input saving of efficient supplier #17 is related to supplier reputation by one, and its output surplus is related to the number of supplied parts by six. This reveals that supplier #17 can preserve its efficiency status by adding one to the current level of its supplier reputation and subtracting six from the current level of supplied parts. Supplier #17 is the top supplier utilizing supplier reputation to produce outputs. In addition, it is ranked first among efficient suppliers.

The projection of discretionary inputs of the super-efficient suppliers is stated on the right-hand side of the discretionary input constraint of model (6). The projection of discretionary outputs of the super-efficient suppliers is, meanwhile, stated on the right-hand side of the discretionary output constraint of model (6). These projections can enhance efficient suppliers to achieve the super efficiency status by identifying the maximum allowable increases of discretionary inputs via identifying their input savings and the maximum allowable decreases of discretionary outputs via identifying their output surpluses. Any value is greater than the maximum allowable amounts of discretionary inputs and/or maximum allowable amounts of discretionary outputs will change the efficient supplier to inefficient. For example, if super-efficient supplier #17 is added more than one to its current level of supplier reputation (i.e. over increase) and/or subtracted more than six from its current level of supplied parts (i.e. over decrease), then its status immediately drops to inefficient. As stated in Section 3, the super efficiency score of each efficient supplier did not take into account slacks of uncontrollable inputs and outputs since these factors are outside the control of their management. Consequently, values of the uncontrollable input and output slacks did not present in Table 3.

4.3. Comparison with Tone's SE-SBM approach

To compare results obtained from the proposed SE-SBM-ND approach in models (2) and (6) with other approach, one of the most popular and successful approaches in the DEA literature to rank the efficiency of DMUs is Tone's [23] SE-SBM approach. Therefore, the approach was applied on the data set of this paper for the comparison purpose. The resulting efficiency scores from our proposed approach are compared with those of Tone's approach. The comparison aims to validate the results and advantage of integrating uncontrollable inputs and outputs into the existing approach of Tone [23]. The existing approach presumes that all inputs and outputs are under management's control. Thus, all inputs and outputs of the utilized data set in this research are assumed to be discretionary. The efficiency scores and rankings of the evaluated suppliers resulting from the existing and the proposed approaches regarding the VRS assumption are presented in Table 4.

Table 4 reports that the super-efficient and inefficient suppliers resulting from the proposed approach have preserved their efficient and inefficient statuses under the existing approach, in which each efficient supplier obtained from the proposed approach is efficient in terms of the existing approach as well. However, the efficiency scores of most of the efficient and inefficient suppliers resulting from the two compared approaches are different, except each of supplier # 3 and supplier # 15 achieved the same super efficiency scores under the compared approaches, as shown in Figure 2. Besides, ranking obtained from the existing approach of each supplier differs from that of the proposed approach, except each of supplier #1, #2, #7, #10, #12, #16, and #17 has the same rank under the compared approaches, as shown in Figure 3. Rankings similarity for these suppliers is due to that the utilized data set only considers a unique non-discretionary input, which makes the objective functions and input and output constraints of the compared approaches are almost similar (see for example the data set of [19], Table 1, p. 559). For a better analysis, data set consists of several uncontrollable inputs and outputs can be taken into consideration.

Table 4. Comparison results.

Supplier	Tone's (2002) approach Efficiency score	Rank	The proposed approach Efficiency score	Rank
1	0.1388	16	0.1217	16
2	0.3485	12	0.3923	12
3	1.0879	5	1.0879	4
4	1.1098	4	1.1647	2
5	1.0303	7	1.0116	8
6	1.4043	2	1.0582	6
7	0.0442	18	0.0581	18
8	0.3723	11	0.4369	10
9	0.3415	13	0.3751	14
10	1.1467	3	1.1357	3
11	0.3386	14	0.2402	15
12	1.0140	9	1.0033	9
13	0.3915	10	0.4099	11
14	0.3158	15	0.3829	13
15	1.0595	6	1.0595	5
16	0.0678	17	0.0616	17
17	1.4166	1	1.5937	1
18	1.0234	8	1.0334	7

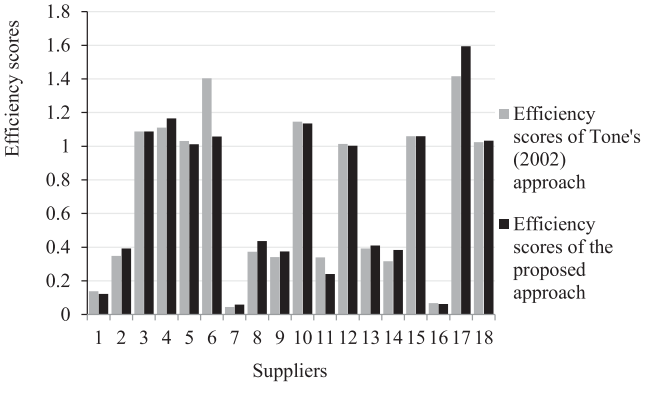


Figure 2. Visual comparison of efficiency scores.

To validate the efficiency measures obtained from the proposed approach and to evaluate their associations with those of the existing approach, Spearman's rank correlation between efficiency scores resulting from the compared approaches was examined. Also, the correlation coefficient between supplier rankings obtained from the comparison was examined. Since the correlations of the efficiency scores and rankings resulting from the comparison, at a significant level of p-value 0.00001 are strongly positive (i.e. 0.9669 and 0.9666), we conclude that uncontrollable inputs and outputs have been incorporated into Tone's approach appropriately, as well as efficiency measures of the proposed approach have been computed properly ([66], p.689).

5. Academic and managerial implications

SCM – the management of activities of a firm that moves products or services from suppliers to customers – has become a significant topic in industrial sectors. In sustainable SCM, suppliers ranking and selection is one of the important operational tasks. Selecting appropriate suppliers is a Multi-Criteria Decision-Making (MCDM) problem in decision analysis. One of MCDM tools is DEA which has long been employed by many efficiency studies to evaluate suppliers, such as Davoudabadi et al.

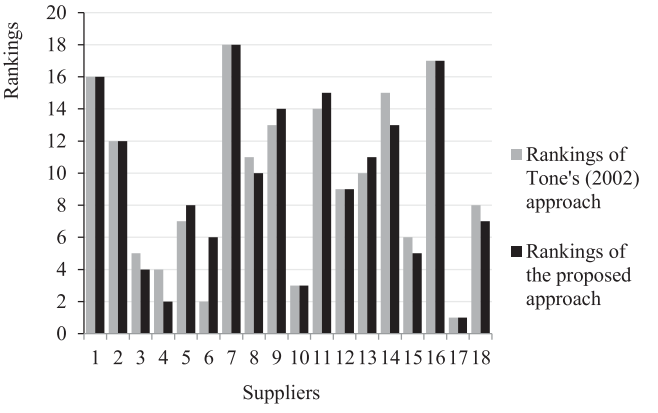


Figure 3. Visual comparison of rankings.

[67], Dutta et al. [2], Farzipoor Saen [54], Izadikhah and Farzipoor Saen [15], Jahanshahloo et al. [41], and Noorizadeh et al. [56]. However, all of the inputs and outputs used in the studies were expected to be discretionary. In supplier selection, there exist many uncontrollable inputs (such as delivery distance) and/or outputs (such as supply variety and defective products).

To cater for this problem, the proposed super efficiency DEA approach integrates both factors of uncontrollable inputs and outputs into Tone's [23] SE-SBM approach. The proposed approach can examine the real impact of uncontrollable factors on efficiency measures. Thus, in terms of an academic aspect, this study constructs a mathematical DEA approach that can effectively measure the performance and efficiency of a collection of teams of individuals participating in an operational decision process. In contrast, in terms of a practical aspect, the approach helps decision makers discriminate and rank suppliers effectively. Additionally, the approach is suitable for various real-world applications of efficiency evaluation, including supplier selection and ranking.

6. Conclusions and further research extensions

Sustainable supplier selection has considered one of the most significant activities for establishing an effective sustainable supply chain and classified as a multi-criteria decision-making problem. The uncontrollable factors of inputs and outputs are factors which cannot be managed by the suppliers' management. These factors exist in almost managerial cases, including supplier selection and ranking. They are, however, not taken into consideration in the standard super efficiency of slacks-based measure approach of Tone [23] for sustainable supplier selection and ranking. Incorporating the factors into Tone's [23] approach can accurately measure the efficiency of suppliers and rank them. Therefore, this paper proposes a super efficiency of slacks-based measure approach in DEA with uncontrollable inputs and outputs for evaluating sustainable suppliers. The efficiency results help an organization select the best supplier to avoid operational and financial problems in today's competitive and dynamic environment. The practicability of the proposed approach was tested using 18 suppliers, retrieved from DEA literature. The results showed that only nine out of the total 18 suppliers were efficient. The efficiency scores of most of the inefficient suppliers were relatively low, indicating that they have much excesses in discretionary inputs and/or shortfalls in discretionary outputs. The approach is applicable for many real-managerial applications, where some of their data are uncontrollable inputs and/or outputs.

Further research extensions can be introduced based on the results of this research, some of them are as below:

- A potential improvement is to propose a new version of the proposed approach in terms of imprecise inputs and outputs – factors which cannot be accurately measured and exist in many real-world problems. Such imprecise factors or uncertain information can be formulated using fuzzy numbers or interval data. To deal with imprecise data, Arana-Jiménez et al. [68] proposed an SBM model to measure inefficiency proportions when inputs and outputs are fuzzy data. An SE-SBM approach with fuzzy data which can effectively distinguish uncertainty was proposed in Hsiao et al. [69]. Emrouznejad and Mustafa [70] proposed an alternative model of linear programming that can involve some information of uncertainty obtained from the intervals of the α − cutapproach.
- Based on some of recent techniques of operational research, another potential improvement can also be considered to assess suppliers in the presence of uncontrollable factors, such as PROMETHEE âĚą and hybrid genetic algorithm (HGA) to realize sustainable supplier for a small- and medium-sized enterprises [71], nonlinear mixed integer programming (NLMIP) [72], and hybrid fuzzy DEMATELAEW-FVIKOR [73].

Note

1. In classical radial models, input-oriented refers to inputs that are reduced proportionally, while outputs maintain their current levels. In contrast, output-oriented refers to outputs that are increased proportionally, while inputs keep their current levels [18,19,20].

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