A Modified-Range Directional Measure for Assessing the Sustainability of Suppliers by DEA/UTASTAR

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ABSTRACT

Sustainability in the supply chain means considering environmental, social, and economic practices. Conventional data envelopment analysis (DEA) models deal with desirable, discretionary, and nonnegative data. However, there might be undesirable outputs, nondiscretionary factors, and negative data. On the other hand, some criteria can be considered as outputs and inputs. These factors are named as the dual-role criteria. The objective of this paper is to develop a non-radial DEA model for dealing with negative data in the presence of undesirable, non-discretionary, and dual-role factors in weight restrictions context. The ordinal regression method, UTASTAR, is performed to define priorities in terms of criteria. The capabilities of the proposed method are compared with other methods. A case study is presented in which the best sustainable suppliers of SAPCO are selected. To check the importance of dual-role variables, two extra cases are considered.

KEYWORDS

Data Envelopment Analysis (DEA), Dual-Role Factors, Negative Data, Nondiscretionary Factors, Sustainable Supplier Selection, Undesirable Factors, UTASTAR, Weight Restrictions

1. INTRODUCTION

Supplier selection plays a key role in supply chain management (SCM). One of the important aims of supply chains is to increase the level of customer satisfaction. The increased outsourcing and reduced supply bases have increased buyers’ confidence (Ballew and Schnorbus, 1994; Handfield and Nichols, 1999; Ballew and Schnorbus, 1994)). Tseng and Chiu, (2013) introduced some non-environmental and environmental factors and suggested using grey relational analysis. Hutchins and Sutherland, (2008) presented a method for examining criteria. They introduced a framework for assessing the impact of social factors on sustainable supply chains. To analyze the sustainability of organizations, we should consider economic, environmental, and social factors (Clift, 2003),
Sustainability factors play a key role in achieving a long-term relationship in SCM (Seuring and Müller, 2008; Mehlawat et al., 2019; Yu et al., 2019). On the other hand, mathematical programming is a good tool to compare the alternatives by considering different indicators. Among the various methods of mathematical programming, data envelopment analysis (DEA) is a successful method and has been used in many settings. Since the novel work of Charnes et al., 1978, DEA has been utilized to assess the relative efficiency of decision making units (DMUs) (Izadikhah and Farzipoor Saen, 2015; Roman et al., 2005). The main objective of this paper is to assess the sustainability of suppliers. The assessment needs some criteria that the conventional DEA models cannot handle them. In assessing the sustainability of suppliers we face with a couple of criteria, including i) Distance that is considered as a nondiscretionary input, ii) Rate of losses that is considered as an undesirable output, iii) Rate of the increasing success of shipping that can take both negative and non-negative values, and iv) Number of obtained ISO certificates that can be regarded as either input or output (dual-role factor).

In the conventional DEA models, to achieve the maximum efficiency score, flexibility of weights is assumed. However, the flexibility of weights can be in contrast with the decision maker’s opinions. Weight restriction has been introduced to overcome weight flexibility in DEA. Also, classical DEA models assume that all inputs and outputs are not only discretionary but also desirable and can be changed at the discretion of management. However, in real-world problems, there might be undesirable outputs and non-discretionary inputs and outputs. It is, therefore, necessary to consider both discretionary and non-discretionary factors in the efficiency evaluation of DMUs (Ruggiero, 1996; Syrjänen, 2004). Although classical DEA models deal with positive data, there are circumstances in which negative inputs and outputs exist (e.g., financial losses when we consider net profit as an output) (Kazemi Matin and Azizi, 2011). Also, some factors are both inputs and outputs, which are named as the dual-role criteria.

Radial models, like CCR (Charnes-Cooper-Rhodes) model, have some disadvantages such as failure to recognize weak efficient DMUs (Izadikhah and Farzipoor Saen, 2016a; Izadikhah and Farzipoor Saen, 2016b; Taewoo, 2019). The non-radial DEA models have some advantages over the radial models. Thus, they have been used in sustainable supplier selection problems (Tone et al., 2020a). As a result, in this paper, we seek to present a non-radial DEA model to deal with the above-mentioned requirements. To this end, this paper presents a non-radial DEA model to handle negative data in the presence of undesirable, non-discretionary, and dual-role factors for selecting sustainable suppliers under weights restrictions. To this end, we extend the range directional measure (RDM) model and name it as modified RDM (MRDM) model. Finally, we test our proposed model in the real world by assessing 26 suppliers of the clutch pressure plate. These suppliers can supply a clutch pressure plate for Supplying Automotive Parts Company (SAPCO). SAPCO is an original equipment manufacturer (OEM) of automotive parts of Irankhodro Company. Irankhodro Co. is the biggest car manufacturer in the Middle East. In this paper, we use the UTASTAR method. For our study, the first four suppliers are selected to be analyzed in more detail. Since UTASTAR allows decision-makers (DMs) to easily build their priority models based on criteria, it is considered as an appropriate approach (Siskos and Yannacopoulos, 1985)). The purpose of UTASTAR is to calculate some utility functions that satisfy the decision maker’s opinion on the preordered set of alternatives. UTASTAR is an enhanced form of UTilités Additives (UTA) model (Jacquet-Lagrèze and Siskos, 1982), which is based on the disaggregation-aggregation approach (Siskos, 1980) that analyzes DM’s behavior and modifies their knowledge of decision-making status through iterative interactions. As a result, the increased intricacy related to such perspectives raises the following questions:

1. How can we handle the negative data in DEA in evaluating the sustainably of suppliers in SCM?
2. How can we evaluate and improve the sustainability of suppliers?
3. What approaches and models are appropriate for assessing the sustainably of suppliers?
4. How can we determine the status of dual-role factors fairly?
5. How can we evaluate the sustainability of suppliers in the existence of undesirable outputs, non-discretionary factors, dual-role factors, and weights restrictions, simultaneously?
6. How can we manage the decision maker’s priority by the UTASTAR model?

The main contributions of the current research are summarized as follows: As far as we know, there is no comprehensive approach to consider weight restrictions, negative data, non-discretionary factors, undesirable data, and dual-role criteria. This paper presents two new DEA models. The first model considers negative data, non-discretionary factors, undesirable data, and dual-role factors. This model is the first model that considers these kinds of variables. To incorporate the weight restrictions into the proposed model, this paper uses a dual version of the first model. Therefore, the second model considers negative data, non-discretionary factors, undesirable data, dual-role factors, and weight restrictions. The proposed model employs the UTASTAR method to allow decision-makers to build their priority based on the criteria. Our models are used to assess the sustainability of suppliers. As far as we know, there is no paper on the DEA/UTASTAR model for evaluating sustainable suppliers.

The remainder of this paper is as follows. Section 2 provides the literature review. Section 3 briefly reviews the RDM model and the UTASTAR method. In Section 4, our proposed model is given. Section 5 demonstrates a case study. In Section 6, the concluding remarks are discussed.

2. LITERATURE REVIEW

2.1 Sustainable Supplier Selection

Sustainability plays an important role in SCM. Suppliers that are not environmentally friendly may damage the organization’s reputation (Dou and Sarkis, (2010)). There are a couple of methods for finding the best suppliers. Fig. 1 presents the supplier selection techniques.

If suppliers are not environmentally friendly, the supply chain is not sustainable. Sustainable SCM (SSCM) reflects the collaboration between companies in the supply chain in terms of economic, environmental, and social aspects (Seuring and Müller, (2008)). In recent years, sustainability has become one of the hot topics in the SCM. Manufacturing green products is a response to the pressures from authorities, buyers, and NGOs (Seuring, (2013)). Sustainability is a major topic for researchers due to the decline in natural reserves and worries on the capital disparity and societal obligation (Govindan et al., (2013)). Dao et al., (2011) addressed that concerns about sustainability have increased.
corporate accountability. Also, communities, businesses, and NGOs are remarkably looking for tools to measure the sustainability progress of organizations (Tsoulfas and Pappis, (2006)).

As mentioned by Dyllick and Hockerts, (2002), the SSCM is a mixture of sustainable development and SCM in which sustainability is evaluated based on economic, environmental, and social factors. Cetinkaya et al., (2011) discussed that the SSCM should not only address the financial issues but also it should help the community. Bai and Sarkis, (2010) employed the gray system and rough set theory to incorporate sustainability indicators into the supplier selection and ranking process. Amindoust et al., (2012) presented a comprehensive list of criteria for sustainable supplier selection. They proposed a method for ranking suppliers based on the criteria. Here, according to Izadikhah et al., (2017a), we provide a brief list of the main factors of sustainability (see Table 1).

Table 1. The main factors of sustainability

| Criteria            | Sub-criteria                        | References                                      |
|---------------------|-------------------------------------|------------------------------------------------|
| Economic            | Cost/price                          | Amindoust et al., (2012); Amindoust, (2018)      |
|                     | Quality                             | Büyüközkan and Çifçi, (2011); Mehdikhani and Valmohammadi, (2019) |
|                     | Technology capability               | Mafakheri et al., (2011); Gören, (2018)          |
|                     | Manufacturing capabilities and size | Aydın Keskin et al., (2010); Memari et al., (2019) |
|                     | Financial capability                | Aydın Keskin et al., (2010)                      |
|                     | The total cost of shipments         | Ahmady et al., (2013); Farzipoor Saen, (2009); Gören, (2018) |
|                     | Number of shipments                 | Mahdiloo et al., (2015); Cheraghaliipour and Farsad, (2018) |
|                     | Delivery                            | de Boer et al., (2001); Amindoust, (2018)        |
|                     | Service capability                  | Yu and Tsai, (2008); Bolturk, (2018)             |
|                     | Environmental expenditures          | Amindoust et al., (2012)                         |
| Environmental       | Environmentally friendly blueprints | Humphreys et al., (2003)                         |
|                     | Green R&D                           | Büyüközkan and Çifçi, (2011); Temur Gül and Bolat, (2018) |
|                     | Contamination management            | Amindoust et al., (2012); Awasthi et al., (2010) |
|                     | Green product                       | Lee et al., (2009); Mehdikhani and Valmohammadi, (2019) |
|                     | Sum of ISO certificates             | Erol et al., (2011); Memari et al., (2019)       |
|                     | Environmentally friendly-design     | Amindoust et al., (2012); Hasan et al., (2020)   |
|                     | Benefits and entitlements of staff  | Amindoust et al., (2012); Kuo et al., (2010); Kris et al., (2021) |
|                     | Entitlements of sponsors            | Amindoust et al., (2012)                         |
| Social              | Work safety and labor health        | Giannakis and Papadopoulos, (2016); Bolturk, (2018) |
|                     | Rule obedience                      | Kuo et al., (2010)                               |
|                     | Hiring practices                    | Bai and Sarkis, (2010)                           |
|                     | Misconduct with animals             | Giannakis and Papadopoulos, (2016)               |
2.2 DEA Models for SCM

DEA is a mathematical programming-based approach, which is used to assess suppliers. Kleinsorge et al., (1992); Weber et al., (2000a); Weber et al., (2000b) Kleinsorge et al., (1992); Weber et al., (2000a); Weber et al., (2000b) Kleinsorge et al., (1992); Weber et al., (2000a); Weber et al., (2000b) Kleinsorge et al., (1992); Weber et al., (2000a); Weber et al., (2000b) Kleinsorge et al., (1992); Weber et al., (2000a); Weber et al., (2000b) developed an approach to evaluate the performance of suppliers by combining DEA and multi-objective programming. Kleinsorge et al., (1992) applied DEA to monitor the suppliers. Liu and Hai, (2005) integrated the voting procedure with the analytical hierarchical process (AHP) method and suggested a DEA approach for choosing the suppliers. In Table 2, a couple of supplier selection techniques based on DEA are summarized.

2.3 DEA and Non-Discretionary Factors

There are some different approaches to deal with non-discretionary inputs and outputs. The first approach was proposed by Banker and Morey, (1986). After that, Ruggiero, (1996) and Ruggiero, (1998) continued their work by relaxing convexity constraint. Some authors have tried to consider non-discretionary factors in their proposed DEA models. Ray, (1991) and Fried et al., (1993) proposed a two-phase DEA model. Muñiz, (2002) developed a new three-phase DEA model by considering non-discretionary factors. Hosseinzadeh Lotfi et al., (2007) presented a sensitivity analysis based on DEA models. Esmaeili, (2009) developed a non-radial measure of efficiency. Saati et al., (2011); Zerafat Angiz and Mustafa, (2013) presented DEA models in a fuzzy environment in the existence of non-discretionary factors. Aliakbarpoor and Izadikhah, (2012a) reviewed articles, which incorporated undesirable or non-discretionary data into DEA models. Khoshandam et al., (2014) and Shabani et al., (2015) proposed DEA models by considering non-discretionary factors. Soltani and Lozano, (2018) take into account the undesirable outputs, nondiscretionary variables, and preference structures. Galagedera, (2019) developed a DEA model to assess mutual fund performance in a multi-dimensional framework. In the study, the ethical level was modeled as a non-discretionary output. Queiroz et al.,

| Researchers | The used approaches |
|-------------|---------------------|
| Talluri et al., (2006); Wu, (2010) | Chance-constrained DEA |
| Wu, (2009) | DEA, Artificial neural networks |
| Zhou et al., (2016); Izadikhah et al., (2017b); Amandoust, (2018); Yousefi et al., (2017); Jafarzadeh et al., (2018) | Fuzzy DEA |
| Chen, (2011) | DEA, TOPSIS |
| Wang and Li, (2014) | DEA, Game theory |
| Khodakarami et al., (2015); Izadikhah and Farzipoor Saen, (2016a); Sarkhosh-Sara et al., (2019) | Two-stage DEA |
| Mahdiloo et al., (2015); Sarkhosh-Sara et al., (2019) | DEA, Undesirable data, MODM |
| Izadikhah and Farzipoor Saen, (2016b); Izadikhah and Farzipoor Saen, (2019) | DEA, Geographic information system, Voting |
| Ehsanbakhsh and Izadikhah, (2015) | DEA, Balanced scorecard (BSC), Inference system based on fuzzy |
| Rashidi and Saen, (2018) | Dynamic DEA |
(2020) investigated the efficiency of Brazilian primary education by a dynamic DEA model in which the socioeconomic levels were treated as non-discretionary variables.

2.4 DEA and Undesirable Data

Sometimes, DMUs might produce bad outputs like contamination, noise, etc. Fig. 2 illustrates the existing methods for considering undesirable data in DEA.

As is seen in Fig. 2, there are two main DEA methods for considering the undesirable data including DEA techniques based on weak disposability and data translation. A review of the literature indicates that the latter is more widely used than the first. See Table 3 for a brief review.

2.5 Weight Restrictions in DEA

All the aforementioned literature relies on arbitrary weights of the factors. However, the arbitrary weights are quite subjective. Charnes et al., (1989) proposed a DEA model based on cone-ratio for considering weight restrictions. After that, Thompson et al., (1990) proposed the assurance region (AR) model. Sarrico and Dyson, (2004) considered the virtual assurance regions. Based on Sarrico and Dyson’s work, Despotis et al., (2010); Galagedera, (2014); Kao and Hung, (2008) developed a method for considering weight restrictions. There are other DEA works that readers can refer to them (e.g., Ebrahimi et al., (2017); Podinovski, (2016); Podinovski and Bouzdine-Chameeva, (2016)). Basso et al., (2018) developed a joint application of DEA and BSC to evaluate the performance of museums. Ebrahimi et al., (2020) presented a mixed binary linear DEA model for finding the most efficient DMU by considering weight restrictions.

Figure 2. The DEA methods for taking into account the undesirable data

Table 3. The undesirable data in DEA literature

| Methods                | References                                                                 |
|------------------------|-----------------------------------------------------------------------------|
| Weak disposability     | Färe and Grosskopf, (2000, 2003); Färe et al., (1993); Korhonen and Luptacik, (2004) |
| Data translation       | Reciprocal                                                                   |
|                        | Golany and Roll, (1989)                                                      |
|                        | Additive inverses                                                            |
|                        | Aliakbarpooor and Izadikhah, (2012b); Maghbouli et al., (2014) Liu et al., (2015); Fusco et al., (2019); Halkos and Petrou, (2019); Piao et al., (2019); Toloo and Hančlová, (2019); Zhang and Cui, (2020); Zhou et al., (2019) |
2.6 Negative Data in DEA Models

To deal with negative values, Scheel, (2001) and Portela et al., (2004) proposed DEA models. Sharp et al., (2007) presented a revised slack-based measure (SBM) to handle negative values in inputs and outputs. To evaluate DMUs in the presence of both negative and positive values, Emrouznejad et al., (2010) developed a semi-oriented radial measure (SORM) model based on DEA. To handle the negative data, Portela and Thanassoulis, (2010) developed a productivity measure based on the RDM model. Allahyar and Rostamy-Malkhalifeh, (2015) developed a new non-radial DEA model and also a model for measuring the return to scale based on negative data. Kordrostami and Jahani Sayyad Noveiri, (2012) proposed a DEA model for considering negative data using flexible data.

Sahoo et al., (2016) developed a non-radial DEA model to determine both the most productive scale size and the returns to scale in the presence of negative data. Izadikah and Farzipoor Saen, (2016a) proposed a two-stage DEA model in the presence of negative data. Khoveyni et al., (2017) presented a DEA model to determine DMUs with congestion in the presence of negative data. Lin and Chen, (2017) developed a radial super-efficiency DEA model, which allows the input-output variables to take both negative and positive values.

Tavana et al., (2018) developed a network DEA model in the presence of negative data. They introduced a dynamic RDM model in a two-stage context to handle both negative and undesirable data. Kaffash et al., (2018) proposed a version of the modified SORM model using directional distance function (DDF) to deal with positive and negative values. Lin and Liu, (2019) developed a DDF-based super-efficiency model to deal with negative data and generated bounded super-efficiency scores. Tone et al., (2020b) proposed a slacks-based measure to handle negative data. Kao, (2020) proposed a generalized radial model to deal with the negative data.

2.7. Dual-Role Factors

In evaluating different organizations and companies we may come across the factors that can be both input and output. For example, in the supplier selection problem, research and development (R&D) costs can be considered as an input and output. R&D is input as it is a cost per se. on the other hand, it is output as it implies the level of innovations in suppliers. Beasley, (1990, 1995) analyzed the research budget as a dual-role factor. Cook et al., (2006) explained the limitations of Beasley methods. Farzipoor Saen, (2010c) presented a DEA model to handle the dual-role criteria. Farzipoor Saen, (2010a) considered a dual-role factor and weight restrictions. Mirhedyatian et al., (2014), using a network DEA model, evaluated suppliers in the presence of dual-role factors. Azizi and Farzipoor Saen, (2015); Kumar et al., (2014); Shabani and Farzipoor Saen, (2016) presented some applications based on DEA models in the existence of dual-role criteria. Izadikah et al., (2017a) developed a DEA model based on the modified enhanced Russell model for controlling the role of dual-role variables in evaluating suppliers’ sustainability in the presence of volume discounts. Toloo et al., (2018) introduced a pair of interval DEA models based on the pessimistic and optimistic standpoints for dealing with interval dual-role factors. Su and Sun, (2018) developed a network DEA model to handle undesirable outputs and dual-role factors.

2.8 Decision Making Using UTASTAR

The ordinary regression analysis method (UTASTAR) is an advanced case for the conventional UTA method (Jacquet-Lagrèze and Siskos, (1982)). This method uses the ranking of m references and deduces one or more piecewise linear value functions. There are a limited number of papers, which discuss applications of UTASTAR. Examples of the use of UTASTAR include a method for evaluating the country risk based on the UTASTAR and MINORA system (Cosset et al., (1992)), and an employer assessment system and a strategic performance evaluation system based on UTASTAR (Grigoroudis et al., (2012); Grigoroudis and Zopounidis, (2012)).

Patiniotakis et al., (2011) developed a fuzzy UTASTAR method for deriving the required fuzzy utility functions. Grigoroudis et al., (2012) developed a performance measurement system using the
UTASTAR method. Mastorakis and Siskos, (2016) developed a multi-criteria measurement system to evaluate investments on new products. They assessed the ranking of obtained categories by UTASTAR. Papapostolou et al., (2017) suggested a method based on UTASTAR to assess potential opportunities. Demesouka et al., (2019) applied a spatial UTASTAR to identify areas for locating a solid waste landfill. Trachanatzi et al., (2020) developed an interactive optimization framework to support tourist decision making by UTASTAR for eliciting tourist preferential information. Zhang et al., (2020) proposed a priority-based intuitionistic multiplicative UTASTAR method to identify the low-carbon tourism destinations.

2.9 Research Gap Analysis

The literature demonstrates that the SSCM and the auto parts industry have received remarkable attention over the last years. The literature shows that the DEA is a powerful tool for assessing the sustainability of suppliers. However, there are some research gaps in the literature, which are listed as follows:

- A novel non-radial DEA model is developed and applied in the auto parts industry sector.
- For the first time, a new DEA model is presented, which considers negative data, non-discretionary factors, undesirable data, and dual-role factors, simultaneously.
- The proposed method uses the UTASTAR to allow the decision-makers to build their priorities based on the criteria.
- As far as we know, there is no paper on the DEA/UTASTAR model for evaluating sustainable suppliers.

In this study, we fill the existing research gaps by proposing a novel non-radial DEA model and apply it in the auto parts industry.

3. PRELIMINARIES

3.1 RDM Model

Consider \( n \) DMUs such that each \( DMU_j \) (\( j=1,..,n \)) consumes \( m \) inputs, \( x_{ij} (i=1,..,m) \), to produce \( s \) outputs, \( y_{rj} (r=1,..,s) \). We assume that the data set is positive. The used nomenclatures are reported in Table 4.

We consider the RDM model under variable returns to scale technology since it can deal with the negative data. Portela et al., (2004) proposed the following RDM model to handle negative data based on directional distance function under variable return to scale (VRS) technology:

\[
\begin{align*}
\max & \quad \beta \\
\text{s.t.} & \\
\sum_{j=1}^{n} \lambda_j x_{ij} + t^-_i = x_{io} - \beta L^-_{io}, & \quad i = 1,..,m, \\
\sum_{j=1}^{n} \lambda_j y_{rj} - t^+_r = y_{ro} + \beta L^+_{ro}, & \quad r = 1,..,s, \\
\sum_{j=1}^{n} \lambda_j = 1, \\
t^- \geq 0, & \quad t^+ \geq 0, \quad \lambda \geq 0.
\end{align*}
\]
where:

$$L_{io}^- = x_{io} - \min_j \{x_{ij}\}, (i = 1, \ldots, m)$$

and:

$$L_{ro}^+ = \max_j \{y_{rj}\} - y_{ro}, (r = 1, \ldots, s)$$

Model (1) does not calculate technical efficiency; therefore the technical efficiency can be determined as $$1 - \beta^*$$, where $$\beta^*$$ is obtained from the optimal solution of Model (1).

### 3.2 UTASTAR Algorithm

UTASTAR is a decision-making method developed by Siskos and Yannacopoulos, (1985). UTASTAR is a modified version of UTA. The UTA was proposed by Jacquet-Lagrèze and Siskos, (1982). UTA

| Symbol | Description | Symbol | Description |
|--------|-------------|--------|-------------|
| DMU<sub>0</sub> | DMU under evaluation; | DMU<sub>j</sub> | j<sup>th</sup> DMU; |
| m | number of inputs; | \(\lambda_j\) | intensity; |
| s | number of outputs; | \(L_{io}^-\) | Lower sided ranges for inputs; |
| \(x_{ij}\) | \(i<sup>th</sup>\) input of \(DMU_j\); | \(L_{ro}^+\) | Lower sided ranges for outputs; |
| \(y_{rj}\) | \(r<sup>th</sup>\) output of \(DMU_j\); | \(1 - \beta^*\) | The efficiency score of RDM and MRDM |
| \(\{D_1I\}\) | Fixed index sets for discretionary inputs | \(\{D_2I\}\) | Fixed index sets for desirable inputs |
| \(\{NI\}\) | Fixed index sets for nondiscretionary inputs | \(\{UI\}\) | Fixed index sets for undesirable inputs |
| \(\{D_1O\}\) | Fixed index sets for discretionary outputs | \(\{D_2O\}\) | Fixed index sets for desirable outputs |
| \(\{NO\}\) | Fixed index sets for nondiscretionary outputs | \(\{UO\}\) | Fixed index sets for undesirable outputs |
| \(\{OA\}\) | Fixed index sets for desirable and discretionary outputs | \(\{IA\}\) | Fixed index sets for desirable and discretionary inputs |
| \(\{OB\}\) | Fixed index sets for desirable and nondiscretionary outputs | \(\{IB\}\) | Fixed index sets for desirable and nondiscretionary inputs |
| \(\{OC\}\) | Fixed index sets for undesirable and discretionary outputs | \(\{IC\}\) | Fixed index sets for undesirable and discretionary inputs |
| \(\{OD\}\) | Fixed index sets for undesirable and nondiscretionary outputs | \(\{ID\}\) | Fixed index sets for undesirable and nondiscretionary inputs |
considers the minimization of only one single error \(\sigma(a)\). In contrast, there is a double positive error function in the UTASTAR method in which the aggregation model becomes:

\[
u'[g(a)] = \sum_{i=1}^{n} u_i[g_i(a)] - \sigma^+(a) + \sigma^-(a); \quad a \in A_R
\]

(2)

In Expression (2), the overestimation and underestimation errors are shown by \(\sigma^+\) and \(\sigma^-\), respectively. Also, the utility functions are denoted by \(u_i\), \(i = 1, \ldots, n\). These functions are non-decreasing real values and are normalized between 0 and 1. Also, another important modification relates to the uniformity of the criteria considered by the following transformations of variables:

\[
w_{ij} = u_1(g_i^{i+1}) - u_1(g_j^i) \geq 0; \forall i = 1, \ldots, n \text{ and } j = 1, \ldots, \alpha_i - 1
\]

(3)

UTASTAR algorithm is summarized as follows:

**Step 1**: State the universal value of reference actions \(u[g(a_k)]\), \(k = 1, \ldots, m\). This is done from two perspectives. First, in terms of marginal values \(u_i(g_i^j)\). Then, in terms of variables based on formula (2) using the following relations:

\[
\begin{cases}
u_i(g_i^i) = 0; & \forall i = 1, \ldots, n \\
u_i(g_i^j) = \sum_{i=1}^{j} w_{ij} \quad \forall i = 1, \ldots, n \text{ and } j = 2, \ldots, \alpha_i - 1
\end{cases}
\]

(4)

**Step 2**: Ranking expressions are defined as follows:

\[
\Delta(a_k, a_{k+1}) = \{u[g(a_k)] - \sigma^+(a_k) + \sigma^-(a_k)\} - \{u[g(a_{k+1})] - \sigma^+(a_{k+1}) + \sigma^-(a_{k+1})\}
\]

(5)

**Step 3**: Run the linear program (LP):

\[
\min \ z = \sum_{k=1}^{m} [\sigma^+(a_k) + \sigma^-(a_k)]
\]

s.t.

\[
\begin{align*}
\Delta(a_k, a_{k+1}) &\geq \delta \quad \text{if } a_k \succ a_{k+1}, \quad \forall k \\
\Delta(a_k, a_{k+1}) &\leq 0 \quad \text{if } a_k \approx a_{k+1}, \quad \forall k \\
\sum_{i=1}^{n} \sum_{j=1}^{\alpha_i - 1} w_{ij} & = 1, \\
w_{ij} & \geq 0, \sigma^+(a_k) \geq 0, \sigma^-(a_k) \geq 0; \forall i, j, k
\end{align*}
\]

(6)

where \(\delta\) is a small positive value.

**Step 4**: Check for multiple or near-optimal solutions for model (6) (stability analysis). If the solution is not unique, then find the mean value functions for the near-optimal solutions:
Feasible region is formed by the constraints of model (6) and is bounded by the following constraint:

\[ \sum_{i=1}^{m} [\sigma^+(a_k) + \sigma^-(a_k)] \leq z^* + \varepsilon \]  

where \( z^* \) is the optimal value of model (6) and \( \varepsilon \) is a very small positive number.

4. PROPOSED MODEL

In this section, first, we propose a scheme where we incorporate both undesirable and non-discretionary factors into DEA models. Assume that \( \{D_I\}, \{NI\}, \{D_O\}, \{NO\} \) indicate fixed index sets independent of \( j \), such that \( x_{ij}, y_{rj} \ (i \in \{D_I\} \text{ and } r \in \{D_O\}) \) are discretionary inputs and outputs, and \( x_{ij}, y_{rj} \ (i \in \{NI\} \text{ and } r \in \{NO\}) \) are non-discretionary inputs and outputs, respectively. Furthermore, assume that \( \{D_I\}, \{UI\}, \{D_O\}, \{UO\} \) indicate fixed index sets independent of \( j \), such that \( x_{ij}, y_{rj} \ (i \in \{DI\} \text{ and } r \in \{D_O\}) \) are desirable inputs and outputs and \( x_{ij}, y_{rj} \ (i \in \{UI\} \text{ and } r \in \{UO\}) \) are undesirable inputs and outputs, respectively. Here, we show the modified production possibility set (MPPS) and define it based on VRS:

\[
\begin{align*}
MPPS = \{ (x, y) | & \quad x_i \geq \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IA\}; \quad x_i \geq \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IB\}; \\
& \quad x_i \leq \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IC\}; \quad x_i \leq \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{ID\}; \\
& \quad y_r \leq \sum_{j=1}^{n} \lambda_j y_{rj}, r \in \{OA\}; \quad y_r \leq \sum_{j=1}^{n} \lambda_j y_{rj}, i \in \{OB\}; \\
& \quad y_r \geq \sum_{j=1}^{n} \lambda_j y_{rj}, r \in \{OC\}; \quad y_r \geq \sum_{j=1}^{n} \lambda_j y_{rj}, i \in \{OD\}; \\
& \quad \sum_{j=1}^{n} \lambda_j = 1, \\
& \quad \lambda_j \geq 0, j = 1, \ldots, n \}
\end{align*}
\]

where \( \{IA\} = \{D_I\} \cap \{D_O\}, \quad \{IB\} = \{D_I\} \cap \{NI\}, \quad \{IC\} = \{D_I\} \cap \{UI\}, \quad \text{and} \quad \{ID\} = \{NI\} \cap \{UI\} \) indicate fixed index sets on inputs and \( \{OA\} = \{D_O\} \cap \{D_O\} \), \( \{OB\} = \{D_O\} \cap \{NO\}, \quad \{OC\} = \{D_O\} \cap \{UO\} \), and \( \{OD\} = \{NO\} \cap \{UO\} \) indicate fixed index sets on outputs. We then use this MPPS to define modified dominance as follows:

**Definition 1 (modified dominance):** \( (\bar{x}, \bar{y}) \in MPPS \) and \( (x, y) \in MPPS \). \( (\bar{x}, \bar{y}) \) dominates \( (x, y) \) with respect to MPPS if and only if:
There is a strict inequity for, as a minimum, one of the elements of the inputs or outputs. To consider multiple dual-role criteria in DEA, as Farzipoor Saen, (2010a) addressed, we suppose that some criteria $w_{ij}, f=1,\ldots,F; j=1,\ldots,n$ are the dual-role criteria. Assume that for these dual-role factors, $A$ indicates fixed index set independent of $j$ and shows discretionary and desirable situation; $B$ indicates fixed index set and shows nondiscretionary and desirable situation; $C$ indicates fixed index set and shows discretionary and undesirable situation; and $D$ indicates fixed index set and shows the nondiscretionary and undesirable situation.

4.1 Justification of the Proposed DEA Model

Now, we modify the RDM model to take into account undesirable factors, nondiscretionary factors, and dual-role factors. Also, this model deals with negative data and can be presented as follows:

\[ \beta^* = \max \beta \]

s.t.

\[
\begin{align*}
\sum_{j=1}^{n} \lambda_{ij} x_{ij} &\leq x_{io} - \beta L_{io}, & i \in \{IA\}; \\
\sum_{j=1}^{n} \lambda_{ij} x_{ij} &\geq x_{io}, & i \in \{IB\}, \\
\sum_{j=1}^{n} \lambda_{ij} x_{ij} &\geq x_{io} + \beta B_{io}, & i \in \{IC\}; \\
\sum_{j=1}^{n} \lambda_{ij} x_{ij} &\leq x_{io}, & i \in \{ID\}, \\
\sum_{j=1}^{n} \lambda_{ij} y_{rj} &\geq y_{ro} - \beta B_{ro}, & r \in \{OA\}; \\
\sum_{j=1}^{n} \lambda_{ij} y_{rj} &\leq y_{ro}, & r \in \{OB\}, \\
\sum_{j=1}^{n} \lambda_{ij} y_{rj} &\geq y_{ro} + \beta L_{ro}, & r \in \{OC\}; \\
\sum_{j=1}^{n} \lambda_{ij} y_{rj} &\leq y_{ro}, & r \in \{OD\}, \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\leq w_{fo} - \beta H_{fo}, & f \in \{A\}; \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\leq w_{fo}, & f \in \{B\}, \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\geq w_{fo} + \beta U_{fo}, & f \in \{C\}; \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\geq w_{fo}, & f \in \{D\}, \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\geq w_{fo} + \beta H_{fo}, & f \in \{A\}; \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\leq w_{fo}, & f \in \{B\}, \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\leq w_{fo} - \beta U_{fo}, & f \in \{C\}; \\
\sum_{j=1}^{n} \lambda_{ij} w_{jf} &\geq w_{fo}, & f \in \{D\}, \\
\sum_{j=1}^{n} \lambda_{ij} &\geq 1, \\
\lambda &\geq 0
\end{align*}
\]

where lower-sided ranges for inputs and upper-sided ranges for outputs are as follows:

\[ L_{io} = x_{io} - \min_{j} \{x_{ij}\}, & i \in \{IA\}, \text{and} \quad L_{ro}^{+} = \max_{j} \{y_{rj}\} - y_{ro}, & r \in \{OA\}, \text{and} \]

\[ \]
Theorem 1: Model (9) is always feasible.

Proof: If we set \( \tilde{\lambda}_o = 1, \tilde{\lambda}_{jwo} = 0 \) and \( \tilde{\beta} = 0 \), then it is easy to see that the vector \( \tilde{\lambda}, \tilde{\beta} \) is a feasible solution of model (9).

Theorem 2: From Model (9) we have \( 0 \leq \beta^* \leq 1 \).

Proof: According to the proof of Theorem 1, \( \beta = 0 \) is feasible in model (9) and since it is maximization, in optimality, we have \( 0 \leq \beta^* \). On the other hand, since

\[
\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \quad (j = 1, \ldots, n)
\]

for inputs, we have

\[
\min_{i} \left\{ x_{ij} \right\} \leq \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} - \beta L_{io}^\tau; \quad i \in \{IA\}
\]

Thus, from the first constraint of model (9) we conclude that:

\[
\min_{i} \left\{ x_{ij} \right\} \leq \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} - \beta L_{io}^\tau; \quad i \in \{IA\}
\]

\[
\Rightarrow \beta \leq \frac{x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij}}{L_{io}} \leq 1
\]

Similar calculations for other constraints indicate that in each feasible solution we have \( \beta \leq 1 \).

Thus, we can easily conclude that \( 0 \leq \beta^* \leq 1 \).

Weight restrictions may be embedded directly into the DEA models or the product of weights of inputs and outputs, referred as virtual input or virtual output. In virtual inputs and virtual outputs restrictions, the proportion of the total virtual output of \( DMU_j \) is considered to be restricted in the interval \([a, b]\) and the proportion of total virtual input of \( DMU_j \) is considered to be restricted in the interval \([c, d]\):

\[
a_r \leq \frac{u_r y_{ij}}{\sum_{r=1}^{s} u_r y_{ij}} \leq b_r \quad r = 1, \ldots, s
\]

\[
c_i \leq \frac{v_i x_{ij}}{\sum_{i=1}^{m} v_i x_{ij}} \leq d_i \quad i = 1, \ldots, m
\]

The above intervals are developed to reflect the decision-making priorities on the relative importance of inputs and outputs. Now, to incorporate the weight restrictions into our proposed model, first we obtain dual of model (9). Therefore, our proposed model in the presence of weight restrictions can be stated as follows:
If role factors, non-discretionary factors, and undesirable data. Now, there are two cases: we should change the movement direction. To solve this problem, we propose the following 

\[
\begin{align*}
\min & \sum_{i \in A \cup B} v_i x_i - \sum_{i \in A \cup B} v_i x_i - \sum_{i \in A \cup B} u_i y_i + \sum_{i \in A \cup B} u_i y_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \\
\text{s.t.} & \sum_{i \in A \cup B} v_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \geq 0, \quad j = 1, \ldots, n, \\
& \sum_{i \in A \cup B} v_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \geq 0, \quad j = 1, \ldots, n, \\
& a \left( \sum_{i \in A \cup B} u_i y_i \right) - u_y \leq 0, \quad u_y - b \left( \sum_{i \in A \cup B} u_i y_i \right) \leq 0, \quad r = 1, \ldots, s, \quad j = 1, \ldots, n, \\
& c \left( \sum_{i \in A \cup B} v_i x_i \right) - v_x \leq 0, \quad v_x - d \left( \sum_{i \in A \cup B} v_i x_i \right) \leq 0, \quad i = 1, \ldots, m, \quad j = 1, \ldots, n, \\
& v_i, u_i, z_j^i, z_j^i \geq 0, \quad \forall i, r, f.
\end{align*}
\]

Therefore, we introduced a unified approach to deal with negative data, weight restrictions, dual-role factors, non-discretionary factors, and undesirable data. Now, there are two cases:

**Case 1:** For \( f \in A \cup B \), one of three possibilities exists for the sign of \( z_j^i - z_j^i \), where \( z_j^i \) and \( z_j^i \) are optimal values obtained from model (12):
- If \( z_j^i - z_j^i < 0 \), then \( w_f \) is “behaving like inputs”.
- If \( z_j^i - z_j^i > 0 \), then \( w_f \) is “behaving like outputs”.
- If \( z_j^i - z_j^i = 0 \), then \( w_f \) is at the equilibrium level.

**Case 2:** For \( f \in C \cup D \), one of three possibilities exists for the sign of \( z_j^i - z_j^i \), where \( z_j^i \) and \( z_j^i \) are optimal values obtained from model (12):
- If \( z_j^i - z_j^i > 0 \), then \( w_f \) is “behaving like inputs”.
- If \( z_j^i - z_j^i < 0 \), then \( w_f \) is “behaving like outputs”.
- If \( z_j^i - z_j^i = 0 \), then \( w_f \) is at the equilibrium level.

**4.2 The Proposed Super-Efficiency Model**

In DEA, there might be more than one efficient DMU. Thus, it cannot provide a complete ranking. One of the ways for breaking ties is to use the super-efficiency approach. By removing the DMU under assessment from models (9) and (12), we find out that the super-efficiency cannot provide a correct score as the RDM model does not generate optimal solutions. Hence, it cannot rank DMUs. As a result, to calculate the super-efficiency of DMUs outside the PPS, we should change the movement direction. To solve this problem, we propose the following super-efficiency model that is a further modification of our proposed model:

\[
\begin{align*}
\rho_p^* = \max & \sum_{i \in A \cup B} v_i x_i + \sum_{i \in A \cup B} v_i x_i + \sum_{i \in A \cup B} u_i y_i + \sum_{i \in A \cup B} u_i y_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \\
\text{s.t.} & \sum_{i \in A \cup B} v_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \leq 0, \quad j \in E \setminus p, \\
& \sum_{i \in A \cup B} v_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{i \in A \cup B} u_i e_i + \sum_{j = 1}^{n} (z_j^i - z_j^i)w_j + \sum_{j = 1}^{n} (-z_j^i + z_j^i)w_j + u_i \leq 0, \quad j \in E \setminus p, \\
& a \left( \sum_{i \in A \cup B} u_i y_i \right) - u_y \leq 0, \quad u_y - b \left( \sum_{i \in A \cup B} u_i y_i \right) \leq 0, \quad r = 1, \ldots, s, \quad j \in E \setminus p, \\
& c \left( \sum_{i \in A \cup B} v_i x_i \right) - v_x \leq 0, \quad v_x - d \left( \sum_{i \in A \cup B} v_i x_i \right) \leq 0, \quad i = 1, \ldots, m, \quad j \in E \setminus p, \\
& v_i, u_i, z_j^i, z_j^i \geq 0, \quad \forall i, r, f.
\end{align*}
\]
where \( \rho_p^* \) is the super-efficiency score for ranking DMUp. We show the set of efficient DMUs of Model (12) by \( E \), and \( E_p \) shows all efficient DMUs except DMUp. The more value of \( \rho_p^* \) is the more distance to the PPS after removing the DMUp is. Therefore, it is a suitable criterion for ranking DMUs.

### 4.3 Proposed Algorithm

The proposed algorithm for assessing suppliers based on sustainability factors has the following steps:

**Step 0:** Determine suppliers of SAPCO. We consider them as \( n \) homogeneous DMUs.

**Step 1:** Determine the categories of data such as the factors of sustainability, negative data, non-discretionary factors, undesirable data, and dual-role factors.

**Step 2:** Calculate the importance of data and set weights restriction on variables.

**Step 3:** Calculate the efficiency of suppliers based on the proposed unified model.

**Step 4:** Set two cases for the status of the dual-role factor.

- **Sub-Step 4-1:** Measure the efficiency of each supplier in the first case.
- **Sub-Step 4-2:** Measure the efficiency of each supplier in the second case.

**Step 5:** Calculate the utility of each supplier using the UTASTAR method.

Fig. 3 shows the proposed algorithm. In Fig. 3, we can see four steps: (i) gathering and categorizing data; (ii) calculations, which solve the presented model; (iii) decision, which involves classifying the dual-role factors based on the obtained optimal solution; (iv) analysis of the obtained results by the UTASTAR method to manage the decision maker’s priorities.

### 5. CASE STUDY: SUPPLYING AUTOMOTIVE PARTS COMPANY (SAPCO)

In 2014, the total number of cars in Iran was over 17 million. Iran’s auto parts industry is less efficient compared with developed countries and faces big challenges as the market continues to become more globalized. Irankhodro Co. is the biggest car manufacturer in the Middle East. SAPCO is the sole supplier of auto parts for Irankhodro Company. SAPCO was established in 1994. SAPCO was ranked as the first engineering company in Iran. SAPCO has 150000 staff. Around 4000 potential manufacturers have been identified by SAPCO and almost 500 suppliers have a direct contract with SAPCO. Currently, SAPCO’s supply chain provides more than 4000 different parts ranging from bolts and nuts to complicated components. SAPCO wishes to assess sustainable suppliers of the pressure plate of the clutch.

#### 5.1 Data and Variables

There are 26 suppliers, which supply a clutch pressure plate for SAPCO. The suppliers are introduced in Table 5. Fig. 4 presents a view of the clutch pressure plate.

To assess sustainable suppliers and select the best ones, the following inputs and outputs are chosen:

**Inputs:**
- Distance (km): This criterion has an impact on the delivery time (Jakhar, (2015)).
- Purchasing price: It includes the cost of acquisition products such as product, inventory, logistics, etc.; (Chaharsooghi and Ashrafi, (2014)).
- The number of obtained ISO certificates: This indicator reflects the level of control and monitors the quality of products (Azadi et al., (2015)).
- Freight charge: It includes the cost of transporting each unit of raw material from suppliers to destination; (Azadi et al., (2015)).
Figure 3. Proposed algorithm

- Categorized Data
  - Non-Discretionary data
  - Undesirable data
  - Negative data
  - Dual-Role factors

- Sustainability Factors
  - Economic
  - Social
  - Environment

- Calculations
  - Set Weight Restrictions
    - Calculate the Efficiency
    - Consider Extra Cases

- Decision
  - Inputs
  - Check the states of Dual-Role Factors
  - Outputs

- Analysis
  - Calculate the Utility of Suppliers

Figure 4. A view of the clutch pressure plate
Outputs:

◦ The number of selling options: According to SAPCO system, there are five methods of selling, i.e., Internet method, long-term method, cash method, communicational payment method, and in the presence of a marketer.
◦ Unit profit: This indicator represents net profit per unit and is an important criterion in SAPCO system.
◦ The number of obtained ISO certificates.
◦ Rate of the increasing success of shipping: It represents the percentage of increases of ability to fulfill shipping orders within the promised period (during 2012-2013); (Chaharsooghi and Ashrafi, 2014) and Portela and Thanassouli, (2010).
◦ Rate of losses: It represents the percentage of wrong supplier delivery (Bai and Sarkis, 2014).

Fig. 5 depicts the proposed supplier selection model for SAPCO.

Table 5. Suppliers of SAPCO

| No. | Supplier name                         | Abbr.  | No. | Supplier name                         | Abbr.  |
|-----|--------------------------------------|--------|-----|--------------------------------------|--------|
| 1   | Fulad Ferdos Industrial Group         | FFIG   | 14  | Mobin Azar Motor Co.                 | MAMC   |
| 2   | Homa Khodrosaz Co.                   | HKC    | 15  | Asia Pearlite Casting Industries     | APCI   |
| 3   | Poladish Group                       | PG     | 16  | Parto Alunite Foundry Industry       | PAFI   |
| 4   | Ardestan Industrial Casting Co.       | AICC   | 17  | Machine Sazi Tabriz Group            | MSTG   |
| 5   | Hunterpart Co.                       | HC     | 18  | Nima Steel Group                     | NSG    |
| 6   | Tabriz Tractor Foundry Co.            | TTFC   | 19  | Telda Co.                            | TC     |
| 7   | Arian Ajza Mashin Gostar Co.          | AAMGC  | 20  | Tuka Sadr Industrial Co.             | TSIC   |
| 8   | Saipa Malleable Co.                  | SMC    | 21  | Sahand Azarin Foundry Industries Co.  | SAFIC  |
| 9   | Atmosphere Industrial & Manufacturing Co. | AIMC | 22  | Shayan Industry Group                | SIG    |
| 10  | Pars Industrial Cast Iron            | PICI   | 23  | Iran Casting Industries              | ICI    |
| 11  | Tohid Khorasan Foundry Industries Co. | TKFIC  | 24  | Semnan Casting CO.                   | SCC    |
| 12  | Armenic Co.                          | AC     | 25  | Yadaksanj Manufacturing Co.          | YMC    |
| 13  | Lentix Industries of Clutch Production | LICP | 26  | Azarin Casting Co.                   | ACC    |

Figure 5. Proposed supplier selection model for SAPCO
Note that the distance is considered as a nondiscretionary input and the rate of losses is considered as an undesirable output. The rate of the increasing success of shipping can be both negative and non-negative. The number of obtained ISO certificates is either input or output. It is input since it can be one of the sources of suppliers. It is output as it is one of the accomplishments of suppliers. Table 6 reports the used factors for evaluating the sustainability of suppliers.

Table 7 describes the participation rate of variables in different criteria. As is seen, 12.5% of variables are non-discretionary (same as undesirable, negative, social factor, and environmental factor), and 75% of variables are economic factors. The inputs consist of 37.5% of the variables. Also, 33.3% of inputs are non-discretionary and all of them are economic factors. A similar analysis can be done for output and dual-role variables.

**Table 6. The main criteria for measuring the suppliers from the sustainability aspects**

| Factors       | Notations | Definitions                        | Type of factor                        | Category     |
|---------------|-----------|------------------------------------|---------------------------------------|--------------|
| Inputs        | $x_{1j}$  | Distance                           | Non-discretionary                     | Economic factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |
|               | $x_{2j}$  | Purchasing price                   | Discretionary                         | Economic factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |
|               | $x_{3j}$  | Freight charge                     | Discretionary                         | Economic factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |
| Outputs       | $y_{2j}$  | Number of selling options          | Discretionary                         | Social factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |
|               | $y_{3j}$  | Unit profit                         | Discretionary                         | Economic factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |
|               | $y_{4j}$  | Rate of the increasing success of shipping | Discretionary                     | Economic factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Negative & Non-negative                |              |
|               | $y_{5j}$  | Rate of losses                      | Discretionary                         | Economic factor |
|               |           |                                    | Undesirable                           |              |
|               |           |                                    | Non-negative                          |              |
| The dual-role criterion | $w_{1j}$ | Number of obtained ISO certificates | Discretionary                         | Environmental factor |
|               |           |                                    | Desirable                             |              |
|               |           |                                    | Non-negative                          |              |

**Table 7. Participation of various variables in different criteria**

|               | Number (%) | Non-discretionary (%) | Undesirable (%) | Negative (%) | Economic factor (%) | Social factor (%) | Environmental factor (%) |
|---------------|------------|------------------------|-----------------|--------------|---------------------|-------------------|--------------------------|
| All Variables | 100        | 12.5                   | 12.5            | 12.5         | 75                  | 12.5              | 12.5                     |
| Input         | 37.5       | 33.3                   | 0               | 0            | 100                 | 0                 | 0                        |
| Output        | 50         | 0                      | 25              | 25           | 75                  | 25                | 0                        |
| Dual-role     | 12.5       | 0                      | 0               | 0            | 0                   | 0                 | 100                      |
Table 8 depicts the dataset of the inputs and outputs. The dataset dates back to 2013. Table 9 provides the statistics of inputs and outputs.

By comparing Tables 8 and 9, we find out that there is no supplier, which its inputs are less than its means. If it happens, the DMU is trivially efficient. Also, there is no supplier, which its outputs are more than its means. Also, if it happens, the DMU is trivially efficient. These two cases show that there are not any trivial efficient DMUs.

Furthermore, all inputs of supplier #4 are more than the mean of its inputs and all outputs of supplier #26 are less than the mean of its outputs. This means that the efficiency score of

| No. | Suppliers (DMUs) | Inputs | Dual-role factor | Outputs |
|-----|-----------------|--------|-----------------|---------|
|     |                 |        | Number of obtained ISO certificates | Number of selling options | Unit profit | Rate of the increasing success of shipping | Rate of losses |
|     |                 | Distance | Purchasing price | Freight charge |              |                                      |                |
| 1   | FFIG            | 47      | 8000            | 50            | 2           | 3       | 2       | 0.8   |
| 2   | HKC             | 21      | 8400            | 165           | 1           | 1       | 1750    | -4.5  | 3.8   |
| 3   | PG              | 624     | 7800            | 190           | 3           | 4       | 2625    | 3     | 1.2   |
| 4   | AICC            | 370     | 8500            | 180           | 2           | 1       | 1740    | -3.5  | 2.5   |
| 5   | HC              | 17      | 7400            | 25            | 4           | 5       | 2620    | 1.3   |       |
| 6   | TTFC            | 620     | 7500            | 190           | 4           | 4       | 2320    | 1.8   |       |
| 7   | AAMGC           | 35      | 8000            | 35            | 2           | 2       | 2100    | 2.4   | 1.6   |
| 8   | SMC             | 32      | 8000            | 35            | 5           | 4       | 1940    | -1.2  | 1.4   |
| 9   | AIMC            | 40      | 7300            | 35            | 4           | 2       | 2640    | -3.5  | 1.8   |
| 10  | AC              | 20      | 8350            | 175           | 1           | 1       | 1700    | -9    | 5.8   |
| 11  | PICI            | 141     | 7500            | 70            | 2           | 5       | 2465    | 12    |       |
| 12  | TKFIC           | 883     | 7300            | 210           | 4           | 2       | 2490    | 3.4   |       |
| 13  | LIPC            | 121     | 8000            | 65            | 3           | 2       | 2500    | 3     | 1.6   |
| 14  | MAMC            | 37      | 7900            | 35            | 2           | 1       | 2000    | 1.3   | 3.3   |
| 15  | APCI            | 135     | 8000            | 70            | 3           | 5       | 1970    | -2.4  | 2.5   |
| 16  | PAFI            | 187     | 7850            | 75            | 3           | 3       | 2580    | 2.1   | 1.7   |
| 17  | MSTG            | 615     | 7500            | 190           | 3           | 3       | 2320    | 6.4   | 3     |
| 18  | NSG             | 458     | 7300            | 145           | 1           | 4       | 2600    | 12.6  | 4     |
| 19  | TC              | 15      | 8400            | 175           | 1           | 1       | 1750    | -2.5  | 6.5   |
| 20  | TSIC            | 24      | 8550            | 185           | 2           | 1       | 1680    | -3.8  | 8.2   |
| 21  | SAFIC           | 635     | 8000            | 190           | 1           | 2       | 1820    | -2.7  | 4     |
| 22  | SIG             | 30      | 7500            | 30            | 4           | 4       | 2650    | 6.8   | 0.8   |
| 23  | ICI             | 138     | 8400            | 180           | 4           | 1       | 1760    | -7    | 9     |
| 24  | SCC             | 220     | 8000            | 85            | 1           | 1       | 1930    | -8    | 10    |
| 25  | YMC             | 22      | 8050            | 25            | 1           | 2       | 1750    | -4.6  | 7     |
| 26  | ACC             | 445     | 7300            | 145           | 2           | 1       | 2600    | -3.2  | 5     |
these DMUs are weak. Based on the decision maker’s opinion, the importance of freight charge, $v_3$, is as follows:

$$0.8 \leq \frac{v_3 x_{3i}}{\sum_{i=1}^{m} v_i x_{1i}} \leq 2.2$$

### 5.2 Results of Proposed DEA Model

The results of our proposed modified model under VRS technology are depicted in Table 10. From Table 10, it is seen that 10 out of 26 suppliers are fully efficient.

Table (12) identifies suppliers 1, 2, 3, 5, 7, 11, 18, 19, 22, and 25 as efficient DMUs because their performance scores are 1. The other suppliers are performed inefficiently and their scores are less than 1. In Table 10, $z^i_f$ and $z^o_f$ are optimal values obtained from model (12) and the column under $Z_f$ illustrates the behavior of the dual-role factor. The number of ISO certificates (the dual-role criterion) in suppliers #17 and #18 is an input and less of this factor is better. In other suppliers, the number of ISO certificates is behaving like an output, which more is better. As is seen, there is no DMU, which its dual-role factor is in equilibrium status. Supplier #23 has the lowest efficiency score among all the suppliers.

From Table 10 we find out that 10 DMUs are recognized as efficient. Note that some DMUs have negative outputs. For example, consider DMU#25. This DMU has a negative output but it is efficient. The reason is that the DMU#25 has small amounts of 1st and 3rd inputs. Also, it has the least 3rd input among all DMUs. Now, consider DMU#26. This DMU has a negative output but it is inefficient as the DMU#26 uses huge amounts of 1st and 3rd inputs. The same discussions can be repeated for other DMUs. As is seen in Table 10, the “number of ISO certificates” is recognized as output by 24 DMUs, i.e. 92% of DMUs. The “number of ISO certificates” is recognized as input by 2 DMUs, i.e. 8% of DMUs.

To check the influence of weight restrictions on the performance evaluations, we eliminate the weight restriction constraint from Model (9). The new results show that the number of efficient DMUs is increased from 10 to 11 and the average efficiency scores are increased from 0.851054408 to 0.8607407. This implies that the weight restrictions have a slight effect on the results and decision-makers can impose tougher weights on the variables.
Table 10. The results of the unified model

| DMUs | Suppliers | Efficiency score | $Z_1^O$ | $Z_1^I - Z_1^O$ |
|------|-----------|------------------|--------|-----------------|
| 1    | FFIG      | 1.0000000        | 0.9046662 | 0.0000000 | 0.9046662 |
| 2    | HKC       | 1.0000000        | 0.9046662 | 0.0000000 | 0.9046662 |
| 3    | PG        | 1.0000000        | 0.4180328 | 0.0000000 | 0.4180328 |
| 4    | AICC      | 0.6476868        | 0.6139976 | 0.0000000 | 0.6139976 |
| 5    | HC        | 1.0000000        | 0.3220007 | 0.0000000 | 0.3220007 |
| 6    | TTFC      | 0.8064516        | 0.1612903 | 0.0000000 | 0.1612903 |
| 7    | AAMGC     | 1.0000000        | 0.3021807 | 0.0000000 | 0.3021807 |
| 8    | SMC       | 0.6200000        | 0.1685714 | 0.0000000 | 0.1685714 |
| 9    | AIMC      | 0.9511738        | 0.3132810 | 0.0000000 | 0.3132810 |
| 10   | AC        | 0.8947879        | 0.4958130 | 0.0000000 | 0.4958130 |
| 11   | PICI      | 1.0000000        | 0.4958130 | 0.0000000 | 0.4958130 |
| 12   | TKFIC     | 0.5701665        | 0.1658406 | 0.0000000 | 0.1658406 |
| 13   | LICP      | 0.8749539        | 0.2902214 | 0.0000000 | 0.2902214 |
| 14   | MAMC      | 0.9429858        | 0.1771559 | 0.0000000 | 0.1771559 |
| 15   | APCI      | 0.7500000        | 0.2500000 | 0.0000000 | 0.2500000 |
| 16   | PAFI      | 0.9414837        | 0.3119533 | 0.0000000 | 0.3119533 |
| 17   | MSTG      | 0.7368421        | 0.0000000 | 0.2280702 | -0.2280702 |
| 18   | NSG       | 1.0000000        | 0.2355156 | 0.0000000 | 0.2355156 |
| 19   | TC        | 1.0000000        | 0.6357587 | 0.0000000 | 0.6357587 |
| 20   | TSIC      | 0.5999111        | 0.1968681 | 0.0000000 | 0.1968681 |
| 21   | SAFIC     | 0.9607843        | 0.9215686 | 0.0000000 | 0.9215686 |
| 22   | SIG       | 1.0000000        | 0.1880527 | 0.0000000 | 0.1880527 |
| 23   | ICI       | 0.2855415        | 0.1628318 | 0.0000000 | 0.1628318 |
| 24   | SCC       | 0.7860262        | 0.3460699 | 0.0000000 | 0.3460699 |
| 25   | YMC       | 1.0000000        | 0.3460699 | 0.0000000 | 0.3460699 |
| 26   | ACC       | 0.7586194        | 0.2413807 | 0.0000000 | 0.2413807 |
To give a deeper discussion about our proposed model, here we define two extra cases. In these two cases, we investigate the situation of neglecting property of considering the “number of obtained ISO certificates” as a dual-role variable. In the first case, we assume that the “number of obtained ISO certificates” is considered as input. Table 11 shows the results.

The results of this case are seen in the third column of Table 11. As is seen, the efficiency scores are lower than or equal to the results of our proposed scores. Fig. 6 depicts the results. We can see that in all DMUs the efficiencies in the first case are lower than or equal to the proposed scores. Ten DMUs are efficient in the proposed model. In case one, 5 DMUs (i.e., 5, 11, 18, 22, 25) are still efficient.

The last row of Table 11 shows that the average of obtained scores in the first case becomes worse. The reason behind this result can be stated as follows. The developed model considers the

| DMUs | Unified Case | Case 1 | Case 2 |
|------|--------------|--------|--------|
|      | Eff. score  | ρ*    | Rank   | Eff. score  | ρ*    | Rank   | Eff. score  | ρ*    | Rank   |
| 1    | 1.0000000   | 2.00   | 6      | 0.7600000   | -     | 8      | 0.5471698   | -     | 13     |
| 2    | 1.0000000   | 1.61   | 7      | 0.4893081   | -     | 15     | 0.3140869   | -     | 24     |
| 3    | 1.0000000   | 1.21   | 9      | 0.6404516   | -     | 9      | 0.6404516   | -     | 10     |
| 4    | 0.6476868   | -      | 22     | 0.3365216   | -     | 25     | 0.3514644   | -     | 21     |
| 5    | 1.0000000   | 5.56   | 4      | 1.0000000   | 4.67  | 2      | 1.0000000   | 5.00  | 1      |
| 6    | 0.8064516   | -      | 17     | 0.0625000   | -     | 11     | 0.7857143   | -     | 8      |
| 7    | 1.0000000   | 1.40   | 8      | 0.8803245   | -     | 6      | 0.5608696   | -     | 12     |
| 8    | 0.6200000   | -      | 23     | 0.4814739   | -     | 16     | 1.0000000   | 3.50  | 3      |
| 9    | 0.9511738   | -      | 12     | 0.6342857   | -     | 10     | 0.9861111   | -     | 6      |
| 10   | 0.8947879   | -      | 15     | 0.4516380   | -     | 18     | 0.2625000   | -     | 26     |
| 11   | 1.0000000   | 2.27   | 5      | 1.0000000   | 1.27  | 5      | 1.0000000   | 1.27  | 5      |
| 12   | 0.5701665   | -      | 25     | 0.4159163   | -     | 21     | 0.8160920   | -     | 7      |
| 13   | 0.8749539   | -      | 16     | 0.5137783   | -     | 14     | 0.5675676   | -     | 11     |
| 14   | 0.9429858   | -      | 13     | 0.7884741   | -     | 7      | 0.5119048   | -     | 15     |
| 15   | 0.7500000   | -      | 20     | 0.4191450   | -     | 20     | 0.5045454   | -     | 16     |
| 16   | 0.9414837   | -      | 14     | 0.4636128   | -     | 17     | 0.5350318   | -     | 14     |
| 17   | 0.7368421   | -      | 21     | 0.3725940   | -     | 23     | 0.7368421   | -     | 9      |
| 18   | 1.0000000   | 5.66   | 3      | 1.0000000   | 6.00  | 1      | 1.0000000   | 4.00  | 2      |
| 19   | 1.0000000   | 1.03   | 10     | 0.5464511   | -     | 13     | 0.3767561   | -     | 19     |
| 20   | 0.5999111   | -      | 24     | 0.3578304   | -     | 24     | 0.3471074   | -     | 22     |
| 21   | 0.9607843   | -      | 11     | 0.4436019   | -     | 19     | 0.3268482   | -     | 23     |
| 22   | 1.0000000   | 7.00   | 1      | 1.0000000   | 2.50  | 4      | 1.0000000   | 2.50  | 4      |
| 23   | 0.2855415   | -      | 26     | 0.2267757   | -     | 26     | 0.5000000   | -     | 17     |
| 24   | 0.7860262   | -      | 18     | 0.5848624   | -     | 12     | 0.2709677   | -     | 25     |
| 25   | 1.0000000   | 5.74   | 2      | 1.0000000   | 3.67  | 3      | 0.4418605   | -     | 18     |
| 26   | 0.7586194   | -      | 19     | 0.4128425   | -     | 22     | 0.3559322   | -     | 20     |
| Mean | 0.851054408 |        |        | 0.609418765 |        |        | 0.605377827 |        |        |
“number of obtained ISO certificates” as input or output in a way that the best relative efficiency is obtained for each DMU. In the second case, we assume that the “number of obtained ISO certificates” is considered as output. The results of this case can be seen in the fourth column of Table 11.

The results show that the efficiency scores in this case in some DMUs become better. Fig. 7 depicts the results. As is seen, in the second case, five DMUs i.e. (5, 11, 18, 22, 25) are efficient. The last row of Table 11 shows that the average of the obtained scores becomes worse. In this case, DMU#8 is efficient as it has the most amount of “number of obtained ISO certificates” and if we consider this variable as output the related DMU becomes efficient. As is seen in Table 11, four DMUs (i.e., 5, 11, 18, 22) are efficient in all cases.

5.4 Analysis Using UTASTAR

Now, to analyze and determine in what way the variable leads to better results, a decision support system (DSS) is considered using the UTASTAR method. To this end, four initial rankings extracted

Figure 6. Comparison between the proposed results and the first case

Figure 7. Comparison between the proposed results and the second case
from Table 11 and rows associated with these four initial rankings of Table 8 are considered. Then, the desired model is considered in the above-mentioned cases.

5.4.1. Solving UTASTAR Model for the First Case

When the desired variable is considered as an input for the UTASTAR algorithm, to solve the UTASTAR model, we need a decision matrix and a ranking of reference alternatives that consider the initial ranking of reference alternatives from Table 8. Required steps according to UTASTAR are as follows:

**Step 1: Calculation of marginal value functions**

\[
\begin{align*}
U(g(A1)) &= w_{21} + w_{22} + w_{41} + w_{51} + 0.33w_{52} + w_{61} + 0.89w_{62} + w_{71} + w_{72} + w_{73} + w_{81} + 0.23w_{82}, \\
U(g(A2)) &= w_{11} + w_{12} + w_{21} + 0.27w_{22} + w_{31} + w_{32} + w_{51} + w_{52} + w_{61} + 0.93w_{62} + w_{71} + 0.67w_{72} + 0.22w_{81}, \\
U(g(A3)) &= W_{11} + 0.02w_{12} + w_{31} + w_{32} + w_{41} + w_{81} + w_{82}, \\
U(g(A4)) &= W_{11} + 0.94w_{12} + w_{21} + 0.47w_{22} + w_{31} + 0.92w_{32} + w_{51} + 0.33w_{52} + w_{61} + w_{62} + w_{71} + 0.99w_{72}.
\end{align*}
\]

**Step 2: Expressions of the linear programming model**

\[
\begin{align*}
\text{Min} z = \sum_{i=1}^{m} [\sigma^+(a_k) - \sigma^-(a_k)] \\
\text{s.t.} \\
-w_{11} - w_{12} + 0.73w_{22} - w_{31} - w_{32} + w_{41} - 0.67w_{52} - 0.04w_{62} + 0.33w_{72} + w_{73} + 0.78w_{81} - 0.23w_{82} - \sigma^+(A1) - \sigma^-(A1) + \sigma^+(A2) - \sigma^-(A2) \geq 0.05; \\
0.98w_{12} + w_{21} + 0.27w_{22} - w_{41} + w_{51} + w_{52} + w_{61} + 0.93w_{62} + w_{71} + 0.67w_{72} - 0.78w_{81} - w_{82} - \sigma^+(A2) - \sigma^-(A2) \geq 0.05; \\
-0.92w_{12} - 0.47w_{22} + 0.08w_{32} + w_{41} - w_{51} - 0.33w_{52} - w_{61} - w_{71} - 0.99w_{72} + w_{81} + w_{82} - \sigma^+(A3) - \sigma^-(A3) \geq 0.05; \\
w_{ij} \geq 0, \sigma^+(a_k) \geq 0, \sigma^-(a_k) \geq 0.
\end{align*}
\]

**Step 3: Solving the linear programming model.**

After solving the linear programming model using Lingo software, the following results are obtained:

\[
\begin{align*}
Z^* &= 0, \\
W_{12} &= 0.0547680375, W_{21} = 0.0538617875, \\
W_{12}' &= 0.0075096625, W_{32} = 0.0497114875, \\
W_{41} &= 0.07413015, W_{51} = 0.0200870625, \\
W_{52} &= 0.1035213988, W_{61} = 0.031696425, \\
W_{62} &= 0.027678575, W_{71} = 0.1052548, \\
W_{72} &= 0.171066625, W_{81} = 0.2548893213.
\end{align*}
\]

By substituting the above weights in the total value function, the utility value of the selected suppliers HC, NSG, SMG, and SIG are obtained as 0.606, 0.503, 0.379, and 0.371, respectively. The results show that in case 1, the supplier with the first rank, i.e. HSG, has a (utility amount) desirability.
of 60.6% as the sustainable supplier for the SAPCO. The important thing is that none of the suppliers was an option with 100% utility for the company.

5.4.2 Solving UTASTAR Model for the Second Case

By performing a similar operation for the second case, the utility value of the selected suppliers HC, NSG, SMG, and SIG are obtained as 0.707, 0.511, 0.452, and 0.345, respectively.

The results show that in the second case, the supplier with the first rank, i.e. HC, has a (utility amount) desirability of 70.7% as the sustainable supplier for the SAPCO. Again, the important thing is that none of the suppliers was an option with 100% utility for the company. But the results show that in the second case the amount of desirability has grown. These results suggest considering the second case as a desired case. The complete process for the implementation of UTASTAR for the second case appears in the Appendix.

5.5 Proposed Method Versus Existing Methods

Here, the proposed model is compared and contrasted with other related DEA models. As far as we know, there is no paper to take into account the non-discretionary, undesirable and negative data, dual-role and sustainability factors, weight restrictions, and the UTASTAR method. First, we compare the proposed DEA method with other DEA methods. Then, using a numerical comparison, we compare the proposed method with the existing DEA models in the presence of dual-role factors.

5.5.1 Comparative Overview of DEA-Based Supplier Selection Methods

Because of the importance of DEA models in performance evaluations of suppliers, we compare our proposed model with the other DEA models. Table 12 shows that our new model has several advantages over the existing models. As is seen in Table 12, our new model has more capabilities compared with the existing models.

5.5.2 Numerical Comparison With Existing Two-Stage DEA Models

Assuming the presence of dual-role factors, here we compare our proposed model with the models proposed by Mahdiloo et al., (2014), Izadikhah et al., (2017a), and Su and Sun, (2018). To this end, consider Table 13.

Table 13 shows that there are five DMUs with one input \(x\), one output \(y\), and two dual-role factors \(w_1\) and \(w_2\). The results of running the four aforementioned models are reported in Table 14. Table 14 shows that our proposed model can solve the DEA problem with dual-role factors. Besides, our proposed model has more capabilities compared with the other three methods. In other words, none of the other three methods can solve the case study of SAPCO.

5.6 Managerial Implications

Mathematical optimization models and decision-making techniques can provide important and practical information. The SSCM contains environmental, social, and economic factors. Sustainable supplier selection can be regarded as a procedure of finding the right suppliers who can provide good products, reasonable prices, on time, and in the right quantities. Besides, sometimes in SSCM problems, there might be a couple of factors that are bad and dual-role. DEA is used widely in the evaluation of sustainable suppliers. However, conventional DEA models deal with desirable, discretionary, and nonnegative data. Nevertheless, in the real world, there might be undesirable outputs and nondiscretionary factors that should be taken into account. In these circumstances, classical DEA models cannot be used. On the other hand, there might be negative inputs and outputs. Also, there are many occasions that variations of variables are not under the control of decision-makers and they are non-discretionary.
Table 12. Comparison of DEA models in the area of supplier selection

| DMUs          | Models                        | Non-discretionary data | Undesirable data | Negative data | Dual-role factors | Sustainability factors | Weight restrictions | Decision maker’s priority |
|---------------|-------------------------------|------------------------|------------------|---------------|-------------------|-----------------------|----------------------|--------------------------|
| 1             | Talluri et al., (2006)        | ×                      | ×                | ×             | ×                 | ×                     | ×                    | ×                        |
| 2             | Wu, (2009)                    | ×                      | ×                | ×             | ×                 | ×                     | ×                    | ×                        |
| 3             | Farzipoor Saen, (2010b)       | ×                      | ×                | ×             | ✓                 | ×                     | ✓                    | ×                        |
| 4             | Chen, (2011)                  | ×                      | ×                | ×             | ×                 | ×                     | ×                    | ×                        |
| 5             | Farzipoor Saen, (2011)        | ×                      | ✓                | x             | ✓                 | ×                     | ×                    | ×                        |
| 6             | Mahdiloo et al., (2014)       | ×                      | ×                | ×             | ✓                 | x                     | x                    | x                        |
| 7             | Wang and Li, (2014)           | ×                      | ×                | ×             | ×                 | x                     | ×                    | ×                        |
| 8             | Khodakarami et al., (2015)    | ×                      | ×                | ×             | ×                 | ✓                     | x                    | ×                        |
| 9             | Mahdiloo et al., (2015)       | ×                      | ✓                | x             | ×                 | ✓                     | ×                    | ×                        |
| 10            | Izadikhah and Farzipoor Saen, (2016b) | ×                  | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 11            | Zhou et al., (2016)           | ×                      | ×                | ×             | ×                 | ✓                     | ×                    | ×                        |
| 12            | Izadikhah and Farzipoor Saen, (2016a) | ×                  | ×                | ✓             | ✓                 | ×                     | ×                    | ×                        |
| 13            | Shabani and Farzipoor Saen, (2016) | ×                  | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 14            | Izadikhah et al., (2017a)     | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 15            | Izadikhah et al., (2017b)     | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 16            | Yousefi et al., (2017)        | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 17            | Amindoust, (2018)             | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 18            | Su and Sun, (2018)            | ×                      | ✓                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 19            | Rashidi and Saen, (2018)      | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 20            | Izadikhah and Farzipoor Saen, (2019) | ×                  | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 21            | Sarkhosh-Sara et al., (2019)  | ×                      | ✓                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 22            | Izadikhah et al., (2020)      | ×                      | ×                | ×             | ✓                 | ×                     | ×                    | ×                        |
| 23            | Our new model                 | ✓                      | ✓                | ✓             | ✓                 | ✓                     | ✓                    | ✓                        |

Table 13. The numerical data

| DMUs          | x    | y    | $w_1$ | $w_2$ |
|---------------|------|------|-------|-------|
| A             | 5    | 25   | 10    | 8     |
| B             | 16   | 12   | 6     | 11    |
| C             | 11   | 19   | 15    | 12    |
| D             | 8    | 30   | 17    | 10    |
| E             | 12   | 22   | 12    | 9     |
Besides, in many cases, the importance of variables might be different. Therefore, we need to use weight restrictions. Our non-radial DEA model can solve this kind of condition. By reviewing the literature, we found out that there are no papers for analyzing the SSCM in the presence of negative data, undesirable, non-discretionary, and dual-role factors in the weight restrictions context. Managers can evaluate the firms in the presence of these kinds of conditions. Our mathematical models may help decision-makers to make better decisions.

Furthermore, using our mathematical models may be difficult for managers and decision-makers. To address this issue, we recommend developing DSS. In this paper, in addition to the use of DEA for evaluating suppliers, using the UTASTAR method, the ranking of selected suppliers is evaluated. In general, the importance of using the UTASTAR model is that it checks whether or not ranking suppliers by the proposed DEA model can address DM’s needs.

### 6. CONCLUSION

DEA was originally developed to evaluate the relative performance of DMUs. Classical DEA models assume that all inputs and outputs are discretionary and desirable (Yousefi et al., 2016). However, in the real world, there might be undesirable outputs and nondiscretionary factors that should be taken into account. On the other hand, there are some circumstances that inputs and outputs are negative. Also, in applying DEA, we may face with dual-role factors. In this paper, we developed a non-radial DEA model for dealing with negative data in the presence of undesirable factors, non-discretionary factors, weight restrictions, and dual-role factors for selecting sustainable suppliers. To this end, we extended the RDM model to deal with negative data. The validity of the presented method was analyzed by two theorems. The proposed method was illustrated by a flowchart. We tested our proposed model by assessing 26 suppliers of the clutch pressure plate. We used three inputs and four outputs and one dual-role factor for assessing the sustainability of suppliers. The number of obtained ISO certificates was considered as a dual-role factor.

The data analysis showed that 12.5% of variables were non-discretionary (same as undesirable, negative, social factor, and environmental factor), and 75% of variables were economic factors. Ten suppliers were recognized as efficient DMUs and the remaining suppliers were recognized as inefficient. In the proposed model two DMUs considered the dual role factor as input and other DMUs considered it as output. In the dataset, there was a restriction on one of the inputs. The proposed model evaluated DMUs by considering the dual-role criterion as input or output in a way that their best efficiency is obtained. The results indicated that 38 percent of DMUs have been recognized as sustainable DMUs.

Besides, to give an in-depth discussion, two extra cases were investigated. In those two cases, the property of considering “Number of obtained ISO certificates” as a dual-role variable was neglected.

### Table 14. The results of the comparison

| DMUs | Mahdiloo et al., (2014) | Izadikhah et al., (2017a) | Su and Sun, (2018) | Our new model |
|------|-------------------------|---------------------------|-------------------|---------------|
|      | Efficiency of $W_1$    | Efficiency of $W_2$       | Efficiency of $W_1$ | Efficiency of $W_2$ |
| A    | 1.000                   | 1.000                     | 1.000             | 1.000         |
| B    | 1.000                   | 1.000                     | 1.000             | 1.000         |
| C    | 1.000                   | 1.000                     | 1.000             | 1.000         |
| D    | 1.000                   | 1.000                     | 1.000             | 1.000         |
| E    | 0.767                   | 0.468                     | 0.542             | 0.512         |
Results showed that the average of efficiencies became worse. The results were summarized in Table 11. Also, the results were compared in Fig. 6 and Fig. 7. The results of these cases showed that 15 percent of DMUs are still sustainable. According to the results, the “number of ISO certificates” was recognized as output in 24 DMUs (i.e., 92% of DMUs) and it is input in 2 DMUs (i.e., 8% of DMUs). To assess the influence of weight restrictions on the performance evaluations, the weight restriction constraint was eliminated. The results showed that the number of efficient DMUs and the average efficiency scores were increased.

For the first time, we mixed our proposed DEA model and UTASTAR to evaluate suppliers based on the sustainability criteria. To select the most sustainable supplies of SAPCO, UTASTAR was used to estimate the utility of selected best rankings derived from the proposed DEA model.

In this paper, we extended the RDM model to handle negative data along with undesirable factors, nondiscretionary factors, and dual-role factors. One can apply our approach to other DEA models. Also, one can integrate fuzzy and/or stochastic data with our suggested models. In this paper, we used the proposed model to measure the sustainability of supply chains. Prospective scholars can apply the suggested models in other fields such as efficiency evaluation of production lines, universities, etc.

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REFERENCES

Ahmady, N., Azadi, M., Sadeghi, S. A. H., & Saen, R. F. (2013). A novel fuzzy data envelopment analysis model with double frontiers for supplier selection. *International Journal of Logistics Research and Applications, 16*(2), 87–98. doi:10.1080/13675567.2013.772957

Aliakbarpoor, Z., & Izadikhah, M. (2012). Evaluation and ranking DMUs in the presence of both undesirable and ordinal factors in data envelopment analysis. *International Journal of Automation and Computing, 9*(6), 609–615. doi:10.1007/s11633-012-0686-5

Aminidoust, A. (2018). A resilient-sustainable based supplier selection model using a hybrid intelligent method. *Computers & Industrial Engineering, 126*, 122–135. doi:10.1016/j.cie.2018.09.031

Aminidoust, A., Ahmed, S., Saghafinia, A., & Bahreininejad, A. (2012). Sustainable supplier selection: A ranking model based on fuzzy inference system. *Applied Soft Computing, 12*(6), 1668–1677. doi:10.1016/j.asoc.2012.01.023

Awasthi, A., Chauhan, S. S., & Goyal, S. K. (2010). A fuzzy multicriteria approach for evaluating environmental performance of suppliers. *International Journal of Production Economics, 126*(2), 370–378. doi:10.1016/j.ijpe.2010.04.029

Aydın Keskin, G., İlhan, S., & Özkan, C. (2010). The Fuzzy ART algorithm: A categorization method for supplier evaluation and selection. *Expert Systems with Applications, 37*(2), 1235–1240. doi:10.1016/j.eswa.2009.06.004

Azadi, M., Jafarian, M., Farzipoor Saen, R., & Mirhedyatian, S. M. (2015). A new fuzzy DEA model for evaluation of efficiency and effectiveness of suppliers in sustainable supply chain management context. *Computers & Operations Research, 54*, 274–285. doi:10.1016/j.cor.2014.03.002

Azizi, H., & Farzipoor Saen, R. (2015). A new approach for considering dual-role factor in supplier selection problem: DEA approach with efficient and inefficient frontiers. *Production and Operations Management, 6*(2), 129–144.

Bai, C., & Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. *International Journal of Production Economics, 124*(1), 252–264. doi:10.1016/j.ijpe.2009.11.023

Bai, C., & Sarkis, J. (2014). Determining and applying sustainable supplier key performance indicators. *Supply Chain Management, 19*(3), 275–291. doi:10.1108/SCM-12-2013-0441

Ballew, P. D., & Schnorbus, R. H. (1994). The impact of the auto industry on the economy. *Chicago Fed Letter, 79*.

Banker, R. D., & Morey, R. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research, 34*(4), 513–521. doi:10.1287/opre.34.4.513

Basso, A., Casarin, F., & Funari, S. (2018). How well is the museum performing? A joint use of DEA and BSC to measure the performance of museums. *Omega, 81*, 67–84. doi:10.1016/j.omega.2017.09.010

Beasley, J. E. (1990). Comparing university departments. *Omega, 8*(2), 171–183. doi:10.1016/0305-0483(90)90064-G

Beasley, J. E. (1995). Determining Teaching and Research Efficiencies. *The Journal of the Operational Research Society, 46*(4), 441–452. doi:10.1057/jors.1995.63

Bolturk, E. (2018). Pythagorean fuzzy CODAS and its application to supplier selection in a manufacturing firm. *Journal of Enterprise Information Management, 31*(4), 550–564. doi:10.1108/JEIM-01-2018-0020

Büyüközkan, G., & Çifçi, G. (2011). A novel fuzzy multi-criteria decision framework for sustainable supplier selection with incomplete information. *Computers in Industry, 62*(2), 164–174. doi:10.1016/j.compind.2010.10.009

Cetinkaya, B., Cuthbertson, R., Ewer, G., Klaas-Wissing, T., Piotrowicz, W., & Tyssen, C. (2011). *Sustainable Supply Chain Management*. Springer.

Chaharsoghi, S. K., & Ashrafi, M. (2014). Sustainable Supplier Performance Evaluation and Selection with Neofuzzy TOPSIS Method. *International Scholarly Research Notices, 1-10*. 10.1155/2014/434168
Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. doi:10.1016/0377-2217(78)90138-8

Charnes, A., Cooper, W. W., Wei, Q. L., & Huang, Z. M. (1989). Cone-ratio data envelopment analysis and multi-objective programming. *International Journal of Systems Science, 20*(7), 1099–1118. doi:10.1080/00207728908910197

Chen, Y.-J. (2011). Structured methodology for supplier selection and evaluation in a supply chain. *Information Sciences, 181*(9), 1651–1670. doi:10.1016/j.ins.2010.07.026

Clift, R. (2003). Metrics for supply chain sustainability. *Clean Technologies and Environmental Policy, 5*(3-4), 240–247. doi:10.1007/s10098-003-0220-0

Cosset, J. C., Siskos, Y., & Zopounidis, C. (1992). Evaluating country risk: A decision support approach. *Global Finance Journal, 3*(1), 79–95. doi:10.1016/1044-0283(92)90006-7

Dao, V., Langella, I., & Carbo, J. (2011). From green to sustainability: Information Technology and an integrated sustainability framework. *The Journal of Strategic Information Systems, 20*(1), 63–79. doi:10.1016/j.jsis.2011.01.002

de Boer, L., Labro, E., & Morlacchi, P. (2001). A review of methods supporting supplier selection. *European Journal of Purchasing & Supply Management, 7*(2), 75–89. doi:10.1016/S0969-7012(00)00028-9

Demesouka, O. E., Anagnostopoulos, K. P., & Siskos, E. (2019). Spatial multicriteria decision support for robust land-use suitability: The case of landfill site selection in Northeastern Greece. *European Journal of Operational Research, 272*(2), 574–586. doi:10.1016/j.ejor.2018.07.005

Despotis, D. K., Stamati, L. V., & Smirlis, Y. G. (2010). Data envelopment analysis with nonlinear virtual inputs and outputs. *European Journal of Operational Research, 202*(2), 604–613. doi:10.1016/j.ejor.2009.06.036

Dou, Y., & Sarkis, J. (2010). A joint location and outsourcing sustainability analysis for a strategic off-shoring decision. *International Journal of Production Research, 48*(2), 567–592. doi:10.1080/00207540903175145

Dyllick, T., & Hockerts, K. (2002). Beyond the business case for corporate sustainability. *Business Strategy and the Environment, 11*(2), 130–141. doi:10.1002/bse.323

Ebrahimi, B., Rahmani, M., & Ghodsypour, S. H. (2017). A new simulation-based genetic algorithm to efficiency measure in IDEA with weight restrictions. *Measurement, 108*, 26–33. doi:10.1016/j.measurement.2017.05.026

Ebrahimi, B., Tavana, M., Toloo, M., & Charles, V. (2020). A Novel Mixed Binary Linear DEA Model for Ranking Decision-Making Units with Preference Information. *Computers & Industrial Engineering, 106720*, 106720. Advance online publication. doi:10.1016/j.cie.2020.106720

Ehsanbakhsh, H., & Izadikhah, M. (2015). Applying BSC-DEA model to performance evaluation of industrial cooperatives: An application of fuzzy inference system. *Applied Research Journal, 1*(1), 9–26.

Emrouznejad, A., Anouze, A. L., & Thanassoulis, E. (2010). A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA. *European Journal of Operational Research, 200*(1), 297–304. doi:10.1016/j.ejor.2009.01.001

Erol, I., Sencer, S., & Sari, R. (2011). A new fuzzy multi-criteria framework for measuring sustainability performance of a supply chain. *Ecological Economics, 70*(6), 1088–1100. doi:10.1016/j.ecolecon.2011.01.001

Esmaeili, M. (2009). A slack-based measure of efficiency for the case of exogenously fixed factors. *Expert Systems with Applications, 36*, 4822–4825. https://www.researchgate.net/deref/ http%3A%2F%2Fdx.doi.org%2F10.1016%2Fj.eswa.2008.05.043?_sg%5B0%5D=6YjP 8whDrFU1TSAKP9b9M uFH3EiJhCowK ElfMBAnAeoT03hfxIf0ewwb5IW N5t-zirMC Jr1cJckgiy Tp5P9LUpw4w MnKa21hRss EVfi5jzp7EUAQTrj5f wwm7CdT7H 8W8kJ15FBQn xST0C84b8f1-XGsCm qPovSyD7mER BDKFhrT2A

Färe, R., & Grosskopf, S. (2000). Network DEA. *Socio-Economic Planning Sciences, 34*(1), 35–49. doi:10.1016/S0038-0121(99)00012-9

Färe, R., & Grosskopf, S. (2003). Nonparametric Productivity Analysis with Undesirable Outputs [Comment]. *American Journal of Agricultural Economics, 85*(4), 1070–1074. doi:10.1111/1467-8276.00510
Färe, R., Grosskopf, S., Lovell, C. A. K., & Yaisawarng, S. (1993). Derivation of Shadow Prices for Undesirable Outputs: A Distance Function Approach. *The Review of Economics and Statistics, 75*(2), 374–380. doi:10.2307/2109448

Farzipoor Saen, R. (2009). A decision model for ranking suppliers in the presence of cardinal and ordinal data, weight restrictions, and nondiscretionary factors. *Annals of Operations Research, 172*(1), 177–192. doi:10.1007/s10479-009-0556-x

Farzipoor Saen, R. (2010a). A new model for selecting third-party reverse logistics providers in the presence of multiple dual-role factors. *International Journal of Advanced Manufacturing Technology, 46*(1-4), 405–410. doi:10.1007/s00170-009-2092-x

Farzipoor Saen, R. (2010b). Restricting weights in supplier selection decisions in the presence of dual-role factors. *Applied Mathematical Modelling, 34*(10), 2820–2830. doi:10.1016/j.apm.2009.12.016

Farzipoor Saen, R. (2011). A decision model for selecting third-party reverse logistics providers in the presence of both dual-role factors and imprecise data. *Asia-Pacific Journal of Operational Research, 28*(2), 239–254. doi:10.1142/S0217595911003156

Fried, H. O., Lovell, C. A. K., & Eeckaut, P. (1993). Evaluating the performance of U.S. credit unions. *Journal of Banking & Finance, 17*(2-3), 251–265. doi:10.1016/0378-4266(93)90031-8

Fusco, E., Vidoli, F., & Rogge, N. (2019). Spatial directional robust Benefit of the Doubt approach in presence of undesirable output: An application to Italian waste sector. *Omega, 102053*. Advance online publication. doi:10.1016/j.omega.2019.03.011

Galagedera, D. U. A. (2014). Modeling risk concerns and returns preferences in performance appraisal: An application to global equity markets. *Journal of International Financial Markets, Institutions and Money, 33*, 400–416. doi:10.1016/j.intfin.2014.09.006

Galagedera, D. U. A. (2019). Modelling social responsibility in mutual fund performance appraisal: A two-stage data envelopment analysis model with non-discretionary first stage output. *European Journal of Operational Research, 273*(1), 376–389. doi:10.1016/j.ejor.2018.08.011

Giannakis, M., & Papadopoulos, T. (2016). Supply chain sustainability: A risk management approach. *International Journal of Production Economics, 171*(Part 4), 455–470. doi:10.1016/j.ijpe.2015.06.032

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega, 17*(3), 237–250. doi:10.1016/0305-0483(89)90029-7

Gören, H. G. (2018). A decision framework for sustainable supplier selection and order allocation with lost sales. *Journal of Cleaner Production, 183*, 1156–1169. doi:10.1016/j.jclepro.2018.02.211

Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production, 47*(0), 345–354. doi:10.1016/j.jclepro.2012.04.014

Grigoroudis, E., Orfanoudaki, E., & Zopounidis, C. (2012). Strategic performance measurement in a healthcare organisation: A multiple criteria approach based on balanced scorecard. *Omega, 40*(1), 104–119. doi:10.1016/j.omega.2011.04.001

Grigoroudis, E., & Zopounidis, C. (2012). Developing an employee evaluation management system: The case of a healthcare organization. *Operations Research, 12*(1), 83–106. doi:10.1007/s12351-011-0103-9

Halkos, G., & Petrou, K. N. (2019). Treating undesirable outputs in DEA: A critical review. *Economic Analysis and Policy, 62*, 97–104. doi:10.1016/j.eap.2019.01.005

Handfield, R. B., & Nichols, E. L. (1999). *Introduction to supply chain management*. Prentice-Hall.

Hasan, M. M., Jiang, D., Ullah, A. M. M. S., & Noor-E-Alam, M. (2020). Resilient supplier selection in logistics 4.0 with heterogeneous information. *Expert Systems with Applications, 139*, 112799. doi:10.1016/j.eswa.2019.07.016
Humphreys, P. K., Wong, Y. K., & Chan, F. T. S. (2003). Integrating environmental criteria into the supplier selection process. *Journal of Materials Processing Technology, 138*(1–3), 349–356. doi:10.1016/S0924-0136(03)00097-9

Hutchins, M. J., & Sutherland, J. W. (2008). An exploration of measures of social sustainability and their application to supply chain decisions. *Journal of Cleaner Production, 16*(15), 1688–1698. doi:10.1016/j.jclepro.2008.06.001

Izadikhah, M., & Farzipoor Saen, R. (2015). A new data envelopment analysis method for ranking decision making units: An application in industrial parks. *Expert Systems: International Journal of Knowledge Engineering and Neural Networks, 32*(5), 598–608. doi:10.1111/exsy.12112

Izadikhah, M., & Farzipoor Saen, R. (2016a). Evaluating sustainability of supply chains by two-stage range directional measure in the presence of negative data. *Transportation Research Part D, Transport and Environment, 49*, 110–126. doi:10.1016/j.trd.2016.09.003

Izadikhah, M., & Farzipoor Saen, R. (2016b). A new preference voting method for sustainable location planning using geographic information system and data envelopment analysis. *Journal of Cleaner Production, 137*, 1347–1367. doi:10.1016/j.jclepro.2016.08.021

Izadikhah, M., & Farzipoor Saen, R. (2019). Solving voting system by data envelopment analysis for assessing sustainability of suppliers. *Group Decision and Negotiation, 28*(3), 641–669. doi:10.1007/s10726-019-09616-7

Izadikhah, M., Farzipoor Saen, R., & Ahmadi, K. (2017). How to Assess Sustainability of Suppliers in the Presence of Dual-Role Factor and Volume Discounts? A Data Envelopment Analysis Approach. *Asia-Pacific Journal of Operational Research, 34*(3), 1–25. doi:10.1142/S0217595917400164

Izadikhah, M., Farzipoor Saen, R., & Shamsi, M. (2020). How to use fuzzy screening system and data envelopment analysis for clustering sustainable suppliers? A case study in Iran. 10.1108/IEIM-09-2019-0262

Jacquet-Lagrèze, E., & Siskos, J. (1982). Assessing a set of additive utility functions for multicriteria decision-making, the UTA method. *European Journal of Operational Research, 10*(2), 151–164. doi:10.1016/0377-2217(82)90155-2

Jafarzadeh, H., Akbari, P., & Abedin, B. (2018). A methodology for project portfolio selection under criteria prioritisation, uncertainty and projects interdependency – combination of fuzzy QFD and DEA. *Expert Systems with Applications, 110*, 237–249. doi:10.1016/j.eswa.2018.05.028

Jakhar, S. K. (2015). Performance evaluation and a flow allocation decision model for a sustainable supply chain of an apparel industry. *Journal of Cleaner Production, 87*, 391–413. doi:10.1016/j.jclepro.2014.09.089

Kaffash, S., Kazemi Matin, R., & Tajik, M. (2018). A directional semi-oriented radial DEA measure: An application on financial stability and the efficiency of banks. *Annals of Operations Research, 264*(1), 213–234. doi:10.1007/s10479-017-2719-5

Kao, C. (2020). Measuring efficiency in a general production possibility set allowing for negative data. *European Journal of Operational Research, 282*(3), 980–988. doi:10.1016/j.ejor.2019.10.027

Kao, C., & Hung, H.-T. (2008). Efficiency analysis of university departments: An empirical study. *Omega, 36*(4), 653–664. doi:10.1016/j.omega.2006.02.003

Kazemi Matin, R., & Azizi, R. (2011). A two-phase approach for setting targets in DEA with negative data. *Applied Mathematical Modelling, 35*(12), 5794–5803. doi:10.1016/j.apm.2011.05.002

Khodakarami, M., Shabani, A., Farzipoor Saen, R., & Azadi, M. (2015). Developing distinctive two-stage data envelopment analysis models: An application in evaluating the sustainability of supply chain management. *Measurement, 70*(0), 62–74. doi:10.1016/j.measurement.2015.03.024

Khoshandam, L., Amirteimoori, A., & Matin, R. K. (2014). Marginal rates of substitution in the presence of non-discretionary factors: A data envelopment analysis approach. *Measurement, 58*, 409–415. doi:10.1016/j.measurement.2014.09.019

Khoveyni, M., Eslami, R., & Yang, G. (2017). Negative data in DEA: Recognizing congestion and specifying the least and the most congested decision making units. *Computers & Operations Research, 79*, 39–48. doi:10.1016/j.cor.2016.09.002
Kleinsorge, I. K., Schary, P. B., & Tanner, R. D. (1992). Data envelopment analysis for monitoring customer supplier relationships. *Journal of Accounting and Public Policy, 11*(4), 357–372. doi:10.1016/0278-4254(92)90004-H

Korhonen, P. J., & Luptacik, M. (2004). Eco-efficiency analysis of power plants: An extension of data envelopment analysis. *European Journal of Operational Research, 154*(2), 437–446. doi:10.1016/S0377-2217(03)00180-2

Kris, M. Y. L., Kristijan, B., & Andrew, W. H. I. (2021). Using Publicized Information to Determine the Sustainable Development of 3-PL Companies. *Journal of Global Information Management, 29*(1), 1–18. doi:10.4018/JGIM.20210101.oa1

Kumar, A., Jain, V., & Kumar, S. (2014). A comprehensive environment friendly approach for supplier selection. *Omega, 42*(1), 109–123. doi:10.1016/j.omega.2013.04.003

Kuo, R. J., Wang, Y. C., & Tien, F. C. (2010). Integration of artificial neural network and MADA methods for green supplier selection. *Journal of Cleaner Production, 18*(12), 1161–1170. doi:10.1016/j.jclepro.2010.03.020

Lee, A. H. I., Kang, H.-Y., Hsu, C.-F., & Hung, H.-C. (2009). A green supplier selection model for high-tech industry. *Expert Systems with Applications, 36*(4), 7917–7927. doi:10.1016/j.eswa.2008.11.052

Lin, R., & Chen, Z. (2017). A directional distance based super-efficiency DEA model handling negative data. *The Journal of the Operational Research Society, 68*(11), 1312–1322. doi:10.1057/s41274-016-0137-8

Lin, R., & Liu, Y. (2019). Super-efficiency based on the directional distance function in the presence of negative data. *Omega, 85*, 26–34. doi:10.1016/j.omega.2018.05.009

Liu, F.-H. F., & Hai, H. L. (2005). The voting analytic hierarchy process method for selecting supplier. *International Journal of Production Economics, 97*(3), 308–317. doi:10.1016/j.ijpe.2004.09.005

Liu, W., Zhou, Z., Ma, C., Liu, D., & Shen, W. (2015). Two-stage DEA models with undesirable input-intermediate-outputs. *Omega, 56*(0), 74–87. doi:10.1016/j.omega.2015.03.009

Mafakheri, F., Breton, M., & Ghoniem, A. (2011). Supplier selection-order allocation: A two-stage multiple criteria dynamic programming approach. *International Journal of Production Economics, 132*(1), 52–57. doi:10.1016/j.ijpe.2011.03.005

Maghbouli, M., Amirteimoori, A., & Kordrostami, S. (2014). Two-stage network structures with undesirable outputs: A DEA based approach. *Measurement, 48*(0), 109–118. doi:10.1016/j.measurement.2013.10.032

Mahdiloo, M., Noorizadeh, A., & Farziipoor Saen, R. (2014). Benchmarking suppliers’ performance when some factors play the role of both inputs and outputs: A new development to the slacks-based measure of efficiency. *Benchmarking, 21*(5), 792–813. doi:10.1108/BIJ-10-2012-0068

Mahdiloo, M., Saen, R. F., & Lee, K.-H. (2015). Technical, environmental and eco-efficiency measurement for supplier selection: An extension and application of data envelopment analysis. *International Journal of Production Economics, 168*, 279–289. doi:10.1016/j.ijpe.2015.07.010

Mastorakis, K., & Siskos, E. (2016). Value focused pharmaceutical strategy determination with multicriteria decision analysis techniques. *Omega, 59, Part A*, 84-96. 10.1016/j.omega.2015.01.020

Mehdikhani, R., & Valmohammadi, C. (2019). Strategic collaboration and sustainable supply chain management: The mediating role of internal and external knowledge sharing. *Journal of Enterprise Information Management, 32*(5), 778–806. doi:10.1108/JEIM-07-2018-0166

Mehlawat, M. K., Kannan, D., Gupta, P., & Aggarwal, U. (2019). Sustainable transportation planning for a three-stage fixed charge multi-objective transportation problem. *Annals of Operations Research. Advance online publication. doi:10.1007/s10479-019-03451-4

Memari, A., Dargi, A., Akbari Jokar, M. R., Ahmad, R., & Abdul Rahim, A. R. (2019). Sustainable supplier selection: A multi-criteria intuitionistic fuzzy TOPSIS method. *Journal of Manufacturing Systems, 50*, 9–24. doi:10.1016/j.jmsy.2018.11.002

Papapostolou, A., Karakosta, C., Nikas, A., & Psarras, J. (2017). Exploring opportunities and risks for RES-E deployment under Cooperation Mechanisms between EU and Western Balkans: A multi-criteria assessment. *Renewable & Sustainable Energy Reviews, 80*, 519–530. doi:10.1016/j.rser.2017.05.190
Patiniotakis, I., Apostolou, D., & Mentzas, G. (2011). Fuzzy UTASTAR: A method for discovering utility functions from fuzzy data. Expert Systems with Applications, 38(12), 15463–15474. doi:10.1016/j.eswa.2011.06.014

Piao, S.-R., Li, J., & Ting, C.-J. (2019). Assessing regional environmental efficiency in China with distinguishing weak and strong disposability of undesirable outputs. Journal of Cleaner Production, 227, 748–759. doi:10.1016/j.jclepro.2019.04.207

Podinovski, V. V. (2016). Optimal weights in DEA models with weight restrictions. European Journal of Operational Research, 254(3), 916–924. doi:10.1016/j.ejor.2016.04.035

Podinovski, V. V., & Bouzdine-Chameeva, T. (2016). On single-stage DEA models with weight restrictions. European Journal of Operational Research, 248(3), 1044–1050. doi:10.1016/j.ejor.2015.07.050

Portela, M. C. A. S., & Thanassoulis, E. (2010). Malmquist-type indices in the presence of negative data: An application to bank branches. Journal of Banking & Finance, 34(7), 1472–1483. doi:10.1016/j.jbankfin.2010.01.004

Portela, M. C. A. S., Thanassoulis, E., & Simpson, G. (2004). Negative Data in DEA: A Directional Distance Approach Applied to Bank Branches. The Journal of the Operational Research Society, 55(10), 1111–1121. doi:10.1057/palgrave.jors.2601768

Queiroz, M. V. A. B., Sampaio, R. M. B., & Sampaio, L. M. B. (2020). Dynamic efficiency of primary education in Brazil: Socioeconomic and infrastructure influence on school performance. Socio-Economic Planning Sciences, 70, 100738. doi:10.1016/j.seps.2019.100738

Rashidi, K., & Saen, R. F. (2018). Incorporating dynamic concept into gradual efficiency: Improving suppliers in sustainable supplier development. Journal of Cleaner Production, 202, 226–243. doi:10.1016/j.jclepro.2018.08.092

Ray, S. C. (1991). Resource use efficiency in public schools: A study of Connecticut data. Management Science, 37(12), 1620–1628. doi:10.1287/mnsc.37.12.1620

Ruggiero, J. (1996). On the measurement of technical efficiency in the public sector. European Journal of Operational Research, 90(3), 553–565. doi:10.1016/0377-2217(94)00346-7

Ruggiero, J. (1998). Non-discretionary inputs in data envelopment analysis. European Journal of Operational Research, 111(3), 461–469. doi:10.1016/S0377-2217(97)00306-8

Saati, S., Hatami-Marbini, A., & Tavana, M. (2011). A data envelopment analysis model with discretionary and non-discretionary factors in fuzzy environments. International Journal of Productivity and Quality Management, 8(1), 45–63. doi:10.1504/IJPQM.2011.041097

Sahoo, B. K., Khoveyni, M., Esami, R., & Chaudhury, P. (2016). Returns to scale and most productive scale size in DEA with negative data. European Journal of Operational Research, 255(2), 545–558. doi:10.1016/j.ejor.2016.05.065

Sarkhosh-Sara, A., Taavasoli, M., & Heshmati, A. (2019). Assessing the sustainability of high-, middle-, and low-income countries: A network DEA model in the presence of both zero data and undesirable outputs. Sustainable Production and Consumption. doi:10.1016/j.spcc.2019.08.009

Scheel, H. (2001). Undesirable outputs in efficiency valuations. European Journal of Operational Research, 132(2), 400–410. doi:10.1016/S0377-2217(00)00160-0

Seuring, S. (2013). A review of modeling approaches for sustainable supply chain management. Decision Support Systems, 54(4), 1513–1520. doi:10.1016/j.dss.2012.05.053

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699–1710. doi:10.1016/j.jclepro.2008.04.020

Shabani, A., & Farzipoor Saen, R. (2016). Developing imprecise dual-role hybrid measure of efficiency for international market selection using ternary variable. International Journal of Industrial and Systems Engineering, 22(3), 305–331. doi:10.1504/IJISe.2016.074708
Shabani, A., Torabipour, S. M. R., Farzipoor Saen, R., & Khodakarami, M. (2015). Distinctive data envelopment analysis model for evaluating global environment performance. *Applied Mathematical Modelling, 39*(15), 4385–4404. doi:10.1016/j.apm.2014.12.053

Sharp, J. A., Meng, W., & Liu, W. (2007). A Modified Slacks-Based Measure Model for Data Envelopment Analysis with ‘Natural’ Negative Outputs and Inputs. *The Journal of the Operational Research Society, 58*(12), 1672–1677. doi:10.1057/palgrave.jors.2602318

Siskos, J. (1980). Method for modeling preferences employing additive utility functions. *Operations Research, 14*(1), 53–82. doi:10.1051/ro/1980140100531

Siskos, Y., & Yannacopoulos, D. (1985). UTASTAR: An ordinal regression method for building additive value functions. *Investigação Operacional, 5*(1), 39–53.

Soltani, N., & Lozano, S. (2018). Potential-based efficiency assessment and target setting. *Computers & Industrial Engineering, 126*, 611–624. doi:10.1016/j.cie.2018.10.013

Su, Y., & Sun, W. (2018). Sustainability evaluation of the supply chain with undesired outputs and dual-role factors based on double frontier network DEA. *Soft Computing, 22*(16), 5525–5533. doi:10.1007/s00500-018-3240-8

Syrjänen, M. J. (2004). Non-discretionary and discretionary factors and scale in data envelopment analysis. *European Journal of Operational Research, 158*(1), 20–33. doi:10.1016/S0377-2217(03)00362-X

Taewoo, N. (2019). Does E-Government Raise Effectiveness and Efficiency?: Examining the Cross-National Effect. *Journal of Global Information Management, 27*(3), 120–138. doi:10.4018/JGIM.2019070107

Talluri, S., Narasimhan, R., & Nair, A. (2006). Vendor performance with supply risk: A chance-constrained DEA approach. *International Journal of Production Economics, 100*(2), 212–222. doi:10.1016/j.ijpe.2004.11.012

Tavana, M., Izadikhah, M., Di Caprio, D., & Farzipoor Saen, R. (2018). A New Dynamic Range Directional Measure for Two-Stage Data Envelopment Analysis Models with Negative Data. *Computers & Industrial Engineering, 115*, 427–448. doi:10.1016/j.cie.2017.11.024

Temur Gül, T., & Bolat, B. (2018). A robust MCDM approach for ERP system selection under uncertain environment based on worst case scenario. *Journal of Enterprise Information Management, 31*(3), 405–425. doi:10.1108/JEIM-12-2017-0175

Thompson, R. G., Langemeier, L. N., Lee, C. T., Lee, E., & Thrall, R. M. (1990). The role of multiplier bounds in efficiency analysis with application to Kansas farming. *Journal of Econometrics, 46*(1/2), 93–108. doi:10.1016/0304-4076(90)90049-Y

Toloo, M., & Hančlová, J. (2019). Multi-valued measures in DEA in the presence of undesirable outputs. *Omega, 102041*. Advance online publication. doi:10.1016/j.omega.2019.01.010

Toloo, M., Keshavarz, E., & Hatami-Marbini, A. (2018). Dual-role factors for imprecise data envelopment analysis. *Omega, 77*, 15–31. doi:10.1016/j.omega.2017.05.005

Tone, K., Chang, T.-S., & Wu, C.-H. (2020a). Handling negative data in slacks-based measure data envelopment analysis models. *European Journal of Operational Research, 282*(3), 926–935. doi:10.1016/j.ejor.2019.09.055

Tone, K., Toloo, M., & Izadikhah, M. (2020b). A modified slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 287*(2), 560–571. doi:10.1016/j.ejor.2020.04.019

Trachanatzis, D., Rigakis, M., Marinaki, M., & Marinakis, Y. (2020). An interactive preference-guided firefly algorithm for personalized tourist itineraries. *Expert Systems with Applications, 159*, 113563. doi:10.1016/j.eswa.2020.113563

Tseng, M. L., & Chiu, A. S. F. (2013). Evaluating ðrm’s green supply chain management in linguistic preferences. *Journal of Cleaner Production, 40*, 22–31. doi:10.1016/j.jclepro.2010.08.007

Tsoulias, G. T., & Pappis, C. P. (2006). Environmental principles applicable to supply chains design and operation. *Journal of Cleaner Production, 14*(18), 1593–1602. doi:10.1016/j.jclepro.2005.05.021

Wang, M., & Li, Y. (2014). Supplier evaluation based on Nash bargaining game model. *Expert Systems with Applications, 41*(9), 4181–4185. doi:10.1016/j.eswa.2013.12.044
Weber, A., Current, J., & Desai, A. (2000a). An optimization approach to determining the number of vendors to employ. *Supply Chain Management*, 5(2), 90–98. doi:10.1108/13598540010320009

Weber, A., Current, J., & Desai, A. (2000b). An optimization approach to determining the number of vendors to employ. *International Journal of Supply Chain Management*, 5(2), 90–98. doi:10.1108/13598540010320009

Wu, D. (2009). Supplier selection: A hybrid model using DEA, decision tree and neural network. *Expert Systems with Applications*, 36(5), 9105–9112. doi:10.1016/j.eswa.2008.12.039

Wu, D. D. (2010). A systematic stochastic efficiency analysis model and application to international supplier performance evaluation. *Expert Systems with Applications*, 37(9), 6257–6264. doi:10.1016/j.eswa.2010.02.097

Yousefi, S., Shabanpour, H., Fisher, R., & Farzipoor Saen, R. (2016). Evaluating and ranking sustainable suppliers by robust dynamic data envelopment analysis. *Measurement*, 83, 72–85. doi:10.1016/j.measure.2016.01.032

Yousefi, S., Soltani, R., Farzipoor Saen, R., & Pishvae, M. S. (2017). A robust fuzzy possibilistic programming for a new network GP-DEA model to evaluate sustainable supply chains. *Journal of Cleaner Production*, 166, 537–549. doi:10.1016/j.jclepro.2017.08.054

Yu, C., Shao, Y., Wang, K., & Zhang, L. (2019). A group decision making sustainable supplier selection approach using extended TOPSIS under interval-valued Pythagorean fuzzy environment. *Expert Systems with Applications*, 121, 1–17. doi:10.1016/j.eswa.2018.12.010

Yu, J.-R., & Tsai, C.-C. (2008). A decision framework for supplier rating and purchase allocation: A case in the semiconductor industry. *Computers & Industrial Engineering*, 55(3), 634–646. doi:10.1016/j.cie.2008.02.004

Zerafat Angiz, L. (2013). Fuzzy interpretation of efficiency in data envelopment analysis and its application in a non-discretionary model. *Knowledge-Based Systems*, 49, 145–151. doi:10.1016/j.knosys.2013.05.001

Zhang, C., Luo, L., Liao, H., Mardani, A., Streimikiene, D., & Al-Barakati, A. (2020). A priority-based intuitionistic multiplicative UTASTAR method and its application in low-carbon tourism destination selection. *Applied Soft Computing*, 88, 106026. doi:10.1016/j.asoc.2019.106026

Zhang, G., & Cui, J. (2020). A general inverse DEA model for non-radial DEA. *Computers & Industrial Engineering*, 142, 106368. doi:10.1016/j.cie.2020.106368

Zhou, X., Pedrycz, W., Kuang, Y., & Zhang, Z. (2016). Type-2 fuzzy multi-objective DEA model: An application to sustainable supplier evaluation. *Applied Soft Computing*, 46, 424–440. doi:10.1016/j.asoc.2016.04.038

Zhou, Z., Xu, G., Wang, C., & Wu, J. (2019). Modeling undesirable output with a DEA approach based on an exponential transformation: An application to measure the energy efficiency of Chinese industry. *Journal of Cleaner Production*, 236, 117717. doi:10.1016/j.jclepro.2019.117717
APPENDIX

Solving UTASTAR Model for the Second Case

To solve the UTASTAR model, we need a decision matrix and a ranking of reference alternatives that consider the initial ranking of reference alternatives from Table 8. Steps are as follows:

Step 1: Calculation of marginal value functions:

\[ U[g(A1)] = w_{11} + w_{12} + 0.71w_{21} + w_{31} + 0.5w_{41} + 0.92w_{51} + 0.35w_{61} + 0.625w_{81} \]
\[ U[g(A2)] = w_{12} + w_{22} + 0.86w_{62} + w_{72} + w_{52} + w_{82} + w_{83} \]
\[ U[g(A3)] = w_{11} + 0.93w_{12} + 0.83w_{32} + w_{41} + 0.75w_{61} \]
\[ U[g(A4)] = w_{11} + 0.94w_{12} + 0.43w_{32} + 0.92w_{41} + 0.5w_{61} + w_{81} + w_{41} + 0.74w_{72} \]

Step 2: Expression of linear program:

\[ \min \ z = \sum_{i=1}^{m} \left[ \sigma^+(a_i) + \sigma^-(a_i) \right] \]

s.t.
\[-w_{11} - 0.29w_{12} + w_{21} + 0.5w_{31} + 0.06w_{41} - 0.65w_{42} + 0.375w_{51} - w_{82} - w_{83} - \sigma^+(A1) + \sigma^-(A1) + \sigma^+(A2) - \sigma^-(A2) >= 0.05 \]
\[-w_{11} - 0.93w_{12} + w_{21} - 0.83w_{31} - w_{41} + 0.86w_{62} + w_{72} + w_{73} + 0.25w_{81} + w_{82} + w_{83} - \sigma^+(A2) + \sigma^-(A2) + \sigma^+(A3) - \sigma^-(A3) >= 0.05 \]
\[-0.01w_{12} - 0.43w_{22} - 0.09w_{32} + 0.5w_{42} - w_{61} - w_{71} - 0.74w_{72} + 0.75w_{81} - \sigma^+(A3) + \sigma^-(A3) + \sigma^+(A4) - \sigma^-(A4) >= 0.05 \]
\[-w_{11} + w_{12} + w_{21} + w_{31} + w_{32} + w_{41} + w_{42} + w_{51} + w_{61} + w_{71} + w_{72} + w_{73} + w_{81} + w_{82} + w_{83} = 1 \]
\[ w_{ij} \geq 0, \sigma^+(a_k) \geq 0, \sigma^-(a_k) \geq 0 \]

Step 3: Solving the linear program.

After solving linear programming model using Lingo software, following results are obtained:

\[ Z^* = 0 \]
\[ W_{12} = 0.0710783125 \]
\[ W_{22} = 0.144456775 W_{32} = 0.0569391125 \]
\[ W_{42} = 0.0375 W_{52} = 0.1633791125 \]
\[ W_{52} = 0.1533907625 W_{62} = 0.0444859375 \]
\[ W_{72} = 0.05625 W_{81} = 0.1851947988 \]
\[ W_{83} = 0.086926265 \]

Substituting the above weights in the total value function, the utility value of the selected suppliers HC, NSG, SMG, and SIG are obtained as 0.707, 0.511, 0.452, and 0.345, respectively.
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