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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),

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Izadikhah et al., (2020)). 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 efðciency 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.

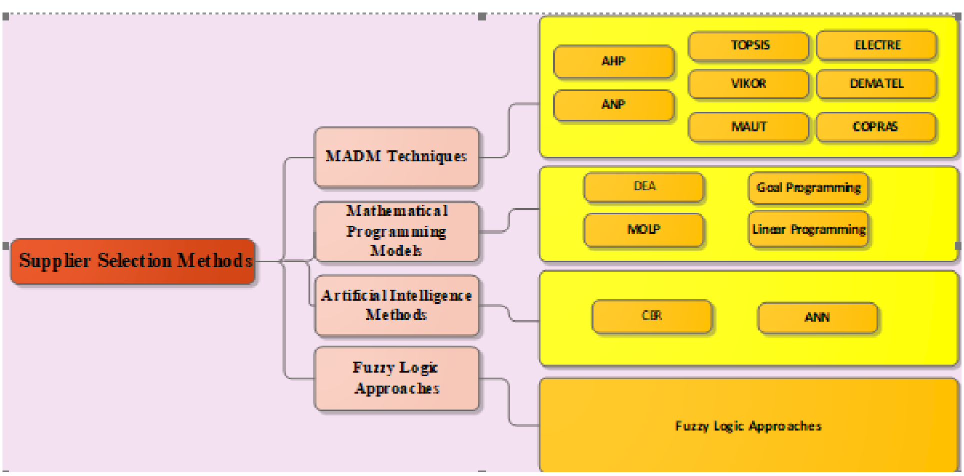
2. LITERATURE REVIEW

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

Figure 1. The techniques for supplier selection



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); Cheraghalipour 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.,

Table 2. Some supplier selection techniques based on DEA models

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); Amindoust, (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

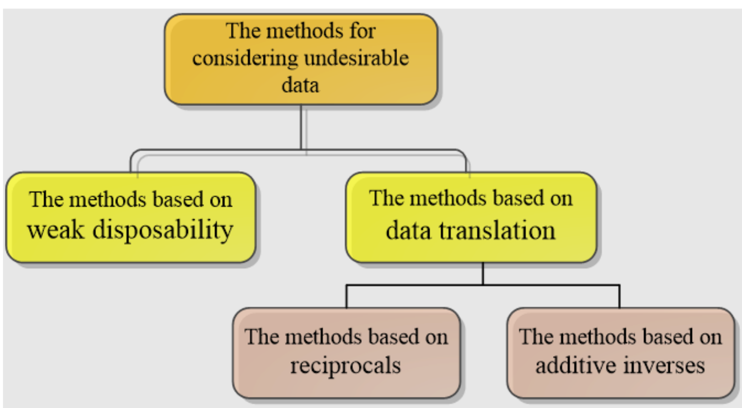


Table 3. The undesirable data in DEA literature

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	Aliakbarpoor 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. Izadikhah 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 modiðed 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. Mirhedayatian 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. Izadikhah 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:

$$\begin{aligned}
&\max \quad \beta \\
&s.t. \\
&\qquad \sum_{j=1}^{n} \lambda_j x_{ij} + t_i^- = x_{io} - \beta L_{io}^-, \quad i = 1,\dots,m, \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - t_r^+ = y_{ro} + \beta L_{ro}^+, \quad r = 1,\dots,s, \\
&\qquad \sum_{j=1}^{n} \lambda_j = 1, \\
&\qquad t^- \geq 0, \quad t^+ \geq 0, \quad \lambda \geq 0.
\end{aligned} \tag{1}$$

Table 4. Nomenclatures

Symbol	Description	Symbol	Description
DMU_0	DMU under evaluation;	DMU_j	j^{th} DMU;
m	number of inputs;	λ_j	intensity;
s	number of outputs;	L_{io}^{-}	Lower sided ranges for inputs;
x_{ij}	i^{th} input of DMU_j;	L_{ro}^{+}	Lower sided ranges for outputs;
y_{rj}	r^{th} 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

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 β^* 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 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:

$$u'[g(a)] = \sum_{i=1}^{n} u_i[g_i(a)] - \sigma^+(a) + \sigma^-(a); \;\; a \in A_R \tag{2}$$

In Expression (2), the overestimation and underestimation errors are shown by σ^+ and σ^-, 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:

$$w_{ij} = u_i(g_i^{j+1}) - u_i(g_i^j) \geq 0; \forall i = 1,\ldots,n \text{ and } j = 1,\ldots,\alpha_i - 1 \tag{3}$$

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 $u_i(g_i)$. Then, in terms of variables based on formula (2) using the following relations:

$$\begin{cases} u_i(g_i^1) = 0; & \forall i = 1,\ldots,n \\ u_i(g_i^j) = \sum_{t=1}^{j-1} w_{it}; & \forall i = 1,\ldots,n \text{ and } j = 2,\ldots,\alpha_i - 1 \end{cases} \tag{4}$$

Step 2: Ranking expressions are defined as follows:

$$\Delta(a_k, a_{k+1}) = \{u[g(a_k)] - \sigma^+(a_k) + \sigma^-(a_k)\} - \{u[g(a_{k+1})] - \sigma^+(a_{k+1}) + \sigma^-(a_{k+1})\} \tag{5}$$

Step 3: Run the linear program (LP):

$$\begin{aligned} &\min \;\; z = \sum_{k=1}^{m} [\sigma^+(a_k) + \sigma^-(a_k)] \\ &s.t. \\ &\left.\begin{aligned} \Delta(a_k, a_{k+1}) \geq \delta \text{ if } a_k \succ a_{k+1}, \\ \Delta(a_k, a_{k+1}) = 0 \text{ if } a_k \approx a_{k+1}, \end{aligned}\right\} \forall k \\ &\sum_{i=1}^{n} \sum_{j=1}^{a_i - 1} w_{ij} = 1, \\ &w_{ij} \geq 0, \sigma^+(a_k) \geq 0, \sigma^-(a_k) \geq 0; \forall i, j, k \end{aligned} \tag{6}$$

where δ 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:

$$u_i(g_i^*) = \sum_{j=1}^{a_i - 1} w_{ij}; \; i = 1, \dots, n \tag{7}$$

Feasible region is formed by the constraints of model (6) and is bounded by the following constraint:

$$\sum_{k=1}^{m} [\sigma^+(a_k) + \sigma^-(a_k)] \le \mathrm{z}^* + \varepsilon \tag{8}$$

where z^* is the optimal value of model (6) and ε 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 $\{D_1I\}, \{NI\}, \{D_1O\}, \{NO\}$ indicate fixed index sets independent of j, such that x_{ij}, y_{rj} ($i \in \{D_1I\}$ and $r \in \{D_1O\}$) are discretionary inputs and outputs, and x_{ij}, y_{rj} ($i \in \{NI\}$ and $r \in \{NO\}$) are nondiscretionary inputs and outputs, respectively. Furthermore, assume that $\{D_2I\}, \{UI\}, \{D_2O\}, \{UO\}$ indicate fixed index sets independent of j, such that x_{ij}, y_{rj} ($i \in \{DI\}$ and $r \in \{D_2O\}$) are desirable inputs and outputs and x_{ij}, y_{rj} ($i \in \{UI\}$ 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:

$$MPPS = \left\{ (x,y) \left| \begin{array}{ll} x_i \ge \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IA\}; & x_i \ge \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IB\}; \\ x_i \le \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{IC\}; & x_i \le \sum_{j=1}^{n} \lambda_j x_{ij}, i \in \{ID\}; \\ y_r \le \sum_{j=1}^{n} \lambda_j y_{rj}, r \in \{OA\}; & y_r \le \sum_{j=1}^{n} \lambda_j y_{rj}, i \in \{OB\}; \\ y_r \ge \sum_{j=1}^{n} \lambda_j y_{rj}, r \in \{OC\}; & y_r \ge \sum_{j=1}^{n} \lambda_j y_{rj}, i \in \{OD\}; \\ \sum_{j=1}^{n} \lambda_j = 1, & \\ \lambda_j \ge 0, j = 1, \dots, n & \end{array} \right. \right\}$$

where $\{IA\} = \{D_1I\} \bigcap \{D_2I\}$, $\{IB\} = \{D_2I\} \bigcap \{NI\}$, $\{IC\} = \{D_1I\} \bigcap \{UI\}$, and $\{ID\} = \{NI\} \bigcap \{UI\}$ indicate fixed index sets on inputs and $\{OA\} = \{D_1O\} \bigcap \{D_2O\}$, $\{OB\} = \{D_2O\} \bigcap \{NO\}$, $\{OC\} = \{D_1O\} \bigcap \{UO\}$, and $\{OD\} = \{NO\} \bigcap \{UO\}$ indicate fixed index sets on outputs. We then use this MPPS to define modified dominance as follows:

Definition 1 (modified dominance): Let $(\tilde{x}, \tilde{y}) \in MPPS$ and $(x,y) \in MPPS$. $(\tilde{x}, \tilde{y})$ dominates (x,y) with respect to MPPS if and only if:

$$\tilde{x}_i \le x_i, i \in \{IA\}; \quad \tilde{x}_i \le x_i, i \in \{IB\};$$
$$\tilde{x}_i \ge x_i, i \in \{IC\}; \quad \tilde{x}_i \ge x_i, i \in \{ID\};$$
$$\tilde{y}_r \ge y_r, r \in \{OA\}; \quad \tilde{y}_r \ge y_r, i \in \{OB\};$$
$$\tilde{y}_r \le y_r, r \in \{OC\}; \quad \tilde{y}_r \le y_r, i \in \{OD\};$$

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_{fj} ,*f=1,…,F; j=1,…,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:

$$
\begin{aligned}
&\beta^* = \max \beta \\
&s.t. \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io} - \beta L_{io}^{-}, \quad i \in \{IA\}; \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io}, \quad i \in \{IB\}, \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} \ge x_{io} + \beta B_{io}^{-}, \quad i \in \{IC\}; \quad \sum_{j=1}^{n} \lambda_j x_{ij} \ge x_{io}, \quad i \in \{ID\}, \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} + \beta L_{ro}^{+}, \quad r \in \{OA\}; \quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, \quad r \in \{OB\}, \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \le y_{ro} - \beta B_{ro}^{+}, \quad r \in \{OC\}; \quad \sum_{j=1}^{n} \lambda_j y_{rj} \le y_{ro}, \quad r \in \{OD\}, \\
&\quad \sum_{j=1}^{n} \lambda_j w_{fj} \le w_{fo} - \beta H_{fo}^{-}, \quad f \in \{A\}; \quad \sum_{j=1}^{n} \lambda_j w_{fj} \le w_{fo}, \quad f \in \{B\}, \\
&\quad \sum_{j=1}^{n} \lambda_j w_{fj} \ge w_{fo} + \beta U_{fo}^{-}, \quad f \in \{C\}; \quad \sum_{j=1}^{n} \lambda_j w_{fj} \ge w_{fo}, \quad f \in \{D\}, \\
&\quad \sum_{j=1}^{n} \lambda_j w_{fj} \ge w_{fo} + \beta H_{fo}^{+}, \quad f \in \{A\}; \quad \sum_{j=1}^{n} \lambda_j w_{fj} \ge w_{fo}, \quad f \in \{B\}, \\
&\quad \sum_{j=1}^{n} \lambda_j w_{fj} \le w_{fo} - \beta U_{fo}^{+}, \quad f \in \{C\}; \quad \sum_{j=1}^{n} \lambda_j w_{fj} \le w_{fo}, \quad f \in \{D\}, \\
&\quad \sum_{j=1}^{n} \lambda_j = 1, \\
&\quad \lambda \ge 0
\end{aligned}
\tag{9}
$$

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

$L_{io}^{-} = x_{io} - \min_j \{x_{ij}\}, \quad i \in \{IA\}$, and $L_{ro}^{+} = \max_j \{y_{rj}\} - y_{ro}, \quad r \in \{OA\}$, and

$$B_{io}^{-} = \max_{j}\{x_{ij}\} - x_{io}, \quad i \in \{IC\}, \text{and } B_{ro}^{+} = y_{ro} - \min_{j}\{y_{rj}\}, \quad r \in \{OC\}, \text{and}$$
$$H_{fo}^{-} = w_{fo} - \min_{j}\{w_{fj}\}, \quad f \in \{A\}, \text{and } H_{fo}^{+} = \max_{j}\{w_{fj}\} - w_{fo}, \quad f \in \{A\}, \text{and}$$
$$U_{fo}^{-} = \max_{j}\{w_{fj}\} - w_{fo}, \quad f \in \{C\}, \text{and } U_{fo}^{+} = w_{fo} - \min_{j}\{w_{fj}\}, \quad f \in \{C\} \tag{10}$$

Model (9) calculates the inefficiency score of DMU_o. The efficiency score can be defined as $1 - \beta^*$.

Theorem 1: Model (9) is always feasible.
Proof: If we set $\left(\tilde{\lambda}_o = 1, \tilde{\lambda}_{j\neq o} = 0\right)$ and $\tilde{\beta} = 0$, then it is easy to see that the vector $\left(\tilde{\lambda}, \tilde{\beta}\right)$ 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 $\sum_{j=1}^{n}\lambda_j = 1, \lambda_j \geq 0, \left(j = 1,\ldots,n\right)$ for inputs, we have $\min_i\left\{x_{ij}\right\} \leq \sum_{j=1}^{n}\lambda_j x_{ij} \leq \max_i\left\{x_{ij}\right\}$. Therefore, $x_{io} - \sum_{j=1}^{n}\lambda_j x_{ij} \leq x_{io} - \min_i\left\{x_{ij}\right\} = L_{io}^{-}$. Thus, from the first constraint of model (9) we conclude that:

$$\min_i\left\{x_{ij}\right\} \leq \sum_{j=1}^{n}\lambda_j x_{ij} \leq x_{io} - \beta L_{io}^{-}; \; i \in \left\{IA\right\}$$
$$\Rightarrow \beta \leq \frac{x_{io} - \sum_{j=1}^{n}\lambda_j x_{ij}}{L_{io}^{-}} \leq 1$$

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 $[a_r, b_r]$ and the proportion of total virtual input of DMU_j is considered to be restricted in the interval $[c_i, d_i]$:

$$a_r \leq \frac{u_r y_{rj}}{\sum_{r=1}^{s} u_r y_{rj}} \leq b_r \qquad r = 1,\ldots,s \tag{11}$$
$$c_i \leq \frac{v_i x_{ij}}{\sum_{i=1}^{m} v_i x_{ij}} \leq d_i \qquad i = 1,\ldots,m$$

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:

$$
\begin{aligned}
&Min \quad \sum_{i\in\{IA\}\cup\{IB\}} v_i x_{io} - \sum_{i\in\{IC\}\cup\{ID\}} v_i x_{io} - \sum_{r\in\{OA\}\cup\{OB\}} u_r y_{ro} + \sum_{r\in\{OC\}\cup\{OD\}} u_r y_{ro} + \sum_{f\in A\cup B}(z_f^I - z_f^O)w_{fo} + \sum_{f\in C\cup D}(-z_f^I + z_f^O)w_{fo} + u_o \\
&s.t. \\
&\sum_{i\in\{IA\}\cup\{IB\}} v_i x_{ij} - \sum_{i\in\{IC\}\cup\{ID\}} v_i x_{ij} - \sum_{r\in\{OA\}\cup\{OB\}} u_r y_{rj} + \sum_{r\in\{OC\}\cup\{OD\}} u_r y_{rj} + \sum_{f\in A\cup B}(z_f^I - z_f^O)w_{fj} + \sum_{f\in C\cup D}(-z_f^I + z_f^O)w_{fj} + u_o \geq 0, \quad j = 1,...,n, \\
&\quad \sum_{i\in\{IA\}} v_i L_{io}^- + \sum_{i\in\{IC\}} v_i B_{io}^- + \sum_{r\in\{OA\}} u_r L_{ro}^+ + \sum_{r\in\{OC\}} u_r B_{ro}^+ + \sum_{f\in A} z_f^I H_{fo}^- + \sum_{f\in A} z_f^O H_{fo}^+ + \sum_{f\in C} z_f^I H_{fo}^- + \sum_{f\in C} z_f^O H_{fo}^+ = 1, \\
&\quad a_r(\sum_{r=1}^{s} u_r y_{rj}) - u_r y_{rj} \leq 0, \qquad u_r y_{rj} - b_r(\sum_{r=1}^{s} u_r y_{rj}) \leq 0, \qquad r = 1,...,s, \quad j = 1,...,n, \\
&\quad c_i(\sum_{i=1}^{m} v_i x_{ij}) - v_i x_{ij} \leq 0, \qquad v_i x_{ij} - d_i(\sum_{i=1}^{m} v_i x_{ij}) \leq 0, \qquad i = 1,...,m, \quad j = 1,...,n, \\
&\quad v_i, u_r, z_f^I, z_f^O \geq 0, \qquad \forall i, r, f
\end{aligned}
\tag{12}
$$

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 $z_f^{I*} - z_f^{O*}$, where z_f^{I*} and z_f^{O*} are optimal values obtained from model (12):

- If $z_f^{I*} - z_f^{O*} < 0$, then w_{fj} is ‘‘behaving like inputs”.
- If $z_f^{I*} - z_f^{O*} > 0$, then w_{fj} is ‘‘behaving like outputs”.
- If $z_f^{I*} - z_f^{O*} = 0$, then w_{fj} is at the equilibrium level.

Case 2: For $f \in C \cup D$, one of three possibilities exists for the sign of $z_f^{I*} - z_f^{O*}$, where z_f^{I*} and z_f^{O*} are optimal values obtained from model (12):

- If $z_f^{I*} - z_f^{O*} > 0$, then w_{fj} is ‘‘behaving like inputs”.
- If $z_f^{I*} - z_f^{O*} < 0$, then w_{fj} is ‘‘behaving like outputs”.
- If $z_f^{I*} - z_f^{O*} = 0$, then w_{fj} 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:

$$
\begin{aligned}
&\rho_p^* = Max - \sum_{i\in\{IA\}\cup\{IB\}} v_i x_{io} + \sum_{i\in\{IC\}\cup\{ID\}} v_i x_{io} + \sum_{r\in\{OA\}\cup\{OB\}} u_r y_{ro} - \sum_{r\in\{OC\}\cup\{OD\}} u_r y_{ro} - \sum_{f\in A\cup B}(z_f^I - z_f^O)w_{fo} - \sum_{f\in C\cup D}(-z_f^I + z_f^O)w_{fo} + u_o \\
&s.t. \\
&-\sum_{i\in\{IA\}\cup\{IB\}} v_i x_{ij} + \sum_{i\in\{IC\}\cup\{ID\}} v_i x_{ij} + \sum_{r\in\{OA\}\cup\{OB\}} u_r y_{rj} - \sum_{r\in\{OC\}\cup\{OD\}} u_r y_{rj} - \sum_{f\in A\cup B}(z_f^I - z_f^O)w_{fj} - \sum_{f\in C\cup D}(-z_f^I + z_f^O)w_{fj} + u_o \leq 0, \quad j \in E \setminus p \\
&\quad \sum_{i\in\{IA\}} v_i L_{io}^- + \sum_{i\in\{IC\}} v_i B_{io}^- + \sum_{r\in\{OA\}} u_r L_{ro}^+ + \sum_{r\in\{OC\}} u_r B_{ro}^+ + \sum_{f\in A} z_f^I H_{fo}^- + \sum_{f\in A} z_f^O H_{fo}^+ + \sum_{f\in C} z_f^I H_{fo}^- + \sum_{f\in C} z_f^O H_{fo}^+ = 1, \\
&\quad a_r(\sum_{r=1}^{s} u_r y_{rj}) - u_r y_{rj} \leq 0, \qquad u_r y_{rj} - b_r(\sum_{r=1}^{s} u_r y_{rj}) \leq 0, \qquad r = 1,...,s, \quad j \in E \setminus p, \\
&\quad c_i(\sum_{i=1}^{m} v_i x_{ij}) - v_i x_{ij} \leq 0, \qquad v_i x_{ij} - d_i(\sum_{i=1}^{m} v_i x_{ij}) \leq 0, \qquad i = 1,...,m, \quad j \in E \setminus p, \\
&\quad v_i, u_r, z_f^I, z_f^O \geq 0, \qquad \forall i, r, f
\end{aligned}
\tag{13}
$$

where ρ_p^* is the super-efficiency score for ranking DMUp. We show the set of efficient DMUs of Model (12) by E, and $E\backslash p$ shows all efficient DMUs except DMUp. The more value of ρ_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

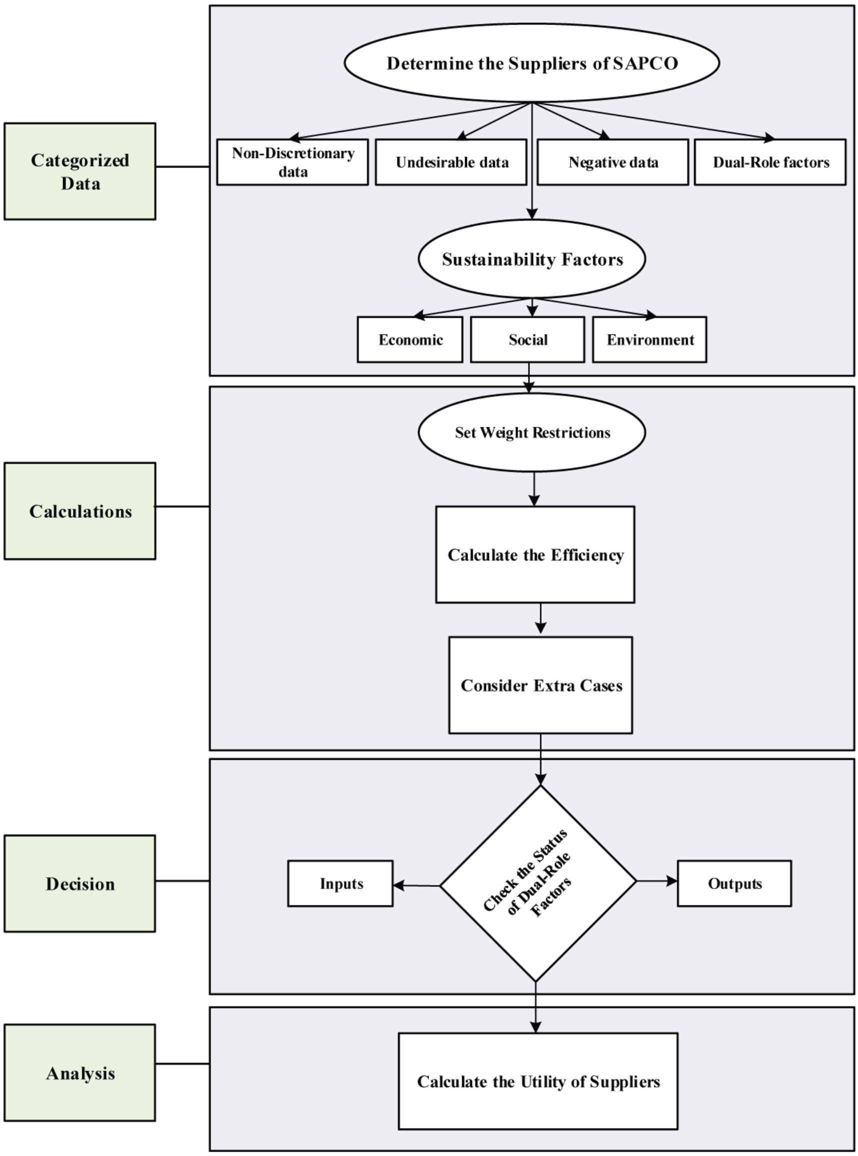


Figure 4. A view of the clutch pressure plate

Table 5. Suppliers of SAPCO

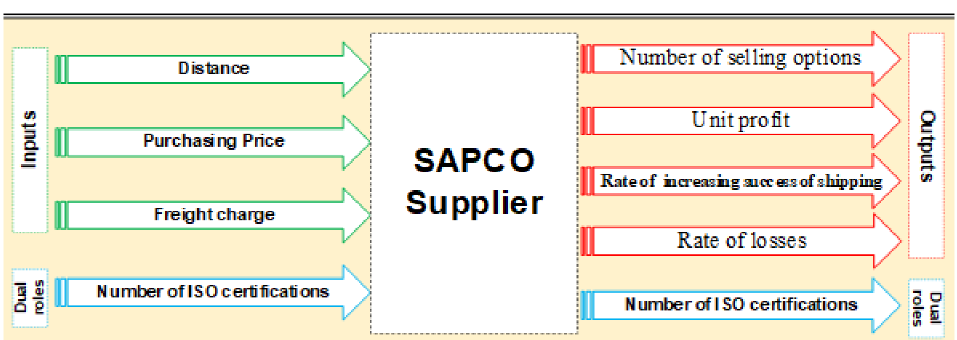
No.	Supplier name	Abbr.	No.	Supplier name	Abbr.
1	Fulad Ferdos Industrial Group	FFIG	14	Mobin Azar Motor Co.	MAMC
2	Homa Khodrosaz Co.	HKC	15	Asia Pearlite Casting Industries	APCI
3	Poladish Group	PG	16	Parto Alunite Foundry Industry	PAFI
4	Ardestan Industrial Casting Co.	AICC	17	Machine Sazi Tabriz 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

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 Thanassoulis, (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.

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

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

Table 8. The dataset

No.	Suppliers (DMUs)	Inputs			Dual-role factor	Outputs			
		Distance	Purchasing price	Freight charge	Number of obtained ISO certificates	Number of selling options	Unit profit	Rate of the increasing success of shipping	Rate of losses
1	FFIG	47	8000	50	2	3	1940	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	5	1.3
6	TTFC	620	7500	190	4	4	2320	1.8	1.1
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	2
12	TKFIC	883	7300	210	4	2	2490	3.4	2
13	LICP	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

Table 9. The dataset summary of 26 suppliers

Variable	Mean	Std. Dev.	Min	Max
Distance	228.1538	260.1613	15	883
Purchasing price	7876.923	407.7329	7300	8550
Freight charge	113.6538	68.8848	25	210
Number of selling options	2.5	1.449138	1	5
Unit profit	2163.077	371.1444	1680	2650
Rate of the increasing success of shipping	0.226923	5.541159	-9	12.6
Rate of losses	3.534615	2.67551	0.8	10
The number of ISO certificates	2.5	1.240967	1	5

these DMUs are weak. Based on the decision maker's opinion, the importance of freight charge, v_3 , is as follows:

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

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.

Model (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_f^{I*} and z_f^{O*} are optimal values obtained from model (12) and the column under $Z_1^I - Z_1^O$ 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	0.0000000	0.2355156	-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

5.3 Data Analysis

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.

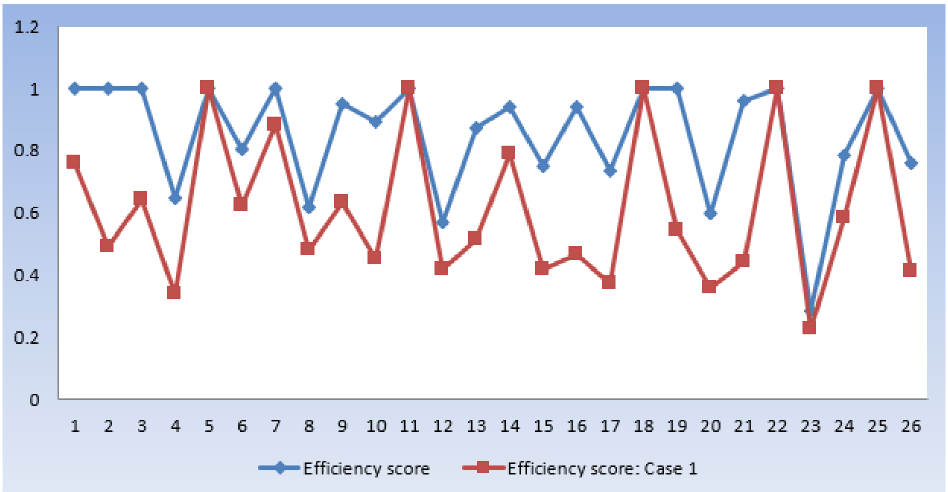
The results of this case are seen in the third column of Table 11. As is seen, the efficiency scores are lower than or equal to the results of our proposed scores. Fig. 6 depicts the results. We can see that in all DMUs the efficiencies in the first case are lower than or equal to the proposed scores. 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

Table 11. The results of two cases and ranking

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	06250000	-	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**		

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



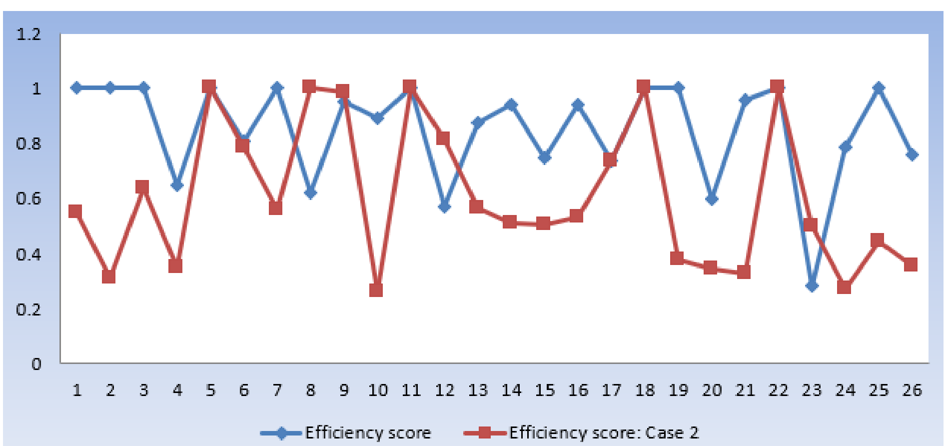
"number of obtained ISO certificates" as input or output in a way that the best relative efficiency is obtained for each DMU. In the second case, we assume that the "number of obtained ISO certificates" is considered as output. The results of this case can be seen in the fourth column of Table 11.

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 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

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

Step 2: Expressions of the linear programming model

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

s.t.

$-w_{11}-w_{12}+0.73w_{22}-w_{31}-w_{32}+w_{41}-0.67w_{52}-0.04w_{62}+0.33w_{72}+w_{73}+0.78w_{81}+0.23w_{81} - \sigma^{+}(A1) + \sigma^{-}(A1) + \sigma^{+}(A2) - \sigma^{-}(A2)>=0.05;$

$0.98w_{12}+w_{21}+0.27w_{22}-w_{41}+w_{51}+w_{52}+w_{61}+0.93w_{62}+w_{71}+0.67w_{72}-0.78w_{81}-w82- \sigma^{+}(A2) + \sigma^{-}(A2) + \sigma^{+}(A3) - \sigma^{-}(A3)>=0.05;$

$-0.92w_{12}-w21-0.47w_{22}+0.08w_{32}+w_{41}-w_{51}-0.33w_{52}-w_{61}-w_{62}-w_{71}-0.99w_{72}+w_{81}+w_{82}- \sigma^{+}(A3) + \sigma^{-}(A3) + \sigma^{+}(A4) - \sigma^{-}(A4)>=0.05;$

$w_{11}+w_{12}+w_{21}+w_{22}+w_{31}+w_{32}+w_{41}+w_{51}+w_{52}+w_{61}+w_{62}+w_{71}+w_{72}+w_{73}+w_{81}+w_{82}=1;$

$w_{ij} \geq 0, \sigma^{+}(a_k) \geq 0, \sigma^{-}(a_k) \geq 0$

Step 3: Solving the linear programming model.

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

$Z^*= 0$
$W_{12}=0.0547680375$ $W_{21}=0.0538617875$
$W_{22}= 0.0075096625$ W32=0.0497114875
$W_{41}=0.07413015$ $W_{51}=0.0200870625$
$W_{52}=0.1035213988$ $W_{61}=0.031696425$
$W_{62}=0.027678575$ $W_{71}=0.1052548$
$W_{73}=0.171066625$ $W_{81}=0.2548893213$

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 $\left(x\right)$, one output $\left(y\right)$, 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)	×	✓	×	✓	×	×	×
6	Mahdiloo et al., (2014)	×	×	×	✓	×	×	×
7	Wang and Li, (2014)	×	×	×	×	×	×	×
8	Khodakarami et al., (2015)	×	×	×	×	✓	×	×
9	Mahdiloo et al., (2015)	×	✓	×	×	✓	×	×
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

Table 14. The results of the comparison

DMUs	Mahdiloo et al., (2014)			Izadikhah et al., (2017a)			Su and Sun, (2018)			Our new model		
	Efficiency	Status of w_1	Status of w_2	Efficiency	Status of w_1	Status of w_2	Efficiency	Status of w_1	Status of w_2	Efficiency	Status of w_1	Status of w_2
A	1.000	Output	Equilibrium	1.000	Output	Input	1.000	Equilibrium	Equilibrium	1.000	Output	Output
B	1.000	Input	Output	1.000	Output	Input	1.000	Equilibrium	Input	1.000	Input	Output
C	1.000	Input	Output	1.000	Input	Output	1.000	Output	Input	1.000	Input	Output
D	1.000	Input	Output	1.000	Input	Output	1.000	Output	Equilibrium	1.000	Output	Input
E	0.767	Output	Input	0.468	Output	Input	0.542	Output	Equilibrium	0.512	Output	Equilibrium

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.

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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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)] = $w_{11}+w_{12}+w_{21}+0.71w_{22}+w_{31}+w_{32}+w_{41}+0.5w_{42}+w_{51}+w_{61}+0.92w_{62}+w_{71}+0.35w_{72}+0.625w_{81}$
U [g (A2)] = $W_{21}+w_{22}+w_{61}+0.86w_{62}+w_{71}+w_{72}+w_{73}+w_{81}+w_{82}+w_{83}$
U [g (A3)] = $W_{11}+0.93w_{12}+w_{31}+0.83w_{32}+w_{41}+w_{42}+0.75w_{81}$
U [g (A4)] =$W_{11}+0.94w_{12}+w_{21}+0.43w_{22}+w_{31}+0.92w_{32}+w_{41}+0.5w_{42}+w_{61}+w_{62}+w_{71}+0.74w_{72}$

Step 2: Expression of linear program:

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

s.t.
$w_{11}+w_{12}-0.29w_{22}+w_{31}+w_{32}+w_{41}+0.5w_{42}+w_{51}+0.06w_{62}-0.65w_{72}-w_{73}-0.375w_{81}-w_{82}-w_{83} - \sigma^{+}(A1) + \sigma^{-}(A1) + \sigma^{+}(A2) - \sigma^{-}(A2) >= 0.05$
$-w11-0.93w_{12}+w_{21}+w_{22}-w_{31}-0.83w_{32}-w_{41}- w_{42}+w_{61}+0.86w_{62}+w_{71}+w_{72}+w_{73}+0.25w_{81}+w_{82} +w_{83} - \sigma^{+}(A2) + \sigma^{-}(A2) + \sigma^{+}(A3) - \sigma^{-}(A3) >= 0.05$
$-0.01w_{12}-w_{21}-0.43w_{22}-0.09w_{32}+0.5w_{42}-w_{61}-w_{62}-w_{71}-0.74w_{72}+0.75w_{81} - \sigma^{+}(A3) + \sigma^{-}(A3) + \sigma^{+}(A4) - \sigma^{-}(A4) >= 0.05$
$w_{11}+w_{12}+w_{21}+w_{22}+w_{31}+w_{32}+w_{41}+w_{42}+w_{51}+w_{61}+w_{62}+w_{71}+w_{72}+w_{73}+w_{81}+w_{82}+w_{83}=1$
$w_{ij} \geq 0, \sigma^{+}(a_k) \geq 0, \sigma^{-}(a_k) \geq 0$

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_{41}=0.0375 W_{42}=0.1637891125
W_{51}=0.1533907625 W_{62}=0.0444859375
W_{73}=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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