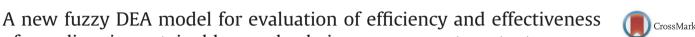


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Majid Azadi^a, Mostafa Jafarian^b, Reza Farzipoor Saen^{a,*}, Seyed Mostafa Mirhedayatian^b

^a Department of Industrial Management, Faculty of Management and Accounting, Karaj Branch, Islamic Azad University, Karaj, Iran ^b Department of Business and Management Science, NHH Norwegian School of Economics, 5045 Bergen, Norway

of suppliers in sustainable supply chain management context

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ABSTRACT

Sustainable supply chain management (SSCM) has received much consideration from corporate and academic over the past decade. Sustainable supplier performance evaluation and selection plays a significant role in establishing an effective SSCM. One of the techniques that can be used for sustainable supplier performance evaluation and selection is data envelopment analysis (DEA). In real world problems, the inputs and outputs might be imprecise. This paper develops an integrated DEA enhanced Russell measure (ERM) model in fuzzy context to select the best sustainable supplier selection problem in a resin production company. The case study demonstrates that the proposed model can measure effectiveness, efficiency, and productivity in uncertain environment with different α levels. Also, it shows that the proposed model aids decision makers to deal with economic, social, and environmental factors when selecting sustainable suppliers.

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1. Introduction

Practitioners and scholars have largely focused on supply chain management (SCM). As Ageron et al. [1] addressed, outsourcing is the main part of SCM. Globalization forces SCM to focus not only on economic criteria but also on good labor conditions and environmentally friendly production. Sustainable development is a combination of economic, environmental, and social factors. Sustainable SCM (SSCM) has become a growing topic for firms in all settings. Achieving social and environmental touchstones within supply chain helps to reach SSCM. Producing sustainable products is a rejoinder to forces coming from governments, consumers, and non-governmental organizations (NGOs) [51].

As addressed by Dyllick and Hockerts [23], SSCM is the combination of sustainable development and supply chain management whereby sustainable development is defined as combining environmental, social, and economic factors. Seuring and Müller [52] discussed that research on SSCM appeared from 2002 onwards. Cetinkaya et al. [13] explained that sustainable supply chains are not limited to green supply chains, but they should consider financial issues and help to the society.

Over the past decades, due to rapid reduction of natural resources and concerns over wealth inequality and corporate social responsibility, sustainability has become important for researchers and scholars [31]. Dao et al. [20] discussed that this concern has forced to increase the responsibility of firms and developed theories to support sustainable managerial decision making. To increase competitive advantage of the firms, supplier selection decision is one of the important issues in SCM. Supplier selection techniques can be used to select suppliers of raw materials to end-of-life service providers. Supplier selection problems deal with both tangible and intangible factors [8].

Conventionally, companies consider criteria such as price, quality, flexibility, and supplier reputation when evaluating supplier performance. Sustainability factors play a critical role for long term achievement of a SCM and the purchasing process becomes more complicated with social and environmental pressures [8,52]. Table 1 demonstrates sustainable supplier selection criteria.

For the first time, data envelopment analysis (DEA) was proposed by Charnes et al. [17]. DEA has been broadly used to take into account multiple criteria in decision making problems. DEA is a nonparametric linear programming technique for evaluating the relative efficiency of decision making units (DMUs). Over the past three decades a variety of DEA models have been used to evaluate the technical efficiency or technical effectiveness of DMUs in different settings. However, most of these works evaluate the performance from the perspective of technical efficiency or technical efficiency or technical efficiency or technical effectiveness [19]. On the other hand, DEA may face with

^{*} Corresponding author. Tel.: +98 26 34418144 6; fax: +98 26 344 18156. *E-mail addresses:* majid.azadi.edu@gmail.com (M. Azadi),

mstf.jafariaan@gmail.com (M. Jafarian), farzipour@yahoo.com (R. Farzipoor Saen), Seyed.Mirhedayatian@nhh.no (S.M. Mirhedayatian).

Table 1Sustainable supplier selection criteria.

Economic criteria	Environmental criteria	Social criteria
Cost/price [36,47,3,10]	Environmental costs [3]	The interests and rights of employees [40,3]
Quality [3,10,40,64,43]	Green design [34,64,43]	The rights of stakeholders [40,3]
Technology capability	Environmental	Work safety and labor
[41,40,64,66,43]	management system [34,41]	health [36]
Organization and management [10,36]	Environmental competencies [33,7]	Information disclosure [40,3]
Production facilities and capacity [36,3]	Green R&D [10,43]	Respect for the policy [40]
Financial capability [36]	Pollution control [7,3]	
Reliability [31]	Green product [41,36,7,45]	
Flexibility [66,31]	Resource consumption [41,40,66]	
Total cost of shipments (TC) [28,2]	Ozone depleting chemicals [40,3]	
Number of shipments	Recycling [3]	
(NS) [44,5]	Water consumption [24]	
	Energy consumption	
	[24,31]	
	Renewable energy [24]	
	Number of obtained ISO	
	standards [24]	

imprecise data. Generally speaking, uncertain information or imprecise data can be expressed in interval or fuzzy numbers [59,28].

The objective of this paper is to propose a new fuzzy integrated Russell model for sustainable supplier selection. This paper proceeds as follows. In Section 2, the literature review is presented. Section 3 introduces the proposed model. Case study is discussed in Section 4. In Section 5 concluding remarks are presented.

2. Literature review

This section is structured as follows. Section 2.1 presents the literature on various supplier selection approaches. Section 2.2 presents the literature on DEA approaches for supplier selection. Section 2.3 discussed sustainable supplier selection approaches. Finally, Section 2.4 presents the literature on fuzzy set theory and fuzzy DEA.

2.1. Supplier selection approaches

Some approaches have been used for supplier selection in the past. To provide a systematic way for scoring suppliers' performance, Yahya and Kingsman [63] used the analytic hierarchy process (AHP) method. To help decision makers with rating and selecting suppliers, a five-step AHP-based model was proposed by Muralidharan et al. [46]. Chan [14] used AHP to develop an interactive model to help decision-makers in selecting suppliers. To select the best suppliers, Liu and Hai [42] used AHP. Chan and Kumar [15] and Chan et al. [16] used fuzzy extended AHP (FEAHP) for a global supplier selection problem. Kull and Talluri [38], combining AHP and goal programming, proposed a tool for supplier selection in the presence of risk measures and product life cycle considerations. Kahraman et al. [35] suggested fuzzy AHP for selecting the best supplier.

Sarkis and Talluri [48] selected the best supplier with respect to organizational factors and strategic performance metrics. They

applied analytic network process (ANP). Shyur and Shih [53] used ANP for supplier selection as well.

Chen et al. [18] proposed a fuzzy decision making method to deal with the supplier evaluation and selection problem in supply chain system. They used linguistic values to assess the ratings and weights for the criteria. Tuzkaya et al. [58] proposed a hybrid fuzzy multicriteria decision approach for evaluating suppliers' environmental performance. Amindoust et al. [3] proposed a supplier evaluation selection method based on the fuzzy inference system. Ferreira and Borenstein [30] presented a new model based on the integration of influence diagram and fuzzy logic to rank and evaluate suppliers. The model was developed to support managers in exploring the weaknesses and strengths of each alternative, to assist the setting of priorities between conflicting criteria. Deng and Chan [21] proposed a fuzzy Dempster multi-criteria decision making (MCDM) method for supplier selection. To this end, they combined fuzzy set theory (FST) and Dempster Shafer Theory (DST).

2.2. The uses of DEA in supplier selection problems

As Kumar et al. [39] addressed, DEA provides a robust approach in supplier selection problems. Weber [61] proposed DEA to select suppliers based upon multiple criteria and determined benchmarks. Since then, a number of DEA approaches have been proposed for supplier selection. Table 2 summarizes a couple of papers on the use of DEA in supplier selection.

2.3. Sustainable supplier selection

In recent years, sustainability factors play vital role in supply chain management [62]. Amindoust et al. [3] proposed a ranking model based on the fuzzy inference system for sustainable supplier selection. Wen et al. [62] proposed an approach based on intuitionistic fuzzy sets' group decision methods for sustainable supplier evaluation. To select the best suppliers, Kumar et al. [39] proposed a unified green DEA (GDEA) model to deal with carbon footprints of suppliers as a dual-role factor.

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DEA approaches for supplier selection.

Author(s)	Approaches	Descriptions
Kleinsorge et al. [37]	DEA	They used DEA to track performance of suppliers
Talluri et al. [54]	Chance constrained DEA (CCDEA)	Proposed a CCDEA model for supplier selection in the presence of stochastic data
Farzipoor Saen [26]	DEA	Proposed a DEA model for ranking suppliers in the presence of volume discount
weber et al. [61]	Multi-objective programming (MOP) and DEA	Proposed MOP and DEA to evaluate suppliers
Farzipoor Saen [29]	DEA	Proposed a DEA model for supplier selection in the presence of undesirable outputs and imprecise data
Azadi and Farzipoor Saen [4]	CCDEA	Proposed a CCDEA model for supplier selection in the presence of stochastic data and undesirable factors
Farzipoor saen [28]	DEA	Proposed a DEA model for ranking suppliers in the presence of imprecise data, weight restriction, and nondiscretionary factors
Azadi et al. [6]	CCDEA	Developed a CCDEA model for supplier selection in the presence of stochastic data and nondiscretionary factors

2.4. Fuzzy set theory and fuzzy DEA

Zimmermann [67] discussed that traditional optimization techniques assume crisp data. For the first time, Bellman and Zadeh [9] suggested how to model the objective functions and/or constraints by fuzzy sets to deal with fuzzy data. As Hatami-Marbini et al. [32] addressed, there might be many applications in DEA that the data are fuzzy. Sengupta [49,50] incorporated fuzzy inputs and outputs into the DEA model by defining tolerance levels in objective function and constraint violations. Using Carlsson and Korhonen's [11] approach, Triantis and Girod [56] suggested fuzzy linear programming model to assess technical efficiency. Then, Triantis [55] developed his previous model to handle fuzzy non-radial DEA measures of technical efficiency.

Authors believe that this paper has significant contributions to an important and very much under-researched topic. The contributions of this paper are as follows:

- For the first time, an integrated non-radial DEA model is developed for sustainable supplier selection. The proposed model measures effectiveness, efficiency, and productivity in fuzzy context.
- The proposed model calculates a new efficiency score which is called fuzzy productivity value. The new model measures sustainability of suppliers.
- The proposed model deals with multiple criteria.
- A possibility approach is applied to convert unsolvable fuzzy proposed model to the solvable linear model. This makes the new model more applicable in real world applications.

3. Proposed model

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As Wang and Li [60] addressed, the radial measures of traditional DEA models are not complete because they are split measures of input and output efficiency. Also, their efficiency index does not incorporate the non-zero input and output slacks into their models. The enhanced Russell graph measure (ERM) treats these issues.

Let us define x_{ij} (i=1,2,...,m) as the amount of input i used by DMU_j, y_{rj} (r=1,2,...,s) is the amount of output r produced by DMU_j. Assuming all the inputs and outputs to be positive, Esmaeili [25] proposed the dual of ERM as follows:

where u_r and v_i are the *r*th output weight and *i*th input weight, respectively. *n* is the number of DMUs, (j=1, 2,..., n). The dual variable ∞ is associated with the first constraint of primal model implying average output efficiency. Note that the primal of the Model (1) is in Esmaeili [25]. The dual variables β and f_r are associated with constraints in the primal of the Model (1) which have no practical implications. They have been proposed for only transforming a non-linear model to linear one. Table 3 provides nomenclatures.

The $E \in [0,1]$ represents the efficiency score of DMU_o . If the objective function of the Model (1) equals 1, the DMU_o is relatively efficient. Otherwise, the DMU is relatively inefficient.

In many cases, measuring the effectiveness of each DMU is as important as the efficiency measurement. The effectiveness addresses how much a company can meet its predetermined goals. The traditional DEA models fail to measure the effectiveness of DMUs. In this paper, we define the effectiveness of a DMU as the ratio of the output to the predetermined goal as follows:

Effectiveness
$$=\frac{\text{output}}{\text{goal}}$$

At this juncture, the new model is proposed. To measure both the efficiency and the effectiveness of the DMU_o , the Model (1) is converted as follows:

$$\max \ \alpha - \beta + \left(\frac{\sum_{t=1}^{r} u_{t} y_{to}}{\sum_{t=1}^{t} \eta_{t} g_{to}} \right)$$
s.t. $\sum_{r=1}^{s} u_{r} y_{rj} - \sum_{i=1}^{m} v_{i} x_{ij} \le 0, \quad j = 1, ..., n$
 $v_{i} x_{io} - \mu_{i} \le \frac{1}{m}, \quad i = 1, ..., m$
 $\frac{\infty}{s} - u_{r} y_{ro} + f_{r} \le 0, \quad r = 1, ..., s$
 $\sum_{i=1}^{m} \mu_{i} - \sum_{r=1}^{s} f_{r} - \beta \le 0,$
 $\frac{\sum_{t=1}^{s} u_{r} y_{rj}}{\sum_{t=1}^{T} \eta_{t} g_{tj}} \le 1, \quad j = 1, ..., n$
 $\propto, \beta, \mu_{i}, f_{r}, u_{r}, v_{i}, \eta_{r} \ge 0, \quad \forall i, r, t.$
(2)

where the *t*th goal of the DMU_o is denoted as g_{to} . The η_t is weight of the *t*th goal. Model (2) can be rewritten as follows:

$$\max P = \left[\sum_{t=1}^{T} \eta_t g_{to}(\alpha - \beta)\right] + \sum_{r=1}^{s} u_r y_{ro}$$

s.t. $\sum_{t=1}^{T} \eta_t g_{to} = 1,$
 $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, ..., n$
 $v_i x_{io} - \mu_i \le \frac{1}{m}, \quad i = 1, ..., m$

Table 3 The nomenclatures.

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i∈	I. i=	1n	collection	of DMUs	

r=1,...,s the set of outputs

 $i=1,\ldots,m$ the set of inputs

DMU_o is the DMU under investigation

 y_{rj} is the *r*th output of *j*th DMU

- x_{ij} is the *i*th input of *j*th DMU
- y_{ro} is the *r*th output of DMU_o
- x_{io} is the *i*th input of DMU_o
- u_r is the weight for the *r*th output
- v_i is the weight for the *i*th input
- \propto , β , μ_i , and f_r are the dual variables
- g_{to} is the *t*th goal of the DMU_o
- η_t is the weight of the *t*th goal
- $ilde{\xi}$ and $ilde{\eta}$ are fuzzy variables
- $\pi(A)$ is the possibility measure of fuzzy set A
- $(\Theta, \mathcal{P}, \pi)$ is the possibility space of fuzzy set Θ
- $\mu_{(\xi)}$ is the membership function of variable ξ
- ε_1 and ε_2 are predetermined acceptable levels of the possibility of objective functions

 $\tau_1,...,\tau_5$ are predetermined acceptable levels of the possibility of constrains

 \tilde{x}_{io} is the *i*th fuzzy input of the DMU_o

- \tilde{x}_{ij} is the *i*th fuzzy input of the DMU_j
- \tilde{y}_{ro} is the *r*th fuzzy output of the DMU_o
- \tilde{y}_{rj} is the *r*th fuzzy output of the DMU_j
- \tilde{g}_{to} is the *t*th fuzzy output of DMU_o
- \tilde{g}_{tj} is the *t*th fuzzy output of *j*th DMU

 $[\]overline{\mathcal{G}}$ is the maximum value denoting return function of effectiveness

 $[\]overline{\mathscr{F}}$ is the maximum value denoting return function of efficiency

$$\frac{\alpha}{s} - u_{r}y_{ro} + f_{r} \leq 0, \quad r = 1, ..., s$$

$$\sum_{i=1}^{m} \mu_{i} - \sum_{r=1}^{s} f_{r} - \beta \leq 0,$$

$$\sum_{r=1}^{s} u_{r}y_{rj} - \sum_{t=1}^{T} \eta_{t}g_{tj} \leq 0, \quad j = 1, ..., n$$

$$\alpha, \beta, \mu_{i}, f_{r}, u_{r}, v_{i}, \eta_{t} \geq 0, \quad \forall i, r, t.$$
(3)

The $P \in [0, 2]$ represents the productivity score of DMU_o . If the optimal value of the Model (3) equals 2, the DMU_o is relatively productive. Otherwise, the DMU is relatively unproductive. As addressed by Dittenhofer [22], there are two reasons to measure productivity of suppliers. One is because productivity is used to check whether or not a supplier is performing in a satisfactory way. The second reason is that measuring productivity is as a motivator for suppliers. Productivity measurement increases competition among suppliers.

Now, fuzzy numbers are incorporated into the Model (3). Considering fuzzy input and output data, the Model (3) can be developed as follows:

$$\max P = \left[\sum_{t=1}^{T} \eta_t \tilde{g}_{to}(\alpha - \beta)\right] + \sum_{r=1}^{s} u_r \tilde{y}_{ro}$$

s.t. $\sum_{t=1}^{T} \eta_t \tilde{g}_{to} = 1,$
 $\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} \le 0, \quad j = 1, ..., n$
 $v_i \tilde{x}_{io} - \mu_i \le \frac{1}{n}, \quad i = 1, ..., m$
 $\frac{\infty}{s} - u_r \tilde{y}_{ro} + f_r \le 0, \quad r = 1, ..., s$
 $\sum_{i=1}^{m} \mu_i - \sum_{r=1}^{s} f_r - \beta \le 0,$
 $\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{t=1}^{T} \eta_t \tilde{g}_{tj} \le 0, \quad j = 1, ..., n$
 $\infty, \beta, \mu_i, f_r, u_r, v_i, \eta_t \ge 0, \quad \forall i, r, t.$
(4)

where $\tilde{x}_{ij}(i = 1, ..., m)$, $\tilde{y}_{rj}(r = 1, ..., s)$, and $\tilde{g}_{ij}(t = 1, ..., T)$ are fuzzy input, fuzzy output, and fuzzy goals of DMU_j (j = 1, 2, ..., n), respectively. This fuzzy integrated DEA model cannot be solved like a crisp model. To overcome this problem, one can apply a possibility approach formulated in terms of fuzzy set theory proposed by Zadeh [65]. This procedure converts the fuzzy integrated DEA model to the standard linear programming (LP) by α – cut technique. In this case, each fuzzy coefficient can be viewed as a fuzzy variable and each constraint can be considered as a fuzzy event. Using possibility theory, possibilities of fuzzy events (i.e., fuzzy constraints) can be determined.

Let Θ be a nonempty set, and \mathcal{P} the power set of Θ . Each element in \mathcal{P} is called an event. To present an axiomatic definition of possibility, it is necessary to assign to each event *A*, a number $\pi(A)$ which indicates the possibility that *A* will occur. Then the triplet $(\Theta, \mathcal{P}, \pi)$ is called a possibility space.

Definition 1. Let $\tilde{\xi}$ be a fuzzy variable defined on a possibility space $(\Theta, \mathcal{P}, \pi)$. The membership of this variable introduced by Zadeh [65] is as follows:

$$\mu_{\tilde{\xi}}(s) = \pi(\theta_i \in \Theta_i | \tilde{\xi}(\theta_i) = s) = \sup \{\pi(\theta_i) | \tilde{\xi}(\theta_i) = s\}, \quad \forall s \in \mathbb{R}$$

Definition 2. Let $(\Theta, \mathcal{P}, \pi)^{\theta_i \in \Theta_i}$ be a possibility space such that $\Theta = \Theta_1 \times \Theta_2 \times \cdots \times \Theta_n$, therefore, for any set *A* we have

$$\pi(A) = \sup_{\theta_i \in \Theta_i} \{ \pi_i(A_i) | A = A_1 \times A_2 \times \cdots \times A_n, A_i \in \mathcal{P} \}.$$

Considering the two above definitions, for variables ξ and $\tilde{\eta}$ from two possibility spaces (Θ_1 , \mathcal{P}_1 , π_1) and (Θ_2 , \mathcal{P}_2 , π_2), the

possibility of the fuzzy event $\xi \geq \tilde{\eta}$ is given by

$$\pi(\tilde{\xi} \ge \tilde{\eta}) = \sup_{s,t \in \mathbb{R}} \{ \min(\mu_{\tilde{\xi}}(s), \mu_{\tilde{\eta}}(t)) | s \ge t \}$$

Regarding the proposed model and the concept of possibility space of fuzzy event, some constraines are defined as a crisp value and other constrains are considered as an uncertain. For this reason, the objective function of fuzzy integrated model can be written as follows:

$$\max \quad \overline{\mathcal{G}} + \overline{\mathcal{F}}$$

s.t.: $\pi \left(\sum_{t=1}^{T} \eta_t \tilde{g}_{to}(\alpha - \beta) \ge \overline{\mathcal{G}} \right) \ge \varepsilon_1$
 $\pi \left(\sum_{r=1}^{s} u_r \tilde{y}_{ro} \ge \overline{\mathcal{F}} \right) \ge \varepsilon_2$ (5)

where ε_1 and ε_2 are predetermined acceptable levels of possibility for the two sections of the objective function. Therefore, the objective value $\overline{\mathcal{G}}$ is the maximum value that the return function $\Sigma_{t=1}^T \eta_t \tilde{g}_{to}(\alpha - \beta)$ can attain with "possibility" level ε_1 or higher.¹ Moreover, the objective value $\overline{\mathcal{F}}$ is the maximum value that the return function $\Sigma_{r=1}^s u_r \tilde{y}_{ro}$ can achieve with the "possibility" level ε_1 or higher, subject to the possibility levels of other fuzzy and crisp constraints. Adding the remaning constrains, fuzzy integrated model can be reformulated by the following form:

$$\begin{aligned} \max \quad P &= \overline{\mathcal{G}} + \overline{\mathcal{F}} \\ \text{s.t.} : \quad \pi \left(\sum_{t=1}^{T} \eta_t \tilde{\mathcal{g}}_{to}(\alpha - \beta) \geq \overline{\mathcal{G}} \right) \geq \varepsilon_1 \\ \pi \left(\sum_{r=1}^{s} u_r \tilde{\mathcal{Y}}_{ro} \geq \overline{\mathcal{F}} \right) \geq \varepsilon_2 \\ \pi \left(\sum_{t=1}^{T} \eta_t \tilde{\mathcal{g}}_{to} = 1 \right) \geq \tau_1 \\ \pi \left(\sum_{r=1}^{s} u_r \tilde{\mathcal{Y}}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} \leq 0 \right) \geq \tau_2 \quad \text{for } j = 1, \dots, n \\ \pi \left(v_i \tilde{x}_{io} - \mu_i \leq \frac{1}{m} \right) \geq \tau_3 \quad \text{for } i = 1, \dots, m \\ \pi \left(\frac{\infty}{s} - u_r \tilde{\mathcal{Y}}_{ro} + f_r \leq 0 \right) \geq \tau_4 \quad \text{for } r = 1, \dots, s \\ \pi \left(\sum_{r=1}^{s} u_r \tilde{\mathcal{Y}}_{rj} - \sum_{t=1}^{T} \eta_t \tilde{\mathcal{g}}_{tj} \leq 0 \right) \geq \tau_5 \quad \text{for } j = 1, \dots, n \\ \sum_{i=1}^{m} \mu_i - \sum_{r=1}^{s} f_r - \beta \leq 0, \\ \infty, \beta, \mu_i, f_r, u_r, v_i, \eta_t \geq 0, \quad \forall i, r, t. \end{aligned}$$

where $\tau_1...,\tau_5$ are the predefined levels that the related constraints should attain the possibility level. In the crisp condition, the DMU_o will be relatively productive if the optimal value of the Model (4) equals 2. Meanwhile, the objective value $[\Sigma_{t=1}^T \eta_t \tilde{g}_{to}(\alpha - \beta)] + \sum_{r=1}^s u_r \tilde{y}_{ro}$ is the productive criterion of the DMU_o. Also, the $\overline{\mathcal{G}}$ and $\overline{\mathcal{F}}$ in the fuzzy integrated model are used to determine if the DMU_o is relatively productive (in the possibilistic sense) at the predetermined possibility level. Let ϵ be the set of $\epsilon_1, \epsilon_2, \tau_1,...,$ and τ_5 . We define an ϵ -possibilistic productive DMU and an ϵ -possibilistic nonproductive DMU as follows:

Definition 3. A DMU is \in -possibilistic productive if its $P = \overline{\mathcal{G}} + \overline{\mathcal{F}}$ value at the *e*-possibility level is greater than or equal to 2; otherwise, it is \in -possibilistic nonproductive.

¹ To the best of our knowledge, usually in optimization problems, there is no discrimination among multiple constraints in terms of possibility level. But, if we have multiple objective functions (in particular in goal programming technique) we can consider different possibility levels for each objective function.

Considering the fuzzy theorem, there is a lemma that can be very useful to interpret the possibility function. Now, this lemma is represented.

Lemma. Let $\tilde{\xi}_1, \tilde{\xi}_2, ..., \tilde{\xi}_n$ be normal and convex fuzzy variables. Then, for any given possibility levels τ_1, τ_2, τ_3 ($0 \le \tau_i \le 1$) we have

where $(\tilde{\xi}_i)_{\tau_i}^L$ and $(\tilde{\xi}_i)_{\tau_i}^U$ are the lower and upper bounds of the τ_i -level set of $\tilde{\xi}_i$ (i=1,..., n). Defining the above lemma, fuzzy

environmental criterion is eco-design cost which is considered as an input. The social criteria include the cost of work safety and labor health that both are considered as inputs. The outputs used in this study are the number of shipments to arrive on time (NOT) and the number of bills received from the supplier without errors (NB). To deal with the uncertainty, in this study the outputs and the targets for outputs are considered as fuzzy numbers.

Considering the proposed model, we formulate the problem to calculate the productivity for the first DMU called National Iranian Oil Company as the following model.

 $\begin{array}{ll} (1): & \pi(\tilde{\xi}_{1}+\tilde{\xi}_{2}+\dots+\tilde{\xi}_{n}\leq a)\geq\tau_{1} & \text{if and only if } (\tilde{\xi}_{1})_{\tau_{1}}^{L}+\dots+(\tilde{\xi}_{n})_{\tau_{1}}^{L}\leq a, \\ (1): & \pi(\tilde{\xi}_{1}+\tilde{\xi}_{2}+\dots+\tilde{\xi}_{n}\geq a)\geq\tau_{2} & \text{if and only if } (\tilde{\xi}_{1})_{\tau_{2}}^{U}+\dots+(\tilde{\xi}_{n})_{\tau_{2}}^{U}\geq a, \\ (1): & \pi(\tilde{\xi}_{1}+\tilde{\xi}_{2}+\dots+\tilde{\xi}_{n}=a)\geq\tau_{3} & \text{if and only if } (\tilde{\xi}_{1})_{\tau_{3}}^{L}+\dots+(\tilde{\xi}_{n})_{\tau_{3}}^{L}\leq a \text{ and } (\tilde{\xi}_{1})_{\tau_{3}}^{U}+\dots+(\tilde{\xi}_{n})_{\tau_{3}}^{U}\geq a, \end{array}$

integrated model can be rewritten as follows:

$$\max P = \overline{g} + \overline{\mathcal{F}}$$
s.t.: $(\alpha - \beta) \left(\sum_{t=1}^{T} \eta_t \, \tilde{g}_{to} \right)_{e_1}^{U} \ge \overline{\mathcal{F}}$
 $\left(\sum_{r=1}^{S} u_r \tilde{y}_{ro} \right)_{e_2}^{U} \ge \overline{\mathcal{F}}$
 $\left(\sum_{t=1}^{T} \eta_t \tilde{g}_{to} \right)_{\tau_1}^{U} \ge 1$
 $\left(\sum_{t=1}^{T} \eta_t \tilde{g}_{to} \right)_{\tau_1}^{L} \le 1$
 $\left(\sum_{r=1}^{S} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} \right)_{\tau_2}^{L} \le 0 \quad \text{for } j = 1, ..., n$
 $(v_i \tilde{x}_{io} - \mu_i)_{\tau_3}^{L} \le \frac{1}{m} \quad \text{for } i = 1, ..., m$
 $\left(\frac{\infty}{s} - u_r \tilde{y}_{ro} + f_r \right)_{\tau_4}^{L} \le 0 \quad \text{for } r = 1, ..., s$
 $\left(\sum_{r=1}^{S} u_r \tilde{y}_{rj} - \sum_{t=1}^{T} \eta_t \tilde{g}_{tj} \right)_{\tau_5}^{L} \le 0 \quad \text{for } j = 1, ..., n$
 $\sum_{i=1}^{m} \mu_i - \sum_{r=1}^{S} f_r - \beta \le 0,$
 $\propto, \beta, \mu_i, f_r, u_r, v_i, \eta_t \ge 0, \quad \forall i, r, t.$
 (7)

In next section, we present a case study to demonstrate the applicability of proposed model.

4. Case study

Azar Resin Chemical Industrial Co. (ARCIC) was established in 1995 in Qazvin province, Iran. The first phase of the company's productions started in 1996 which comprises amino resins (butylated urea formaldehyde and butylated melamine formaldehyde). This company is one of the most active and leading companies among the resin manufacturing factories in Iran.

The ARCIC wishes to select the most sustainable suppliers of raw materials. Table 4 depicts the data set related to inputs, fuzzy outputs, and its fuzzy targets. To select the best sustainable suppliers a list of criteria are provided by managers. The cardinal inputs include the total cost of shipments (TC),² the price, and the number of shipments per month (NS) as economic criteria. The

Let $\tilde{g}_{tj} = (g_{tj}^a, g_{tj}^b, g_{tj}^c)$ is a triangular fuzzy number for the *t*th goal of DMU_j, $\tilde{y}_{rj} = (y_{rj}^a, y_{rj}^b, y_{rj}^c)$ is a triangular fuzzy number of the *r*th output of DMU_j, and $\tilde{x}_{ij} = (x_{ij}^a, x_{ij}^b, x_{ij}^c)$ is a triangular fuzzy number of the *i*th input of DMU_j. In this case, the linear programming that is the conversion of fuzzy model is presented as follows³:

$$\max P = \overline{g} + \overline{g} + \overline{g}$$
s.t.: $(\alpha - \beta) \sum_{t=1}^{T} \eta_t (g_{t1}^c - \varepsilon_1 (g_{t1}^c - g_{t1}^b)) \ge \overline{g}$

$$\sum_{r=1}^{s} u_r (y_{r1}^c - \varepsilon_2 (y_{r1}^c - y_{r1}^b)) \ge \overline{g}$$

$$\sum_{t=1}^{T} \eta_t (g_{t1}^c - \tau_1 (g_{t1}^c - g_{t1}^b)) \ge 1$$

$$\sum_{t=1}^{T} \eta_t (g_{t1}^c - \tau_1 (g_{t1}^c - g_{t1}^b)) \le 1$$

$$\sum_{r=1}^{s} u_r (y_{rj}^a + \tau_2 (y_{rj}^b - y_{rj}^a)) - \sum_{i=1}^{m} v_i (x_{ij}^a + \tau_2 (x_{ij}^b - x_{ij}^a)) \le 0 \quad \text{for } j = 1, ..., n$$

$$v_i (x_{i1}^a + \tau_3 (x_{i1}^b - x_{i1}^a)) - \mu_i \le \frac{1}{m} \quad \text{for } i = 1, ..., m$$

$$\frac{\infty}{s} - u_r (y_{r1}^a + \tau_4 (y_{r1}^b - y_{r1}^a)) + f_r \le 0 \quad \text{for } r = 1, ..., s$$

$$\sum_{r=1}^{s} u_r (y_{rj}^a + \tau_2 (y_{rj}^b - y_{rj}^a)) - \sum_{t=1}^{T} \eta_t (g_{tj}^a + \tau_5 (g_{tj}^b - g_{tj}^a)) \le 0 \quad \text{for } j = 1, ..., n$$

$$\sum_{i=1}^{m} \mu_i - \sum_{r=1}^{s} f_r - \beta \le 0,$$

$$\infty, \beta, \mu_i, f_r, u_r, v_i, \eta_t \ge 0, \quad \forall i, r, t.$$

$$(8)$$

Due to the first non-linear constrain, this model has been run by the GAMS software. Furthermore, this model has been run by various solvers such as BARON, CONOPT, and INPOPT. According to the results, all the solvers have generated the same solution. A sample of proposed model for supplier #1 has been given in Appendix.

In this case study, all the fuzzy constraints should be satisfied with the same possibility level, i.e., $\varepsilon_1 = \varepsilon_2 = \tau_1 = ... = \tau_5$. The results for five different possibility levels (0, 0.25, 0.5, 0.75, and 1) are provided in Table 5. In Table 5, the number in each cell is the productivity value (PV) of the corresponding DMU at the specified

² Note that the measures selected in this paper are not exhaustive by any means, but are some general measures that can be utilized to evaluate suppliers.

⁽footnote continued)

Decision makers should carefully identify appropriate inputs and outputs used in the decision-making process.

³ To convert either fuzzy equations into crisp equations or to use fuzzy arithmetic, the third constraint of the Model (6) is divided into two parts which appeared in third and fourth constraints of the Model (8).

Table 4

The data set related to inputs, fuzzy outputs, and its fuzzy targets.

No.	Supplier (DMU)	Inputs				Outp	outs					Goal	S				
						NOT			NB			Targ	et NC	T	Targ	et NE	;
		TC (1,000,000 rials)	NS	Eco-design cost (10,000 rials)	The cost of work safety and labor health (10000 Rials)	L	М	U	L	М	U	L	М	U	L	М	U
1	National Iranian Oil Company	316	251	61	18	199	219	239	76	83	90	203	226	239	84	89	91
2	Shazand Petrochemical Corporation	281	164	45	21	153	173	193	28	35	42	153	179	202	32	38	44
3	Esfahan Petrochemical Company	309	198	83	40	203	223	243	78	85	92	208	224	243	80	87	96
4	Farabi Petrochemical Company	291	218	37	45	167	187	207	85	92	99	167	193	215	93	92	103
5	Iran Petrochemical Commercial Company	597	178	52	29	197	217	237	163	170	177	202	222	247	172	176	177
6	Alborz Chelic Company	341	142	19	33	129	149	169	129	136	143	132	154	171	136	139	150
7	Chemical Aland Industrial Group		149		18	193		233	111		125				113		
8	Movalledan Chemical Company	254	172	53	35	134	154	174	250	257	264	134	160	176	252	260	264
9	Chemical Carbon Acid Company	328	135	83	47	184	204	224	58	65	72	191	214	228	68	65	76
10	Nima Chemigostar Industrial Co.	310	173	41	16	113	133	153	88	95	102	114	137	161	96	98	108
11	Gipa Company	321	121	57	45	125	145	165	153	160	167	129	153	174	162	164	177
12	Farzam Chemical Group	329	204		53	195	215		90	97	107		225		102	99	
12	Pars Pak Kimia Company	475	204		42	155			139						142		
14	Shiraz Petrochemical Company	259	189		85	129		169							142		113
15	Tabriz Petrochemical Company	274	217	38	51	85	105	125	68	75	82	85	110	135	74	83	83
16	Razi Petrochemical Company	264	158	25	35	193	213	233	45	52	59	201	217	234	55	56	62
17	Hegmataneh Petrochemical Company	327	124	32	16	107	127	147	271	278	285	110	133	155	281	281	289
18	Jam Petrochemical Company	429	207	57	49	142	162	182	46	53	60	146	168	189	49	63	65
19	Laleh Petrochemical Company	262	138	25	31	122	142	162	173	180	187	130	148	162	174	188	190
20	Kharg Petrochemical Company	385	238	74	22	106	126	146	119	126	133	115	130	150	128	135	136
21	Marun Petrochemical Company	249	217	69	72	150	170	190	90	97	104	154	177	194	93	97	110
22	Karoon Petrochemical Company	337	203	27	33	104	124	144	271	278	285	113	126	150	274	281	294
23	Khuzestan Petrochemical Company	365	292	85	71	185	205	225	143	150	157	188	212	227	147	156	163
24	Fajr Petrochemical Company	296	185	49	18	112	132	152	177	184	191	114	132	155	177	193	198
25	Khorasan Petrochemical Company	428	242	39	22	94	114	134	78	85	92	101	124	139	79	95	99
26	Mobin Petrochemical Company	327	218	43	48	173	193	213	113	120	127	182	193	223	116	122	131

possibility level. The 17th DMU (Hegmataneh Petrochemical Co.) is the most productive DMU in four possibility levels (0.25, 0.5, 0.75, and 1) with the productivity measures 1.97, 1.93, 1.89, and 1.83, respectively. Also, the productivity of the DMU₁₅ (Tabriz Petrochemical Co.) is the worst with productivity measures 0.98, 1.01, 1.04, 1.07, and 1.09, for all possibility levels.

Here, we wish to present the results of the efficiency and

the effectiveness separately. Assuming $\alpha = 0.5$, Table 6 depicts

the results of effectiveness, efficiency, and productivity of the

suppliers. Also, rank of every supplier is given. Fig. 1 shows summary

of the results. As Table 6 depicts, Hegmataneh Petrochemical Co. is

the best DMU in terms of effectiveness. Esfahan Petrochemical Co.

4.1. The results of efficiency and effectiveness

and Razi Petrochemical Co. are the most efficient DMUs. Generally, Hegmataneh Petrochemical Co. is the most productive and sustainable DMU. Therefore, it is selected as the best supplier of ARCIC.

4.2. Sensitivity analysis

Here, we wish to analyze sensitivity of the results against changes in α . We investigate five α different values. In decision making problems, if we deal with high risk the α should be close to zero. If we deal with low risk the α should be close to one. Table 7 depicts the results of changing α on effectiveness, efficiency, and productivity. As is seen, the α values are 0, 0.25, 0.5, 0.75, and 1. As Table 7 shows, changing α values do not have significant impact on ranking results. Therefore, decision maker is not concerned about selecting α value.

Table 5

Efficiency and effectiveness scores.

No.	Supplier (DMU)	Alpha =	=1	Alpha =	-0.75	Alpha =	=0.5	Alpha =	=0.25	Alpha	=0
		PV	Rank	PV	Rank	PV	Rank	PV	Rank	PV	Rank
1	National Iranian Oil Company	1.46	16	1.46	14	1.46	14	1.47	13	1.46	12
2	Shazand Petrochemical Corporation	1.27	22	1.25	23	1.23	23	1.2	23	1.18	23
3	Esfahan Petrochemical Company	1.46	14	1.45	16	1.44	16	1.43	17	1.42	18
4	Farabi Petrochemical Company	1.49	12	1.48	12	1.47	13	1.46	14	1.43	15
5	Iran Petrochemical Commercial Company	1.56	8	1.56	8	1.56	7	1.55	7	1.54	7
6	Alborz Chelic Company	1.78	5	1.77	5	1.76	5	1.75	5	1.74	5
7	Chemical Aland Industrial Group	1.54	11	1.54	10	1.53	10	1.52	10	1.5	10
8	Movalledan Chemical Company	1.85	2	1.85	2	1.84	2	1.82	2	1.81	2
9	Chemical Carbon Acid Company	1.35	21	1.34	21	1.33	21	1.33	21	1.31	21
10	Nima Chemigostar Industrial Complex	1.46	15	1.45	15	1.44	17	1.43	19	1.41	19
11	Gipa Company	1.57	7	1.57	7	1.56	7	1.54	8	1.53	9
12	Farzam Chemical Group	1.48	13	1.47	13	1.47	12	1.47	12	1.46	13
13	Pars Pak Kimia Company	1.54	10	1.55	9	1.55	9	1.54	9	1.53	8
14	Shiraz Petrochemical Company	1.42	20	1.43	20	1.44	19	1.44	16	1.43	16
15	Tabriz Petrochemical Company	0.98	26	1.01	26	1.04	26	1.07	26	1.09	26
16	Razi Petrochemical Company	1.44	17	1.44	19	1.42	20	1.41	20	1.4	20
17	Hegmataneh Petrochemical Company	1.97	1	1.93	1	1.89	1	1.83	1	1.77	3
18	Jam Petrochemical Company	1.1	25	1.11	25	1.12	25	1.12	25	1.12	25
19	Laleh Petrochemical Company	1.81	4	1.82	4	1.82	3	1.82	3	1.82	1
20	Kharg Petrochemical Company	1.23	23	1.25	22	1.28	22	1.3	22	1.3	22
21	Marun Petrochemical Company	1.44	18	1.44	18	1.44	18	1.43	18	1.42	17
22	Karoon Petrochemical Company	1.83	3	1.83	3	1.82	4	1.79	4	1.77	4
23	Khuzestan Petrochemical Company	1.43	19	1.45	17	1.45	15	1.45	15	1.45	14
24	Fajr Petrochemical Company	1.7	6	1.69	6	1.68	6	1.67	6	1.65	6
25	Khorasan Petrochemical Company	1.14	24	1.16	24	1.17	24	1.18	24	1.18	23
26	Mobin Petrochemical Company	1.55	9	1.54	10	1.52	11	1.5	11	1.47	11

Table 6

The results with alpha = 0.5.

No.	Supplier (DMU)	Effectiveness	Rank	Efficiency	Rank	Productivity	Rank
1	National Iranian Oil Company	0.462	15	0.995	5	1.457	14
2	Shazand Petrochemical Corporation	0.236	23	0.987	15	1.223	23
3	Esfahan Petrochemical Company	0.43	19	1	1	1.437	17
4	Farabi Petrochemical Company	0.479	13	0.985	17	1.464	13
5	Iran Petrochemical Commercial Company	0.554	9	0.988	13	1.542	8
6	Alborz Chelic Company	0.794	5	0.988	13	1.782	5
7	Chemical Aland Industrial Group	0.536	10	0.984	19	1.52	10
8	Movalledan Chemical Company	0.831	3	0.999	3	1.83	2
9	Chemical Carbon Acid Company	0.338	21	0.99	10	1.328	21
10	Nima Chemigostar Industrial Co.	0.465	14	0.974	22	1.439	16
11	Gipa Company	0.583	7	0.966	24	1.549	7
12	Farzam Chemical Group	0.481	12	0.985	17	1.466	12
13	Pars Pak Kimia Company	0.563	8	0.976	21	1.539	9
14	Shiraz Petrochemical Company	0.438	18	0.995	5	1.433	18
15	Tabriz Petrochemical Company	0.081	26	0.955	25	1.036	26
16	Razi Petrochemical Company	0.423	20	1	1	1.43	20
17	Hegmataneh Petrochemical Company	0.901	1	0.989	12	1.89	1
18	Jam Petrochemical Company	0.136	25	0.972	23	1.108	25
19	Laleh Petrochemical Company	0.837	2	0.991	9	1.828	3
20	Kharg Petrochemical Company	0.28	22	0.982	20	1.262	22
21	Marun Petrochemical Company	0.447	17	0.986	16	1.433	18
22	Karoon Petrochemical Company	0.816	4	0.998	4	1.814	4
23	Khuzestan Petrochemical Company	0.451	16	0.99	10	1.441	15
24	Fajr Petrochemical Company	0.679	6	0.993	7	1.672	6
25	Khorasan Petrochemical Company	0.205	24	0.952	26	1.157	24
26	Mobin Petrochemical Company	0.518	11	0.992	8	1.51	11

4.3. Managerial implications

In this subsection, an analysis of the results of this study is given. In recent years, SSCM has become an increasingly significant topic. Supplier evaluation and selection process is one of the crucial operational tasks in the context of SSCM. Selecting appropriate sustainable suppliers is a MCDM problem for any organization. This task should be easily and clearly understood and applied by managers. Mathematical models provide remarkable information that can be employed by managers in making strategic or operational decisions. Some mathematical programming approaches have been used for selecting suppliers. Nevertheless, because of intricacy of decision making process involved in supplier evaluation and selection, all the previous approaches, except for DEA models, rely on methods that assign subjective weights to multiple criteria. It is a daunting task for decision makers to assign precise numbers to criteria. However, none of the DEA models deal with efficiency, effectiveness, and productivity, simultaneously. Here, the proposed model measures efficiency, effectiveness, and productivity, simultaneously. On the other hand, in many supplier selection problems, the inputs and outputs might be fuzzy. As a result, selecting suitable

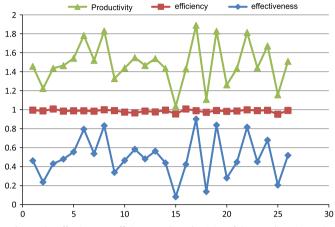


Fig. 1. The effectiveness, efficiency, and productivity of the suppliers ($\alpha = 0.5$).

Table 7

The result of changing α on ranking results.

supplier becomes too difficult for managers. The fuzzy model presented in this paper is a method to deal with fuzzy data. Moreover, to solve the proposed fuzzy model, a possibility approach is applied to convert the unsolvable fuzzy model to the solvable linear model. In addition, we used GAMS software for solving the proposed model.

5. Concluding remarks

According to Carter and Easton [12], sustainability is a popular buzzword. The buzzword is because of some reasons such as supply and demand characteristics related to energy consumption, people understanding of climate change, and higher clearness related to environmental and the social actions of firms. These issues are relevant to decision makers since their shareholders, government, and their employees ask them to solve the environmental and social issues which are influenced by their operations. In particular, supply chain managers are in critical position to influence positively or negatively their environmental and social performance. As addressed by Ageron et al. [1], sustainability of supply chain management is vital for the success

Suppliers (DMUs)	Alpha=0				Alpha =0.25				Alpha =0.5			
	Effectiveness	Efficiency	Productivity	Rank	Effectiveness	Efficiency	Productivity	Rank	Effectiveness	Efficiency	Productivity	Rank
National Iranian Oil Company	0.446	1.015	1.461	12	0.455	1.009	1.464	13	0.462	0.995	1.457	14
Shazand Petrochemical Corporation	0.209	0.974	1.183	23	0.223	0.98	1.203	23	0.236	0.987	1.223	23
Esfahan Petrochemical Company	0.411	1.005	1.416	18	0.421	1.01	1.431	17	0.43	1.007	1.437	17
Farabi Petrochemical Company	0.458	0.976	1.434	15	0.469	0.984	1.453	14	0.479	0.985	1.464	13
Iran Petrochemical Commercial Company	0.554	0.981	1.535	7	0.554	0.987	1.541	7	0.554	0.988	1.542	8
Alborz Chelic Company	0.754	0.984	1.738	5	0.774	0.988	1.762	5	0.794	0.988	1.782	5
Chemical Aland Industrial Group	0.524	0.98	1.504	10	0.53	0.986	1.516	10	0.536	0.984	1.52	10
Movalledan Chemical Company	0.81	0.998	1.808	2	0.82	1	1.82	3	0.831	0.999	1.83	2
Chemical Carbon Acid Company	0.32	0.991	1.311	21	0.33	0.993	1.323	21	0.338	0.99	1.328	21
Nima Chemigostar Industrial Co.	0.451	0.958	1.409	19	0.458	0.969	1.427	19	0.465	0.974	1.439	16
Gipa Company	0.573	0.953	1.526	9	0.578	0.962	1.54	8	0.583	0.966	1.549	7
Farzam Chemical Group	0.465	0.991	1.456	13	0.474	0.992	1.466	12	0.481	0.985	1.466	12
Pars Pak Kimia Company	0.551	0.977	1.528	8	0.557	0.979	1.536	9	0.563	0.976	1.539	9
Shiraz Petrochemical Company	0.433	1	1.433	16	0.435	1.001	1.436	16	0.438	0.995	1.433	18
Tabriz Petrochemical Company	0.147	0.947	1.094	26	0.113	0.954	1.067	26	0.081	0.955	1.036	26
Razi Petrochemical Company	0.391	1.01	1.401	20	0.407	1.009	1.416	20	0.423	1.007	1.43	20
Hegmataneh Petrochemical Company	0.798	0.968	1.766	3	0.85	0.98	1.83	1	0.901	0.989	1.89	1
Jam Petrochemical Company	0.152	0.966	1.118	25	0.144	0.972	1.116	25	0.136	0.972	1.108	25
Laleh Petrochemical Company	0.817	1	1.817	1	0.827	0.997	1.824	2	0.837	0.991	1.828	3
Kharg Petrochemical Company	0.325	0.978	1.303	22	0.306	0.983	1.289	22	0.28	0.982	1.262	22
Marun Petrochemical Company	0.436	0.981	1.417	17	0.442	0.987	1.429	18	0.447	0.986	1.433	18
Karoon Petrochemical Company	0.794	0.971	1.765	4	0.806	0.987	1.793	4	0.816	0.998	1.814	4
Khuzestan Petrochemical Company	0.458	0.992	1.45	14	0.454	0.994	1.448	15	0.451	0.99	1.441	15
Fajr Petrochemical Company	0.667	0.98	1.647	6	0.673	0.988	1.661	6	0.679	0.993	1.672	6
Khorasan Petrochemical	0.22	0.963	1.183	23	0.213	0.961	1.174	24	0.205	0.952	1.157	24
Company Mobin Petrochemical	0.501	0.97	1.471	11	0.51	0.984	1.494	11	0.518	0.992	1.51	11
Company												

Suppliers (DMUs)	Alpha =0.75				Alpha $=1$			
	Effectiveness	Efficiency	Productivity	Rank	Effectiveness	Efficiency	Productivity	Rank
National Iranian Oil Company	0.47	0.982	1.452	14	0.478	0.969	1.447	17
Shazand Petrochemical Corporation	0.251	0.993	1.244	22	0.265	1	1.265	22
Esfahan Petrochemical Company	0.44	1.003	1.443	17	0.449	1	1.449	16
Farabi Petrochemical Company	0.49	0.985	1.475	12	0.5	0.984	1.484	12
Iran Petrochemical Commercial Company	0.553	0.987	1.54	8	0.551	0.979	1.53	9
Alborz Chelic Company	0.814	0.987	1.801	5	0.832	0.979	1.811	5
Chemical Aland Industrial Group	0.541	0.982	1.523	11	0.546	0.975	1.521	11
Movalledan Chemical Company	0.841	0.996	1.837	2	0.849	0.984	1.833	2
Chemical Carbon Acid Company	0.347	0.986	1.333	21	0.356	0.981	1.337	21
Nima Chemigostar Industrial Co.	0.472	0.978	1.45	15	0.478	0.975	1.453	15
Gipa Company	0.588	0.968	1.556	7	0.593	0.963	1.556	7
Farzam Chemical Group	0.488	0.978	1.466	13	0.495	0.969	1.464	13
Pars Pak Kimia Company	0.568	0.971	1.539	9	0.572	0.958	1.53	10
Shiraz Petrochemical Company	0.44	0.987	1.427	20	0.442	0.972	1.414	19
Tabriz Petrochemical Company	0.048	0.954	1.002	26	0.019	0.945	0.964	26
Razi Petrochemical Company	0.44	1.004	1.444	16	0.456	1	1.456	14
Hegmataneh Petrochemical Company	0.945	0.989	1.934	1	0.984	0.984	1.968	1
Jam Petrochemical Company	0.127	0.968	1.095	25	0.114	0.963	1.077	25
Laleh Petrochemical Company	0.847	0.984	1.831	3	0.855	0.967	1.822	4
Kharg Petrochemical Company	0.255	0.977	1.232	23	0.232	0.967	1.199	23
Marun Petrochemical Company	0.453	0.983	1.436	18	0.458	0.975	1.433	18
Karoon Petrochemical Company	0.825	1	1.825	4	0.833	1	1.833	2
Khuzestan Petrochemical Company	0.447	0.984	1.431	19	0.443	0.97	1.413	20
Fajr Petrochemical Company	0.686	0.996	1.682	6	0.692	0.993	1.685	6
Khorasan Petrochemical Company	0.198	0.938	1.136	24	0.191	0.919	1.11	24
Mobin Petrochemical Company	0.527	0.999	1.526	10	0.535	1	1.535	8

of entire supply chain management. Many practitioners and researchers have presented the benefits of SSCM. Finding an efficient and effective supplier in sustainability context is one of the most significant issues in order to increase the competitive advantage of companies. This study proposed a novel fuzzy integrated DEA model for evaluating the sustainability of suppliers.

Further researches can be done based on the results of this paper. Some of them are as follows:

- Similar research can be repeated for sustainable supplier evaluation and selection in the presence of stochastic data. Chanceconstrained programming (CCP) is a kind of stochastic optimization approach. It is suitable for solving optimization problems with random variables included in constraints and sometimes in the objective function. Stochastic programming deals with optimization problems whose parameters take values from given discrete or continuous probability distributions.
- Similar research can be repeated for sustainable supplier evaluation and selection in the presence of dual-role factors. In real world problems, there might be flexible factors which play the role of both inputs and outputs. This sort of variable are called dual-role factors.
- In this study the proposed model was used in supplier selection problem. The proposed model can be used in other problems such as personnel selection, international market selection, and technology selection.

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Appendix

The GAMS code for DMU₁ at the level a=1 is as follows:

sets T 'GOAL'/T1,T2/ R 'OUTPUT'/R1,R2/ I 'INPUT'/I1*I4/ I ' DMII'/I1*I26/

υ	IVI	U	/J	I*J	26	/;	

	TABLE A(J,I)			
	I1	12	13	I4
J1	301	241	56	15
J2	266	154	40	18
J3	294	188	78	37
J4	276	208	32	42
J5	582	168	47	26
J6	326	132	14	30
J7	460	139	69	15
J8	239	162	48	32
J9	313	125	78	44
J10	295	163	36	13
J11	306	111	52	42
J12	314	194	33	50
J13	460	202	27	39
J14	244	179	51	82
J15	259	207	33	48
J16	249	148	20	32
J17	312	114	27	13
J18	414	197	52	46
J19	247	128	20	28
J20	370	228	69	19
J21	234	207	64	69

J22	322	193	22	30		TABLE B	UP(J,R)	
J23 J24	350 281	282 175	80 44	68 15		R1	R2	
J24 J25	413	232	44 34	15				
J26	312	208	38	45;	J1	239	90	
	TABLE BI	OW(LR)			J2 J3	193 243	42 92	
					J3 J4	207	99	
	R1	R2			J5	237	177	
J1	199	76			J6	169 233	143	
J2	153	28			J7 J8	255 174	125 264	
J3	203	78			J9	224	72	
J4	167 107	85			J10	153	102	
J5 J6	197 129	163 129			J11	165	167	
J0 J7	123	111			J12	235	104	
J8	134	250			J13	196	153	
J9	184	58			J14 J15	169 125	111 82	
J10	113	88			J15 J16	233	59	
J11	125	153			J17	147	285	
J12 J13	195 156	90 139			J18	182	60	
J15 J14	156 129	97			J19	162	187	
J15	85	68			J20	146	133	
J16	193	45			J21	190	104	
J17	107	271			J22 J23	144 225	285 157	
J18	142	46			J25 J24	152	191	
J19	122	173			J25	134	92	
J20	106	119			J26	213	127;	
J21 J22	150 104	90 271				TABLE C		
J23	185	143				IADLE C	01(),1)	_
J24	112	177				T1	T2	
J25	94	78			11	220	01	
J26	173	113;			J1 J2	239 202	91 44	
	TABLE CI	LOW(J,T)			J2 J3	243	96	
					J4	215	103	
	T1	T2			J5	247	177	
J1	203	84			J6	171	150	
J2	153	32			J7 J8	237 176	134 264	
J3	208	80			ја Ј9	228	76	
J4	167	93			J10	161	108	
J5	202	172			J11	174	177	
J6 J7	132 203	136 113			J12	243	104	
J8	134	252			J13	200	162	
J9	191	68			J14	170 135	113 83	
J10	114	96			J15 J16	234	62	
J11	129	162			J17	155	289	
J12	205	100			J18	189	65	
J13 J14	162 134	142 103			J19	162	190	
J14 J15	85	74			J20	150	136	
J16	201	55			J21	194	110	
J17	110	281			J22	150	294	
J18	146	49			J23 J24	227 155	163 198	
J19	130	174			J25	139	99	
J20	115	128			J26	223	131;	
J21 J22	154 113	93 274						
J22 J23	188	274 147			VARIABL AA BB		F , MU , P 'OBJECT' , G , FF	
J24	114	177						
J25	101	79				E VARIABLES		
J26	182	116;			AA,BB,	GA,U,V,	F, MU, GG, FF;	

EQUATIONS **OBJECTIVE** CONST1 CONST2 CONST3 *CONST4 CONST5(1) CONST6(I) CONST7(R) CONST8(1) CONST9; OBJECTIVE.. P = e = GG + FF; CONST1.. (AA-BB) * SUM(T,GA(T)*CUP('J1',T)) = g = GG;CONST2.. SUM(R, U(R)*BUP('J1',R)) =g=FF; CONST3.. SUM(T, GA(T)*CUP('J1',T)) = e = 1; *CONST4.. SUM(T, GA(T)*CUP('J1',T)) =1=1; CONST5(J).. SUM(R, U(R)*BLOW(J,R))-SUM(I, V(I)*A(J,I)) =1=0; CONST6(I).. V(I)A('II',I)-MU(I)=I=(1/4);CONST7(R).. (AA/2)-U(R)*BLOW('11',R)+F(R) = 1=0;CONST8(J).. SUM(R, U(R)*BLOW(J,R))-SUM(T, GA(T)* CLOW(I,T)) = I = 0: CONST9.. SUM(I, MU(I))- SUM(R, F(R))-BB =1=0;

MODEL LINEAR /ALL/; SOLVE LINEAR using NLP maximizing P; display p. l;

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