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Theory of binary-valued data envelopment analysis: an application in assessing the sustainability of suppliers

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Abstract

Purpose – The objective of this study is to present a binary-valued data envelopment analysis (DEA) theory. The authors' proposed approach, for the first time, combines binary-valued and integer-valued theories concurrently in the DEA context. To do so, new production possibility sets (PPSs) with some distinguished features are developed.

Design/methodology/approach – The authors address integer inputs and outputs in the proposed approach by introducing a new PPS.

Findings – To take into account the binary data, the authors develop axiomatic DEA principles. The binary production principles guarantee any combination of convexity and feasibility. Furthermore, the authors develop a new DEA model to consider integer and real data. A case study is presented to show the usefulness of the developed models. Using the proposed models, the authors obtained benchmarks to solve the sustainable supplier selection problems.

Originality/value – (1) For the first time, binary-valued and integer-valued theories are presented in an integrated DEA model. (2) To deal with the pure binary data, a new PPS is proposed. (3) To consider real, integer and binary data, a new PPS is introduced. (4) New technologies are developed to propose feasible solutions. (5) The proposed models can project inefficient decision-making units (DMUs) on efficiency frontier given binary, integer and real data. (6) A case study is given for the performance evaluation of sustainable suppliers.

Keywords Data envelopment analysis (DEA), Binary-valued data, Integer-valued data, Efficiency measurement, Sustainable suppliers

Paper type Research paper

1. Introduction

Data envelopment analysis (DEA) is one of the most powerful approaches to measure the efficiency of a set of decision-making units (DMUs). Because of the numerous advantages of DEA, it has been developed and applied in many settings such as supply chains (SCs), education, healthcare and energy (Kaffash *et al.*, 2020; Wang *et al.*, 2020; Zhao *et al.*, 2019). In standard DEA models, it is presumed that inputs and outputs deal with real-valued data. However, in real-world problems, there might be binary inputs and outputs. Accepting to refund or not refund raw materials by suppliers is a good example of binary data. Thus, in

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assessing the sustainability of suppliers, this type of data is considered binary. The literature survey shows that none of the existing DEA models can take binary-valued data into account. The presence of integer-valued data is another key issue in efficiency evaluation problems using DEA. For example, the number of personnel is an integer input. There are a few scholarly works to address integer inputs and outputs in the DEA context. However, there is no DEA model to address both integer and binary data.

Supplier evaluation and selection are considered one of the most important and challenging tasks to manage SCs (Kellner *et al.*, 2019; Rashidi *et al.*, 2020). Agreement and work with reliable suppliers is also a complicated and significant strategic decision for managers and decision-makers of SCs (Dey *et al.*, 2015; Xie *et al.*, 2011). Suppliers assessment affects inventory planning (Türk *et al.*, 2017), production planning and control (Che, 2017; Hlioui *et al.*, 2017; Nguyen and Chen, 2018), financial performance (Yu and Huo, 2019), quality management (Negash *et al.*, 2020), risk management (Kaur and Singh, 2021; Rao *et al.*, 2017; Wong, 2020), purchasing management (Bolander *et al.*, 2018) and customer satisfaction (Lewin, 2009; Saorín-Iborra and Cubillo, 2019).

With respect to suppliers' key role in different parts and various dimensions of an organization, the importance of selecting appropriate suppliers has received much attention by scholars. Over the last few years, owing to some factors such as media pressures, people's awareness and international regulations, companies have realized to consider sustainability dimensions in the process of supplier evaluation and selection. Therefore, under such conditions, proposing and developing advanced methods for supplier selection and evaluation within sustainable SCs has emerged as an urgent topic. Sustainability in SCs is defined as considering economic, environmental and social aspects in each echelon of SCs such as suppliers, manufacturers and distributors (Barbosa-Póvoa *et al.*, 2018; Ding *et al.*, 2016).

The objective of this study is to present a binary-valued DEA theory. We address integer inputs and outputs in the proposed approach by introducing some new production possibility sets (PPS). In summary and to the best of our knowledge, this study makes significant contributions as follows:

(1) For the first time, binary-valued and integer-valued theories are presented in an integrated DEA model.

(2) To deal with the pure binary data, a new PPS is proposed.

(3) To consider real, integer and binary data, a new PPS is introduced.

(4) New technologies are developed to propose feasible solutions.

(5) The proposed models can project inefficient DMUs on efficiency frontier given binary, integer and real data.

(6) A case study is given for the performance evaluation of sustainable suppliers.

The rest of this paper is organized as follows. Section 2 provides the literature review. In Section 3, we propose a binary-valued DEA model. Section 4 provides a case study along with the managerial implications. Finally, conclusions and future research directions are presented in Section 5.

2. Literature review

2.1 Integer DEA

The traditional DEA models assume that inputs and outputs deal with real-valued data. However, in many real-world applications, inputs and outputs can only take integer values such as the number of workers and the number of fabricated products. Although in some cases rounding the obtained benchmarks to the nearest number is a solution, it can lead to inaccuracy in efficiency assessments and performance benchmarks (Matin and Kuosmanen, 2009). For the first time, Lozano and Villa (2006) proposed an integer-valued theory to address integer inputs and outputs in DEA. Kuosmanen and Matin (2009) presented axioms of “natural divisibility” and “natural disposability” in integer DEA models. The proposed theory was improved by Matin and Kuosmanen (2009) based on returns to scale axioms. Kazemi Matin and Emrouznejad (2011) developed the axiomatic foundation of integer DEA models for considering bounded outputs. Chen *et al.* (2012) presented a DEA model for including both undesirable outputs and integer data to assess city bus systems’ operational performance. To assess and select suppliers, Azadi and Saen (2014) proposed a DEA model in the existence of integer and stochastic data. Wu and Zhou (2015) presented an integer-valued DEA model to address the input excesses and output shortfalls. Karimi *et al.* (2016) proposed an integer DEA model to identify congestion of DMUs. They presented a mixed integer programming (MIP) model for calculating efficiency scores. To measure the efficiency in network structures dealing with integer-valued data and non-discretionary data, Taleb *et al.* (2018) developed a super-efficiency slacks-based measure (SBM) model. Chen *et al.* (2017) mixed the integer data and bounded data to deal with the binary data, which is quite naïve. Pourmahmoud and Gholam Azad (in press) presented a DEA model to deal with the binary data. However, their model has major issues, which will be discussed in Section 3. Navidi *et al.* (2021) developed a DEA method, which can assess congestion without running a DEA model. Their method can deal with negative and integer data. Chen *et al.* (2021) assessed academic journals by integer DEA. Khoveyni *et al.* (2019) developed a slack-based DEA model to identify congestion of DMUs in the presence of integer data. Alirezaee and Rafiee Sani (2018) developed an axiomatic basis for DEA to deal with integer data in the existence of production trade-offs. Zhou *et al.* (2018) proposed DEA models to assess the quality of air in the presence of integer data.

2.2 Sustainable supplier selection

Amindoust *et al.* (2012) presented a fuzzy inference system to evaluate and select sustainable suppliers. Azadi *et al.* (2015) proposed a fuzzy enhanced Russell measure (ERM) model to measure the efficiency and effectiveness of sustainable suppliers. Türk *et al.* (2017) presented a two-stage method to rank suppliers and allocate orders. They applied a multi-objective evolutionary algorithm (MOEA) to minimize conflict objectives of SCs and vendor risk. Amindoust (2018) developed a hybrid intelligent approach for selecting resilient-sustainable suppliers. To evaluate and select sustainable vendors, Khan *et al.* (2018) developed a framework in terms of sustainability performance. The proposed approach uses the fuzzy-inference system for prioritizing vendors from sustainability aspects and fuzzy-Shannon entropy for determining the sustainability criteria weights. Mohammed (2020) developed a fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to evaluate suppliers based on sustainability aspects. Bai *et al.* (2019) developed a group decision-support approach for sustainable supplier selection. Ahmadi *et al.* (2020) combined preference ranking organization method for enrichment of evaluations (PROMETHEE) and best worst method (BWM) and developed a decision framework for evaluating sustainable innovative vendors. Hendiani *et al.* (2020) used interval type-2 fuzzy preference relations for developing a multi-criteria decision-making (MCDM) model to select sustainable suppliers. Goswami and Ghadge (2020) proposed a framework to assess and select sustainable suppliers using single and bi-objective DEA efficiency modeling methods. Negash *et al.* (2020) developed a method for measuring product quality based on the process yield index to select sustainable suppliers. Jain and Singh (2020) presented a fuzzy inference system for clustering criteria to assess the vendors’ sustainability efficiency and select the best vendor. To select sustainable suppliers, Chen *et al.* (2020) developed an integrated rough-fuzzy method. Ortiz-Barrios *et al.* (2021) proposed a hybrid MCDM model to assess and select a sustainable supplier using fuzzy analytic hierarchy process (FAHP) and fuzzy decision-making trial and evaluation laboratory (FDEMATEL). Beiki *et al.* (2021) integrated language entropy weight method (LEWM) and multi-objective programming (MOP) to select sustainable suppliers. Tseng *et al.* (2021) reviewed sustainable operation as a field that moves towards Industry 4.0 and suggested future research topics.

2.3 Knowledge gap

None of the cited DEA models do deal with binary data. To the best of our knowledge, there is no paper to deal with binary data in DEA. This paper is the first attempt to deal with binary data. The new model is used to assess the sustainability of suppliers.

3. Binary-valued DEA model

Here, we present the binary-valued DEA model for the first time and develop it further to consider integer values in efficiency measurement. Table 1 lists the notations used in this study.

Assume that there are n DMUs $\{(x_j, y_j)|j = 1, \ldots, n\}$. $\boldsymbol{x_j} = (x_{1j}, \ldots, x_{mj})^T$ and $\boldsymbol{y_j} = (y_{1j}, \ldots, y_{sj})^T$ are inputs' vectors and outputs' vectors of DMU_j, respectively. Also, $X = [\boldsymbol{x}_1, \ldots, \boldsymbol{x_n}]^T$ and $Y = [\boldsymbol{y}_1, \ldots, \boldsymbol{y_n}]^T$ are $m \times n$ matrix of inputs and $s \times n$ matrix of

Notations	Explanations
DMU_o	The DMU under evaluation
m	The number of inputs
s	The number of outputs
x_j	The input vector of DMU_j
y_j	The output vector of DMU_j
$\lambda = (\lambda_1, \ldots, \lambda_n) \in \{0, 1\}^n$	The binary variables for forming binary production technology
$\mu = (\mu_1, \ldots, \mu_n)$	The vector of structural variables for forming a non-negative combination of DMUs
T	The production technology
T_{CRS}	The production technology with real data and constant returns to scale
T_{VRS}	The production technology with real data and variable returns to scale
$T_{\text{Bin}}^{\text{DEA}}$	The production technology with binary data
$T_{\text{CRS}}^{\text{Mixed-Bin-DEA}}$	The production technology with binary, integer, and real data
θ_i	The reduction ratio of the ith input of DMU_o
φ_r	The increase ratio of the rth output of DMU_o
I^R	The set of inputs with real data
I^I	The set of integer inputs
I^B	The set of binary inputs
O^R	The set of outputs with real data
O^I	The set of integer outputs
O^B	The set of binary outputs
x_j^R	The vector of real data of inputs
x_j^I	The vector of integer inputs
x_j^B	The vector of binary inputs
y_j^R	The vector of real data of outputs
y_j^I	The vector of integer outputs
y_j^B	The vector of binary outputs

Table 1. The notations

outputs, respectively. The classical DEA models assume that all data are real numbers. In DEA, given production principles, a technology T is introduced and part of the frontier of T is considered as approximate of the production function. The production principles are as follows:

Principle 1 (Including observations): All the observed activities $DMU_j = (\boldsymbol{x}_j, \boldsymbol{y}_j)$, $(j = 1, \ldots, n)$ belong to T.

Principle 2 (Feasibility): If $(\overline{\boldsymbol{x}}, \overline{\boldsymbol{y}}) \in T$ and $\boldsymbol{x} \geq \overline{\boldsymbol{x}}$, then $(\boldsymbol{x}, \overline{\boldsymbol{y}}) \in T$. If $\boldsymbol{y} \leq \overline{\boldsymbol{y}}$, then $(\overline{\boldsymbol{x}}, \boldsymbol{y}) \in T$.

Principle 3 (Convexity): If $(\boldsymbol{x}, \boldsymbol{y}), (\overline{\boldsymbol{x}}, \overline{\boldsymbol{y}}) \in T$, then for each $\mu \in [0, 1]$, we have $(\mu \boldsymbol{x} + (1-\mu)\overline{\boldsymbol{x}}, \mu \boldsymbol{y} + (1-\mu)\overline{\boldsymbol{y}}) \in T$.

Principle 4 (Ray unboundedness or constant returns to scale (CRS)): For each $(\boldsymbol{x}, \boldsymbol{y}) \in T$ and $\mu \geq 0$, we have $(\mu \boldsymbol{x}, \mu \boldsymbol{y}) \in T$.

Given the principles, different sorts of technologies can be generated. For instance, using the four principles, the PPS is as follows:

$$T_{\text{CRS}} = \left\{ (\mathbf{x}, \mathbf{y}) | \mathbf{x} \geq \sum_{j=1}^{n} \mu_j \mathbf{x}_j; \boldsymbol{y} \leq \sum_{j=1}^{n} \mu_j \mathbf{y}_j; \mu_j \geq 0, j = 1, \ldots, n \right\}$$

By removing the CRS assumption, variable returns to scale (VRS) technology is obtained:

$$T_{\text{VRS}} = \left\{ (\mathbf{x}, \mathbf{y}) | (\mathbf{x}, \mathbf{y}) \in T_{\text{CRS}}; \sum_{j=1}^{n} \mu_j = 1 \right\}$$

The other technologies can be obtained by combining the production principles (Cooper *et al.*, 2000).

Note 1: Using the production technology, the DMUs are evaluated. The evaluation can be input-oriented, output-oriented and non-oriented. For instance, to evaluate DMU$_o$, the following non-radial approach is considered:

$$\min \frac{\frac{1}{m}\sum_{i=1}^{m}\theta_i}{\frac{1}{s}\sum_{r=1}^{s}\varphi_r}$$

s.t.

$$(\theta_i x_{io}, \varphi_r y_{ro}) \epsilon\, T \tag{1}$$

$$\theta_i \leq 1, \ \varphi_r \geq 1 \quad \forall i, r$$

where T can be one of the technologies of DEA. The DMU$_o$ is efficient if the objective function of model (1) is 1. Otherwise, it is inefficient.

The standard DEA models assume that there exist real data. However, in the real world, there might be binary data. For instance, to select suppliers, one of the binary variables can be whether or not the supplier has a quality control department.

Example 1: In Table 2, DMU C is inefficient as it is dominated by DMUs A and B.

Table 2.
The dataset

DMUs	Input 1	Input 2	Output
A	1	0	1
B	0	1	1
C	1	1	1

Since all the DMUs have similar fixed outputs, the Farrell frontier can be drawn. Assuming real values, consider Figure 1.

The right-hand side of line segment AB (In the first quarter) is PPS. If we wish to assess the efficiency of DMU C radially, the intersection of AB and OC is the radial projection point of DMU C. As is seen, the radial projection point is not binary. Points A, B and C are the only binary points in the PPS. Since DMUs A and B cannot dominate DMU C radially, DMU C is radial efficient, which is wrong.

3.1 Data envelopment analysis in the presence of pure binary data

Assume that there are n DMUs, which consume m inputs to produce s outputs. In fact, DMU$_j$ $(j = 1, \ldots, n)$ produces output $y_{rj} \in \{0, 1\}$ using input $x_{ij} \in \{0, 1\}$.

Definition of binary sum operator (Pourmahmoud and Gholam Azad, in press): For each $\delta_d \in \{0,\ 1\}, d = 1, \ldots, D$, binary sum operator is defined as follows:

$$\sum_{d=1}^{D} \delta_d = \begin{cases} 0 & \forall d, \ \ \delta_d = 0 \\ 1 & \exists d, \ \ \delta_d = 1 \end{cases}$$

Pourmahmoud and Gholam Azad (in press) proposed the following binary principles:

(1) (B1) Binary observations: $(X_j, Y_j) \in \Gamma \ \Rightarrow (X_j, Y_j) \in T \quad \forall j = 1, \ldots, n.$

(2) (B2) No output can be produced without some input: If $Y \geq 0$ and $Y \neq 0$, then $(0, Y) \notin T$.

(3) (B3) Binary additivity: $(X, Y),\ (X', Y') \in T \Rightarrow \ (X + X', Y + Y') \in T$.

(4) (B4) Binary disposability: $(X, Y) \in T$ and $(U, V) \in \Gamma,\ V \leq Y \ \Rightarrow \ (X + U, Y - V) \in T$.

(5) (B5) Point-to-point frontier: $(X, Y) \in T$ and $\exists \lambda \in \{0, 1\};\ (\lambda X, \lambda Y) \in \Gamma \Rightarrow (\lambda X, \lambda Y) \in T$.

(6) (B6) Minimum extrapolation: T is the minimum set that satisfies (B1) to (B5).

Given the above binary principles, Pourmahmoud and Gholam Azad (in press) suggested the following theorem:

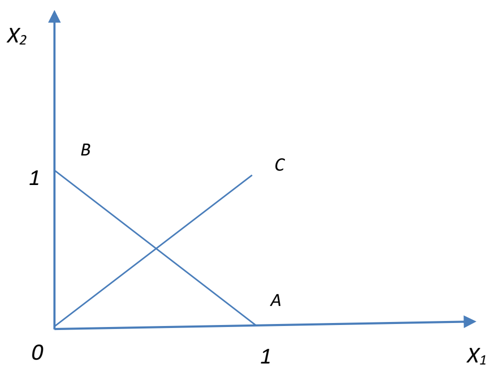

Figure 1.
The PPS of DMUs

Theorem 1. Under axioms (B1)–(B2), T_{BDEA} is the minimum extrapolation of PPS.

$$T_{\mathrm{BDEA}} = \left\{ (X, Y) \in \Gamma |\; X \geq \sum_{j=1}^{n} \lambda_j X_j;\, Y \leq \sum_{j=1}^{n} \lambda_j Y_j;\;\; \lambda_j \in \{0,1\};\;\; \forall j \right\}$$

Apart from their vague proof, T_{BDEA} does not satisfy (B1) to (B5), simultaneously. According to (B5), $(0,0) \in T_{\mathrm{BDEA}}$. On the other hand, according to the definition of binary sum operator and (B3) principle, at least for one input, there is $\sum_{j=1}^{n} \lambda_j X_{ij} = 1$ because at least one of the components of the inputs equals 1. Thus, given the $X \geq \sum_{j=1}^{n} \lambda_j X_j$, T_{BDEA} should be $0 \geq 1$, which violates the theorem of Pourmahmoud and Gholam Azad (in press). The other issue of Pourmahmoud and Gholam Azad (in press) is the existence of zero in the efficiency scores, which is unreasonable.

Here, the axiomatic principles of DEA for binary data are developed addressing the issues of Pourmahmoud and Gholam Azad (in press). The following new technology is introduced:

(1) Including observations principle: $(\boldsymbol{x}_j, \boldsymbol{y}_j) \in T, \quad \forall\, j = 1, \ldots, n$ and

(2) Binary production principle:

$$\forall\, i, r\colon (x_i, y_r) \in T \text{ and } x_i' \leq x_i,\, y_r' \geq y_r,\, x_i', y_r' \in \{0,1\} \Rightarrow (x', y') \in T$$

Theorem 2. The following set is the smallest set that satisfies principles 1 and 2:

$$T_{\mathrm{Bin}}^{\mathrm{DEA}} = \left\{ (x, y) \in \{0,1\}^{m+s} \middle| x_i \geq \sum\nolimits_{j=1}^{n} \lambda_j x_{ij}; y_r \leq \sum\nolimits_{j=1}^{n} \lambda_j y_{rj}; \sum\nolimits_{j=1}^{n} \lambda_j = 1; \lambda_j \in \{0,1\}; j = 1, \ldots, n \right\}$$

Proof: It is clear that $T_{\mathrm{Bin}}^{\mathrm{DEA}}$ satisfies both axiomatic principles 1 and 2. Now, we show that $T_{\mathrm{Bin}}^{\mathrm{DEA}}$ is the smallest set that satisfies two principles. If T is an arbitrary set that satisfies the two principles, then we show $T_{\mathrm{Bin}}^{\mathrm{DEA}} \subseteq T$. Assume that $(\bar{x}, \bar{y}) \in \{0,1\}^{m+s}$ and $(\bar{x}, \bar{y}) \in T_{\mathrm{Bin}}^{\mathrm{DEA}}$. Thus, there exists $\bar{\lambda} = (\bar{\lambda}_1, \ldots, \bar{\lambda}_n) \in \{0,1\}^n$ so that

$$\bar{x}_i \geq \sum_{j=1}^{n} \bar{\lambda}_j x_{ij}; \bar{y}_r \leq \sum_{j=1}^{n} \bar{\lambda}_j y_{rj}; \sum_{j=1}^{n} \bar{\lambda}_j = 1; j = 1, \ldots, n; i = 1, \ldots, m; r = 1, \ldots, s$$

Since T satisfies both principles, given principle 1, we have

$$(x_j, y_j) \in T,\; \forall j = 1, \ldots, n$$

On the other hand, given satisfying the set T in axiomatic principle 2, we have

$$\bar{x}_i \geq \sum_{j=1}^{n} \bar{\lambda}_j x_{ij}; \bar{y}_r \leq \sum_{j=1}^{n} \bar{\lambda}_j y_{rj}; \sum_{j=1}^{n} \bar{\lambda}_j = 1;\; (\bar{x}_i, \bar{y}_r) \in \{0,1\}, \forall j = 1, \ldots, n; i = 1, \ldots, m; r = 1, \ldots, s \rightarrow (\bar{\mathrm{x}}, \bar{\mathrm{y}}) \in T$$

As a result, $T_{\mathrm{Bin}}^{\mathrm{DEA}} \subseteq T$ and the theorem are proved.

Note 1: Instead of simultaneous development of convexity, feasibility and CRS principles, the binary production principle deals with binary data. The binary production principle guarantees that any combination of the three principles can be obtained by the binary production principle.

Note 2: The binary production technology can be constructed by permutation of zero and one in which 2^{m+s} binary points with $m+s$ dimensions are generated. However, it leads to a wrong efficiency assessment. For example, consider the following two DMUs with one input and one output:

$$\mathrm{DMU}_A = (1,0),\ \ \mathrm{DMU}_B = (1,1)$$

Using zero and one permutation, four points $(0,0),(1,1),(0,1),(1,0)$ form binary production technology. Given the production principles, DMU (0, 1) is infeasible.

Note 3: The PPS helps to assess the efficiency scores. Given binary inputs and outputs, the radial models cannot assess the efficiency scores. Thus, non-radial models can be used. For instance, the model of efficiency assessment of DMU_o can be as follows:

$$\min\ \frac{\frac{1}{m}\sum_{i=1}^{m}\theta_i}{\frac{1}{s}\sum_{r=1}^{s}\varphi_r}$$

s.t.

$$(\theta_i x_{io},\, \varphi_r y_{ro}) \epsilon\, T_{\mathrm{Bin}}^{\mathrm{DEA}} \tag{2}$$

If the objective function of model (2) is 1, then DMU_o is binary efficient. Otherwise, DMU_o is inefficient. The proposed technology of Theorem 2 is a PPS to evaluate efficiency in the presence of pure binary data by which model (2) is developed.

3.2 Data envelopment analysis in the presence of mixed binary data

In the real world, there might be real, integer and binary data. Assume that there are the following inputs and outputs:

$$I = I^R \cup I^I \cup I^B$$

$$O = O^R \cup O^I \cup O^B$$

where R, I and B are real, integer and binary data, respectively. Also, assume that there are n DMUs, which are as follows:

$$S = \left\{ (\boldsymbol{x}_j, \boldsymbol{y}_j) = \left(\boldsymbol{x}_j^R, \boldsymbol{x}_j^I, \boldsymbol{x}_j^B, \boldsymbol{y}_j^R, \boldsymbol{y}_j^I, \boldsymbol{y}_j^B \right) \middle| j = 1, \ldots, n \right\}$$

Now, the production principles are defined.

(1) Including observations principle:

$$(x_j, y_j) \in T, \forall j = 1, \ldots, n$$

(2) Convexity principle:

$$\left(x_j^R, x_j^I, x_j^B, y_j^R, y_j^I, y_j^B\right), \left(x_j^{R'}, x_j^{I'}, x_j^B, y_j^{R'}, y_j^{I'}, y_j^B\right) \in T,\ \lambda \in [0,1]$$

$$\lambda\left(x_j^I, y_j^I\right) + (1-\lambda)\left(x_j^{I'}, y_j^{I'}\right) \in Z_+^I,\ \ \to \lambda\left(x_j^R, x_j^I, x_j^B, y_j^R, y_j^I, y_j^B\right)$$
$$+ (1-\lambda)\left(x_j^{R'}, x_j^{I'}, x_j^B, y_j^{R'}, y_j^{I'}, y_j^B\right) \in T$$

(3) Feasibility principle of real, integer, and binary data:

$$\left(x_j^R, x_j^I, x_j^B, y_j^R, y_j^I, y_j^B\right) \in T,\ 0 \le \left(x_j^{R'}, x_j^{I'}, x_j^{B'}, -y_j^{R'}, -y_j^{I'}, -y_j^{B'}\right) \le \left(x_j^R, x_j^I, x_j^B, y_j^R, y_j^I, y_j^B\right),\ x_j^{I'}, y_j^{I'} \in Z_+^I;\ x_j^{B'}, y_j^{B'} \in \{0,1\} \rightarrow \left(x_j^{R'}, x_j^{I'}, x_j^{B'}, y_j^{R'}, y_j^{I'}, y_j^{B'}\right) \in T$$

(4) The partial ray unboundedness:

$$\left(x_j^R, x_j^I, x_j^B, y_j^R, y_j^I, y_j^B\right) \in T,\ \lambda \ge 0,\ \lambda\left(x_j^I, y_j^I\right) \in Z_+^I, \rightarrow \left(\lambda x_j^R, \lambda x_j^I, x_j^B, \lambda y_j^R, \lambda y_j^I, y_j^B\right) \in T$$

Theorem 3. The following PPS is the smallest set that satisfies principles 1 to 4:

$$T_{\mathrm{CRS}}^{\mathrm{Mix-Bin-DEA}} = \left\{ (x,y) = \left(x^R, x^I, x^B, y^R, y^I, y^B\right) \left| \begin{array}{c} x^R \ge \sum_{j=1}^{n} \mu_j x_j^R\ ;\ y^R \le \sum_{j=1}^{n} \mu_j y_j^R \\ x^I \ge \sum_{j=1}^{n} \mu_j x_j^I\ ;\ y^I \le \sum_{j=1}^{n} \mu_j y_j^I; \left(x^I, y^I\right) \in Z_+^I \\ x_i^B \ge \sum_{j=1}^{n} \lambda_j x_{ij}^B\ ;\ y_r^B \le \sum_{j=1}^{n} \lambda_j y_{rj}^B;\ x_i^B, y_r^B \in \{0,1\} \\ \sum_{j=1}^{n} \lambda_j = 1;\ \lambda_j \varepsilon \{0,1\} \mu_j \ge 0, j = 1, \ldots, n \end{array} \right. \right\}$$

Proof: First, the PPS is considered as follows:

$$T_{\mathrm{CRS}}^{\mathrm{Mixed-Bin-DEA}} = T_{\mathrm{Bin}}^{\mathrm{DEA}} \times T_{\mathrm{Mixed}}^{\mathrm{DEA}}$$

where

$$T_{\mathrm{Bin}}^{\mathrm{DEA}} = \left\{ \left(x^B, y^B\right) \left| x_i^B \ge \sum_{j=1}^{n} \lambda_j x_{ij}^B; y_r^B \le \sum_{j=1}^{n} \lambda_j y_{rj}^B; x_i^B, y_r^B \in \{0,1\}; \sum_{j=1}^{n} \lambda_j = 1; \lambda_j \varepsilon \{0,1\},\ j = 1, \ldots, n \right. \right\}$$

$$T_{\mathrm{Mixed}}^{\mathrm{DEA}} = \left\{ (x,y) = \left(x^R, x^I, y^R, y^I\right) \left| \begin{array}{c} x^R \ge \sum_{j=1}^{n} \mu_j x_j^R; y^R \le \sum_{j=1}^{n} \mu_j y_j^R \\ x^I \ge \sum_{j=1}^{n} \mu_j x_j^I; y^I \le \sum_{j=1}^{n} \mu_j y_j^I; \left(x^I, y^I\right) \in Z_+^I \\ \mu_j \ge 0, j = 1, \ldots, n \end{array} \right. \right\}$$

It is shown that $T_{\mathrm{Bin}}^{\mathrm{DEA}}$ and $T_{\mathrm{Mixed}}^{\mathrm{DEA}}$ are the smallest sets that satisfy the four principles. The including observations principle and binary production principle are related to $T_{\mathrm{Bin}}^{\mathrm{DEA}}$. As is shown in Theorem 2, this set is the smallest set that satisfies the principles. It is sufficient to show that $T_{\mathrm{Mixed}}^{\mathrm{DEA}}$ is the smallest set that satisfies the four principles. It is clear that $T_{\mathrm{Mixed}}^{\mathrm{DEA}}$ satisfies the four principles. It is shown that if a set like T satisfies all 4 principles, then $T_{\mathrm{Mixed}}^{\mathrm{DEA}} \subseteq T$. Assume that $\left(x^R, x^I, y^R, y^I\right) \in T_{\mathrm{Mixed}}^{\mathrm{DEA}}$. Thus, there exists $\bar{\lambda} = \left(\bar{\lambda}_1, \ldots, \bar{\lambda}_n\right)$, so that

$$x^R \ge \sum_{j=1}^{n} \bar{\lambda}_j x_j^R; y^R \le \sum_{j=1}^{n} \bar{\lambda}_j y_j^R; x^I \ge \sum_{j=1}^{n} \bar{\lambda}_j x_j^I; y^I \le \sum_{j=1}^{n} \bar{\lambda}_j y_j^I; \bar{\lambda}_j \ge 0;\ \left(x^I, y^I\right) \in Z_+^I; j = 1, \ldots, n$$

Since T satisfies the four principles, given principle 1, we have

$$\left(x_j^R, x_j^I, y_j^R, y_j^I\right) \in T,\ \forall j = 1, \ldots, n$$

Also, given principle 2 and $\left(\sum_{j=1}^{n} \bar{\mu}_j x_j^I, \sum_{j=1}^{n} \bar{\mu}_j y_j^I\right) \in Z_+^I$, we have

$$\left(\sum_{j=1}^{n} \bar{\mu}_j x_j^R, \sum_{j=1}^{n} \bar{\mu}_j x_j^I, \sum_{j=1}^{n} \bar{\mu}_j y_j^R, \sum_{j=1}^{n} \bar{\mu}_j y_j^I\right) \in T, \sum_{j=1}^{n} \bar{\mu}_j = 1;\ \bar{\mu}_j \geq 0,\ j = 1, \ldots, n$$

On the other hand, based upon principle 3, we have

$$x^R \geq \sum_{j=1}^{n} \bar{\mu}_j x_j^R;\ x^I \geq \sum_{j=1}^{n} \bar{\mu}_j x_j^I;\ y^R \leq \sum_{j=1}^{n} \bar{\mu}_j y_j^R;\ y^I \leq \sum_{j=1}^{n} \bar{\mu}_j y_j^I;\ \sum_{j=1}^{n} \bar{\mu}_j = 1;\ \bar{\mu}_j \geq 0,$$
$$j = 1, \ldots, n;\ \left(x^I, y^I\right) \in Z_+^I \rightarrow \left(x^R, x^I, y^R, y^I\right) \in T$$

Finally, given principle 4 we have

$$x^R \geq \sum_{j=1}^{n} \bar{\lambda}_j x_j^R;\ x^I \geq \sum_{j=1}^{n} \bar{\lambda}_j x_j^I;\ y^R \leq \sum_{j=1}^{n} \bar{\lambda}_j y_j^R;\ y^I \leq \sum_{j=1}^{n} \bar{\lambda}_j y_j;\ \bar{\lambda}_j \geq 0,$$
$$j = 1, \ldots, n;\ \left(x^I, y^I\right) \in Z_+^I \rightarrow \left(x^R, x^I, y^R, y^I\right) \in T$$

where $\bar{\lambda}_j = \alpha \bar{\lambda}_j, \alpha > 0$. Thus, $T_{\text{Mixed}}^{\text{DEA}} \subseteq T$ and the theorem are proved.

Thus, $T_{\text{CRS}}^{\text{Mixed-Bin-DEA}}$ is the most comprehensive PPS in which all the real, integer and binary data are considered, simultaneously.

At this juncture, a feasible model for evaluating efficiency in the presence of binary, integer and real data is proposed. The new non-radial input-oriented DEA model in the context of mixed binary-valued data can be presented as follows:

$$\theta^* = \min\ \frac{1}{m} \sum_{i=1}^{m} \theta_i$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} \mu_j x_{ij}^R \leq \theta_i x_{io}^R && i \in I^R \\
&\sum_{j=1}^{n} \mu_j x_{ij}^I \leq \theta_i x_{io}^I && i \in I^I, \\
&\sum_{j=1}^{n} \lambda_j x_{ij}^B \leq \theta_i x_{io}^B && i \in I^B \\
&\sum_{j=1}^{n} \mu_j y_{rj}^R \geq y_{ro}^R && r \in O^R \\
&\sum_{j=1}^{n} \mu_j y_{rj}^I \geq y_{ro}^I && r \in O^I \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^B \geq y_{ro}^B && r \in O^B \\
&\mu_j \geq 0, \lambda_j \in \{0, 1\} && j = 1, \ldots, n \\
&\sum_{j=1}^{n} \lambda_j = 1 && \\
&\theta_i x_{io}^B \in \{0, 1\} && i \in I^B \\
&0 \leq \theta_i \leq 1 && i = 1, \ldots, m \\
&\left(\theta_i x_{io}^I, \sum_{j=1}^{n} \mu_j y_{rj}^I\right) \in Z_+^I &&
\end{aligned} \tag{3}$$

Model (3) is a non-radial input-oriented model. In this model, the real inputs are dealt with like the classical non-radial models. However, the integer inputs are dealt with by following Kuosmanen and Matin (2009) approach. In other words, the $\theta_i x_{io}^I$ is forced to be an integer. Similarly, $\theta_i x_{io}^B$ is forced to be binary.

Lemma 1. Model (3) is always feasible and $0 < \theta^* \leq 1$.

Proof: If $\mu_o = \lambda_o = 1$ and $\mu_j = \lambda_j = 0(h = 1, \ldots, n; j \neq o)$, then a feasible solution of model (3) is obtained, in which the objective function of model (3) becomes 1. On the other hand, since the objective function is minimization, $\theta^* \leq 1$. Also, since the left-hand side of the three first constraints of model (3) are non-negative, $\theta_i (i = 1, \ldots, m)$ should be non-negative. The three-second constraints, which correspond with the outputs, prevent θ_i to be zero. Thus, we conclude that $\theta^* > 0$, and the lemma is proved.

Definition 1. DMU_o is said to be efficient in terms of the proposed non-radial mixed binary-valued DEA model in (3) if its efficiency score equals one (i.e. $\theta^* = 1$), otherwise the DMU_o is inefficient.

Note 4: Assuming CRS, we developed new models and, as is seen, there are no returns to scale assumption for binary factors, and the returns to scale assumption is associated with the real and integer factors. The VRS, increasing returns to scale and decreasing returns to scale version of the developed models can be written, which only the constraints related to real and integer factors are affected.

Note 5: Given Lemma 1, model (3) can evaluate the efficiency of DMU_o in the presence of binary, integer and real data. Also, using model (3), the projected inputs of DMU_o are calculated as follows:

$$\left(\theta_i^* x_{io}^R, \theta_i^* x_{io}^I, \theta_i^* x_{io}^B\right) \in R_+^{|I^R|} \times Z_+^{|I^I|} \times \{0,1\}^{|I^B|} \tag{4}$$

As is seen, the projected input is matched with binary, integer and real data. However, former DEA models cannot differentiate the projected inputs in terms of binary, integer and real data.

4. Case study

Energy Keshvar Company (EKC) was founded in 1969 and is one of the leading Iranian companies in manufacturing cooling and heating products [1]. One of the main materials of EKC is cold-rolled steel. EKC wishes to assess the sustainability of suppliers of cold-rolled steel. The inputs for assessing suppliers' sustainability include price, delivery time, environmental cost, and cost of work safety and labor health. The outputs are payment time, refund, the number of environmental certificates and the number of product types. Environmental costs and the number of environmental certificates are environmental indicators, and the cost of work safety is considered as a social indicator, respectively. Other variables such as price, delivery time, payment time, refund and the number of product types are considered as economic indicators. Note that refund is a binary variable. Furthermore, the number of environmental certificates and the number of product types are integer variables. Table 3 shows the data set related to sustainable suppliers of EKC. The dataset dates back to 2018. Dataset is collected from archives and documents of EKC. Using model (2) and the CCR (Charnes–Cooper–Rhodes) model, the results are reported in Table 4.

4.1 Results and discussions

Classic DEA models deal with real-valued data. However, in the real world, there might be binary data. Matin and Kuosmanen (2009) suggested the theory of integer data in DEA.

Table 3. The data set related to sustainable suppliers

Suppliers (DMUs)	Inputs: Price (rial)	Delivery time (Day)	Environmental costs (rial)	Cost of work safety and labor health (rial)	Payment time (Month)	Refund	Outputs: The number of environmental certificates	The number of product types
Foolad Mobarake	30,400	90	219,000,000	275,000,000	0	0	8	9
Haft Almas	33,000	60	225,000,000	301,000,000	0	1	8	9
Varagh Khodroo	34,000	90	198,000,000	236,000,000	0	0	6	7
Posko	38,000	120	217,000,000	172,000,000	0	0	7	9
Kasra	35,000	10	130,000,000	139,000,000	1	1	4	6
Ahan Alate Parse	35,000	10	145,000,000	215,000,000	1	1	6	6
Ahan Alate Shabani	34,800	10	81,000,000	105,000,000	1	1	3	7
Pishtaz Felezate Eghbali	34,800	10	138,000,000	91,000,000	1	1	3	5
Foolad Sanat Tirajeh	34,600	10	268,000,000	176,000,000	1	1	5	8
Fadak Mandegar	33,600	12	212,000,000	134,000,000	1	1	3	5
Foolad Gharb	36,000	10	257,000,000	139,000,000	1	1	7	9
Sard Gilan	35,000	15	203,000,000	215,000,000	2	1	8	7
Amir Kabir Kashan	34,800	10	119,000,000	135,000,000	1	1	8	8
Saba Foolad Zagros	35,300	10	95,000,000	165,000,000	1	1	5	7
Taraz	35,600	15	250,000,000	134,000,000	2	1	4	5
Exin Ahvaz	35,000	10	234,000,000	175,000,000	1	1	7	9
Foolad Bahman	32,000	90	219,000,000	275,000,000	2	0	8	9
Foolad Kavian	34,000	60	120,000,000	135,000,000	2	0	5	7

(*continued*)

Table 3.

Suppliers (DMUs)	Inputs: Price (rial)	Inputs: Delivery time (Day)	Inputs: Environmental costs (rial)	Inputs: Cost of work safety and labor health (rial)	Inputs: Payment time (Month)	Inputs: Refund	Outputs: The number of environmental certificates	Outputs: The number of product types
Foolad Kavir Kashan	30,400	90	175,000,000	236,000,000	0	0	5	9
Persian Foold	35,600	90	247,000,000	150,000,000	0	1	7	8
Foolad Rohina	35,000	90	81,000,000	174,000,000	0	0	4	5
Foold Sharood	36,500	90	142,000,000	136,000,000	0	0	6	7
Foolad Saba	34,600	15	195,000,000	150,000,000	2	1	5	5
Foolad Mehr	35,000	20	143,000,000	165,000,000	2	0	4	4

Table 4. The results using model (2) and CCR model

DMUs	The sustainability scores using model (2)	The projection point of refund	The projection point of the number of environmental certificates	The projection point of the number of product types	The sustainability scores using CCR model	The projection point of refund	The number of environmental certificates	The projection point of the number of product types
Foolad Mobarake	1	0	8	9	1	0	8	9
Haft Almas	0.91	1	8	9	1	1	8	9
Varagh Khodroo	0.50	0	6	7	0.50	0.90	6	7
Posko	0.68	0	8	9	0.68	1.09	8.44	9
Kasra	0.81	1	4	6	0.86	1	4	7
Ahan Alate Parse	0.74	1	6	6	0.82	1	6	7
Ahan Alate Shabani	1	1	3	7	1	1	3	7
Pishtaz Felezate Eghbali	1	1	3	5	1	1	3	5
Foolad Sanat Tirajeh	0.82	1	7	8	1	1	5	8
Fadak Mandegar	0.66	1	3	5	1	1	3	5
Foolad Gharb	1	1	7	9	1	1	7	9
Sard Gilan	1	1	8	7	1	1	8	7
Amir Kabir Kashan	1	1	8	8	1	1	8	8
Saba Foolad Zagros	1	1	5	7	1	1	5	7
Taraz	1	1	4	5	1	1	4	5
Exin Ahvaz	1	1	7	9	1	1	7	9

(*continued*)

DMUs	The sustainability scores using model (2)	The projection point of refund	The projection point of the number of environmental certificates	The projection point of the number of product types	The sustainability scores using CCR model	The projection point of refund	The number of environmental certificates	The projection point of the number of product types
Foolad Bahman	1	0	8	9	1	0	8	9
Foolad Kavian	1	0	5	7	1	0	5	7
Foolad Kavir Kashan	1	0	5	9	1	0	5	9
Persian Foold	0.61	1	7	8	0.61	1.02	7.26	8
Foolad Rohina	0.50	0	4	5	0.50	0.65	4	5
Foolad Sharood	0.62	0	6	7	0.62	0.90	6	7
Foolad Saba	1	1	5	5	1	1	5	5
Foolad Mehr	1	0	4	4	1	0	4	4

Table 4.

Nevertheless, they did not discuss the binary data in DEA. To the best of our knowledge, this paper is the first attempt to incorporate binary data into the DEA. The proposed models were validated by a case study. The findings are interesting. The second and sixth columns of Table 4 depict the sustainability score using the new model (2) and CCR model. Using model (2), the third, the fourth and the fifth columns show the projection point of refund (binary variable), the projection point of the number of environmental certificates (integer variable) and the projection point of the number of product types (integer variable), respectively. However, the projection points of the CCR model are given in columns 7 to 9 of Table 4. As is seen, using the CCR model, the projection points of refund (binary variable) for suppliers Varagh Khodroo, Posko, Persian Foolad, Foolad Rohina and Foolad Sharood are not binary. Also, using the CCR model, the projection point of the number of environmental certificates for Posko and Persian Foolad is non-integer. This shows that the CCR model cannot assess the DMUs' efficiency in the presence of binary and integer data. Note that rounding up the projected points of binary and integer variables is not a good idea. For instance, consider Varagh Khodro. The projected point of binary and integer variables, using model (2), is (0, 6, 7), and the projected point of binary and integer variables, using rounded up CCR model, is (1, 6, 7), which is different from model (2).

4.2 Managerial implications

Supplier selection is one of the most essential tasks of SC managers (Rashidi *et al.*, 2020). Selecting the most sustainable suppliers is a complicated decision of managers (Xie *et al.*, 2011). Selecting proper suppliers improves planning (Türk *et al.*, 2017), quality of goods and services (Negash *et al.*, 2020), and customer satisfaction (Lewin, 2009). On the other hand, as is seen in the case study, in the real world, there might be binary data, which managers have to deal with it. This paper developed new models to deal with the situations that there are binary data. The proposed models provide managers and decision-makers with some insights. Due to social media pressures, intense competition in international markets and customers' awareness, managers need to address the sustainability aspects in their decision-making. The proposed models can assist managers to deal with both binary and integer data, simultaneously. Compared with the traditional DEA models, providing better results is another feature of the proposed models. Furthermore, suppliers can identify their inefficiency reasons and improve their performance by more accurate benchmarks.

Figure 2 compares the sustainability scores using model (2) and the CCR model. As is seen, the results of model (2) are less than or equal to the CCR model. This implies higher discrimination power of model (2). Also, it implies that taking into account both binary and integer variables affects the results.

5. Conclusions and future research directions

The classical DEA models assume that the inputs and outputs deal with real values. However, there are situations that inputs and outputs can only take binary data. Ignoring binary data causes inaccurate results and unrealistic benchmarks. To address this issue, for the first time, we presented the theory of binary-valued DEA. To take into account the binary data, we developed axiomatic DEA principles. The binary production principles guarantee any combination of convexity and feasibility. The CRS principles can be obtained by the binary production principle. Furthermore, we developed a new DEA model to consider integer and real data. Also, to tackle a real-world problem, for the first time, we incorporated both binary-valued and integer-valued theories into DEA. Moreover, the developed model provides better projection points on the efficiency frontier. A case study was presented to show the usefulness of the developed models. Using the proposed models, we obtained better

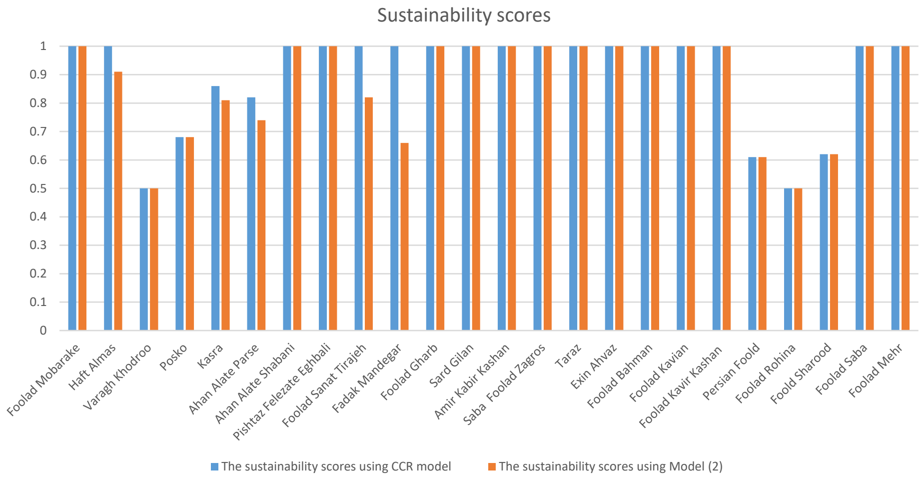

Figure 2.
Sustainability comparison of model (2) and CCR model

results and realistic benchmarks to solve the sustainable supplier selection problems. Our proposed model also can identify unsustainable suppliers.

This research, as the first research in the field of binary data in DEA, opens new horizons for prospective researchers. Here, several future research directions can be suggested based on the theory presented in this paper. In the sustainability evaluation of suppliers, there are some factors such as service-quality credence and service-quality experience that play the role of both inputs and outputs (Azadi and Saen, 2011; Saen, 2010). Developing a model considering dual-role factors and binary-valued data is a research direction for prospective researchers. On the other hand, in real-world problems, the decision-maker may face uncertainty. In these sorts of situations, developing fuzzy, stochastic and robust versions of the proposed models can help managers to select the most sustainable suppliers. Furthermore, the proposed theory can be applied in other settings such as market selection, personnel evaluation, technology selection, etc.

Note

1. https://en.energyind.webexir.net/

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