An integrated bi-objective data envelopment analysis model for measuring returns to scale

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ABSTRACT

Classical efficiency studies on data envelopment analysis (DEA) consider all its inputs and outputs are desirable factors and real valued-data. Additionally, the DEA models only focus either on input-oriented projection minimizing inputs for an inefficient decision making unit (DMU) while keeping outputs at their maximum level, or output-oriented projection maximizing outputs under the present level of input consumption. To simultaneously deal with input excesses and output shortfalls maximizing both projections, this paper proposes a bi-objective DEA model in the context of undesirable factors and mixed integer requirements. These factors and requirements were integrated into the objective function and constraints of the existing bi-objective models. In addition, the proposed model estimates the returns to scale of DMUs that depends on the projections of input reduction and output augmentation. The applicability and usefulness of the proposed model were tested using the dataset of 39 Spanish airports retrieved from the literature. Besides, the proposed model was compared with the three existing bi-objective DEA models in the literature to test its validity.

Keywords: Data envelopment analysis; Mixed integer-valued data; Returns to scale; Undesirable factors

1. Introduction

Data envelopment analysis (DEA) measures the relative efficiency of a set of organisational units in various settings, called decision making units (DMUs). The DMUs consume multiple inputs to produce multiple outputs. The most well-known DEA model is the CCR model, proposed by Charnes et al. (1978). The CCR model measures the efficiency based on the oriented radial model: input or output oriented. Later, Banker et al. (1984) integrated the economic concept of returns to scale (RTS) with the proposed variable returns to scale (VRS) model. The RTS is a scale reflecting a proportionate increase in outputs resulting from a proportionate increase in inputs (Thanassoulis, 2001). The RTS can be used as an economic measure to determine an efficiency level. A DMU is efficient if it can maintain its current level of outputs with fewer inputs or increase the outputs with the same level of inputs. It can be constant returns to scale (CRS), increasing returns to scale (IRS) or decreasing returns to scale (DRS). The CRS reveals that any increase in inputs can proportionally produce any increase in outputs. In contrast, the proportional changes of inputs less or greater than that of outputs reflect increasing returns to scale (IRS) or decreasing returns to scale (DRS) (Daraio & Simar, 2007; Sherman & Zhu, 2006). However, the RTS technique of Banker et al. (1984) was only applicable for technical efficient DMUs.

To classify the RTS for efficient and inefficient DMUs, a simple method based on two variants of oriented BCC models (input and output oriented) was then proposed by Golany and Yu (1997). The model was proposed for desirable (good) and real values of inputs and outputs. The desirable inputs (such as coal consumption) and outputs (such as gross domestic product) should be minimized and maximized to improve the performance of a DMU. However, assuming all inputs and outputs as desirable factors and real valued-data may pose two main issues. First, considering undesirable inputs and outputs (i.e., bad inputs (such as input waste in a recycling process) and outputs (such as CO_2 emission) that their levels have to be maximized and minimized) as desirable factors in performance measures, as considered in literature reviews, may mislead decision makers of DMUs. In reality, undesirable outputs and desirable inputs should be decreased, while desirable outputs and undesirable inputs should be increased in order to improve the performance of an inefficient DMU. Thus, how to correctly treat both desirable and undesirable inputs and outputs should be studied. Second, simply rounding the real values of inputs and outputs to their nearest integer values may cause inaccurate and misleading efficiency evaluation (Hussain et al., 2016). In reality, many input and output variables of DMUs are to be integer values, and their resulted unused or extra amount of the input and output variables calculated by DEA must also be integers. For example, see the data and results of the airport application discussed in Section 4. In such a case, the integer values simply based on real-valued approximation would not be enough to accurately measure the DMUs' efficiency. Thus, how to treat inputs and outputs where some of their values are restricted to be integers should be examined. Other issues related to RTS can also occur. Therefore, how to identify the operation regions of evaluated DMUs where some of their inputs and/or outputs are simultaneously subject to undesirable factors and integer values should also be measured appropriately.

Efficiency improvement of undesirable factors that considers undesirable inputs or outputs based on the concept of the radial DEA model has been conducted by many efficiency studies, such as Hwang et al. (2012), Färe et al. (1989), Seiford and Zhu (2002), Zhou and Ang (2008) and Tyteca (1997). However, these studies only focused on the efficiency improvement from one side (inputs or outputs) and cannot simultaneously handle both inputs and outputs for improvement. The simultaneous improvement in undesirable inputs and outputs can be achieved by treating them as desirable outputs and inputs, as introduced by Amirteimoori et al. (2006) and Vencheh et al. (2005). However, all the studies were proposed in terms of radial models. The main limitation of radial models is that the models assume the proportional changes of inputs or outputs and ignore the existence of slacks in efficiency scores (Rashidi et al., 2015).

To cater for the limitation, a non-radial slack-based measure (SBM) model in the presence of undesirable outputs was first proposed by Tone (2003). The model effectively deals with the slacks of desirable inputs and outputs, as well as the slacks of undesirable outputs and allows the desirable inputs and undesirable outputs to be decreased, and the desirable outputs to be increased at different rates. Based upon the model of Tone (2003), many efficiency studies have been conducted, such as Chang (2013), Lee et al. (2014), Lozano and Gutiérrez (2011), Rashidi et al. (2015) and Zhang and Choi (2013). All these studies considered various factors of undesirable outputs, such as waste water, delay time of airplane and CO_2 emissions. However, they ignored the real impact of both undesirable inputs and outputs on efficiency measures. Both factors were then integrated into a non-radial DEA model, as conducted by the studies of Chen et al. (2012), Jahanshahloo et al. (2005) and Liu et al. (2010). In spite of the salient features of the mentioned studies considering radial and non-radial models, they did not consider decision makers' preferences on inputs and outputs. To describe decision makers' preferences, Wei et al. (2008) proposed a bi-objective general DEA model dealing with two projections of input reduction and output extension. However, their model did not define the preferences on desirable and undesirable inputs and/or outputs. These preferences were later considered by Liu et al. (2010) by proposing a non-radial DEA model with undesirable inputs and outputs.

However, Liu et al. (2010) assumed that all the values of desirable and undesirable inputs and outputs are real in their proposed method, conflicting with many managerial situations. A CCR model considering some inputs and outputs as integer values was proposed by Lozano and Villa (2006). Their model was improved by Lozano and Villa (2007) to include the technology of VRS. Later, an axiom classifying inputs and outputs into the subsets of real and integer values was introduced by Kuosmanen and Matin (2009). They proposed an input-oriented CCR model in mixed integer-valued DEA. This model was then improved by Du et al. (2012) to introduce an output-oriented model under VRS. To obtain more accurate efficiency measures, an input-oriented SBM model in mixed integer-valued data was considered by Khezrimotlagh et al. (2013). However, their model did not consider decision makers' preference in terms of integer-valued data. The integer requirements of inputs and outputs were integrated into a bi-objective DEA model by Wu and Zhou (2015). Their model, however, considered all inputs and outputs as desirable factors. Additionally, the model did not estimate the region of RTS (constant, increasing or decreasing) associated with a DMU under assessment, since it could only identify the values of inputs reduction and outputs augmentation when imposing relevant constraints.

To consider decision makers' preferences and estimate RTS in the presence of undesirable factors and mixed integer inputs and outputs, this paper proposes a methodology that develops a new bi-objective DEA model. The methodology integrates undesirable factors, introduced in Liu et al. (2010), into the bi-objective model of Wu and Zhou (2015) and estimates RTS, utilizing the method of Golany and Yu (1997), for the case of undesirable factors and mixed integer valued-data. Thus, the contribution of this paper resides in two main aspects. In terms of the theoretical aspect, the proposed model can estimate the RTS for efficient and inefficient DMUs where some of their inputs and/or outputs are undesirable mixed integer values. It also imposes the weak disposability assumption on undesirable inputs and outputs, increasing the applicability of the model in dealing with real-world problems. In terms of the practical aspect, for the first time, this paper evaluates the efficiency and RTS of a system (i.e., Spanish airports) involving undesirable factors and mixed integer values of inputs and outputs. To the best of authors' knowledge, there have not been any efficiency studies attempting to propose undesirable factors and mixed integer values of inputs and outputs into a bi-objective DEA model.

The rest of this paper is structured as follows. Section 2 presents some previous studies on bi-objective models, undesirable factors and mixed integer requirements, serving the methodology of this paper. The methodology of developing a new bi-objective model to estimate RTS with undesirable factors and mixed integer inputs and outputs is elaborated in Section 3. Section 4 discusses the usefulness and applicability of the proposed model, using the empirical data of 39 Spanish airports. The validity of the model was tested by comparing its results with the results obtained from the three existing models. Finally, Section 5 presents the concluding remarks of this paper, summarizes its main contributions and suggests the directions for future research.

2. Preliminaries

Assume that there are n DMUs needing to be measured their efficiency. Each DMU consumes m inputs to produce s outputs, where x_{ij} denotes the amount of ith input consumed by the jth DMU, while y_{rj} denotes the amount of the rth output produced by the same DMU. Additionally, the amounts of x_{ij} and y_{rj} are assumed to be non-negative. The input-oriented model for assessing the efficiency of an evaluated DMU$_o$ under the assumption of VRS was developed by Banker et al. (1984). The model can be exhibited as follows:

$$\min \theta_o - \varepsilon\left(\sum_{i=1}^{m} s_{io}^{-} + \sum_{r=1}^{s} s_{ro}^{+}\right) \tag{1}$$

s.t:

$$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_o x_{io} - s_{io}^{-}, \qquad i = 1, \ldots, m, \tag{1a}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro} + s_{ro}^{+}, \qquad r = 1, \ldots, s, \tag{1b}$$

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

$$\lambda_j \geq 0, \qquad j = 1, \ldots, n, \tag{1d}$$

$$s_{io}^{-}, s_{ro}^{+} \geq 0 \tag{1e}$$

where ε is a very small positive value (a non-Archimedean infinitesimal). The value of ε should be small enough to avoid an unbounded solution of the linear programming problem and achieve strongly efficient. To prevent erroneous results due to the non-Archimedean ε value, the two-stage approach can also be used (see Appendix A). The assumption of VRS is imposed by convexity constraint (1c). Non-negative multipliers used for calculating the linear combination of DMUs being evaluated is represented by constraint (1c). Constraint (1e), meanwhile, ensures that the values of input and output slacks are non-negative (i.e., a non-negativity constraint).. Hence, model (1) is used to evaluate the efficiency of DMUs whose target is to decrease inputs and maintain the existing level of outputs (input-oriented) to achieve the efficiency status of DMU$_o$. DMU$_o$ is fully-efficient if its efficiency score is equal to one (i.e., the optimal value of θ_o is equal to one), and all its input and output slacks are equal to zero (i.e., the optimal values of $s_{io}^{-}, s_{ro}^{+}\ \forall i, r$ are equal to zero). DMU$_o$ is weakly-efficient if the optimal value of θ_o is equal to one, and there exists at least one of its slacks whose optimal value greater than zero. Otherwise, DMU$_o$ is inefficient.

On the other hand, the output-oriented BCC model of Banker et al. (1984) under the VRS assumption can be presented as follows:

$$\max \psi_o + \varepsilon\left(\sum_{i=1}^{m} s_{io}^{-} + \sum_{r=1}^{s} s_{ro}^{+}\right) \tag{2}$$

s.t:

$$\sum_{j=1}^{n} \lambda_j x_{ij} = x_{i0} - s_{io}^{-}, \qquad i = 1, \ldots, m, \tag{2a}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \psi_o y_{ro} + s_{ro}^{+}, \qquad r = 1, \ldots, s, \tag{2b}$$

and constraints (1c)–1(e).

In contrast to model (1), model (2) evaluates the efficiency of DMUs using the existing level of inputs while paying the attention to augment the level of outputs for inefficient DMUs (Wu & Zhou, 2015). DMU$_o$ is efficient if the optimal value of ψ_o is equal to one and the optimal values of input and output slacks are equal to zero (i.e., $s_{io}^{-} = s_{ro}^{+} = 0$). Otherwise, DMU$_o$ is inefficient. Additionally, each inefficient DMU can improve its performance by imitating peers of efficient DMUs (Ramanathan, 2003). To solve models (1) and (2) and obtain their efficiency measures, the two-stage approach can be used (see Saranga, 2009, p.710).

Classical DEA models, including the above two models, are salient tools for efficiency evaluation and provide the efficiency scores for efficient and inefficient DMUs. The performance of an inefficient DMU can be improved using the efficiency projection, projecting each inefficient DMU onto the efficiency frontier constructed by efficient DMUs. The efficiency projection aims to proportionally decrease (increase) inputs (outputs) while maintaining outputs (inputs) at their same levels regarding an oriented DEA model (input or output oriented). However, the projection of oriented models often causes Pareto-inefficient portions of the production frontier (Lins et al., 2004). Consequently, it is difficult for radial models to describe decision makers' preferences. The preferences should consider both projections[1] to decrease inputs and increase outputs simultaneously. Hence, both projections can be obtained by integrating the input-oriented and output-oriented models, i.e., by integrating the objective functions of models (1) and (2) to formulate a non-oriented DEA model dealing with a single objective function, as proposed by Golany and Yu (1997). Their model differs from the studies conducted by Omrani et al. (2018), Goswami and Ghadge (2020) and Jiang et al. (2020), who proposed different versions of bi-objective models dealing with weight restrictions and separate two types of objective functions (i.e., input minimization and output maximization). Their model also differs from other non-oriented DEA models (e.g., Banker et al., 2004; Seiford & Zhu, 1999; Tone, 2001), since it describes decision makers' preferences by integrating the efficiency projections of input-oriented and output-oriented models (i.e., θ_o, ψ_o) into the objective function and input and output constraints to formulate a bi-objective model dealing with a single objective function. By integrating these projections, the model can reduce inputs and increase outputs simultaneously. Therefore, the the objective function of the bi-objective model proposed by Golany and Yu (1997) can be presented in model (3).

$$\min\ \tau_o = \frac{\theta_o}{\psi_o} - \varepsilon\left(\sum_{i=1}^{m} s_{io}^{-} + \sum_{r=1}^{s} s_{ro}^{+}\right) \tag{3}$$

s.t:

constraints (1a), 2(b) and (1c)–1(e).

To solve model (3) and obtain its optimal efficiency measures, the two-stage approach can be used. Stage-1 calculates the input and output projections (i.e., θ_o, ψ_o). The calculated projections are then used in stage-2 to calculate the input and output slacks. The two-stage approach is based on the transfomation of Cooper et al. (2006, p.53) (see also Saranga, 2009, p.710). The technical efficiency score for DMU$_o$ calculated by model (3) is presented using τ_o. The model offers extra efficiency performance from the point of view of both inputs and outputs. The efficiency of DMUs is measured by reducing the level of inputs and/or increasing the level of outputs simultaneously. DMU$_o$ is said to be fully-efficient if and only if $\tau_o = 1$, which is equivalent to all the values of input and output slacks being zero. However, the model of Golany and Yu (1997) did not consider the effect of undesirable factors of inputs and/or outputs on efficiency measures. These factors were considered by many efficiency studies (e.g., Amirteimoori et al., 2006; Färe & Grosskopf, 2004; Jahanshahloo et al., 2005; Vencheh et al., 2005). However, these studies ignored decision makers' preferences. The preferences for the case of undesirable inputs and outputs were later considered in Liu et al. (2010), who combined both oriented BCC models in the presence of undesirable factors. They then proposed a new bi-objective DEA model simultaneously dealing with desirable-undesirable inputs and outputs, as presented in model (4).

$$\min\ \tau_o = \frac{\theta_o}{\psi_o} - \varepsilon\left(\sum_{i\in I^D} s_{io}^{\mathrm{D},-} + \sum_{i\in I^U} s_{io}^{\mathrm{U},+} + \sum_{r\in R^D} s_{ro}^{\mathrm{D},+} + \sum_{r\in R^U} s_{ro}^{\mathrm{U},-}\right) \tag{4}$$

s.t:

$$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_o x_{io} - s_{io}^{\mathrm{D},-}, \qquad i \in I^{\mathrm{D}}, \tag{4a}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} = \psi_o x_{io} + s_{io}^{\mathrm{U},+}, \qquad i \in I^{\mathrm{U}}, \tag{4b}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \psi_o y_{ro} + s_{ro}^{\mathrm{D},+}, \qquad r \in R^{\mathrm{D}}, \tag{4c}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \theta_o y_{ro} - s_{ro}^{\mathrm{U},-}, \qquad r \in R^{\mathrm{U}}, \tag{4d}$$

$$0 < \theta_o \le 1, \quad \psi_o \ge 1, \tag{4e}$$

$$s_{io}^{\mathrm{D},-},\ s_{io}^{\mathrm{U},+},\ s_{ro}^{\mathrm{D},+},\ s_{ro}^{\mathrm{U},-} \ge 0,$$

and constraints (1c)–1(d).

We assume that the inputs and outputs of model (4) can each be partitioned into the subsets of desirable (D) and undesirable (U). Thus, $I = I^{\mathrm{D}} \cup I^{\mathrm{U}}$, $I^{\mathrm{D}} \cap I^{\mathrm{U}} = \varnothing$ and $R = R^{\mathrm{D}} \cup R^{\mathrm{U}}$, $R^{\mathrm{D}} \cap R^{\mathrm{U}} = \varnothing$, where $I = \{1,\ldots, m\}$, $R = \{1,\ldots, s\}$

[1] Projection is the operation where the efficiency of an inefficient DMU is improved by omitting its inputs excess and/or outputs shortfall and decreasing its inputs and/or increasing its outputs (see Cooper et al., 2011; Tone, 2001).

, and m and s are defined as in model (1). The index sets of I^{D}, I^{U}, R^{D} and R^{U} are confined to the desirable and undesirable inputs and outputs.

In many real life settings, some inputs and outputs are restricted to integer values, such as student enrolment and patents at a university and passengers at an airport. The idea of dealing with some inputs and outputs as integer values (commonly known as mixed integer) was first laid out by Lozano and Villa (2006). Their model, however, did not comply with the properties of DEA proposed by Banker et al. (1984) (i.e., convexity condition, returns to scale and free disposability[2]), leading to overestimating the efficiency measures. To obtain accurate efficiency measures, Kuosmanen and Matin (2009) proposed new axioms (natural divisibility and natural disposability) and derived a new production possibility set (PPS) for the BCC model of Banker et al. (1984). The new axioms appropriately classified inputs and outputs into real and integer values, which significantly contributed to the development of a new version of input-oriented model in mixed integer-valued DEA. The model was then extended by Du et al. (2012) for the output-oriented VRS model to deal with an integer valued dataset.

According to Lozano and Villa (2006), the inputs and outputs can be classified into the subsets of non-integer (NI) and integer (IN). Thus, $I = I^{\mathrm{NI}} \cup I^{\mathrm{IN}}, I^{\mathrm{NI}} \cap I^{\mathrm{IN}} = \varnothing$ and $R = R^{\mathrm{NI}} \cup R^{\mathrm{IN}}, R^{\mathrm{NI}} \cap R^{\mathrm{IN}} = \varnothing$, where I and R are defined as in model (4), and I^{NI}, I^{IN}, R^{NI} and R^{IN} are the index sets of real and integer inputs and outputs. The index sets of real and integer inputs (i.e., I^{NI} and I^{IN}), as well as the subsets of real and integer outputs (i.e., R^{NI} and R^{IN}) should be mutually disjoint (i.e., each input or output cannot involve the two conditions of reality and integrality simultaneously) (see Taleb et al., 2018). The integer inputs and outputs are subject to the integrality condition of inputs and outputs without violating the generality (Matin & Kuosmanen, 2009).

By assuming that (X_j, Y_j) as the pairs of input and output vectors of n DMUs, and all data are non-negative but at least one component of every input and output vector is positive (i.e., $X_j \geq 0,\ X_j \neq 0,\ Y_j \geq 0,\ Y_j \neq 0,\ j = 1, \ldots, n$), the PPS of the mixed integer-valued DEA proposed by Lozano and Villa (2006) can be written as follows:

$$\mathrm{PPS} = \left\{ (X_l, Y_l) \middle| X_l^{\mathrm{IN}} \geq \sum_j \lambda_j X_j^{\mathrm{IN}},\ X_l^{\mathrm{NI}} \geq \sum_j \lambda_j X_j^{\mathrm{NI}},\ Y_l^{\mathrm{IN}} \leq \sum_j \lambda_j Y_l^{\mathrm{IN}},\ Y_l^{\mathrm{NI}} \leq \sum_j \lambda_j Y_l^{\mathrm{NI}},\ \sum_j \lambda_j = 1,\ \lambda_j \geq 0, \forall j \right\} \quad (6)$$

where,

$$(X_j^{\mathrm{IN}}, Y_j^{\mathrm{IN}}) \in \left\{ (X_j, Y_j) \middle| X_j \text{ is integer input vector, } Y_j \text{ is integer output vector} \right\},$$

$$(X_j^{\mathrm{NI}}, Y_j^{\mathrm{NI}}) \in \left\{ (X_j, Y_j) \middle| X_j \text{ is real input vector, } Y_j \text{ is real output vector} \right\}.$$

Despite the improvements in dealing with the integer requirements of radial DEA models, some studies (e.g., Du et al., 2012; Kuosmanen & Matin, 2009) ignored the impact of decision makers' preferences on efficiency measures. The preferences and the integer requirements were later integrated into a non-radial model by Wu and Zhou (2015) termed the bi-objective integer-valued DEA model, which is as follows:

$$\min\ \tau_o = \frac{\theta_o}{\psi_o} - \varepsilon \left(\sum_{i \in I^{NI}} s_{io}^{\mathrm{NI},-} + \sum_{i \in I^{IN}} s_{io}^{\mathrm{IN},-} + \sum_{r \in R^{NI}} s_{ro}^{\mathrm{NI},+} + \sum_{r \in R^{IN}} s_{ro}^{\mathrm{IN},+} \right) \quad (7)$$

s.t:

$$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_o x_{io} - s_{io}^{\mathrm{NI},-}, \qquad i \in I^{\mathrm{NI}},$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_o x_{i0} - s_{io}^{\mathrm{IN},-}, \qquad i \in I^{\mathrm{IN}},$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \psi_o y_{ro} + s_{ro}^{\mathrm{NI},+}, \qquad r \in R^{\mathrm{NI}},$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \psi_o y_{ro} + s_{ro}^{\mathrm{IN},+}, \qquad r \in R^{\mathrm{IN}},$$

$$s_{io}^{\mathrm{NI},-},\ s_{io}^{\mathrm{IN},-},\ s_{ro}^{\mathrm{NI},+},\ s_{ro}^{\mathrm{IN},+} \geq 0,$$

and constraints (1c)–1(d) and 4(e).

[2] Free disposability refers to any additional amounts of inputs that can always be reduced without effecting the existing level of outputs (see Liu et al., 2010).

Model (7) considers decision makers' preferences in both formulas of real and integer inputs and outputs to provide the management of DMU$_o$ with accurate efficiency measures. DMU$_o$ is fully-efficient if and only if its efficiency score (i.e., τ_o) is equal to one, which is equivalent to all the slacks of real and integer inputs and outputs being zero ($\tau_o = 1$, $s_{io}^{\mathrm{NI},-} = s_{io}^{\mathrm{IN},-} = s_{ro}^{\mathrm{NI},+} = s_{ro}^{\mathrm{IN},+} = 0$). The non-radial slacks of real and integer inputs and outputs, which are $s_{io}^{\mathrm{NI},-}$, $s_{io}^{\mathrm{IN},-}$, $s_{ro}^{\mathrm{NI},+}$ and $s_{ro}^{\mathrm{IN},+}$, reflect the difference between their reference set (convex combination) and the related inputs or outputs of DMU$_o$ (Du et al., 2012). The two constraints ($0 < \theta_o \le 1$, $\psi_o \ge 1$) guarantee their equivalence to the oriented BCC model. The optimal values of the two projections θ_o and ψ_o obtained from the model's objective function can be used to estimate the RTS of DMU$_o$, as proposed by Golany and Yu (1997).

Position of this paper: Undesirable inputs and outputs (e.g., Liu et al., 2010), and integer requirements (e.g, Wu & Zhou, 2015) of non-radial measurement have been integrated into the bi-objective DEA model (e.g., Golany & Yu, 1997) to estimate RTS. Integrating these factors and requirements into the existing bi-objective models is the aim of this paper. The integration should avoid the existence of any methodological bias, which can be measured by comparing the proposed model with the existing models.

RTS is utalized to categorize the operating region of a DMU under evaluation whether it is operating within the CRS, IRS or DRS region based on the relation between input and output quantities. RTS are considered to be increasing (or decreasing) if a proportional increase in all the inputs results in a more (or less) than proportional increase in the outputs. The initial idea of estimating RTS was first prepared in Banker (1984) and Banker et al. (1984) by imposing a convexity constraint into the CCR model. The constraint ensures that DMUs operated at various scales (CRS, IRS or DRS) are identified as efficient and can be represented by $\sum_{j=1}^{n} \lambda_j = 1$, where λ_j is a scalar, whose value is non-negative. If the efficiency value of CCR model is equal to the efficiency value of BCC model for a DMU under evaluation, the RTS is constant. In this case, $\sum_j \lambda_j = 1$ in any CCR outcome. Otherwise, if these efficiency values are not equal and $\sum_j \lambda_j < 1$ (or $\sum_j \lambda_j > 1$) in any CCR outcome, RTS is increasing (or decreasing). See Seiford and Zhu (1999). The efficient frontier[3] is formed by convex linear combinations of efficient DMUs (Ramanathan, 2003). In terms of VRS, RTS has an unobscured meaning only if a DMU under assessment is on the efficient frontier. On the one hand, CRS of an efficient DMU reflects that any increase in inputs cannot increase efficiency, since this technique assumes that the relationship between the efficiency and the scale of operations is not significant. IRS, meanwhile, reflects that any increase in inputs will produce a high increase in the outputs' level. Any increase in inputs producing a small increase in outputs prevails DRS. On the other hand, the estimation of RTS for an inefficient DMU can be measured if the DMU can be improved to be efficient (Saranga, 2009; Seiford & Zhu, 1999).

The three conditions depend on the most productive scale size (MPSS) of Banker (1984). In this approach, if a DMU is lower than MPSS, then its efficiency can be increased by increasing scale (IRS); otherwise, its efficiency can be increased by decreasing scale (DRS). In contrast, the scale of an efficient DMU can be changed without affecting its efficiency (CRS). However, the issue related to linear dependency (the optimal solution to the formulation of linear programming is unique) has raised with these conditions, as argued by Banker and Thrall (1992) and Zhu and Shen (1995). Thus, Banker and Thrall (1992) proposed a technique to handle the general case of non-unique optimal solutions. The technique requires to knowledge all optimal solutions by solving two auxiliary models of linear programming for DMU$_o$ being evaluated. A simple procedure based upon two formulations of linear programming of the BCC model (input- and output-oriented models) to estimate the RTS was later proposed by Golany and Yu (1997). Their technique differs from previous techniques of RTS, since it depends on the efficiency projections of input reduction and output augmentation (i.e., $0 < \theta_o \le 1$, $\psi_o \ge 1$) obtained by the two oriented models. The model of Golany and Yu (1997) provides a precise classification of RTS (CRS, IRS or DRS).

In the meantime, the concept of RTS with undesirable outputs has been extended by several studies, such as Sueyoshi and Goto (2011b, 2012, 2013), to include environmental performance by proposing Damages to Scale (DTS). The mathematical concepts of DTS and RTS are basically the same. However, they are completely different in their economical implications. For example, in the operational performance of undesirable outputs, the increasing DTS (IDTS) implies that a proportionate increase in inputs results in a greater proportionate increase in undesirable outputs. This indicates that if the operational size of a DMU is increased, then the DMU produces more undesirable outputs—more damages. The operational size of the DMU should, thus, be decreased to enhance its environmental efficiency (Sueyoshi & Goto, 2011a). The decreasing DTS (DDTS), meanwhile, implies that a proportionate increase in inputs

[3] A frontier that is formed by the efficient DMUs being evaluated and envelops all inputs and outputs of the production possibility set (Avkiran, 2001; Taleb et al., 2018, p.20).

results in a less proportionate increase in undesirable outputs. The operational size of the DMU should, thus, be increased to enhace its environmental efficiency.

3. Proposed methodology

Previous studies introduced by Liu et al. (2010), Golany and Yu (1997) and Wu and Zhou (2015) have provided significant contributions to the bi-objective DEA literature. However, no studies have considered the real impact of both undesirable factors and mixed integer values of inputs and outputs on efficiency measures and then classified the region of RTS. To enable the bi-objective model to deal with real-life situations, this paper proposes a methodology to integrate both undesirable factors and integer requirements into model (3) under the weak disposability assumption[4] and then propose a new bi-objective DEA model in the presence of undesirable factors and mixed integer-valued data. Note that weak disposability is imposed to handle the situations where the decrease of any undesirable outputs of a system would typically decrease its other desirable outputs, and the increase of any undesirable inputs would also increase other desirable inputs, as observed in many real-life systems (for example, see the case application in Section 4). If the weak disposability assumption is dropped from the proposed model, the model will then lose its ability to handle the features. However, its contribution to literature will still be new since the model proposes undesirable factors in the context of mixed integer inputs and outputs for measuring returns to scale that has not been considered in previous studies (e.g., Liu et al., 2010; Golany & Yu, 1997; Wu & Zhou, 2015).

Since the inputs and outputs can be classified into the subsets of desirable (good) and undesirable (bad) and mixed integer values, the mathematical description of the proposed model is expressed as follows:

$$
\begin{aligned}
&I = I_{\mathrm{NI}}^{\mathrm{D}} \cup I_{\mathrm{NI}}^{\mathrm{U}} \cup I_{\mathrm{IN}}^{\mathrm{D}} \cup I_{\mathrm{IN}}^{\mathrm{U}},\ I_{\mathrm{NI}}^{\mathrm{D}} \cap I_{\mathrm{NI}}^{\mathrm{U}} = \varnothing,\ I_{\mathrm{IN}}^{\mathrm{D}} \cap I_{\mathrm{IN}}^{\mathrm{U}} = \varnothing \\
&R = R_{\mathrm{NI}}^{\mathrm{D}} \cup R_{\mathrm{NI}}^{\mathrm{U}} \cup R_{\mathrm{IN}}^{\mathrm{D}} \cup R_{\mathrm{IN}}^{\mathrm{U}},\ R_{\mathrm{NI}}^{\mathrm{D}} \cap R_{\mathrm{NI}}^{\mathrm{U}} = \varnothing,\ R_{\mathrm{IN}}^{\mathrm{D}} \cap R_{\mathrm{IN}}^{\mathrm{U}} = \varnothing
\end{aligned} \tag{8}
$$

In expression (8), we partition I as $I = I_{\mathrm{NI}}^{\mathrm{D}} \cup I_{\mathrm{NI}}^{\mathrm{U}} \cup I_{\mathrm{IN}}^{\mathrm{D}} \cup I_{\mathrm{IN}}^{\mathrm{U}}$ and $R = R_{\mathrm{NI}}^{\mathrm{D}} \cup R_{\mathrm{NI}}^{\mathrm{U}} \cup R_{\mathrm{IN}}^{\mathrm{D}} \cup R_{\mathrm{IN}}^{\mathrm{U}}$, where $I_{\mathrm{NI}}^{\mathrm{D}}$ and $R_{\mathrm{NI}}^{\mathrm{D}}$ are the index sets of desirable real inputs and outputs, and $I_{\mathrm{IN}}^{\mathrm{D}}$ and $R_{\mathrm{IN}}^{\mathrm{D}}$ are the index sets of desirable integer inputs and outputs. In addition, $I_{\mathrm{NI}}^{\mathrm{U}}$ and $R_{\mathrm{NI}}^{\mathrm{U}}$ are the index sets of undesirable real inputs and outputs, and $I_{\mathrm{IN}}^{\mathrm{D}}$ and $R_{\mathrm{IN}}^{\mathrm{U}}$ are the index sets of undesirable integer inputs and outputs. The basic assumption of desirable inputs and outputs in DEA models is strong disposability, while the basic assumption of undesirable inputs and outputs is weak disposability. In this paper, the weak disposability assumption of the undesirable inputs and outputs is imposed on the proposed PPS, while the strong disposability assumption is imposed on the desirable inputs and outputs.

The PPS of our proposed model can be considered as an extension of the PPS of the mixed integer-valued DEA proposed by Lozano and Villa (2006) by accommodating it for both undesirable factors and mixed integer-valued data. It can be defined in the same manner as the PPS provided in expression (6).

The PPS should satisfy the following two conditions:

i. Undesirable mixed integer inputs and outputs are weakly disposable
ii. Desirable and undesirable mixed integer inputs and outputs are null-joint[5]

The first condition states the weak disposability assumption for undesirable inputs and outputs, while the second condition states that all undesirable inputs and outputs can be eliminated if and only if the production process of an evaluated DMU is ceased, i.e., producing desirable inputs and/or outputs without simultaneously producing some undesirable inputs and/or outputs is technically infeasible (see Bi et al., 2012; Li & Hu, 2012). For example, the desirable outputs of generated electricity are always accompanied with the undesirable output of sulfur dioxide pollution. Without the pollution, electricity cannot be generated. Additionally, our bi-objective model integrates the objective functions of two oriented BCC models (input- and output-oriented) to deal with a single objective function in terms of undesirable factors and mixed integer-valued data. Hence, the proposed bi-objective model in the context of undesirable factors and mixed integer inputs and outputs is expressed in model (9).

[4] The weak disposability assumption assumes that any increase in undesirable inputs will also increase certain desirable inputs and any decrease in undesirable outputs will also decrease desirable outputs (Lozano et al., 2013). However, the weak or strong disposability assumption in a DEA model must be based on the nature of a case application that it handles (Liu et al., 2010).

[5] From the side of inputs, null-joint reflects that desirable inputs can be accompanied with undesirable inputs, if the former is consumed. From the side of outputs, null-joint reflects that undesirable outputs cannot be produced if the production process is ceased.

$$\min \ \tau_o = \frac{\theta_o}{\psi_o} - \varepsilon\left(\sum_{i\in I_{\text{NI}}^{\text{D}}} s_{io}^{\text{D,NI},-} + \sum_{i\in I_{\text{IN}}^{\text{D}}} s_{io}^{\text{D,IN},-} + \sum_{r\in R_{\text{NI}}^{\text{D}}} s_{ro}^{\text{D,NI},+} + \sum_{r\in R_{\text{IN}}^{\text{D}}} s_{ro}^{\text{D,IN},+}\right) \quad (9)$$

s.t:

$$\sum_{j=1}^{J}\lambda_j x_{ij} = \theta_o x_{i0} - s_{io}^{\text{D,NI},-}, \qquad i\in I_{\text{NI}}^{\text{D}},$$

$$\sum_{j=1}^{J}\lambda_j x_{ij} \le \theta_o x_{i0} - s_{io}^{\text{D,IN},-}, \qquad i\in I_{\text{IN}}^{\text{D}},$$

$$\sum_{j=1}^{J}\lambda_j x_{ij} = \psi_o x_{io}, \qquad i\in I_{\text{NI}}^{\text{U}},$$

$$\sum_{j=1}^{J}\lambda_j x_{ij} \ge \psi_o x_{io}, \qquad i\in I_{\text{IN}}^{\text{U}},$$

$$\sum_{j=1}^{J}\lambda_j y_{rj} = \psi_o y_{ro} + s_{ro}^{\text{D,NI},+}, \qquad r\in R_{\text{NI}}^{\text{D}},$$

$$\sum_{j=1}^{J}\lambda_j y_{rj} \ge \psi_o y_{ro} + s_{ro}^{\text{D,IN},+}, \qquad r\in R_{\text{IN}}^{\text{D}},$$

$$\sum_{j=1}^{J}\lambda_j y_{rj} = \theta_o y_{ro}, \qquad r\in R_{\text{NI}}^{\text{U}},$$

$$\sum_{j=1}^{J}\lambda_j y_{rj} \le \theta_o y_{ro}, \qquad r\in R_{\text{IN}}^{\text{U}},$$

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

$$\lambda_j \ge 0, \qquad j = 1,\ldots,J,$$

$$s_{io}^{\text{D,NI},-},\ s_{io}^{\text{D,IN},-},\ s_{ro}^{\text{D,NI},+},\ s_{ro}^{\text{D,IN},+} \ge 0$$

As considered in Section 2, ε is a very small positive value[6]. θ_o and ψ_o denote the two projections having a salient role in measuring efficiency from both sides of the reduction in desirable inputs and undesirable outputs, as well as the augmentation in desirable outputs and undesirable inputs. Hence, these projections provide extra performance by simultaneously dealing with a single objective function of input minimization and output maximization. Therefore, the best improvement in the productivity of DMU*o* (i.e., technical and scale efficiency) can be found by minimizing the ratio $\frac{\theta_o}{\psi_o}$ or maximizing its reciprocal $\frac{\psi_o}{\theta_o}$. In this case, θ_o is to reduce the slacks of desirable inputs, while ψ_o is to augment the slacks of desirable outputs, subject to the constraints defining PPS. The non-radial slacks of desirable real and integer inputs and outputs are denoted by $s_{io}^{\text{D,NI},-}$, $s_{io}^{\text{D,IN},-}$, $s_{ro}^{\text{D,NI},+}$ and $s_{ro}^{\text{D,IN},+}$. These slacks reflect the difference between the model's convex combination of desirable mixed integer inputs and outputs and related inputs and outputs. Observe that undesirable output slacks are not included in model (9). The reason for not including the undesirable slacks of inputs and outputs is that model (9) has been formulated under weak disposability of undesirable factors to ensure that any increase in undesirable inputs will increase desirable inputs, and any decrease in undesirable outputs will also decrease desirable outputs. This assumption suits the nature of undesirable inputs and outputs in many real-life applications, e.g., the considered case application in Section 4.

All these projections and slacks represent the optimal values to model (9). The efficiency scores of the model are computed based on the slacks of desirable inputs and outputs. The slacks provide the obvious view on which variables cause an evaluated DMU to be technically inefficient. With the results of these slacks, the directions for improvement are easily obtained for each desirable input and output. Note that the constraints of desirable and undesirable integer inputs and outputs are formulated as inequalities, since the convex combinations of the efficient frontier are not always to be integer values. The reference targets of desirable and undesirable integer inputs and outputs need not to be equal to their projections on the efficient frontier. However, they must be controlled by their convex combinations of efficient DMUs (see Chen et al., 2012; Taleb et al., 2018). Hence, the reference set of the integer DEA model is free from integer conditions (Du et al., 2012). Additionally, since model (9) imposes the weak disposability assumption on undesirable inputs and outputs, as considered in formula (9), the constraints of real inputs and outputs are formulated to be as equality. The equality form of the undesirable input and output constraints makes the current level of undesirable input and output

[6] In this study we assumed that $\varepsilon = 10^{-6}$. However, we further use the two-stage procedure to double check the provided results and make sure that there are no any erroneous results by replacing $\varepsilon = 10^{-6}$ (see Appendix A).

of a DMU being evaluated is the same as that of the reference set (linear combination) of other DMUs. Therefore, the slacks of inputs and outputs are eliminated from these constraints. Note that model (9) is proposed under the technology of VRS, since it assumes that any increase in inputs will cause an increase in outputs disproportionately.

Definition 1. A DMU$_o$ evaluated by model (9) is said to be fully-efficient if and only if its efficiency score is equal to one, $\tau_o = 1$. This condition is equivalent to all slacks being to zero. Otherwise, DMU$_o$ is inefficient. Thus, performance of an inefficient DMU$_o$ should be appropriately improved by decreasing its desirable (undesirable) inputs (outputs) and increasing its desirable (undesirable) outputs (inputs).

In model (9), the accurate efficiency scores and targets can be derived in both mixed integer requirements and desirable and undesirable factors. The value of τ_o is less than or equal to one, and DMU$_o$ is efficient if and only if $\tau_o = 1$.

Remark 1. It can be noted that the efficiency values of model (9) are mostly less than the efficiency values of existing model (4) of Liu et al. (2010). In model (4), all the values of desirable and undesirable inputs and outputs were assumed to be considered as real values. Meanwhile, by integrating mixed integer desirable and undesirable inputs and outputs in model (9) and adding the relevant constraints into the model in comparison with model (4), it is expected that the efficiency scores of model (9) to be less than the efficiency scores provided by model (4). However, it would be possible that the efficiency values in model (9) be equal to or greater than the efficiency measures of model (4) in certain cases (see the efficiency results of model (9) and the efficiency values of the model of Liu et al. (2010) reported in Table 3).

Up to this point, the efficiency measures of model (9) have been identified. In model (9), the two projections (θ_o, ψ_o) are to reduce desirable inputs and increase desirable outputs simultaneously. Besides, these projections have a vital role in estimating the RTS region of DMU$_o$. Figure 1 displays four identified regions of RTS in the two dimensional space θ_o and ψ_o.

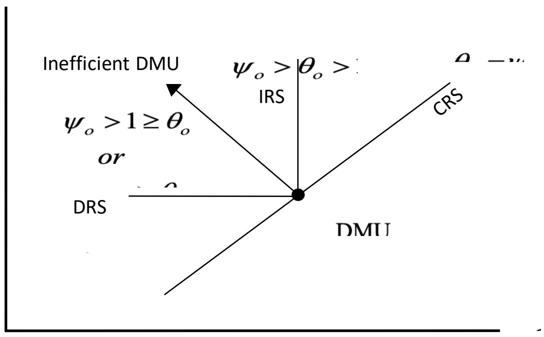

Figure 1. Projection regions of RTS for DMU$_o$ (Source: Golany and Yu (1997))

Hence, in terms of undesirable factors and mixed integer requirements, the projection regions of RTS estimated by model (9) can be identified as follows:

a) $1 > \psi_o > \theta_o$ indicates that RTS is decreasing
b) $\psi_o > \theta_o > 1$ indicates that RTS is increasing
c) $\theta_o = \psi_o$ indicates that RTS is constant
d) $\psi_o > 1 \geq \theta_o$ or $\psi_o \geq 1 > \theta_o$ indicates that evaluated DMU$_o$ is technically inefficient

In region (a), the values of both projections are smaller than one, and θ_o is absolutely smaller than ψ_o. This means that the PPS of DMU$_o$ is feasible. The feasibility can be achieved when DMU$_o$ uses fewer desirable inputs to produce less desirable outputs. To do so, DMU$_o$ reduces desirable inputs by a large factor than the reduction in the desirable outputs (i.e., DRS situation). Meanwhile, DMU$_o$ is projected on the region of IRS when it uses a small level of desirable inputs to produce more desirable outputs. To achieve this, it decreases desirable inputs by a small factor than the expansion in the desirable outputs. Since the features of desirable factors are opposite to that of undesirable factors, the DRS situation can also be identified in terms of undesirable factors, when DMU$_o$ uses fewer undesirable inputs to produce less undesirable outputs. However, in doing so, it decreases undesirable outputs by a large factor than the expansion in the undesirable inputs. IRS for undesirable factors can be identified when DMU$_o$ uses more undesirable inputs to produce less undesirable outputs by increasing undesirable inputs by a large factor than the reduction in the undesirable outputs.

In contrast, efficient DMU$_o$ is projected on CRS when both projections of decreasing (increasing) desirable inputs (desirable outputs) or increasing (decreasing) undesirable inputs (undesirable outputs) are equal to one. To obtain the efficiency scores and reference targets for the efficient and inefficient DMUs evaluated by model (9), we run a two-stage approach, as presented in Appendix B. Model (9) that integrates undesirable inputs and outputs with mixed integer-valued data and estimates RTS involves three scenarios, as shown in Figure 2.

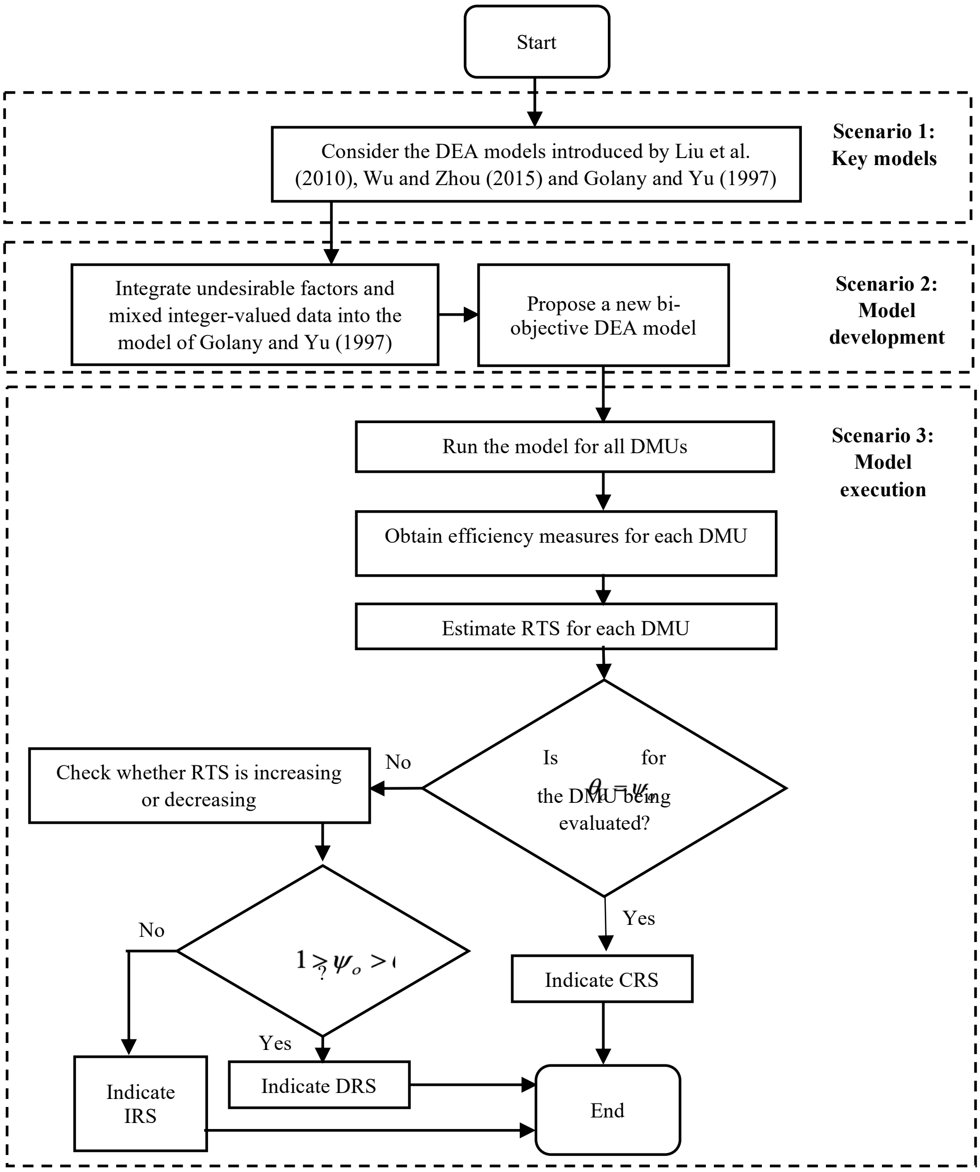

Figure2. Flowchart of the new bi-objective DEA model

4. Case application

To test the applicability and usefulness of model (9), this paper utilises the dataset of 39 Spanish airports retrieved from a study conducted by Lozano et al. (2013). Each airport is an independent DMU utilising five inputs and five outputs. The resources related to the desirable integer inputs of the airports are apron capacity (APRON), total run way (RUNAREA), the number of baggage belts (BAGB), the number of gates (BOARDG) and the number of check-in counters (CHECKIN). The outputs are classified into two classes: desirable and undesirable mixed integer values. The desirable integer outputs are aircraft traffic movements (ATM), annual passenger movement (APM), while a real desirable output is cargo handled (CARGO). The integer and real undesirable outputs are the number of delayed flights (NDF) and accumulated flight delays (AFD). More details about the units of measurement and the variable description can be found in Lozano and Gutiérrez (2011) and Lozano et al. (2013). Based on the input and output variables, the efficiency of the airports was then calculated using model (9), as considered in the next subsection.

4.1 Numerical results

To calculate the efficiency measures[7] of the 39 airports, stage-1 of model (9) considered in model (B.1), Appendix B was first run. Depending on the efficiency measures obtained from stage-1, stage-2 was then run to calculate the slacks of the considered desirable mixed integer inputs and outputs. The resulted measures calculated under the assumption of VRS are outlined in Table1.

Table 1. Efficiency measures of the proposed bi-objective DEA model

DMUs	Efficiency scores	Desirable input slacks					Desirable output slacks		
		APRON	RUNAREA	BAGB	BOARDG	CHECKIN	ATM	APM	CARGO
1	0.8512	0	25311	1	0	3	0	0	0
2	0.6024	0	223788	0	1	0	0	212	215.0789
3	1	0	0	0	0	0	0	0	0
4	0.5681	10	136548	2	0	0	0	0	6691.7370
5	0.8142	0	109740	2	10	0	0	0	7833.8890
6	0.7281	0	1185341	4	10	18	0	392	104.0687
7	1	0	0	0	0	0	0	0	0
8	0.7680	0	21237	0	0	3	0	0	8.1222
9	1	0	0	0	0	0	0	0	0
10	1	0	0	0	0	0	0	0	0
11	0.8510	16	49211	2	0	0	5	0	2007.5710
12	1	0	0	0	0	0	0	0	0
13	1	0	0	0	0	0	0	0	0
14	1	0	0	0	0	0	0	0	0
15	1	0	0	0	0	0	0	0	0
16	1	0	0	0	0	0	0	0	0
17	1	0	0	0	0	0	0	0	0
18	1	0	0	0	0	0	0	0	0
19	0.8793	0	121	0	2	13	0	0	2297.7730
20	0.4622	11	295166	1	3	0	0	926	1421.3550
21	1	0	0	0	0	0	0	0	0
22	1	0	0	0	0	0	0	0	0
23	1	0	0	0	0	0	0	0	0
24	1	0	0	0	0	0	0	0	0
25	1	0	0	0	0	0	0	0	0
26	0.8562	0	138809	0	0	0	0	430	0
27	1	0	0	0	0	0	0	0	0
28	0.7691	0	255052	2	0	0	0	818	63.3338
29	0.5424	0	29057	0	0	0	0	0	0
30	0.7115	0	34297	0	1	0	0	0	825.7285
31	0.6108	17	340427	4	15	6	0	353	6484.7750
32	1	0	0	0	0	0	0	0	0
33	1	0	0	0	0	0	0	0	0
34	1	0	0	0	0	0	0	0	0
35	1	0	0	0	0	0	0	0	0
36	1	0	0	0	0	0	0	0	0
37	0.4515	0	144177	0	1	0	0	0	737.4973
38	0.6391	0	38346	0	0	0	0	0	1191.5830
39	1	0	0	0	0	0	0	0	0

To achieve the efficiency status, each airport should increase its desirable outputs and decrease its desirable inputs simultaneously or reduce its undesirable outputs, which in turns decreases some desirable outputs (i.e., weak disposability). The increase (decrease) of undesirable inputs (outputs) cannot occur without sacrificing other inputs and outputs. Otherwise, if the level of undesirable inputs and/or outputs is immoderate, the airport will be considered as inefficient and potential improvement needs to be computed. The efficiency score τ_o, the desirable integer input slack ($s_{io}^{\mathrm{D,IN},-}$) and the desirable mixed integer output slacks ($s_{ro}^{\mathrm{D,NI},+}$, $s_{ro}^{\mathrm{D,IN},+}$) calculated by model (9) for each airport are revealed in Table 1. Note that Table 1 does not show the slacks of integer and real undesirable outputs, NDF and AFD, since both of the slacks have been ignored in the objective function and constraints of model (9). The main reason for this is that model (9) imposes the weak disposability assumption of undesirable outputs. As defined in Definition 1, the slacks of desirable mixed integer inputs and outputs of each efficient DMU are equal to zero, while some or all input and output slacks of each inefficient DMU are positive values.

The overall efficiency scores of the airports range from 0.4515 to 1.00 with the average of 0.8744. As observed, 23 out of the total 39 airports are efficient, while the other 16 airports are inefficient. For inefficient airports, the average efficiency score is 0.6940. The obtained results are remarkable, since 23 airports (i.e., 58.97%) are technical efficient,

[7] The calculation of efficiency measures was performed using Lingo software version 14.

and the efficiency scores of most of the inefficient airports are relatively high. To assist the inefficient airports identify their benchmarks, model (9) provides their potential improvement in the context of desirable and undesirable mixed integer inputs and outputs. As shown in Table 1, the inefficiencies are related to desirable mixed integer input and output of their run areas and cargos handled. These input and output reflect the main sources of inefficiency. The excesses (and shortfalls) in the desirable input and output should properly be managed by the airport management.

Identifying the operational region of RTS for the airports, determining the operational behaviour of their inputs and outputs, would be helpful for decision makers. Based on the four conditions of RTS in Section 3, the projections of desirable (undesirable) input (output) reduction and desirable (undesirable) output (input) augmentation in the presence of mixed integer-valued data were calculated using model (B.1) in Appendix B. The model simultaneously minimizes the projections of desirable inputs and undesirable outputs while maximizing the projections of desirable output and undesirable inputs. The optimal values of these two projections for the airports are reported in Table 2.

Table 2. Returns to scale identification for 39 Spanish airports

DMU	θ_o	ψ_o	RTS
1	1.5727	1.8475	Increasing
2	1.6293	2.7043	Increasing
3	1	1	Constant
4	1.8990	3.3425	Increasing
5	2.4042	2.9527	Increasing
6	7.5191	10.1599	Increasing
7	1	1	Constant
8	0.6672	0.8684	Decreasing
9	1	1	Constant
10	1	1	Constant
11	1.2633	1.4845	Increasing
12	1	1	Constant
13	1	1	Constant
14	1	1	Constant
15	1	1	Increasing
16	1	1	Constant
17	1	1	Constant
18	1	1	Constant
19	1.2619	1.4335	Increasing
20	3.9871	6.1609	Increasing
21	1	1	Constant
22	1	1	Constant
23	1	1	Constant
24	1	1	Constant
25	1	1	Constant
26	2.2896	2.6312	Increasing
27	1	1	Constant
28	2.3007	2.9811	Increasing
29	1.6488	3.0380	Increasing
30	1.3082	1.8296	Increasing
31	3.0363	3.1598	Increasing
32	1	1	Constant
33	1	1	Constant
34	1	1	Constant
35	1	1	Constant
36	1	1	Constant
37	1.3758	2.9522	Increasing
38	1.4525	2.2586	Increasing
39	1	1	Constant

Table 2 presents the classification of RTS for efficient and inefficient airports. Observe that 23 airports are classified in the CRS region, since they are efficient, and their projections of desirable-undesirable inputs and outputs are equal to one. 15 inefficient airports are functioned in the IRS region, while only one inefficient airport is operated in the DRS region. Thus, IRS represents the appropriate operating region for the majority of the VRS inefficient Spanish airports. This implies that the scale level of most of the inefficient airports is not optimal. Hence, the airports operated in the IRS region have excess capacities. Any additional unit of desirable inputs and/or undesirable outputs will cause a high increase in the desirable outputs and/or undesirable inputs. Thus, the airports operated in the IRS region need to focus on their operations to fairly increase (decrease) desirable (undesirable) outputs to achieve most productive scale size (Banker, 1984). In the same context, any increase in the desirable inputs and/or undesirable outputs which could cause a small increase in the desirable outputs and/or undesirable inputs simultaneously can be denoted by DRS. The desirable (undesirable) outputs of the DRS airport should appropriately be increased (decreased). All these efficiency measures have been obtained in terms of desirable-undesirable factors and mixed integer-valued data. Thus, the importance of proposing these factors into the existing bi-objective DEA models needs to be illustrated.

4.2 Illustration and validation of the proposed model

To illustrate the main difference between model (9) and the studies conducted by Golany and Yu (1997), Liu et al. (2010) and Wu and Zhou (2015) in terms of efficiency scores and RTS, model (9) considers three specific aspects (i.e., undesirable factors, integer-valued data and RTS). The efficiency scores and RTS classification obtained from model (9) and the three existing models were calculated and shown in Table 3.

Table 3. Efficiency measures of the proposed model and the existing models

DMU	Efficiency scores of model (9)	Efficiency scores of the model of Golany and Yu (1997)	Efficiency scores of the model of Liu et al. (2010)	Efficiency scores of the model of Wu and Zhou (2015)	RTS of model (9)	RTS of the model of Golany and Yu (1997)	RTS of the model of Liu et al. (2010)	RTS of the model of Wu and Zhou (2015)
1	0.8512	0.9125	0.9623	1	Increasing	Increasing	Inefficient	Constant
2	0.6024	0.2017	1	0.3791	Increasing	Increasing	Constant	Inefficient
3	1	1	1	1	Constant	Constant	Constant	Constant
4	0.5681	0.4357	0.5749	0.4395	Increasing	Increasing	Inefficient	Inefficient
5	0.8142	0.7072	0.8690	0.7727	Increasing	Increasing	Inefficient	Inefficient
6	0.7281	0.7516	1	1	Increasing	Increasing	Constant	Constant
7	1	1	1	1	Constant	Constant	Constant	Constant
8	0.7680	0.8170	0.7863	0.8170	Decreasing	Increasing	Inefficient	Inefficient
9	1	1	1	1	Constant	Constant	Constant	Constant
10	1	0.3209	1	1	Constant	Constant	Constant	Constant
11	0.8510	0.6393	0.8511	0.6393	Increasing	Increasing	Inefficient	Inefficient
12	1	1	1	1	Constant	Constant	Constant	Constant
13	1	1	1	1	Constant	Constant	Constant	Constant
14	1	0.7863	1	0.9375	Constant	Increasing	Constant	Inefficient
15	1	1	0.7934	1	Constant	Constant	Inefficient	Constant
16	1	1	1	1	Constant	Constant	Constant	Constant
17	1	0.2014	1	0.6745	Constant	Increasing	Constant	Inefficient
18	1	0.8794	1	1	Constant	Increasing	Constant	Constant
19	0.8793	0.7668	0.8502	0.8032	Increasing	Increasing	Inefficient	Inefficient
20	0.4622	0.6034	1	1	Increasing	Increasing	Constant	Constant
21	1	1	1	1	Constant	Constant	Constant	Constant
22	1	1	1	1	Constant	Constant	Constant	Constant
23	1	0.7042	1	1	Constant	Increasing	Constant	Constant
24	1	1	1	1	Constant	Constant	Constant	Constant
25	1	1	1	1	Constant	Constant	Constant	Constant
26	0.8562	0.9120	1	1	Increasing	Increasing	Constant	Constant
27	1	1	1	1	Constant	Constant	Constant	Constant
28	0.7691	0.8143	1	1	Increasing	Increasing	Constant	Constant
29	0.5424	0.6172	0.6256	0.8168	Increasing	Increasing	Inefficient	Inefficient
30	0.7115	0.7040	0.7290	0.7398	Increasing	Increasing	Inefficient	Inefficient
31	0.6108	0.4501	0.6576	0.4539	Increasing	Increasing	Inefficient	Inefficient
32	1	1	1	1	Constant	Constant	Constant	Constant
33	1	0.8813	1	0.9015	Constant	Decreasing	Constant	Inefficient
34	1	1	1	1	Constant	Constant	Constant	Constant
35	1	0.7592	1	0.7761	Constant	Increasing	Constant	Inefficient
36	1	1	1	1	Constant	Constant	Constant	Constant
37	0.4515	0.5083	0.4775	0.5748	Increasing	Increasing	Inefficient	Inefficient
38	0.6391	0.6704	0.6622	0.7448	Increasing	Increasing	Inefficient	Inefficient
39	1	1	1	1	Constant	Constant	Constant	Constant

Compared to Golany and Yu (1997), for most of the airports, model (9) produces greater or equal efficiency scores except for ten airports, i.e., DMU1, DMU6, DMU8, DMU20, DMU26, DMU28, DMU29, DMU30, DMU37 and DMU38. Additionally, model (9) improved the solution by registering some inefficient airports obtained from those provided by the models of Golany and Yu (1997), Liu et al. (2010), and Wu and Zhou (2015) as efficient. This illustrates that a DMU can increase its performance when undesirable factors are integrated with integer requirements. As a result, model (9) reported that 23 airports are efficient compared to the model of Golany and Yu (1997) of only 16 airports being efficient. The average efficiency scores of all airports in model (9) (0.8744) is greater than that of the model of Golany and Yu (1997) (0.7960).

Due to imposing the two additional constraints of input reduction and output augmentation into the model of Liu et al. (2010), its resulted efficiency scores are greater than or equal to that of model (9) (see Remark 1). Thus, there is a higher number of efficient airports under the model of Liu et al. (2010), i.e., 27 of the total 39 airports. Similarly, most of the efficiency scores calculated by model (9) are less than or equal to that of the model of Wu and Zhou (2015). As such, the efficiency scores of 29 airports reported by the the model of Wu and Zhou (2015) are greater than or equal to that of model (9). This is because Wu and Zhou (2015) impose additional constraints for the two projections of input reduction and output augmentation. We illustrate that imposing projections of input reduction and output augmentation into these two existing models could increase the efficiency scores. Therefore, the following remark can be deduced:

Remark 2. The technical efficiency score τ_o identified from the integrated bi-objective in model (9) is mostly less than or equal to the technical efficiency score identified from the existing models, i.e., Liu et al. (2010), and Wu and Zhou (2015). The main reason for this is that model (9) simultaneously deals with undesirable factors and integer requirements, reflecting the consistency of model (9) with underlying technology of these factors and requirements. Besides, the constraints of model (9) assure that production of the reference group is feasible.

Moreover, the validation of model (9) in terms of RTS was also measured. The RTS regions estimated by model (9) and the three existing models are presented in Table 3. It can be observed that the RTS regions obtained by model (9) and the model of Golany and Yu (1997) are almost the same, since both models apply the same features in calculating the projections of input reduction and output augmentation for RTS identification. Out of the 39 airports, only seven airports have changed their RTS regions. For example, inefficient DMUs 14 and 17 improve their performance to be efficient units in model (9). For this, their RTS regions have changed from IRS to CRS. As described, the efficiency scores of the airports calculated by model (9) are mostly smaller or equal to that obtained from Liu et al. (2010). As a result, 16 airports have changed their RTS regions. Additionally, as considered in Remark 2, the efficiency scores calculated by model (9) are mostly less than or equal to that obtained from the bi-objective model of Wu and Zhou (2015). However, the models of Golany and Yu (1997) and Liu et al. (2010) cannot identify the RTS of inefficient DMUs. Contrastingly, model (9) can identify the RTS of all inefficient DMUs (i.e., IRS or DRS) because it does not impose additional constraints to identify projections of input reduction and output augmentation.

5. Conclusions

Some inputs and outputs in many settings are simultaneously undesirable factors with mixed integer-valued data. This situation cannot be handled by classical DEA models that consider all inputs and outputs are desirable factors and real-valued data. For this, their reference targets are likely to be desirable and real values, limiting their implementation in real settings. Thus, this paper proposes a new bi-objective DEA model that can simultaneously handle undesirable factors and mixed integer values of inputs and outputs. The undesirable factors and integer requirements were integrated into the standard bi-objective model to obtain more precise efficiency scores and reference targets. The proposed model was run on a data set of flight delays resulting from airport traffic overcrowding to evaluate the efficiency of 39 Spanish airports in the year 2008. Each airport was considered as an independent DMU, whose efficiency score and inputs-output slacks should be calculated to improve its performance. The model is novel for two reasons. First, it simultaneously integrates undesirable factors and mixed integer inputs and outputs to estimate RTS for efficient and inefficient DMUs. Second, it evaluates the efficiency of a real life setting, i.e., an airport system where these factors are to be taken into account to accurately evaluate its efficiency which has not been considered in the literature.

Additionally, the model has contributed to the literature in the context of estimating RTS, since it can identify RTS of efficient and inefficient DMUs by identifying four conditions of RTS classification in the presence of undesirable factors and mixed integer values. The four conditions depend on the projections of input reduction and output augmentation. Hence, the regions of RTS for airports have been identified under the VRS technique. Efficient airports are identified under the CRS region, while inefficient airports are identified under the DRS or IRS region. The results of RTS show that most of the inefficient airports are classified under IRS, implying that their scale level is not optimal.

To measure the effect of integrating the undesirable factors and mixed integer values of inputs and outputs on an organization's activities, particularly in airport operations, we illustrate the validity of the model by comparing its efficiency measures with that obtained from the existing models, conducted by Golany and Yu (1997), Liu et al. (2010) and Wu and Zhou (2015). These existing models did not take into account the simultaneous effect of undesirable factors and mixed integer requirements on efficiency measures, producing inaccurate efficiency evaluation. Compared to the bi-objective model of Golany and Yu (1997), the proposed model mostly calculated greater or equal efficiency scores, revealing the significance of integrating undesirable factors and mixed integer values. In contrast, the efficiency scores resulting from the proposed model were mostly less than or equal to that resulting from the bi-objective model of Liu et al. (2010) and were most likely to be less than or equal to that resulting from the bi-objective model of Wu and Zhou (2015). The main reason is that the models of Liu et al. (2010) and Wu and Zhou (2015) impose two additional constraints to determine the parameter values of inputs reduction and outputs augmentation. Meanwhile, the values of these projections can be easily determined using the proposed model and the model of Golany and Yu (1997). Therefore, the classification of the RTS for most DMUs resulting from the bi-objective models of Liu et al. (2010) and Wu and Zhou (2015) is relatively different to that of the proposed model, while the RTS resulting from the existing model of Golany and Yu (1997) is most likely similar with that of the proposed model.

The proposed model can simultaneously deal with mixed integer desirable and undesirable inputs and outputs. However, due to the unavailability of undesirable inputs in the dataset, this paper only dealt with mixed integer desirable inputs and desirable and undesirable outputs of Spanish airports. A specific feature of the proposed model considers inputs that are beyond the control of a DMU (i.e., non-discretionary). This means that the DEA model should not reduce inputs below their current level. Another direction of this paper would be to explore a network DEA model dealing with undesirable factors and integer requirements. Besides that, future studies can capture the dynamic nature of DMUs with panel data rather than cross-sectional data.

Appendix A. How to deal with ε if it leads to any erroneous results.

We first consider the following VRS model (Banker et al., 1984):

$$
\begin{aligned}
&\min\ \theta_o, && && \text{(A.1)}\\
&\text{s.t:}\\
&\sum_{j=1}^{n}\lambda_j x_{ij} = \theta_o x_{io} - s_{io}^-, && i = 1, \ldots, m,\\
&\sum_{j=1}^{n}\lambda_j y_{rj} = y_{ro} + s_{ro}^+, && r = 1, \ldots, s,\\
&\sum_{j=1}^{n}\lambda_j = 1,\\
&\lambda_j \geq 0, && j = 1, \ldots, n,\\
&s_{io}^-,\ s_{ro}^+ \geq 0,
\end{aligned}
$$

which is employed for stage I. Assuming that θ_o^* is the optimal value of θ_o in linear programming model (A.1), we further consider stage II, in which the slacks are maximized in the following model:

$$
\begin{aligned}
&\max\left(\sum_i s_{io}^- + \sum_r s_{ro}^+\right), && && \text{(A.2)}\\
&\text{s.t:}\\
&\sum_{j=1}^{n}\lambda_j x_{ij} = \theta_o^* x_{io} - s_{io}^-, && i = 1, \ldots, m,\\
&\sum_{j=1}^{n}\lambda_j y_{rj} = y_{ro} + s_{ro}^+, && r = 1, \ldots, s,\\
&\sum_{j=1}^{J}\lambda_j = 1,\\
&\lambda_j \geq 0, && j = 1, \ldots, n,\\
&s_{io}^-,\ s_{ro}^+ \geq 0,
\end{aligned}
$$

where θ_o^* is the value obtained by solving model (A.1) in Phase I. DMU$_o$ is fully efficient if θ_o^* is equal to one and the optimal values of the slacks (i.e., $s_{io}^-, s_{ro}^+\ \forall i, j$) in model (A.2) are equal to zero. If we want to join models (A.1) and (A.2) together in a single objective, the VRS in model (1) can be considered (see Cooper, Seiford, & Tone, 2000). In this study, we assumed that $\varepsilon = 10^{-6}$. However, we cannot deduce that a small value of ε yields accurate results, since it depends on a data set (see Ali & Seiford, 1993, p.293; Cooper et al., 2006, p. 70-71). In certain cases, it may lead to erroneous results by replacing $\varepsilon = 10^{-6}$. We further use the two-stage procedure similar to the above mentioned procedure in our proposed method which accomplishes all that is required. In this case, we will be able to double check the results provided by replacing $\varepsilon = 10^{-6}$ and make sure that there is no any erroneous results (see Cooper, Seiford, & Tone, 2000).

Appendix B

Stage-1

$$
\min\ \frac{\theta_o}{\psi_o} \qquad \text{(B.1)}
$$

s.t:

$$
\begin{aligned}
&\sum_{j=1}^{J} \lambda_j x_{ij} \le \theta_o x_{io}, && i \in I_{\mathrm{NI}}^{\mathrm{D}},\\
&\sum_{j=1}^{J} \lambda_j x_{ij} \le \theta_o x_{io}, && i \in I_{\mathrm{IN}}^{\mathrm{D}},\\
&\sum_{j=1}^{J} \lambda_j x_{ij} = \psi_o x_{io}, && i \in I_{\mathrm{NI}}^{\mathrm{U}},\\
&\sum_{j=1}^{J} \lambda_j x_{ij} \ge \psi_o x_{io}, && i \in I_{\mathrm{IN}}^{\mathrm{U}},\\
&\sum_{j=1}^{J} \lambda_j y_{rj} \ge \psi_o y_{ro}, && r \in R_{\mathrm{NI}}^{\mathrm{D}},\\
&\sum_{j=1}^{J} \lambda_j y_{rj} \ge \psi_o y_{ro}, && r \in R_{\mathrm{IN}}^{\mathrm{D}},\\
&\sum_{j=1}^{J} \lambda_j y_{rj} = \theta_o y_{ro}, && r \in R_{NI}^{D},\\
&\sum_{j=1}^{J} \lambda_j y_{rj} \le \theta_o y_{ro}, && r \in R_{\mathrm{IN}}^{\mathrm{U}},\\
&\sum_{j=1}^{J} \lambda_j = 1, &&\\
&\lambda_j \ge 0, && j = 1, \ldots, J
\end{aligned}
$$

Stage-1 determines the efficiency value, θ_o and ψ_o for DMU$_o$ being evaluated.

Stage-2

Stage-2 determines the maximum value of the sum of desirable mixed integer input excess and desirable mixed integer output shortfalls for DMU$_o$. Thus, the mathematical formula of stage-2 is the same of that presented in model (9). In this two-stage bi-objective model, DMU$_o$ is considered as fully-efficient if and only if (i) $\tau_o = 1$, and (ii) all desirable inputs and outputs slack are equal zero. If only condition (i) is satisfied, then DMU_o is termed as weakly-efficient. If conditions (i) and (ii) are not prevail, then DMU$_o$ is technically inefficient.

To solve Stage-1 and Stage-2, the transformation of Cooper et al. (2006) is used. For example, the Lingo statements for DMU1 are as follows:

Stage-1 for DMU1

```
min = t1/t2 ;

5 * x1 + 2 * x2 + . . . + 18 * x39 <= t1 * 5;
87300 * x1 + 162000 * x2 + . . . + 157500 * x39 <= t1 * 87300;
3 * x1 + x2 + . . . + 2 * x39 <= t1 * 3;
4 * x1 + 2 * x2 + . . . + 3 * x39 <= t1 * 4;
10 * x1 + 4 * x2 + . . . + 7 * x39 <= t1 * 10;
17.719 * x1 + 2.113 * x2 + . . . + 12.225 * x39 >= t2 * 17.719;
1174.970 * x1 + 19.254 * x2 + . . . + 67.818 * x39 >= t2 * 1174.970;
283.571 * x1 + 8.924 * x2 + . . . + 34989.727 * x39 >= t2 * 283.571;
1218 * x1 + 58 * x2 + . . . + 669 * x39 <= t1 * 1218;
23783.4 * x1 + 1376.5 * x2 + . . . + 11585.8 * x39 <= t1 * 23783.4;
x1 + x2 + . . . + x39 = 1;
```

Stage-2 for DMU1

```
min = 0.851 - 0.000001 * ((DIIS1 + DIIS2 + DIIS3 + DIIS4 + DIIS5 + DIOS1 + DIOS2 + DROS1));

5 * x1 + 2 * x2 + . . . + 18 * x39 <= (t1 * 5) - DIIS1;
87300 * x1 + 162000 * x2 + . . . + 157500 * x39 <= (t1 * 87300) - DIIS2;
3 * x1 + x2 + . . . + 2 * x39 <= (t1 * 3) - DIIS3;
```

```
4 * x1 + 2 * x2 + . . . + 3 * x39 <= (t1 * 4) - DIIS4;
10 * x1 + 4 * x2 + . . . + 7 * x39 <= (t1 * 10) - DIIS5;
17.719 * x1 + 2.113 * x2 + . . . + 12.225 * x39 >= (t2 * 17.719) + DIOS1;
1174.970 * x1 + 19.254 * x2 + . . . + 67.818 * x39 >= (t2 * 1174.970) + DIOS2;
283.571 * x1 + 8.924 * x2 + . . . + 34989.727 * x39 = (t2 * 283.571) + DROS1;
1218 * x1 + 58 * x2 + . . . + 669 * x39 <= (t1 * 1218);
23783.4 * x1 + 1376.5 * x2 + . . . + 11585.8 * x39 = (t1 * 23783.4);
x1 + x2 + . . . + x39 = 1;
t1= 1.5727 ;
t2= 1.8475;
@GIN (DIIS1);
@GIN (DIIS2);
@GIN (DIIS3);
@GIN (DIIS4);
@GIN (DIIS5);
@GIN (DIOS1);
@GIN (DIOS2);
```

where, x1, …, x39 are DMUs being evaluated, t1 and t2 are the projections of input reduction and output augmentation whose values are calculated by the model's objective function, 0.000001 is a non-Archimedean infinitesimal value, DIIS1, DIIS2, DIIS3, DIIS4, DIIS5, DIOS1, DIOS2 are desirable integer input and output slacks, DROS1 is a desirable real output slack and @GIN is Lingo's function to restrict inputs and outputs as integer values.

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