

RESEARCH ARTICLE

Additive integer-valued data envelopment analysis with missing data: A multi-criteria evaluation approach

Chunhua Chen^{1,2}, Jianwei Ren^{3,4,5}, Lijun Tang⁵, Haohua Liu^{1*}

1 School of Business Administration, Jiangxi University of Finance and Economics, Nanchang, Jiangxi, China, **2** Inner Mongolia Branch of Agricultural Bank of China, Hohhot, Inner Mongolia, China, **3** Transportation Institute, Inner Mongolia University, Hohhot, Inner Mongolia, China, **4** School of Mathematical Sciences, Inner Mongolia University, Hohhot, Inner Mongolia, China, **5** School of Business, University of Plymouth, Plymouth, Devon, United Kingdom

☯ These authors contributed equally to this work.

* xljhaohua@126.com



OPEN ACCESS

Citation: Chen C, Ren J, Tang L, Liu H (2020) Additive integer-valued data envelopment analysis with missing data: A multi-criteria evaluation approach. PLoS ONE 15(6): e0234247. <https://doi.org/10.1371/journal.pone.0234247>

Editor: Baogui Xin, Shandong University of Science and Technology, CHINA

Received: February 21, 2020

Accepted: May 21, 2020

Published: June 11, 2020

Copyright: © 2020 Chen et al. This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Data Availability Statement: All relevant data are within the manuscript and its Supporting Information files.

Funding: This paper was supported by the National Natural Science Foundation of China (71862026, <http://www.nsf.gov.cn/>), China Postdoctoral Science Foundation (2018T110209, <http://j.chinapostdoctor.org.cn/>), Natural Science Foundation of Inner Mongolia (2018MS07006, <http://kjt.nmg.gov.cn/>), and State Scholarship Found of China Scholarship Council (201808155025, <https://www.csc.edu.cn/>). Jianwei

Abstract

Traditional data envelopment analysis (DEA) models assume that all the inputs and outputs data are available. However, missing data is a common problem in data analysis. Although several scholars have developed techniques to conduct DEA with missing data, these techniques have some disadvantages. A multi-criteria evaluation approach is proposed to measure the efficiency of decision making units (DMUs) with missing data. In this approach, analysts first estimate the upper and lower bounds of DMUs' efficiency using the proposed I-addIDEA-U models (interval additive integer-valued DEA models with undesirable outputs) that can be applied to address integer-valued variables and undesirable outputs. Then, DMUs' "relative" efficiency is evaluated using the proposed "Halo + Hot deck" DEA method (if there is no correlation between variables) or regression DEA techniques (if there is a correlation between variables). Finally, the multi-index comprehensive evaluation method is applied to determine which scenario (the lower bound of efficiency, the "relative" efficiency, or the upper bound of efficiency) should be selected. With a case study, it is shown that the proposed multi-criteria evaluation approach is more effective than traditional approaches such as the mean imputation DEA method, the deletion DEA method, and the dummy entries DEA method.

1. Introduction

Traditional data envelopment analysis (DEA) models assume that all the inputs and outputs data are available [1, 2]. If the data related to some vital variables of decision making units (DMUs) are missing, traditional DEA models cannot be applied to measure the performance of these DMUs [3, 4]. However, missing data is a common problem in data analysis [5].

To deal with the problem of missing data many methods have been proposed, e.g., deletion, imputation, and multiple imputation [6, 7]. (1) The deletion methods (deleting all variables with missing data or all units with missing data) are easy to implement, but they may lead to biased estimates [8]. (2) The imputation methods mainly include the mean imputation, Hot deck imputation, and regression imputation [9, 10]. Mean imputation means that the missing data

Ren received these awards. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. Inner Mongolia Branch of Agricultural Bank of China provided support in the form of salaries for Chunhua Chen, but did not have any additional role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript. The specific roles of these authors are articulated in the 'author contributions' section.

Competing interests: I have read the journal's policy and the authors of this manuscript have the following competing interests: One or more of the authors are employed by a commercial company: Inner Mongolia Branch of Agricultural Bank of China (Chunhua Chen). This does not alter our adherence to PLOS ONE policies on sharing data and materials.

are replaced by the mean of the available data. It is simple, but the variability in the dataset is reduced [11]. In the Hot deck imputation method, missing data are replaced with the available values from a "similar" unit. Hot deck imputation is an effective method and has been widely used in practice [12, 13]. Regression imputation is also a widely used method in which missing data are replaced with the values obtained from regression techniques, e.g., linear regression, logistic regression, polynomial regression, Probit regression, and Tobit regression [14, 15]. (3) Multiple imputation is also an attractive method, which has been regarded as a more accurate and less biased method [16]. According to the multiple imputation method, missing data should be imputed based on the distributions and variability of other data elements in the sample [17]. (4) There are also some other methods for dealing with missing data, e.g., the maximum likelihood [18, 19], Bayesian [20, 21], and the expectation maximization [22, 23].

Several scholars have researched DEA with missing data in different ways. O'neal et al. applied the deletion method and proposed DEA models (the deletion DEA) to measure DEA efficiency, but this approach was problematic because deleting DMUs may lead to changes in the other DMUs' relative efficiency [24]. Kuosmanen used dummy entries (zero for output variables and large enough numbers for input variables) to reduce the effects of DMUs with missing data on the relative efficiency of the other DMUs [25]. Gardijan and Lukač applied the dummy entries method and proposed DEA models (the dummy entries DEA) to measure the efficiency of the food and drink industry [26]. Interval DEA approach is another widely used method in which missing data are replaced with a lower bound and an upper bound so that the lower and upper bounds of efficiency can be evaluated [27–29]. Kao and Liu developed a fuzzy DEA approach that allowed analysts to use the available data to evaluate membership functions of fuzzy efficiency [30]. In fact, the fuzzy DEA approach is similar to the interval DEA approach. The difference between the two approaches is that the fuzzy DEA approach is based on the fuzzy theory while the interval DEA approach uses deterministic techniques [31–36]. Zha et al. developed a Halo DEA approach (Halo effect is a psychological term) to impute missing data [37]. Chen et al. presented a multiple linear regression analysis DEA approach (regression DEA) [38].

However, the above-mentioned techniques have a few disadvantages. First, they use simple imputation methods or deletion methods to handle missing data, which may lead to erroneous results. Second, while they modify basic radial DEA models to measure the efficiency of DMUs with missing data, they are unable to deal with integer-valued variables or undesirable variables. If decision-makers simply round up the DEA solutions to the nearest integers, the results may be wrong [39–42]. Integer-valued DEA models have attracted researchers because inputs and outputs can only be integer numbers in many cases. Lozano and Villa [39], Du et al. [40], Ajirilo et al. [41], Kordrostami et al. [42], Ren et al. [43], and other scholars have applied integer-valued DEA models to many fields, e.g., universities, Olympic games, and pallet rental companies. Measuring the efficiency of DMUs with undesirable outputs is another hot topic in DEA research. There are several approaches to handle undesirable outputs, e.g., weak disposability assumption [44], direction distance function [45, 46], linear or non-linear monotonic decreasing transformation [47, 48], treating undesirable outputs as inputs [49], and applying the SBM (Slacks-Based Measure) approach and proposing additive DEA models [50].

Another disadvantage of radial DEA models is that they have weaker discriminatory ability than non-radial DEA models [51, 52]. Radial DEA models can only proportionally reduce inputs or increase outputs, while non-radial DEA models, e.g., the additive DEA [53], the enhanced Russell measure [54], and the slacks-based measure [55], do not need to make the assumption of proportional changes [56].

In this study, to handle missing data in DEA a multi-criteria evaluation approach is proposed based on the Hot deck imputation, regression imputation, Halo effect, interval DEA, integer DEA, additive DEA, DEA with undesirable outputs, and multi-index comprehensive

evaluation. The main advantages of this approach are as follows. (1) The approach not only estimates the upper and lower bounds of DMUs' efficiency but also evaluates the "relative" efficiency of these DMUs based on the "Halo + Hot deck" DEA method (if there is no correlation between variables) or regression DEA techniques (if there is a correlation between variables). Therefore, the evaluation results are relatively diverse, which avoids the shortcoming of simple imputation methods as mentioned above. (2) A multi-index comprehensive evaluation system, which involves many important factors related to the variables with missing data, is established to determine which scenario (the lower bound of efficiency, the "relative" efficiency, or the upper bound of efficiency) should be selected. The multi-index comprehensive evaluation method guarantees that the resulting efficiency is more reliable. (3) Interval additive integer-valued DEA models with undesirable outputs are proposed. These models can be used to handle integer-valued variables and undesirable outputs.

The rest of this paper is structured as follows. The multi-criteria evaluation approach (including the interval additive integer-valued DEA models with undesirable outputs and the "Hao + Hot deck" imputation method) is presented in Section 2. In Section 3, the proposed approach is applied to the pallet rental industry, and the effectiveness of the methodology is examined by analyzing error rates. Conclusions and the contributions of this paper are presented in Section 4.

2. Methodology

Assume that Q represents a group of DMUs. Each DMU_i ($DMU_i \in Q, i = 1, 2, \dots, q$) consumes r inputs x_{ji} ($j = 1, 2, \dots, r$) to produce m desirable outputs y_{pi} ($p = 1, 2, \dots, m$) and t undesirable outputs z_{hi} ($h = 1, 2, \dots, t$). Further assume that the data related to some DMUs' important variables are missing. The multi-criteria evaluation approach for measuring the performance of DMU_k ($DMU_k \in Q$) is shown in Fig 1, and the corresponding algorithm is as follows.

Step 1: Measuring DMU_k 's interval efficiency.

First, the analysts should replace missing data with their values under DMU_k 's (the DMU under evaluation, $DMU_k \in Q$) best condition (see Subsection 2.1, model 1). Second, analysts should replace missing data with their values under DMU_k 's worst condition (see Subsection 2.1, model 2). Then, analysts can apply the interval additive integer-valued DEA models with undesirable outputs, which is proposed in Subsection 2.1, to calculate the upper bound of DMU_k 's efficiency (θ_k^U) under DMU_k 's best condition and the lower bound of DMU_k 's efficiency (θ_k^L) under DMU_k 's worst condition. Therefore, DMU_k 's interval efficiency $[\theta_k^L, \theta_k^U]$ can be evaluated.

Step 2: Measuring DMU_k 's "relative" efficiency.

Analysts should study the relationship between the variables with missing data and the other variables. There are several methods for correlation analysis, e.g. the scatter diagram method, Pearson's correlation coefficient, Spearman's rank correlation coefficient, and the least squares method [57].

If there is a correlation between variables, analysts should replace missing data with the values obtained from the regression imputation method and apply the DEA to calculate DMU_k 's "relative" efficiency (θ_k^R). Otherwise, analysts should replace missing data with the values obtained from the "Halo + Hot deck" imputation method and apply the DEA ("Halo + Hot deck" DEA) to calculate DMU_k 's "relative" efficiency (θ_k^H). The "Halo + Hot deck" imputation method is presented in Subsection 2.2. Regarding the regression imputation method, since it is well-understood, the paper does not provide a detailed explanation. As mentioned in Section 1, there are many regression techniques, so analysts should select the

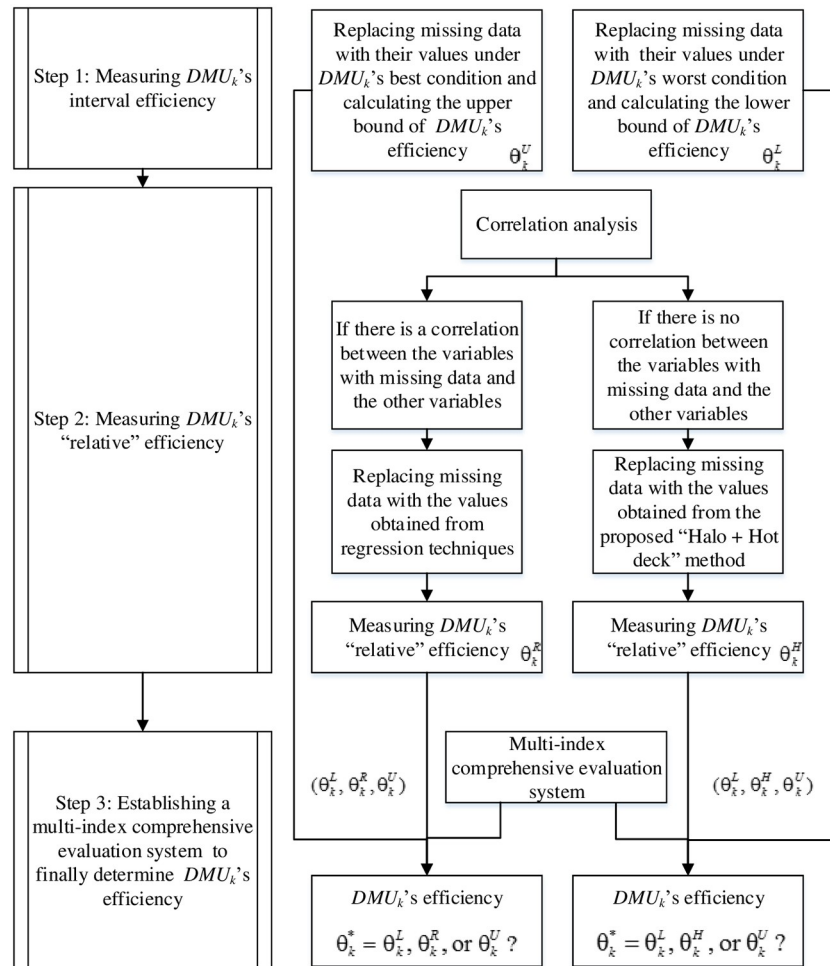


Fig 1. The proposed multi-criteria evaluation approach for measuring the performance of DMUs with missing data.

<https://doi.org/10.1371/journal.pone.0234247.g001>

right regression technique based on the detailed analysis of variables, e.g., the type of variables and shape of the regression line. There must be $\theta_k^L \leq \theta_k^R \leq \theta_k^U$ or $\theta_k^L \leq \theta_k^H \leq \theta_k^U$ (see Subsection 2.2).

Step 3: Establishing a multi-index comprehensive evaluation system to finally determine DMU_k 's efficiency.

To finally determine DMU_k 's efficiency ($\theta_k^* = \theta_k^L, \theta_k^R, \text{ or } \theta_k^U ?$; $\theta_k^* = \theta_k^L, \theta_k^H, \text{ or } \theta_k^U ?$) analysts should establish a multi-index comprehensive evaluation system. The indicators should be related to the variables with missing data, and the evaluation method can be qualitative or quantitative. An example is proposed in Section 3. Decisions makers can rank all DMUs after they finally determine the efficiency of all DMUs.

2.1 Interval additive integer-valued DEA models with undesirable outputs

Assume that some of the inputs and desirable outputs can only take integer values. Following Du et al. [40] and Ren et al. [43], J^{NI} and J^I respectively represent the subsets of real-valued and

integer-valued inputs, while P^{NI} and P^I respectively denote the subsets of real-valued and integer-valued desirable outputs. Hence, $x_{ji} \in J^{NI} (j = 1, 2, \dots, g)$ and $x_{ji} \in J^I (j = g + 1, g + 2, \dots, r)$ respectively imply DMU_k 's real-valued and integer-valued inputs, while $y_{pi} \in P^{NI} (p = 1, 2, \dots, o)$ and $y_{pi} \in P^I (p = o + 1, o + 2, \dots, m)$ respectively indicate DMU_k 's real-valued and integer-valued desirable outputs.

Model (1) and model (2), which are interval additive integer-valued DEA models with undesirable outputs, are developed to measure the upper and lower bounds of DMU_k 's interval efficiency, respectively. Additive DEA models are proposed because they are non-radial DEA models that can distinguish all inefficiencies [53]. To deal with undesirable outputs the SBM approach is applied and additive DEA models are proposed [50].

To calculate the upper bound of DMU_k 's efficiency (model 1), the analysts should replace missing data with their values under DMU_k 's best condition (as stated above), which means that analysts should replace DMU_k 's missing data related to inputs, desirable outputs, and undesirable outputs with $x_{jk}^L = \min(\text{all } x_{ji} \text{ with precise data})$, $y_{pk}^U = \max(\text{all } y_{pi} \text{ with precise data})$, and $z_{hk}^L = \min(\text{all } z_{hi} \text{ with precise data})$, respectively. If there are also some DMUs ($DMU_i \in Q, i \neq k$) with missing data besides DMU_k , analysts should also replace their missing data related to inputs, desirable outputs, and undesirable outputs with $x_{ji}^U = \max(\text{all } x_{ji} \text{ with precise data}), i \neq k$, $y_{pi}^L = \min(\text{all } y_{pi} \text{ with precise data}), i \neq k$, and $z_{hi}^U = \max(\text{all } z_{hi} \text{ with precise data}), i \neq k$, respectively.

$$\begin{aligned}
 \max = & \frac{1}{m+r+t} \left(\sum_{p=1}^o \frac{s_p^+}{y_{pk}^U} + \sum_{p=o+1}^m \frac{s_p^{I+}}{y_{pk}^U} + \sum_{j=1}^g \frac{s_j^-}{x_{jk}^L} + \sum_{j=g+1}^r \frac{s_j^{I-}}{x_{jk}^L} + \sum_{h=1}^t \frac{s_h^-}{z_{hk}^L} \right) \\
 \text{s.t.} & \sum_{i=1, i \neq k}^q x_{ji}^U \lambda_i + x_{jk}^L \lambda_k + s_j^- = x_{jk}^L, j = 1, 2, \dots, g \\
 & \sum_{i=1, i \neq k}^q x_{ji}^U \lambda_i + x_{jk}^L \lambda_k \leq \tilde{x}_{jk}, j = g + 1, g + 2, \dots, r \\
 & x_{jk}^L - s_j^{I-} = \tilde{x}_{jk}, j = g + 1, g + 2, \dots, r \\
 & \sum_{i=1, i \neq k}^q y_{pi}^L \lambda_i + y_{pk}^U \lambda_k - s_p^+ = y_{pk}^U, p = 1, 2, \dots, o \\
 & \sum_{i=1, i \neq k}^q y_{pi}^L \lambda_i + y_{pk}^U \lambda_k \geq \tilde{y}_{pk}, p = o + 1, o + 2, \dots, m \\
 & y_{pk}^U + s_p^{I+} = \tilde{y}_{pk}, p = o + 1, o + 2, \dots, m \\
 & \sum_{i=1, i \neq k}^q z_{hi}^U \lambda_i + z_{hk}^L \lambda_k + s_h^- = z_{hk}^L, h = 1, 2, \dots, t \\
 & \sum_{i=1}^q \lambda_i = 1 \\
 & \lambda_i \geq 0, i = 1, 2, \dots, q \\
 & s_j^- \geq 0, j = 1, 2, \dots, g \\
 & s_j^{I-} \geq 0, j = g + 1, g + 2, \dots, r \\
 & s_p^+ \geq 0, p = 1, 2, \dots, o \\
 & s_p^{I+} \geq 0, p = o + 1, o + 2, \dots, m \\
 & s_h^- \geq 0, h = 1, 2, \dots, t \\
 & \tilde{x}_{jk} \in J^I, j = g + 1, g + 2, \dots, r \\
 & \tilde{y}_{pk} \in P^I, p = o + 1, o + 2, \dots, m
 \end{aligned} \tag{1}$$

where λ_i indicates the weight for DMU_i ; s_j^- , s_j^{I-} , s_p^+ , s_p^{I+} , and s_h^- respectively represent the slack variables for real-valued inputs, integer-valued inputs, real-valued desirable outputs, integer-valued desirable outputs, and undesirable outputs, respectively; \tilde{x}_{jk} ($j = g + 1, g + 2, \dots, r$) and \tilde{y}_{pk} ($p = o + 1, o + 2 \dots, m$) are the targets for integer-valued inputs and integer-valued desirable outputs, respectively. Note that the superscript “U” and “L” respectively indicate the upper bound and lower bound values of the related variables.

To calculate the lower bound of DMU_k 's efficiency (model 2), the analysts should replace missing data with their values under DMU_k 's worst condition (as stated above), which means that analysts should replace DMU_k 's missing data related to inputs, desirable outputs, and undesirable outputs with $x_{jk}^U = \max(\text{all } x_{ji} \text{ with precise data})$, $y_{pk}^L = \min(\text{all } y_{pi} \text{ with precise data})$, and $z_{hk}^U = \max(\text{all } z_{hi} \text{ with precise data})$, respectively. If there are also some DMUs ($DMU_i \in Q, i \neq k$) with missing data besides DMU_k , as discussed above, analysts should also respectively replace their missing data related to inputs, desirable outputs, and undesirable outputs with $x_{ji}^L = \min(\text{all } x_{ji} \text{ with precise data}), i \neq k$, $y_{pi}^U = \max(\text{all } y_{pi} \text{ with precise data}), i \neq k$, and $z_{hi}^L = \max(\text{all } z_{hi} \text{ with precise data}), i \neq k$.

$$\begin{aligned}
 \max = & \frac{1}{m + r + t} \left(\sum_{p=1}^o \frac{s_p^+}{y_{pk}^L} + \sum_{p=o+1}^m \frac{s_p^{I+}}{y_{pk}^L} + \sum_{j=1}^g \frac{s_j^-}{x_{jk}^U} + \sum_{j=g+1}^r \frac{s_j^{I-}}{x_{jk}^U} + \sum_{h=1}^t \frac{s_h^-}{z_{hk}^U} \right) \\
 \text{s.t.} & \sum_{i=1, i \neq k}^q x_{ji}^L \lambda_i + x_{jk}^U \lambda_k + s_j^- = x_{jk}^U, j = 1, 2, \dots, g \\
 & \sum_{i=1, i \neq k}^q x_{ji}^L \lambda_i + x_{jk}^U \lambda_k \leq \tilde{x}_{jk}, j = g + 1, g + 2, \dots, r \\
 & x_{jk}^U - s_j^{I-} = \tilde{x}_{jk}, j = g + 1, g + 2, \dots, r \\
 & \sum_{i=1, i \neq k}^q y_{pi}^U \lambda_i + y_{pk}^L \lambda_k - s_p^+ = y_{pk}^L, p = 1, 2, \dots, o \\
 & \sum_{i=1, i \neq k}^q y_{pi}^U \lambda_i + y_{pk}^L \lambda_k \geq \tilde{y}_{pk}, p = o + 1, o + 2 \dots, m \\
 & y_{pk}^L + s_p^{I+} = \tilde{y}_{pk}, p = o + 1, o + 2 \dots, m \\
 & \sum_{i=1, i \neq k}^q z_{hi}^L \lambda_i + z_{hk}^U \lambda_k + s_h^- = z_{hk}^U, h = 1, 2, \dots, t \\
 & \sum_{i=1}^q \lambda_i = 1 \\
 & \lambda_i \geq 0, i = 1, 2, \dots, q \\
 & s_j^- \geq 0, j = 1, 2, \dots, g \\
 & s_j^{I-} \geq 0, j = g + 1, g + 2, \dots, r \\
 & s_p^+ \geq 0, p = 1, 2, \dots, o \\
 & s_p^{I+} \geq 0, p = o + 1, o + 2 \dots, m \\
 & s_h^- \geq 0, h = 1, 2, \dots, t \\
 & \tilde{x}_{jk} \in J^I, j = g + 1, g + 2, \dots, r \\
 & \tilde{y}_{pk} \in P^I, p = o + 1, o + 2, \dots, m
 \end{aligned} \tag{2}$$

The mathematical notations used in model (2) are the same as those used in model (1). Different from traditional additive DEA models, both model (1) and model (2) are unit-invariant [58]. Model (1) and model (2) cannot provide the efficiency scores, so Eqs (3) and (4) are proposed to calculate the upper bound and lower bound of DMU_k 's efficiency, respectively.

$$\theta_k^U = \frac{1 - \frac{1}{r} \left(\sum_{j=1}^g s_j^- * / x_{jk}^L + \sum_{j=g+1}^r s_j^{I-} * / x_{jk}^L \right)}{1 + \frac{1}{m+t} \left(\sum_{p=1}^o s_p^+ * / y_{pk}^U + \sum_{p=o+1}^m s_p^{I+} * / y_{pk}^U + \sum_{h=1}^t s_h^- * / z_{hk}^L \right)} \tag{3}$$

in which $\{\lambda_i^*, s_j^-, s_j^{I-}, s_p^+, s_p^{I+}, s_h^-, \tilde{x}_{jk}^*, \tilde{y}_{pk}^*\}$ is the optimum solution resulting from model (1). There must be $0 \leq \theta_k^U \leq 1$. $\theta_k^U = 1$ implies that DMU_k is additive-efficient under DMU_k 's best condition because θ_k^U equals to 1 if and only if all slacks variables are equal to 0. The greater value of θ_k^U , the better performance of DMU_k .

$$\theta_k^L = \frac{1 - \frac{1}{r} \left(\sum_{j=1}^g s_j^- * / x_{jk}^U + \sum_{j=g+1}^r s_j^{I-} * / x_{jk}^U \right)}{1 + \frac{1}{m+t} \left(\sum_{p=1}^o s_p^+ * / y_{pk}^L + \sum_{p=o+1}^m s_p^{I+} * / y_{pk}^L + \sum_{h=1}^t s_h^- * / z_{hk}^U \right)} \tag{4}$$

in which $\{\lambda_i^*, s_j^-, s_j^{I-}, s_p^+, s_p^{I+}, s_h^-, \tilde{x}_{jk}^*, \tilde{y}_{pk}^*\}$ is the optimum solution resulting from model (2). There must be also $0 \leq \theta_k^L \leq 1$. $\theta_k^L = 1$ implies that DMU_k is additive-efficient under DMU_k 's worst condition. The greater value of θ_k^L , the better performance of DMU_k .

2.2 “Halo + Hot deck” imputation method

2.2.1 Halo effect. Halo effect is a psychological term proposed by Thorndike in 1920 [59]. It means that an individual’s positive thoughts about a company (person, product, brand, and so on) in one area positively affect how he/she thinks of the company in other areas [60]. This theory can be applied to evaluate DMUs’ relative efficiency. If DMU_k 's relative efficiency (θ_k^N) is better than that of other DMUs’ when not taking into account the variables with missing data (deleting the variables with missing data when measuring the performance of DMUs), it can be thought that this DMU’s relative efficiency (θ_k^*) would also be better when taking into account the variables with missing data. Model (1) and Eq (3) (or model 2 and Eq 4) can be applied to calculate θ_k^N by deleting all the symbols related to the variables with missing data. However, the Halo effect may lead to bias. To overcome this shortcoming, we propose the multi-criteria evaluation approach (See Fig 1).

2.2.2 “Halo + Hot deck”. According to the Hot deck imputation method, as mentioned in Section 1, the missing data should be replaced with the observed values from a “similar” unit. Therefore, based on the ideas of the Halo effect and Hot deck imputation, the missing data related to DMU_k can be replaced with the values of a DMU with “similar efficiency θ_k^N ”. The “Halo + Hot deck” imputation method is as follows.

Based on the relative efficiency of all DMUs without considering the variables with missing data, a “similar” DMU whose relative efficiency is less than DMU_k 's efficiency and a “similar” DMU whose relative efficiency is greater than DMU_k 's efficiency can be found. Then, the missing data about DMU_k can be replaced with the average of the two “similar” DMUs’ related values. The missing data related to DMU_k are not replaced with the values of the “closest” DMU because it may lead to larger errors. Note that there may be several DMUs that have the same

efficiency scores as DMU_k 's. In that case, analysts can just replace the missing data about DMU_k with the average of these "same" DMUs' related values.

2.2.3 Measuring the "relative" efficiency. Model (1) and Eq (3) (or model 2 and Eq 4) can be applied to calculate the "relative" efficiency θ_k^H based on the "Halo + Hot deck" imputation method (this method is called "Halo + Hot deck" DEA which means the "Halo + Hot deck" imputation method + the DEA approach), but analysts should set $x_{jk}^L = x_{jk}^H$ as well as $x_{ji}^U = x_{ji}^H (i \neq k)$ (or $x_{jk}^U = x_{jk}^H$ as well as $x_{ji}^L = x_{ji}^H (i \neq k)$), $z_{hk}^L = z_{hk}^H$ as well as $z_{hi}^U = z_{hi}^H (i \neq k)$ (or $z_{hk}^U = z_{hk}^H$ as well as $z_{hi}^L = z_{hi}^H (i \neq k)$), and $y_{pk}^U = y_{pk}^H$ as well as $y_{pi}^L = y_{pi}^H (i \neq k)$ (or $y_{pk}^L = y_{pk}^H$ as well as $y_{pi}^U = y_{pi}^H (i \neq k)$). The superscript H indicates that the values of the variables with missing data are obtained from the "Halo + Hot deck" imputation method.

There must be $\theta_k^L \leq \theta_k^H \leq \theta_k^U$ because there are $x_{ji}^L \leq x_{ji}^H \leq x_{ji}^U$, $y_{pi}^L \leq y_{pi}^H \leq y_{pi}^U$, and $z_{hi}^L \leq z_{hi}^H \leq z_{hi}^U$ for $i = 1, 2, \dots, q$. Similarly, there must be $\theta_k^L \leq \theta_k^R \leq \theta_k^U$ because there are $x_{ji}^L \leq x_{ji}^R \leq x_{ji}^U$, $y_{pi}^L \leq y_{pi}^R \leq y_{pi}^U$, and $z_{hi}^L \leq z_{hi}^R \leq z_{hi}^U$ for $i = 1, 2, \dots, q$. The superscript R indicates that the values of the variables with missing data are obtained from regression imputation methods.

3. Numerical illustrations

This section applies the proposed approach to analyze the efficiency of pallet rental companies. There is limited quantitative research in the pallet rental industry because the data related to this industry are not publicly available [61, 62]. Therefore, it is necessary to propose an approach to evaluate the performance of pallet rental companies when some important data are missing, and this research is important to the pallet rental industry. Also, this industry involves undesirable outputs, e.g., pallet loss, and some of the inputs are integer numbers. The proposed approach is able to deal with these types of data.

3.1 Data

There are twelve pallet rental companies in the dataset including Commonwealth Handling Equipment Pool (CHEP), Intelligent Global Pooling Systems (iGPS), PECO Pallet, H & H Pallet Leasing, La Palette Rouge (LPR), Pooling Partner, Contraloadad, Nippon Pallet Pool System, Japan Pallet Rental (JPR), Korea Pallet Pool (KPP), Loscam, and Jituo Pallet Pool. Each company uses two integer-valued inputs (employees x_{1i} and pallets x_{2i}) to produce one real-valued desirable output (annual revenue y_{1i}) and one real-valued undesirable output (annual pallet loss rate z_{1i}), and the data related to these companies in 2018 are shown in Table 1 [43, 62]. The data about x_{1i} , x_{2i} , and y_{1i} (unit: million U.S. dollars) are obtained from the official websites of these companies as well as other relevant websites, and the values of z_{1i} (unit: percent) are estimated by managers in these companies. Model (1) and Eq (3) (or model 2 and Eq 4) can be applied to evaluate the efficiency of these companies using these precise data, and the resulting efficiency (θ_i^P) is precise. The results are also shown in Table 1. Note that analysts should set $x_{1i}^U = x_{1i}^L = x_{1i}$, $x_{2i}^U = x_{2i}^L = x_{2i}$, $y_{1i}^U = y_{1i}^L = y_{1i}$, and $z_{1i}^U = z_{1i}^L = z_{1i}$ for $i = 1, 2, \dots, 12$.

To apply the proposed multi-criteria evaluation approach to this case, it is assumed that the data about some DMUs' annual pallet loss rates are missing (z_{1i}^M). Note that z_{1i}^M represents missing data while z_{1i} indicates precise data. Twelve scenarios ($l = 1, 2, \dots, 12$) are considered. Scenario l indicates that the value of DMU_l 's annual pallet loss rate is missing. For example, Scenario 4 represents that the value of DMU 4's annual pallet loss rate is missing. Then, the proposed approach can be applied to measure the efficiency of all companies (θ_i^*).

Table 1. Variables and the precise efficiency.

DMU	x_{1i}	x_{2i}	y_{1i}	z_{1i}	θ_i^p
1	239	10000000	85.34	2	1.000
2	7500	460000000	4048.30	2	1.000
3	310	92000000	248.60	8	0.189
4	875	40000000	370.72	10	0.272
5	284	9600000	226.03	1	1.000
6	130	3000000	45.21	12	0.346
7	101	3000000	58.07	10	0.520
8	175	10000000	75.00	12	0.240
9	144	8000000	49.90	10	0.218
10	16	22500	1.97	12	1.000
11	109	7000000	313.80	8	1.000
12	20	5000	1.50	12	1.000
Ave.	825.25	53552291.67	460.37	8.25	0.649
Max.	7500.00	460000000.00	4048.30	12.00	1
Min.	16.00	5000.00	1.50	1.00	0.189
Std. Dev.	2114.20	130618453.80	1136.78	4.22	0.384

<https://doi.org/10.1371/journal.pone.0234247.t001>

The effectiveness of the proposed approach can be estimated by the error rate ε that can be

calculated by $\varepsilon = \frac{\sum_{i=1}^{12} \varepsilon_i}{12}$ where $\varepsilon_i = \sum_{i=1}^{12} \frac{|\theta_i^* - \theta_i^p|}{\theta_i^p}$. The lower the value of ε is, the better the performance of the approach should be.

3.2 Measuring the efficiency of pallet rental companies using the proposed multi-criteria evaluation approach

In this subsection, the proposed approach is applied to measure the efficiency of the twelve companies.

3.2.1 Interval efficiency. As stated in Section 2, analysts should first measure DMU_k 's interval efficiency. The lower and upper bounds of DMU 5's annual pallet loss rate are 2 and 12, respectively, while the lower and upper bounds of the other DMUs' annual pallet loss rates are all 1 and 12, respectively. Tables 2 and 3 show the interval efficiency resulting from the proposed interval additive integer-valued DEA models with undesirable outputs (model 1 as well as Eq 3 and model 2 as well as Eq 4).

In Tables 2 and 3, the sub-scenario *l*-U, the sub-scenario *l*-H, and the sub-scenario *l*-L represent the efficiency of these companies under DMU_k 's best condition, "Halo + Hot deck" condition, and worst condition, respectively. Therefore, the efficiency of DMU_k in the three sub-scenarios is indicated by $\theta_k^U, \theta_k^H, \theta_k^L$, respectively.

Note that the "Halo + Hot deck" DEA efficiency of $DMU_k (\theta_k^H)$ is also shown in Tables 2 and 3 for the sake of clarity. X indicates the efficiency of the DMU_k under estimation, and X represents the efficiency of $DMU_i (i \neq k)$ that changes with different values of DMU_k 's missing data. DMU 2, DMU 10, DMU 11, and DMU 12 are fully efficient because their efficiency scores are equal to 1 in all scenarios. All DMUs are efficient under their own best condition. The value of DMU 2's annual pallet loss rate does not affect the ranking of these companies. Thus, analysts do not need to further evaluate the "relative" efficiency of these DMUs in Scenario 2. The values of some DMUs' annual pallet loss rates (i.e., DMU 2, DMU 5, DMU 6,

Table 2. Efficiency resulting from the interval approach (DMU 1-DMU 6).

Scenario	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6
1-U	1.000	1.000	0.189	0.272	1.000	0.346
1-H	0.234	1.000	0.189	0.272	1.000	0.346
1-L	0.231	1.000	0.189	0.272	1.000	0.346
2-U	1.000	1.000	0.189	0.272	1.000	0.346
2-H	1.000	1.000	0.189	0.274	1.000	0.346
2-L	1.000	1.000	0.189	0.274	1.000	0.346
3-U	1.000	1.000	1.000	0.272	1.000	0.346
3-H	1.000	1.000	0.169	0.272	1.000	0.346
3-L	1.000	1.000	0.165	0.272	1.000	0.346
4-U	1.000	1.000	0.189	1.000	1.000	0.346
4-H	1.000	1.000	0.189	0.264	1.000	0.346
4-L	1.000	1.000	0.189	0.257	1.000	0.346
5-U	1.000	1.000	0.189	0.272	1.000	0.346
5-H	1.000	1.000	0.189	0.272	0.560	0.346
5-L	1.000	1.000	0.189	0.272	0.409	0.346
6-U	0.501	1.000	0.189	0.272	1.000	1.000
6-H	1.000	1.000	0.189	0.272	1.000	0.575
6-L	1.000	1.000	0.189	0.272	1.000	0.346
7-U	0.491	1.000	0.189	0.272	1.000	0.346
7-H	1.000	1.000	0.189	0.272	1.000	0.346
7-L	1.000	1.000	0.189	0.272	1.000	0.346
8-U	0.556	1.000	0.189	0.272	1.000	0.346
8-H	1.000	1.000	0.189	0.272	1.000	0.346
8-L	1.000	1.000	0.189	0.272	1.000	0.346
9-U	0.543	1.000	0.189	0.272	1.000	0.346
9-H	1.000	1.000	0.189	0.272	1.000	0.346
9-L	1.000	1.000	0.189	0.272	1.000	0.346
10-U	0.485	1.000	0.189	0.272	1.000	0.307
10-H	1.000	1.000	0.189	0.272	1.000	0.346
10-L	1.000	1.000	0.189	0.272	1.000	0.346
11-U	0.223	1.000	0.136	0.207	0.466	0.327
11-H	1.000	1.000	0.179	0.261	1.000	0.343
11-L	1.000	1.000	0.401	0.450	1.000	0.359
12-U	0.497	1.000	0.189	0.272	1.000	0.314
12-H	1.000	1.000	0.189	0.272	1.000	0.331
12-L	1.000	1.000	0.189	0.272	1.000	0.346

<https://doi.org/10.1371/journal.pone.0234247.t002>

DMU 7, DMU 8, DMU 9, DMU 10, DMU 11, DMU 12) are very important because they have effects on other DMUs' efficiency. For example, the values of DMU 11's annual pallet loss rate can affect the efficiency of DMU 1, DMU 3, DMU 4, DMU 5, DMU 6, DMU 7, DMU 8, and DMU 9. If a DMU's efficiency can be affected by another DMU, its efficiency score would decrease when the value of that DMU's annual pallet loss rate decreases. Therefore, the "annual pallet loss rate" is an important variable for measuring the efficiency of pallet rental companies, and analysts should consider it when measuring efficiency.

3.2.2 Measuring the "relative" efficiency. The scatter diagram method is applied to analyze the relationship between the annual pallet loss rate and the other variables. SPSS software is used to draw scatter diagrams. The results are shown in Figs 2, 3 and 4. If the R-square is

Table 3. Efficiency resulting from the interval approach (DMU 7-DMU 12).

Scenario	DMU 7	DMU 8	DMU 9	DMU 10	DMU 11	DMU 12
1-U	0.520	0.240	0.218	1.000	1.000	1.000
1-H	0.520	0.240	0.218	1.000	1.000	1.000
1-L	0.520	0.240	0.218	1.000	1.000	1.000
2-U	0.520	0.240	0.218	1.000	1.000	1.000
2-H	0.520	0.240	0.218	1.000	1.000	1.000
2-L	0.520	0.240	0.218	1.000	1.000	1.000
3-U	0.520	0.240	0.218	1.000	1.000	1.000
3-H	0.520	0.240	0.218	1.000	1.000	1.000
3-L	0.520	0.240	0.218	1.000	1.000	1.000
4-U	0.520	0.240	0.218	1.000	1.000	1.000
4-H	0.520	0.240	0.218	1.000	1.000	1.000
4-L	0.520	0.240	0.218	1.000	1.000	1.000
5-U	0.531	0.240	0.218	1.000	1.000	1.000
5-H	0.557	0.240	0.218	1.000	1.000	1.000
5-L	0.557	0.240	0.218	1.000	1.000	1.000
6-U	0.481	0.240	0.218	1.000	1.000	1.000
6-H	0.498	0.240	0.218	1.000	1.000	1.000
6-L	0.520	0.240	0.218	1.000	1.000	1.000
7-U	1.000	0.240	0.218	1.000	1.000	1.000
7-H	1.000	0.240	0.218	1.000	1.000	1.000
7-L	0.448	0.240	0.218	1.000	1.000	1.000
8-U	0.520	1.000	0.218	1.000	1.000	1.000
8-H	0.520	0.491	0.218	1.000	1.000	1.000
8-L	0.520	0.240	0.218	1.000	1.000	1.000
9-U	0.520	0.240	1.000	1.000	1.000	1.000
9-H	0.520	0.240	0.263	1.000	1.000	1.000
9-L	0.520	0.240	0.214	1.000	1.000	1.000
10-U	0.396	0.240	0.218	1.000	1.000	1.000
10-H	0.434	0.240	0.218	1.000	1.000	1.000
10-L	0.520	0.240	0.218	1.000	1.000	1.000
11-U	0.432	0.217	0.199	1.000	1.000	1.000
11-H	0.466	0.236	0.215	1.000	1.000	1.000
11-L	0.672	0.255	0.275	1.000	1.000	1.000
12-U	0.406	0.240	0.218	1.000	1.000	1.000
12-H	0.439	0.240	0.218	1.000	1.000	1.000
12-L	0.520	0.240	0.218	1.000	1.000	1.000

<https://doi.org/10.1371/journal.pone.0234247.t003>

greater than 0.8, there is a relationship between variables. In the case study, all the R-squares are less than 0.8, so there is no relationship between the annual pallet loss rate and the other variables. It is worth noting that the outliers (the values of DMU 2) have been removed from the diagrams and the results also show that there is no relationship between the annual pallet loss rate and the other variables. In fact, Pearson's correlation coefficient and Spearman's rank correlation coefficient are also applied to analyze the relationship between variables, and the results are the same. Therefore, missing data should be replaced with the values obtained from the proposed "Halo + Hot deck" imputation method.

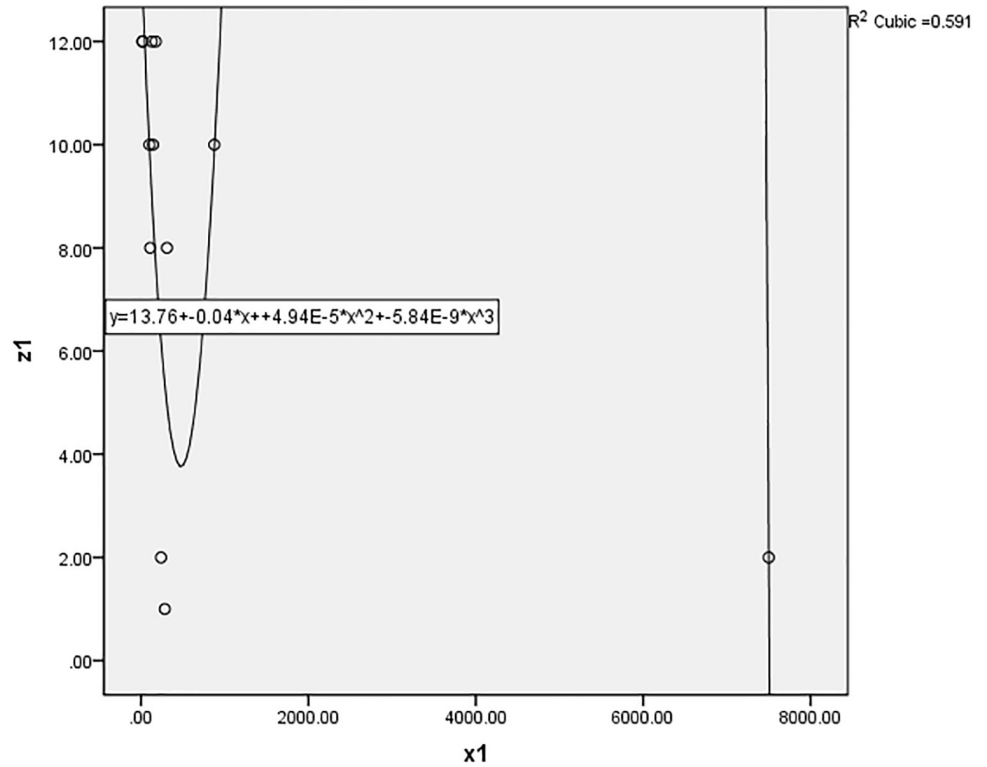


Fig 2. The relationship between the number of “employees” and the “annual pallet loss rate”.

<https://doi.org/10.1371/journal.pone.0234247.g002>

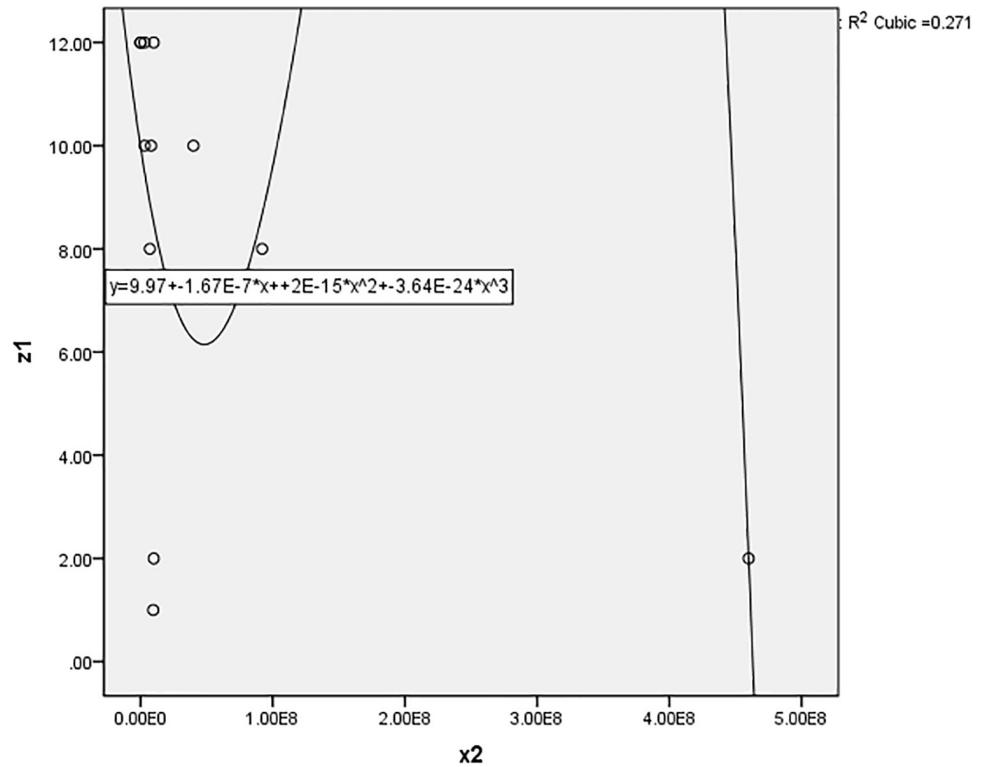


Fig 3. The relationship between the number of “pallets” and the “annual pallet loss rate”.

<https://doi.org/10.1371/journal.pone.0234247.g003>

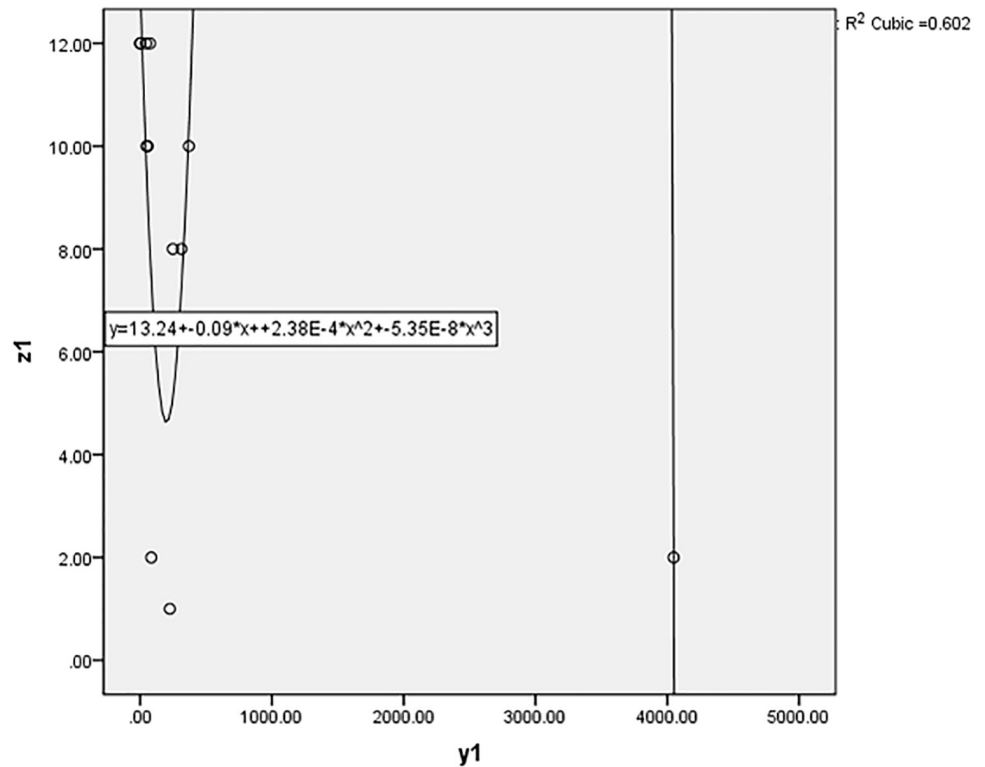


Fig 4. The relationship between the “annual revenue” and the “annual pallet loss rate”.

<https://doi.org/10.1371/journal.pone.0234247.g004>

Model (1) and Eq (3) are modified (deleting all symbols related to undesirable outputs) and applied to measure the relative efficiency (θ_k^N) of all DMUs without considering the variable with missing data (the annual pallet loss rate). Table 4 shows the results.

Table 5 shows the values of z_{1i}^H obtained from the “Halo + Hot deck” imputation method. z_{1i}^M is replaced with z_{1i}^H . The annual pallet loss rates of DMU 3’s “similar” DMUs, i.e., DMU 6 and DMU 8, are the same so that it is needed to employ another DMU (DMU 4). There are

Table 4. Efficiency when deleting the variable with missing data.

DMU	Efficiency	Ranking
1	0.157	11
2	1.000	1
3	0.169	9
4	0.301	7
5	0.401	5
6	0.239	8
7	0.334	6
8	0.158	10
9	0.130	12
10	1.000	1
11	1.000	1
12	1.000	1

<https://doi.org/10.1371/journal.pone.0234247.t004>

Table 5. Results obtained from the “Halo + Hot Deck” imputation.

DMU	z_{ii}^H	The interval of z_{ii}^M	The “similar” DMUs
1	11.00	[10, 12]	(DMU 8, DMU9)
2	10.00	[8, 12]	(DMU 10, DMU 11, DMU 12)
3	11.00	[10,12]	(DMU 4, DMU 6, DMU 8)
4	11.00	[10, 12]	(DMU 6, DMU 7)
5	7.00	[2, 12]	(DMU 2, DMU7, DMU 10, DMU11, DMU12)
6	9.00	[8, 10]	(DMU 3, DMU 4)
7	5.50	[1, 10]	(DMU 4, DMU 5)
8	5.00	[2, 8]	(DMU 1, DMU 3)
9	7.00	[2, 12]	(DMU 1, DMU 8)
10	7.00	[2, 12]	(DMU 2, DMU 11, DMU 12)
11	7.00	[2, 12]	(DMU 2, DMU 10, DMU12)
12	7.00	[2, 12]	(DMU 2, DMU 10, DMU 11)

<https://doi.org/10.1371/journal.pone.0234247.t005>

four DMUs rank No. 1 so that DMU 5’s “similar” DMUs include five DMUs, i.e., DMU 2, DMU 7, DMU 10, DMU 11, and DMU 12. DMU 9 ranks the 12th, so its missing data should be replaced with the average of the annual pallet loss rates of DMU 1 and DMU 8. Model (1) and Eq (3) are used to measure the “relative” efficiency θ_k^H of all companies and the results are shown in Tables 2 and 3.

3.2.3 Establishing a multi-index comprehensive evaluation system to finally determine the efficiency of these pallet rental companies. The annual pallet loss rate can be affected by many factors. Experts who have researched the pallet rental industry for more than three years in the United States, the United Kingdom, and China were reviewed. They proposed the following multi-index comprehensive evaluation system to determine the values of the annual pallet loss rate (as shown in Table 6). “Experience” indicates how long a company has operated. The longer a company has operated, the better its performance would be in reducing the annual pallet loss rate. For example, if a company has operated for over 50 years, it can be regarded as the most experienced in reducing the pallet loss rate. Thus, this company’s score in the indicator “Experience” is 10. “Information management technology” indicates the level of a pallet rental company using MIS (basic management information system), barcode, RFID (radio-frequency identification), PTS (pallets tracking system), and other techniques. If a company has applied all these techniques to control pallets, this company’s score in the indicator “Information management technology” is 10. It means that the company has applied the most advanced information management technologies to reduce its pallet loss rate. “Team” represents a company’s investments in human resources for reducing the pallet loss rate. “Non-professional team” means that the company has invested in human resources but there is not a professional team that dedicates to reduce the annual pallet loss rate, so its score in the

Table 6. Multi-index comprehensive evaluation system.

Indicator	Scoring criteria
Experience	Below 1, 0; 1–10, 2; 10–20, 4; 20–30, 6; 30–50, 8; over 50, 10
Information management technology	None, 0; MIS 2.5, MIS + Barcode, 5; MIS + Barcode + RFID, 7.5; MIS + Barcode + RFID + PTS + others, 10
Team	None, 0; Non-professional team, 5; Professional team, 10
Process improvement	None, 0; 3σ, 5; 6σ, 10

<https://doi.org/10.1371/journal.pone.0234247.t006>

Table 7. Score.

DMU	Score	The selected scenario
1	35	1-U
2	35	2-U
3	23.5	3-H
4	23.5	4-H
5	33	5-U
6	14	6-L
7	18	7-L
8	14	8-L
9	16	9-L
10	15.5	10-L
11	23	11-H
12	9.5	12-L

<https://doi.org/10.1371/journal.pone.0234247.t007>

indicator “Team” is 5. “Process improvement” indicates the level of a company’s control of its business. If a company utilizes 6 sigma (6σ), i.e., the highest level, as standard practice, its score in the indicator “Process improvement” is 10.

The group of experts was asked to score each pallet rental company based on the multi-index comprehensive evaluation system. The results are shown in Table 7. Note that these experts did not know these companies’ precise annual pallet loss rates. If the score of a company is below 20 (below 50% of the total score), this company is under the worst condition (DMU 6, DMU 7, DMU 8, DMU 9, DMU 10, and DMU 12). If the score of a company is between 20 and 32 (50%-80% of the total score), this company is under the “Halo + Hot deck” condition (DMU 3, DMU 4, and DMU 11). If the score of a company is greater than 32 (over 80% of the total score), this company is under the best condition (DMU 1, DMU 2, and DMU 5). For instance, if the value of DMU 1’s annual pallet loss rate is missing, its efficiency should be θ_1^U and the efficiency of the other DMUs should take the values in the sub-scenario 1-U (the first row, Tables 2 and 3). Finally, analysts can rank these pallet rental companies based on the efficiency obtained from the proposed multi-criteria evaluation approach.

3.3 Analysis

In order to examine the validity of the proposed multi-criteria evaluation approach, the results obtained from the proposed approach and those obtained from other methods are compared. Based on the proposed interval additive integer-valued DEA models with undesirable outputs, the deletion method (the deletion DEA), the dummy entries method (the dummy entries DEA), and the mean imputation method (the mean imputation DEA) are applied to measure the twelve pallet rental companies’ efficiency in each scenario. The efficiency of DMUs obtained from the deletion DEA method (deleting the variable “annual pallet loss rate”) has been shown in Table 4. According to the dummy entries method, analysts should use large enough numbers for the pallet loss rates of DMUs with missing data because the undesirable output is expected to be minimized. Therefore, the resulting efficiency of DMUs obtained from the dummy entries DEA method should be θ_k^L (under DMU_k ’s worst condition), which has been shown in Tables 2 and 3. The efficiency of DMUs obtained from the mean imputation DEA method is shown in Tables 8 and 9.

Then, the error rates of the four methods, i.e., the multi-criteria evaluation approach (MEA), the mean imputation DEA method (MIM), the deletion DEA method (DM), and the

Table 8. Efficiency resulting from the mean imputation DEA method (DMU 1–DMU 6).

Scenario	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6
1-M	0.241	1.000	0.189	0.272	1.000	0.346
2-M	1.000	1.000	0.189	0.274	1.000	0.346
3-M	1.000	1.000	0.189	0.272	1.000	0.346
4-M	1.000	1.000	0.189	0.454	1.000	0.346
5-M	1.000	1.000	0.189	0.272	0.445	0.346
6-M	1.000	1.000	0.189	0.272	1.000	1.000
7-M	1.000	1.000	0.189	0.272	1.000	0.346
8-M	1.000	1.000	0.189	0.272	1.000	0.346
9-M	1.000	1.000	0.189	0.272	1.000	0.346
10-M	1.000	1.000	0.189	0.272	1.000	0.346
11-M	1.000	1.000	0.189	0.272	1.000	0.346
12-M	1.000	1.000	0.189	0.272	1.000	0.334

<https://doi.org/10.1371/journal.pone.0234247.t008>

Table 9. Efficiency resulting from the mean imputation DEA method (DMU 7–DMU 12).

Scenario	DMU 7	DMU 8	DMU 9	DMU 10	DMU 11	DMU 12
1-M	0.520	0.240	0.218	1.000	1.000	1.000
2-M	0.520	0.240	0.218	1.000	1.000	1.000
3-M	0.520	0.240	0.218	1.000	1.000	1.000
4-M	0.520	0.240	0.218	1.000	1.000	1.000
5-M	0.557	0.240	0.218	1.000	1.000	1.000
6-M	0.520	0.240	0.218	1.000	1.000	1.000
7-M	1.000	0.240	0.218	1.000	1.000	1.000
8-M	0.520	0.255	0.218	1.000	1.000	1.000
9-M	0.520	0.240	0.224	1.000	1.000	1.000
10-M	0.441	0.240	0.218	1.000	1.000	1.000
11-M	0.520	0.240	0.218	1.000	1.000	1.000
12-M	0.446	0.240	0.218	1.000	1.000	1.000

<https://doi.org/10.1371/journal.pone.0234247.t009>

Table 10. Error rate.

Scenario	MEA	MIM	DM	DEM
1	0.0000	0.7586	0.8428	0.7693
2	0.0000	0.0049	0.0000	0.0070
3	0.1076	0.0000	0.1039	0.1284
4	0.0315	0.6672	0.1043	0.0562
5	0.0201	0.6252	0.5992	0.6616
6	0.0000	1.8863	0.3088	0.0000
7	0.1382	0.9227	0.3575	0.1382
8	0.0000	0.0643	0.3407	0.0000
9	0.0175	0.0274	0.4046	0.0175
10	0.0000	0.1522	0.0000	0.0000
11	0.2365	0.0000	0.0000	2.4265
12	0.0000	0.1768	0.0000	0.0000
Average error	0.0460	0.4405	0.2551	0.3504

<https://doi.org/10.1371/journal.pone.0234247.t010>

dummy entries DEA method (DEM), can be calculated using the formulas proposed in Subsection 3.1. The results are shown in Table 10. The average error rate of the proposed multi-criteria evaluation approach is the lowest (0.0460), while the average error rate of the mean imputation DEA method is the greatest (0.4405). The average error rate of the deletion DEA method is 0.2551, and the average error rate of the dummy entries DEA method is 0.3504. Therefore, the proposed multi-criteria evaluation approach (“interval additive integer-valued DEA models with undesirable outputs”, the “Halo + Hot deck” imputation method, and the multi-index comprehensive evaluation method) is better than the other methods, and it can help analysts measure the efficiency of DMUs with missing data.

4. Conclusions

DEA, especially non-radial DEA, is a useful nonparametric technique to measure efficiency. DEA is a “data oriented” method so that analysts need to collect enough data. However, missing data is a common problem in data analysis. Therefore, it is necessary to develop effective methods to conduct DEA with missing data.

The contributions of this paper are as follows. (1) Interval additive integer-valued DEA models with undesirable outputs are proposed, which enables analysts to handle integer-valued variables and undesirable outputs when measuring efficiency. (2) The “Halo + Hot deck” imputation method is presented to deal with missing data, which is simple and easy. (3) A multi-criteria evaluation approach is proposed to measure the efficiency of DMUs with missing data based on the “interval additive integer-valued DEA models with undesirable outputs”, the “Halo + Hot deck” imputation method, and the multi-index comprehensive evaluation method. The proposed approach is applied to the pallet rental industry, and the case study proves that the proposed approach is more effective than traditional approaches such as the mean imputation DEA method, the deletion DEA method, and the dummy entries DEA method.

However, the paper still has some limitations. For example, (1) there are some other methods to deal with missing data, and the multiple imputation has been regarded as a more accurate and less biased method. It is worth combining the multiple imputation method and DEA to evaluate the efficiency of DMUs with missing data; (2) in the case study, only two inputs, one desirable output, and one undesirable output were selected because there are very few public data about the pallet rental industry. In the future, more data should be collected and the performance of pallet rental companies should be measured in more detail.

Supporting information

S1 Code. I-addIDEA-U.
(DOCX)

Acknowledgments

The authors would appreciate the editor and the reviewers for their valuable comments.

Author Contributions

Data curation: Chunhua Chen, Jianwei Ren, Haohua Liu.

Funding acquisition: Jianwei Ren.

Methodology: Chunhua Chen, Jianwei Ren, Lijun Tang, Haohua Liu.

Software: Chunhua Chen, Lijun Tang, Haohua Liu.

Supervision: Haohua Liu.

References

1. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. *European Journal of Operational Research*. 1978; 2(6): 429–444.
2. Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*. 1984; 30(9): 1078–1092.
3. Chen PC, Yu MM, Shih JC, Chang CC, Hsu SH. A reassessment of the Global Food Security Index by using a hierarchical data envelopment analysis approach. *European Journal of Operational Research*. 2019; 272(2): 687–698.
4. Yu MM, Chen LH. Evaluation of efficiency and technological bias of tourist hotels by a meta-frontier DEA model. *Journal of the Operational Research Society*. 2019; 12(4): 1–5.
5. Stead AD, Wheat P. The case for the use of multiple imputation missing data methods in stochastic frontier analysis with illustration using English local highway data. *European Journal of Operational Research*. 2020; 280(1): 59–77.
6. Berchtold A. Treatment and reporting of item-level missing data in social science research. *International Journal of Social Research Methodology*. 2019; 22(5): 431–439.
7. Krause RW, Huisman M, Steglich C, Snijders T. Missing data in cross-sectional networks—An extensive comparison of missing data treatment methods. *Social Networks*. 2020; 62: 99–112.
8. Madden G, Apergis N, Rappoport P, Banerjee A. An application of nonparametric regression to missing data in large market surveys. *Journal of Applied Statistics*. 2018; 45(7): 1292–1302.
9. Wang Y, Li K, Gan S, Cameron C. Missing data imputation with OLS-based autoencoder for intelligent manufacturing. *IEEE Transactions on Industry Applications*. 2019; 55(6): 7219–7229.
10. Schichtel BA, Gebhart KA, Morris KH, Cheatham JR, Vimont J, Larson RS, et al. Long-term trends of wet inorganic nitrogen deposition in Rocky Mountain National Park: Influence of missing data imputation methods and associated uncertainty. *Science of the Total Environment*. 2019; 687: 817–826. <https://doi.org/10.1016/j.scitotenv.2019.06.104> PMID: 31412485
11. Mehrotra DV, Liu F, Permutt T. Missing data in clinical trials: Control-based mean imputation and sensitivity analysis. *Pharmaceutical Statistics*. 2017; 16(5): 378–392. <https://doi.org/10.1002/pst.1817> PMID: 28631331
12. Im J, Cho IH, Kim JK. FHDI: An R package for fractional hot deck imputation. *The R Journal*. 2018; 10(1): 140–154.
13. Andridge RR, Little RJ. A review of hot deck imputation for survey non-response. *International Statistical Review*. 2010; 78(1): 40–64. <https://doi.org/10.1111/j.1751-5823.2010.00103.x> PMID: 21743766
14. Maity AK, Pradhan V, Das U. Bias reduction in logistic regression with missing responses when the missing data mechanism is nonignorable. *The American Statistician*. 2019; 73(4): 340–349.
15. Qiu Y, Liang B. Robust logistic regression of family data in the presence of missing genotypes. *Journal of Applied Statistics*. 2019; 46(5): 926–945.
16. Akande O, Reiter J, Barrientos AF. Multiple imputation of missing values in household data with structural zeros. *Survey Methodology*. 2019; 45(2): 271–294.
17. Hammon A, Zinn S. Multiple imputation of binary multilevel missing not at random data. *Journal of The Royal Statistical Society Series C-Applied Statistics*. 2020; 69(3): 547–564.
18. Zhang Q, Yuan KH, Wang L. Asymptotic bias of normal-distribution-based maximum likelihood estimates of moderation effects with data missing at random. *British Journal of Mathematical and Statistical Psychology*. 2019; 72(2): 334–354. <https://doi.org/10.1111/bmsp.12151> PMID: 30474256
19. Li W, Yang S, Han P. Robust estimation for moment condition models with data missing not at random. *Journal of Statistical Planning and Inference*. 2020; 207: 246–254.
20. Jiang Q, Yan X, Huang B. Neighborhood variational Bayesian multivariate analysis for distributed process monitoring with missing data. *IEEE Transactions on Control Systems Technology*. 2018; 27(6): 2330–2339.
21. Li Z, Yu H, Zhang G, Wang J. A Bayesian vector autoregression-based data analytics approach to enable irregularly-spaced mixed-frequency traffic collision data imputation with missing values. *Transportation Research Part C: Emerging Technologies*. 2019; 108(11): 302–319.
22. Zhang K, Gonzalez R, Huang B, Ji G. Expectation-maximization approach to fault diagnosis with missing data. *IEEE Transactions on Industrial Electronics*. 2014; 62(2): 1231–1240.

23. Malan L, Smuts CM, Baumgartner J, Ricci C. Missing data imputation via the expectation-maximization algorithm can improve principal component analysis aimed at deriving biomarker profiles and dietary patterns. *Nutrition Research*. 2020; 75:67–76. <https://doi.org/10.1016/j.nutres.2020.01.001> PMID: 32035304
24. O'neal PV, Ozcan YA, Ma Y. Benchmarking mechanical ventilation services in teaching hospitals. *Journal of Medical Systems*. 2002; 26(3): 227–240. <https://doi.org/10.1023/a:1015058217867> PMID: 12018609
25. Kuosmanen T. Modeling blank data entries in data envelopment analysis. Econ-WPA working paper at WUSTL. 2012; 10: 2. Available from: <https://econwpa.ub.uni-muenchen.de/econ-wp/em/papers/0210/0210001.pdf>.
26. Gardijan M, Lukač Z. Measuring the relative efficiency of the food and drink industry in the chosen EU countries using the data envelopment analysis with missing data. *Central European Journal of Operations Research*. 2018; 26(3): 695–713.
27. Smirlis YG, Maragos EK, Despotis DK. Data envelopment analysis with missing values: An interval DEA approach. *Applied Mathematics and Computation*. 2006; 177(1): 1–10.
28. Azizi H. A note on data envelopment analysis with missing values: An interval DEA approach. *The International Journal of Advanced Manufacturing Technology*. 2013; 66(9–12): 1817–1823.
29. Poordavoodi A, Goudarz, Javadi HS. Toward a more accurate web service selection using modified interval DEA models with undesirable outputs. *Computer Modeling in Engineering & Sciences*. 2020; 123(2): 525–570.
30. Kao C, Liu ST. Fuzzy efficiency measures in data envelopment analysis. *Fuzzy Sets and Systems*. 2000; 113(3): 427–437.
31. Wu J, Xiong B, An Q, Zhu Q, Liang L. Measuring the performance of thermal power firms in China via fuzzy Enhanced Russell measure model with undesirable outputs. *Journal of Cleaner Production*. 2015; 102: 237–245.
32. Bakhtavar E, Yousefi S. Analysis of ground vibration risk on mine infrastructures: Integrating fuzzy slack-based measure model and failure effects analysis. *International Journal of Environmental Science and Technology*. 2019; 16(10): 6065–6076.
33. Arya A, Yadav SP. Development of intuitionistic fuzzy super-efficiency slack based measure with an application to health sector. *Computers & Industrial Engineering*. 2018; 115: 368–380.
34. Wu MQ, Zhang CH, Liu XN, Fan JP. Green supplier selection based on DEA model in interval-valued Pythagorean fuzzy environment. *IEEE Access*. 2019; 7: 108001–108013.
35. Jafarian-Moghaddam AR, Ghoseiri K. Multi-objective data envelopment analysis model in fuzzy dynamic environment with missing values. *The International Journal of Advanced Manufacturing Technology*. 2012; 61(5–8): 771–785.
36. Arya A, Yadav SP. Performance efficiency of public health sector using intuitionistic fuzzy DEA. *International Journal of Uncertainty Fuzziness and Knowledge-Based Systems*. 2020; 28(2):289–315
37. Zha Y, Song A, Xu C, Yang H. Dealing with missing data based on data envelopment analysis and halo effect. *Applied Mathematical Modelling*. 2013; 37(9): 6135–6145.
38. Chen Y, Li Y, Wu H, Liang L. Data envelopment analysis with missing data: A multiple linear regression analysis approach. *International Journal of Information Technology & Decision Making*. 2014; 13(1): 137–153.
39. Lozano S, Villa G. Data envelopment analysis of integer-valued inputs and outputs. *Computers & Operations Research*. 2006; 33(10): 3004–3014.
40. Du J, Chen CM, Chen Y, Cook WD, Zhu J. Additive super-efficiency in integer-valued data envelopment analysis. *European Journal of Operational Research*. 2012; 218(1): 186–192.
41. Ajirlo SF, Amirteimoori A, Kordrostami S. Two-stage additive integer-valued data envelopment analysis models. *Journal of Modelling in Management*. 2019; 14(1): 199–213.
42. Kordrostami S, Amirteimoori A, Noveiri MJ. Inputs and outputs classification in integer-valued data envelopment analysis. *Measurement*. 2019; 139: 317–325.
43. Ren J, Chen C, Gao B, Zhang J. Performance evaluation of pallet rental companies: A non-oriented super-efficiency integer-valued DEA model. *IEEE Access*. 2019; 7: 151628–151637.
44. Färe R, Grosskopf S, Lovell CK, Pasurka C. Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *The Review of Economics and Statistics*. 1989; 71(1): 90–98.
45. Chung YH, Färe R, Grosskopf S. Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*. 1997; 51(3): 229–240.
46. Layer K, Johnson AL, Sickles RC, Ferrier GD. Direction selection in stochastic directional distance functions. *European Journal of Operational Research*. 2020; 280(1): 351–364.

47. Seiford LM, Zhu J. Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*. 2002; 142(1): 16–20.
48. Halkos G, Petrou KN. Treating undesirable outputs in DEA: A critical review. *Economic Analysis and Policy*. 2019; 62: 97–104.
49. Yu SH. Benchmarking and performance evaluation towards the sustainable development of regions in Taiwan: A minimum distance-based measure with undesirable outputs in additive DEA. *Social Indicators Research*. 2019; 144(3): 1323–1348.
50. Chen CM, Du J, Huo J, Zhu J. Undesirable factors in integer-valued DEA: Evaluating the operational efficiencies of city bus systems considering safety records. *Decision Support Systems*. 2012; 54(1): 330–335.
51. Caldas P, Ferreira D, Dollery B, Marques R. Are there scale economies in urban waste and wastewater municipal services? A non-radial input-oriented model applied to the Portuguese local government. *Journal of Cleaner Production*. 2019; 219: 531–539.
52. Chen X, Wu G, Li D. Efficiency measure on the truck restriction policy in China: A non-radial data envelopment model. *Transportation Research Part A: Policy and Practice*. 2019; 129: 140–154.
53. Charnes A, Cooper WW, Golany B, Seiford L, Stutz J. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics*, 1985; 30(1–2): 91–107.
54. Pastor JT, Ruiz JL, Sirvent I. An enhanced DEA Russell graph efficiency measure. *European Journal of Operational Research*. 1999; 115(3): 596–607.
55. Tone K. A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*. 2001; 130(3):498–509.
56. Arteaga FJ, Tavana M, Di Caprio D, Toloo M. A dynamic multi-stage slacks-based measure data envelopment analysis model with knowledge accumulation and technological evolution. *European Journal of Operational Research*. 2019; 278(2): 448–462.
57. Meghanathan N. Centrality and partial correlation coefficient-based assortativity analysis of real-world networks. *The Computer Journal*. 2019; 62(9): 1247–1264.
58. Yu SH, Hsu CW. A unified extension of super-efficiency in additive data envelopment analysis with integer-valued inputs and outputs: An application to a municipal bus system. *Annals of Operations Research*. 2019; 13(11): 1–21.
59. Thorndike EL. A constant error in psychological ratings. *Journal of Applied Psychology*. 1920; 4(1): 25–29.
60. Amos C, Brockhaus S, Fawcett AM, Fawcett SE, Knemeyer AM. Blinded by the light? Analyzing sustainability authenticity, customer service perceptions, and halo effects. *The International Journal of Logistics Management*. 2019; 30(1): 117–139.
61. Ren J, Chen C, Xu H, Zhao Q. An optimization model for the operations of a pallet pool with both radio-frequency identification–tagged pallets and non-tagged pallets. *Advances in Mechanical Engineering*. 2018; 10(1): 1–13.
62. Chen C, Liu H, Liu B, Zhang J, Gao B, Ren J. Measuring the performance of pallet rental companies: Integer-valued DEA models with generalized reference sets. *IEEE Access*. 2020; 8: 3374–3386.