International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

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**To cite this article:** Majid Azadi, Zohreh Moghaddas, T.C.E. Cheng & Reza Farzipoor Saen (2021): Assessing the sustainability of cloud computing service providers for Industry 4.0: a state-of-the-art analytical approach, International Journal of Production Research, DOI: 10.1080/00207543.2021.1959666

**To link to this article:** https://doi.org/10.1080/00207543.2021.1959666

Published online: 07 Aug 2021.

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
https://doi.org/10.1080/00207543.2021.1959666



# Assessing the sustainability of cloud computing service providers for Industry 4.0: a state-of-the-art analytical approach

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**ABSTRACT**

While interests in Industry 4.0 technologies such as cloud computing and the Internet of Things (IoT) are growing, an ongoing challenge is to properly evaluate the performance of the providers of such technologies. Methods have been developed and applied to assess the efficiency of cloud service providers (CSPs) for Industry 4.0. However, most existing methods suffer from such shortcomings as subjective weights and computing complexity, rendering it difficult to succinctly differentiate the performance of CSPs in a competitive market. Besides, the literature has not taken into account many different types of data such as ratios, integers, and undesirable factors that can affect the performance of CSPs. Most importantly, most existing studies do not consider the sustainability of CSPs in evaluating their performance. To address the above issues, we present a comprehensive analytical method based on data envelopment analysis (DEA) to gauge the sustainability of CSPs for Industry 4.0. Validating the usefulness of our method using a real-life dataset, we provide not only a viable means with sound academic underpinning but also significant managerial insights for practitioners to assess the sustainability of CSPs for Industry 4.0.

**ARTICLE HISTORY**
Received 28 January 2021
Accepted 17 July 2021

**KEYWORDS**
Industry 4.0; cloud service provider (CSP); cloud computing; data envelopment analysis (DEA); quasi-fixed inputs; integer data

## 1. Introduction

Supply chain management (SCM) and operations management have embraced the benefits and challenges of Industry 4.0 in the last few years. Industry 4.0 technologies such as cloud computing, the Internet of Things (IoT), sensors and actuators, blockchain, and artificial intelligence (AI) can enhance the performance of firms and sustain their supply chains by providing opportunities for innovation and competitiveness growth (Wamba et al. 2015). Recent studies show and discuss that Industry 4.0 benefits firms in terms of improved product quality (Rosin et al. 2020), decreased production cost (Ralston and Blackhurst 2020), enhanced sustainable performance (Kamble, Gunasekaran, and Gawankar 2018; Ivanov, Dolgui, and Sokolov 2019), flexible production (Ivanov et al. 2016a and Dolgui et al. 2019), and reduced investment risk (Thibaud et al. 2018). Other studies report the positive impacts of Industry 4.0 on logistics (Winkelhaus and Grosse 2020), supply chain (Ivanov, Dolgui, and Sokolov 2019; Ivanov et al. 2016b) and lean production (Kamble et al. 2020).

To identify and implement Industry 4.0 scenarios, companies need to address design principles in Industry 4.0 such as information transparency, interoperability, decentralised decisions, and technical assistance (Singh and Sidhu 2017). The main characteristics of Industry 4.0 are recognised using integration dimensions, including vertical integration, horizontal integration, and end-to-end digital integration (Silvestri et al. 2020). To adopt Industry 4.0, companies need to establish foundations, including smart sensors, mobile devices, IoT platforms, robots, and information technology (IT) systems, which interact with each other in a unified framework (Kamble et al. 2020). Industry 4.0 is characterised by digital and automatic processes, and advanced information technologies in production and service in a secure environment (Culot et al. 2020).

Cloud computing has received considerable attention as a key technology in Industry 4.0 (Ahn, Park, and Hur 2019; Ghobakhloo 2020; Vahedi-Nouri et al. 2020; Wang et al. 2019; Zheng et al. 2021). Unlike the conventional approaches for storage, computing, and network resources to satisfy customer needs, cloud computing gives clients on-demand services, which are presented over a network. Typically, cloud service providers (CSPs) offer three types of services, including infrastructure as

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a service (IaaS), platform as a service (PaaS), and software as a service (SaaS) (Azadi et al. 2019). IaaS abstracts physical hardware such as servers and networks in the form of virtual servers and provides cloud customers with various components of a computing environment. PaaS provides a platform on top of the abstracted hardware for developing cloud applications. SaaS provides software applications and provides access to specific software without the need for installation or configuration. Businesses are increasingly hosting their applications on the cloud infrastructure such as IaaS, PaaS, and SaaS for improving their performance (Azadi et al. 2020). Nevertheless, a major issue with cloud services in Industry 4.0 is the efficiency measurement of CSPs (Filiopoulou et al. 2021). To measure the sustainability of CSPs, buyer deals with multiple criteria such as price, quality, social, and environmental factors. This, in turn, makes the sustainability evaluation of CSPs difficult for buyers of cloud services. Rather than choosing a CSP blindly, a framework for assessing CSPs will help businesses make the optimal choice. Given that many pertinent factors need to be considered for selecting a proper CSP, firms need to assess potential CSPs based on some key criteria such as economic, environmental, and social. Firms that fail to select a proper CSP will suffer high costs and low quality. Thus, there is an essential need for assessing and selecting CSPs that provide their customers with different types of cloud services, including IaaS, PaaS, and SaaS.

Data envelopment analysis (DEA) is a potent technique for evaluating the performance of decision-making units (DMUs). DEA is a nonparametric approach to measure the performance of a set of peer entities that take into consideration multiple inputs and multiple outputs. Termed DMUs, the peer entities might be companies operating in a particular market sector or a group of individuals involved in a business process (Emrouznejad and Yang 2018). DEA is a popular tool for performance measurement and benchmarking in many areas such as education, healthcare, and transportation. DEA can deal with multiple variables, including qualitative and quantitative measures. Furthermore, DEA does not need to specify the relationships among the performance measures (Shafiee, Lotfi, and Saleh 2014). Nevertheless, despite the wide application of DEA, its application to evaluating CSPs is scarce. Furthermore, our literature survey shows that there is no reference to evaluate the sustainability of CSPs. Moreover, the existing DEA models cannot deal with different types of data such as integer, ratio, undesirable outputs, and quasi-fixed.

In this paper, we develop a novel DEA model to measure the sustainability of CSPs as a key technology of Industry 4.0. Our approach not only addresses the technical issues in the literature but also fills the gaps of measuring the sustainability of CSPs for Industry 4.0 to enhance the performance of production systems. The major contributions of this paper are as follows:

- We propose a DEA model for evaluating the sustainability of CSPs in the presence of integer data and undesirable outputs.
- Our DEA model can deal with the quasi-fixed inputs directly.
- Our DEA model can handle ratio data directly.
- Our DEA model considers the manager's viewpoints on the outputs' weights using the trade-off principle.
- Our DEA model can fully rank sustainable CSPs.
- A case study is presented to validate our proposed model.

We organise the rest of the paper as follows: In Section 2, we review the related literature to identify the research gaps and position our work. In Section 3, we introduce a new DEA model for sustainability evaluation of CSPs for Industry 4.0. In Section 4, a case study is presented. Finally, in Section 5, we conclude the paper and suggest topics for future research.

## 2. Literature review

### *2.1. Sustainable supply chain management (SSCM) and Industry 4.0 technologies*

The SSCM takes into account various sustainability measures, including economic, environmental, and social factors (Ageron, Gunasekaran, and Spalanzani 2012). Over the past two decades, multinational firms have focussed on SSCM. Our literature survey indicates that the success of SSCM hinges on some factors (Khan et al. 2021). Production cost reduction, increased resource utilisation, information sharing, and forecasting accuracy are motivators for firms to pursue SSCM (Kamble, Gunasekaran, and Gawankar 2018). Furthermore, due to pressures from stakeholders and global competition, firms need to strive for sustainability in their operations, which in turn increases the complexity and uncertainty of their supply chains (Wamba et al. 2015). To address such issues, Industry 4.0 technologies such as cloud computing, IoT, and blockchain have been developed and applied in different supply chain settings. Gawankar, Gunasekaran, and Kamble (2020) investigated the role of big data in SCs and organisational performance in the retailing industry. They presented some insights for retail supply chain practitioners on planning big data analytics investments. Venkatesh et al. (2020) presented a framework that combines IoT, blockchain, and big data analytics for vendors to monitor their SSCM more efficiently.

Ghadimi et al. (2019) developed an approach for selecting intelligent sustainable suppliers in supply chains using multi-agent technology. The approach provides a framework for communicating and sharing structured information between vendors and producers.

CSPs as providers of Industry 4.0 technologies face a couple of barriers. Lack of control over the physical infrastructures leads to concerns about adopting cloud services (Wang et al. 2020). Trust depends on the credibility, transparency, and reliability of service providers during a period (Singh and Sidhu 2017). Security can be facilitated using technological means, including encryption, authorisation, and intrusion detection (Wang et al. 2020). As outsourcing information systems require heavy investment, some companies are reluctant to outsource, which is another barrier of CSPs (Cheng et al. 2018). Furthermore, many buyers, in particular small companies, are unaware of numerous advantages of cloud services and try to avoid adopting cloud services (Azadi et al. 2019). Also, lack of knowledge is another obstacle to adopt cloud services.

### 2.2. Performance assessment of cloud service providers (CSPs)

Several approaches have been developed to select CSPs. Choudhury et al. (2012) presented a framework to rank CSPs in static and dynamic environments. The framework considers different indicators such as consumers' requirements and reliability of assessing CSPs. However, the approach proposed by Choudhury et al. (2012) does not consider managers' viewpoints on the weights of indicators. Ghosh, Ghosh, and Das (2014) presented a system for measuring the performance of CSPs based on dynamic trust, service-level agreements (SLA), and reputation feedback. Nonetheless, a major issue with the proposed model is that it does not consider some key indicators to evaluate and select CSPs. Singh and Sidhu (2017) presented a framework for determining the trustworthiness of CSPs. Nevertheless, the proposed framework deals with complex calculations.

Huang, Hsu, and Tzeng (2012) proposed a hybrid multi-criteria decision-making (MCDM) approach to improve the service quality of CSPs. The model comprises different techniques of MCDM to select the best CSP. However, their model deals with a lot of stages for the performance evaluation of CSPs. Garg, Versteeg, and Buyya (2013) presented a rating system to rank CSPs using the analytical hierarchy process (AHP). Menzel et al. (2014) proposed a method for measuring the efficiency of CSPs based on genetic algorithms and AHP. However, AHP is based on the subjective judgment of decision-makers. Azadi et al. (2019) applied network DEA to gauge CSPs' efficiency. However, their model cannot deal with different types of data such as integer, ratio, and undesirable outputs and they did not consider the sustainability indicators for assessing CSPs.

### 2.3. Data envelopment analysis (DEA)

DEA is a potent approach for evaluating the relative efficiency of a set of homogenous DMUs (Yousefi et al. 2016; Farzipoor Saen 2009). DEA has been applied in many sectors such as health care, higher education, and manufacturing. Charnes, Cooper, and Rhodes (1978) first developed DEA. Banker, Charnes, and Cooper (1984) extended the Charnes-Cooper-Rhodes (CCR) model to the Banker-Charnes-Cooper (BCC) model. In the conventional DEA models such as CCR and BCC, it is assumed that producing more outputs and consuming fewer inputs is a criterion of efficiency. Nevertheless, this assumption fails to present a correct evaluation of DMUs' performance when the decision-maker deals with the undesirable outputs. For instance, $CO_2$ emissions are considered as bad outputs. Industrial wastewater is another example of undesirable output (Zhou et al. 2019). There are a couple of seminal works on DEA and undesirable outputs, e.g. Färe et al. (1989), Pittman (1983), and Yaisawarng and Klein (1994). Recently, researchers have addressed the undesirable outputs in DEA (Pishgar-Komleh et al. 2020; Shirazi and Mohammadi 2020; Zhou et al. 2019). Nevertheless, the majority of the existing DEA models, which deal with the undesirable outputs cannot capture integer and ratio data.

The standard DEA models assume that all the inputs and outputs have real values. However, in many practical applications, some inputs and outputs are integers. For instance, to analyze the efficiency of hospitals, the number of doctors and beds are integer (Du et al. 2012). Lozano and Villa (2006) incorporated integer data into DEA. However, their proposed is not consistent with the minimum extrapolation principle of DEA. To address this issue, Matin and Kuosmanen (2009) proposed an integer DEA model based on the concepts of natural disposability and natural divisibility. Wu and Zhou (2015) improved the work of Lozano and Villa (2006) by proposing a mixed-objective integer model. Azadi and Saen (2014) proposed a DEA model in the existence of both stochastic data and integer data for measuring the efficiency of suppliers. On the other hand, some inputs cannot be controlled by decision-makers and their change needs considerable time and resources. These types of inputs are called quasi-fixed inputs (Essid, Ouellette, and Vigeant 2014). As an example, consider a hospital with many wards, buildings, and rooms (as inputs). The

**Table 1.** Comparison of our model with previous papers.

| Studies | Real data | Undesirable output | Integer data | Quasi-fixed inputs | Ratio data | Weight restrictions |
|---|---|---|---|---|---|---|
| Charnes, Cooper, and Rhodes (1978) | √ | × | × | × | × | × |
| Banker, Charnes, and Cooper (1984) | √ | × | × | × | × | × |
| Färe et al. (1989) | √ | √ | × | × | × | × |
| Pittman (1983) | √ | √ | × | × | × | × |
| Yaisawarng and Klein (1994) | √ | √ | × | × | × | × |
| Pishgar-Komleh et al. (2020) | √ | √ | × | × | × | × |
| Zhou et al. (2019) | √ | √ | × | × | × | × |
| Shirazi and Mohammadi (2020) | √ | √ | × | × | × | × |
| Lozano and Villa (2006) | √ | × | √ | × | × | × |
| Matin and Kuosmanen (2009) | √ | × | √ | × | × | × |
| Azadi and Saen (2014) | √ | × | √ | × | × | × |
| Wu and Zhou (2015) | √ | × | √ | × | × | × |
| Fried, Schmidt, and Yaisawarng (1999) | √ | × | × | √ | × | × |
| Ruggiero (1996) | √ | × | × | √ | × | × |
| Villano and Tran (2018) | √ | × | × | √ | × | × |
| Yang, Fukuyama, and Song (2019) | √ | × | × | √ | × | × |
| Hollingsworth and Smith (2003) | √ | × | × | × | √ | × |
| Emrouznejad and Amin (2009) | √ | × | × | × | √ | × |
| Olesen, Petersen, and Podinovski (2015) | √ | × | × | × | √ | × |
| Olesen, Petersen, and Podinovski (2017) | √ | × | × | × | √ | × |
| Hatami-Marbini and Toloo (2019) | √ | × | × | × | √ | × |
| Wong and Beasley (1990) | √ | × | × | × | × | √ |
| Saen (2010a) | √ | √ | × | × | × | √ |
| Saen (2009, 2010b) | √ | × | × | × | × | √ |
| Wang, Luo, and Liang (2009) | √ | × | × | × | × | √ |
| Podinovski (2016) | √ | × | × | × | × | √ |
| Our proposed model | √ | √ | √ | √ | √ | √ |

decision-maker cannot reduce these inputs overnight. There are studies, which deal with quasi-fixed inputs in DEA, e.g. Fried, Schmidt, and Yaisawarng (1999), Ruggiero (1996), Villano and Tran (2018), and Yang, Fukuyama, and Song (2019).

Also, there might be ratio data in many real-world applications. For instance, the percentage of gross domestic product (GDP) is a sort of ratio data (Emrouznejad and Amin 2009; Hollingsworth and Smith 2003). Hollingsworth and Smith (2003) considered the ratio data in DEA. To handle the ratio data, Emrouznejad and Amin (2009) proposed the convexity assumption in the DEA structure. Olesen, Petersen, and Podinovski (2015) presented variable returns-to-scale (VRS) and constant returns-to-scale (CRS) DEA models to handle ratio data. Olesen, Petersen, and Podinovski (2017) proposed the notion of potential ratio efficiency for DEA models with ratio data. However, they suffer from sufficient discrimination power. To address this issue, Hatami-Marbini and Toloo (2019) proposed the modified multiplier and envelopment DEA models. Another pitfall of the traditional DEA models concerns the decision-maker's subjective judgments (Saen 2010a). To address this issue, Wong and Beasley (1990) proposed weight restrictions in DEA. However, the proposed model of Wong and Beasley (1990) may lead to infeasibility. Sarrico and Dyson (2004) used virtual assurance regions to tackle the infeasibility issue. There are also studies on ways to handle weight restrictions in DEA, e.g. Podinovski (2016), Saen (2009; 2010b), and Wang, Luo, and Liang (2009). Although several DEA models have been proposed over the last few decades, none of them is able to deal with different types of data. Table 1 compares our model with the previous papers.

Also, by conducting a bibliometric analysis of studies on performance evaluation of CSPs, we searched 'cloud computing' and 'data envelopment analysis' in the title, abstract, and keywords of studies tracked in Scopus. Utilising the VOSviewer software, we used the comma-separated values (CSV) file as the output of Scopus. In the CSV file, there are data such as authors, affiliations, paper title, journal, keywords, citations, and year of publication. We depict co-occurrences of keywords in a network, in which the links show the connections between two keywords and the nodes represent a keyword. Co-occurrences mean the frequencies that a keyword pairing is used in papers. The higher the frequency is, the stronger is the link between two keywords. To make the analysis more logical, we combined similar keywords, e.g. data envelopment analysis, data envelopment analysis models, windows multiplicative data envelopment analysis, and data envelopment analysis (DEA). To make the figure simple and clear, we set the minimum number of occurrences of a keyword to 2 in the VOSviewer software. Figure 1 shows the clustering of keywords, where each cluster has a specific colour. The major cluster is the green cluster, which is the biggest. The main keywords of the green cluster contain 'data envelopment analysis', 'cloud computing', and 'efficiency'. Figure 1 indicates the existence of five clusters

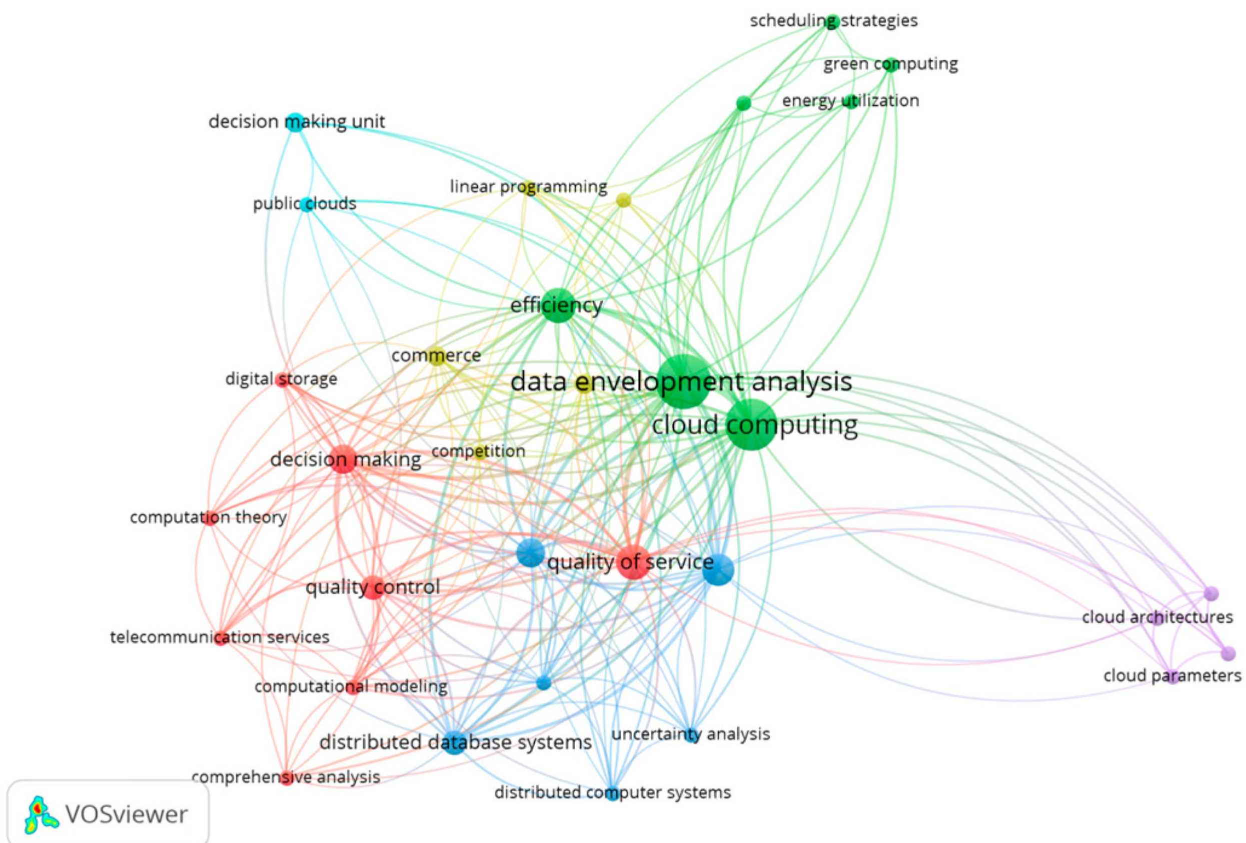


**Figure 1.** The keywords' clusters.

in the domain of 'data envelopment analysis' and 'cloud computing'.

### 2.4. The existing gaps in the literature

Though a great deal of research has been conducted for assessing and selecting CSPs, these researches suffer from various limitations and gaps. Distinguishing CSPs based on their efficiency and quality of service criteria not only can assist the consumers to select the best CSP but also can help CSPs to identify their inefficiency reasons. A key issue of the existing methods in the literature is that they cannot deal with different types of data, including ratio, integer, and undesirable outputs in measuring the sustainability of CSPs. This, in turn, results in inaccuracy in the evaluation and selection of CSPs. Most importantly, most existing studies do not consider the sustainability aspects in the assessment and selection of CSPs. We conduct this study to fill these research gaps by proposing a novel DEA model to measure the sustainability of CSPs for Industry 4.0.

## 3. Proposed method

We propose a novel DEA model that can deal with several types of inputs and outputs, including quasi-fixed inputs, integer outputs, ratio outputs, and undesirable outputs. The associated constraints of the undesirable outputs have an equal sign to keep them unchanged and only exist in the production possibility set (PPS). For the quasi-fixed inputs, we develop a new approach to handle them. Banker and Morey (1986), Kim and Lee (2001), and Bilodeau et al. (2004) found that changes in the quasi-fixed inputs are not easy for managers as long time and massive investments are needed. There are two approaches to deal with the quasi-fixed inputs, namely the one-stage and multi-stage approaches. In the one-stage approach, the quasi-fixed inputs are processed only in one stage. In the multi-stage approach, the quasi-fixed inputs are processed in a couple or more stages. We adopt the one-stage approach based upon the axiomatic principles of DEA as this approach is less computationally demanding. The main idea is based on the dependency of inputs on one another to generate outputs. For instance, if we reduce the number of staff as an input, we will have a useless workplace space as another input. Thus, there is dependency among the inputs, which we need to take into account. Table 2 depicts the used nomenclature.

Assume that there are $n$ DMUs. Let $DMU_o$ denotes the DMU under evaluation, and $x_o \in R_m^+$ and $y_o \in R_s^+$ are the

**Table 2.** The used nomenclature.

| | |
|---|---|
| $x_j$ | Input vector of $DMU_j$ |
| $y_j$ | Output vector of $DMU_j$ |
| $\hat{x}_j$ | Vector of dominated inputs for $DMU_j$ |
| $\hat{y}_j$ | Vector of dominated outputs for $DMU_j$ |
| $T_c$ | PPS with a constant returns-to-scale form of technology |
| $x_j^1$ | Vector of changeable inputs for $DMU_j$ |
| $x_j^2$ | Vector of quasi-fixed inputs for $DMU_j$ |
| $\eta$ | Positive real number |
| $\alpha_j(0 \leq \alpha_j \leq 0)$ | Real number of $DMU_j$ |
| $\lambda_j(\lambda_j \geq 0)$ | Intensity variable of $DMU_j$ |
| $\alpha_j x_j^1$ | Vector of dominated variables for $DMU_j$ |
| $\alpha_j x_j^2$ | Vector of quasi-fixed inputs for $DMU_j$ |
| $\hat{y}_j$ | Vector of dominated outputs of $DMU_j$ |
| $\hat{T}$ | PPS with a variable returns-to-scale form of technology |

inputs and outputs of $DMU_o$, respectively. Consider the basic axioms of the CCR model as follows:

$\dot{A}1$. Feasibility: For $j$: $(x_j, y_j) \in T_c$.
$\dot{A}2$. Convexity: $T_c$ is a convex set.
$\dot{A}3$. Constant returns-to-scale: For $(x_j, y_j) \in T_c$: $(\eta x_j, \eta y_j) \in T_c, \eta \in R^+$.
$\dot{A}4$. Free disposability: If $(x_j, y_j) \in T_c$, $y_j \geq \hat{y}_j \geq 0$, and $x_j \leq \hat{x}_j$, the $(\hat{x}_j, \hat{y}_j) \in T_c$.
$\dot{A}5$. Minimum extrapolation: $T_c$ is the minimal set that satisfies axioms $\dot{A}1$–$\dot{A}4$.

For axioms $\dot{A}1$–$\dot{A}5$, the PPS is defined. The PPS introduced as $T_c$ in (1) is defined as a set of semi-positive $(x, y)$ as follows:

$$T_c = \left\{ (x, y) \middle| x \geq \sum_{j=1}^{n} \lambda_j x_j, \sum_{j=1}^{n} \lambda_j y_j \leq y, \lambda_j \geq 0, \ j = 1, \ldots, n \right\}_j \tag{1}$$

Now, we present the axiomatic principles of DEA in the presence of quasi-fixed inputs. Let $x_o^1 \in R_{m_1}^+, x_o^2 \in R_{m_2}^+$, and $y_o \in R_s^+$ be changeable and real inputs, quasi-fixed inputs, and outputs of $DMU_o, o \in j = \{1, \ldots, n\}$, respectively. Consider the basic axioms developed to cope with quasi-fixed inputs as follows:

$\dot{B}1$. Feasibility: For $j$:$(x_j^1, x_j^2, y_j) \in \hat{T}$.

$\dot{B}2$. Convexity: $\hat{T}$ is a convex set. Thus, $(\sum_{j=1}^{n} \lambda_j x_j^1, \sum_{j=1}^{n} \lambda_j x_j^2, \sum_{j=1}^{n} \lambda_j y_j) \in \hat{T}, \sum_{j=1}^{n} \lambda_j = 1, \forall j : \lambda_j \geq 0$,

$\dot{B}3$. Disposability of changeable and real inputs, quasi-fixed inputs, and outputs: If for any $DMU_j, j = 1, \ldots, n$, $(x_j^1, x_j^2, y_j) \in \hat{T}_c, y \geq \hat{y}_j$, and $0 < \alpha_j \leq 1$, then $(\alpha_j x_j^1, \alpha_j x_j^2, y_j) \in \hat{T}$. Thus, $(\sum_{j=1}^{n} \alpha_j \lambda_j x_j^1, \sum_{j=1}^{n} \alpha_j \lambda_j x_j^2, \sum_{j=1}^{n} \lambda_j y_j) \in \hat{T}, \sum_{j=1}^{n} \lambda_j = 1, \forall j : \lambda_j \geq 0, 0 < \alpha_j \leq 1$.
For example, the changeable input is the number of staff and the quasi-fixed input is building area. Given *toformthebenchmarks*, by fixing the output, to reduce staff by 20% requires a 20% reduction in the building area.

$\dot{B}4$. Minimum extrapolation: $\hat{T}$ is the minimal set that satisfies axioms $\dot{B}1$–$\dot{B}3$.

The PPS with variable returns-to-scale as defined by $\hat{T}_v$ in (2) is as follows:

$$\hat{T}_v = \{(\hat{x}_1, \hat{x}_2, y) | \hat{x}_1 \geq \sum_{j=1}^{n} \lambda_j \alpha_j x_j^1,$$
$$\hat{x}_2 = \sum_{j=1}^{n} \lambda_j \alpha_j x_j^2, \sum_{j=1}^{n} \lambda_j y_j \leq y, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0,$$
$$0 < \alpha_j \leq 1, j = 1, \ldots, n\} \tag{2}$$

Note that for the changeable inputs and quasi-fixed inputs, their changes are dependent. The changes are not similar for the DMUs. Here, to form the benchmarks, the contributions of changeable inputs and quasi-fixed inputs, which are dependent on each other are determined. $\alpha_j$ is the percentage of input of $\text{DMU}_j$ in forming the benchmarks. $\lambda_j$ is the contribution of input of $\text{DMU}_j$ in forming the benchmarks. Since $\hat{T}_v$ is nonlinear, we need to linearise it. Consider the following relation:

$$\lambda_j = (1 - \alpha_j)\lambda_j + \alpha_j \lambda_j \tag{3}$$

Using the following change of variables, we linearise the constraints $\hat{T}_v$ as follows:

$$\begin{cases} (1 - \alpha_j)\lambda_j = \delta_j \\ \alpha_j \lambda_j = \gamma_j \end{cases} \rightarrow \lambda_j = \delta_j + \gamma_j \tag{4}$$

Given (4), $\delta_j$ is part of the inputs of $\text{DMU}_j$, which is reduced, and $\gamma_j$ is part of the inputs of $\text{DMU}_j$, which forms the benchmarks. Thus, we have the following PPS $(\hat{T}_v)$

$$\hat{T}_v = \{(\hat{x}^1, \hat{x}^2, y) | \sum_{j=1}^{n} \gamma_j x_j^1 \leq \hat{x}_1,$$
$$\sum_{j=1}^{n} \gamma_j x_j^2 = \hat{x}_2,$$
$$\sum_{j=1}^{n} (\delta_j + \gamma_j) y_j \geq y,$$

$$\sum_{j=1}^{n}(\delta_j+\gamma_j)=1,$$
$$\delta_j\geq 0, \gamma_j\geq 0,\ j=1,\ldots,n\} \qquad (5)$$

In PPS (5), the inputs are weighted by $\alpha_j\lambda_j$ and the outputs are weighted by $\alpha_j\lambda_j$ and $(1-\alpha_j)\lambda_j$. In the constraints of the inputs and outputs, there are $n$ inefficient DMUs $(0,0,\gamma_j)$ where $\gamma_j$ is their intensity coefficient. Indeed, for each inefficient DMU $(0,0,\gamma_j)$, $(x_j^1,x_j^2,y_j)$ exists in the dataset. Since the PPS is formed by scaling a convex combination of the extreme points, which include a convex combination of the inefficient DMUs, it is not necessary to add them to PPS (5). Consider the following relations

$$\sum_{j=1}^{n}\delta_j(0)+\sum_{j=1}^{n}\gamma_j x_j^1\leq\hat{x}_1,$$
$$\sum_{j=1}^{n}\delta_j(0)+\sum_{j=1}^{n}\gamma_j x_j^2=\hat{x}_2,$$
$$\sum_{j=1}^{n}\delta_j y_j+\sum_{j=1}^{n}\gamma_j y_j\geq y,$$
$$\sum_{j=1}^{n}(\delta_j+\gamma_j)=1 \qquad (6)$$

An important feature of (6) is that the right-hand side of the inputs and outputs' constraints have no scaling variables. Thus, many types of models for efficiency evaluation can be developed and the models will be linear. Consider Figure 2, in which the output feasibility is ignored to make the figure easy to follow. Without loss of generality, assume that an inefficient DMU in the three-dimensional PPS $(X^1, X^2, Y)$ is projected on $D$ via increasing the output. In Figure 2, $x^1$ and $x^2$ are a changeable input and a quasi-fixed input, respectively. Figure 2 depicts four DMUs and Table 3 reports the dataset. The frontier of the triangle $ABC$ is the Pareto efficiency production frontier.

The different levels of the quasi-fixed input $x^2$ for DMUs $A$ and $C$, DMU $D$, and DMU $B$ in PPS (5) are $x^2=1$, $x^2=2$, and $x^2=3$, respectively. The DMU $D$ is projected on the Pareto efficiency frontier by $x^1-s^-=2.5-0.5=2$. The projected point is called $D'$ at ($x^1=2$, $x^2=2$). Given PPS (5), the benchmark (projected point) is a convex combination of the extreme efficient DMUs. The extreme DMUs that make the projection point on the Pareto efficiency frontier are members of the reference set of the inefficient DMUs. In Figure 2, $D'$ is the projection of $D$ on the Pareto efficiency frontier, which is a convex combination of the extreme efficient DMUs $B$ and $C$. Using PPS (1) and assuming variable returns-to-scale, we have

**Table 3.** The dataset.

| DMU | $x^1$ | $x^2$ |
|---|---|---|
| $A$ | 4 | 1 |
| $B$ | 1 | 3 |
| $C$ | 2 | 1 |
| $D$ | 2.5 | 2 |

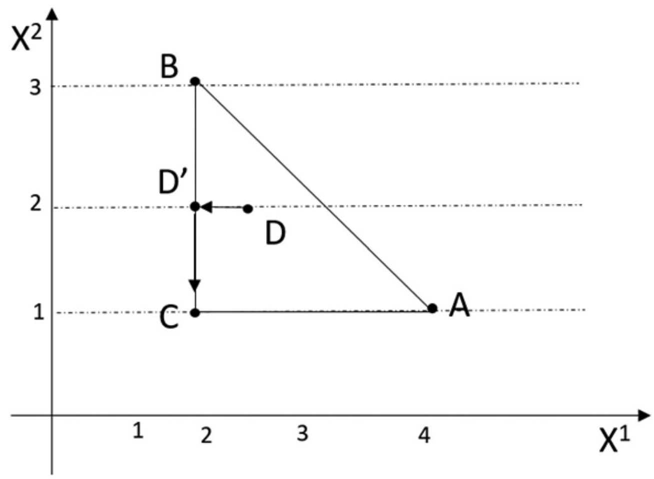


**Figure 2.** The inputs and production frontier.

$$\begin{cases}\lambda_B x_B^1+\lambda_C x_C^1=x_D^1-s^1\\ \lambda_B x_B^2+\lambda_C x_C^2=x_D^2\end{cases}\rightarrow\begin{cases}\lambda_B(1)+\lambda_C(2)=2\\ \lambda_B(3)+\lambda_C(1)=2\end{cases}$$
$$\rightarrow\begin{cases}\lambda_B^*=\dfrac{2}{5}\\ \lambda_C^*=\dfrac{4}{5}\end{cases} \qquad (7)$$

As a result, $D'$ is on the efficiency frontier. Also, DMUs $B$ and $C$ are the reference set of DMU $D$. We derive the efficiency of DMU $D$ as follows:

$$\text{Relative Efficiency}_{DMU_D}=\frac{x_{D'}^1}{x_D^1}=\frac{2}{2.5}=0.8$$
$$\text{Relative Efficiency}_{DMU_D}=\frac{x_{D'}^2}{x_D^2}=\frac{2}{2}=1 \qquad (8)$$

Now, by principle $\dot{B}_3$ and PPS (5), we have

$$\begin{cases}\alpha_B\lambda_B x_B^1+\alpha_C\lambda_C x_C^1=x_D^1-s^1\\ \alpha_B\lambda_B x_B^2+\alpha_C\lambda_C x_C^2=x_D^2\end{cases}$$
$$\rightarrow\begin{cases}\alpha_B\lambda_B(1)+\alpha_C\lambda_C(2)=2\\ \alpha_B\lambda_B(3)+\alpha_C\lambda_C(1)=2\end{cases}\rightarrow\begin{cases}\lambda_B^*=0,\alpha_B^*=0\\ \lambda_C^*=1,\alpha_C^*=1\end{cases} \qquad (9)$$

Expression (7) shows that DMU $D$ is projected on $C$, for which the related $x^1$ and $x^2$ are less than those related to $D$. Using (10), we derive the efficiency of DMU $D$ as follows:

$$\text{Relative Efficiency}_{DMU_D} = \frac{x_C^1}{x_D^1} = \frac{2}{2.5} = 0.8$$
$$\text{Relative Efficiency}_{DMU_D} = \frac{x_C^2}{x_D^2} = \frac{1}{2} = 0.5 \tag{10}$$

Given (8) and (10), the efficiency evaluation of DMUs based upon PPS (5) is better than the efficiency evaluation using PPS (1) in the presence of quasi-fixed inputs. Assuming fixed returns-to-scale and taking PPS (5) into account, we have

$$\begin{aligned}\hat{T}_c = \{(\hat{x}^1, \hat{x}^2, y) |& \sum_{j=1}^{n} c\gamma_j x_j^1 \leq \hat{x}_1,\\ & \sum_{j=1}^{n} c\gamma_j x_j^2 = \hat{x}_2,\\ & \sum_{j=1}^{n} c(\delta_j + \gamma_j) y_j \geq y,\\ & \sum_{j=1}^{n} c(\delta_j + \gamma_j) = c,\\ & c \geq 0, \delta_j \geq 0, \gamma_j \geq 0,\ j = 1, \ldots, n\}\end{aligned} \tag{11}$$

Using the change of variable $c\delta_j = \bar{\delta}_j, c\gamma_j = \bar{\gamma}_j, \forall j$, we find that the constraint $0 \leq \sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) = c$ is redundant and is removed from the set. Therefore, we have

$$\begin{aligned}\hat{T}_c = \{(\hat{x}^1, \hat{x}^2, y) |& \sum_{j=1}^{n} \bar{\gamma}_j x_j^1 \leq \hat{x}_1,\\ & \sum_{j=1}^{n} \bar{\gamma}_j x_j^2 = \hat{x}_2,\\ & \sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) y_j \geq y,\\ & \bar{\delta}_j \geq 0, \bar{\gamma}_j \geq 0,\ j = 1, \ldots, n\}\end{aligned} \tag{12}$$

Assuming non-increasing returns-to-scale, using the change of variables $c\delta_j = \bar{\delta}_j$, $c\gamma_j = \bar{\gamma}_j$, $c \in [0, 1], \forall j$, we convert $\sum_{j=1}^{n} (\delta_j + \gamma_j) \leq 1$ into $\sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) \leq c \leq 1$. Assuming non-decreasing returns-to-scale, using the change of variables $c\delta_j = \bar{\delta}_j$, $c\gamma_j = \bar{\gamma}_j, c \geq 1$, $\forall j$, we convert $\sum_{j=1}^{n} (\delta_j + \gamma_j) \geq 1$ into $\sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) \geq c \geq 1$. Thus, assuming non-increasing and non-decreasing returns-to-scale, we derive the PPS is as follows:

$$\begin{aligned}\hat{T} = \{(\hat{x}^1, \hat{x}^2, y) |& \sum_{j=1}^{n} \bar{\gamma}_j x_j^1 \leq \hat{x}_1,\\ & \sum_{j=1}^{n} \bar{\gamma}_j x_j^2 = \hat{x}_2,\\ & \sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) y_j \geq y,\\ & \sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) \leq c,\ 0 \leq c \leq 1,\ NIRTS\\ & \sum_{j=1}^{n} (\bar{\delta}_j + \bar{\gamma}_j) \geq c,\ c \geq 1,\ NDRTS\\ & \bar{\delta}_j \geq 0, \bar{\gamma}_j \geq 0,\ j = 1, \ldots, n\}\end{aligned} \tag{13}$$

**Lemma 3.1:** *The PPS $\hat{T}_v$ satisfies principles $\dot{B}_1$ to $\dot{B}_3$.*

***Proof:*** *Given Theorem 3.1, the lemma is obvious.* ■

**Lemma 3.2:** *If $T$ is an arbitrary PPS that satisfies principles $\dot{B}_1$ to $\dot{B}_3$, then $T$ includes $\hat{T}_v$.*

***Proof:*** *Consider an arbitrary activity $(x^1, x^2, y)$ in $\hat{T}_v$. Expression (2) holds for this activity in the presence of non-negative variables $\alpha_j$ and $\lambda_j$. We show that $(x^1, x^2, y)$ is feasible in $T$. The left-hand side of (2) is obtained from the activity $(x_j^1, x_j^2, y_j)$. Hence, it is a member of $T$. Since the PPS $T$ satisfies principles $\dot{B}_1$ to $\dot{B}_3$, it includes the right-hand side of (2) as well.* ■

**Theorem 3.1:** *PPS (2) is the smallest set that satisfies principles $\dot{B}_1$ to $\dot{B}_3$.*

***Proof:*** *According to Lemmas 3.1 and 3.2, the correctness of Theorem 3.1 is evident.* ■

To deal with ratio outputs, we propose a new approach. There are studies on DEA that deal with ratio inputs and outputs, e.g. Hatami-Marbini and Toloo (2019). However, they assume that the ratios are obtained from dividing the numerator by the denominator. The main issue in previous research is that the ratios may not be obtained from dividing the numerator by the denominator. For instance, the reliability of a system is not obtained from dividing the numerator by the denominator. Therefore, we need to develop a method to deal with such situations. It is assumed that the benchmark of the ratio data is within the interval (0, 100]. Thus, we add a constraint in the model, rendering it unnecessary to have the numerator and denominator of a ratio, as follows:

$$0 \leq \sum_{j=1}^{n} (\delta_j + \gamma_j) y_j^1 \leq 100 \tag{14}$$

where $y_j^1$ is a subset of the outputs of DMU$_j$, which is a ratio output. Therefore, in the optimal solution, the projected ratio outputs are in the interval (0, 100]. Hence, we can directly incorporate the ratio outputs into the model.

Now, given the quasi-fixed inputs, we introduce the model for measuring efficiency based upon PPS (5). Tone (2001) developed the slack-based measure (SBM) to evaluate the efficiency of DMUs. The SBM takes into account all the inefficiency in the inputs and outputs. In our developed model, using slacks, we consider changes in inputs and outputs. Note that changes are not considered by slacks for the quasi-fixed inputs as the manager has no control over such inputs. The constraints of the quasi-fixed inputs have an equality sign. However, as discussed before, the changes in inputs and quasi-fixed inputs are dependent. In other words, in each feasible solution, the contribution percentages of changeable inputs and quasi-fixed inputs in forming benchmarks are similar. Let $\gamma_j$ be the contribution percentage. In (17) below, there are two types of inputs, namely $x^1$ shows changeable inputs and $x^2$ shows quasi-fixed inputs. Given the non-radial changes in the changeable inputs, if $s^- > 0$, then $\gamma_j$ contributes to forming the benchmark. Hence, reductions in the changeable inputs and quasi-fixed inputs are dependent on one another. However, the changes are unequal as, for each DMU, we consider a dependent variable on $j$. Model (17) can deal with four types of outputs, including real output $y^1$, integer output $y^2$, ratio output $y^3$, and undesirable output $y^4$. For the real and integer outputs, we consider non-radial increases. Thus, we add the following constraint (17).

$$\sum_{j=1}^{n} (\delta_j + \gamma_j) y_j^2 \in Z^+ \tag{15}$$

For the ratio outputs, we consider non-radial increases to less than or equal to 100%. To this end, we add constraint (14) in model (17). The undesirable outputs are considered as inputs. Thus, based on PPS (5), we can incorporate different types of outputs into our model. Since the different types of outputs have different importance for the decision-maker, we impose weight restrictions on them. Podinovski (2016) observed that the weight restrictions in the multiplier form are equivalent to the trade-off principle in the envelopment form of DEA. We impose a constraint that incorporates the importance of outputs as follows:

$$\sum_{r=1}^{s} \alpha_r u_r \leq 0 \forall r, \alpha_r \in R, \tag{16}$$

where $u_r$ is the $r$th output weight and $a_r$ is a real number. Given the trade-off principle in the envelopment form, we can present the $a_r$ in constraint (16) in a trade-off matrix. Let $Z$ to be the trade-off matrix and $\pi$ to be the associated dual variable. We formulate model (17) in terms of the slacks and PPS (5) as follows:

$$Min \ \ \rho = \frac{1 + \frac{1}{m_1} \sum\limits_{i_1=1}^{m_1} \frac{s_{i_1}^-}{x_{i_1 o}^1}}{1 + \frac{1}{s_1} \sum\limits_{r_1=1}^{s_1} \frac{s_{r_1}^+}{y_{r_1 o}^1} + \frac{1}{s_2} \sum\limits_{r_2=1}^{s_2} \frac{s_{r_2}^+}{y_{r_2 o}^2} + \frac{1}{s_3} \sum\limits_{r_3=1}^{s_3} \frac{s_{r_3}^+}{y_{r_3 o}^3}}$$

$$\begin{aligned}
s.t. \quad & \sum_{j=1}^{n} \gamma_j x_{i_1 j}^1 = x_{i_1 o}^1 + s_{i_1}^- \qquad i_1 = 1, \ldots, m_1, && (a)\\
& \sum_{j=1}^{n} \gamma_j x_{i_2 j}^2 = x_{i_1 o}^2 \qquad i_2 = 1, \ldots, m_2, && (b)\\
& \sum_{j=1}^{n} (\delta_j + \gamma_j) y_{r_1 j}^1 + \sum_{t_1=1}^{g_1} \pi_{t_1} z_{r_1 t_1} = y_{r_1 o}^1 - s_{r_1}^+ \\
& \qquad r_1 = 1, \ldots, s_1, && (c)\\
& \sum_{j=1}^{n} (\delta_j + \gamma_j) y_{r_2 j}^2 + \sum_{t_2=1}^{g_2} \pi_{t_2} z_{r_2 t_2} \leq \eta_{r_2} \\
& \qquad r_2 = 1, \ldots, s_2, && (d)\\
& \eta_{r_2} = y_{r_2 o}^2 + s_{r_2}^+ \ (\eta_{r_2} \in Z^+) \\
& \qquad r_2 = 1, \ldots, s_2, && (e)\\
& \sum_{j=1}^{n} (\delta_j + \gamma_j) y_{r_3 j}^3 + \sum_{t_3=1}^{g_3} \pi_{t_3} z_{r_3 t_3} = y_{r_2 o}^3 - s_{r_3}^+ \\
& \qquad r_3 = 1, \ldots, s_3, && (f)\\
& 0 \leq y_{r_2 o}^3 - s_{r_3}^+ \leq 100 \qquad r_3 = 1, \ldots, s_3, && (g)\\
& \sum_{j=1}^{n} \gamma_j y_{r_4 j}^4 = y_{r_4 o}^4 \qquad r_4 = 1, \ldots, s_4, && (h)\\
& \sum_{j=1}^{n} (\delta_j + \gamma_j) = 1 && (k)\\
& \delta_j \geq 0, \gamma_j \geq 0 \qquad j = 1, \ldots, n, && (l)\\
& s_{i_1}^- \geq 0, s_{r_1}^+ \geq 0, s_{r_2}^+ \geq 0, s_{r_3}^+ \geq 0 \\
& \qquad \forall i_1, \forall r_1, \forall r_2, \forall r_3, && (p)\\
& \pi_{t_1} \geq 0, \pi_{t_2} \geq 0, \pi_{t_3} \geq 0, \pi_{t_4} \geq 0 \\
& \qquad \forall t_1, \forall t_2, \forall t_3, \forall t_4, && (q)
\end{aligned} \tag{17}$$

In model (17), the constraint set (a) refers to the changeable inputs, which we wish to reduce by the non-negative $s^-$. The constraint set (b) refers to the quasi-fixed inputs. The constraint set (c) shows the real outputs, which the model tries to increase by the non-negative $s^+$. The constraint set (d) refers to the integer outputs in which the outputs' trade-off is considered. The constraint set (e) guarantees that the benchmarks are integers. The constraint sets (f) and (g) guarantee that the changes in the ratio outputs are less than 100% in which the outputs' trade-offs are considered. The constraint set (h) considers the undesirable outputs as inputs. The constraint set (k) refers to variable returns-to-scale.

**Theorem 3.2:** *There is always* $0 < \rho^* \leq 1$.

***Proof:*** *Since* $s^- \geq 0$ *and* $x^1 > s^-$, *we have*

$$\frac{1}{m_1}\sum_{i_1=1}^{m_1}\frac{s_{i_1}^{*-}}{x_{i_1o}^1} < 1 \rightarrow 1 - \frac{1}{m_1}\sum_{i_1=1}^{m_1}\frac{s_{i_1}^{*-}}{x_{i_1o}^1} > 0 \rightarrow \rho^* > 0$$

*Also, since* $s^+ \geq 0$, *we have*

$$1 + \frac{1}{s_1}\sum_{r_1=1}^{s_1}\frac{s_{r_1}^{*+}}{y_{r_1o}^1} + \frac{1}{s_2}\sum_{r_2=1}^{s_2}\frac{s_{r_2}^{*+}}{y_{r_2o}^2} + \frac{1}{s_3}\sum_{r_3=1}^{s_3}\frac{s_{r_3}^{*+}}{y_{r_3o}^3} \geq 1 \rightarrow \rho^* \leq 1 \qquad \blacksquare$$

**Theorem 3.3:** *The DMU under evaluation is Pareto-efficient if and only if* $\rho^* = 1$.

***Proof:*** *If* $\rho^* = 1$, *then*

$$1 - \frac{1}{m_1}\sum_{i_1=1}^{m_1}\frac{s_{i_1}^{*-}}{x_{i_1o}^1} = 1 + \frac{1}{s_1}\sum_{r_1=1}^{s_1}\frac{s_{r_1}^{*+}}{y_{r_1o}^1} + \frac{1}{s_2}\sum_{r_2=1}^{s_2}\frac{s_{r_2}^{*+}}{y_{r_2o}^2} + \frac{1}{s_3}\sum_{r_3=1}^{s_3}\frac{s_{r_3}^{*+}}{y_{r_3o}^3} \rightarrow \frac{1}{m_1}\sum_{i_1=1}^{m_1}\frac{s_{i_1}^{*-}}{x_{i_1o}^1} + \frac{1}{s_1}\sum_{r_1=1}^{s_1}\frac{s_{r_1}^{*+}}{y_{r_1o}^1} + \frac{1}{s_2}\sum_{r_2=1}^{s_2}\frac{s_{r_2}^{*+}}{y_{r_2o}^2} + \frac{1}{s_3}\sum_{r_3=1}^{s_3}\frac{s_{r_3}^{*+}}{y_{r_3o}^3} = 0 \rightarrow$$

$$s_{i_1}^{*-} = s_{r_1}^{*+} = s_{r_2}^{*+} = s_{r_3}^{*+} = 0$$

*If the DMU under evaluation is not Pareto-efficient, then there is a dominant DMU in the PPS. This violates* $\rho^* < 1$. ■

**Theorem 3.4:** *In the input-oriented radial model of the PPS, we have* $\rho^* \leq \theta^*$.

***Proof:*** *Assuming that in the input-oriented radial model, the inputs' constraints are as follows*:

$$\begin{aligned} &\sum_{j=1}^{n}\gamma_j x_{i_1j}^1 \leq \theta x_{i_1o}^1 \quad i_1 = 1,\ldots,m_1, \\ &\sum_{j=1}^{n}\gamma_j x_{i_2j}^2 = x_{i_2o}^2 \quad i_2 = 1,\ldots,m_2, \end{aligned} \qquad (18)$$

■

In the non-radial model (17), the input constraints are as follows:

To rank DMUs, we use the super-efficiency approach proposed by Tone (2002). Given model (17), the following model ranks the DMUs:

$$Min \quad \sigma = \frac{1 + \frac{1}{m_1}\sum_{i_1=1}^{m_1}\frac{s_{i_1}^-}{x_{i_1o}^1}}{1 - \frac{1}{s_1}\sum_{r_1=1}^{s_1}\frac{s_{r_1}^+}{y_{r_1o}^1} - \frac{1}{s_2}\sum_{r_2=1}^{s_2}\frac{s_{r_2}^+}{y_{r_2o}^2} - \frac{1}{s_3}\sum_{r_3=1}^{s_3}\frac{s_{r_3}^+}{y_{r_3o}^3}}$$

$$\begin{aligned}
s.t. \quad & \sum_{\substack{j=1\\ j\neq o}}^{n}\gamma_j x_{i_1j}^1 = x_{i_1o}^1 + s_{i_1}^- \quad i_1 = 1,\ldots,m_1, & (a)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}\gamma_j x_{i_2j}^2 = x_{i_2o}^2 \quad i_2 = 1,\ldots,m_2, & (b)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}(\delta_j+\gamma_j)y_{r_1j}^1 + \sum_{t_1=1}^{g_1}\pi_{t_1}z_{r_1t_1} = y_{r_1o}^1 - s_{r_1}^+ \\
& \qquad r_1 = 1,\ldots,s_1, & (c)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}(\delta_j+\gamma_j)y_{r_2j}^2 + \sum_{t_2=1}^{g_2}\pi_{t_2}z_{r_2t_2} \leq \eta_{r_2} \\
& \qquad r_2 = 1,\ldots,s_2, & (d)\\
& y_{r_2o}^2 - s_{r_2}^+ = \eta_{r_2} \; (\eta_{r_2} \in Z^+) \\
& \qquad r_2 = 1,\ldots,s_2, & (e)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}(\delta_j+\gamma_j)y_{r_3j}^3 + \sum_{t_3=1}^{g_3}\pi_{t_3}z_{r_3t_3} = y_{r_2o}^3 - s_{r_3}^+ \\
& \qquad r_3 = 1,\ldots,s_3, & (f)\\
& 0 \leq y_{r_2o}^3 - s_{r_3}^+ \leq 100 \quad r_3 = 1,\ldots,s_3, & (g)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}\gamma_j y_{r_4j}^4 = y_{r_4o}^4 \quad r_4 = 1,\ldots,s_4, & (h)\\
& \sum_{\substack{j=1\\ j\neq o}}^{n}(\delta_j+\gamma_j) = 1 & (k)\\
& \delta_j \geq 0, \gamma_j \geq 0 \quad j = 1,\ldots,n, j\neq o & (l)\\
& s_{i_1}^- \geq 0, s_{r_1}^+ \geq 0, s_{r_2}^+ \geq 0, s_{r_3}^+ \geq 0 \\
& \qquad \forall i_1, \forall r_1, \forall r_2, \forall r_3, & (p)\\
& \pi_{t_1} \geq 0, \pi_{t_2} \geq 0, \pi_{t_3} \geq 0, \pi_{t_4} \geq 0 \\
& \qquad \forall t_1, \forall t_2, \forall t_3, \forall t_4, & (q)
\end{aligned} \qquad (19)$$

For the efficient DMUs, model (19) generates $\sigma^* \geq 1$. The greater the objective function of model (19), the higher rank of DMU.

## 4. Case study

Founded in 1995, Azar Resin Company (ARC) is located in one of the industrial townships in Iran. It has established itself as a leading domestic producer of resin. To invest in Industry 4.0 technologies, ARC has planned to purchase cloud computing services from the best sustainable CSP based on quality-of-service indicators. To this end, ARC has prepared a list of 30 potential CSPs, including Pars Parva System and Afranet.[1] The dataset dates back to 2020. Table 4 reports the data.

The price, the amount of used fossil electricity, latency, and cost of work safety and labour health are inputs. The price and latency are economic indicators. The amount of used fossil electricity, and cost of work safety and labour health are environmental and social indicators, respectively. Also, the amount of used fossil electricity is a quasi-fixed input as the decision-maker has no control over it in a short time. The outputs include memory, storage, data transfer, availability, security, $CO_2$ emissions, availability, number of CPUs, and percentage of renewable electricity. Note that $CO_2$ emissions are an undesirable output. The number of CPUs is integer data. Furthermore, availability and security are ratio data. All the outputs are economic indicators, except for $CO_2$ emissions and the percentage of renewable electricity, which are environmental indicators.

### 4.1. Results and discussions

Table 5 reports the results. First, we assess the sustainability of the 30 CSPs using the CCR model and report the results in the second column of Table 5. As is seen, 22 out of 30 CSPs are sustainable (efficient). Applying the BCC model, we obtain the results in the third column of Table 5 that show that 24 out of 30 CSPs are efficient. This means an increase in the number of efficient CSPs. Column 4 illustrates the sustainability scores using the SBM model. There are still a great number of efficient CSPs. The CCR, BCC, and SBM results show that a majority of the CSPs are efficient.

Column 5 shows the results using the SBM model in the presence of undesirable outputs. Furthermore, we report in column 6 the results of the SBM model in the presence of undesirable output and integer data. In column 7, we report the sustainability scores computed by the SBM model in the presence of undesirable outputs, and integer and ratio data. Column 8 reports the results that incorporate the quasi-fixed inputs into the SBM model. Moreover, we take the decision-makers priorities into account in assigning weights to the indicators as follows: price = 9, percentage of fossil electricity = 5, latency = 3, cost of work safety and labour health = 5, memory = 9, storage = 7, data transfer = 7, availability = 9, security = 9, $CO_2$ emissions = 7, and percentage of renewable electricity = 5, and report the results in column 9.

Given the undesirable outputs, integer and ratio data, quasi-fixed inputs, and weight restrictions, we take a super-efficiency approach to rank the CSPs. The last column of Table 5 reports the ranking results using model (19), which shows that all the CSPs are fully ranked. It is noted that CSP 7 is the most sustainable DMU. Therefore, ARC should purchase cloud computing services from CSP 7.

As is seen, there are integers, undesirable output, and ratio data. Columns 2, 3, and 4 show the results of the CCR, BCC, and SBM models, respectively. Since in the SBM model all the inefficiencies of inputs and outputs are taken into account, the CCR and BCC scores are bigger than or equal to SBM scores. In columns 5 and 6, the SBM scores considering the undesirable output and integer data are presented, respectively. Column 7 reports the results considering ratio data. Column 8 shows the results considering quasi-fixed input, which are obtained by model (17). As is seen, there is a significant difference between columns 7 and 8. For the sake of brevity, here only CSP 2 is discussed. The same discussions can be repeated for other CSPs. The four inputs of CSP 2 are 150295, 78, 287, and 862. The optimal outputs slacks of CSP 2 are 14, 145.0277, 5.684, 0, 12.82303, 3, 4, and 0. The only positive $\gamma^*$ of CSP 2 is 0.30719, which is related to CSP 22. The optimal slacks of price, latency, and cost of work safety and labour health of CSP 2 are 104754.2, 261.5033, and 361.281, respectively. Using the inputs slacks, the price, latency, and cost of work safety and labour health of CSP 2 are reduced. Since the amount of used fossil electricity is a quasi-fixed input and the decision-maker has no control over it, there is no slack for it. In fact, CSP 22 is a benchmark for CSP 2.

### 4.2. Managerial insights for decision-makers

Our proposed method can support industrial managers in several ways. Since investing in Industry 4.0 technologies is costly, it is necessary to apply an advanced analytical approach for assessing and selecting the most sustainable CSP. Besides, owing to the increasing importance of sustainability issues in today's industrial organisations, managers should take sustainability into account in their decisions. It should be noted that sustainability not only decreases the media pressure on organisations but also assists managers in meeting customers' needs.

Our approach allows managers and decision-makers to include their priorities in sustainability assessment of CSPs in Industry 4.0. Furthermore, since our approach deals with both changeable and non-changeable indicators, it helps managers make short- and long-term decisions based on the existing capabilities. Furthermore, since our proposed model deals with different types of data, it provides better results. This, in turn, assists managers to make appropriate decisions on the sustainability assessment of CSPs in Industry 4.0. Finally, compared with the existing approaches, our approach is an easy tool

**Table 4.** The dataset of CSPs.

| | Inputs | | | | Outputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CSP (DMU) | Price (T/month) | Amount of used fossil electricity (w) | Latency (ms) | Cost of work safety and labour health (T 1000/year) | Memory (GB) | Storage (GB) | Data transfer (TB) | Availability (monthly) | Security | $CO_2$ emissions (kg/year) | Number of CPUs | Percentage of renewable electricity |
| 1 | 605420 | 180 | 195 | 1740 | 8 | 140 | 10 | 99.89% | 89% | 92 | 4 | 40% |
| 2 | 150295 | 78 | 287 | 862 | 2 | 60 | 3.5 | 99.97% | 71% | 47 | 2 | 25% |
| 3 | 210580 | 115 | 143 | 1165 | 4 | 115 | 5 | 100% | 100% | 68 | 2 | 32% |
| 4 | 125600 | 265 | 89 | 1953 | 16 | 200 | 10 | 99.98% | 100% | 129 | 8 | 45% |
| 5 | 623504 | 173 | 165 | 1430 | 7 | 250 | 5 | 100% | 84% | 63 | 4 | 20% |
| 6 | 45200 | 44 | 391 | 735 | 1 | 45 | 1 | 99.99% | 75% | 46 | 1 | 15% |
| 7 | 135980 | 131 | 73 | 2190 | 4 | 500 | 1 | 100% | 100% | 171 | 4 | 30% |
| 8 | 127500 | 51 | 268 | 1292 | 1 | 40 | 3 | 99.99% | 80% | 65 | 2 | 50% |
| 9 | 612530 | 195 | 214 | 1150 | 8 | 170 | 10 | 99.94% | 100% | 115 | 6 | 30% |
| 10 | 171525 | 63 | 241 | 971 | 2 | 100 | 5 | 99.99% | 84% | 63 | 3 | 70% |
| 11 | 712982 | 72 | 139 | 1196 | 2 | 150 | 18 | 99.94 | 90% | 127 | 4 | 10% |
| 12 | 598305 | 149 | 76 | 945 | 8 | 100 | 6 | 100% | 78% | 95 | 2 | 40% |
| 13 | 1355472 | 176 | 45 | 1682 | 8 | 300 | 8 | 100% | 100% | 146 | 6 | 25% |
| 14 | 128400 | 231 | 95 | 1280 | 16 | 200 | 10 | 99.75% | 92% | 112 | 6 | 45% |
| 15 | 52700 | 48 | 278 | 815 | 2 | 80 | 2 | 100% | 74% | 51 | 2 | 65% |
| 16 | 643100 | 161 | 193 | 1180 | 7 | 300 | 10 | 99.98% | 90% | 74 | 4 | 20% |
| 17 | 601925 | 135 | 124 | 1012 | 8 | 150 | 6 | 100% | 80% | 105 | 4 | 50% |
| 18 | 619420 | 209 | 245 | 1395 | 8 | 140.2 | 8 | 99.94% | 100% | 116 | 4 | 60% |
| 19 | 62815 | 193 | 319 | 793 | 8 | 100 | 2 | 100% | 76% | 67.9 | 6 | 55% |
| 20 | 740482 | 215 | 413 | 1460 | 10 | 180 | 6 | 99.98% | 94% | 179 | 3 | 70% |
| 21 | 142500 | 117 | 301 | 1172 | 4 | 60 | 4 | 99.96% | 65% | 78 | 2 | 35% |
| 22 | 148250 | 245 | 83 | 1630 | 16 | 200 | 8 | 99.99% | 100% | 153 | 4 | 20% |
| 23 | 141270 | 182 | 175 | 1750 | 8 | 500 | 2 | 100% | 95% | 182 | 3 | 35% |
| 24 | 648052 | 163 | 141 | 924 | 8 | 200 | 6 | 99.99% | 77% | 95 | 6 | 60% |
| 25 | 697560 | 178 | 251 | 1370 | 8 | 170 | 10 | 99.93% | 86% | 127 | 6 | 40% |
| 26 | 141525 | 96 | 319 | 913 | 4 | 80.5 | 6 | 100% | 78% | 51 | 2 | 30% |
| 27 | 218925 | 182 | 192 | 1825 | 8 | 140 | 8 | 99.98% | 94% | 82 | 6 | 20% |
| 28 | 139430 | 267 | 219 | 2192 | 16 | 250 | 8 | 99.85 | 100% | 123 | 6 | 50% |
| 29 | 592541 | 159 | 127 | 1680 | 8 | 300 | 8 | 100% | 88% | 95 | 4 | 65% |
| 30 | 39420 | 65 | 415 | 637 | 2 | 50 | 2 | 99.98% | 73% | 57 | 1 | 20% |

**Table 5.** The results.

| CSP | CCR | BCC | SBM | SBM with undesirable outputs | SBM with undesirable outputs and integer data | SBM with undesirable outputs, and integer, and ratio data | SBM with undesirable outputs, integer and ratio data, and quasi-fixed inputs | SBM with undesirable outputs, integer and ratio data, quasi-fixed inputs, and weights restrictions | SBM with undesirable outputs, integer and ratio data, quasi-fixed inputs, weight restrictions, and super-efficiency | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.7838 | 0.7941 | 0.5891 | 1 | 1 | 1 | 0.4179 | 0.4361 | 0.4361 | 21 |
| 2 | 0.9553 | 0.9553 | 0.6023 | 1 | 1 | 1 | 0.1565 | 0.1550 | 0.1550 | 29 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 0.9979 | 0.3111 | 0.3111 | 24 |
| 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0825 | 7 |
| 5 | 0.8392 | 0.8772 | 0.6175 | 1 | 1 | 1 | 0.3568 | 0.2839 | 0.2839 | 25 |
| 6 | 1 | 1 | 1 | 1 | 1 | 1 | 0.1289 | 0.1041 | 0.1041 | 30 |
| 7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.7319 | 1 |
| 8 | 1 | 1 | 1 | 1 | 1 | 1 | 0.1924 | 0.1840 | 0.1840 | 28 |
| 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.6109 | 0.6109 | 19 |
| 10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0125 | 12 |
| 11 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.2895 | 3 |
| 12 | 1 | 1 | 1 | 1 | 1 | 1 | 0.9891 | 1.0000 | 1.0033 | 15 |
| 13 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.1320 | 6 |
| 14 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0509 | 8 |
| 15 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0095 | 13 |
| 16 | 1 | 1 | 1 | 1 | 1 | 1 | 0.9792 | 0.3758 | 0.3758 | 22 |
| 17 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0000 | 17 |
| 18 | 0.9731 | 1 | 0.9 | 1 | 1 | 1 | 1 | 0.7547 | 0.7547 | 18 |
| 19 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0025 | 16 |
| 20 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.2579 | 4 |
| 21 | 0.8092 | 0.8105 | 0.5311 | 0.5123 | 0.5281 | 0.5187 | 0.2469 | 0.2314 | 0.2314 | 27 |
| 22 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.1634 | 5 |
| 23 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.7291 | 2 |
| 24 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0082 | 14 |
| 25 | 0.9001 | 0.9313 | 0.7023 | 0.6973 | 0.7189 | 0.718 | 0.6113 | 0.5719 | 0.5719 | 20 |
| 26 | 1 | 1 | 1 | 1 | 1 | 1 | 0.2644 | 0.2385 | 0.2385 | 26 |
| 27 | 0.9602 | 0.9911 | 0.6557 | 1 | 1 | 1 | 0.3881 | 0.3552 | 0.3552 | 23 |
| 28 | 0.9866 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0293 | 9 |
| 29 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0274 | 11 |
| 30 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.0000 | 1.0282 | 10 |

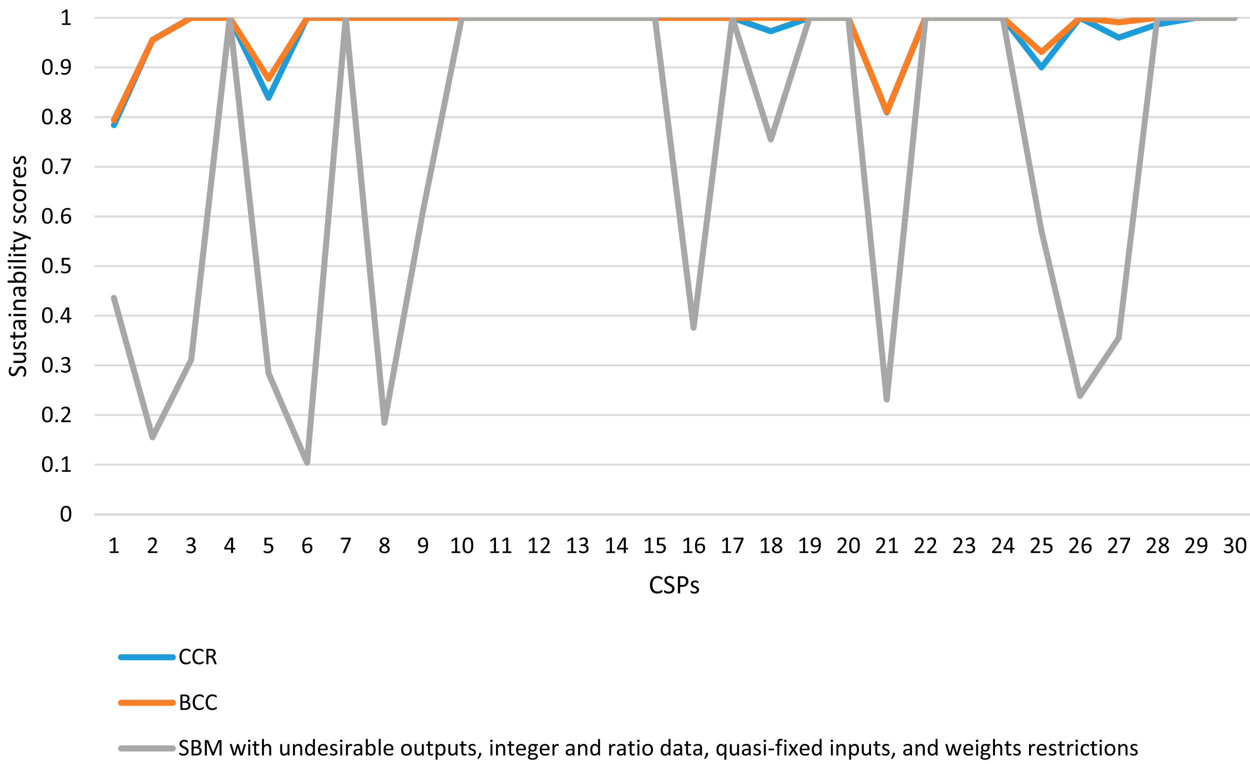


**Figure 3.** Summary of the results.

for managers and decision-makers to model, compute, and analyze the sustainability of CSPs. As the last column of Table 5 shows, CSP 7 is the most sustainable DMU. It means that ARC should purchase the cloud computing services from CSP 7.

Figure 3 summarises the results. As is seen, firstly, all the sustainability scores are between zero and one. Secondly, in most cases, the sustainability scores of the CCR and BCC models are similar. Thirdly, the sustainability scores obtained from our proposed approach have more discrimination power than BCC and CCR models. Finally, since our proposed model can deal with the undesirable outputs, integer and ratio data, quasi-fixed inputs, and weight restrictions, compared with the CCR and BCC models, there are higher fluctuations in the sustainability scores. This shows the importance of considering the undesirable outputs, integer and ratio data, quasi-fixed inputs, and weights restrictions in real-world problems.

## 5. Conclusions and future researches

Because of the numerous advantages of Industry 4.0 technologies, many firms are motivated to invest in such technologies. Nonetheless, a lack of a comprehensive and advanced approach for assessing and selecting sustainable CSPs is a key challenge for decision-makers. None of the existing studies consider influential data such as quasi-fixed inputs, undesirable outputs, and ratio and integer data simultaneously. In this paper, we proposed an advanced analytical model based on the DEA approach. Our method dealt with the ratio data, integer data, quasi-fixed inputs, and undesirable outputs. Moreover, our approach took into account managers' viewpoints on the weights of outputs using the trade-off principle. Our approach fully ranked all the DMUs. We demonstrated the usefulness of the proposed method through a case study.

The main limitation of this research is data collection. We had to select twelve criteria. However, there are other criteria such as reliability and usability, which can be used to evaluate the sustainability of CSPs. Since we had no access to these sorts of data, we could not incorporate them into the analysis.

There are a couple of topics for future researches. In this study, we assumed that the CSPs are black boxes. However, the decision-maker might be interested in assessing all the stages of a CSP. That is, in a cloud supply chain, IaaS serves PaaS suppliers. PaaS suppliers serve SaaS suppliers, and all the services can be delivered to cloud service customers. Therefore, future researchers can work on developing network DEA models to assess the sustainability of CSPs as a supply chain. Another future research direction is to develop a novel DEA model for assessing the sustainability of CSPs in the existence of dual-role factors. In other words, in many real-world applications, there might be factors such as service-quality credence and service-quality experience, which can play the role of both inputs and outputs. These sorts of factors are called dual-role factors. Developing a new DEA model for dealing with the dual-role factors can be another interesting research topic. Furthermore, in this study, we developed a novel DEA model for measuring the performance of sustainable CSPs in Industry 4.0. Based on the proposed model, new DEA models can be developed to assess the sustainability of Blockchain or IoT providers in Industry 4.0.

## Acknowledgements

The authors would like to appreciate Professor Alexandre Dolgui the Editor-in-Chief of International Journal of Production Research, the guest editors, and three anonymous Reviewers for their constructive comments.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Note

1. Note that, as requested by the companies, we removed the names of the CSPs in the tables.

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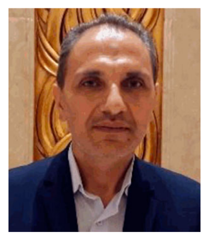

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