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Abstract

Purpose – The purpose of this paper is to consider the following problem: the authors consider a new constructed unit system to indicate the characteristics of the inputs and outputs of different decision-making units (DMUs) and propose several modified models to calculate their efficiencies based on overall value judgment and weight restriction in the production process.

Design/methodology/approach – This paper applies principal component analysis (PCA) to analyze the original value judgment information, and the key indices in the production process are extracted. The modified data envelopment analysis (DEA) models are proposed and DEA efficiencies and their projections are calculated.

Findings – By incorporate PCA and DEA, the authors propose new virtual DMUs composed of unique optimal multipliers of each DMU. Crucial indexes are extracted and the weights of inputs and output are ranked through using PCA by taking the preference and value judgments of all DMUs into consideration. Weight constraints from the ranking are utilized to improve the traditional CCR-DEA model. The empirical results validate the feasibility of the approach.

Practical implications – The method can be used in many organizations which have excessive amounts of inputs and outputs variables, such as banks, chain stores, car factory, etc.

Originality/value – This paper presents an integrated methodology of using PCA and DEA for considering the preferences of the inputs and outputs and value judgment of all DMUs and ranks the importance of the indicators from the overall perspectives.

Keywords Decision making, Operational research, Linear programming, Management

Paper type Research paper

1. Introduction

Decision makers are keen on seeking practical and feasible ways to improve the efficiency of their firms (Edvardsen and Førsund, 2003; Zheng *et al.*, 2003). As a result, efficiency improvement has been widely studied in production application as well as in academic research (Bogetoft, 1994; Yang and Morita, 2013). For example, Bian and Yang (2010) developed a modified model to evaluate the resource and environment efficiencies and discussed how to improve them. Chen *et al.* (2015) proposed that improvement of environmental efficiency is vitally important for reducing environmental risk and level of ecological scarcity.

Alternatively, data envelopment analysis (DEA), developed by Charnes *et al.* (1978), is a popular non-parametric data-oriented approach which deals with the efficiency of a decision-making unit (DMU) under the boundary of an empirical production possibility set. Current DEA researchers have made great progress in the field of efficiency measurement (Amado *et al.*, 2012; Banker *et al.*, 2010; Cook and Seiford, 2009). For example, Wu and Liao (2014) illustrated the operational efficiency of airlines by integrating the methods of balanced

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scorecard and DEA. Besides the concern of how to measure efficiency, researchers have also shown great interest in searching best practices for inefficient DMUs to be efficient (Schaffnit *et al.*, 1997; Zheng *et al.*, 2003). González and Álvarez (2001) examined the most relevant benchmark in multiple DMUs and proposed a model for imitation of the inefficient DMUs. Focussing on knowledge components, Gonzalez and Carcaba (2004) proposed a learning strategy that was developed based on the similarity between the inefficient firm and the benchmarked firm for the inefficient firms to become efficient. By considering the decision makers' preferences and other factors that might impact the learning process, Yong and Liang (2007) provided a modified model to reallocate the inputs and outputs of the inefficient DMUs to be efficient with minimum improvement. Yang and Morita (2013) illustrated a method to improve the efficiency of a bank by selecting an appropriate scheme from various perspectives. There are other papers that incorporate more detailed elements of DM's preferences into the DEA model. For example, Wong *et al.* (2009) and Yang *et al.* (2009) suggested a hybrid mini-max reference point-DEA approach to incorporate the DM's preference information into efficiency assessment and efficiency improvement. Yang *et al.* (2010) constructed a hybrid mini-max reference point-DEA by incorporating the value judgments of both branch managers and head-office directors.

However, current researches on efficiency improvement ignore the prices and values of inputs and outputs. In some cases, due to the different preferences, decision makers may not always choose the most appropriate inputs for the production. It is meaningful to detect critical and preferable inputs and outputs from multiple index systems to explore an appropriate way to improve their performances as well as to match the preferences of the overall value judgment of all DMUs.

Apart from the nature of the inputs and outputs used in assessing efficiency, questions can also be raised concerning the appropriate number of inputs and outputs to describe an activity process. The selection of the input and output indicators is very significant in the efficiency evaluation process. On the one hand, we should try our best to identify the input and output indicators related to production processes comprehensively; on the other hand, the number of the input and output indicators should be less than or equal to half the number of DMUs, so as to make the results more accurate. However, in real practice, it is difficult to make a choice between accuracy and completeness in a clear view. As a result, it is difficult in using a relatively valid and feasible assessment to evaluate their efficiencies.

In the DEA literature, several flows of researches have been proposed to investigate the real impact of the data dimensionality on efficiency from different perspectives. Jenkins and Anderson (2003) represented that the more the number of input and output variables is, the less discerning power of the DEA model is. Cinca and Molinero (2004) illustrated the efficiency of the DMUs is largely depends on the number of inputs and outputs. It is urgent to reduce the data dimensionality in DEA area, especially in the presence of large dimensionality of data set (Bian, 2012). The identification and selection of the input and output variables is an important stage in carrying out the DEA analysis to obtain the relative efficiency of a set of DMUs. To overcome above problems, it is necessary to incorporate additional considerations into existing DEA models so as to properly control data dimensionality. Therefore, it is useful to implement principal component analysis (PCA) in order to reduce the number of variables in a DEA structure.

Based on the original value judgment in the conventional DEA approaches, this paper constructs a "virtual unit" to substitute the corresponding DMU. The values of each virtual unit come from the optimal weights of each DMU. A modified DEA model is proposed to avoid the frequent occurrence of non-uniqueness of the optimal weights.

And by applying PCA to n "virtual units" we get several but fewer principal components. The obtained principal components are less dependent from statistical noise of real life data and the information of value judgment is extracted from the original inputs and outputs data. Moreover, a new indicator system, consisted only by crucial/important indicators from the original indices system, is built to describe the overall preferences of all DMUs. A ranking of the priority of the weights is developed to reflect the overall value judgment with all DMUs. In addition, a modified DEA approach concerning priority information is proposed to evaluate the performances of the DMUs. Further, models concerning adjustments of crucial inputs and outputs are presented to provide useful and effective decision information for DMUs to improve their efficiencies.

The rest of paper is organized as follows. Section 2 describes the theoretical background of the DEA method and the PCA. In section 3, our modified DEA model based on value judgment is presented. In section 4, the differences between our model and conventional DEA models are illustrated by a numerical example. Conclusions are made in the last section.

2. Background

2.1 Basic models in DEA

Suppose there are n observed DMUs, and each consumes m inputs to produce s outputs. u_{rj} and v_{ij} are the weights of the rth output and the ith input of DMU_j, respectively. According to the traditional benefit-cost theories, the efficiency e_j of DMU_j is defined as the ratio of the weighted outputs to weighted inputs, illustrated as:

$$e_j = \sum_{r=1}^{s} u_{rj} y_{rj} / \sum_{i=1}^{m} v_{ij} x_{ij}$$

In general, u_{rj}, v_{ij} are unknown. Suppose $v_{ij} \geqslant 0$, $u_{rj} \geqslant 0$, and each DMU has at least one positive input and one positive output. Charnes *et al.* (1978) proposed a "ratio-form" DEA model to measure the operational efficiency of DMU_o, which was described as follows:

$$\begin{aligned} & e_o = \max \sum_{r=1}^{s} u_{ro} y_{ro} / \sum_{i=1}^{m} v_{io} x_{io} \\ & s.t. \sum_{r=1}^{s} u_{ro} y_{rj} / \sum_{i=1}^{m} v_{io} x_{ij} \leqslant 1, j = 1, \ldots, n \\ & u_{ro}, v_{io} \geqslant \varepsilon, r = 1, \ldots, s; i = 1, \ldots, m \end{aligned} \tag{1}$$

Using CCR transformation, model (1) can be converted into the following equivalent model:

$$\begin{aligned} & e_o = \max \sum_{r=1}^{s} u_{ro} y_{ro} \\ & s.t. \sum_{i=1}^{m} v_{io} x_{io} = 1 \\ & \sum_{r=1}^{s} u_{ro} y_{rj} - \sum_{i=1}^{m} v_{io} x_{ij} \leqslant 0, j = 1, \ldots, n \\ & u_{ro}, v_{io} \geqslant \varepsilon, r = 1, \ldots, s; i = 1, \ldots, m \end{aligned} \tag{2}$$

Supposing u^*_{ro}, v^*_{io}; $r=1, \ldots, s$, $i=1, \ldots, m$ and e^*_o represent the optimum values of Model (2), we get the value judgment of DMU_o. Solve Model (2) for each DMU, respectively, the corresponding optimal set of the weights is obtained, which illustrates the preferable production information of the inputs and outputs. Specifically, it is worth mentioning that multiple values might exist for the optimal weights of a DMU, which possibly reduces the usefulness of the DEA methods.

2.2 Value judgment

Value judgment is established to improve feasibility and coherence within DEA framework. Researchers have proposed various preferences and features to be embedded into the traditional DEA approaches to enrich the basic constraints of the weights. Dyson and Thanassoulis (1988) suggested that u_{rj} and v_{ij} are varied in a particular range. Additional constraints were forced to emerge in DEA models, such as $\delta_i \leqslant v_{ij} \leqslant \tau_i$; $\rho_r \leqslant u_{rj} \leqslant \eta_r$, which was called the absolute weight restriction. However, Podinovski (2001) proposed that the constrained model with absolute weight restriction might not distinguish the optimal relative efficiency accurately. Further, Thompson *et al.* (1995) characterized a special case of the cone ratio termed as Assurance Region to prohibit large differences in the values of multipliers. Podinovski (1999) suggested that the possibility of a DMU being viewed as efficient and being benchmarked by other DMUs decreases greatly under this condition. Hamdan and Rogers (2008) introduced a restricted DEA model by incorporating weight restrictions and value judgment. There is a stream of literature on value judgment with Assurance Region. Thompson *et al.* (1995) characterized a special case of the cone ratio termed as Assurance Region to prohibit large differences in the values of multipliers. Liu (2014) introduced the assurance region in two-stage DEA model to measure the fuzzy efficiency in the presence of fuzzy input-output data. Halkos *et al.* (2014) developed an additive approach based on assurance region for efficiency decomposition in two-stages DEA.

Moreover, value judgment is closely related to the selection of the reference sets and the preferences of the decision makers. Current researches are making great effort to classify various conditions of value judgment, which can be summarized as follows: first, take special interdependency of the inputs and outputs into consideration when modeling the production process (Ali *et al.*, 1991; Beasley, 1990); second, raise the abilities of DEA methods to discriminate the efficiencies among the CCR-efficient DMUs (Anderson *et al.*, 2002; Green *et al.*, 1996); third, decrease the influence of the inputs and outputs with a large discrepancy when measuring the operational efficiencies of the DMUs (Cook *et al.*, 1991; Roll and Golany, 1993); fourth, add the preferences of the decision makers in specified models to guide potential adjustments of the inputs and outputs (Jain *et al.*, 2015; Seiford and Zhu, 2002; Zhu, 1996).

In this paper, we incorporate PCA into DEA studies to replace the original inputs and output with a smaller group of inputs and outputs which can represent most of the information displayed by the original indicators. In fact, PCA is a dimensionality reduction technique to ease complexity in multivariate data analyses (Beltrami, 1873). According to Adler and Golany (2001), if most of the population variance can be attributed to the first few components, then those principal components can replace the original variables with minimal loss of information. We also use PCA to obtain the value judgment of the decision makers and the preferences of the inputs and outputs variables. It is worth mentioning that any value judgment constraint in DEA models can reduce (or at least, maintain) the efficiencies of the DMUs, making the application of the DEA methods more feasible and practical.

3. Methodology

This section presents the process of how to incorporate value judgment of the weights calculated from original inputs and outputs into conventional DEA models. The method is described in following order. First, an approach is proposed to avoid the problem of multiplicity of weights existed in the traditional DEA model; second, PCA is applied on virtual weights obtained at the first step to eliminate redundant information and to rank the importance of the variables; finally, a new DEA specification is suggested to incorporate this information, and a procedure is proposed to find the optimal path for efficiency improvement for each DMU.

3.1 Non-uniqueness of the weights of inputs and outputs

However, the optimal weights derived from conventional CCR model may not be unique. Doyle and Green (1994) demonstrated that non-uniqueness of the weights often occur and possibly reduce the usefulness of DEA approach. A secondary objective function is proposed for alternative criterion of weights selection. We propose a modified DEA model as follows:

$$\begin{aligned} \theta_o^{CCR} &= \max\sum_{r=1}^{s} u_{ro}y_{ro} - \varepsilon\cdot\sum_{\substack{j=1\\ j\neq o}}^{n}\phi_j \\ s.t.&\sum_{i=1}^{m} v_{io}x_{io} = 1 \\ &\sum_{r=1}^{s} u_{ro}y_{rj} - \sum_{i=1}^{m} v_{io}x_{ij} + \phi_j = 0, j = 1,\ldots,n \\ &\phi_j \geqslant 0, j = 1,\ldots,n \\ &v_{io} \geqslant \varepsilon, i = 1,\ldots,m \\ &u_{ro} \geqslant \varepsilon, r = 1,\ldots,s \end{aligned} \tag{3}$$

where ε is a non-Archimedean infinitesimal.

By choosing a set of partial multipliers of the inputs and outputs, Model (3) can optimize the DMU's efficiency as well as minimize the overall inefficiency of the other DMUs, the dual model of (3) is presented as follows:

$$\begin{aligned} &\min \theta + \tau_{s_1} + \gamma_{m_1} \\ s.t.&\sum_{j=1}^{n}\lambda_j y_{rj} + \tau_r + \tau_{r-1} \geqslant y_{ro}, r = 1,\ldots,m_1 \\ &\sum_{j=1}^{n}\lambda_j x_{ij} + \gamma_i - \gamma_{i-1} \leqslant \theta x_{io}, i = 1,\ldots,s_1 \\ &\tau_r \leqslant 0, r = 1,\ldots,m_1 \\ &\gamma_i \leqslant 0, i = 1,\ldots,s_1 \end{aligned} \tag{4}$$

In Model (4), it is obvious that feasible optimal values of the weights could be found to guarantee that the problem will not face with infeasibility. For example, when we distinctively take $\tau_r = 0$ and $\gamma_i = 0$, Model (4) is transferred to be the traditional CCR model, which means there are feasible values for Model (4):

Property 1. The optimal solution θ_o^{CCR*} from Model (3) increases with the input/output indicator increases.

Proof. In fact, Model (4) is the dual model of (3) and the optimal solution of Model (4) equal to Model (3). Without loss of generality, we only consider the situation of the number of the outputs increases. As for Model (4), there exist the number of output indicators m_1, m_2 and $m_1 > m_2$, so the former will have $m_1 - m_2$ additional constraints when other conditions remain unchanged. So the results for m_1 outputs no less than that for m_2. Therefore, the optimal solution θ_o^{CCR*} from Model (3) increases with the number of input/output indicator. ■

3.2 Construction of virtual decision-making units (VDMU) and data selection

Without the comparison with the other DMUs, the inputs and outputs of the DMU may contain less preferable information regarding the intrinsic characters of the production process of special DMUs. On the contrary, the optimal weights originated from the DEA method reflect the production process and the preferences of the decision makers. Thus, it is worth trying to incorporate such weights information into the production by replacing the original inputs and outputs with the corresponding optimal values of the weights obtained above. In addition, the objective of PCA is to identify a new set of variables such that the new variables can represent most of the population variance (Kheirkhah *et al.*, 2013). Next, we propose the detailed rules to judge variables, which have important influence in the determination of efficiency.

Based on this rationale, we first construct a "VDMU" for each DMU, composed of $u_{rj}^*, v_{ij}^*, r = 1, \ldots, s, i = 1, \ldots, m$, which are the optimal weights calculated by Model (3). Since the weights originated from Model (3) not only demonstrate the characteristic of minimizing the overall inefficiencies of the other DMUs, but also the full consideration for the other DMUs, it is more reasonable and preferable to utilize weights than the original data of inputs and outputs when preferable information is taken into consideration.

Second, based on the original indicator system, PCA is used to analyze all VDMUs, through which fewer principal components containing major information of the multipliers can be obtained. Then it is possible to classify the inputs and outputs into two categories, that is to say, necessary and unnecessary. When measuring the performances of the production processes of all DMUs, the former is more important, and the latter is of less importance and can be neglected. A revised indicator system composed of indicators belong to the "necessary" category is developed to measure the efficiencies of the DMUs.

Further, factor scores corresponding to each weight of the input and output are obtained from a rotated component matrix, which reveals the relative importance of the inputs and outputs. Thus, the priority of the factors is revised in consequences, and the ranking of the multipliers is obtained to indicate the importance of the indicators in the new indicator system. The above proposed rule is implemented in a two-stage approach. First, we select the multipliers that are large enough (such as the absolute value exceeds 0.85) from each principal component, and construct a new indicator system. Second, if an indicator (e.g. x_5, in p_1 (the first principal component)) is prior to another one (e.g. x_4 in p_2 (the second principal component)) and they hold similar absolute values, x_5 is preferred to x_4, and the value judgment of x_5 is greater than x_4.

Other indicators are operated in the same way. The new indicator system is sorted by the importance of each factor. The more important the factor is, the more anterior it is placed.

3.3 Modified DEA methods based on value judgment

In this paper we shall first explore the output-oriented DEA model. It is quite possible that the method employed here can be carried over to the other kinds of DEA models. Assuming that new indicator system is arranged as $x_1, x_2, \ldots, x_{m1}$ and $y_1, y_2, \ldots, y_{s1}$, a modified output-oriented DEA model based on the overall value judgment is proposed as follows:

$$
\begin{aligned}
& e_o^{OVJDEA} = \max \sum_{r=1}^{s_1} u_{ro} y_{ro} \\
& s.t. \sum_{i=1}^{m_1} v_{io} x_{io} = 1 \\
& \quad \sum_{r=1}^{s_1} u_{ro} y_{rj} - \sum_{i=1}^{m_1} v_{io} x_{ij} \leqslant 0, j = 1, \ldots, n \\
& \quad v_{io} \geqslant v_{i+1,o}, i = 1, \ldots, m_1 \\
& \quad u_{ro} \geqslant u_{r+1,o}, r = 1, \ldots, s_1 \\
& \quad u_{ro}, v_{io} \geqslant \varepsilon, r = 1, \ldots, s_1; i = 1, \ldots, m_1
\end{aligned} \tag{5}
$$

Model (5) contains two additional weight constraints expressed as $v_{io} \geqslant v_{i+1,o}$, $i = 1, \ldots, m_1$ and $u_{ro} \geqslant u_{r+1,o}$, $r = 1, \ldots, s_1$, which are viewed as overall judgments of DMUs. At the same time, the constraints on weights here, to some extent, are more flexible than the absolute constraints contained in cone ratio and assurance region models:

Property 2. The efficiency $e_o^{OVJDEA*}$ from model (5) is no greater than the efficiency θ_o^{CCR*} from model (3).

Proof. In fact, the objective function of Models (3) and (5) are same if we omitted the infinitesimal $-\varepsilon \cdot \sum_{\substack{j=1 \\ j \neq o}}^{n} \phi_j$. The only difference is that Model (5) has several additional constraints: $v_{io} \geqslant v_{i+1,o}$, $i = 1, \ldots, m_1$ and $u_{ro} \geqslant u_{r+1,o}$, $r = 1, \ldots, s_1$. Therefore, the efficiency of Model (5) is no greater than that of Model (3). ■

In previous DEA research, several ways have been suggested to help inefficient units to improve their efficiencies. For example, if $u_{ro}^*, v_{io}^* (r = 1, \ldots, s; \quad i = 1, \ldots, m)$ are the optimal values of Model (2), whether DMU_o is efficient can be detected from the ratio of $\sum_{r=1}^{s} u_{ro}^* y_{ro} / \sum_{i=1}^{m} v_{io}^* x_{io}$. In Model 2, the weighted inputs are equal to 1. If the weighted outputs are less than 1, a possible way to improve its efficiency is to increase its outputs. However, it is not easy to know which output(s) is (are) and to what degree that is (are) needed to be increased. The following process is suggested to find the exact output(s) and the exact amount that is (are) needed to be increased in the context of minimal change of the inputs and outputs.

Suppose $u_{ro}^{*}, v_{io}^{*} (r = 1, \ldots, s_1; \quad i = 1, \ldots, m_1)$ represent the unique optimum multipliers, and $e_o^{OVJDEA*}$ represents the efficiency of DMU_o calculated by Model (5). $e_o^{OVJDEA*} < 1$ indicates that DMU_o is inefficient under overall value judgment consideration. A linear re-distribution model, that is to say Model (6), is provided to dispatch the inefficiency formulated as $\alpha_o^{*} = 1 - e_o^{OVJDEA*}$ into each input and output. The output-oriented re-distribution model is constructed as follows:

$$\begin{aligned} &\min \sum_{r=1}^{m_1} \frac{s_{ro}^{+}}{y_{ro}} \\ &s.t. \sum_{r=1}^{s_1} u_{ro}^{*} \left(y_{ro} + s_{ro}^{+} \right) = 1 \\ &s_{ro}^{+} \geqslant 0, r = 1, \ldots, s_1 \end{aligned} \tag{6}$$

When the inputs of the inefficient DMU are reallocated, i.e. $\beta_o^{*} = \sum_{i=1}^{m_1} v_{io}^{*} x_{io} - \sum_{r=1}^{s_1} u_{ro}^{*} y_{ro}$, the input-oriented re-distribution model is as follows:

$$\begin{aligned} &\min \sum_{r=1}^{s_1} \frac{s_{io}^{-}}{x_{io}} \\ &s.t. \sum_{i=1}^{m_1} v_{io}^{*} \left(x_{io} - s_{io}^{-} \right) = \sum_{r=1}^{s_1} u_{ro}^{*} y_{ro} \\ &s_{io}^{-} \geqslant 0, i = 1, \ldots, m_1 \end{aligned} \tag{7}$$

According to Model (6) we can get $e_o^{OVJDEA*}$, together with the formulation of $\alpha_o^{*} = 1 - e_o^{OVJDEA*}$, α_o^{*} can be re-distributed in the output that coincides with the largest u_{ro}^{*}. If the largest u_{ro}^{*} is not unique, then dispatch α_o^{*} freely among the corresponding outputs, which do not affect the optimum improvement of the inefficient DMUs. Moreover, it provides a way for the decision makers to adjust the resources of the inputs and outputs by their preferences. When considering re-distributing the inputs, the process discussed above can be applied, which is described by the Model (7).

According to Models (6) or (7), inefficient DMUs can be converted into efficient ones by either increasing least possible outputs $s_{ro}^{+}* (r = 1, \ldots, s_1)$ or decreasing least possible inputs $s_{io}^{+}* (i = 1, \ldots, m_1)$.

4. Numerical illustration

In an effort to validate the feasibility of the proposed approach, we conduct numerical simulations to evaluate the efficiencies of the cultural and creative industries and investigate the influence of the indicators on the efficiency changes in 2011 of the 31 provinces in China.

4.1 Data description

We select the data of 31 regions (provinces, autonomous regions and municipalities) in mainland China for analysis. The inputs include the number of infrastructure for cultural activities (x_1), operating expense of culture (x_2), the number of the practitioners in culture creative industry (x_3), public library ownership per capita (x_4), the number of patent license (x_5), investment in fixed assets of cultural entertainment industry (x_6) and investment in fixed assets of information transmission computer services and software industry (x_7). The outputs are revenues of the culture creative industry (y_1), the total print run of the publishing industry (y_2), broadcast television broadcasting time (y_3), profit margins entertainment industry (y_4) and added value of cultural and creative industries accounted in GDP (y_5). The data set of inputs and outputs are obtained from the Chinese cultural relics *Statistical Yearbook* 2012, the China National Bureau of Statistics web site and Chinese cultural and creative industries network. The original data are shown in Tables I and II.

4.2 The results

Table III reports the results calculated by Model (3). Each DMU is replaced by a VDMU, data of which is obtained from the optimal values of the multipliers of the corresponding DMU.

PCA is applied to analyze the optimal multipliers of the inputs and outputs. The total variance explained for the input and the output are displayed in Tables IV and V, respectively. For the input indicators, there are four principal components associating with

Region	x_1	x_2	x_3	x_4	x_5	x_6	x_7
Beijing	1,213	16.17	122.9	0.87	33,511	59.5	142.4
Tianjin	706	5.63	30	0.97	11,006	49.9	47.7
Shanghai	3,060	18.63	108.94	2.96	48,215	35.3	115.6
Chongqing	4,244	7.74	38.24	0.36	12,080	52.1	76.7
Shandong	4,993	13.89	100	0.38	51,490	392.5	54.1
Jiangsu	8,714	16.31	111.9	0.56	138,382	158.9	152.6
Zhejiang	5,888	24.2	75	0.69	114,643	60.6	155.8
Anhui	5,259	7.68	58	0.21	16,012	101.2	83.5
Jiangxi	5,023	7.34	24.4	0.34	4,349	77.8	62.8
Fujian	3,609	10.19	69.27	0.46	18,063	71.2	140.3
Ningxia	1,172	2.45	8.02	0.73	1,081	10.6	2.2
Xinjiang	3,405	7.13	2.51	0.51	2,562	16.1	41.4
Qinghai	626	4.11	10	0.64	264	9.5	15.5
Shanxi	2,955	8.95	37.67	0.3	10,034	40.1	77.8
Gansu	2,473	5.56	3.26	0.41	1,868	23.8	22.1
Guangdong	7,804	26.99	291.09	0.44	119,343	204.7	253
Guangxi	4,531	8.01	35.14	0.41	3,647	58.3	78.1
Hainan	950	2.74	10.16	0.33	714	41.5	17.6
Sichuang	11,537	14.39	49.2	0.32	32,212	135.6	107
Yunnan	6,881	8.69	6.2	0.34	3,823	49.5	51.2
Guizhou	3,883	5.37	21	0.23	3,086	18.9	45.3
Tibet	906	2.11	2	0.18	124	6.7	9.8
Hubei	4,383	11.44	64.8	0.41	17,362	106.8	74.6
Hunan	6,432	8.61	100	0.3	13,873	85	108.7
Henan	4,220	9.51	46.03	0.2	16,539	141.4	56.3
Liaoning	5,981	11.34	33.9	0.68	17,093	181.3	146.5
Jilin	3,128	9.03	50	0.5	4,343	82	48.1
Heilongjiang	5,160	7.46	35	0.43	6,780	38.1	64.5
Hebei	4,828	7.03	41.69	0.22	10,061	119.9	40.8
Shanxi	3,777	7.8	29	0.34	4,752	60.4	40.9
Inner Mongolia	3,602	11.3	6	0.38	2,096	117.1	60.2

Table I. The original data of inputs

Table II.
The original data of outputs

Region	y_1	y_2	y_3	y_4	y_5
Beijing	2,828.92	108.9	22.64	12.03	12.3
Tianjin	1,222.82	10.2	28.5	26.33	3.33
Shanghai	3,491.11	20.4	30.67	13.9	9.8
Chongqing	953.43	8	35.93	42.01	3
Shandong	3,127.88	37.9	179.2	40	3.2
Jiangsu	4,792.98	33.5	158.61	34.05	3.34
Zhejiang	3,453.4	36	142.19	29.77	3.8
Anhui	1,208.58	14.7	114.49	64.36	3.79
Jiangxi	860.17	9.3	99.63	37.31	2.43
Fujian	1,399	11.1	83.98	29.28	4.2
Ningxia	77.69	1.4	25.41	46.12	1.94
Xinjiang	325.35	5.2	166.73	46.78	0.33
Qinghai	78.99	1.1	12.58	52.1	1.66
Shanxi	1,032.8	9	98.38	44.81	2.82
Gansu	260.65	5.9	68.36	45.71	1.26
Guangdong	3,948.21	50	142.76	24.02	5.6
Guangxi	998.96	9.9	75.79	31.59	1.88
Hainan	270.33	2.9	18.8	25.05	2.1
Sichuang	1,983.44	20	152.05	44.55	3.03
Yunnan	1,041.29	8.3	101.58	41.07	6.1
Guizhou	1,085.3	4.6	40.47	39.78	2.44
Tibet	78.8	0.8	8.57	28.44	1.03
Hubei	1,519.69	24	110.33	60.63	4.31
Hunan	662.53	17.3	104.94	37.71	5.2
Henan	2,348.22	24.1	149.52	43.48	1.57
Liaoning	2,737.13	18.2	142.02	49.09	3.1
Jilin	765.06	11.7	89.53	44.93	4
Heilongjiang	913.01	9	108.02	50.51	2.1
Hebei	952.94	16.9	132.62	36.79	2.45
Shanxi	1,051.46	22.3	84.05	38.88	3.12
Inner Mongolia	769.58	3.4	126.79	61.23	1.29

eigenvalue greater than one. We can see that the first to fourth component accounts for 33.357, 21.185, 16.703 and 15.638 percent of the total variance, respectively. As a consequence, four components reaches 86.883 percent of the accumulated variance. Similarly, three components of the outputs reaches 83.476 percent of the accumulated variance. Thus, the results indicate that the cumulative contribution ratios of four principal components for inputs and three principal components for outputs (the cumulative value is 83.476 percent) are large enough to include almost all the information of the original data.

The results of the rotated component are recorded in Tables VI and VII, respectively. It is obvious that x_2, with the highest factor score in the component 1, is superior, which means it is more important than the others in the view of the DMUs and the sample. Same analyses can be applied to all the other indicators. Thus, we conclude that the overall value judgment for the inputs and outputs after data reduction is $v_2 \succ v_6 \succ v_5 \succ v_3$ and $u_1 \succ u_3 \succ u_2$. For the simplicity of expression and calculation, we rearrange the indicators to form a new indicator system, listed as (x_2, x_6, x_5, x_3; y_1, y_3, y_2).

As a parametrical method, PCA can identify the variables which have maximal contribution to efficiency for most DMUs. However, PCA method has its own weakness

Region	v_1	v_2	v_3	v_4	v_5	v_6	v_7	u_1	u_2	u_3	u_4	u_5
Beijing	0.008	0.925	0	0.005	0	0.062	0	0.413	0.083	0.041	0.009	0.454
Tianjin	0.030	0.738	0	0.048	0	0.184	0	0.467	0	0.157	0.049	0.326
Shanghai	0.043	0.742	0.005	0	0.007	0.065	0.138	0.610	0	0.062	0.002	0.326
Chongqing	0.294	0.226	0.166	0.314	0	0	0	0.214	0	0	0.262	0.277
Shandong	0.141	0.765	0	0.013	0	0	0.081	0.352	0	0.441	0	0.206
Jiangsu	0.112	0.689	0	0.007	0	0.191	0	0.597	0	0.282	0.017	0.103
Zhejiang	0.204	0.351	0.292	0.046	0	0.107	0	0.725	0	0.180	0.004	0.091
Anhui	0.162	0.602	0	0.014	0	0.222	0	0.270	0	0.386	0.108	0.236
Jiangxi	0	0.334	0	0.316	0.351	0.000	0	0.372	0.077	0.490	0	0
Fujian	0.101	0.728	0	0.029	0	0.142	0	0.285	0	0.258	0.044	0.239
Ningxia	0.197	0.312	0	0.427	0	0.063	0	0.039	0	0.167	0.573	0.221
Xinjiang	0.142	0.762	0	0.047	0	0.048	0	0.099	0	0.767	0.106	0.028
Qinghai	0.177	0.389	0	0.423	0	0.012	0	0.016	0	0.097	0.670	0.217
Shanxi	0.246	0.544	0	0.091	0	0.119	0	0.254	0	0.315	0.274	0.157
Gansu	0.348	0	0.004	0.311	0	0.023	0.315	0	0.077	0.403	0.377	0.143
Guangdong	0.097	0	0	0.453	0	0.450	0	0.600	0	0.130	0	0.269
Guangxi	0	0.202	0	0	0.746	0.052	0	0.541	0.191	0.201	0	0
Hainan	0.193	0.392	0.070	0.225	0	0.121	0	0.117	0	0.157	0.278	0.448
Sichuang	0	0	0	0.484	0	0.516	0	0.055	0	0.742	0	0.088
Yunnan	0.206	0.666	0	0.022	0	0.106	0	0.227	0	0.335	0.066	0.372
Guizhou	0.199	0.705	0	0.026	0	0.069	0	0.405	0	0.229	0.111	0.255
Tibet	0.269	0.474	0	0.186	0	0.071	0	0.070	0	0.099	0.623	0.207
Hubei	0.403	0	0	0.287	0	0.015	0.294	0	0	0.316	0.269	0.411
Hunan	0	0.881	0	0.119	0	0.000	0	0	0.104	0.358	0	0.535
Henan	0.093	0.636	0	0.005	0	0.266	0	0.458	0	0.422	0.042	0.079
Liaoning	0.002	0.925	0.022	0.008	0	0.043	0	0.575	0	0.206	0.058	0.161
Jilin	0.336	0.200	0	0.259	0	0.036	0.169	0.018	0	0.365	0.210	0.407
Heilongjiang	0	0.810	0	0.066	0	0.124	0	0.209	0.107	0.295	0.339	0
Hebei	0.225	0.662	0	0.004	0	0.097	0.012	0.155	0	0.622	0	0.223
Shanxi	0.005	0.533	0	0.125	0	0.177	0.160	0.163	0.205	0.244	0.242	0.146
Inner Mongolia	0.491	0.199	0.032	0.240	0	0	0.038	0.055	0	0.510	0.288	0.147

Table III. Virtual decision making units based upon preferable multipliers

Table IV. Total variance explained for the input

Component	Initial eigenvalues Total	% of variance	Cumulative %	Extraction sums of squared loadings Total	% of variance	Cumulative %	Rotation sums of squared loadings Total	% of variance	Cumulative %
1	2.335	33.357	33.357	2.335	33.357	33.357	2.107	30.094	30.094
2	1.483	21.185	54.542	1.483	21.185	54.542	1.653	23.618	53.712
3	1.169	16.703	71.245	1.169	16.703	71.245	1.191	17.017	70.730
4	1.095	15.638	86.883	1.095	15.638	86.883	1.131	16.153	86.883
5	0.538	7.686	94.569						
6	0.380	5.431	100.000						
7	1.46E−006	2.08E−005	100.000						

Note: Extraction method, principal component analysis

Table V. Total variance explained for the output

Component	Initial eigenvalues Total	% Of variance	Cumulative %	Extraction sums of squared loadings Total	% Of variance	Cumulative %	Rotation sums of squared loadings Total	% Of variance	Cumulative %
1	1.667	33.349	33.349	1.667	33.349	33.349	1.627	32.539	32.539
2	1.412	28.234	61.583	1.412	28.234	61.583	1.374	27.480	60.019
3	1.095	21.893	83.476	1.095	21.893	83.476	1.173	23.457	83.476
4	0.804	16.079	99.556						
5	0.022	0.444	100.000						

Note: Extraction method, principal component analysis

Table VI. Rotated component matrix of inputs

Indicator	Component 1	Component 2	Component 3	Component 4
x_1	0.375	0.706	−0.321	0.248
x_2	−0.959	−0.174	−0.154	−0.107
x_3	0.076	0.050	−0.046	0.947
x_4	0.888	−0.020	−0.078	−0.016
x_5	0.060	−0.037	0.988	−0.035
x_6	0.372	−0.796	−0.254	−0.162
x_7	0.332	0.698	−0.123	−0.365

Table VII. Rotated component matrix of outputs

Indicator	Component 1	Component 2	Component 3
y_1	−0.914	0.262	0.134
y_2	0.040	0.128	0.861
y_3	0.042	−0.979	−0.045
y_4	0.873	0.246	0.079
y_5	0.158	0.520	−0.637

that it may miss some important information. In some cases, the weights u_{11} and u_{12} have quite sizable values while $u_{13}, \ldots, u_{1n}$ have very small values which may warrant the inclusion or exclusion of output variable 1.

Our proposed model does not consider this kind of situation. One possible way to solve this situation is to increase additional constraints to illustrate decision makers' preference and more suitable to practical situation. For example, when the input or output indicator is not selected, we can manually add index to the indicator set, and vice versa.

Table VIII presents the results of the efficiencies from the various DEA models and indicator systems proposed in the previous section. The second and third columns report the CCR efficiency from the Model (3) and its ranking. It reveals that 23 of the DMUs are efficient, and we cannot further distinguish those efficient DMUs that can be benchmarked by inefficient DMUs. The fourth and fifth columns report the CCR efficiency and its ranking using the new indicator system that contains four inputs and three outputs from the Model (3). The number of the efficient DMUs is reduced to 14 and the gap of the efficiencies among DMUs is bigger than the first case. It can distinguish more inefficient DMUs with the decrease of the number of the inputs and

Region	θ_1^{CCR}	Ranking	θ_2^{CCR}	Ranking	θ^{OVJDEA}	Ranking
Beijing	1.000	1	1.000	1	0.854	11
Tianjin	1.000	1	0.948	16	0.941	8
Shanghai	1.000	1	1.000	1	1.000	1
Chongqing	0.754	31	0.566	30	0.558	26
Shandong	1.000	1	0.929	18	0.869	10
Jiangsu	1.000	1	1.000	1	1.000	1
Zhejiang	1.000	1	1.000	1	0.754	14
Anhui	1.000	1	0.848	21	0.666	16
Jiangxi	0.939	27	0.902	19	0.624	19
Fujian	0.826	30	0.685	28	0.625	18
Ningxia	1.000	1	0.493	31	0.255	31
Xinjiang	1.000	1	1.000	1	0.523	28
Qinghai	1.000	1	0.807	22	0.581	25
Shanxi	1.000	1	0.770	23	0.581	24
Gansu	1.000	1	1.000	1	0.456	29
Guangdong	1.000	1	0.622	29	0.588	23
Guangxi	0.933	28	0.933	17	0.784	13
Hainan	1.000	1	1.000	1	0.955	7
Sichuang	0.885	29	0.736	25	0.603	21
Yunnan	1.000	1	1.000	1	0.796	12
Guizhou	1.000	1	1.000	1	1.000	1
Tibet	1.000	1	0.999	15	1.000	1
Hubei	0.996	25	0.702	27	0.598	22
Hunan	0.997	24	0.728	26	0.373	30
Henan	1.000	1	1.000	1	1.000	1
Liaoning	1.000	1	1.000	1	1.000	1
Jilin	1.000	1	0.749	24	0.528	27
Heilongjiang	0.949	26	0.890	20	0.629	17
Hebei	1.000	1	1.000	1	0.623	20
Shanxi	1.000	1	1.000	1	0.699	15
Inner Mongolia	1.000	1	1.000	1	0.937	9

Table VIII. Efficiency evaluation of economic competence of the regions outputs. Several districts, such as Tianjin, Shandong, Ningxia, transfer from the efficient frontier to the interior and their ranking changes obviously. Especially for Ningxia that its ranking from number one down to the last one. The sixth and seventh columns report the efficiencies and its ranking from the Model (5), which shows that the number of the CCR-efficient DMUs was reduced significantly to six. The results illustrate that the proposed approach provides a methodology to deal with the weights flexibility problem in DEA framework and incorporate the managerial preferences into the decision-making strategy and process effectively.

Table VIII shows the relative efficiency scores of the regions derived from traditional CCR model and the proposed approach. Specifically, with the decrease of input and output indicators, the efficiency of the corresponding DMUs is getting smaller, and the number of the efficient DMUs is reduced. The efficiency from Model (5) is less than or equal to that of (3) for the same amount of inputs and outputs and the results are consistent with the Property 2. When we incorporate the value judgment among the DMUs, there are only six DMUs benchmarked for inefficient ones which improves the distinguish power among the evaluated DMUs.

Table IX suggests the preferred paths of efficiency improvement for the inefficient DMUs, which are more effective and practically applicable. For example, decreasing x_2 (the operating expense of culture), and increasing y_1 (the revenues of the culture creative industry) for Beijing. The result considers preferred overall value judgment of the DMUs and the sample simultaneously. Thus, they are easier to be accepted by all the DMUs.

Table IX.
Preferable path of efficiency improvement of inefficient DMUs

Region	Inputs improvement	Outputs improvement
Beijing	$\Delta x_2 = -3.14$	$\Delta y_1 = 505.84$
Tianjin	$\Delta x_2 = -0.41$	$\Delta y_1 = 77.11$
Chongqing	$\Delta x_2 = -4.06$	$\Delta y_1 = 755.98$
Shandong	$\Delta x_2 = -1.98$	$\Delta y_1 = 503.57$
Zhejiang	$\Delta x_2 = -7.31$	$\Delta y_1 = 1,186.68$
Anhui	$\Delta x_2 = -3.51$	$\Delta y_1 = 671.95$
Jiangxi	$\Delta x_2 = -3.20$	$\Delta y_1 = 584.46$
Fujian	$\Delta x_2 = -4.69$	$\Delta y_1 = 898.05$
Ningxia	$\Delta x_5 = -933.34$	$\Delta y_1 = 305.02$
Xinjiang	$\Delta x_5 = -1,408.81$	$\Delta y_1 = 453.02$
Qinghai	$\Delta x_5 = -207.08$	$\Delta \mathrm{y}_1 = 66.96$
Shanxi	$\Delta x_2 = -4.29$	$\Delta y_1 = 821.13$
Gansu	$\Delta x_5 = -1,229.70$	$\Delta y_1 = 399.57$
Guangdong	$\Delta x_2 = -15.13$	$\Delta \mathrm{y}_1 = 2,898.61$
Guangxi	$\Delta x_5 = -914.34$	$\Delta y_1 = 298.81$
Hainan	$\Delta x_5 = -\ 2.52$	$\Delta \mathrm{y}_1 = 13.90$
Sichuang	$\Delta x_2 = -7.41$	$\Delta y_1 = 1,419.16$
Yunnan	$\Delta x_5 = -906.94$	$\Delta y_1 = 294.70$
Hubei	$\Delta x_2 = -5.79$	$\Delta y_1 = 1,110.14$
Hunan	$\Delta x_2 = -6.89$	$\Delta \mathrm{y}_1 = 1,320.84$
Jilin	$\Delta x_2 = -2,369.46$	$\Delta y_1 = 774.34$
Heilongjiang	$\Delta x_2 = -3.18$	$\Delta y_1 = 608.80$
Hebei	$\Delta x_2 = -3.65$	$\Delta y_1 = 668.55$
Shanxi	$\Delta x_2 = -2.73$	$\Delta y_1 = 498.41$
Inner Mongolia	$\Delta x_5 = -186.07$	$\Delta y_1 = 60.29$

5. Conclusions

Value judgment is an important factor to inputs and outputs when efficiency improvement is considered by DMUs. This paper constructs an model to overcome the problem of multiple values of the weights existed in the conventional DEA approach as well as to find a special set of the weights for each DMU that are most consistent with the other weights of the DMUs. New "VDMU"), composed of unique optimal multipliers of each DMU, are proposed to describe the characteristics of the production process. Built on this original index system, crucial indexes are extracted and the weights of input and output are ranked through using the PCA method. Then we represent the modified DEA models to calculate the efficiencies of the DMUs.

The approach proposed in this paper takes the preferences for the inputs and outputs and value judgments of all DMUs into consideration and ranks the importance of the input and output variables from the overall (i.e. all DMUs) perspective. The weight constraints that resulted from the ranking are utilized to improve the traditional CCR-DEA models. In this way, it eliminates the deficiencies existed in the traditional models, which mainly focus on the self-efficiencies while ignore the efficiencies of the other DMUs. By selecting relatively important indicators from DMUs, decision makers cannot only achieve more reasonable efficiencies, but also detect important indicators and processes that can be help to improve efficiencies more effectively. We argue that the results conducted from this approach are more persuadable and valid.

Moreover, the proposed models are especially useful in specified DEA applications. For example, when there are too many priori variables in a relatively small sample, our methods allow for reasonable variable selection and reduction. An empirical application to the cultural and creative industries in China is reported to justify the feasibility of the models.

The proposed approach is to deal with the variable reduction with least loss of information based on PCA and DEA theory. Future research can extend our line of inquiry in several directions. First, whiles applying PCA on the input-output weights obtained from the conventional DEA approach appears to be a novel approach and based on sound theory, care must be taken to ensure important input/output variables for which the DMU performs well and which are critical to determining the efficiency level of such DMU are not eliminated from consideration. Second, we may pay attention to incorporate other variable reduction methods and stochastic models into the DEA theory. The performances of different approaches are suggested for careful comparison.

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