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DEA as a tool for auditing: application to Chinese manufacturing industry with parallel network structures

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Abstract Performing a high-quality manufacturing audit can be time consuming and costly given the large number and scale of manufacturing firms and enterprises. Chinese economy has experienced some rapid and significant growth over the past 30 years, which is largely due to contributions from the development of manufacturing industry. Auditing tools are very much needed in auditing the Chinese manufacturing industry. Data envelopment analysis (DEA) has been used as an auditing tool in selecting audit objects that are treated as decision making units (DMUs). These DMUs are characterized by a set of performance measures. DEA then uses data on these performance measures to identify potential audit objects. However, conventional DEA treat each DMU or system as a "black-box" and does not take the operations of individual components within the "black-box" into consideration. For example, a large number of firms or enterprises exist in a manufacturing industry. When the conventional DEA is applied to the industries, the performance of the firms is often ignored. This paper proposes a new parallel DEA model where each input/output of the system is not the sum of those of all its components. Such a situation arises from the need of auditing firms or enterprises in Chinese manufacturing industries. For example, the cost margin of a particular industry may not equal to the sum of that of all its component firms within the industry because this metric is measured in percentage. The proposed approach is applied to the manufacturing industry of China.

Keywords Data envelopment analysis (DEA) · Parallel systems · Effciency · Manufacturing industry · Auditing · Performance

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1 Introduction

Data envelopment analysis (DEA) is a linear programming based approach for evaluating the relative efficiency or performance of peer decision making units (DMUs) with multiple performance measures. These performance measures or metrics are classified as inputs and outputs in DEA (Cook et al. 2014). DEA has gained considerable attention in various areas and obtained rich theoretical developments (Cook and Seiford 2009). Chilingerian and Sherman (1996) use DEA to benchmark physician practice patterns while Chen et al. (2015) study the regional energy efficiency in China. Sherman (1984) is the first study that uses DEA as a managerial audit methodology. Using DEA and AHP methods, Sueyoshi et al. (2009) propose a decision support framework for internal audit prioritization in a rental car company. Kamyabi and Salahinejad (2014) examine operational auditing efficiency for audit firms. In short, DEA can be regarded as a tool for selecting audit objects when a large-scale data are present.

In conventional DEA, DMUs are generally treated as "black-box" in the sense that the internal structures of the DMUs are ignored. In recent years, many studies have focused on examining the internal structures of the DMUs. For example, a DMU is divided into several sub-units that link to each other as a two-stage process (Seiford and Zhu 1999; Chen and Zhu 2004; Chen et al. 2012) or even a network structure (Färe and Grosskopf 1996; Kao 2009).

A typical network structure is a parallel system where each DMU has a set of components with the same input and output measures. Several models are developed to study the performance of parallel systems. Färe and Primont (1984) propose a distance model to evaluate the performance of firms that have several plants operating independently. Färe et al. (1997) evaluate the performance of 57 Southern Illinois grain farms by a system distance measure model. Bi et al. (2012) use the conventional input system distance function to estimate relative efficiency by applying a parametric bootstrap method.

Beasley (1995) proposes a joint DEA maximization model for obtaining teaching and research efficiencies of university departments. Yu (2008) measures the performance of 60 bus companies in Taiwan by using a process distance measure model, where the bus services are separated into highway and urban ones. Directional distance measures are used to measure efficiency for parallel systems with undesirable outputs (Yu and Fan 2006). Some parallel system model applications include performance evaluation of police service (Diez-Ticio and Mancebon 2002), acute hospital trusts (Tsai and Mar Molinero 2002), financial holding companies (Chao et al. 2010).

The conventional multiplier-based DEA model is used to measure parallel system efficiency and the system efficiency is found to be equal to the maximum of the process efficiencies (Yang et al. 2000). Cook et al. (2000) propose a model to evaluate the sales, service and aggregate efficiencies within the branches of a bank simultaneously. Cook and Green (2004) further study the performance of 10 plants in the steel molding and sheet steel industry. Ratio-form system efficiency model is used to study the performance of commercial banks and cost efficiency in the treatment of solid waste (Rogge and Jaeger 2012). Vaz et al. (2010) study the performance of 78 retail stores in Portugal by using a value-based model.

In order to model parallel production systems, a relational DEA model is proposed by Kao (2009) to calculate the system and component efficiencies, and applied to measuring the efficiency of forest districts with multiple working circles in Taiwan. The parallel model is constructed by minimizing the inefficiency slacks of a DMU, and decomposes the inefficiency slacks into its production sub-units. Kao and Lin (2012) apply the same method to efficiency evaluation of 52 chemistry departments in the UK. Kao and Hwang (2010) further develop a parallel system model with slacks. The system and sub-unit efficiencies can be calculated together, and the system slack is the sum of process slacks. Based on Kao's (2009) relational

DEA model, Bi et al. (2011) examine problems about resource allocation and target setting for a parallel production system.

Castelli et al. (2004) discuss a hierarchical structure when there is only one layer. Castelli et al. (2010) further develop the DEA model into shared flow, multi-level, and network models. In those parallel models, each sub-unit is treated independently. Considering the relationship of these sub-units, Du et al. (2015b) further investigate this kind of parallel structure by using both cooperative and non-cooperative game theories, and propose two DEA models when priority sequence is available for sub-units.

With respect to the parallel systems, traditional models above assume each input/output value of the system is the sum of that of all its sub-units. However, there are situations when some (or all) inputs/outputs of the system are not the sum of those of all its sub-units. For example, cost margin, current asset turnover and total assets contribution rate are all key metrics to evaluate the profitability of enterprises. If an output metric is one of them, then the output value of the system is not equal to the sum of that of all its sub-units.

In this paper, we propose a new parallel DEA model under the assumption of variable returns to scale (VRS) and each input/output of the system is not equal to the sum of that of all its sub-units. Then, the proposed parallel DEA approach is applied to Chinese manufacturing industry from the perspective of auditing. We not only consider 29 Chinese manufacturing industries but also group each manufacturing industry into four types of enterprises. Different from existing applications that only discuss performance improvement for inefficient DMUs, we further analyze how to select audit objects using the DEA results.

The remainder of the paper is organized as follows. A parallel DEA approach for measuring overall and sub-unit efficiencies is developed in Sect. 2. In Sect. 3, a data set of firms in Chinese manufacturing industry is used to illustrate how to selecting audit objects using our proposed DEA approach. Conclusions are given in Sect. 4.

2 DEA models for parallel systems

Suppose that there are n DMUs denoted by $\text{DMU}_o(o = 1, \ldots, n)$, and each DMU_o has m inputs and s outputs denoted by x_{io} $(i = 1, \ldots, m)$ and $y_{ro}(r = 1, \ldots, s)$, respectively. For measuring the efficiency or performance of DMU_o, the conventional DEA solves the following output-oriented model (Banker et al. 1984)

$$
\begin{aligned}
\theta_o^* = \text{Min} & \frac{\sum_{i=1}^m v_i x_{io} + v_o}{\sum_{r=1}^s u_r y_{ro}} \\
s.t. \quad & \frac{\sum_{i=1}^m v_i x_{ij} + v_o}{\sum_{r=1}^s u_r y_{rj}} \geq 1, \quad j = 1, \ldots, n \\
& u_{r,} v_i \geq \varepsilon, \quad r = 1, \ldots, s, \quad i = 1, \ldots, m \\
& v_o \text{ free in sign}
\end{aligned}
\tag{1}
$$

where u_r and v_i are the most favorable multipliers to be applied to the r th output and i th input for DMU_o in calculating its efficiency θ_o, and v_o is a free variable. The frontier generated by model (1) assumes variable returns to scale (VRS). The current paper uses the VRS assumption because firms in different Chinese manufacturing industries are of different sizes.

Now, suppose that each DMU_o is composed of a set of k components denoted by $\text{DMU}_o^p(p = 1, \ldots, k)$ as shown in Fig. 1. And each of them utilizes the same m inputs x_{io}^p $(i = 1, \ldots, m)$ to produce the same s outputs y_{ro}^p $(r = 1, \ldots, s)$. Unlike the assumption

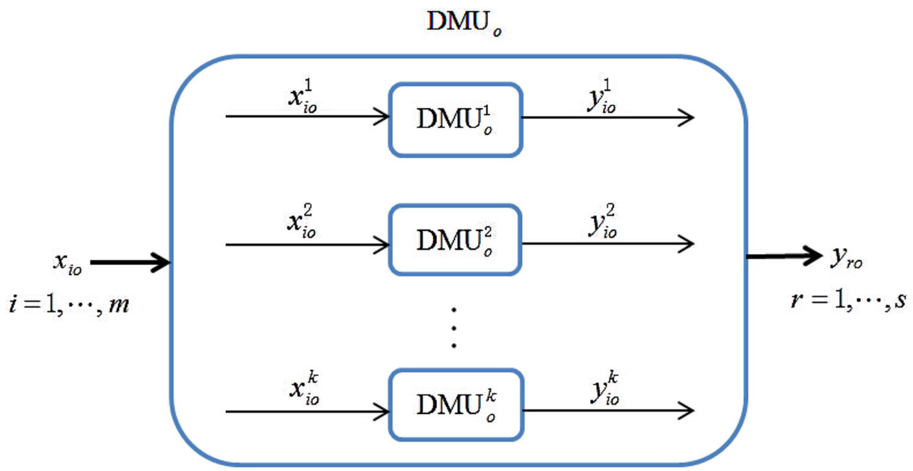

Fig. 1 A parallel internal structure with k components

in Kao (2009) and Du et al. (2015b), in this paper, the sum of all x_{io}^p over p and the sum of all y_{ro}^p over p are not equal to x_{io} and y_{ro}, respectively.

Similar to Du et al. (2015b), we optimize each DMU's overall efficiency subject to the constraints not only on DMU$_j$, but also on its components DMU$_j^p$($p = 1, \ldots, k$). And the weight attached to each input/output is assumed to be unified in both system and component levels. For DMU$_o$ under evaluation, we propose a centralized model as follows

$$\begin{aligned} \theta_o^* &= \text{Min} \frac{\sum_{i=1}^m v_i x_{io} + v_o}{\sum_{r=1}^s u_r y_{ro}} \\ s.t.\ & \frac{\sum_{i=1}^m v_i x_{ij} + v_o}{\sum_{r=1}^s u_r y_{rj}} \geq 1, \quad j = 1, \ldots, n \\ & \frac{\sum_{i=1}^m v_i x_{ij}^p + v_o}{\sum_{r=1}^s u_r y_{ij}^p} \geq 1, \quad p = 1, \ldots, k, \quad j = 1, \ldots, n \\ & u_{r,} v_i \geq \varepsilon, \quad r = 1, \ldots, s, \quad i = 1, \ldots, m \\ & v_o \text{ free in sign} \end{aligned} \tag{2}$$

Note that in Du et al. (2015b), $x_{ij} = \sum_{p=1}^k x_{ij}^p, y_{rj} = \sum_{p=1}^k y_{rj}^p$ under the condition of constant returns to scale (CRS). While in the current paper, $x_{ij} \neq \sum_{p=1}^k x_{ij}^p, y_{rj} \neq \sum_{p=1}^k y_{rj}^p$. To calculate the system efficiency of DMU$_o$, we solve the following linear model (3) which is equivalent to model (2) by Charnes–Cooper transformation (Charnes and Cooper 1962)

$$\begin{aligned} \theta_o^* &= \text{Min} \sum_{i=1}^m v_i x_{io} + v_o \\ s.t.\ & \sum_{i=1}^m v_i x_{ij} - \sum_{r=1}^s \mu_r y_{rj} + v_o \geq 0, \quad j = 1, \ldots, n \\ & \sum_{i=1}^m v_i x_{ij}^p - \sum_{r=1}^s \mu_r y_{rj}^p + v_o \geq 0, \quad p = 1, \ldots, k, \quad j = 1, \ldots, n \end{aligned} \tag{3}$$

$$\sum_{r=1}^{s}\mu_r y_{ro}=1$$
$$\mu_{r,}\nu_i\geq\varepsilon,\quad r=1,\ldots,s,\quad i=1,\ldots,m$$
$$\nu_o \text{ free in sign}$$

After DMU$_o$'s overall efficiency is obtained from model (3), the component efficiency can be obtained for each sub-unit when maintaining the optimal overall efficiency. Assume that sub-unit 1 is given pre-emptive priority, the following model (4) determines its efficiency score while maintaining the overall efficiency score at θ_o^*

$$\begin{aligned}
&\theta_o^{1*}=\text{Min}\sum_{i=1}^{m}\nu_i x_{io}^1+\nu_o\\
&s.t.\quad \sum_{i=1}^{m}\nu_i x_{ij}-\sum_{r=1}^{s}\mu_r y_{rj}+\nu_o\geq 0,\quad j=1,\ldots,n\\
&\sum_{i=1}^{m}\nu_i x_{ij}^p-\sum_{r=1}^{s}\mu_r y_{rj}^p+\nu_o\geq 0,\quad p=1,\ldots,k,\quad j=1,\ldots,n\\
&\sum_{r=1}^{s}\mu_r y_{ro}^1=1\\
&\sum_{i=1}^{m}\nu_i x_{io}-\theta_o^*\sum_{r=1}^{s}\mu_r y_{ro}+\nu_o=0,\\
&\mu_{r,}\nu_i\geq\varepsilon,\quad r=1,\ldots,s,\quad i=1,\ldots,m\\
&\nu_o \text{ free in sign}
\end{aligned}\tag{4}$$

For sub-unit with the qth ($q=2,\ldots,k$) priority, the following model (5) optimizes its efficiency score while maintaining the optimal efficiencies for the entire system and sub-units with the first to the $(q-1)$th priority.

$$\begin{aligned}
&\theta_o^{q*}=\text{Min}\sum_{i=1}^{m}\nu_i x_{io}^q+\nu_o\\
&s.t.\quad \sum_{i=1}^{m}\nu_i x_{ij}-\sum_{r=1}^{s}\mu_r y_{rj}+\nu_o\geq 0,\quad j=1,\ldots,n\\
&\sum_{i=1}^{m}\nu_i x_{ij}^p-\sum_{r=1}^{s}\mu_r y_{rj}^p+\nu_o\geq 0,\quad p=1,\ldots,k,\quad j=1,\ldots,n\\
&\sum_{r=1}^{s}\mu_r y_{ro}^q=1\\
&\sum_{i=1}^{m}\nu_i x_{io}-\theta_o^*\sum_{r=1}^{s}\mu_r y_{ro}+\nu_o=0\\
&\sum_{i=1}^{m}\nu_i x_{io}^t-\theta_o^{t*}\sum_{r=1}^{s}\mu_r y_{io}^t+\nu_o=0,\quad t=1,\ldots,q-1\\
&\mu_{r,}\nu_i\geq\varepsilon,\quad r=1,\ldots,s,\quad i=1,\ldots,m\\
&\nu_o \text{ free in sign}
\end{aligned}\tag{5}$$

Therefore, an efficiency decomposition is obtained for all component units of DMU_o as $(\theta_o^{1*}, \theta_o^{2*}, \ldots, \theta_o^{k*})$. Note that there is no explicit "leader-follower" relationship among our four enterprises of manufacture industry in our application section. As a result, we only apply the "centralized" model (4) in the next section.

3 Application to manufacturing industry from the audit perspective

Chinese economy has experienced some rapid and significant growth over the past 30 years, which is largely due to contributions from the development of manufacturing industry. Therefore, it is very important for us to evaluate the performance of the Chinese manufacturing industry. Sun et al. (1999) use DEA to estimate the efficiency of 28 manufacturing industries across 29 provinces in China. In order to select the most competitive manufacturing industries in China, using three-stage DEA model, Fang et al. (2013) discuss how energy consumption affects performance in different industrial sectors under the restriction of low-carbon economy. Using DEA models, Zhang and Zhang (2013) evaluate the environmental efficiency of Chinese manufacturing. However, most researchers analyze the efficiency of manufacturing industries with conventional DEA models (e.g., Wang et al. 2010; Fang et al. 2013) and do not open the "black box" to further investigate the performances of firms and enterprises within specific manufacturing industries or sectors.

Considering the internal structure and undesirable output, Li et al. (2014) develop a two-stage network DEA model and evaluates the efficiency of Chinese 28 different manufacturing industries. However, each manufacturing industry includes four types of ownership structures. Therefore, it is important to look inside the "black box" and evaluate each manufacturing industry's efficiency considering different ownership structures. Also, the existing literature only discusses performance improvement for inefficient DMUs. The current paper tries to explore how to select audit objects or firms (enterprises) within different manufacturing industries.

In this section, we apply the proposed parallel DEA model to Chinese manufacturing industry, and provide potential supports for audit department and help the audit department select audit objects. Since the audit department needs to formulate annual audit plan each year, to improve audit performance, it is very important for the audit department to select audit objects scientifically. Under normal circumstances, a planning department can select inefficient DMUs or select DMUs that their efficiency is lower because these DMUs may have great possibility of operating risk. But we should also pay attention to efficient DMUs (or DMUs with higher efficiency scores). Abnormal higher efficiency scores than expected may indicate accounting fraud. Fraudulent activities can lead to the downfall of the entire organization and massive investment losses. Efficient DMUs should also be regarded as possible auditing objects. Here we illustrate the approach of selecting audit objects with data from manufacturing industry of China.

3.1 Input and output metrics

The input and output measures for our research are reported in Table 1.

For three output measures, their values are all in percentages. These measures represent the average of an industry or enterprise, and the values related to these measures are in relative

Table 1 Input and output metrics for manufacture industry application

	Metric	Unit	Type
Inputs	Annual average number of employees per enterprise	Person	Real
	Average total assets per enterprise	One hundred million yuan	Real
	Average main business cost per enterprise	One hundred million yuan	Real
Outputs	Cost margin	Percentage	Real
	Current assets turnover	Percentage	Real
	Total assets contribution rate	Percentage	Real

number. Due to this reason, for three input metrics, we adopt the average as their values as the scale and the number of enterprises are different for each enterprise type.

3.1.1 Input

The inputs of the manufacturing industry, which are also the inputs of four types of enterprises, are:

(1) *Annual average number of employees per enterprise* An industry's total number of employees divided by the number of enterprises. The number of employees refers to labor input used in the production process. Generally labor input should refer to the amount of labor used in the actual production process and should be measured by working hours of standard labor intensity. However, due to the lack of data, the majority of studies on performance evaluation of manufacturing industry in China use the number of employees as a proxy of labor input (Sun et al. 1999; Yang et al. 2015).
(2) *Average total assets per enterprise* An industry's total assets divided by the number of enterprises. Total assets include all the current assets and the fixed assets that a company has. The assets also refer to the amount of resources used in the production process, and are frequently used as the input in a number of studies (Liu and Li 2012; Zhu 2000).
(3) *Average major business cost per enterprise* An industry's total major business cost divided by the number of enterprises. Major business cost is the direct cost of production or sales related the core business products or services that must be invested, including raw materials, travel expenses and depreciation of fixed assets, and others. Major business cost is a major cost that companies generate from their operations. Therefore, average major business cost per enterprise is selected as the third input in this study.

3.1.2 Output

The outputs of the manufacture industry, which are also the outputs of four types of enterprises, are:

(1) *Cost margin* Total profit divided by total cost. This measure indicates how much profit a company can get if it spends one dollar. The higher the rate, the more the profit and the better the company performs financially. Therefore, cost margin is an important economic benefit metric.
(2) *Current assets turnover* Net income of main business divided by average current assets. Current assets turnover measures a company's ability to generate earnings from its current assets and shows how efficiently a company can use its current assets to generate

earnings. The higher the ratio, the more efficient the company turns its assets into profits. This metric can also gauge the management and production of a company. Normally, a lower ratio means that the company is most likely having management or production problems. Current assets turnover is an important metric to evaluate an enterprise's asset utilization.

(3) *Total assets contribution rate* The sum of total profit, total taxes and interest expense divided by average assets. It indicates how profitable a company is relative to its total assets and how efficient its management is at using assets to generate earnings. It is a core metric to measure a company's profitability financial performance.

3.2 Data

The current paper focuses on large-scale industrial enterprises in 29 manufacturing industries in China (see Table 3). In China, these large-scale enterprises play a key role in contributing to China's GDP. An enterprise is classified as large-scale if its annual revenue exceeds 20 million RMB from its major business operations. Each Chinese manufacturing industry includes four types of enterprises. They are state-owned and state holding industrial enterprises (SIE), private industrial enterprises (PIE), collective industrial enterprises (CIE) and foreign investment and Hong Kong, Macao and Taiwan-invested industrial enterprises (FIE).

The data set of large-scale industrial enterprises is obtained from the Information Website of Development Research Center of the State Council (China) in 2011. For the system (manufacturing industry) and four types of enterprises, descriptive statistics for six metrics is reported in Table 2. The average of all the input metrics for SIE is the largest, and the average of all the input metrics for PIE is the lowest. The average of annual average number of employees per enterprise for SIE, CIE and FIE is higher than that for the system and PIE. The average of average total assets per enterprise for SIE is higher than that for the system, and the mean of average total assets per enterprise for PIE, CIE and FIE is smaller than that for the system. The average of the average major business cost per enterprise for SIE and FIE is higher than that for the system while the average of the average major business cost per enterprise for PIE and CIE is smaller than that for the system. Hence, we predict that relationship on efficiency for four types of enterprises is as follows: PIE > CIE > FIE > SIE. Note that the prediction only considers the input metrics.

The system or an entire manufacturing industry and FIE have similar average cost margin (8.4 and 8.6 %, respectively), and SIE and PIE have similar average cost margin (7.9 and 7.8 %, respectively). Only FIE's average cost margin is higher than the system's, and CIE's average cost margin is the lowest. For the average current asset turnover and the average total assets contribution rate, there is a following relationship: CIE > PIE > System > FIE > SIE. This may imply FIE and SIE's current assets turnover and total assets contribution rate are needed to improve, and SIE, PIE and CIE's cost margin are needed to improve.

3.3 Results

3.3.1 Analysis for the proposed parallel DEA model

Results from models (3), (4) and (5) are reported in Table 3, and the rankings of manufacturing industries' efficiencies are shown in parentheses next to the efficiency scores. The third column reports overall efficiency scores obtained from model (3). The fourth column reports

Table 2 Descriptive statistics

DMU	Annual average number of employees per enterprise	Average total assets per enterprise	Average main business cost per enterprise	Cost margin (%)	Current assets turnover (%)	Total assets contribution rate (%)
System						
Mean	317.2626	3.1166	2.4538	8.4	2.7	19.3
SD	230.6259	7.5617	2.5813	4.1	0.7	13.0
Min	145.1253	0.4635	0.8133	3.4	1.7	8.9
Max	1346.6216	41.6841	12.5453	26.8	4.9	83.5
SIE						
Mean	881.3513	11.7279	8.3868	7.9	1.8	13.4
SD	781.4640	18.3457	14.1180	6.2	0.5	14.6
Min	157.1429	1.3748	1.0141	1.2	1.1	4.8
Max	4364.1026	90.8810	76.0558	27.0	2.6	84.0
PIE						
Mean	168.8021	0.7473	1.1872	7.8	3.6	22.0
SD	37.0303	0.3437	0.5723	1.2	1.1	5.3
Min	121.3930	0.3250	0.6812	4.7	0.8	9.4
Max	257.3174	1.9142	3.4452	10.2	6.7	35.0
CIE						
Mean	396.9673	1.1280	2.0861	7.1	5.6	28.0
SD	273.5920	1.3343	1.6762	2.6	2.5	11.2
Min	137.2549	0.2560	0.8102	3.7	1.9	11.8
Max	1244.6429	5.8323	8.1031	17.8	12.7	58.5
FIE						
Mean	418.5721	2.8919	3.1302	8.6	2.2	14.7
SD	182.6705	2.1507	2.8586	5.0	0.5	4.0
Min	143.9490	0.7611	0.8800	3.7	1.0	8.1
Max	1080.1270	10.7748	14.5321	31.0	3.0	24.2

Table 3 Results based on the proposed model

DMU	Manufacturing industries	Overall efficiency	SIE efficiency	PIE efficiency	CIE efficiency	FIE efficiency
1	Agricultural and sideline food processing industry	1.5996 (15)	3.4982 (11)	1.2059 (13)	1.7653 (8)	3.0201 (24)
2	Food manufacturing	1.5232 (11)	4.9538 (16)	1.1682 (11)	1.1385 (3)	2.3368 (15)
3	Beverage manufacturing	1.2520 (5)	1.9009 (4)	1.0000 (1)	1.0000 (1)	2.9661 (22)
4	The tobacco manufactures industry	1.0000 (1)	1.0000 (1)	3.1735 (29)	3.5450 (29)	1.0000 (1)
5	Textile industry	2.0341 (22)	9.8440 (24)	1.5919 (23)	1.9561 (12)	2.4578 (17)
6	Textile and garment, footwear, headgear manufacturing	1.4209 (8)	3.7259 (12)	1.3179 (16)	2.4235 (21)	1.5061 (4)
7	Leather, fur, feathers (down) and its products industry	1.3213 (6)	3.7679 (13)	1.1212 (9)	1.8677 (11)	1.7313 (10)
8	Wood processing and wood, bamboo, rattan, palm and grass products industry	1.1704 (3)	5.0754 (17)	1.0000 (1)	1.6486 (7)	1.8060 (11)
9	Furniture manufacturing	1.5671 (14)	2.6748 (7)	1.1936 (12)	1.0000 (1)	2.5137 (18)
10	Paper and paper products industry	1.8545 (19)	15.7532 (28)	1.3076 (15)	2.0182 (13)	2.5954 (19)
11	Printing, reproduction of recorded media industry	1.1203 (2)	1.3537 (2)	1.0000 (1)	1.2621 (4)	1.4701 (3)
12	Educational and sports supplies manufacturing	1.8017 (18)	2.3199 (5)	1.0991 (6)	1.7675 (9)	2.9937 (23)
13	Chemical materials and chemical products manufacturing	1.5510 (13)	8.5842 (23)	1.1000 (7)	1.5282 (6)	1.3498 (2)
14	Pharmaceutical manufacturing	1.3940 (7)	2.7458 (8)	1.1113 (8)	3.1874 (27)	1.7137 (9)
15	Chemical fiber manufacturing	2.6450 (27)	12.6619 (26)	2.2769 (26)	2.0340 (15)	2.3540 (16)
16	Rubber products industry	2.4343 (25)	15.6179 (27)	1.4474 (21)	2.1026 (17)	4.4325 (29)
17	Plastic products industry	1.6098 (16)	4.1643 (15)	1.2106 (14)	2.0819 (16)	2.7601 (20)
18	Non-metallic mineral products industry	1.1941 (4)	1.6899 (3)	1.0707 (4)	1.3185 (5)	1.6727 (8)
19	Ferrous metal smelting and rolling processing industry	3.6496 (29)	5.4537 (18)	2.6332 (27)	3.0224 (24)	3.4345 (25)
20	Non-ferrous metal smelting and rolling processing industry	2.5692 (26)	10.0396 (25)	1.6859 (24)	2.3342 (19)	2.7904 (21)

Table 3 continued

DMU	Manufacturing industries	Overall efficiency	SIE efficiency	PIE efficiency	CIE efficiency	FIE efficiency
21	Fabricated metal	1.6258 (17)	3.4039 (10)	1.3233 (17)	2.0310 (14)	2.2850 (14)
22	General equipment manufacturing	1.4561 (9)	6.1532 (19)	1.1485 (10)	1.8443 (10)	1.5669 (5)
23	Special equipment manufacturing	1.5501 (12)	6.7040 (21)	1.0834 (5)	2.5526 (23)	1.6667 (7)
24	Transportation equipment manufacturing	2.1998 (23)	6.3416 (20)	1.8862 (25)	2.4460 (22)	1.9796 (12)
25	Electrical machinery and equipment manufacturing	2.4178 (24)	7.8167 (22)	1.5032 (22)	3.2527 (28)	3.9669 (28)
26	Communications equipment, computers and other electronic equipment manufacturing	3.5988 (28)	4.0818 (14)	2.6559 (28)	2.2676 (18)	3.5644 (27)
27	Instrumentation and culture, office machinery manufacturing	2.0153 (21)	2.4244 (6)	1.4359 (20)	3.1237 (26)	3.5097 (26)
28	Crafts and other manufacturing	1.9300 (20)	16.3600 (29)	1.4241 (19)	3.0626 (25)	2.1161 (13)
29	Waste resources and materials recycling and processing	1.4758 (10)	3.1137 (9)	1.3274 (18)	2.3981 (20)	1.6372 (6)

the state-owned and state holding industrial enterprises' efficiency scores obtained from model (4). The fifth to seventh columns report efficiency scores of the private industrial enterprises, the collective industrial enterprises, the foreign investment and Hong Kong, Macao and Taiwan-invested industrial enterprises obtained from model (5), respectively.

The results show only DMU 4 is efficient with respect to its efficiency of the system, SIE and FIE. Two industries are efficient for PIE and CIE: DMU 3 and DMU 8 are efficient for PIE, and DMU 3 and DMU 9 are efficient for CIE. Obviously, the proposed parallel DEA model has a higher discrimination power. We find that, for each industry, there is always an enterprise type where its efficiency score has a great difference compared to the system's efficiency score. For example, consider DMU 1, its efficiency score for SIE (3.4982) has a great difference compared to the system's efficiency score (1.5996). Moreover, the ranking of the system efficiency may be totally different from that of an enterprise type's efficiency for an industry, for example, in DMU 14. Its ranking of the system efficiency is 7, but the ranking of CIE's efficiency is 27. Therefore, we cannot make a decision only through the system efficiency as to which industry or enterprise to be selected as an audit object.

On the basis of above description, which manufacturing industry should be considered as audit objects? For the purpose of illustration, suppose the top ten and the last ten manufacturing industries are regarded as audit objects. In Table 4, the top ten manufacturing industries are denoted by "✓" for the system and each type of enterprise, the last ten manufacturing industries are denoted by "×", and the rest of manufacturing industries are denoted by blanks. Then, audit objects can be selected according to Table 4. The results show only three industries (DMUs 11, 18 and 25) show a consistent pattern along with four types of enterprises if we choose audit objects based on overall efficiency scores.

For a DMU, its system efficiency is ranked higher while its component efficiency may be ranked lower with respect to a certain type of enterprise. For example, the ranking of system efficiency of DMU 3 is number 5. But it is ranked number twenty-two for FIE. Similarly, the system efficiency score is ranked lower for a DMU, but it could be ranked higher with respect to a certain type of enterprise. For example, DMU 27's system efficiency score is ranked number twenty-one, but it is ranked number six for SIE.

Therefore, we should not only select audit objects according to overall efficiency scores, but also open the "black box" to examine the internal sub-units' performance. If an industry's overall efficiency score is lower, we need to identify which type of enterprise affects the overall efficiency mostly, and then the audit department should focus on this type of enterprise in audit process. On the other hand, if an industry's overall efficiency score is higher, we need to identify whether there is a type of enterprise that its efficiency is lower.

Note that efficient DMUs or DMUs of higher efficiency scores are also considered as audit objects because an enterprise's high earnings is often caused by a product or business, but other products or businesses usually occur a loss. Certainly, if the enterprise's operations are healthy, then the audit department can regard this enterprise's advantages as a standard which guides other peer enterprises. In short, the efficient and inefficient DMUs are both needed to be considered as audit objects in our case.

3.3.2 Comparisons among three different models

In Table 4, we report the audit objects based on our proposed parallel DEA model. Next, we examine if the audit objects are the same for the centralized DEA model or the conventional DEA model. In order to facilitate the comparison, Table 5 reports the results of the proposed parallel DEA model, the centralized DEA model and the conventional DEA model. The proposed parallel DEA model is models (3)–(5). The centralized DEA model is model (2),

Table 4 The top ten and the last ten of efficiency scores (proposed parallel model)

DMU	Overall efficiency	SIE efficiency	PIE efficiency	CIE efficiency	FIE efficiency
1				✓	×
2				✓	
3	✓	✓	✓	✓	×
4	✓	✓	×	×	✓
5	×	×	×		
6	✓			×	✓
7	✓		✓		✓
8	✓		✓	✓	
9		✓		✓	
10		×			
11	✓	✓	✓	✓	✓
12		✓	✓	✓	×
13		×	✓	✓	✓
14	✓	✓	✓	×	✓
15	×	×	×		
16	×	×	×		×
17					×
18	✓	✓	✓	✓	✓
19	×		×	×	×
20	×	×	×		×
21		✓			
22	✓		✓	✓	✓
23		×	✓	×	✓
24	×	×	×	×	
25	×	×	×	×	×
26	×		×		×
27	×	✓	×	×	×
28	×	×		×	
29	✓	✓		×	✓

since six metrics are in average or percentage, sub-units can be looked as homogenous with the system. The conventional DEA model is model (1). Here “Pro”, “Cen” and “Con” represent the proposed parallel DEA model, the centralized DEA model, and the conventional DEA model, respectively.

It can be seen that the efficiency obtained from the conventional DEA model is the largest, and the efficiency obtained from the proposed parallel DEA model is the lowest for each DMU.

Obviously, the proposed parallel DEA model is more discriminating than the centralized DEA model and the conventional DEA model. Note that a larger efficiency score in Table 5 means a lower efficiency since we use the output-oriented DEA model. Because we select audit objects according to DMUs’ ranking, we can only compare the rankings of the system and each type of enterprise. The ranking results are reported in Table 6.

Table 5 Results of three DEA models

DMU	System efficiency			SIE efficiency			PIE efficiency			CIE efficiency			FIE efficiency		
	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con
1	1.600	1.600	1.205	3.498	3.283	1.073	1.206	1.011	1.000	1.765	1.244	1.221	3.020	2.820	1.000
2	1.523	1.523	1.083	4.954	3.518	1.059	1.168	1.154	1.062	1.139	1.000	1.000	2.337	1.975	1.000
3	1.252	1.252	1.000	1.901	1.188	1.000	1.000	1.000	1.000	1.000	1.000	1.000	2.966	2.300	1.000
4	1.000	1.000	1.000	1.000	1.000	1.000	3.174	1.051	1.038	3.545	3.257	2.013	1.000	1.000	1.000
5	2.034	2.034	1.418	9.844	4.352	1.215	1.592	1.592	1.453	1.956	1.667	1.626	2.458	2.439	1.145
6	1.421	1.421	1.144	3.726	3.536	1.000	1.318	1.315	1.231	2.424	1.811	1.776	1.506	1.506	1.000
7	1.321	1.321	1.000	3.768	3.330	1.173	1.121	1.094	1.048	1.868	1.534	1.509	1.731	1.731	1.000
8	1.170	1.170	1.000	5.075	3.924	1.000	1.000	1.000	1.000	1.649	1.331	1.319	1.806	1.800	1.000
9	1.567	1.567	1.227	2.675	1.588	1.000	1.194	1.194	1.088	1.000	1.000	1.000	2.514	2.420	1.214
10	1.855	1.855	1.484	15.753	5.786	1.640	1.308	1.255	1.251	2.018	1.663	1.546	2.595	2.595	1.507
11	1.120	1.120	1.000	1.354	1.334	1.000	1.000	1.000	1.000	1.262	1.163	1.000	1.470	1.400	1.070
12	1.802	1.802	1.438	2.320	2.303	1.000	1.099	1.000	1.000	1.768	1.229	1.226	2.994	2.929	1.000
13	1.551	1.551	1.248	8.584	3.313	1.012	1.100	1.015	1.000	1.528	1.388	1.000	1.350	1.348	1.000
14	1.394	1.394	1.042	2.746	2.026	1.307	1.111	1.111	1.000	3.187	1.315	1.280	1.714	1.671	1.009
15	2.645	2.645	1.736	12.661	3.965	1.177	2.277	2.011	1.901	2.034	1.907	1.773	2.354	2.354	1.177
16	2.434	2.434	1.462	15.617	5.207	1.119	1.447	1.280	1.187	2.103	1.793	1.764	4.433	3.506	1.069
17	1.610	1.610	1.315	4.164	3.288	1.103	1.211	1.152	1.143	2.082	1.370	1.000	2.760	2.675	1.255
18	1.194	1.194	1.000	1.690	1.688	1.062	1.071	1.067	1.060	1.319	1.180	1.056	1.673	1.672	1.128
19	3.650	3.650	1.712	5.454	5.121	1.065	2.633	2.247	1.615	3.022	3.022	2.820	3.435	3.435	1.000
20	2.569	2.569	1.554	10.039	3.520	1.063	1.686	1.559	1.422	2.334	1.955	1.733	2.790	2.790	1.078

Table 5 continued

DMU	System efficiency			SIE efficiency			PIE efficiency			CIE efficiency			FIE efficiency		
	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con	Pro	Cen	Con
21	1.626	1.626	1.338	3.404	3.091	1.360	1.323	1.286	1.278	2.031	1.578	1.445	2.285	2.274	1.141
22	1.456	1.456	1.231	6.153	3.780	1.874	1.149	1.102	1.075	1.844	1.584	1.433	1.567	1.567	1.137
23	1.550	1.550	1.283	6.704	3.616	1.994	1.083	1.058	1.051	2.553	1.911	1.755	1.667	1.667	1.230
24	2.200	2.200	1.387	6.342	2.550	1.361	1.886	1.727	1.426	2.446	2.070	1.824	1.980	1.787	1.000
25	2.418	2.418	1.614	7.817	4.804	2.131	1.503	1.501	1.379	3.253	3.129	2.458	3.967	3.061	1.291
26	3.599	3.599	2.025	4.082	4.080	2.092	2.656	1.676	1.336	2.268	2.268	2.260	3.564	3.564	1.015
27	2.015	2.015	1.336	2.424	2.380	1.464	1.436	1.424	1.229	3.124	1.901	1.551	3.510	2.724	1.251
28	1.930	1.930	1.415	16.360	4.752	1.749	1.424	1.424	1.356	3.063	2.224	2.198	2.116	2.027	1.000
29	1.476	1.476	1.000	3.114	2.353	1.000	1.327	1.000	1.000	2.398	1.369	1.252	1.637	1.637	1.000

Table 6 Ranking of three models

DMU	Overall efficiency			SIE efficiency			PIE efficiency			CIE efficiency			FIE efficiency		
	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con
1	15	15	11	11	12	14	14	6	1	9	8	9	24	24	1
2	11	11	9	16	16	10	12	15	14	4	1	1	16	15	1
3	5	5	1	1	2	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	8	10	1	1	1	1	1	1
5	22	22	21	24	24	19	24	25	27	13	18	19	18	19	22
6	8	8	10	12	18	1	17	20	19	22	20	24	6	6	1
7	6	6	1	13	15	17	10	11	11	12	14	16	12	12	1
8	3	3	1	17	21	1	1	1	1	8	10	13	1	14	1
9	14	14	12	1	4	1	13	16	1	1	1	1	19	1	24
10	19	19	24	28	29	24	16	17	20	14	17	17	20	20	29
11	2	2	1	4	3	1	1	1	1	5	5	1	1	5	17
12	18	18	22	6	7	1	7	1	1	10	7	10	23	25	1
13	13	13	14	23	14	9	8	7	1	7	13	1	5	4	1
14	7	7	8	8	6	20	9	13	1	28	9	12	11	10	14
15	27	27	28	26	22	18	27	28	29	16	22	23	17	18	23
16	25	25	23	27	28	16	22	18	17	18	19	22	29	28	16
17	16	16	16	15	13	15	15	14	16	17	12	1	21	21	27
18	4	4	1	5	5	11	5	10	13	6	6	8	10	11	19
19	29	29	27	18	27	13	28	29	28	25	28	29	25	27	1
20	26	26	25	25	17	12	25	24	25	20	24	20	22	23	18

Table 6 continued

DMU	Overall efficiency			SIE efficiency			PIE efficiency			CIE efficiency			FIE efficiency		
	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con	Pro.	Cen.	Con
21	17	17	18	10	11	21	18	19	21	15	15	15	15	17	21
22	9	9	13	19	20	26	11	12	15	11	16	14	7	7	20
23	12	12	15	21	19	27	6	9	12	24	23	21	9	9	25
24	23	23	19	20	10	22	26	27	26	23	25	25	13	13	1
25	24	24	26	22	26	29	23	23	24	29	29	28	28	26	28
26	28	28	29	14	23	28	29	26	22	19	27	27	27	29	15
27	21	21	17	7	9	23	21	21	18	27	21	18	26	22	26
28	20	20	20	29	25	25	20	22	23	26	26	26	14	16	1
29	10	10	1	9	8	1	19	1	1	21	11	11	8	8	1

It can be seen from Table 6, the rankings of the system efficiency are the same based upon the proposed parallel model and the centralized DEA model, but the rankings of the system efficiency for the conventional DEA model are inconsistent with those for the proposed parallel model and the centralized DEA model. There are 7 DMUs whose efficiency score are equal to 1 by applying the conventional DEA model, so it is not easy to distinguish them. We also find it is different for the audit department to select audit objects by comparing the sub-units' efficiency. For example, if the audit department audits state-owned and state holding industrial enterprises, DMUs 14, 21 and 27 show a big ranking difference between the conventional DEA model and one of the other two approaches. For private industrial enterprises, DMUs 1 and 29 show a big ranking difference between the proposed parallel model and one of the other two approaches. DMU 9 shows a big ranking difference between the conventional DEA model and one of the other two approaches. With respect to collective industrial enterprises, DMUs 14 and 29 show a big ranking difference between the proposed parallel model and one of the other two approaches. DMU 17 shows a big ranking difference between the conventional DEA model and one of the other two approaches. With regard to foreign investment and Hong Kong, Macao and Taiwan-invested industrial enterprises, DMU 9 shows a big ranking difference between the centralized DEA model and one of the other two approaches. DMUs 11, 12, 22 and 28 show a big ranking difference between the conventional DEA model and one of the other two approaches. Therefore, audit plan may be different with the change of DEA approaches, and it is important for audit department to select a DEA approach which can discriminate the DMUs.

3.3.3 Comparisons among different types of enterprises within a specific manufacturing industry

In the previous sections, the results are obtained when the system and each sub-unit are treated independently. But the system efficiency scores cannot be compared with its sub-units' efficiency scores, and the efficiency scores have not been compared among different sub-units. There is a need to compare the efficiency scores among the system and different sub-units. We next seek a DEA approach which can calculate the efficiency of the system and its different sub-units under the same frontier.

In fact, the system efficiency and sub-units' efficiency can be calculated by applying the centralized DEA model because 145 DMUs are regarded as independently and they share the same frontier. The efficiency scores and rankings of the DMUs based on the centralized DEA model are shown in Table 7. The last row reports the average efficiency scores of four types of enterprises. It can be seen that the average efficiency score of private enterprises is the maximum, and that of collective enterprises, foreign investment and Hong Kong, Macao and Taiwan-invested enterprises, and state-owned and state holding industrial enterprises ranks 2 to 4, respectively. The result is consistent with the reality.

As can be seen from Table 7, a DMU's overall efficiency is higher while not all its sub-units' efficiency scores are higher and vice versa. For DMU 4, its overall efficiency is higher, but the collective company's efficiency is lower. Suppose our target is selecting sub-DMUs of poor performance. If we have selected DMU 4 as the audit object, then we should focus on the collective company. For DMU 12, its overall efficiency is lower but the private company's efficiency is higher. So, if we select DMU 12 as the audit object, we should focus on other types of enterprises besides the private company.

In Table 8, the meanings of "H" represents a sub-unit's efficiency is larger than the system and "L" represents a sub-unit's efficiency is smaller than the system. Note that we only compare efficiency scores among different types of enterprises, and analyze which type of

Table 7 Results and ranking of efficiency scores (centralized model)

DMU	Overall efficiency	SIE efficiency	PIE efficiency	CIE efficiency	FIE efficiency
1	1.5996 (15)	3.2828 (12)	1.0109 (6)	1.2442 (7)	2.8204 (24)
2	1.5232 (11)	3.5177 (16)	1.1543 (15)	1.0000 (1)	1.9746 (13)
3	1.2520 (5)	1.1878 (2)	1.0000 (1)	1.0000 (1)	2.2995 (16)
4	1.0000 (1)	1.0000 (1)	1.0510 (8)	3.2565 (29)	1.0000 (1)
5	2.0341 (22)	4.3515 (24)	1.5919 (25)	1.6671 (17)	2.4390 (19)
6	1.4209 (8)	3.5358 (18)	1.3153 (20)	1.8113 (19)	1.5061 (4)
7	1.3213 (6)	3.3303 (15)	1.0935 (11)	1.5343 (13)	1.7313 (10)
8	1.1704 (3)	3.9236 (21)	1.0000 (1)	1.3313 (9)	1.7995 (12)
9	1.5671 (14)	1.5878 (4)	1.1936 (16)	1.0000 (1)	2.4199 (18)
10	1.8545 (19)	5.7864 (29)	1.2549 (17)	1.6626 (16)	2.5954 (20)
11	1.1203 (2)	1.3338 (3)	1.0000 (1)	1.1629 (4)	1.3998 (3)
12	1.8017 (18)	2.3029 (7)	1.0000 (1)	1.2294 (6)	2.9289 (25)
13	1.5510 (13)	3.3128 (14)	1.0152 (7)	1.3883 (12)	1.3484 (2)
14	1.3940 (7)	2.0261 (6)	1.1113 (13)	1.3154 (8)	1.6711 (8)
15	2.6450 (27)	3.9651 (22)	2.0111 (28)	1.9071 (21)	2.3540 (17)
16	2.4343 (25)	5.2068 (28)	1.2803 (18)	1.7930 (18)	3.5060 (28)
17	1.6098 (16)	3.2884 (13)	1.1518 (14)	1.3700 (11)	2.6751 (21)
18	1.1941 (4)	1.6884 (5)	1.0669 (10)	1.1803 (5)	1.6718 (9)
19	3.6496 (29)	5.1210 (27)	2.2469 (29)	3.0224 (27)	3.4345 (27)
20	2.5692 (26)	3.5199 (17)	1.5587 (24)	1.9546 (23)	2.7904 (23)
21	1.6258 (17)	3.0907 (11)	1.2859 (19)	1.5781 (14)	2.2742 (15)
22	1.4561 (9)	3.7800 (20)	1.1016 (12)	1.5840 (15)	1.5669 (5)
23	1.5501 (12)	3.6156 (19)	1.0575 (9)	1.9112 (22)	1.6667 (7)
24	2.1998 (23)	2.5504 (10)	1.7274 (27)	2.0704 (24)	1.7869 (11)
25	2.4178 (24)	4.8039 (26)	1.5005 (23)	3.1290 (28)	3.0611 (26)
26	3.5988 (28)	4.0800 (23)	1.6762 (26)	2.2676 (26)	3.5644 (29)
27	2.0153 (21)	2.3796 (9)	1.4239 (21)	1.9012 (20)	2.7238 (22)
28	1.9300 (20)	4.7515 (25)	1.4241 (22)	2.2241 (25)	2.0274 (14)
29	1.4758 (10)	2.3530 (8)	1.0000 (1)	1.3685 (10)	1.6372 (6)
Average efficiency		3.2646	1.2864	1.7195	2.2302

enterprises can increase a DMU's overall efficiency score or make a DMU's overall efficiency decrease.

We note that each DMU has one or more sub-units whose efficiency is larger/smaller than the system. Therefore, if we need audit all the DMUs and our target is selecting sub-DMUs of poor performance, then for each DMU, we can select the types of enterprises whose efficiency scores are smaller than the system as audit objects. Thus, the audit department can select audit objects based on Table 8.

From the previous analysis, we provide a method how to select audit objects. If we treat the system and sub-units independently, we can select audit objects by the proposed parallel DEA model. If we need audit all the DMUs, then we can select audit objects by the centralized DEA model.

Table 8 Horizontal comparison for a DMU (centralized model)

DMU	Overall efficiency	SIE efficiency	PIE efficiency	CIE efficiency	FIE efficiency
1	1.5996 (15)	L	H	H	L
2	1.5232 (11)	L	H	H	L
3	1.2520 (5)	H	H	H	L
4	1.0000 (1)	H	H	L	H
5	2.0341 (22)	L	H	H	L
6	1.4209 (8)	L	H	L	L
7	1.3213 (6)	L	H	L	L
8	1.1704 (3)	L	H	L	L
9	1.5671 (14)	L	H	H	L
10	1.8545 (19)	L	H	H	L
11	1.1203 (2)	L	H	L	L
12	1.8017 (18)	L	H	H	L
13	1.5510 (13)	L	H	H	H
14	1.3940 (7)	L	H	H	L
15	2.6450 (27)	L	H	H	H
16	2.4343 (25)	L	H	H	L
17	1.6098 (16)	L	H	H	L
18	1.1941 (4)	L	H	H	L
19	3.6496 (29)	L	H	H	H
20	2.5692 (26)	L	H	H	L
21	1.6258 (17)	L	H	H	L
22	1.4561 (9)	L	H	L	L
23	1.5501 (12)	L	H	L	L
24	2.1998 (23)	L	H	H	H
25	2.4178 (24)	L	H	L	L
26	3.5988 (28)	L	H	H	H
27	2.0153 (21)	L	H	H	L
28	1.9300 (20)	L	H	L	L
29	1.4758 (10)	L	H	H	L

4 Conclusions and future extensions

In earlier work by Kao (2009) and Du et al. (2015b), parallel DEA models are proposed. These parallel DEA models both consider the operations of individual components in calculating the system efficiency. And each input/output of the system is the sum of that of all its components, which is not always true in real world. The discussion in previous literature is based upon the assumption of constant returns to scale, which doesn't meet the reality in some cases as returns to scale may be variable. As a result, this paper develops a modified parallel DEA model.. In the case of the manufacturing industry of China, we find only one DMU is efficient throughout the entire manufacturing industry. We rank each industry without applying the super-efficiency model (Andersen and Petersen 1993).

Moreover, this proposed model is applied to auditing area. The audit department usually selects audit objects based on personal experience but not from the performance perspective.

Generally, we always care about improvements for inefficient DMUs and do not analyze the efficient DMUs. But for the audit department, it is needed to look into the "black box" of the DMUs regardless of inefficient or efficient DMUs. The audit department not only needs to identify which sub-unit is inefficient, but also wants to figure out which sub-unit is efficient.

The conventional DEA model does not consider the relationship among the sub-units. Thus, the discrimination power of the conventional DEA model is inferior to the proposed DEA model. Since many DMUs' efficiency scores are equal to 1, selecting audit objects is difficult for the conventional DEA model. To select audit objects scientifically, we argue that the audit department can combine the proposed parallel DEA model with the centralized DEA model.

In this paper, the proposed parallel DEA model supposes that the attached weights are the same for the system and its component units. However, it is not always true, for example, Du et al. (2015a) propose a series of DEA models that non-homogenous sub-units operate in parallel network structures with intermediate measures or links. Thus, we may develop new parallel models when the component units are non-homogeneous for future research.

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