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Measuring energy and environmental efficiency of transportation systems in China based on a parallel DEA approach

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ABSTRACT

Because of China's rapid economic development, its transportation system has become one of China's high-energy-consumption and high-pollution-emission sectors. However, little research has been done which pays close attention to China's transportation system, especially in terms of energy and environmental efficiency evaluation. In this paper, data envelopment analysis (DEA) is applied to measure the energy and environment performance of transportation systems in China with the goal of sustainable development. This paper treats transportation as a parallel system consisting of subsystems for passenger transportation and freight transportation, and extends a parallel DEA approach to evaluate the efficiency of each subsystem. An efficiency decomposition procedure is proposed to obtain the highest achievable subsystem efficiency. Our empirical study on 30 of mainland China's provincial-level regions shows that most of them have a low efficiency in their transportation system and the two parallel subsystems. There are large efficiency differences between the passenger and freight transportation subsystems. In addition, unbalanced development has occurred in the three large areas of China, with the east having the highest efficiency, followed by central China and then west. Therefore, more measures should be taken to balance and coordinate the development between the three large areas and between the two subsystems within them. Our analysis approach gives data for determining effective measures.

Introduction

The Chinese "Reform and Opening Up" policy has brought significant economic development in China. For example, from 1978 to 2013, the average annual growth rate of China's gross domestic product (GDP) was 15.73%, which has given the nation the second largest economy in the world following the United States. However, the quick growth rate in economy is at the cost of high energy consumption and high volume of pollution emission (Nordström and Vaughan, 1999; Wang et al., 2007). The energy shortage and pollution emission have already become significant problems for economic growth and sustainable societal development in China (Wu et al., 2013, 2014).

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Transportation is known to be a high-energy-consumption sector throughout the world (Chang et al., 2013; Zhou et al., 2014). For example, according to the National Bureau of Statistics of China, in 2012 the Chinese transportation sector's energy consumption volume was 302 million tons of standard coal and it is one of the few sectors whose consumption increase rate has been more than 7.2% in the past 10 years (Cui and Li, 2014). To compound the problem, the increasing consumption of energy has generated large quantities of undesirable gases including carbon dioxide (CO_2). For example, according to the International Energy Agency (IEA) (2011), the worldwide transportation sector became the world's second largest greenhouse gas emitting sector and accounted for 22% of the world's CO_2 emissions. Therefore, it is particularly important to analyze the energy and environmental efficiency of transportation sectors since doing so may provide much information to decision makers seeking to improve transportation performance.

Traditionally, there are two main approaches for evaluating efficiency: stochastic frontier analysis (SFA) approach and data envelopment analysis (DEA) approach. As a parametric approach, SFA is suitable only for one-output scenarios and the results largely depend on the predicted forms of the production functions. Therefore, incorrect results may be obtained due to using an incorrect form of production function. Recently, evaluating energy and environmental efficiency has been an important application of DEA. Developed by Charnes et al. (1978), DEA is a non-parametric mathematical approach, which is used to evaluate the relative performance of a group of homogenous DMUs, particularly a group with multiple inputs and multiple outputs (Cooper et al., 2007; Zhu, 2004; Cook and Seiford, 2009; Saen, 2005). As a nonparametric technique, DEA is not limited by any functional form and does not require the numerous assumptions that arise from the use of statistical methods for function estimation and efficiency measurement, yet DEA can evaluate DMU performance very well. According to Cooper et al. (2004), DEA has been extensively applied in the performance evaluation and benchmarking of hospitals (see, e.g. Prior, 2006; Du et al., 2014), supply chains of enterprises (see, e.g. Mahdiloo et al., 2012; Chen et al., 2006), and other entities (see, e.g. Mahdiloo et al., 2011; Saen et al., 2005; Chu et al., 1992; Chang et al., 2014). Therefore, DEA is applied as the main approach in our paper to evaluate the energy and environmental efficiency of the transportation systems in 30 Chinese provincial-level regions.

In the prior DEA literature, Zhou et al. (2008b) summarized the application of DEA to evaluate environmental and energy efficiency. In terms of energy efficiency, Hu and Wang (2006) proposed the traditional Charnes–Cooper–Rhodes (CCR) model to analyze energy efficiencies of 29 administrative regions in China during the period 1995–2002. Their model did not consider undesirable outputs such as pollutants. Wu (2012) examined industrial energy efficiency based on both static and dynamic data of China by using several DEA models. Song et al. (2013) utilized a super-SBM model to measure and calculate the efficiency of BRICS. In terms of environmental efficiency, Zhang et al. (2008) proposed a DEA approach to analyze the Chinese industrial sector's eco-efficiency. Zhou et al. (2008a) applied DEA technologies to measure the carbon emission performance of eight world regions. Song and Wang (2014) measured China's regional environmental efficiency scores by applying a DEA decomposition approach from the perspectives of technological progress and government regulation. Bian and Yang (2010) applied DEA models to estimate energy and environment efficiencies simultaneously. Shi et al. (2010) proposed three extended DEA models to evaluate energy overall efficiency, pure technical efficiency, and scale efficiency of 28 administrative regions in China. Wang et al. (2012) analyzed the industrial sector energy and environment efficiency of China's 30 provinces for 2005–2009 and concluded that the western area had the greatest amount of energy redundancies.

In addition, there are also several published studies on energy and environmental efficiency evaluation of specific transportation systems in various parts of the world. Based on energy efficiency, Ramanathan (2000) applied the DEA to compare the energy efficiencies of alternative transport modes in India. Tongzon (2001) adopted DEA method to evaluate the efficiency of four Australian and twelve international container ports. Lin and Hong (2006) measured the operational performance of 20 major airports around the world. Wei et al. (2013) used a super-efficiency DEA model to evaluate Chinese urban transportation. Cui and Li (2014) applied a new, three-stage, virtual frontier model using DEA to evaluate transportation energy efficiencies. Regarding the environmental efficiency of transportation systems, McMullen and Noh (2007) applied a directional distance function approach to demonstrate the importance of considering a transit agency's goal of reducing emissions. Chang et al. (2013) proposed a non-radial DEA model with the slacks-based measure to analyze the environmental performance of China's transportation sector. Bi et al. (2014) presented a non-radial DEA model with multidirectional efficiency analysis (MEA) for the measurement of regional environmental efficiencies within China's transportation sector during 2006–2010. Egilmez and Park (2014) proposed a two-step hierarchical methodology to quantify the transportation related carbon, energy, and water footprints of U.S. manufacturing sectors and evaluate the environmental vs. economic performance based on eco-efficiency scores.

Surveying prior research, we find that although the DEA method is widely used in energy efficiency and environmental performance evaluation, only a few extant studies on transportation systems are available, especially for energy and environmental efficiency research. In addition, all prior studies assumed the transportation system as an entirety, while in reality transportation systems include both passenger transportation and freight transportation. According to Kao (2012), DMUs can be considered in a parallel structure, if each DMU has the same number of different processes and each corresponding process performs the same function. In this sense, each region of China in this paper is a parallel system and the two types of transport (passenger and freight) are two parallel subsystems. With this decomposition, decision makers can easily find the inefficiency of the two subsystems. Thus, relevant proper measures can be taken to improve overall efficiency. Fig. 1 shows the basic parallel system for the transportation system of each region.

Combining Zhou et al. (2014) and Cui and Li (2014), this paper selects passenger seats, energy (transportation energy consumption volume), capital (transportation fixed assets investment), and highway mileage as the passenger transportation

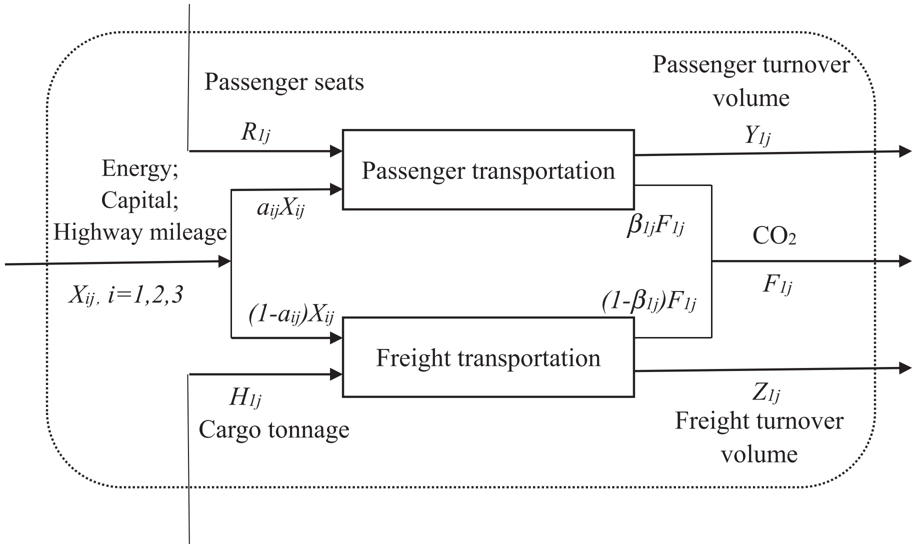

Fig. 1. A parallel system comprised of two transportation subsystem.

subsystem's inputs. Since highway mileage is an important factor which can better reflect transportation efficiency, it is chosen as a new input in this paper. Passenger turnover volume is selected as the desirable output and the volume of CO_2 emission produced by passenger transportation as the undesirable output. In freight transportation system, the inputs are cargo tonnage, energy, capital, and highway mileage, with the outputs being freight turnover volume and CO_2 emission. Obviously, energy, capital, highway mileage, and CO_2 emission are seen as the shared inputs/outputs because we cannot determine precisely each subsystem's share of these three kinds of inputs and one undesirable output, but we can obtain overall inputs and outputs for the whole parallel system.

The shared resource flow in many parallel production scenario is defined as the resources which can be shared among different departments (Beasley, 1995; Amirteimoori and Nashtaei, 2006; Cook and Green, 2004; Yu, 2008). Beasley (1995) indicated that different departments of a university may share equipment and general expenditures. Tsai and Molinero (2002) noted that DMUs in health services may have some inputs and outputs that are associated solely with a particular activity, and some inputs and outputs which are shared between several activities. Cook et al. (2000) studied shared resources involving the sales and service functions within the branches of a bank. For details on parallel system with the shared resources, one can refer to Castelli et al. (2010). However, the above papers all assumed uniform proportions of shared inputs for all DMUs when evaluating the efficiency of a DMU. In practice, different DMUs may have different proportions of each shared resource.

In this paper, we proposed a weighted average efficiency formula, namely additive efficiency proposed by Chen et al. (2009), to evaluate the overall efficiency of a transportation system. In addition, considering the non-unique efficiency decomposition for parallel systems, a better efficiency decomposition for the individual system has also been built.

There are three contributions of this paper. First, it considers for the first time both passenger transportation and freight transportation in one parallel system to reflect transportation performance. This decomposition of the whole transportation systems can better facilitate decision makers finding the weaknesses of each subsystem so that more effective suggestion can be made to improve the performance of that subsystem. Second, our method allows setting different proportions of shared resources for different DMUs, which may better conform to reality. Third, we propose a deterministic efficiency decomposition approach to calculate efficiencies of parallel subsystems, rather than randomly selecting one of subsystems' efficiency combinations.

The structure of this paper is as follows. Section 'Methodology' (Methodology) presents a methodology about our studies. In Section 'Empirical study' (Empirical study), an application about transportation system of China's 30 provincial-level regions is analyzed. Finally conclusions and directions for future research are shown in Section 'Conclusions' (Conclusions).

Methodology

Overall system performance assessment model

In this section, we present a DEA model to evaluate the efficiency of transportation systems of China's 30 provincial-level regions. In the DEA analysis, each DMU corresponds to a region. In this paper, input-orientation is assumed, since the needs are saving energy and protecting the environment (Cui and Li, 2014).

Denote each region as DMU_j $(j = 1, \ldots, 30)$ as in Fig. 1. DMU_j's subsystem 1 (denoted by $k = 1$) consumes inputs $X_{ij}^1,\ i = 1,2,3$ and R_{1j} to produce desirable output Y_{1j} and undesirable F_{1j}^1, and its subsystem 2 (denoted by $k = 2$) consumes inputs $X_{ij}^2,\ i = 1,2,3$ and H_{1j} to produce desirable output Z_{1j} and undesirable output F_{1j}^2. In Fig. 1, $X_{ij},\ i = 1,2,3$ and F_{1j} denote the shared resources. In this paper, subsystem 1 and 2 correspond to the passenger transportation subsystem and freight transportation subsystem, respectively. Let parameter α_{ij} and β_{1j} denote the proportion of inputs and output to be assigned to the passenger transportation subsystem.

Denote the DMU (region) being evaluated by DMU_0, and the efficiency for the subsystem 1, subsystem 2, and combined system by $E_{10},\ E_{20}$, and E_0 respectively. Based upon the assumption of constant returns to scale (CRS) (Charnes et al., 1978), we propose to combine the two subsystems in a weighted average of efficiency scores as the overall efficiency, a concept can be written as follows:

$$
\begin{aligned}
Max\quad & E_0 = w_1 \times E_{10} + w_2 \times E_{2o} \\
s.t.\quad & E_{1j} = \frac{u_1 Y_{1j} - \varphi_1 \beta_{1j} F_{1j}}{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i \alpha_{ij} X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& E_{2j} = \frac{\pi_1 Z_{1j} - \varphi_1 (1 - \beta_{1j}) F_{1j}}{\rho_1 H_{1j} + \sum_{i=1}^{3} v_i (1 - \alpha_{ij}) X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& u_1, \varphi_1, \eta_1, \pi_1, \rho_1 \geqslant 0, \\
& v_i \geqslant 0, \quad i = 1, \ldots, 3 \\
& L_i \leqslant \alpha_{ij} \leqslant U_i \quad i = 1, \ldots, 3\ j = 1, \ldots, 30 \\
& L \leqslant \beta_{1j} \leqslant U \qquad j = 1, \ldots, 30
\end{aligned}
\tag{1}
$$

Some further explanations of this model (1) follow:

1. The rationale for the negative sign of the second term of the numerator for the two subsystems efficiency of model (1) is that the outputs F_{1j} are undesirable and they should be decreased in the production process (Korhonen and Luptacik, 2004; Amirteimoori, 2013).
2. w_1 and w_2 denote the weights of passenger transportation subsystem and freight transportation subsystem respectively, we require $w_1 + w_2 = 1$.
3. L_i, L, U_i and U are the lower and upper bounds for shared resource. These lower and upper bounds are used to avoid extreme bias toward one of the subsystems (Cook and Hababou, 2001; Chen et al., 2010).

Definition 1. DMU_j is said to be *overall efficient* if and only if $E_j = 1, j = 1, \ldots, 30$.

Definition 2. Subsystems k of DMU_j is said to be *efficient* if $E_{kj} = 1, k = 1, 2 j = 1, \ldots, 30$.

Theorem 1. *A DMU is said to be overall efficient if and only if each subsystem is efficient.*

Proof. First, we prove the necessary condition of Theorem 1. According to definition 1, if DMU_0 is *overall efficient*, then $E_0 = 1$. Because $E_0 = w_1 E_{10} + w_2 E_{20}$, and $0 \leqslant E_{10} \leqslant 1, 0 \leqslant E_{20} \leqslant 1$, thus the two subsystem efficiencies E_{10} and E_{20} must satisfy $E_{10} = E_{20} = 1$.

Next, we prove the sufficiency of the theorem. If its two subsystems are efficient, i.e., $E_{10} = E_{20} = 1$, then because $E_0 = w_1 E_{10} + w_2 E_{20}$, then the overall efficiency E_0 must be equal to 1. According to definition 1, DMU_0 must be overall efficient.

To sum up for DMU_0, considering the two subsystems is overall efficient if and only if its two subsystems are all efficient. □

We use w_1 and w_2 to represent the relative importance or contribution of the efficiency of each subsystem to the overall performance of the given DMU in the combined system. In order to start the process of converting model (1) into a linear program, one reasonable weight choice of each subsystem is the proportion of total resources devoted to each subsystem, reflecting the relative size and importance of a subsystem. Thus, following Chen et al. (2009, 2010) and Amirteimoori (2013), we define:

$$
w_1 = \frac{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i \alpha_{ij} X_{ij}}{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i X_{ij} + \rho_1 H_{1j}} \quad \text{and} \quad w_2 = \frac{\rho_1 H_{1j} + \sum_{i=1}^{3} v_i (1 - \alpha_{ij}) X_{ij}}{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i X_{ij} + \rho_1 H_{1j}} \tag{2}
$$

where $\eta_1 R_{1j} + \sum_{i=1}^{3} v_i X_{ij} + \rho_1 H_{1j}$ represents the total amounts of input resource consumed by the combined system DMU_j, while $\eta_1 R_{1j} + \sum_{i=1}^{3} v_i \alpha_{ij} X_{ij}$ and $\rho_1 H_{1j} + \sum_{i=1}^{3} v_i (1 - \alpha_{ij}) X_{ij}$ represent the sizes of the passenger transportation and freight transportation subsystems, respectively. Thus, we have

$$E_0 = w_1 \times E_{10} + w_2 \times E_{2o} = \frac{u_1 Y_{10} - \varphi_1 F_{10} + \pi_1 Z_{10}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \tag{3}$$

In contrast with many other research effort (Amirteimoori, 2013; Chen et al., 2010), we should note that our weights w_1 and w_2 must be restricted to a certain region. Specifically, we require $w_1 \geqslant a$ and $w_2 \geqslant b$ to eliminate some improper weights, where a and b represent the minimum weight for passenger transportation subsystem and freight transportation subsystem respectively in calculating the overall efficiency of DMU_0.

Substituting (3) into model (1)'s objective function, the overall efficiency of the combined system for DMU_0 can be evaluated by solving the following fractional model (4).

$$\begin{aligned}
Max \quad & E_0 = \frac{u_1 Y_{10} - \varphi_1 F_{10} + \pi_1 Z_{10}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \\
s.t. \quad & E_{1j} = \frac{u_1 Y_{1j} - \varphi_1 \beta_{1j} F_{1j}}{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i \alpha_{ij} X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& E_{2j} = \frac{\pi_1 Z_{1j} - \varphi_1 (1 - \beta_{1j}) F_{1j}}{\rho_1 H_{1j} + \sum_{i=1}^{3} v_i (1 - \alpha_{ij}) X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& w_1 = \frac{\eta_1 R_{10} + \sum_{i=1}^{3} v_i \alpha_{i0} X_{i0}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \geqslant a \\
& w_2 = \frac{\rho_1 H_{10} + \sum_{i=1}^{3} v_i (1 - \alpha_{i0}) X_{i0}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \geqslant b \\
& u_1, \varphi_1, \eta_1, \pi_1, \rho_1 \geqslant 0, \\
& v_i \geqslant 0, \quad i = 1, \ldots, 3 \\
& L_i \leqslant \alpha_{ij} \leqslant U_i \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \leqslant \beta_{1j} \leqslant U \quad j = 1, \ldots, 30
\end{aligned} \tag{4}$$

Model (4) is a nonlinear program, and we need to transform it into a standard linear program in three steps which are as follows:

Step 1: Charnes–Cooper transformation.

Let $T = \frac{1}{A}, u'_1 = Tu_1, \varphi'_1 = T\varphi_1, \eta'_1 = T\eta_1, \pi'_1 = T\pi_1, \rho'_1 = T\rho_1, v'_i = Tv_i$, where A denotes $\eta_1 R_{1j} + \sum_{i=1}^{3} v_i X_{ij} + \rho_1 H_{1j}$. Then program (4) can be transformed into (5).

$$\begin{aligned}
Max \quad & E_0 = u'_1 Y_{10} - \varphi'_1 F_{10} + \pi'_1 Z_{10} \\
s.t. \quad & u'_1 Y_{1j} - \varphi'_1 \beta_{1j} F_{1j} - \left(\eta'_1 R_{1j} + \sum_{i=1}^{3} v'_i \alpha_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \pi'_1 Z_{1j} - \varphi'_1 (1 - \beta_{1j}) F_{1j} - \left(\rho'_1 H_{1j} + \sum_{i=1}^{3} v'_i (1 - \alpha_{ij}) X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \eta'_1 R_{10} + \sum_{i=1}^{3} v'_i \alpha_{i0} X_{i0} \geqslant a \\
& \rho'_1 H_{10} + \sum_{i=1}^{3} v'_i (1 - \alpha_{i0}) X_{i0} \geqslant b \\
& \eta'_1 R_{10} + \sum_{i=1}^{3} v'_i X_{i0} + \rho'_1 H_{10} = 1 \\
& u'_1, \varphi'_1, \eta'_1, \pi'_1, \rho'_1 \geqslant 0, \\
& v'_i \geqslant 0, \quad i = 1, \ldots, 3 \\
& L_i \leqslant \alpha_{ij} \leqslant U_i \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \leqslant \beta_{1j} \leqslant U \quad j = 1, \ldots, 30
\end{aligned} \tag{5}$$

Step 2: Variable alternation.

Model (5) is still nonlinear since there exist $v'_i \alpha_{ij}$ and $\varphi'_1 \beta_{1j}$ in some constraints, so set $\xi_{ij} = v'_i \alpha_{ij} (i = 1, \ldots, 3 \; j = 1, \ldots, 30)$ and $\psi_{1j} = \varphi'_1 \beta_{1j} (j = 1, \ldots, 30)$. Then model (5) can be converted into the following linear program (6).

$$
\begin{aligned}
Max \quad & E_0 = u'_1 Y_{10} - \varphi'_1 F_{10} + \pi'_1 Z_{10} \\
s.t. \quad & u'_1 Y_{1j} - \psi_{1j} F_{1j} - \left(\eta'_1 R_{1j} + \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \pi'_1 Z_{1j} - \varphi'_1 F_{1j} + \psi_{1j} F_{1j} - \left(\rho'_1 H_{1j} + \sum_{i=1}^{3} v'_i X_{ij} - \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \eta'_1 R_{10} + \sum_{i=1}^{3} v'_i \alpha_{i0} X_{i0} \geqslant a \\
& \rho'_1 H_{10} + \sum_{i=1}^{3} v'_i X_{i0} - \sum_{i=1}^{3} \xi_{i0} X_{i0} \geqslant b \\
& \eta'_1 R_{10} + \sum_{i=1}^{3} v'_i X_{i0} + \rho'_1 H_{10} = 1 \\
& L_i v'_i \leqslant \xi_{ij} \leqslant U_i v'_i, \xi_{ij} \geqslant 0, \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \varphi'_{1i} \leqslant \psi_{1j} \leqslant U \varphi'_1, \psi_{1j} \geqslant 0 \quad j = 1, \ldots, 30 \\
& u'_1, \varphi'_1, \eta'_1, \pi'_1, \rho'_1 \geqslant 0, \\
& v'_i, \geqslant 0, \quad i = 1, \ldots, 3
\end{aligned}
\tag{6}
$$

By solving linear program (6), the optimal solutions $(u'^*_1, v'^*_i, \varphi'^*_1, \pi'^*_1, \rho'^*_1, \eta'^*_p, \xi^*_{ij}, \psi^*_{1j})$ will be obtained.

Step 3: Obtaining the optimal solutions for each $DMU_j (j = 1, \ldots, 30)$. Since $\xi_{ij} = v'_i \alpha_{ij}$ and $\psi_{1j} = \varphi'_1 \beta_{1j}$, we have $\alpha^*_{ij} = \frac{\xi^*_{ij}}{v'^*_i} (i = 1, \ldots, 3 \; j = 1, \ldots, 30)$ and $\beta^*_{1j} = \frac{\psi^*_{ij}}{\varphi'^*_1} (j = 1, \ldots, 30)$.

Through the above three steps, we can obtain each region's optimal overall efficiency and the optimal proportions for the shared resources.

Subsystem performance assessment model: efficiency decomposition

Once we obtain an optimal solution to model (6), the individual subsystem's efficiency scores can be calculated accordingly. However, model (6) may have multiple optimal solutions, so the individual subsystem's efficiency may also not be unique. Therefore, we follow Kao and Hwang's (2008) approach to find a set of multipliers which produce the highest passenger or freight transportation subsystem efficiency score while maintaining the overall efficiency score of the combined systems. This is an approach which has not previously been applied in a parallel system.

Denote the optimal overall efficiency score for DMU_0 obtained from model (6) as E^*_0. The maximum efficiency value achievable for subsystem 1 (passenger transportation), denoted E^*_{10} while maintaining the overall efficiency score can be determined via the following model (7).

$$
\begin{aligned}
Max \quad & E_{10} = \frac{u_1 Y_{10} - \varphi_1 \beta_{10} F_{10}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i \alpha_{i0} X_{i0}} \\
s.t. \quad & E_{1j} = \frac{u_1 Y_{1j} - \varphi_1 \beta_{1j} F_{1j}}{\eta_1 R_{1j} + \sum_{i=1}^{3} v_i \alpha_{ij} X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& E_{2j} = \frac{\pi_1 Z_{1j} - \varphi_1 (1 - \beta_{1j}) F_{1j}}{\rho_1 H_{1j} + \sum_{i=1}^{3} v_i (1 - \alpha_{ij}) X_{ij}} \leqslant 1, \quad j = 1, \ldots, 30 \\
& E^*_0 = \frac{u_1 Y_{10} - \varphi_1 F_{10} + \pi_1 Z_{10}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \\
& w_1 = \frac{\eta_1 R_{10} + \sum_{i=1}^{3} v_i \alpha_{i0} X_{i0}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \geqslant a \\
& w_2 = \frac{\rho_1 H_{10} + \sum_{i=1}^{3} v_i (1 - \alpha_{i0}) X_{i0}}{\eta_1 R_{10} + \sum_{i=1}^{3} v_i X_{i0} + \rho_1 H_{10}} \geqslant b \\
& u_1, \varphi_1, \eta_1, \pi_1, \rho_1 \geqslant 0, \\
& v_i \geqslant 0, \quad i = 1, \ldots, 3 \\
& L_i \leqslant \alpha_{ij} \leqslant U_i \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \leqslant \beta_{1j} \leqslant U \qquad j = 1, \ldots, 30
\end{aligned}
\tag{7}
$$

Model (7) can be converted into the following linear program by the steps explained above.

$$\begin{aligned}
Max\quad & E_{10}^{*}=u_1'Y_{10}-\psi_{10}F_{10}\\
s.t.\quad & u_1'Y_{1j}-\psi_{1j}F_{1j}-\left(\eta_1'R_{1j}+\sum_{i=1}^{3}\xi_{ij}X_{ij}\right)\leqslant 0,\quad j=1,\ldots,30\\
& \pi_1'Z_{1j}-\varphi_1'F_{1j}+\psi_{1j}F_{1j}-\left(\rho_1'H_{1j}+\sum_{i=1}^{3}v_i'X_{ij}-\sum_{i=1}^{3}\xi_{ij}X_{ij}\right)\leqslant 0,\quad j=1,\ldots,30\\
& u_1'Y_{10}-\varphi_1'F_{10}+\pi_1'Z_{10}-E_0^{*}\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)=0\\
& a\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)-(\eta_1'R_{10}+\sum_{i=1}^{3}\xi_{i0}X_{i0})\leqslant 0\\
& b\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)-\left(\rho_1'H_{10}+\sum_{i=1}^{3}v_i'X_{i0}-\sum_{i=1}^{3}\xi_{i0}X_{i0}\right)\leqslant 0\\
& \eta_1'R_{10}+\sum_{i=1}^{3}\xi_{i0}X_{i0}=1\\
& L_iv_i'\leqslant\xi_{ij}\leqslant U_iv_i',\xi_{ij}\geqslant 0\quad i=1,\ldots,3\ j=1,\ldots,30\\
& L\varphi_1'\leqslant\psi_{1j}\leqslant U\varphi_1',\psi_{1j}\geqslant 0\quad j=1,\ldots,30\\
& u_1',\varphi_1',\eta_1',\pi_1',\rho_1'\geqslant 0,\\
& v_i'\geqslant 0,\quad i=1,\ldots,3
\end{aligned}\tag{8}$$

Using the traditional approach of many studies (see. e.g., Kao and Hwang, 2008; Halkos et al., 2014; Chen et al., 2010), subsystem 2's (freight transportation) efficiency score can be calculated as $E_{20}=\frac{E_0^*-\omega_1^*E_{10}^*}{\omega_2^*}$, where ω_1^* and ω_2^* are the optimal weights based upon model (6), and E_{10}^* represents the optimal efficiency of subsystem 1 while maintaining the overall efficiency in model (8). However, in this paper, we should point out that ω_1^* and ω_2^* may also not be unique because of the multiple optimal solutions of model (6). Therefore, we propose to produce the highest efficiency score for subsystem 2 while maintaining the overall efficiency score E_0^* and subsystem 1's maximum achievable efficiency E_{10}^*. The maximum achievable value of E_{20}^{1*} can be determined via the following linear model (9).

$$\begin{aligned}
Max\quad & E_{20}^{1*}=\pi_1'Z_{10}-\varphi_1'F_{10}+\psi_{10}F_{10}\\
s.t.\quad & u_1'Y_{1j}-\psi_{1j}F_{1j}-\left(\eta_1'R_{1j}+\sum_{i=1}^{3}\xi_{ij}X_{ij}\right)\leqslant 0,\quad j=1,\ldots,30\\
& \pi_1'Z_{1j}-\varphi_1'F_{1j}+\psi_{1j}F_{1j}-\left(\rho_1'H_{1j}+\sum_{i=1}^{3}v_i'X_{ij}-\sum_{i=1}^{3}\xi_{ij}X_{ij}\right)\leqslant 0,\quad j=1,\ldots,30\\
& u_1'Y_{10}-\varphi_1'F_{10}+\pi_1'Z_{10}-E_0^{*}\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)=0\\
& u_1'Y_{10}-\psi_{1j}F_{10}-E_{10}^{*}\left(\eta_1'R_{10}+\sum_{i=1}^{3}\xi_{i0}X_{i0}\right)=0\\
& a\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)-\left(\eta_1'R_{10}+\sum_{i=1}^{3}\xi_{i0}X_{i0}\right)\leqslant 0\\
& b\left(\eta_1'R_{10}+\sum_{i=1}^{3}v_i'X_{i0}+\rho_1'H_{10}\right)-\left(\rho_1'H_{10}+\sum_{i=1}^{3}v_i'X_{i0}-\sum_{i=1}^{3}\xi_{i0}X_{i0}\right)\leqslant 0\\
& \rho_1'H_{10}+\sum_{i=1}^{3}v_i'X_{i0}-\sum_{i=1}^{3}\xi_{i0}X_{i0}=1\\
& L_iv_i'\leqslant\xi_{ij}\leqslant U_iv_i',\xi_{ij}\geqslant 0\quad i=1,\ldots,3\ j=1,\ldots,30\\
& L\varphi_i'\leqslant\psi_{1j}\leqslant U\varphi_1',\psi_{1j}\geqslant 0\quad j=1,\ldots,30\\
& u_1',\varphi_1',\eta_1',\pi_1',\rho_1'\geqslant 0,\\
& v_i'\geqslant 0,\qquad i=1,\ldots,3
\end{aligned}\tag{9}$$

Similarly, the following linear program can be established to maximize subsystem 2's efficiency score E_{20}^* while maintaining the overall efficiency score.

$$
\begin{aligned}
Max \quad & E_{20}^{*} = \pi_1' Z_{10} - \varphi_1' F_{10} + \psi_{1j} F_{10} \\
s.t. \quad & u_1' Y_{1j} - \psi_{1j} F_{1j} - \left(\eta_1' R_{1j} + \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \pi_1' Z_{1j} - \varphi_1' F_{1j} + \psi_{1j} F_{1j} - \left(\rho_1' H_{1j} + \sum_{i=1}^{3} v_i' X_{ij} - \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& u_1' Y_{10} - \varphi_1' F_{10} + \pi_1' Z_{10} - E_0^{*} \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) = 0 \\
& a \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) - \left(\eta_1' R_{10} + \sum_{i=1}^{3} \xi_{i0} X_{i0} \right) \leqslant 0 \\
& b \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) - \left(\rho_1' H_{10} + \sum_{i=1}^{3} v_i' X_{i0} - \sum_{i=1}^{3} \xi_{i0} X_{i0} \right) \leqslant 0 \\
& \rho_1' H_{10} + \sum_{i=1}^{3} v_i' X_{i0} - \sum_{i=1}^{3} \xi_{i0} X_{i0} = 1 \\
& L_i v_i' \leqslant \xi_{ij} \leqslant U_i v_i', \xi_{ij} \geqslant 0 \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \varphi_1' \leqslant \psi_{1j} \leqslant U \varphi_1', \psi_{1j} \geqslant 0 \quad j = 1, \ldots, 30 \\
& u_1', \varphi_1', \eta_1', \pi_1', \rho_1' \geqslant 0, \\
& v_i' \geqslant 0, \qquad i = 1, \ldots, 3
\end{aligned}
\tag{10}
$$

Subsystem 1's maximum achievable efficiency of E_{10}^{2*} while maintaining the overall efficiency E_0^{*} and subsystem 2's maximum achievable efficiency E_{20}^{*} can be determined via the following linear model (11).

$$
\begin{aligned}
Max \quad & E_{10}^{2*} = u_1' Y_{10} - \psi_{1j} F_{10} \\
s.t. \quad & u_1' Y_{1j} - \psi_{1j} F_{1j} - \left(\eta_1' R_{1j} + \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& \pi_1' Z_{1j} - \varphi_1' F_{1j} + \psi_{1j} F_{1j} - \left(\rho_1' H_{1j} + \sum_{i=1}^{3} v_i' X_{ij} - \sum_{i=1}^{3} \xi_{ij} X_{ij} \right) \leqslant 0, \quad j = 1, \ldots, 30 \\
& u_1' Y_{10} - \varphi_1' F_{10} + \pi_1' Z_{10} - E_0^{*} \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) = 0 \\
& \pi_1' Z_{10} - \varphi_1' F_{10} + \psi_{1j} F_{10} - E_{20}^{*} \left(\rho_1' H_{10} + \sum_{i=1}^{3} v_i' X_{i0} - \sum_{i=1}^{3} \xi_{i0} X_{i0} \right) = 0 \\
& a \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) - \left(\eta_1' R_{10} + \sum_{i=1}^{3} \xi_{i0} X_{i0} \right) \leqslant 0 \\
& b \left(\eta_1' R_{10} + \sum_{i=1}^{3} v_i' X_{i0} + \rho_1' H_{10} \right) - \left(\rho_1' H_{10} + \sum_{i=1}^{3} v_i' X_{i0} - \sum_{i=1}^{3} \xi_{i0} X_{i0} \right) \leqslant 0 \\
& \eta_1' R_{10} + \sum_{i=1}^{3} \xi_{i0} X_{i0} = 1 \\
& L_i v_i' \leqslant \xi_{ij} \leqslant U_i v_i', \xi_{ij} \geqslant 0 \quad i = 1, \ldots, 3 \; j = 1, \ldots, 30 \\
& L \varphi_1' \leqslant \psi_{1j} \leqslant U \varphi_1', \psi_{1j} \geqslant 0 \quad j = 1, \ldots, 30 \\
& u_1', \varphi_1', \eta_1', \pi_1', \rho_1' \geqslant 0, \\
& v_i' \geqslant 0, \quad i = 1, \ldots, 3
\end{aligned}
\tag{11}
$$

Solving the above models, we can obtain each model's optimal value $E_{10}^{*}, E_{20}^{1*}, E_{20}^{*}$, and E_{10}^{2*}. If $E_{10}^{*} = E_{10}^{2*}$ and $E_{20}^{*} = E_{20}^{1*}$, we can come to the conclusion that a unique efficiency decomposition is obtained.

Empirical study

The data set

In this section, we examine the energy and environmental efficiency of the transportation systems of 30 provincial-level regions in mainland China in 2012, excluding Tibet, due to incomplete data from that region. The above-mentioned input–output measures used in our paper are summarized in Table 1.

The data related to non-energy input (PS, capital, HM, and CT), energy input, and desirable output (PTV, FTV) are available in the China Statistical Yearbook 2013, China Energy Statistical Yearbook 2013, Ministry of Transport of the People's Republic of China, and Economy Prediction System. However, there are no official statistics yet on provincial CO_2 emission in China. Therefore our research estimated the CO_2 emissions in the regional transportation sector for the year 2012 using a fuel based carbon footprint model, which has been successfully applied by Chang et al. (2013) and Bi et al. (2014).

Based on the Intergovernmental Panel on Climate Change guidelines (IPCC, 2006) for National Greenhouse Gas Inventories for calculating CO_2 data, we can estimate CO_2 emissions from fossil fuels using the following equation.

$$CO_2\ emission = \sum_{i=1}^{n} A \times CCF_i \times HE_i \times COF_i \times \frac{44}{12} \quad (12)$$

From model (12), we know that CO_2 emissions are related to the amount of all carbonaceous fuel combusted (A), the carbon content factor (CCF), the heat equivalent (HE), and the carbon oxidation factor (COF) of carbonaceous fuel. The last number (44/12) represents the ratio of the molecular weight of CO_2(44) to the molecular weight of carbon (12). $CCF \times HE_i \times COF_i \times \frac{44}{12}$ is the CO_2 emission factor of a fuel. It represents the amount of carbon emission factor by the type of carbonaceous fossil fuel. However, as for the CO_2 emission factor, there are several different international standards. Chang et al. (2013) indicated that the domestic report from the Energy Research Institute (ERI) of the National Development and Reform Commission (NDRC) (2007) in China can best represent the true carbon emission factors, and so it is used in this paper. The CO2 emission factors shown in Table 2 reflect several major types of carbonaceous fuels in China.

The amount of consumption of each fuel by each province in the transportation sector can be collected from China Statistical Yearbook 2013. Thus, the CO_2 emissions of each region of China can be calculated according to formula (12), so all input/output data has obtained. The descriptive statistics for the inputs and outputs of these 30 regions are presented in Table 3.

Results and analysis

We apply our methodology provided in Section 'Methodology' to calculate the efficiency of transportation systems of China's 30 provincial-level regions. Firstly, we require that the weights of each subsystem within the overall system are not smaller than 0.2, that is, $a = b = 0.2$. In addition, we set $0.25 \leqslant \alpha_{ij} \leqslant 0.75$ and $0.25 \leqslant \beta_{1j} \leqslant 0.75$ for the proportion of shared resource to conform to reality. With those figures employed in the above models, we get the evaluated results which are listed in Table 4.

In Table 4, column 3 shows the overall systems' efficiency scores E_j^* of transportation systems of these 30 provincial-level regions in mainland China. Columns 4 and 6 show the highest achievable efficiency scores E_{1j}^* and E_{2j}^* for transportation subsystems of passenger and freight respectively while maintaining the overall system efficiency. The highest achievable efficiency scores E_{2j}^{1*} (E_{1j}^{2*}) of passenger (freight) transportation subsystem while maintaining the overall system efficiency and freight (passenger) transportation subsystem efficiency are specified in columns 5 and 7. Columns 8–11 show the optimal proportions of shared resource (energy, capital, HM, and CO_2 respectively) for the passenger transportation subsystem. In addition, the last row of Table 4 shows the average efficiency scores of the 30 provincial-level regions.

From Table 4, the following conclusions can be drawn. First, there are three regions which are overall efficient in terms of the transportation system: Tianjin, Shanghai, and Anhui. Data in those three rows shows that each subsystem of these three regions is efficient, which clearly demonstrates Theorem 1. In addition, there are some regions with low overall efficiency, such as Xinjiang (0.4034), Ningxia (0.4123), Yunnan (0.3299), and Heilongjiang (0.4747). The average overall efficiency score of the 30 regions is 0.6682, a result which indicates that China is faced with a relatively low efficiency in transportation systems.

Table 1
Variables of inputs and outputs.

Transportation system		Variable	Units
Passenger Transportation subsystem	Inputs	Passenger seats (PS)	Per seat
		Energy	10 thousand TCEs
		Capital	100 million RMB
		Highway mileage (HM)	Kilometers
	Outputs	Passenger turnover volume (PTV)	100 million passenger-km
		CO_2	Tons
Freight Transportation subsystem	Inputs	Cargo tonnage (CT)	Tons
		Energy	10 thousand TCEs
		Capital	100 million RMB
		Highway mileage (HM)	Kilometers
	Outputs	Freight turnover volume (FTV)	10 million ton-km
		CO_2	Tons

Table 2
CO_2 emission factors by major carbonaceous fuel types in China.

Fuels	Coal	Petrol	Kerosene	Diesel	Fuel oil	Nature gas
CCF	27.28	18.9	19.6	20.17	21.09	15.32
HE	192.14	448	447.5	433.3	401.9	0.384
COF (%)	92.3	98	98.6	98.2	98.5	99

Notes: CCF and HE are expressed in units of tons carbon/trillion Joules, and trillion Joules/10^4 tons (m^3), respectively.

Table 3
Descriptive statistics for the inputs and outputs of 30 regions in China.

Variables	Passenger transportation		Shared resources				Freight transportation	
	Output PTV	Input PS	CO2	Energy	Capital	HM	Input CT	Output FTV
Mean	958.21	721545.97	20015404.28	973.75	815.02	138151.72	2706758.24	5411.86
Median	649.13	617668.5	17921337.93	865.624	800.379	152356.5	1859244.5	3652.45
S.D.	680.4	387080.9	12,940,981	621.75	438.52	73037.36	2244361.66	4477.62
Max.	2998.23	1,639,611	55909075.66	2707.103	1742.749	293,499	9,241,756	20373.4
Min.	110.11	84,626	2475784.57	120.761	100.291	12,541	207,753	527.6

Table 4
The efficiencies of the 30 provincial-level regions in mainland China.

DMU	Region	E_j^*	E_{1j}^*	E_{2j}^{1*}	E_{2j}^*	E_{1j}^{2*}	α_{1j}	α_{2j}	α_{3j}	β_{1j}
1	Beijing	0.7915	1.0000	0.0779	0.0779	1.0000	0.75	0.75	0.75	0.75
2	Tianjin	1.0000	1.0000	1.0000	1.0000	1.0000	0.31	0.30	0.25	0.52
3	Hebei	0.8626	0.9994	0.3157	1.0000	0.8352	0.25	0.26	0.25	0.75
4	Shanxi	0.4619	0.5528	0.0851	0.6985	0.4146	0.25	0.25	0.25	0.58
5	Inner Mongolia	0.4852	0.5790	0.0221	0.8640	0.4094	0.25	0.25	0.25	0.58
6	Liaoning	0.6698	0.7857	0.2062	0.6187	0.6800	0.25	0.45	0.25	0.75
7	Jilin	0.5957	0.7311	0.0341	0.5646	0.6019	0.25	0.25	0.25	0.26
8	Heilongjiang	0.4747	0.5815	0.0168	0.4686	0.4757	0.25	0.25	0.25	0.68
9	Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	0.26	0.26	0.26	0.56
10	Jiangsu	0.7277	1.0000	0.2503	0.3635	0.8491	0.60	0.62	0.69	0.75
11	Zhejiang	0.7599	1.0000	0.3327	0.7283	0.7663	0.56	0.56	0.54	0.29
12	Anhui	1.0000	1.0000	1.0000	1.0000	1.0000	0.43	0.43	0.69	0.44
13	Fujian	0.5145	0.6117	0.0677	0.8516	0.4471	0.25	0.30	0.25	0.73
14	Jiangxi	0.8711	1.0000	0.3557	1.0000	0.8453	0.25	0.25	0.25	0.71
15	Shandong	0.8228	1.0000	0.1139	0.9172	0.8039	0.25	0.25	0.25	0.75
16	Henan	0.7550	0.8918	0.2079	1.0000	0.7060	0.25	0.25	0.25	0.58
17	Hubei	0.6951	0.8605	0.0283	0.6150	0.7186	0.25	0.25	0.25	0.26
18	Hunan	0.7199	0.8769	0.0923	0.7591	0.7121	0.25	0.26	0.25	0.59
19	Guangdong	0.8773	1.0000	0.3863	0.7652	0.8997	0.73	0.68	0.72	0.75
20	Guangxi	0.6554	1.0000	0.1539	0.3858	0.7096	0.59	0.56	0.52	0.71
21	Hainan	0.5893	1.0000	0.3385	0.8406	0.5056	0.50	0.60	0.45	0.75
22	Chongqing	0.4964	0.5936	0.0789	0.7723	0.4412	0.25	0.26	0.25	0.51
23	Sichuan	0.5405	0.6634	0.0493	0.4436	0.5599	0.25	0.27	0.25	0.55
24	Guizhou	0.4835	0.5938	0.0422	0.3798	0.5042	0.25	0.27	0.25	0.08
25	Yunnan	0.3299	0.4063	0.0190	0.2188	0.3522	0.25	0.25	0.25	0.55
26	Shaanxi	0.6907	0.8521	0.0202	0.6185	0.7051	0.25	0.25	0.25	0.56
27	Gansu	0.7884	0.9488	0.1470	1.0000	0.7461	0.25	0.25	0.45	0.75
28	Qinghai	0.5696	0.6906	0.0855	0.7691	0.5296	0.25	0.26	0.25	0.75
29	Ningxia	0.4123	0.8006	0.2829	0.8487	0.2669	0.54	0.55	0.53	0.01
30	Xinjiang	0.4034	0.4878	0.0657	0.5635	0.3714	0.26	0.25	0.25	0.53
Average		0.6681	0.8169	0.2292	0.7044	0.6619	0.34	0.35	0.35	0.64

Second, when decomposing the whole system overall efficiency into the two subsystems' efficiencies, we can find big differences between them. For example, when we maximize the passenger transportation subsystem's achievable efficiency while maintaining the whole system overall efficiency, there are 11 regions which are efficient in the passenger transportation subsystem. However, there are only 4 regions which are efficient in the freight transportation subsystem if we maintain the whole system's overall efficiency. The maximum average achievable passenger and freight transportation subsystem efficiencies when maintaining the overall efficiency are 0.8169 and 0.7044, respectively. In addition, although each subsystem has 3 efficient regions when maintaining the whole system's overall efficiency and the other subsystem's efficiency, the passenger transportation subsystem's average efficiency is 0.6619, which is obviously greater than the 0.2292 figure for the

Table 5
Areas of China and constituent provincial-level regions.

Area	Regions
East	Beijing, Tianjin, Hebei, Liaoning, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan
Central	Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi
West	Chongqing, Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang

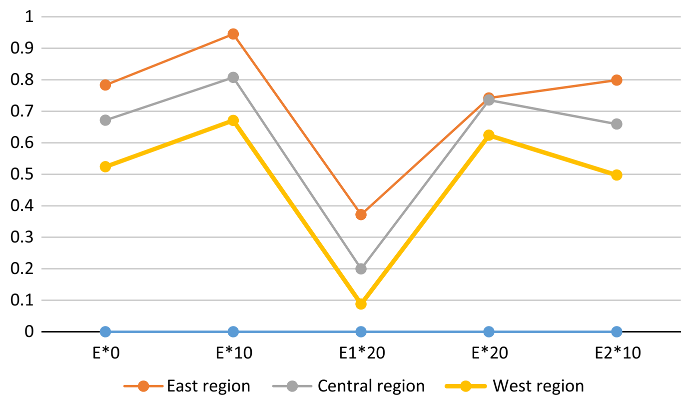

Fig. 2. The efficiency of eastern, central, and western areas of China.

freight transportation subsystem. In other words, the passenger transportation in China's transportation sector performs better than freight transportation.

Third, we find there are four regions with $E^*_{10} = E^{2*}_{10}$ and $E^*_{20} = E^{1*}_{20}$. They are Beijing, Tianjin, Shanghai, and Anhui. This result indicates that these four regions have a unique efficiency decomposition. The other 26 regions all have $E^*_{10} \neq E^{2*}_{10}$ or $E^*_{20} \neq E^{1*}_{20}$. Therefore, using our proposed approach for overall efficiency decomposition can better distinguish the two subsystems.

From the optimal proportions of shared resources for the passenger transportation subsystem, we know how each region can choose its optimal division of shared resource for passenger and freight transportation subsystems. Taken Fujian for example. The optimal proportions of energy, capital, HM, and CO_2 for passenger transportation are 0.25, 0.3, 0.25, and 0.73 respectively. In other words, the optimal proportions for freight transportation are 0.75, 0.7, 0.75, and 0.27. Comparing these figures to the actual proportions, we see that Fujian should increase the input resource and decrease the CO_2 emission in its freight transportation subsystem. From the average proportions of energy, capital, HM, and CO_2 for passenger transportation (0.34, 0.35, 0.35, and 0.64), we can conclude that the national Chinese government should increase the freight transportation subsystem's inputs and decrease its CO_2 emission to improve the transportation system's overall efficiency.

To analyze the efficiency of transportation systems on a larger scale, we divide the 30 regions into three categories, eastern area, central area, and western area. These areas and their constituent regions are listed in Table 5.

From Table 5, we know there are 11, 10, and 9 regions in the east, center, and west of China respectively. In order to clearly reflect the difference of the three areas, we illustrate each area's average efficiency in the following Fig. 2.

The overall efficiency of the eastern area is 0.7832, which is the highest efficiency score, followed by the central area with 0.6714 and the western area with 0.5239. That is, the east of China does the best in transportation system considering the energy and environmental factors. This is reasonable in real life because the east has relatively better development of economy and transportation. Through the overall efficiency decomposition, we know that the eastern area compared with central and eastern areas has the highest efficiency not only in terms of overall system, but also in each subsystem. In addition, we know that each area has relatively low energy and environmental efficiency in the whole transportation system, passenger transportation subsystem, and freight transportation subsystem. These results conform to the truth that China's development strategy has paid more attention to expanding the transportation industry than to handing the accompanying problems of environmental pollution and energy shortage. Thus, local governments should enforce the implementation of pollution and energy policies rather than just emphasizing the establishment of policies that promote transportation sector growth. In addition, Chinese governments at the national and regional levels also should balance and coordinate the development between the passenger and freight transportation subsystems due to the great differences between them.

Conclusions

Over the last three decades, China has become the greatest energy consumer and pollution emitter in the world. As a major contributor to that energy consumption and pollution emission, China's transportation system is worthy of intense study and measuring its performance has become an important topic. Unfortunately, little research has paid close attention to China's transportation system, and there is a particular lack of research on energy and environmental efficiency evaluation.

In our paper, DEA is applied to evaluate the performance of the transportation systems of 30 provincial-level regions in mainland China for the year 2012. One contribution of this research is that we divide the transportation sector into a parallel system which contains two subsystems, namely passenger transportation and freight transportation. With this decomposition, local governments can better differentiate the weaknesses of the two subsystems, and thus more effective effort can be devoted to improving the overall efficiency. The two-subsystem idea in our paper enriches the theory and the method of energy research and supplies a new view on evaluation of the performance of transportation systems. A second contribution is applying a weighted additive strategy to combine the efficiencies of the two subsystems and thereby measure the combined system's overall efficiency. Our paper gives the necessary and sufficient conditions for a region being overall efficient. Our third contribution, related to the problem of finding optimal solutions, is our proposal of deterministic efficiency decomposition approach to calculate efficiency of each parallel subsystem.

Our empirical study on China's 30 provincial-level regions concludes that: (i) The average overall efficiency of Chinese transportation systems tells us that many regions have a poor efficiency in their transportation systems. (ii) From the overall efficiency decomposition into the two subsystems, we know that passenger transportation has relatively better efficiency than freight transportation. Thus, more measures should be taken by local governments to improve the efficiency of freight transportation. (iii) According to the optimal proportions of shared resources for passenger transportation subsystem, we can obtain that more shared input resources (energy, capital, and HM) and less shared output resource (CO_2) should be the distributed to the freight transportation subsystem. (iv) From an area perspective, the regions in eastern China have the highest average overall efficiency, followed by the regions in central China and then the regions in western China. Thus, the national Chinese government should pay greater attention to the central and the western area whose transportation facilities are relatively undeveloped.

It should be noted that the data collected for our paper is for only one year (2012). We suggest that extending the empirical study to multiple years may be a fruitful extension of our research to thus capture a more dynamic picture of transportation system development in China.

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