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EVALUATING THE COMPREHENSIVE BENEFIT OF PUBLIC TRANSPORT SERVICE – THE PERSPECTIVE OF THREE STAKEHOLDERS

ABSTRACT

Most studies investigate the benefit of public transport service from either the perspective of the operators or the public individually, failing to bind them together. Furthermore, they have not considered the significance of the government in quantifying the benefit. This paper explores the comprehensive benefit of public transport service from the perspectives of three stakeholders; namely, the operators, the public, and government. We develop a comprehensive benefit evaluation tool that is able to quantify production efficiency, service effect, and environmental effect, and test the effectiveness of the tool through a case study in 36 central cities of China. A network data envelopment analysis (NDEA) is used to evaluate the efficiency of the production and service sub-process, and comprehensive benefits. The results reveal the following: (1) during the period 2010–2017, the production efficiency in 36 central cities showed a downward trend; (2) the service effectiveness did not change considerably from 2010 to 2013 but declined gradually during the period 2014–2017; (3) the comprehensive benefits rarely changed during the period 2010–2013, but gradually got worse in response to reductions in the production efficiency and service effectiveness during the period 2014–2017. This study offers a robust tool to measure the benefits of public transport in China for better decision-making, in terms of transit operation and management.

KEYWORDS

public transport service; stakeholder; comprehensive benefit; network data envelopment analysis.

1. INTRODUCTION

As one of the urban infrastructure constructions, public transport plays a very important role in urban construction and is an important guarantee of economic stability and economic development in cities [1–3]. Prior development of urban public transport is not only an essential requirement to relieve traffic congestion, improve quality of public life, and increase the basic public service standards provided by the government. It is also a strategic selection to construct an environmentally-friendly society [4, 5]. As one of quasi-public products, public transport possesses both profitability and public welfare. Scholars usually use the word “performance” when evaluating public transport services. Wang et al. [6] proposed that it is more appropriate to replace “performance” with “benefit” in consideration of the characteristics of public transport services. Public transport involves three stakeholders (namely, the operators, the public, and the government) [7]. Different stakeholders pursue or have concerns over different benefits [5, 8]. For example, the operators consider cost and efficiency. They emphasise pursuit of profitability and give prior concerns to economic benefits. The public desires better public services to meet their demands for daily commuting. Thus, they have increasing concerns over social benefits. The government sectors focus on safety and environmental issues of public transport, improvement of service efficiency, and quality level of public transport. They attach extra attention to the comprehensive benefits. Evaluation of public transport benefits must consider both public welfare and profitability. Existing literature evaluates economic benefits (measured by efficiency) [9–13] or social benefits (measured by passenger satisfaction) [5, 14–18] from the perspective of the operators or the public individually, failing to bind them together. However, public transport services involve three stakeholders. Owing to such multi-objective and multi-subject characteristics, the benefits of public transport must undergo systematic evaluation from the perspective of collaborative participation of three stakeholders [19]. To address this problem, this study constructed a comprehensive benefit estimation model of urban public transport from the perspectives of the operators, the public, and the government. The current status of benefits of public transport services was disclosed. Research conclusions are conducive to identify weak links against the development of urban public transport, increase resource allocation efficiency, promote sustainable development, and serve for traffic-based construction of a powerful nation.

The evaluation method of public transport service can be divided into the parametric analysis represented by stochastic frontier approach (SFA) [9, 10, 20] and the non-parametric analysis represented by data envelopment analysis (DEA) [12, 13, 21–23]. The non-parametric analysis such as DEA has been more widely applied in the benefit evaluation of public transport service for the strength of avoiding subjective weight determination and capturing the interplay between multiple inputs and outputs [24]. Considering that the public transport service system is not a "black box" but a network production system that covers production and service sub-process, the traditional DEA cannot accurately calculate the benefits of decision-making units which have network production systems [25]. Therefore, exploring a new evaluation method is necessary. Different from traditional DEA, the network data envelopment analysis (NDEA) involves additional intermediate variables to further decompose the operation process and to estimate efficiencies of sub-processes. This procedure is generally known as "opening the black box" [26, 27]. At present, NDEA is widely used in the efficiency evaluation of education, banking, and medical industry [28–31]. Only a few scholars have discussed the efficiency of public transport with NDEA [25, 32].

NDEA is developed on the basis of traditional DEA [33]. The traditional DEA is highly appreciated in studies of public transport efficiency in recent years. Furthermore, the evaluation of public transport efficiency often uses public transport enterprises or routes as the subject [34–36]. There are few evaluations of macroscopic efficiency on a city level. Additionally, the efficiency of public transport determines output indexes from the perspectives of production efficiency and service effect [37]. Although the production efficiency and service effect can generally measure economic and social benefits, the environmental effects have been attracting increasing attention in recent years. For example, the operators are changing to new alternative energy vehicles as a response to the national proposal to reduce emission and save energy. However, the benefit evaluation of public transport service based on environmental resources remains absent.

In order to solve the problems that most existing studies do not consider stakeholders from multiple perspectives and ignore the impact of environmental factors on benefit, employees, vehicles, and route length were chosen as the input index system, whereas indexes that represent services, society, and environment were chosen as the output index system. A comprehensive benefit evaluation index system for public transport services was built to quantify production efficiency, service effect, and environmental effect. This is one of our contributions. Moreover, a comprehensive benefit evaluation model was constructed based on the NDEA model. This is the second contribution of this paper. In this study, public transport systems in 36 central cities of China in the period 2010–2017 were used as the research objects in the empirical analysis. Comprehensive benefits of these public transport systems were estimated. This paper offers a robust tool to measure the benefits of public transport in China for better decision-making, in terms of transit operation and management.

The paper is structured in five sections. The remainder of this paper is structured as follows: Section 2 describes the research methodology applied in this study which includes the construction of the NDEA model and selection of the evaluation index. Section 3 elaborates an empirical analysis, which estimates the comprehensive benefits of public transport services in 36 central cities of China. Section 4 summarises the significant findings and an outlook for future research. Section 2 and Section 3 are the core content of this paper.

2. METHODOLOGY

2.1 Construction of the NDEA model

The DEA is a non-parametric objective evaluation method introduced by Farrell [38] and extensions by Charnes et al. [39] and Banker et al. [40], which can be used to evaluate and rank the efficiency of multi-input and multi-output decision-making units (DMUs). Traditional DEA is extensively used to the efficiency evaluation of public transport [12, 13, 21–23, 41]. The public transport system is not a "black box" but a network production system covering the production and service sub-process. The traditional DEA fails to calculate the efficiency of DMU with network production systems. NDEA is developed based on the traditional DEA and involves additional intermediate variables to further decompose the operation process and evaluate the efficiencies of processes [26, 27]. Hence, NDEA was applied to construct the comprehensive benefit of public transport service.

In our case study, each public transport service system in 36 central cities of China is treated as a DMU. Let us say there are N public transport service systems. The jth DMU (j=1,2,...,N) uses input indexes x_{ij} to produce intermediate output indexes z_{oj} and final output indexes y_{ri}. We also assume that $X_j=(x_{ij})\in R^{M\times N}$, $Z_j=(z_{oj})\in R^{L\times N}$ and $Y_j=(y_{rj})\in R^{S\times N}$ are non-negative. The NDEA of the public transport service in the production and service sub-process can be described as follows:

$$\max(\theta_j^1+\theta_j^2)$$
$$\text{s.t}\begin{cases}\sum_{j=1}^{N}\lambda_{ij}^1 x_{ij}\le(1-\theta_j^1)x_{ij}, & i=1,2,\dots,m\\ \sum_{j=1}^{N}\lambda_{oj}^1 z_{oj}\ge z_{oj}, & o=1,2,\dots,L\\ \sum_{j=1}^{N}\lambda_{oj}^2 z_{oj}\le z_{oj}, & o=1,2,\dots,L\\ \sum_{j=1}^{N}\lambda_{rj}^2 y_{rj}\ge(1+\theta_j^2)y_{rj}, & r=1,2,\dots,s\\ \lambda_j,\theta_j^1,\theta_j^2\ge 0, & j=1,2,\dots,N\end{cases} \tag{1}$$

where θ denotes the directional distance functional value. θ_j^1 and θ_j^2 denote the directional distance functional values of the production and service sub-process DMU_j, respectively. The weight coefficient is λ_j. λ^1 and λ^2 are positive intensity variables related to the production and service sub-process, respectively.

The NDEA is constructed under the hypothesis that the scale benefit is constant. Rows 1 and 2 of the NDEA are constraints proposed for the production sub-process. From the input perspective, it requires decreasing the number of inputs under the premise that the output is constant. The first rows of the NDEA imply that the inputs of virtual units are not higher than DMU_j. The second row requires that the outputs of virtual unit are no lower than DMU_j. Rows 3 and 4 of the model are constraints against the consumption process. For the output, it requires increasing the number of outputs upon constant inputs. After gaining the optimal solution of the NDEA, the values of the production and service sub-process can be calculated.

Efficiency of production sub-process is:

$$E_j^1=(1+\theta_j^1)^{-1} \tag{2}$$

Effectiveness of service sub-process is:

$$E_j^2=(1+\theta_j^2)^{-1} \tag{3}$$

The comprehensive benefit of the operation process is:

$$E_j=\sqrt{E_j^1E_j^2}=\sqrt{(1+\theta_j^1)^{-1}(1+\theta_j^2)^{-1}} \tag{4}$$

Some possible situations may occur:

1) θ_j^1 or θ_j^2 is 0. In other words, E_j^1 or E_j^2 is 1, indicating that the DMU_j is weak DEA efficient in the first or second process.

2) Both θ_j^1 and θ_j^2 are 0. In other words, both E_j^1 and E_j^2 are 1, indicating that the DMU_j is NDEA efficient.

2.2 Construction of evaluation index

The public transport service system is a network production system covering the production and service sub-process. According to the time series of the operation process of public transport, many preparations are undertaken in the early operation, such as purchase of vehicles, design of a route network, organising job affairs of relevant workers, etc. Business activities can be started as long as they are carried out after sufficient preparations. Public transport provides commuting services. Obviously, different affairs exist for different operation stages of public transport. All of these staged affairs are generated progressively and are irreversible. Hence, the operation process of public transport is

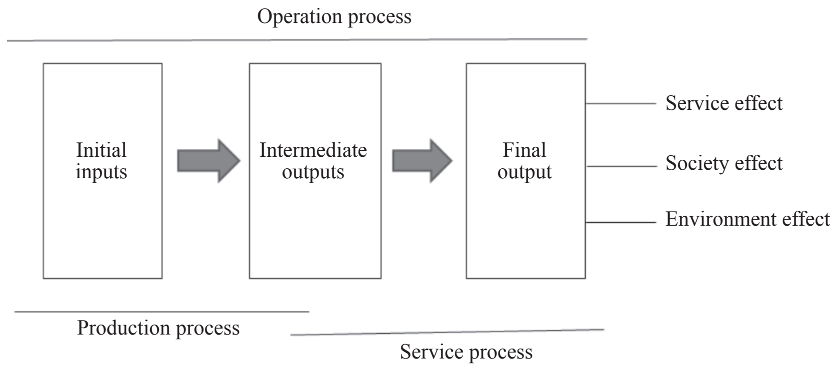

Figure 1 – Model framework of the operation process of public transport

divided into production and service sub-process. The production sub-process covers all preparations for subsequent business activities, while the service sub-process mainly covers transportation businesses (See *Figure 1*).

We should not ignore the fact that the DEA scores are highly sensitive to the selection of input and output variables [42]. The selection of evaluation indexes has an important impact on the evaluation results. However, to date, no uniform standard on selection of evaluation indexes exists. We determine input and output indexes according to the following three principles in this study:

a) The comprehensive benefit of public transport service must be systematically measured as much as possible.
b) Input and output indexes must be diversified and operable.
c) Strong linear relations must be avoided in the same type of indexes.

Evaluation indexes were chosen according to the above principles. Initial input variables, intermediate variables, and final output variables were determined.

Initial input variables. Generally, the cost indexes are selected as the input indexes, which are formed by fundamental production elements, such as capitals, energy consumption and labour forces [41, 43–45]. Given that the indexes such as main business cost are unavailable and costs mainly consist of labour forces and machinery equipment, initial inputs were determined as the number of employees (x_1), number of standard vehicles (x_2), and route length (x_3) in this study. x_1 and x_2 are the most direct input resources in the operation process of public transport, representing labour forces and fixed assets of bus companies. x_3 reflects the operation scope of public transport and refers to the mile sum of all routes of the operators.

Intermediate output variables. Benefit-type indexes are chosen as output indexes. Most studies apply supply indexes (e.g. vehicle-km and seat-km) and indexes that reflect demands (e.g. passenger-km and passenger) as the output indexes [20, 41, 46, 47]. Intermediate output variable is the output index of the production sub-process and the input index of the service sub-process. Considering that the intermediate output variable serves as a connecting link between the production and service sub-process, the vehicle-km (z_0) was set as the intermediate output variable, which reflects the operation capability in the production sub-process and the service supply capacity in the service sub-process.

Final output variables. With comprehensive considerations to the benefits of three stakeholders, the final output variable of public transport services was built to quantify production efficiency, service effect, and environmental effect. One final output index was determined from each perspective, namely passenger flow (y_1), road occupancy index (y_2), and CO_2 emission (y_3). y_1 reflects the number of served passengers in the operation process of public transport and is a main statistical index to measure public transport services. y_2 reflects road conditions and represents the occupation of social resources. The higher the numerical value of y_2, the more social resources are occupied [48]. Environmental variables generally focus on vehicle gas emission of buses, and exhaust gases include CO_2, CO, NO_X, and HC. Among them, CO_2 emission is far higher than the emissions of other gases. Consequently, CO_2 emission is the most representative environmental index. Moreover, CO_2 is one of the six greenhouse gases requiring reduction according to regulations in the Kyoto Protocol and an important content of strengthening energy saving, emission reduction, and pollution control in China's "Outline for Construction of Traffic Power". Therefore, we chose CO_2 emission to represent the environmental variable in this study.

Five of the above seven input and output indexes, such as x_1, x_2, x_3, z_0, and y_1, can be acquired directly from statistical data. y_2 and y_3 cannot be obtained by direct investigation and must be calculated from formulas.

The calculation formula of y_2 is as follows:

$$y_2 = \frac{x_2 \cdot Average\ mileage}{Road\ area} \tag{5}$$

where $x_2 = \sum_j (V_j \cdot CC_j)$, x_2 denotes the total number of standard vehicles; V_j denotes the number of vehicles of the jth type; and CC_j denotes the conversion coefficient for the jth type of vehicles (see *Table 1*). *Average mileage* denotes the average operating mileages of all types of vehicles classified by *Table 1*. *Road area* denotes the area of urban road.

Table 1 – Conversion coefficients of various types of vehicles.

Categories	Vehicle length range L (meter)	Conversion coefficient
1	$L \le 5$	0.5
2	$5 < L \le 7$	0.7
3	$7 < L \le 10$	1.0
4	$10 < L \le 13$	1.3
5	$13 < L \le 16$	1.7
6	$16 < L \le 18$	2.0
7	$L > 18$	2.5
8	Double vehicle	1.9

Note: The conversion coefficient taken from the China Transport Statistical Yearbook.

The calculation formula of y_3 is as follows:

$$y_3 = \sum Mileage \cdot Rate_j \cdot EF_j \tag{6}$$

where *Mileage* denotes the operating mileages including passenger mileages and empty mileages. $Rate_j$ denotes the proportion of the number of buses with jth emission standards to the total number of buses. EF_j denotes the emission factors of buses with jth emission standards. j=1,2,3. The emission proportions of buses are determined according to the number of standard vehicles in National II, National III, National IV, and above emission standards. Emission factors of buses of National II, III, IV, and above are 1082.5 $g \cdot km^{-1}$, 1129.7 $g \cdot km^{-1}$ and 1072.8 $g \cdot km^{-1}$, respectively.

Finally, an index system based on production efficiency, service effect, and environmental effect is constructed to measure the comprehensive benefits of public transport services, as specified in *Table 2*.

3. EMPIRICAL ANALYSIS

3.1 Data description

Based on the operation cost data of public transport service systems in 36 central cities of China during the period 2010–2017, as well as China Transport Statistical Yearbook [49], China City Statistical Yearbook [50], China City Construction Statistical Yearbook [51], and the official website of the city statistics, measurement data of input and output evaluation indexes of these public transport service systems were acquired. The results are shown in *Table 3*.

Table 2 – Input-output indicators

Input and output evaluation indexes		Description
Initial inputs	Number of employees x_1	The number of employees includes the number of temporary employees, but excludes the number of workers in other industries subordinated to bus companies, which represents the labour force variable.
	Number of standard vehicles x_2	The number of standard vehicles is calculated by different types of vehicles based on conversion coefficients, which represents capital variable.
	Route length x_3	It reflects the operation scope of public transport and refers to the sum of lengths of all routes.
Intermediate output	Vehicle-km z_0	It refers to the total annual operating mileages of service vehicles for businesses, including passenger mileages and deadhead mileages.
Final outputs	Passenger flow y_1	It refers to the total number of served passengers during the reporting stage.
	Road occupancy index y_2	It reflects the occupation of social resources.
	CO_2 emission y_3	It represents an environmental variable.

Table 3 – Descriptive statistics of evaluation indexes

Input-output evaluation indexes		Statistical features			
		Max	Min	Mean	SD
Initial inputs	x_1 (persons)	88,115	1,192	17,823.91	17,268.43
	x_2 (vehicles)	36,572	409	8,179.01	6,453.47
	x_3 (km)	24,504	500	7,270.25	6,103.34
Intermediate output	z_0 (10,000 km)	138,540	2,190	39,156.51	31,098.98
Final output	y_1 (10,000 passengers)	515,416	6,772	107,043.55	82,814.75
	y_2 (standard vehicles/m^2)	63,347.98	130.91	8,002.85	10,161.40
	y_3 (100 tons)	15,271.96	238.21	3,926.60	3,201.71

3.2 Results analysis

Input and output data of 36 central cities were brought into the two-stage NDEA model. The NDEA model was solved with Lingo 17.0 software. Reciprocals of y_2 and y_3 were used because the higher the expected values of output variables are, the better. We analysed the production efficiency of the production sub-process, the service effectiveness of the service sub-process, and the comprehensive benefit of the operation process. Moreover, a comparative analysis on region classification and urban scale was carried out. Urban region was divided into Eastern, Central, and Western China (See *Table 4*). According to the permanent resident population in urban areas in 2017, the 36 central cities were divided into super-sized cities, mega-sized cities, large-sized cities, medium-sized cities, and small-sized cities (See *Table 5*).

Efficiency analysis of different sub-processes

According to the efficiency classification standard proposed by Zhang et al. [41] and Lao and Liu [52], DMUs can be divided into three categories: Efficient ($E \geq 1$); Fairly efficient ($0.6 \leq E < 1$); Inefficient ($E < 0.6$). E denotes the efficiency score.

Table 4 – Area classification of DMUs.

Urban sized	City name (The brackets are the DMUs label)
Eastern China	Shanghai(1), Nanjing(2), Hangzhou(3), Ningbo(4), Fuzhou(5), Xiamen(6), Jinan(7), Qingdao(8), Beijing(9), Tianjin(10), Shijiazhuang(11), Shenyang(12), Dalian(13), Guangzhou(14), Shenzhen(15), Haikou(16)
Central China	Taiyuan(17), Changchun(18), Harbin(19), Nanchang(20), Hefei(21), Zhengzhou(22), Changsha(23), Wuhan(24)
Western China	Hohhot(25), Chengdu(26), Chongqing(27), Guiyang(28), Lhasa(29), Kunming(30), Xian (31), Lanzhou(32), Yinchuan(33), Xining(34), Urumqi(35), Nanning(36)

Table 5 – Urban sized classification of DMUs.

Urban sized	Population	City name (The brackets are the DMUs label)
Super-sized city	Equal to or more than ten million	Shanghai(1), Beijing(9), Shenzhen(15), Chongqing(27)
Mega-sized city	Between five million and ten million	Nanjing(2), Tianjin(10), Guangzhou(14), Wuhan(24), Chengdu(26)
Large-sized city	Between one million and five million	Hangzhou(3), Jinan(7), Shenyang(12), Dalian(13), Taiyuan(17), Changchun(18), Harbin(19), Zhengzhou(22), Changsha(23), Kunming(30), Ningbo(4), Fuzhou(5), Xiamen(6), Qingdao(8), Shijiazhuang(11), Haikou(16), Nanchang(20), Hefei(21), Hohhot(25), Guiyang(28), Xi'an(31), Lanzhou(32), Yinchuan(33), Xining(34), Urumqi(35), Nanning(36)
Medium-sized city	Between 50 thousand and one million	----
Small-sized city	Equal to or less than 50 thousand	Lhasa(29)

From *Figure 2*, the production efficiency of the production sub-process in most central cities fluctuated slightly in eight years, and ranged between 0.6 and 0.7. This finding reveals that production efficiency was fairly efficient, with slightly different overall level. According to the longitudinal time series, the cities with fluctuating efficiency of the production sub-process focused on DMUs 16–24, which were in Central China. Nanchang (DMU 20) maintained a relatively high production efficiency, which was attributed to the high utilisation of employees and the high operating mileages. The production efficiency of Lanzhou (DMU 32) and Shijiazhuang (DMU 11) dropped suddenly in 2013 and kept declining subsequently. This finding was related to the sharp reduction of operating mileages. In Haikou (DMU 16) efficiency dropped from 1 to 0.8 due to the reduction of employees and vehicle-km in 2013 and 2014. According to the analysis of cross-sectional data, the production efficiency of the production sub-process in most cities was lower than 0.7, indicating the low production efficiency of the public transport service systems in most cities during the eight years. Such low production efficiency was caused by the universal low utilisation of employees and low operating mileages.

Figure 3 shows that service effectiveness of the service sub-process in most central cities largely fluctuated in eight years, and the overall service effectiveness was relatively low. This finding

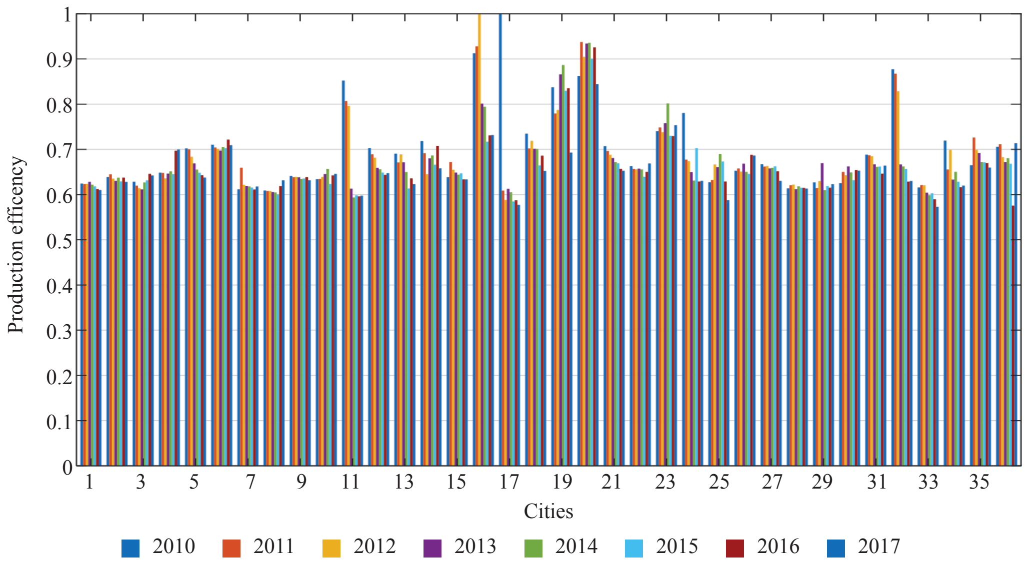

Figure 2 – Production efficiency (The number stands for DMUs)

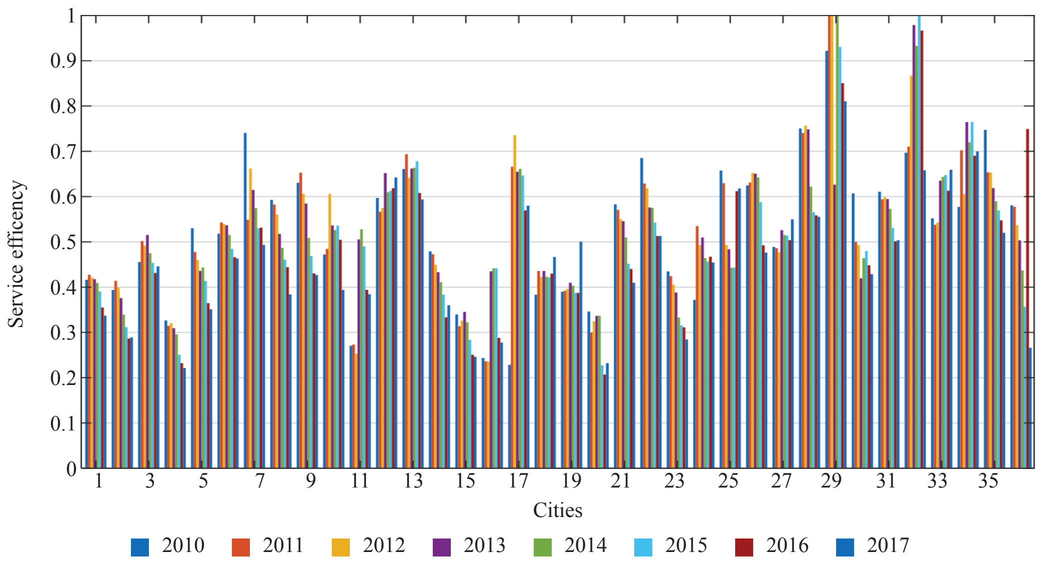

Figure 3 – Service effectiveness (The number stands for DMUs)

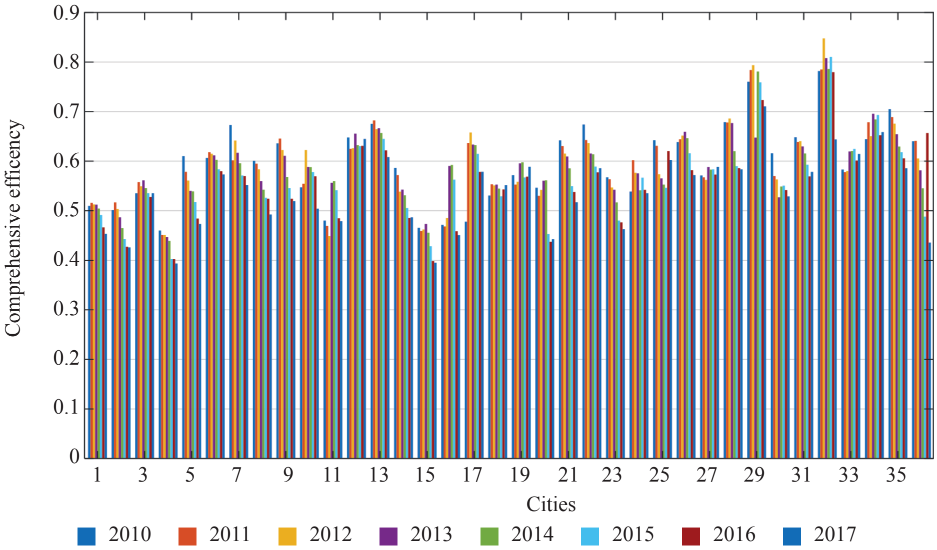

Figure 4 – Comprehensive benefits (The number stands for DMUs)

reflected that most cities were in relatively ineffective and less efficient state. According to the longitudinal time series, Lhasa (DMU 29) and Lanzhou (DMU 32) were the most representative cities of the fluctuation. Service effectiveness of Lhasa (DMU 29) was kept at a relatively high level during the period 2010–2012, but suddenly dropped to around 0.6 in 2013. This phenomenon occurred because the road occupancy index and CO_2 emission increased with the increase in operating mileages, whereas passenger capacity did not increase significantly. The service effectiveness of Lanzhou (DMU 32) increased continuously because the reduced operation miles still supported the original passenger capacity. The cross-sectional data analysis showed that service effectiveness was generally lower than 0.6. The service effectiveness of public transport remains to be significantly improved.

Comprehensive benefits of public transport in 36 central cities during the period 2010–2017 are shown in *Figure 4*. The overall efficiency of the 36 central cities has a relatively small range of change and is in a relatively ineffective state. Only two cities, Lhasa (DMU 29) and Lanzhou (DMU 32), maintain a relatively high efficiency, close to 0.8.

The varying trends of public transport efficiency are shown in *Figure 5*. The production efficiency E^1 presented a downward trend over eight years due to the low utilisation of service vehicles. Service effectiveness E^2 presented a smooth transition in the first four years and then declined gradually in the remaining four years, which was caused by the decreasing passenger capacity. Generally, the comprehensive benefits E^3 rarely changed during the period

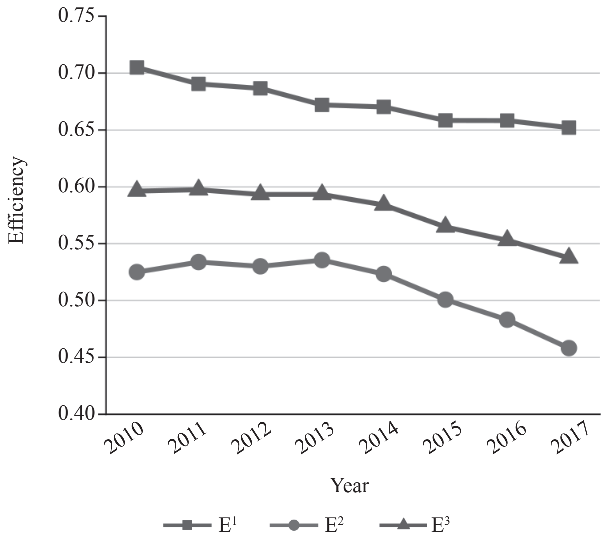

Figure 5 – Variation trends of E^1, E^2 and E^3 of public transport in China

2010–2013, but gradually got worse in response to the reductions of production efficiency and service effectiveness during the period 2014–2017.

Efficiency analysis of different regions

Figure 6 shows that the production efficiency in Central China is higher than in Eastern and Western China. The production efficiency in Central China substantially dropped in 2011, which was attributed to the sharp reduction in operating mileages. Production sub-process in Eastern and Western China presented similar developments. Total inputs and outputs during the production sub-process in Central and Western China are half of those in Eastern China. The production efficiency of the production sub-process in Eastern, Central, and Western

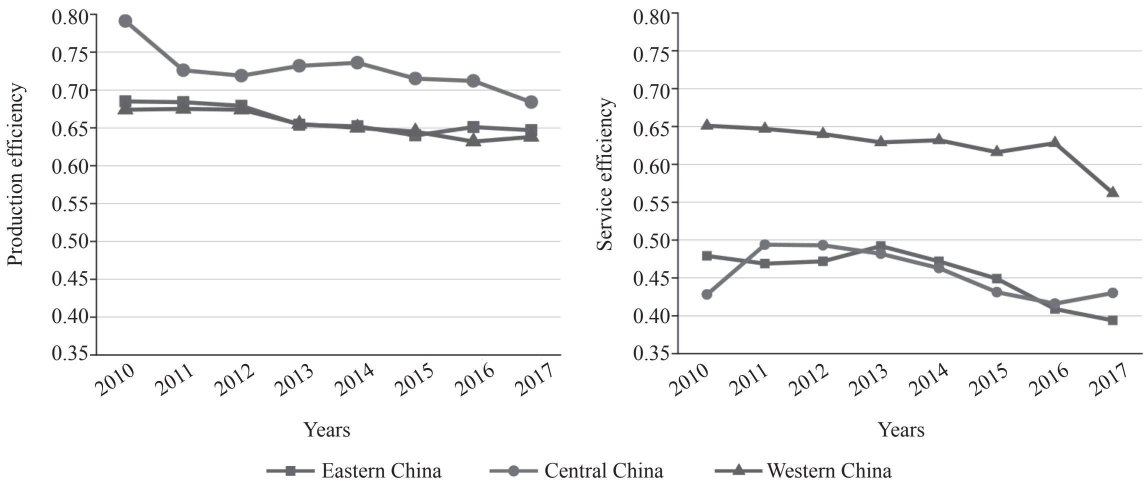

Figure 6 – Production efficiency and service effectiveness in different regions

China decreased continuously during the period 2010–2015, which was more related to the lower growth rate of operating mileages than the growth rate of input indexes. The efficiency value increased slightly between 2016 and 2017 because the continuous growth of operating vehicles, total route length, and vehicle-km have improved total efficiency.

Service effectiveness in Western China was far higher than in Eastern and Central China. This finding can be interpreted by the good performances of Western China in passenger capacity and road situations under the premise of low operation miles. By contrast, Central China had an equivalent passenger capacity as Western China, but it had a more serious road occupancy conditions and higher inputs to route operation. The service scale of Eastern China was twice that of Western China, but the passenger capacity was insufficient. The service effectiveness of Eastern China was slightly higher than that of Central China given that the road occupancy situation was somewhat relieved.

Table 6 shows the comprehensive benefits of public transport in Eastern, Central, and Western China.

In view of time series, comprehensive benefits of Western China continued to decrease, while the final comprehensive benefits of Eastern and Central China were 0.499 and 0.533, respectively, after several fluctuations. According to cross sectional data, the average comprehensive benefits are the highest in the western region, at 0.635; the middle region is the second at 0.564; the eastern region is the last at 0.541. At the same time, since the SD of the western cities is small, the fluctuation of the efficiency value is relatively small.

Efficiency analysis of different city scales

Since Lhasa is the only small-sized city, it is not representative. Therefore, we only analysed the efficiency of super-sized, mega-sized, and large-sized cities. Production efficiency and service effectiveness of different city sizes are shown in *Figure 7*.

In the production sub-process, super-sized cities showed the lowest production efficiency, whereas large-sized cities showed the highest, followed by mega-sized cities. According to further analysis, the production efficiency of large-sized cities was relatively high, but it had considerable fluctuation. This finding is due to the fact that utilisation of service vehicles in large-sized cities was high, but the total operation miles of new vehicles was decreasing. Production efficiencies of mega-sized and

Table 6 – Comprehensive benefits of the operation process in different regions

Regions	Years								Mean	Max	Min	SD
	2010	2011	2012	2013	2014	2015	2016	2017				
Eastern China	0.563	0.557	0.556	0.564	0.551	0.532	0.510	0.499	0.541	0.564	0.499	0.025
Central China	0.568	0.589	0.586	0.586	0.574	0.544	0.533	0.533	0.564	0.589	0.533	0.024
Western China	0.659	0.657	0.652	0.638	0.634	0.623	0.624	0.592	0.635	0.659	0.592	0.022

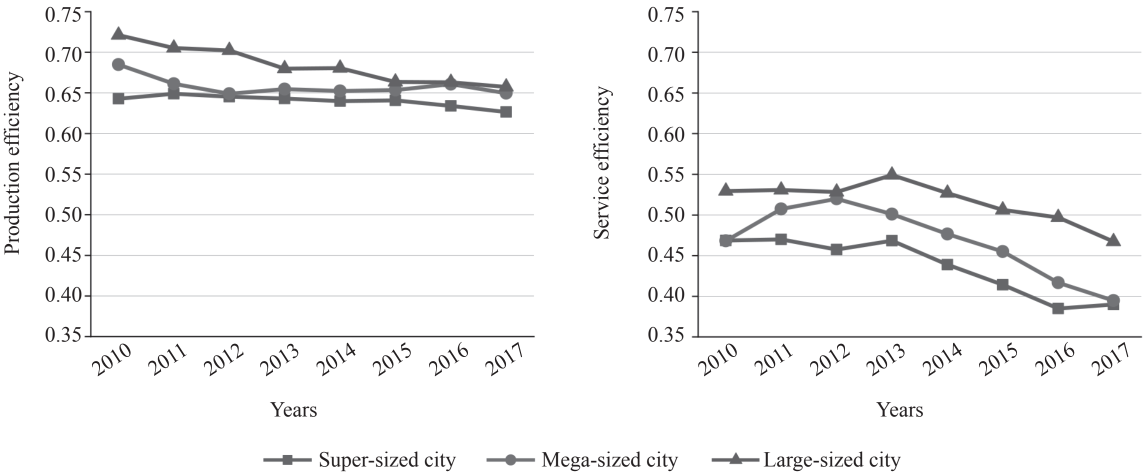

Figure 7 – Production efficiency and Service effectiveness in different city scales

super-sized cities were not low thanks to the support of urban economy and demands for essential commuting purposes.

In the service sub-process, the efficiency ranking of different scale cities is similar to the production sub-process. Large-sized cities are the most relatively efficient, mega-sized cities ranked second, and super-sized cities ranked last. Moreover, the efficiency change trends of large-sized cities and mega-sized cities are very similar. According to further analysis, the higher service effectiveness of large-sized cities was attributed to the good road conditions. Although operation scale in super-sized and mega-sized cities was large, their contributions to environmental and congestion controls were significantly small, thus resulting in low service effectiveness.

The comprehensive benefits of different sizes of cities are shown in *Table 7*. Generally, large-sized cities showed the highest comprehensive benefits of public transport, mega-sized cities rank second, and super-sized cities rank last, with average efficiency values of 0.584, 0.551, and 0.525, respectively. The fluctuation range of the efficiency ranges from small to large, then large-sized cities, super-sized cities, and mega-sized cities. Among super-sized cities, Beijing, which only has standard efficiencies of production and service sub-process, presented the highest comprehensive benefits of public transport, with an efficiency value of 0.584. Among mega-sized cities, Chengdu ranked first. Similar to Beijing, the production efficiencies and service effectiveness in Chengdu reached the qualification level. Nanjing and Guangzhou have poor ranks of comprehensive benefits due to significantly lower service effectiveness than production efficiency. For large-sized cities, Lanzhou occupied the top position due to its high production efficiency and outstanding service effectiveness.

Model comparison

Based on the NDEA, the comprehensive benefits of 36 DMUs were evaluated and compared with the efficiency values calculated by traditional DEA, as shown in *Figure 8*. It can be seen that the efficiency values obtained by the two methods are quite different. The results of the DEA show that the efficiency of cities fluctuate greatly, mostly around 0.7 and 0.8, in a fairly efficient state, and even a few cities such as Xiamen, Lhasa, and Lanzhou have efficiency values that exceed 0.9 and are close to 1. The efficiency value obtained by the NDEA is significantly lower than the efficiency value calculated by the DEA, and most of them remain around 0.6, with some cities

Table 7 – Comprehensive benefits of the operation process in different city scales

Urban scale	Years								Mean	Max	Min	SD
	2010	2011	2012	2013	2014	2015	2016	2017				
Super-sized city	0.546	0.547	0.540	0.546	0.528	0.512	0.490	0.489	0.525	0.547	0.489	0.025
Mega-sized city	0.562	0.578	0.578	0.570	0.554	0.542	0.521	0.505	0.551	0.578	0.505	0.027
Large-sized city	0.604	0.602	0.598	0.603	0.591	0.570	0.562	0.545	0.584	0.604	0.545	0.023

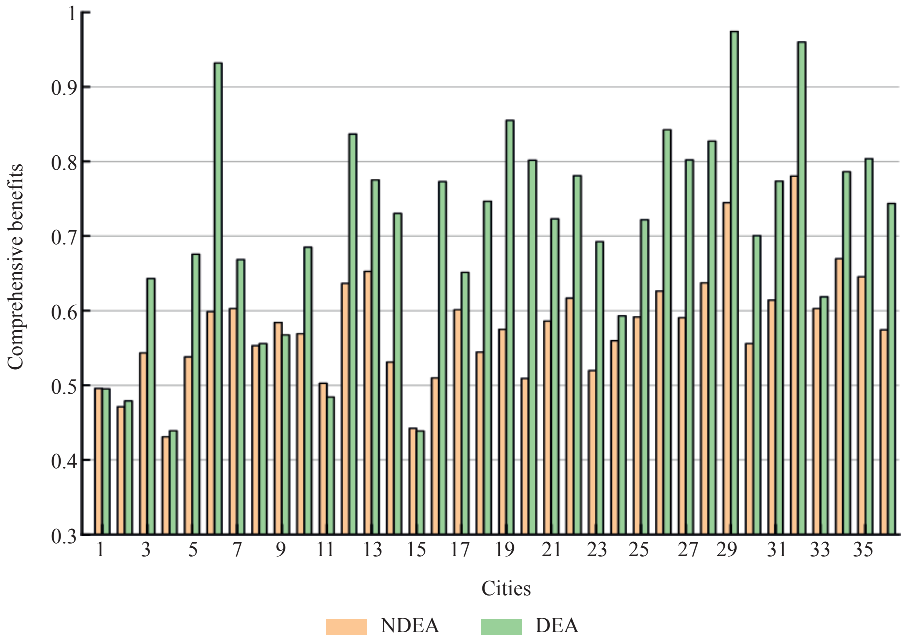

Figure 8 – Comparison of comprehensive benefits of NDEA and DEA (The number stands for DMUs)

even below 0.5. Since the DEA does not break the "black box" and considers the relationship between the sub-processes further, the high efficiency value is obtained. In contrast, the NDEA is more comprehensive, so it has a lower but more objective evaluation result.

3.3 Discussion

The comparative analysis shows that the NDEA can measure the efficiency more accurately than the DEA. The NDEA not only obtains the overall efficiency, but also the efficiency of each sub-process.

There are several issues that can be discussed further. Comparing the two efficiencies (e.g. production efficiency and service effectiveness) from three different perspectives (e.g. a single DMU, different regions, and different city scales), the results show that the efficiency of the production sub-process is higher and more stable than the efficiency of the service sub-process. The result is caused by the continuous growth of employees, route length, and operating vehicles in the production sub-process, as well as the reduction of passenger flow and the continuous increased road occupancy in the service sub-process. Because the comprehensive benefit value is calculated according to the production efficiency and service effectiveness, its change trend is affected by both.

There are some ways to improve the efficiency of public transport. Firstly, in the production sub-process, the operators should improve the utilisation of employees and the route length. Increasing public transport investment in Eastern China and Western China has to keep up with increasing operating mileages. Super-sized cities and mega-sized cities should maintain high vehicle operating mileages. Secondly, in the service sub-process, bus operators must reduce the road occupancy index, CO_2 emissions and increase passenger flow while ensuring a high vehicle-km; Eastern China and Central China should focus on solving the problems of congestion and CO_2 emissions. Finally, the high road occupancy index leads to urban road congestion. In order to alleviate congestion and improve efficiency, the operators should arrange bus frequency and operation route reasonably under the premise of ensuring the highest number of passengers as possible. In addition, the government needs to increase financial support to improve transport infrastructure.

4. CONCLUSIONS

Based on the stakeholder theory, a comprehensive benefit evaluation index system of public transport services is established on the basis of the production and service sub-process. From the perspective of the government, the operators and the public, this evaluation system chooses employees, service vehicles, and route length as input indexes; by contrast, it uses efficiency, satisfaction, going green, and sustainability as the output indexes. Moreover, a comprehensive benefit evaluation model of urban public transport is constructed based on the NDEA. Production efficiencies, service effectiveness, and the comprehensive benefits of public transport in 36 central cities were estimated. Results show the following:

1) Efficiency of different sub-processes: During the period 2010–2017, the production efficiency in most central cities fluctuated slightly, and this efficiency value ranged within 0.6–0.7. This finding reflects that the production efficiency in these cities was in a fairly efficient state, with a small difference in overall efficiency. While the service effectiveness in most central cities largely fluctuated in the period 2010–2017, with a relatively low overall efficiency which indicates that most of them are in a relatively invalid and low-efficiency state. Overall, production efficiency is higher than service effectiveness due to the increase of inputs such as employees, vehicles, and route length increases the operating mileages, while passengers have continued to decrease and congestion has been aggravated.
2) Efficiency of different regions: In view of different regions, the production efficiency in Central China was better than in Eastern and Western China. Service effectiveness in Western China was significantly higher than in Eastern and Central China. Production efficiency of the three regions is higher than service effectiveness, and the efficiency gap between the production and service sub-process in Eastern China and Central China is significantly larger than that in Western China. Western China presented the highest comprehensive benefits, followed by Central and Eastern China successively. Central China and Eastern China can improve efficiency by focusing on alleviating congestion and reducing CO_2 emissions.
3) Efficiency of different city scales: In view of different city scale, super-sized cities showed the lowest production efficiency, whereas large-sized cities showed the highest efficiency. Service effectiveness of large-sized cities was far higher than other city types, followed by super-sized and mega-sized cities. Moreover, large-sized cities had the highest comprehensive benefits. Mega-sized and super-sized cities had similar comprehensive benefits of public transport.
4) The NDEA combined with the directional distance function is more objective and accurate than the DEA. It can be seen from the results of the NDEA that enhancing the utilisation of employees and arranging the operation plan is an effective way for the operators to improve efficiency. The operators also need cooperation with governments to alleviate congestion and reduce vehicle emissions during the service process. In addition, East China and West China have to further increase investment in public transport service. The operators in super-sized cities and mega-sized cities need to increase the number of operating vehicles and extend the route length to ensure high operating mileages.
5) The 12th Five-Year Plan proposed requirements on environmental protection and efficiency for the construction of "Bus City" demonstration projects. However, the production efficiency decreased due to the expansion of production scale and the service effectiveness was low due to the increasing road occupancy condition and CO_2 emissions. To sum up, contributions in production scale, road occupancy conditions, and CO_2 emissions are effective ways to improve comprehensive benefits of public transport in the future.

In the period 2010–2017, the production efficiency E1 in 36 central cities presented a downward trend, whereas the service effectiveness transited smoothly in the first four years but declined gradually in the remaining four years. Comprehensive benefits of public transport rarely changed in the period 2010–2013, but gradually got worse in response to reductions in the production efficiency and service effectiveness in the period 2014–2017.

This study contributes to the studies on efficiencies of the public transport services in the following aspects: (1) With comprehensive considerations to the stakeholders of public transport service system, a two-stage comprehensive benefit evaluation system of public transport services is proposed on the basis of services, society, and environment. This study provides a comprehensive framework, and it can simultaneously consider various indexes and stakeholders. (2) The public transport services system is not a "black box" but a network production system covering the production and service sub-process. The traditional DEA model cannot accurately calculate efficiency of decision units with network production system. To solve this problem, a comprehensive benefit evaluation model of the public transport services is constructed based on the NDEA model. This model increases judgment capability.

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公共交通服务综合效益评价：三方利益相关者的视角

摘要：

大多数研究主要从公交企业或公众单方面角度评价公共交通服务效益，未能将它们结合在一起。此外，没有考虑到政府在评价效益时所起的重要性。本研究从公交企业、公众和政府三方利益相关者的角度探讨了公共交通服务效益，开发了一个能够量化运营效率、服务效果和环境效应的综合效益评估工具，并通过对中国*36*个中心城市的案例研究，验证了该工具的有效性。采用网络数据包络分析法对生产和服务子流程的效率以及综合效益进行评估。结果表明：从*2010*年到*2017*年，*36*个中心城市的运营效率呈下降趋势；从*2010*年到*2013*年，*36*个中心城市的服务效果变化不大，但在*2014*年到*2017*年期间，服务效果逐渐下降；在*2010*年至*2013*年期间，公共交通服务的综合效益变化不大，但在*2014*年至*2017*年期间随着运营效率和服务效果的降低，其综合效益逐渐恶化。本研究提供了一个强有力的工具来衡量中国公共交通服务效益，以便更好地在公交运营和管理方面提供决策依据。

关键词：

公共交通服务；利益相关者；综合效益；
网络数据包络分析

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