2. EFFICIENCY ASSESSMENT OF URBAN PUBLIC TRANSPORT SYSTEMS IN CHINA

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Under the background of reducing greenhouse gas emissions from transport sector and due to the high priority of urban public transport in construction and planning, it is becoming increasingly important to investigate the system efficiency so that proper policies could be made to improve its performance. Based on the panel data from China's 31 provinces over the period 2000-2006, this paper estimates the energy consumption of urban public transport systems and assesses their efficiencies by data envelopment analysis (DEA) and Malmquist Productivity Index (MPI) approaches. The results show firstly the efficiency of overall urban public transport system is relatively low. However the MPI analysis indicates the whole system has registered an improvement from 2000 to 2006. Secondly, the urban public transport systems in eastern and coastal areas have relatively higher efficiencies than those in western and inland regions, which is consistent with the uneven distribution of economic level and investment on public transport among China provinces. Thirdly, the policy implication is that the increase of investment in public transport sector especially in the less developed areas, together with the development of urban rail transit mode would be effective ways enhancing the efficiencies of urban public transport systems.

Key Words : *data envelopment analysis, urban public transport, efficiency, China*

1. INTRODUCTION

In recent years, energy conservation and mitigation of climate change has been increasingly concerned. Transportation, representing the fastest growing source of greenhouse gas (GHG) emissions, accounted for 26% of total energy use and 23% of energy-related GHG emissions in 2004[1)]. For this reason the improvement of transport efficiency to reach an environmentally sustainable development has been taken as a strategic issue world widely. Among all transport scopes, urban public transport is always given the top priority in construction and planning, because it is one of the most important premises for economic development and regarded as an effective way to reduce GHG emissions[2)].

In China, where it holds the world's largest population and is the second largest energy consumer in the world, CO_2 emissions ranks the world second making it under great pressure of mitigation. Since the beginning of 21st century, more and more intensive transport policies have been implemented with the general targets aiming at encouraging the development of urban public transport. However, due to the institutional and financial deficiencies, it is still problematic for this industry such as low service quality, in-coordination of routes, deficit of operating company and heavy burden of governmental subsidy, etc. Thus in the context of reducing GHG emissions and meeting the substantial increase of mobility, the main objective of this paper is to investigate the performance of China urban public transport systems and offer a basis for policymaker to improve the said industry.

A number of research has been done regarding the efficiency of public transport. As a start, Tomazinis[3)] defined a series of indicators to assess the performance of public transit systems. Fielding et al.[4)] specified three categories of indicators namely efficiency, effectiveness and overall indicators to evaluate the performance of public transit system. Subsequently, Finn et al.[5)] estimated the Norwegian bus industry by using a stochastic cost frontier model and found that there was no significant difference in the efficiency between privately and publicly owned operators. Viton[6)] used a DEA method to measure the efficiency of a public transit system relative to other agencies within the same peer group and suggested that US bus productivity has improved slightly over the 1988-1992 period. Sampaio et al.[7] analyzed the characteristics of several public transport systems in Brazil and European countries by a DEA model, finding that efficient systems had a more democratic power partition among communalities and established a broader tariff system. However, a survey of the literature indicates the absence of efficiency assessment of urban public transport systems in China, although the performance analysis has been conducted in many other fields such as electricity generation plants, regional water efficiency and environmental performance measurement, etc.[8]. The reason may in part due to the data limitation on fuel consumption of urban public transport, which is usually used as a necessary input for efficiency analysis.

To bridge the literature gap, we propose a method for estimating the energy consumption of urban public transport sector and adopt a DEA approach assessing the system performance. The rest of the article is organized as follows. Section 2 describes the method and data for efficiency analysis and proposes a method for estimating energy consumption of China's urban public transport sector. Section 3 presents the results from spatial and temporal aspects and analyzes the reasons affecting system performance. Section 4 summarizes the paper with conclusions.

2. METHODOLOGY AND DATA

(1) DEA approach

As known, DEA is recognized as a non-parametric mathematical programming approach for frontier estimation and a practical decision support tool. It is credited for not requiring a explicitly specification for the production function form and capable of handling multiple inputs and outputs. It is firstly proposed by Farrell[9] and popularized by Charnes et al.[10]. In Charnes et al.'s work, they proposed an input-oriented model assuming constant returns to scale (CRS). Subsequently a large number of papers have extended this method with alternative sets of assumptions such as output-orientation and variable returns to scale (VRS) etc.[11]. In modeling, urban public transport system is viewed as decision-making unit (DMU). We assume that there are N DMUs that use K inputs to obtain M outputs. For the ith DMU, input and output are denoted by the vectors x_i and y_i respectively. For each DMU, the envelopment can be derived from the following linear programming problem,

$$\begin{aligned} \min_{\theta,\lambda} \quad & (\theta) \\ \text{s.t.} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0 \end{aligned} \tag{1}$$

where θ is a scalar and λ is a N×1 vector of constants. X is the input matrix (K×N). Y is the output matrix (M×N). The value of θ obtained will be the efficiency score of the ith DMU. It will satisfy $\theta \leqslant 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU.

Eq. (1) assumes the CRS when not all DMUs are operating with optimal scale, which may result in efficiency scores affected by the scale efficiency. According to Banker et al.[11], the use of VRS specification will permit the calculation of efficiency devoid of scale efficiency effects. By adding the convexity constraint ($N1\lambda=1$) to CRS linear programming problem, we can obtain that,

$$\begin{aligned} \min_{\theta,\lambda} \quad & (\theta) \\ \text{s.t.} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & N1^T\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \tag{2}$$

where N1 is an N×1 vector of ones. The VRS approach forms a convex hull of intersecting planes which envelope the data points more tightly than that in CRS and thus provides technical efficiency scores with larger or equal to those from CRS model.

Generally DEA only considers efficiency analysis at a given point of time. When panel data is available, a MPI model can be used to measure the efficiency change over time,

$$\mathrm{MPI}^{t+1}(y_{t+1},x_{t+1},y_t,x_t) = \left[\frac{D^t(x_{t+1},y_{t+1})}{D^t(x_t,y_t)} \times \frac{D^{t+1}(x_{t+1},y_{t+1})}{D^{t+1}(x_t,y_t)}\right]^{1/2} \tag{3}$$

where MPI^{t+1} denotes a geometric average of the productivity change of the production point (x_{t+1}, y_{t+1}) relative to the production point (x_t, y_t). MPI>1, MPI=1 and MPI<1 respectively indicate that the productivity of DMU has improved, remained unchanged and deteriorated from t to t+1. D_t is a distance function measuring the efficiency of conversion of inputs x_t to outputs y_t in the period of t.

(2) Input/output variables, data and study area

As shown in Fig.1, the urban public transport system in China is generally composed of bus, trolley, taxi and rail modes, which is further divided by fuels. Ferry is dropped out due to data limitation. In this paper, rail mode represents the urban subway and light rail transport only. Among China's 31 provinces, there were only 4 had rail systems in 2000. And the number increased to 11 in 2006.

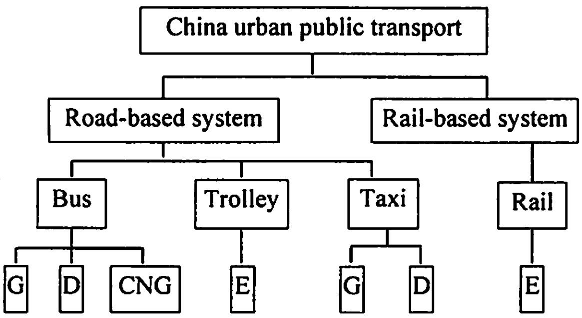


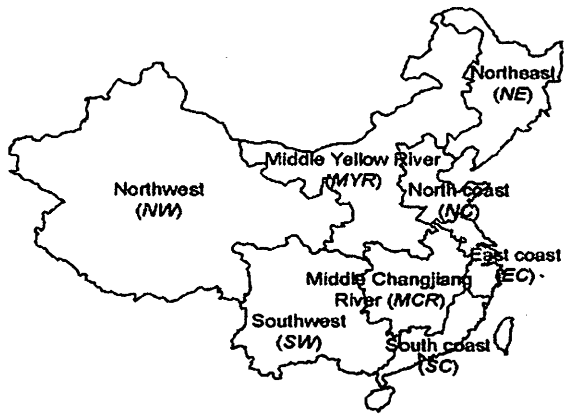
Fig.1 Hierarchy of China urban public transport system

Note: G, D, CNG and E stands for gasoline, diesel, compressed natural gas and electricity respectively.

As summarized by many existing literatures[6), 7)], transport service efficiency analysis is generally based in three basic inputs, namely labor, capital and energy. In this paper, labor is measured by total number of employees. Capital is represented by the number of vehicles. Energy consumption is through the estimation which is explained in the next part. As for output, several authors suggested the use of vehicles per km as a measurement of efficiency and the passengers per km as a measure of effectiveness[12)]. Considering the data availability, we choose the total passengers transported as output variable.

The data on urban public transport are collected from 31 provinces from 2000 to 2006. In detail, annual data including vehicle number, number of employees, total passengers transported, annual distance traveled by vehicles and fuel intensity etc. are mainly taken from "China Statistical Yearbook"[13)], "China Urban Construction Statistical Yearbook"[14)], published reports and papers.

To illustrate the general socio-economic characteristics of the study areas, we aggregate 31 provinces into 8 regions according to the economic homogeneity before reporting them (Fig.2). The clustering follows the method proposed by the Development Research Center of State Council of China[15)]. By choosing area, population, GDP and investment on urban public transport as indices, defining each one as the proportion of regional value to China's total, Table 1 illustrates the unbalanced regional features. The eastern and coastal regions (NE, NC, EC and SC) cover only 20% of whole country's territory. However, they accommodate 43% of total population and create 63% of GDP in China. The investment on urban pubic transport is also plentiful, which shared over 80% of national total in 2004. On the contrary, the western and inland regions (SW and NW) share over 50% of area while only 24% of population concentrates there and 14% of GDP are created. The investment share was less than 10%.



NE: Liaoning, Jilin, Heilongjiang
NC: Beijing, Tianjin, Hebei, Shandong
EC: Shanghai, Jiangsu, Zhejiang
SC: Fujian, Guangdong, Hainan
MYR: Shanxi, Inner Mongolia, Henan, Shaanxi
MCR: Anhui, Jiangxi, Hubei, Hunan
SW: Guangxi, Chongqing, Sichuan, Guizhou, Yunnan
NW: Tibet, Gansu, Qinghai, Ningxia, Xinjiang

Fig. 2 Eight regions in China

Table 1 China's regional characteristics (%)

	Area	Population	GDP	Investment
NE	9.3	8.5	9.8	5.2
NC	4.5	14.4	18.5	18.7
EC	2.5	10.7	19.9	41
SC	4	9.5	14.3	19.8
MYR	20.6	14.9	10.5	1.7
MCR	8.5	18.5	13.2	5.5
SW	16.4	19.1	10.9	7.3
NW	34.2	4.4	2.9	0.6
China	100	100	100	100

Note: the shares of population and GDP are the average value during 1995-2006. Investment on urban public transport is the value in 2004.

(3) Energy use of urban public transport systems

The following equation is proposed to estimate the energy consumption (E) of both road- and rail-based urban public transport systems.

$$\textbf{Road:}\ E_{m,t} = \sum_{j} \mathrm{VN}_{m,j,t} \cdot \mathrm{DTV}_{m,j,t} \cdot \mathrm{FI}_{m,j,t} \cdot a_j \qquad (4)$$

$$\textbf{Rail:}\ E_{rail,t} = \mathrm{PN}_{rail,t} \cdot \mathrm{DTP}_{rail,t} \cdot \mathrm{FI}_{rail,t} \cdot a_j$$

where subscript m, j represent road-based mode and fuel type. VN is vehicle number. DTV is the annual distance traveled by vehicle in kilometers. PN is passenger transported by rail. DTP is average trip length traveled by passenger. FI is the fuel intensity, which is defined as fuel/km for road-based mode, and fuel/passenger-km for rail mode. a is heat conversion factor, which takes value as 3.2×10^7 J/L for gasoline, 3.6×10^7 J/L for diesel, 3.9×10^7 J/m^3 for CNG, and 3.6×10^6 J/kWh for electricity[16).

Since there is no published statistical data on DTV in China, we follow the works of the International Road Federation[17) for references. For FI, China government has been implementing intensive regulations and norms to improve fuel economy in recent years. Notably, the Standardization Administration of the People's Republic of China issued the "Maximum Limits of Fuel consumption for Passenger Cars" in 2004, stressing the realization of target that the fuel consumption per km of car and light duty vehicles could decrease 5-10% in 2001-2005 than that in 2000. In this context and taking the existing literature as a base, the value of DTV, FI and proportion of gasoline, diesel and CNG vehicles for bus and taxi are assigned in Table 2. In addition, following the previous researches conducted in some municipalities such as Beijing and Shanghai etc.[18), DTP and FI for rail mode are assigned as 9 km/passenger and 0.05 kWh/passenger-km.

Table 2 Parameters for estimation of energy consumption of road-based modes

		Proportion (%)		DTV ('000 km)		FI	
		2004	2006	2004	2006	2004	2006
Bus	G	11	13	51	50	0.43	0.42
	D	78	75	51	50	0.32	0.31
	CNG	11	12	51	50	0.38	0.38
Trolley	E	-	-	33	32	1.4	1.4
Taxi	G	98.7	97.5	25	24	0.16	0.15
	D	1.3	2.5	25	24	0.16	0.15

Note: The unit of FI for bus and taxi is (L or m^3)/km, while for trolley it is kWh/km.

3. RESULTS

Firstly, Table 3 illustrates the geometric average efficiency of each urban public transport system during the period of 2000-2006. Overall the total efficiency in China is relatively low with the mean around 0.65. The reasons may partly due to the growing fuel price, governmental control on fare increment and insufficient subsidy etc. However, when comparing to the value on DEA frontier, we find there still has great potential for improvement. In detail, the urban public transport system of Beijing, the only one out of the total 31 systems, is considered technically efficient under the CRS assumption. When VRS is assumed, Tibet is also considered efficient. As discussed above, the VRS efficiency only measures pure technical efficiency excluding the effect of scale of operations. Taking Tibet as an example, the scale efficiency, the ratio of CRS to VRS efficiency, is 0.11 (<1) meaning that its urban public transport system is not able to register efficiency because it is not operating at the most productive scale size, and its current size of operations reduces its VRS efficiency by 89%.

Secondly, Fig.3 describes the spatial distribution of efficiencies and their trends from 2000 to 2006. It is observed that 13 systems present efficiency scores above the national mean (0.65). These are Beijing, Zhejiang, Guangdong, Shanghai, Sichuan, Chongqing, Liaoning, Jiangsu, Jiangxi, Hubei, Guangxi, Fujian, and Hunan. Most of them are in the eastern and costal areas of China, where the economic level is relatively higher than those in the western and inland areas. Furthermore, most systems have registered improvements in efficiency (MPI>1), except for Beijing, Xinjiang and Qinghai. The average MPI of all China's urban public transport systems is 1.03, and Tibet shows a highest progress with MPI value touching 1.1.

To investigate the influence of investment on the efficiency of urban public transport systems, Fig 4 depicts the statistical relationship between investment and system efficiency. Here CRS score is used because in the real world imperfect competition, constraints on finance, etc. may cause a DMU to be not operating at optimal scale. While CRS model could result in the measurement of system efficiency confounded by scale efficiency. It is observed that the significance of the regression is 0.84 suggesting the urban public transport systems in developed areas, where the economic level and investment are higher, have relatively larger efficiencies than those in the less developed areas. For example, in 2004 the investment on urban public transport in Shanghai and Beijing, the most developed municipalities in terms of per capita GDP, was 14 billion yuan RMB. The urban public transport efficiency of these two municipalities was 1.0 and 0.97 respectively. On the contrary, the investment in Gansu and Guizhou, the least developed provinces, was only 0.14 billion yuan The average efficiency of these two provinces was 0.32 and 0.37 respectively.

Table 3 Average efficiency of urban public transport system in 2000-2006

Province	CRS efficiency	VRS efficiency	Scale efficiency	Province	CRS efficiency	VRS efficiency	Scale efficiency
Beijing	1.00	1.00	1.00	Gansu	0.62	0.76	0.82
Zhejiang	0.93	0.96	0.97	Xinjiang	0.61	0.68	0.91
Guangdong	0.92	0.93	0.99	Anhui	0.59	0.64	0.92
Shanghai	0.91	0.92	0.99	Yunnan	0.59	0.71	0.84
Sichuan	0.86	0.89	0.96	Qinghai	0.56	0.88	0.63
Chongqing	0.81	0.88	0.92	Tianjin	0.55	0.61	0.89
Liaoning	0.80	0.80	0.99	Shanxi	0.54	0.62	0.86
Jiangsu	0.80	0.81	0.98	Jilin	0.52	0.56	0.93
Jiangxi	0.80	0.94	0.85	Heilongjiang	0.50	0.53	0.94
Hubei	0.79	0.82	0.97	Henan	0.49	0.52	0.93
Guangxi	0.76	0.88	0.87	Hebei	0.43	0.47	0.91
Fujian	0.72	0.79	0.91	Inner Mongolia	0.42	0.52	0.81
Hunan	0.72	0.76	0.94	Ningxia	0.41	0.76	0.54
Shaanxi	0.65	0.73	0.89	Hainan	0.38	0.75	0.50
Guizhou	0.64	0.75	0.85	Tibet	0.11	1.00	0.11
Shandong	0.63	0.65	0.97				
China	Mean of CRS efficiencies		Mean of VRS efficiencies		Mean of scale efficiencies		
	0.65		0.76		0.86		

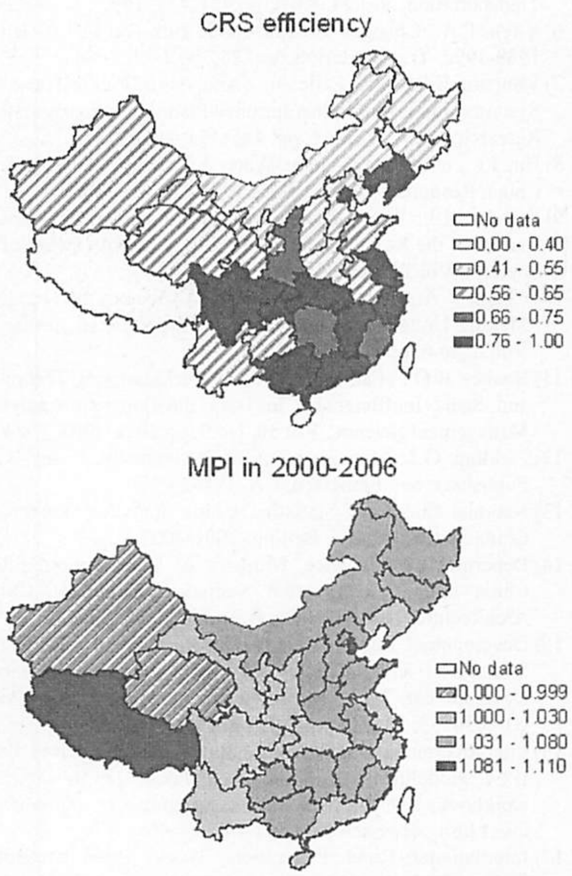


Fig. 3 Average CRS and MPI for 31 systems in 2000-2006

Note: the shadow in the above figure denotes the efficiency is below the national average. The shadow in the below one represents the regradation of system efficiency.

Moreover due to the advantage of rail transit over other transport modes, its effect on system efficiency is probed in Fig. 5. We calculate the annual average CRS efficiency for those systems with and without rail mode respectively. In those provinces having urban rail mode, the average CRS efficiency is higher than that of provinces without rail transit and the average efficiency of all systems. For example, in 2006, the average CRS efficiency of systems with rail is 0.8, while that of systems without rail is around 0.6. The merits of rail such as rapid speed, trustworthy timetable, comfortable vehicle conditions and massive load etc. make it an effective and efficient way curbing the growing energy consumption and enhancing the system efficiency.

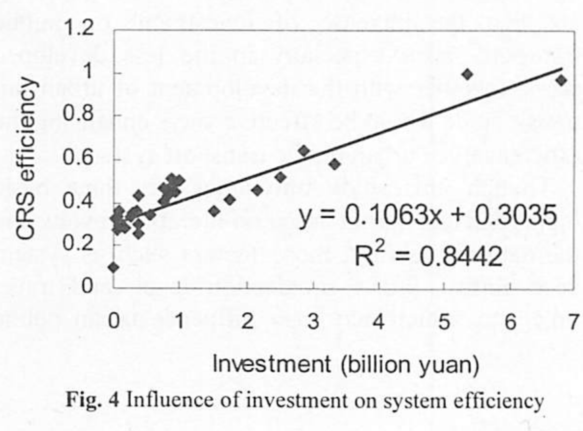


Fig. 4 Influence of investment on system efficiency

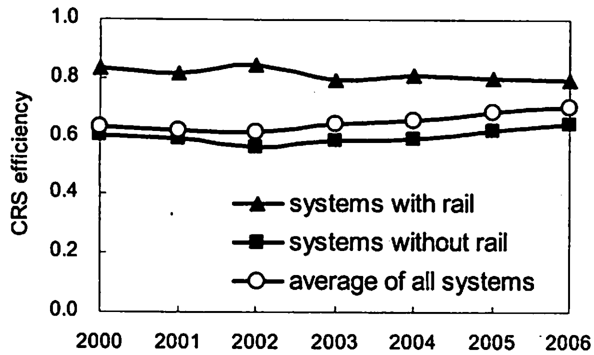


Fig. 5 Influence of rail transit on system efficiency

5. CONCLUSIONS AND DISCUSSIONS

This paper focuses on the urban public transport systems in 31 provinces of China considering four modes, i.e. bus, trolley, taxi and rail. We propose a method for estimating the energy consumption of urban public transport sector and adopt a DEA approach assessing the system performance. The findings are summarized as follows,

Firstly, the systems in most provinces have a relative low efficiencies, with national average CRS value around 0.65. The system in Beijing, the only one out of total 31 provinces, are considered technically efficient. Moreover nearly half of the total systems, whose efficiency value is above the national mean, are in the eastern and coastal regions of China. On the contrary, those systems in the western and inland areas are of low efficiencies below the national average.

Secondly, in the time-series efficiency analysis from 2000 to 2006, MPI index indicates that although the overall efficiency of urban public transport systems in China is still low, most of the provinces, except for Beijing, Xinjiang and Qinghai, have registered an improvement of system efficiency with average MPI around 1.03.

Thirdly, the policy implications from this study are that the increase of investment on public transport sector especially in the less developed areas, together with the development of urban rail transit mode would be effective ways enhancing the efficiencies of urban public transport systems.

Though, this study only considers three basic inputs and one output based on literature review and the data availability, those factors such as system accessibility, user's satisfaction level, and travel time, etc. which may also influence urban public transport system's performance are not yet considered at this stage. In the future works, it will be one of the important directions of our endeavor.

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