A Data Envelopment Analysis for Evaluating the Performance of China’s Urban Public Transport Systems

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This paper investigates the efficiency of urban public transport systems in China using a data envelopment analysis (DEA) approach. Based on the data from 652 China cities in 2004 and 2006, we found that the overall efficiency of urban public transport systems is relatively low but showed signs of improvement from 2004 to 2006. The urban public transport systems in east coast, south coast and middle Changjiang river areas have relatively higher efficiencies than those of others, which is consistent with the uneven distribution of the economic level and investment on public transport among regions throughout China. The policy implications on the basis of this study are that increased investment on the public transport sector, especially in less developed areas, together with the development of an urban rail transit mode would be effective ways of enhancing the efficiencies of urban public transport systems.

Keywords: data envelopment analysis, urban public transport, efficiency, China

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1. INTRODUCTION

In recent years, more attention has been paid to energy conservation and the mitigation of climate change. As the fastest growing source of greenhouse gas (GHG) emissions, transportation accounted for 26% of total energy use and 23% of energy-related GHG emissions in 2004 (Intergovernmental Panel on Climate Change, 2007). For this reason the improvement of transport efficiency to achieve an environmentally sustainable development has been taken as a strategic issue worldwide. 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 urban economic development and regarded as an effective way to reduce GHG emissions (International Association of Public Transport, 2006).

In China, home to the world’s largest population and as the second largest energy consumer in the world, CO₂ emissions rank second in the world under great pressure to improve in terms of environmental issues. Since the beginning of 21st century, more and more intensive transport policies have been implemented by central and local governments with the general goal of encouraging the development of urban public transport. However, due to institutional and financial deficiencies, it is this industry is still problematic especially in the following areas: low service quality, in-coordination of routes, deficits of operating companies and the heavy burden of governmental subsidies, etc. Thus the main objective of this paper is to investigate the performance of China’s urban public transport systems and offer a basis for policymakers to improve the said industry.

Regarding the efficiency of public transport, a number of research has been conducted over the past decades. Generally this research can be divided into three categories. First, as a start, is the indicator analysis, which defines a series of indicators to evaluate the efficiency of studied systems (Tomazinis, 1977; Fielding et al., 1985; Anderson and Fielding, 1982; Hartgen and Segedy, 1996). Second is the parametric analysis, which is characterized by a production function of constant parameters. The specification of a functional form is the main limitation of the parametric approach, as efficiency measures vary according to the adopted function. (Aigner and Chu, 1968; Finn et al., 1997). Third is the non-parametric analysis. It does not require the prior specification of a function. The estimation of the frontier of the production set only requires that the production set satisfy some properties. DEA is a well known non-parametric mathematical programming approach for frontier estimation, which was firstly proposed by Farrell (1957) and popularized by Charnes et al. (1978). Viton (1998) 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 improved slightly over the 1988–1992 period. Karlaftis (2004) used DEA and globally efficient frontier productions functions to investigate the efficiency and effectiveness of 259 US urban transit systems over a five-year period and found that efficiency and effectiveness are positively related. Sampaio et al. (2008) analyzed the characteristics of several public transport systems in Brazil and European countries using 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 an efficiency assessment of urban public transport systems in China, although performance analyses have been conducted in many other fields such as electricity generation plants, regional water efficiency and environmental performance measurement, etc. (Lam and Shiu, 2001; Liang et al., 2004; Hu et al., 2006). The reason may in part be 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 sectors and adopt a DEA approach for assessing system performance.
2. METHODOLOGY

2.1 DEA Approach

Figure 1 shows the flow chart of DEA process, in which it firstly defines the decision-making units (DMU), and then set the criteria to apply to the efficiency analysis. Based on the criteria and data availability, input and output factors can be selected. Finally, by executing the DEA program under different assumptions such as constant return to scale (CRS), variable returns to scale (VRS) and Malmquist Productivity Index (MPI), the relative efficiency of DMUs can be estimated.

In modeling, urban public transport systems are viewed as DMUs. We assume that there is NDMUs that use K inputs to obtain M outputs. For i th 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:
min_{\theta, \lambda} (\theta) \\
\text{st} - y_i + Y \lambda \geq 0, \\
\theta x_i - X \lambda \geq 0, \\
\lambda \geq 0 

(1)

where $\theta$ is a scalar and $\lambda$ is a $N \times 1$ vector of constants. $X$ is the input matrix ($K \times N$). $Y$ is the output matrix ($M \times N$). The value of $\theta$ obtained will be the efficiency score of the $i$th DMU. It will satisfy $\theta \leq 1$, 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. (1984), 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:

min_{\theta, \lambda} (\theta) \\
\text{st} - y_i + Y \lambda \geq 0, \\
\theta x_i - X \lambda \geq 0, \\
N1 \lambda = 1 \\
\lambda \geq 0 

(2)

$N1$ is an $N \times 1$ 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 provide technical efficiency scores with larger or equal to those obtained by 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:

$$
\text{MPI}^{t+1}(y_{t+1}, x_{t+1}, y_t, x_t) = \left[ \frac{D'(x_{t+1}, y_{t+1})}{D'(x_t, y_t)} \times \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)} \right]^{1/2}
$$

(3)

$\text{MPI}^{t+1}$ denotes a geometric average of the productivity change of the production point $(x_{t+1}, y_{t+1})$ relative to the production point $(x_t, y_t)$. $\text{MPI}>1, \text{MPI}=1$ and $\text{MPI}<1$ respectively indicate that the productivity of DMU has improved, remained unchanged and deteriorated from $t$ to $t+1$. $D'$ is a distance function measuring the efficiency of conversion of inputs $x_t$ to outputs $y_t$ in the period of $t$. 
2.2 Input/Output Variables, Data and Study Area

As shown in Figure 2, the urban public transport system in China is generally composed of bus, trolley, taxi and rail modes, which can be further divided by fuels. Ferry transport was dropped due to data limitations.

[Figure 2] Hierarchy of China urban public transport system

As summarized by existing literature (Karlaftis, 2004; Sampaio et al., 2008), transport service efficiency analysis is generally based on three basic inputs, namely labor, capital and energy. In this paper, labor is measured by the total number of employees. Capital is represented by the number of vehicles. Energy consumption is measured through the following estimation. 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 (Fielding, 1987). Considering the data availability, we chose the total passengers transported as our output variable.

The data on urban public transport was collected from 652 China cities in 2004 and 2006. In detail, annual data including vehicle numbers, number of employees, total passengers transported, annual distance traveled by vehicles and fuel intensity etc. were mainly taken from “China Statistical Yearbook” (National Bureau of Statistics, 2005, 2007), “China Urban Construction Statistical Yearbook” (Department of Finance, Ministry of Construction, PRC , 2004, 2006), published reports and papers. Here, the 652 urban public transport systems are considered as DMUs. Each system has the number of employees, number of vehicles and energy consumption as the input and has the passengers transported as the output.

To illustrate the general socio-economic characteristics of the study areas, we aggregate China into 8 regions according to the economic homogeneity before reporting them (Figure 3). The clustering follows the method proposed by the Development Research Center of State Council of China (2005). 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 the country’s total territory. However, they accommodate 43% of total population and create 63% of GDP in
China. The investment on urban public 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 with only 24% of the population concentration and 14% of GDP. 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

(Figure 3) Eight regions in China

(Table 1) China’s regional characteristics (in percentage)

<table>
<thead>
<tr>
<th></th>
<th>NE</th>
<th>NC</th>
<th>EC</th>
<th>SC</th>
<th>MYR</th>
<th>MCR</th>
<th>SW</th>
<th>NW</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>9.3</td>
<td>4.5</td>
<td>2.5</td>
<td>4.0</td>
<td>20.6</td>
<td>8.5</td>
<td>16.4</td>
<td>34.2</td>
<td>100</td>
</tr>
<tr>
<td>Population</td>
<td>8.5</td>
<td>14.4</td>
<td>10.7</td>
<td>9.5</td>
<td>14.9</td>
<td>18.5</td>
<td>19.1</td>
<td>4.4</td>
<td>100</td>
</tr>
<tr>
<td>GDP</td>
<td>9.8</td>
<td>18.5</td>
<td>19.9</td>
<td>14.3</td>
<td>10.5</td>
<td>13.2</td>
<td>10.9</td>
<td>2.9</td>
<td>100</td>
</tr>
<tr>
<td>Investment</td>
<td>5.2</td>
<td>18.7</td>
<td>41.0</td>
<td>19.8</td>
<td>1.7</td>
<td>5.5</td>
<td>7.3</td>
<td>0.6</td>
<td>100</td>
</tr>
</tbody>
</table>

Note: The shares of population and GDP are the average value between 1995–2006. Investment on urban public transport is the 2004 value.

2.3 Energy Consumption 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.

Road-based mode:
$$E_{m,t} = \sum_j VN_{m,j,t} \cdot DTV_{m,j,t} \cdot FI_{m,j,t} \cdot a_j$$

Rail-based mode:
$$E_{rail,t} = PN_{rail,t} \cdot DTP_{rail,t} \cdot FI_{rail,t} \cdot a_j$$
Subscript $m$, $j$ represent road-based mode and fuel type respectively. 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/pasenger-km for rail mode. $a$ is heat conversion factor, which takes value as $3.2 \times 10^7$ J/L for gasoline, $3.6 \times 10^7$ J/L for diesel, $3.9 \times 10^7$ J/m$^3$ for CNG, and $3.6 \times 10^6$ J/kWh for electricity.

Since there is no published statistical data on DTV in China, we followed the works of Wang et al. (2007) and the International Road Federation (2005) 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 (2004) issued the “Maximum Limits of Fuel consumption for Passenger Cars” in 2004, stressing the realization of the target for fuel consumption per km of car and light duty vehicles could decrease 5–10% in 2001–2005 compared to 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 research conducted in some municipalities such as Beijing and Shanghai etc. (Chen et al., 2006; Huang et al., 2005), DTP and FI for rail mode are assigned as 9 km/passenger and 0.05 kWh/passenger-km.

<table>
<thead>
<tr>
<th>Proportion (%)</th>
<th>DTV (thousand km)</th>
<th>FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus: Gasoline</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>Bus: Diesel</td>
<td>78</td>
<td>75</td>
</tr>
<tr>
<td>Bus: CNG</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>Trolley: Electricity</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Taxi: Gasoline</td>
<td>98.7</td>
<td>97.5</td>
</tr>
<tr>
<td>Taxi: Diesel</td>
<td>1.3</td>
<td>2.5</td>
</tr>
</tbody>
</table>

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

### 3. RESULTS

Figure 4 shows the distribution of CRS efficiencies among 652 cities, and Table 3 illustrates the efficiencies of urban public transport systems in eight regions and their changes from 2004 to 2006. Overall the total efficiency in China is relatively low with the mean CRS around 0.45. About 40% of total systems show higher efficiencies than the national average, while only 3% of total systems have efficiencies larger than 0.9.

In detail, the efficiencies of urban public transport systems in East Coast (EC), South Coast (SC), Middle Changjiang River (MCR) regions are considered relatively efficient under the CRS assumption, whose regional average CRS scores are larger than national mean (0.45). While the systems in North West (NW),
Middle Yellow River (MYR), South West (SW), North Coast (NC) and North East (NE) regions have relatively lower efficiencies than the national average. Their values are 0.36, 0.37, 0.43, 0.44 and 0.45 respectively. As discussed above, the VRS efficiency only measures pure technical efficiency excluding the effect of scale of operations. Taking NE as an example, the scale efficiency, the ratio of CRS to VRS efficiency, is 0.93 (<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 7%. The MPI values in all 8 regions are larger than 1, which indicates, that although the efficiency of China’s urban public transport systems are low there is a sign of improvement. The North East (NE) region registered the highest progress with a MPI value touching 1.20.

<table>
<thead>
<tr>
<th>Region</th>
<th>CRS Efficiency</th>
<th>VRS Efficiency</th>
<th>Scale Efficiency</th>
<th>MPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE</td>
<td>0.45</td>
<td>0.48</td>
<td>0.94</td>
<td>1.20</td>
</tr>
<tr>
<td>NC</td>
<td>0.44</td>
<td>0.46</td>
<td>0.96</td>
<td>1.19</td>
</tr>
<tr>
<td>EC</td>
<td>0.57</td>
<td>0.59</td>
<td>0.97</td>
<td>1.06</td>
</tr>
<tr>
<td>SC</td>
<td>0.50</td>
<td>0.62</td>
<td>0.81</td>
<td>1.08</td>
</tr>
<tr>
<td>MYR</td>
<td>0.37</td>
<td>0.40</td>
<td>0.93</td>
<td>1.17</td>
</tr>
<tr>
<td>MCR</td>
<td>0.48</td>
<td>0.52</td>
<td>0.92</td>
<td>1.16</td>
</tr>
<tr>
<td>SW</td>
<td>0.43</td>
<td>0.45</td>
<td>0.96</td>
<td>1.14</td>
</tr>
<tr>
<td>NW</td>
<td>0.36</td>
<td>0.40</td>
<td>0.90</td>
<td>1.12</td>
</tr>
<tr>
<td>China</td>
<td>0.45</td>
<td>0.49</td>
<td>0.92</td>
<td>1.14</td>
</tr>
</tbody>
</table>

Note: CRS, VRS and scale efficiency are geometric average value of 2004 and 2006.

To investigate the factors influencing the efficiency of urban public transport systems, Figure 5 depicts the relationship between governmental investment on urban public transport and system efficiency. Here the CRS score is used for regression analysis because in the real world imperfect competition, constraints on finance,
etc. may cause a DMU to be not operating at optimal scale. The CRS model could result in the measurement of system efficiency confounded by scale efficiency. The significance of the regression being 0.53 suggests that 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 systems 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 (nearly 100-fold of that in Beijing and Shanghai). The average efficiency of these two provinces was 0.32 and 0.37 respectively.

Moreover due to the advantage of rail transit over other modes, its effect on system efficiency is probed in Table 4. We calculate the annual average CRS efficiency for those systems, with and without rail modes, respectively. In those cities with rail mode, the average CRS efficiency is higher than that of cities without rail transit. For example, in 2006, the average CRS efficiency of systems with rail is 0.93, while that of systems without rail is around 0.50. The merits of rail including rapid speed, trustworthy timetables, comfortable vehicle conditions and massive loads, etc. make it an effective and efficient way to curb the growing energy consumption and enhance the system efficiency.

<table>
<thead>
<tr>
<th>Invest (billion yuan)</th>
<th>CRS efficiency</th>
<th>Systems with rail</th>
<th>Systems without rail</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>y = 3.50 x</td>
<td>2004</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>$R^2 = 0.53$</td>
<td>2006</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.50</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

Due to large energy consumption and associated GHG emissions, China is under great pressure to agree to the mitigation of climate change. Regarding the significant role of urban public transport in reducing GHG emissions and the increasing priorities being placed on planning and development, efficiency assessment is important to highlight aspects for improvement.

This paper focuses on the urban public transport systems in 652 cities of China considering four modes, i.e. bus, trolley, taxi and rail. We proposed 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 average efficiency of total urban public transport is low, with average CRS values around 0.45. About 40% of the total systems have a higher efficiency than the national average. Most of them are in the east coast, south coast and middle Changjiang river regions of China.

Secondly, the MPI index indicates that although the overall efficiency of urban public transport systems in China is still low, most of them have registered an improvement of system efficiency from 2004 to 2006 with the average MPI around 1.14.

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

On the other hand, this study only considers three basic inputs and one output based on literature reviews and due to data availability, those factors such as system accessibility, user’s satisfaction level, and travel time, etc. which also influence urban public transport system’s performance were not yet considered, at this stage. In future studies, it will be one of the important directions of our endeavor.

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