Performance of Urban Public Transport Systems in China: Data Envelopment Analysis

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ABSTRACT

This paper investigates the efficiency of urban public transport systems in China by a data envelopment analysis (DEA) approach. Based on the data from 652 China cities in 2004 and 2006, we find that the efficiency of overall urban public transport system is relatively low but with a sign 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 economic level and investment on public transport among China regions. The policy implications on the basis of 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.
1. INTRODUCTION

In recent years, energy conservation and mitigation of climate change have been paid more and more attentions. 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 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 urban economic development and regarded as an effective way to reduce GHG emissions (International Association of Public Transport, 2006).

In China, where it holds the world’s largest population and is the second largest energy consumer in the world, CO₂ 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 by central and local governments 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 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.

Regarding the efficiency of public transport, a number of researches have been conducted in the past decades. Generally they 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 a priori 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 is 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 has 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 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. (Lam and Shiu, 2001; Liang et al., 2004; Hu et al., 2006). 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.

2. METHODOLOGY

2.1 DEA approach

In modeling, urban public transport systems are viewed as decision-making units (DMU). We assume that there is \( N \) DMUs 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,

\[
\begin{align*}
\min_{\theta, \lambda} & \quad (\theta) \\
\text{st} & \quad -y_i + Y\lambda \geq 0, \\
& \quad \theta x_i - X\lambda \geq 0, \\
& \quad \lambda \geq 0
\end{align*}
\]

(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 \( (M \times N) \). Eq. (1) involves fewer constraints than in Eq. (2) \( (K+M<N+1) \), thus is commonly preferred to be used for programming. 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 constant return to scale (CRS) when not all DMUs are operating with optimal scale may result in efficiency scores affected by the scale efficiency. According to Banker et al. (1984), the use of variable returns to scale (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,

\[
\begin{align*}
\min_{\theta, \lambda} & \quad (\theta) \\
\text{st} & \quad -y_i + Y\lambda \geq 0, \\
& \quad \theta x_i - X\lambda \geq 0, \\
& \quad N1\lambda = 1 \\
& \quad \lambda \geq 0
\end{align*}
\]

(2)

where \( N1 \) 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 provides technical efficiency scores with are 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 Malmquist Productivity Index (MPI) approach can be used to measure the efficiency change over time,
\[ \text{MPI}^{t+1}(y_{t+1}, x_{t+1}, y_t, x_t) = \left[ \frac{D'(x_{t+1}, y_{t+1})}{D'(x_t, y_t)} \times \frac{D'(x_{t+1}, y_{t+1})}{D'(x_t, y_t)} \right]^{1/2} \]  (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 \(t+1\). \(D'\) 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 Fig.1, 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 is dropped out due to data limitation.

As summarized by many existing literatures (Karlaftis, 2004; Sampaio *et al.*, 2008), 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 (Fielding, 1987). Considering the data availability, we choose the total passengers transported as output variable.


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 (Fig.2). 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 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](image)

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 during 1995-2006. Investment on urban public transport is the value in 2004.

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.

\[
E_{\text{road},j} = \sum_j VN_{m,j} \cdot DTV_{m,j} \cdot FI_{m,j} \cdot a_j \\
E_{\text{rail},j} = PN_{\text{rail},j} \cdot DTP_{\text{rail},j} \cdot FI_{\text{rail},j} \cdot a_j
\]

(6)

where subscript \( m, j \) represent road-based mode and fuel type respectively. VN is vehicle number. DTV is the annual distance traveled by vehicle. 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 $3.2 \times 10^7$ 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 follow the works of Wang et al. (2007) and 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 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. (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 2 Parameters for estimation of energy consumption of road-based modes |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Proportion (%)  | DTV (thousand km) | FI               |
| Bus            |      |      |      |      |      |      |
| Gasoline       | 11   | 13   | 51   | 50   | 0.43 | 0.42 |
| Diesel         | 78   | 75   | 51   | 50   | 0.32 | 0.31 |
| CNG            | 11   | 12   | 51   | 50   | 0.38 | 0.38 |
| Trolley        |      |      |      |      |      |      |
| Electricity    | -    | -    | 33   | 32   | 1.4  | 1.4  |
| Taxi           |      |      |      |      |      |      |
| Gasoline       | 98.7 | 97.5 | 25   | 24   | 0.16 | 0.15 |
| Diesel         | 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

Fig 3 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 change 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 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 the 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 a highest progress with MPI value touching 1.20.

![Fig. 3 Distribution of CRS efficiencies among 652 urban public transport systems](image)

**Table 3 Average efficiency of urban public transport systems in 8 regions**

<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>CRS efficiency</td>
<td>0.45</td>
<td>0.44</td>
<td>0.57</td>
<td>0.50</td>
<td>0.37</td>
<td>0.48</td>
<td>0.43</td>
<td>0.36</td>
<td>0.45</td>
</tr>
<tr>
<td>VRS efficiency</td>
<td>0.48</td>
<td>0.46</td>
<td>0.59</td>
<td>0.62</td>
<td>0.40</td>
<td>0.52</td>
<td>0.45</td>
<td>0.40</td>
<td>0.49</td>
</tr>
<tr>
<td>Scale efficiency</td>
<td>0.93</td>
<td>0.94</td>
<td>0.97</td>
<td>0.81</td>
<td>0.94</td>
<td>0.93</td>
<td>0.95</td>
<td>0.90</td>
<td>0.92</td>
</tr>
<tr>
<td>MPI</td>
<td>1.20</td>
<td>1.19</td>
<td>1.06</td>
<td>1.08</td>
<td>1.17</td>
<td>1.16</td>
<td>1.14</td>
<td>1.12</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, Fig 4 depicts the relationship between governmental investment on urban public transport and system efficiency. It is observed that the significance of the correlation between investment and CRS score is 0.53 suggesting 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 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 mode respectively. In those cities having 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 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.

4. CONCLUSIONS

Due to the large energy consumption and associated GHG emissions, China is under great pressure of mitigation of climate change. Regarding the significant role of urban public transport in reducing GHG emissions and its increasing priority been raised in 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 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 average efficiency of total urban public transport is low with average CRS value around 0.45. About 40% of the total systems have a higher efficiency than national average. Most of them are in the east coast, south coast and middle Changjiang river regions of China.

Secondly, 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 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.

Table 4 Influence of rail transit on system efficiency

<table>
<thead>
<tr>
<th>CRS efficiency</th>
<th>Systems with rail</th>
<th>Systems without rail</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>0.96</td>
<td>0.93</td>
</tr>
<tr>
<td>2006</td>
<td>0.43</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Fig. 4 Influence of investment on system efficiency

\[ y = 3.50x \]

\[ R^2 = 0.53 \]
ACKNOWLEDGMENT

This research was supported by the Grant-in-Aid for Japan Society for the Promotion of Science research fellows (No. 19-07397).

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