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Factors affecting performance of urban bus transport systems in India: A Data Envelopment Analysis (DEA) based approach

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Abstract

City bus systems in India have been witnessing a decline in service consumption and revenue despite having a high proportion of transit dependent passengers. Improving their performance and encouraging higher transit ridership are required for Indian cities to meet their mobility demands in a resource efficient manner. We present an objective framework to measure efficiencies of these systems and to carry out a disaggregated analysis of the key internal and external variables impacting their efficiency. A Data Envelopment Analysis (DEA) based approach was adopted for benchmarking the performance of eight city bus services. Three categories of performance efficiency i.e. service supply, consumption and revenue were measured using relevant input and output variables derived for the seven year study period between 2009-10 and 2015-16. The analysis identifies the best and least performing STUs in each category and the potential reduction in resource consumption to improve their efficiency. Regression analysis of these efficiencies was carried out to establish correlation with external variables representing city size, land-use development characteristics and economic performance. The analysis identified low service consumption even in cities with high supply and revenue efficiency, highlighting the need for improved planning that enables demand oriented services. Cities also need to improve their service supply and revenues adequately to be efficient even as the cities grow in size and economy. The findings from this study provide policy and planning inputs to improve bus systems in other developing countries with similar public transport systems, city development and mobility characteristics.

Keywords: City bus systems; Performance efficiency; Benchmarking; Data Envelopment Analysis

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1. Introduction

India is home for 17.75% of the world population with an urban population that is projected to grow from 377 million in 2011 to about 473 million by 2021 and 820 million by 2051 (UN, 2015). Buses are the most used form of public transport in the country, serving about 68 million users per day travelling 1.48 billion passenger kilometers every day (MoRTH, 2017). However, with increasing income and vehicle ownership, there has been a significant increase in the modal share of private cars and motorcycles over past couple of decades, leading to increased congestion, air pollution and road traffic crashes. Cities need to provide high quality public transport systems to arrest the growth of personal mobility and to serve the mobility needs of the growing population in a sustainable manner.

City bus services in India are mostly provided by Government run State road Transport Undertakings (STUs) Special Purpose Vehicles (SPVs) established for providing the service. Despite high user dependence on city bus systems, they are operating in losses ranging from 6 to 27 percent, over the past decade (CIRT, 2011 ; UITP, 2018). As a result, these systems were unable to scale up their services according to the increasing travel needs of cities. Their losses can be attributed to multiple reasons including increased costs caused by inefficiencies in planning and operations, reduced revenue caused by providing access to buses in low demand areas and the lack of financial support from the City governments for the subsidized fares offered to students and senior citizens etc. However, the specific contributions of various factors to the overall losses hasn’t been established in literature, thereby limiting the knowledge on the initiatives needed to improve the bus systems.

The current article addresses this gap in literature by presenting a methodology to establish the role of various internal and external factors impacting the operational and financial performance of bus systems. A Data Envelopment Analysis (DEA) based approach was adopted to benchmark the operational and financial efficiencies of Indian city bus systems over the past seven years. The relative contribution of various inputs to the system were established to establish their specific contribution to various categories of outputs i.e. service supply, consumption and revenue efficiency. Further, the impact of external factors like city development, travel demand patterns and economic characteristics on the efficiency of the bus system were also derived through regression analysis of city bus performance efficiencies and the external variables. Even though the analysis was carried out for the Indian context, the methodology and variables used to identify measures for improving bus system efficiencies are applicable even in other developed and developing country contexts.

2. Literature review

To compare the performance of various bus systems and identifying the variables impacting their efficiency, the literature review focused on methods for benchmarking of public transport performance efficiency and the key internal and external variables required for the analysis.

2.1 Methods for benchmarking public transport systems

Efficiency represents the performance of an organization or a service by the amount of output produced for a given amount of input (energy, time, money). The outputs of manufacturing industries are clearly identifiable entities while in case of public transport services, the outputs can be quantified in different ways. The fundamental reason for this difference is that the output of a transport system is a service that cannot be stored for future use (Jarboui, Forget, & Boujelbene, 2012). Efficiency evaluation of a service enterprise depends on how well the service is managed, how well that is received and how big the organization is (Sherman & Zhu, 2006).

Benchmarking involves comparison of individual service enterprise efficiencies to the most efficient service of the sample under consideration. Benchmarking of services or entities is most commonly carried out through frontier techniques which put the most efficient services on the frontier and evaluate the efficiencies of the rest of the services relative to the efficiency frontier (Kotsemir, 2013). The methods used for benchmarking analysis can be classified into parametric and non-parametric techniques. Stochastic Frontier Analysis (SFA) is the most preferred technique for parametric benchmarking while for non-parametric benchmarking, Data Envelopment Analysis (DEA) is the preferred technique (Aigner, Lovell, & Schmidt, 1977) (Meeusen & van Den Broeck, 1977).

In the context of the current study, DEA was observed to offer more flexibility compared to SFA, due to limitations of SFA in considering more than one output variable and including external variables within the frontier analysis thereby not establishing their relationship with efficiencies explicitly (Garcia Sanchez, 2009). DEA offers the flexibility to evaluate the relatively less efficient unit against the best performing unit and to quantify the scope for resource and cost savings by making the relatively inefficient units as-efficient-as the most efficient or the best practice unit (Sherman & Zhu, 2006). Even though DEA is widely applied across various sectors, its application for the transport sector has been increasing only recently (Emrouznejad, Parker, & Tavares, 2008) (Liu, Lu, Lu, & Lin, 2013).

DEA further has two key methods of benchmarking i.e. Charnes, Cooper and Rhodes (CCR Model) and Banker, Charnes and Cooper (BCC Model). CCR model is based on constant returns to scale (CRS) which means that an increase in all the inputs by a factor will have a proportional increase in the output by the same factor, and vice-versa (Charnes, Cooper, & E. Rhodes, 1978). The efficiencies calculated using this CCR-CRS model are known as Overall Technical Efficiencies (OTE). BCC model is based on variable returns to scale (VRS) which means that an increase in all the inputs by a factor may not change the output by the same factor, and vice-versa (Banker, Charnes, & Cooper, 1984). The efficiencies calculated using this BCC-VRS model are known as Pure Technical Efficiencies (PTE). The ratio of these two efficiencies (OTE/PTE) gives us Scale efficiencies (SE), which measures the likely efficiency of a (Jarboui et al., 2012).

2.2 Internal and external variables impacting public transport efficiency

Although DEA does not propose any mechanism to attain efficiency, it helps in quantifying the changes that are needed by inefficient unit to become efficient according to the outputs being sought (Saxena & Saxena, 2010). Hence, selection of input and output variables plays a pivotal role in determining the efficiencies. (Daraio et al., 2016) and (Jarboui et al., 2012) provided an overview of the exhaustive list of input and output variables used in public transport efficiency evaluation literature and their frequency of usage. Majority of the literature on efficiency evaluation of transit focuses on the system’s efficiency as a function of its productivity with respect to their inputs (Emrouznejad et al., 2008). However, the effectiveness of the services provided in meeting the objectives of the Government and passengers have received limited focus. (Chu, Fielding, & Lamar, 1992) propose that the output variables for efficiency should be classified according to productivity i.e. service provided for the given inputs and effectiveness i.e. consumption of the services provided. (Daraio et al., 2016) have classified the variables further i.e. input variables are classified into Physical measures, Capital Expenses (CAPEX) and Operating Expenses (OPEX) , the output variables were classified into Service Supply, Service Consumption, and Revenue. The current article adopts a similar classification system to derive efficiencies according to users’, operators’ and the city’s perspective, while maintaining the homogeneity in the selection of input variables.

In addition to the internal input and output variables, efficiency of a transit system also depends on external variables that influence its performance. These include the city characteristics like population density, economic development and mobility characteristics like trip lengths, population with access to services etc. (Daraio et al., 2016) propose a two-level analysis to measure the impact of these external variables on efficiency i.e. to use DEA analysis to quantify impact of internal variables and use regression analysis to identify the external variables with the maximum impact on the efficiency.

2.3 Benchmarking of Indian bus systems

Applications of DEA to measure performance efficiency of Indian bus systems have been limited. (Agarwal, Yadav, & Singh, 2010) used DEA to compare the performance of 35 STUs providing intra-city and inter-city services for the year 2004-05 using both CCR and BCC methods. The scale efficiency of each of the STUs and the percentage reduction potential for various input resources to reach the efficiency frontier were derived. Similarly, (Saxena &

Saxena, 2010) applied CCR and BCC methods of DEA to study the performance of 25 Indian STUs between 2002-03 and 2004-05. They derive the relative efficiencies of STUs and identify their potential for improving their technical and scale efficiencies. However, both the articles combine intra-city and inter-city bus systems for their analysis, which wasn't an accurate comparison considering their varying operational characteristics, passenger requirements etc. Further neither of these studies evaluate the impact of external variables on the STUs' efficiency. Hence the findings from these studies don't provide conclusive insights on the specific measures needed to improve city bus systems.

(Vaidya, 2014) classified measurement variables into three categories of operations, finance and accident-based and later analyzed the importance of each category based on Analytical Hierarchy Process (AHP). However, this study did not consider the variables related to service consumption and did not provide a detailed insight on how to utilize the calculated efficiency numbers towards overall improvement. The current study not only considers variables from supply, consumption and revenue perspective, but it also evaluates the obtained efficiencies for their dependencies on external factors.

3. Methodology and Data

We adopted the two-level analysis proposed by (Daraio et al., 2016) to benchmark Indian city bus systems based on their input-output variables and estimate the impact of external variables on performance efficiency through regression analysis. A DEA based benchmarking was carried out considering each State Transport Undertakings (STUs) providing city bus services as a Decision-Making Unit (DMU). A total of eight city bus systems were benchmarked over the seven-year period between 2009-10 and 2015-16. The analysis was carried out separately for three categories of outputs i.e. service supply, service consumption and revenue efficiency to enable a more disaggregated understanding of their performance. The variables considered for analysis, formulation of DEA and the data collection are explained in the following sections.

3.1 Data collection and selection of variables for benchmarking

The current article analyses the city bus services across eight metropolitan cities in India. Table 1 provides a summary of State Transport Undertaking (STUs) providing bus services along with other key city development and mobility characteristics. Secondary data required for benchmarking of these systems i.e. the physical and financial performance of was collected for seven financial years between 2009-10 and 2015-2016 (CIRT, 2011; 2012; 2013; 2014) (MoRTH, 2015; 2016; 2017). Data for a total of 36 variables was initially collected, out of which only 16 variables which were consistently reported by all STUs for all the years were shortlisted for further analysis. Table 2 presents the 16 variables i.e. 9 input and 7 output variables were considered for benchmarking according to the input and output variable classification recommended by (Daraio et al., 2016) and (Jarboui et al., 2012). The final variables for benchmarking were selected from within these variables.

(Boussofiane, Dyson, & Thanassoulis, 1991) (Bowlin, 1998) and (Dyson et al., 2001) recommend the number of DMUs to be two to three times the total number of input and output variables. Further, strong correlation between input and output variables is preferred while correlation amongst input variables and output variables doesn't have any impact on the DMU's efficiency. Given that the current study benchmarks eight cities, the total number of variables for each category of benchmarking i.e., service supply, consumption and revenue efficiency, was limited to four. Three input variables which are common across all categories of benchmarking and one output variable for each category of benchmarking were shortlisted based on correlation analysis. The DEA model was run using several combinations of strongly correlated variables, while shortlisted the variables one-by-one, based on the percentage change in the significance value. Only the variables which caused a 20% or more variation in DEA were retained while the rest were discarded.

Table 1 List of all selected city's with STUs and their background information

S.no	City	STU acronym	STU abbreviation	Population+	Area*	Density	Average trip length (km) +	% Trip length distribution (5-10 km) +	GDP	Economy Index Score*
1	Bangalore	BMTC	Bangalore Metropolitan Transport Corporation	8499399	800	10624	7.45	27.15	2959.71	44
2	Kolkata	CSTC	Calcutta State Road Transport Corporation	14112536	186.23	75780	5.44	27.18	1822.11	36
3	Chennai	MTC	Metropolitan Transport Corporation (Chennai)	8696010	175	49691	6.98	29.60	2630.38	43
4	New Delhi	DTC	Delhi Transport Corporation	16314838	1482.71	11003	7.65	23.05	4057.71	36
5	Ahmedabad	AMTS	Ahmedabad Municipal Transport Services	6352254	468.92	13547	6.74	26.56	2959.15	32
6	Mumbai	BEST	Brihanmumbai Electric Supply and Transport Undertaking	18414288	1400.4	13149	4.90	24.80	3986.77	41
7	Chandigarh	CHNTU	Chandigarh Transport Undertaking	1025682	105.68	9706	6.14	32.45	3629.40	39.6
8	Pune	PMPML	Pune Mahanagar Parivahan Mahamandal Limited	5049968	276.4	18271	7.25	25.75	2915.96	40

+(Census, 2012)* Economy Index Score was derived from (ISB, 2017)

Table 2. Category and names of input and output variables considered for sensitivity analysis

S.no	Input category	Input Variables	Output category	Output Variables
1.	Physical measure	Buses held	Service Supply	Effective kilometers
2.		Total staff	Service consumption	Passengers carried
3.		Staff per bus		Passenger kilometers travelled
4.	OPEX	Staff cost		Load factor
5.		Fuel & Lubricant cost	Revenue	Total revenue
6.		Total cost per bus per day		Total earnings per bus per day
7.		Fuel efficiency		Traffic revenue
8.	CAPEX	Capital expenditure		
9.	OPEX + CAPEX	Total cost		

3.2 Formulation of DEA

An input-oriented DEA based benchmarking method was adopted to establish the reduction potential for each of the inputs for various categories of outputs. The CCR model based on constant returns to scale was adopted for analysis, with each STU considered as one Decision Making Unit (DMU). The objective function of the DEA formulation is to maximize efficiency h of target DMU j_0 where a total of n DMUs operate with m inputs and s outputs; y_{rj} is the amount of r[th] output from entity j, and x_{ij} is the amount of i^{th} input from the same entity j. The decision variables $u = (u_1, u_2,\ldots, u_r, \ldots, us)$ and $v = (v_1, v_2, \ldots, v_r, \ldots, v_m)$ are weights given to the s outputs and m inputs respectively. Thus, the objective equation is iterated n times to calculate the relative efficiencies of one entity at a time. The weights are constrained such that they are positive, and the efficiency of any entity is not greater than one. This is ensured by, an infinitesimally small positive value.

$$\max h_{j_0}(u,v) = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} \qquad (1)$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad , \quad j=1,2,\ldots n, \qquad (2)$$

$$\frac{u_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij}} \geq \varepsilon \; , \quad r=1,2,\ldots,s \qquad (3)$$

$$\frac{v_{ij_0}}{\sum_{i=1}^{m} v_i x_{ij}} \geq \varepsilon \; , \quad i=1,2,\ldots,m \qquad (4)$$

MaxDEA 7.1 Basic, an open source spreadsheet based application, was used for the DEA (Cheng, 2014). The application forms a frontier based on efficient units within the reference data set and generates a “Lambda” or “Efficiency Reference Set” for the inefficient units (De Borger, Kerstens, & Costa). The lambda values, when multiplied with the existing input resources of the inefficient DMU, form a composite hypothetical unit, whose difference with the original DMU will result in the excess amount of resources being utilized for each input. In DEA, this excess input resources are represented by “Proportionate Movement”. Positive values indicate the need to increase the inputs while negative values indicate the potential to reduce the input. If a DMU doesn’t attain the efficiency frontier despite applying the “Proportionate Movement” to the resources, “Slack” would be required to push the units towards efficiency frontier. Finally, “Projection” represents the efficient target of input or output resource that should be used. For the input oriented CCR model, Equation 5 represents the calculation of projected values, based on the proportionate and Slack values of an inefficient unit (Agarwal et al., 2010). For a target DMU with an optimal efficiency h, and x_{ij} is the amount of i^{th} input from the same entity j, $\overline{x_{ij}}$ represents the final projected amount of resource that is required.

$$\overline{x_{ij}} = h * x_{ij} - S^{-}{}_{ij} \qquad (5)$$

4. Analysis and Findings

The benchmarking of the eight DMUs was carried out for three categories of output variables i.e. Service Supply, Service consumption and Revenue efficiency. Such classification of efficiencies enables a disaggregated analysis of the efficiency in utilizing resources towards various types of outputs expected from the bus system. Correlation between input and output variables presented in Table 2 and sensitivity analysis for impact of variables on the efficiency of DMU were carried out to derive three common input variables across three categories and one output variable for each efficiency category. Table 3 presents the final input and output variables selected for analysis. Buses held, Total staff and Total cost incurred by the DMU in a year were used as the input variables across benchmarking categories. Buses held and total staff are physical measures of a DMU while the total cost indicates the Capital and Operational expenditure. Effective kilometers of services delivered was shortlisted as the output variable for service supply while the total passenger kilometers travelled was shortlisted as the output measure of service consumption. Total revenue earned by the DMU was identified as the output variable to benchmark revenue efficiency. Table 4 presents the data for these variables for the eight DMUs over the seven year analysis period of 2009-10 to 2015-16 (CIRT, 2011; 2012; 2013; 2014) (MoRTH, 2015; 2016; 2017).

Table 3. Input and Output variables used for DEA

S.no	Input Variables	Output Variables		
		Supply	Consumption	Revenue
1.	Buses held	Effective kilometers	Passenger kilometers	Total revenue
2.	Total staff			
3.	Total cost			

Table 4. Collected data for envelopment analysis

DMU	Year	Input variables			Output variables (millions)		
		Buses held	Staff size	Total cost (₹)	Effective km	Passenger-km	Total revenue (₹)
BMTC	2009-2010	5715	30996	10665.852	441.755	17853.455	11317.114
	2010-2011	6110	32953	12771.981	458.02	20102.498	13275.48
	2011-2012	6091	32300	14816.969	465.52	21147.919	15031.123
	2012-2013	6330	34273	18080.043	463.838	1768.675	16604.558
	2013-2014	6603	36054	21615.39	479.59	20739.15	20139.422
	2014-2015	6649	36474	23217.481	470.855	21725.39	22568.443
	2015-2016	6448	35554	21937.573	336.079	15647.842	22074.839
CSTC	2009-2010	978	6719	2245.967	39.876	1912.8	1881.047
	2010-2011	956	6102	2514.274	34.858	1210.8	654.141
	2011-2012	839	5813	2338.896	29.488	1199.6	616.303
	2012-2013	779	5485	2185.394	26.037	107.72	704.371
	2013-2014	718	5059	2305.252	21.57	1012	619.76
	2014-2015	813	4998	4323.608	28.263	765.294	3580.866
	2015-2016	782	4799	3991.58	20.766	630.6	2737.544
MTC	2009-2010	3210	23000	9087.101	332.929	19468.839	8109.957
	2010-2011	3414	23500	11515.853	347.153	21796.336	9202.018

	2011-2012	3444	22146	12986.384	351.149	21324.943	10488.936
	2012-2013	3585	23519	13549.396	344.274	1754.435	12568.025
	2013-2014	3666	23982	15314.308	360.043	19216.87	13605.34
	2014-2015	3787	25219	17235.678	351.468	18996.3	13308.877
	2015-2016	3832	24930	18044.847	353.523	19086.8	13048.102
DTC	2009-2010	3845	29495	26193.709	209.2	8492.375	5766.428
	2010-2011	5765	35557	33221.134	292.228	13040.882	9869.886
	2011-2012	6078	40721	37118.796	374.029	9023.697	12808.057
	2012-2013	5603	34376	42647.21	353.568	1075.353	13503.168
	2013-2014	5341	35503	25962.005	316.521	15542.679	12324.597
	2014-2015	4977	32864	51013.328	287.098	11018.687	11098.667
	2015-2016	4564	30527	57009.114	267.35	10579.387	10049.879
AMTS	2009-2010	966	5592	2368.532	50.7255	2114.95	1177.033
	2010-2011	942	5274	2300.869	52.505	2102.1	1089.058
	2011-2012	985	4715	2605.44	48.946	2128.8	1196.175
	2012-2013	1120	5428	3300.97	54.106	239.597	1432.761
	2013-2014	1036	5225	3739.094	54.182	1535.2	1536.879
	2014-2015	946	5503	3768.47	53.18	1585.16	1302.854
	2015-2016	993	5498	4069.058	58.031	1790.219	1303.97
BEST	2009-2010	4078	29750	14315.525	252.407	12756.596	9266.689
	2010-2011	4652	30183	14941.642	261.517	12307.1	11127.817
	2011-2012	4669	36028	17093.669	255.53	12335.26	13176.375
	2012-2013	4259	36796	20321.438	265	1409.6	13986.396
	2013-2014	4314	36610	22158.48	254.93	9843.2	14351.038
	2014-2015	4247	35705	23676.728	243.826	9071.596	15096.552
	2015-2016	4094	34174	25157.009	234.399	7348.993	14537.774
CHNTU	2009-2010	409	2096	1373.775	40.91	1881.86	982.612
	2010-2011	471	2136	1490.584	43.947	2021.562	1114.84
	2011-2012	493	2055	1620.023	42.639	1961.4	1182.075
	2012-2013	472	1921	1774.53	37.316	67.16	1143.478
	2013-2014	468	1826	1755.198	35.442	1541.92	1043.016
	2014-2015	432	2102	1806.691	33.568	1544.1	1110.708
	2015-2016	494	1967	2051.943	39.487	1597.5	1340.527
PMPML	2009-2010	1620	10294	4272.009	108.323	4109	3865.02
	2010-2011	1562	9780	4324.008	103.202	3639.5	4185.293
	2011-2012	1634	9633	4704.1	100.33	3436.986	4254.6
	2012-2013	1832	11385	5952.349	105.61	460.488	4940.56
	2013-2014	1841	10466	7020.325	109.679	4476.558	6026.25
	2014-2015	2087	10186	8750.659	114.672	4939.986	7073.793
	2015-2016	2075	9945	18044.847	114.616	4949.825	7767.524

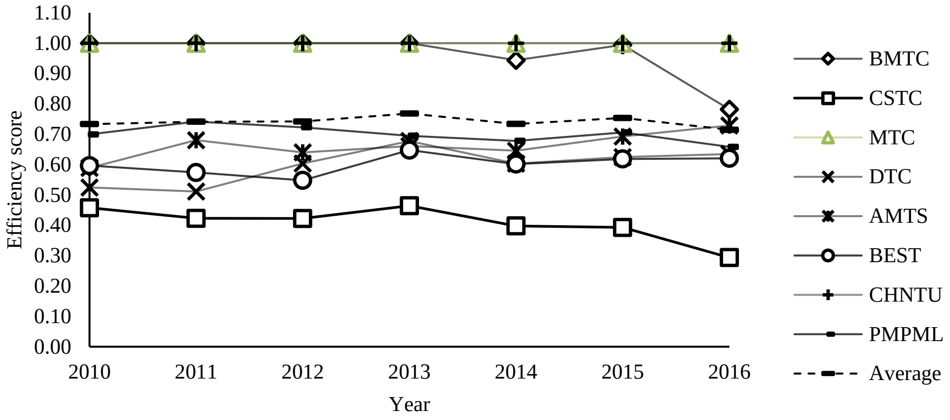

Figure 1. Yearly variation of supply efficiencies of all STUs

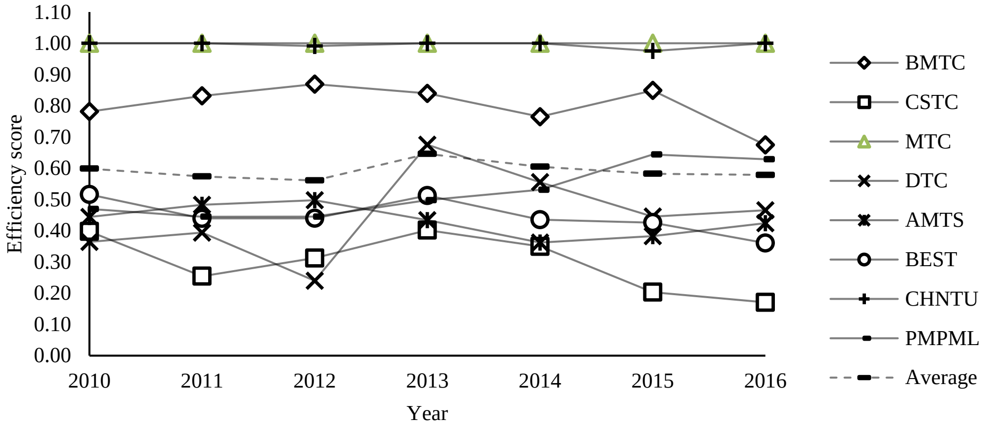

Figure 2. Yearly variation of consumption efficiencies of all STUs

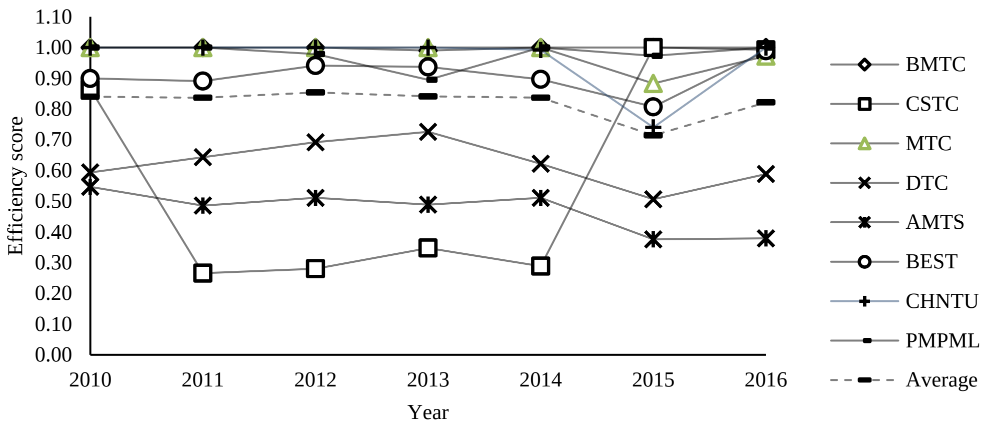

Figure 3. Yearly variation of revenue efficiencies of all STUs

Table 5. Percentage of resources that can be reduced based on category

DMU	Year	Supply			Consumption			Revenue		
		Buses held	Staff size	Total cost	Buses held	Staff size	Total cost	Buses held	Staff size	Total cost
BMTC	2009-10	0%	0%	0%	48%	32%	22%	0%	0%	0%
	2010-11	0%	0%	0%	48%	34%	17%	0%	0%	0%
	2011-12	0%	0%	0%	44%	32%	13%	0%	0%	0%
	2012-13	0%	0%	0%	37%	23%	16%	25%	9%	1%
	2013-14	26%	11%	6%	40%	28%	24%	0%	0%	0%
	2014-15	24%	7%	1%	35%	21%	15%	0%	0%	0%
	2015-16	51%	43%	33%	43%	33%	33%	0%	0%	0%
	Average	***14%***	***9%***	***6%***	***42%***	***29%***	***20%***	***4%***	***1%***	***0%***
CSTC	2009-10	54%	59%	54%	68%	66%	60%	14%	22%	14%
	2010-11	58%	60%	58%	80%	79%	75%	73%	75%	73%
	2011-12	58%	66%	58%	77%	79%	69%	72%	77%	72%
	2012-13	54%	65%	54%	70%	72%	60%	74%	76%	65%
	2013-14	69%	72%	60%	73%	75%	65%	72%	78%	71%
	2014-15	61%	61%	67%	81%	80%	84%	0%	0%	0%
	2015-16	83%	83%	85%	0%	0%	90%	1%	15%	1%
	Average	***62%***	***67%***	***62%***	***64%***	***64%***	***72%***	***44%***	***49%***	***42%***
MTC	2009-10	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2010-11	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2011-12	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2012-13	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2013-14	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2014-15	0%	0%	0%	0%	0%	0%	12%	22%	12%
	2015-16	0%	0%	0%	0%	0%	0%	3%	20%	3%
	Average	***0%***	***0%***	***0%***	***0%***	***0%***	***0%***	***2%***	***6%***	***2%***
DTC	2009-10	48%	51%	78%	64%	66%	85%	41%	45%	75%
	2010-11	49%	49%	71%	61%	61%	77%	36%	36%	69%
	2011-12	40%	42%	63%	76%	77%	85%	31%	34%	57%
	2012-13	32%	32%	66%	32%	32%	67%	27%	27%	64%
	2013-14	40%	41%	48%	44%	45%	52%	38%	39%	47%
	2014-15	38%	38%	72%	56%	55%	80%	49%	53%	74%
	2015-16	53%	55%	82%	53%	55%	82%	41%	58%	59%
	Average	***43%***	***44%***	***69%***	***55%***	***56%***	***75%***	***38%***	***42%***	***64%***
AMTS	2009-10	41%	41%	41%	63%	56%	56%	45%	45%	45%
	2010-11	32%	32%	32%	65%	57%	52%	56%	51%	51%
	2011-12	38%	36%	36%	65%	53%	50%	50%	49%	49%
	2012-13	48%	34%	34%	66%	57%	57%	62%	51%	51%
	2013-14	42%	35%	35%	68%	64%	64%	55%	49%	52%
	2014-15	39%	31%	31%	67%	62%	62%	62%	63%	62%
	2015-16	63%	58%	58%	63%	58%	58%	62%	63%	62%
	Average	***43%***	***38%***	***38%***	***65%***	***58%***	***57%***	***56%***	***53%***	***53%***
BEST	2009-10	40%	41%	52%	48%	49%	58%	10%	12%	27%
	2010-11	43%	43%	43%	58%	56%	56%	11%	11%	17%
	2011-12	45%	55%	45%	57%	64%	56%	6%	23%	6%
	2012-13	35%	51%	49%	49%	61%	59%	6%	29%	26%
	2013-14	40%	54%	51%	56%	66%	65%	10%	31%	27%
	2014-15	38%	51%	49%	57%	66%	65%	19%	41%	23%
	2015-16	64%	72%	72%	64%	72%	72%	1%	39%	1%
	Average	***44%***	***52%***	***52%***	***56%***	***62%***	***62%***	***9%***	***27%***	***18%***

CHNTU	2009-10	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2010-11	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2011-12	0%	0%	0%	36%	1%	26%	0%	0%	0%
	2012-13	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2013-14	0%	0%	0%	0%	0%	0%	32%	1%	31%
	2014-15	0%	0%	0%	29%	2%	22%	41%	26%	26%
	2015-16	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Average	***0%***	***0%***	***0%***	***9%***	***0%***	***7%***	***10%***	***4%***	***8%***
PMPML	2009-10	30%	30%	30%	57%	53%	53%	0%	0%	0%
	2010-11	26%	27%	26%	64%	60%	56%	0%	0%	0%
	2011-12	28%	30%	28%	66%	63%	56%	2%	6%	2%
	2012-13	31%	34%	31%	57%	55%	50%	23%	19%	11%
	2013-14	39%	30%	34%	51%	47%	47%	0%	0%	0%
	2014-15	29%	29%	30%	53%	36%	49%	23%	3%	3%
	2015-16	37%	37%	69%	37%	37%	69%	0%	0%	0%
	Average	***31%***	***31%***	***35%***	***55%***	***50%***	***54%***	***7%***	***4%***	***2%***

The efficiency scores of various DMUs for the three categories of analysis across the seven years analysed are presented in Table 5. Bus services Bangalore, Chandigarh and Chennai were observed to perform the best across categories. Among the less efficient DMUs, Kolkata had the least efficiency across categories, followed by Ahmedabad and Delhi. Amongst the three categories of efficiency analysed, cities performed best on revenue efficiency with an average efficiency of 0.82 across cities. This was followed by supply efficiency with an average efficiency of 0.74 while the consumption efficiency had the least value of 0.59. These values indicate the significant potential for improvement in consumption efficiency in Indian city bus services. Further, the slack analysis was carried out for the eight DMUs to identify the potential reduction of resources required to improve their efficiency performance. Since input oriented DEA was adopted for the study, the analysis gives the reduction potential for each input variable. Table 6 presents the percentage reduction potential of each input variable for various DMUs and years of analysis. Across DMUs, the input resources for consumption efficiency have the maximum potential for reduction which can be attributed to the lowest efficiency performance in this category. However, the reduction potential between input variables within categories were relatively similar.

Since the same set of input variables were used across the three categories of efficiencies and the slack values of the input variables within each category are relatively similar, it can be inferred that analysing the output variables are the key to understanding the difference in efficiency values between the categories of measurement. Therefore increasing the passenger-km of ridership for a given service is the key to improving consumption efficiencies. Many previous studies highlighted the lack of adequate public transport in Indian cities (Tiwari, 2002) (Badami & Haider, 2007; Gadepalli, 2016; Pucher, Korattyswaropam, Mittal, & Ittyerah, 2005). Low consumption efficiencies, even in cities with good supply efficiencies and high latent demand for public transport indicate that the buses don’t serve the high demand areas and peak demand hours in cities. There exists a need for improved service planning in Indian cities to improve their consumption efficiencies.

4.1 External factors

The DEA analysis identified the relative performance of DMUs representing various Indian cities and the improvements needed in various internal factors like input variables to improve their efficiency. Additionally, it is also necessary to analyse the impact of various external factors that impact the performance efficiency of buses. These include variables representing socio-economic and mobility characteristics of the users, the land-use and economic development pattern of the city etc. (Daraio et al., 2016). The data available on external factors likely to impact bus systems efficiency is limited. Table 1 presents the few key data points available through (Census, 2012) and (ISB, 2017). The variables shortlisted for analysis include city population, area, urban population density, Average Trip Length, Trip Distribution (0 - 5 km, 5-10 km, 10-30 km), mode share of buses in the city, Gross Domestic Product (GDP) of the city and its economic score calculated as a function of the . A regression based analysis was carried out to establish correlation between the performance efficiencies of DMUs and the external factors identified. Since the data was available only for the year 2011, the regression analysis was restricted to the efficiency scores of that year. The findings for each category of efficiencies is explained below.

4.1.1. Service supply efficiency Vs city size

The size of a city was considered as a key external variable impacting service supply efficiencies of bus systems. Population and city area were taken as the proxies to represent city size. Population exhibited a significant correlation with efficiency and has a negative relationship (Figure 4), indicating that the service supply efficiency reduces with increasing population. Even area of city exhibited a negative relationship, even though the correlation was much lower (Figure 5). Both the findings imply that the Indian bus systems aren't scaling up adequately with increasing city size.

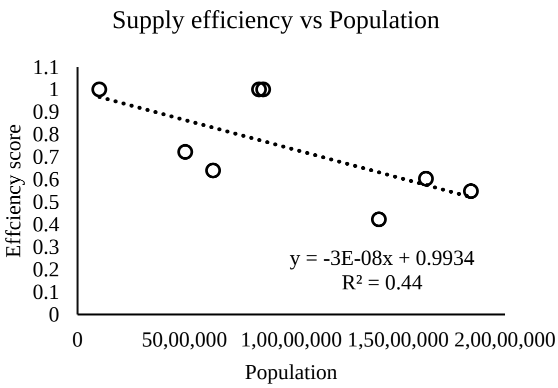

Figure 5. Relationship between supply efficiencies and population of the city

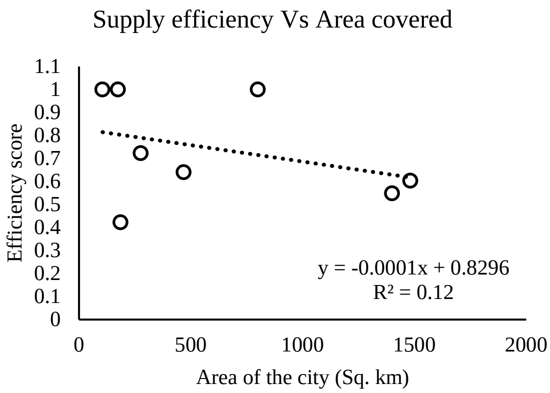

Figure 4. Relationship between supply efficiencies and area of the city

4.1.2. Service consumption Vs land-use development characteristics

(Booz, Allen, & Hamilton, 2003) identify land-use development characteristics as one of the key determinants of travel demand elasticities of public transport. Therefore, population density and trip length characteristics of the eight case cities have been regressed against their service consumption efficiencies to understand their level of correlation. Additionally, the buses per million population was also tested for correlation with supply efficiency. Figure 6 to Figure 9 present the findings corresponding to this analysis. Population density and average trip length of the city were found to have negligible correlation with the consumption efficiencies of bus systems. However, a further disaggregation of tri length characteristics revealed that the variable-proportion of trips of length between 5-10 km, was observed to have significant positive correlation with consumption efficiency. Even buses per million population exhibited significant positive correlation with consumption efficiency. It can be concluded that cities with high share of trips in the category of 5-10 km and more availability of buses are likely to have a higher bus consumption efficiency.

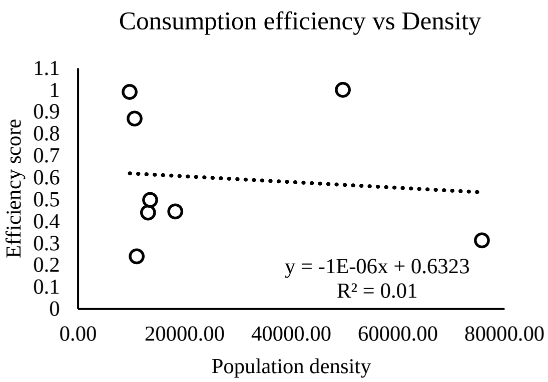

Figure 6. Consumption efficiencies compared against density of a city

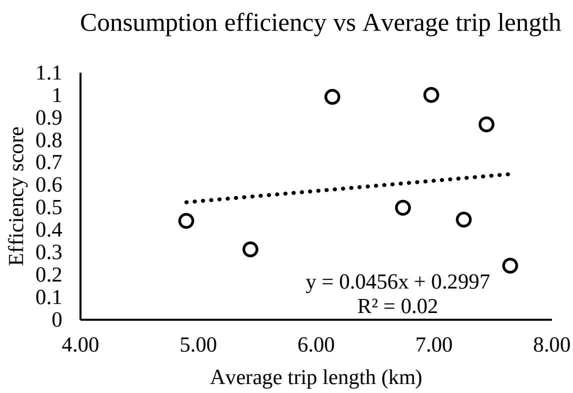

Figure 7. Consumption efficiencies compared against avg. trip length in a city

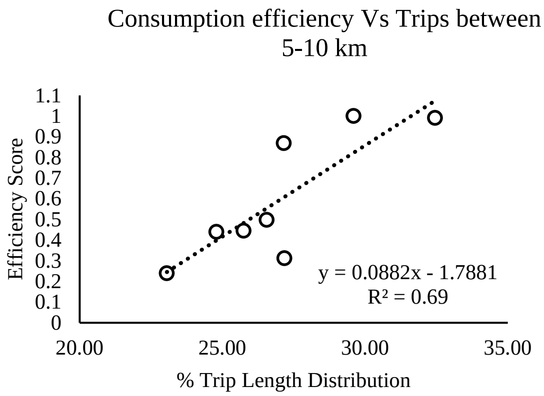

Figure 8. Consumption efficiencies compared against % trip length distribution (5-10 km)

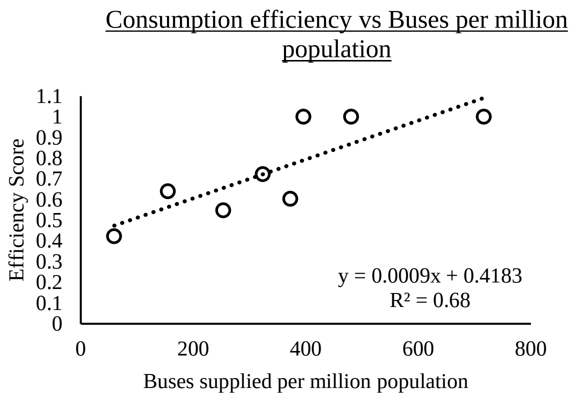

Figure 9. Consumption efficiencies compared against buses supplied per million population

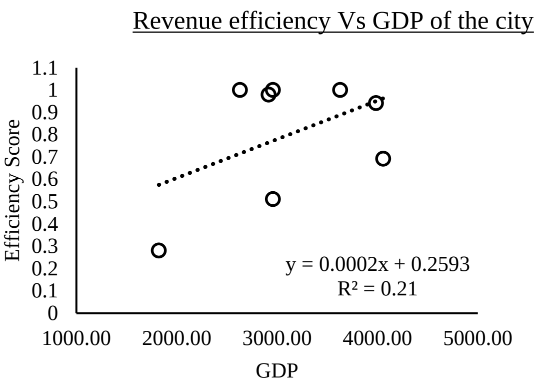

Figure 10. Revenue efficiencies compared against GDP of a city

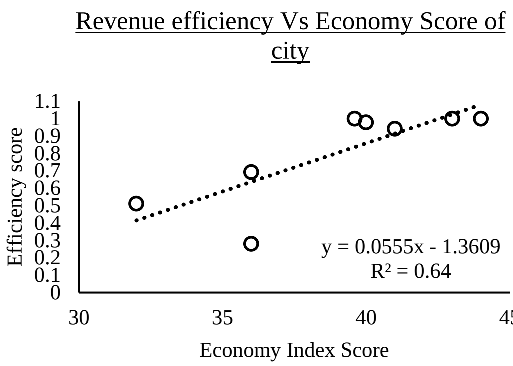

Figure 11 Revenue efficiencies compared against economic index scores

4.1.3. Revenue efficiency Vs Economic performance of a city

The revenue efficiencies of the case cities was correlated with economic indicators of a city to test if the overall economic wellbeing of a city also results in improved revenue efficiency for the bus system The Gross Domestic Product (GDP) of the city and a composite economic score derived from proxy indicators like employment levels, equity and growth of new businesses (ISB, 2017). Figures 10 and 11 present the findings of the analysis. Both the indicators were observed to have a significant correlation and a positive relationship, inferring that improving economic situation of a city is likely to have a positive impact on the revenue efficiency of the bus systems as well.

5. Conclusions

The article presents a comprehensive analysis of the performance of Indian city bus systems and the key internal and external variables that impact their performance. A DEA based analysis was used to benchmark State Transport Undertakings (STUs) providing city bus services across eight cities over a period of seven years between 2009-10 and 2015-16. Each STU was considered as a DMU for DEA analysis. The key internal variables impacting performance of STUs were shortlisted based on data availability and sensitivity analysis between various variables identified from literature. An input oriented DEA analysis was carried to measure service supply, service consumption and revenue efficiency of the eight case cities, considering each STU as a DMU. Slack analysis was carried out to determine the reduction potential for each input resource. The key external variables likely to impact these efficiencies were identified from literature. Secondary data for these variables was collected for the eight cities and tested for correlation with various categories of performance efficiencies corresponding to the city.

Buses held, Total staff and Total cost incurred on bus service provision were identified as the key input variables for all categories of efficiency measurement. Effective kilometers, Passenger kilometers and Total revenue were derived to be the variables to measure service supply, service consumption and revenue performance of the bus systems. The DEA analysis revealed that Indian bus systems perform best on revenue efficiency with an average efficiency of 0.82 across STUs, followed by an average supply efficiency of 0.74. The consumption efficiency of STUs was the least performing category with an average efficiency of only 0.59 i.e. the input resources for service consumption can be brought down by 41% for the STUs to continue performing at the same level. These findings, where compared with the literature indicating high unmet public transport demand in Indian cities leads to the conclusion that the bus operations aren't well aligned with travel patterns of users. This further highlights the need for improved service panning that adequately incorporates the travel demand patterns in cities. Chennai (MTC) and Chandigarh (CHNTU) were observed to be the most efficient cities over the years, while Kolkata (CSTC) was the least efficient STU. The specific reduction potential for each input resource were derived for all the STUs using slack analysis.

The correlation analysis of various categories of efficiencies with external variables has shown some revealing results. Supply efficiency of STUs is negatively correlated with city size variables implying that performance efficiency drops with increasing size of city. The consumption efficiency was positively correlated with percentage of trips between 5-10 km in length and the number of buses in the city per million inhabitants. This implies the need to update operations such that trips are performed in areas with the highest likely demand. The positively correlation between number of buses per million inhabitants shows that overall consumption efficiency increases with increasing the overall supply of buses. Revenue efficiency was positively correlated with the GDP of the city and its economic score, implying that STUs perform better as the overall economic strength of the city improves.

The analysis from the article can inform future studies on performance efficiency measurement of bus systems in India and other similar developing countries. The analysis can be taken forward by implementing the proposed methodology in various use cases at the city level i.e. to derive a disaggregated assessment of their route and/ or depot level efficiency, potential for resource optimisation and impact of external variables impacting bus efficiency.

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