Civil Engineering and Architecture 12(5): 3512-3529, 2024 http://www.hrpub.org
DOI: 10.13189/cea.2024.120528

Evaluating Public Transport Efficiency: A Cross-Regional SFA Approach

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Received April 27, 2024; Revised June 29, 2024; Accepted July 21, 2024

Cite This Paper in the Following Citation Styles

(a): *[1] P. Praveen Kumar, Varghese George, Raviraj H. Mulangi, Akash S. Khandri , "Evaluating Public Transport Efficiency: A Cross-Regional SFA Approach," Civil Engineering and Architecture, Vol. 12, No. 5, pp. 3512 - 3529, 2024. DOI: 10.13189/cea.2024.120528.*

(b): *P. Praveen Kumar, Varghese George, Raviraj H. Mulangi, Akash S. Khandri (2024). Evaluating Public Transport Efficiency: A Cross-Regional SFA Approach. Civil Engineering and Architecture, 12(5), 3512 - 3529. DOI: 10.13189/cea.2024.120528.*

Abstract Bus-based public transport systems are considered to provide affordable means of transport to trip-makers in urban and rural areas. Consequently, public transport organizations are prone to losses since these agencies focus on providing mobility to people on commercially viable routes while providing accessibility and mobility to underdeveloped remote regions. The primary objective of this study was to effectively use a parametric approach, such as Stochastic Frontier Analysis (SFA), in the evaluation of the performance of public transport organizations operating in India. The present study employed nine key performance indicators (KPIs) to evaluate 31 State Road Transport Undertakings (SRTUs) in India over a period of seven years (2010-2017). The nine KPIs, such as total cost, staff, fleet, fuel, capacity-km, effective-km, passenger-km, revenue, and passengers carried, were used to develop three performance measurement categories: *cost efficiency*, *cost-effectiveness*, and *service effectiveness*. After developing 29 initial models, the best ones were selected based on Akaike's Information Criterion (AIC) and Bayesian Information Criteria (BIC), and performance evaluation of SRTUs was carried out with the SFA approach using the Cobb-Douglas production function. The study revealed that the top 25 percentile of best-performing SRTUs in terms of *cost-efficiency* were those serving rural areas with average efficiency scores higher than 0.7668. Similarly, in terms of *cost-effectiveness*, it was observed that the best-performing SRTUs comprised a mix of both rural and urban SRTUs with average efficiency scores higher than 0.9156. Also, in terms of *service-effectiveness*, the best-performing SRTUs included buses operated mainly in urban areas in addition to a few serving hilly and rural areas with average efficiency scores higher than 0.6509. The findings of this study provide insights into the performance of SRTUs in India and highlight the importance of using KPIs to evaluate and improve their performance. This study also demonstrates the effectiveness of using the SFA in the performance evaluation of public transport organizations, especially when the data related to the KPIs are partially inconsistent. This is due to the facility that permits the formulation of a production function that assists in identifying random errors, allowing the replacement of erroneous data.

Keywords Stochastic Frontier Analysis, Performance Evaluation, Parametric Approach, Public Bus Transport, Efficiency and Effectiveness

1. Introduction

Bus transit is one of the most frequent modes of transit in several countries. The important factors influencing commuters include travel time to reach their destinations, the affordability of the cost of travel, comfort, and safety. In a number of developing nations, the public transport sector has failed to satisfy the increasing travel demand and expectations of travelers. Moreover, the inability of public transportation undertakings to provide enhanced levels of service using modern technology has resulted in stagnant ridership and poor performance levels. On the other hand, there has been a surge in the dependence on personal modes of transport, resulting in increasing delays, traffic congestion, air pollution, and noise pollution, all of which have a detrimental influence on the environment, health, and safety.

One of the basic approaches to improving the public transport sector lies in ensuring efficiency and effectiveness at all levels of functioning. Evaluation of efficiency is of critical importance to public transport operators, while the analysis of effectiveness is necessary to ensure that a larger section of commuters is benefitted. However, the evaluation of efficiency and effectiveness that involves a number of variables in the transport sector is a complex exercise. Additionally, in the transportation sector, it is difficult to precisely quantify the amount of resources required to satisfy the travel demand while ensuring efficiency in operations.

Statistical approaches such as AIC and BIC can be employed to determine the important variables that influence the performance of organizations. The analysis of efficiency and effectiveness in complex operating conditions can be performed using a parametric approach such as the *Stochastic Frontier Analysis* (SFA), where the efficiency frontier can be modeled using the Cobb-Douglas production function. The SFA considers the effect of random error in the analysis of inefficiencies [1].

The present study incorporates the application of the SFA approach in evaluating the efficiency and effectiveness of bus transport organizations in India. This method has been widely employed in various contexts to assess efficiency and productivity. For instance, Couto and Graham [2] applied SFA to European railway systems, highlighting the significant role of allocative inefficiency, while Zhang [3] evaluated rail transit organizations in China with a focus on operational efficiency and Service effectiveness. The framework of the present study will be of advantage to transport managers in optimizing the deployment of resources, and in the improvement of bus services in rural, urban, and hilly areas of the region. The findings of this study will assist in identifying critical areas of operation that need special attention.

The study also demonstrates the effectiveness of using the SFA in the performance evaluation of public transport organizations, especially when the data related to the KPIs are partially inconsistent. This is due to the facility that permits the formulation of a production function that assists in identifying random errors, allowing the replacement of erroneous data.

2. Literature Review

Several parametric and non-parametric methods are adopted to measure the efficiency of transport operators. Murillo-Zamorano and Vega-Cervera [4] discussed the merits and demerits of parametric and non-parametric approaches to measure the productive efficiency of an industrial sector. Ayadi and Hammami [5] compared both parametric and non-parametric approaches for evaluating the efficiency of the public transport system in Tunisia. These comparative studies between parametric and non-parametric methods indicated that the parametric approach could be considered ideal while handling data that involves random errors in measurement, data collection, and processing, as in the case of sample surveys. One of the advantages of the parametric approach, such as the SFA, is that it permits the formulation of a production function that assists in determining the random errors and the inefficiency distinctively. On the other side, non-parametric approaches do not incorporate such flexibilities.

One of the pioneering studies on the application of the SFA approach was demonstrated by Aigner et al. [6] in computing the inefficiencies in the US Primary Metals industry based on data for the period 1957-58 and also in determining inefficiencies in the US Agricultural sector for the period 1960-65. In these studies, the cross-sectional data was used in the analysis, followed by the computation of random errors and inefficiency. It was assumed in this study that the inefficiencies are half-normally distributed while the random errors are normally distributed.

Similarly, Battese and Coelli [7] proposed the application of the SFA approach in computing the inefficiencies involved in paddy production for selected villages in India based on panel data spread over 10 years. Here, the truncated normal distribution was assumed in the computation of the inefficiencies. Additionally, Battese and Coelli [8] also performed studies on inefficiencies in agricultural production in India, considering factors such as age, years of formal schooling of farmers, and the number of years of observation made by farmers on crop productivity.

Literature related to the application of SFA in the field of performance evaluation of transport services started appearing in the late 1990s. Parisio [9] performed studies on the evaluation of cost-efficiency of eight important European railroad organizations, out of which four were very large organizations for the period 1973–89. Measures of technical efficiency were computed based on a stochastic trans-log cost function.

Cullinane et al. [10] conducted investigations on the technical efficiency of the world's top 30 ranked container ports using the DEA and the SFA methods. However, the application of the two approaches revealed that there was a high degree of correlation in the results and that the estimated efficiency values were almost comparable. Similar comparative studies were performed by Ayadi and Hammami [5] on the application of an SFA and DEA in the evaluation of efficiencies in 12 regional transport organizations in Tunisia for a period of 10 years between

2000 and 2009. The DEA, a non-parametric approach, focused on studies related to maximizing the production for a given fixed cost, while the parametric approach based on the SFA enabled the computation of inefficiencies in the system. The analysis indicated that the existing functioning of public transport organizations in Tunisia was inefficient.

Couto and Graham [3] conducted studies on the efficiency and productivity of European railways based on data from 1972 to 1999. The analysis using the SFA approach was performed using a trans-log cost function to identify the technical and allocative efficiency of the overall productivity. The study revealed that the excessive capacity and over-employment of labor inputs contributed to *cost efficiency*. In Sweden, Holmgren [11] performed studies on the application of the SFA in the computation of efficiency in public transport operations in various counties during 1986-2009. The study considered the influence of capital, labor, and fuel on passenger trips produced and revenue generated. A trans-log cost function was formulated to compute the *cost efficiency* of public transport organizations. The analysis performed also facilitated the ranking of Swedish public transport organizations. The study indicated that the efficiency of the public transport organizations showed a decreasing trend across all counties during the time period.

Sami et al. [12] performed studies on the measurement of technical efficiencies of 64 public road transport operators in 18 countries for a period of twelve years from 2000 to 2011. In this study, the influence of input variables, such as the total operation cost and the number of employees, was measured on the output variable revenue generated. The analyses were performed using the trans-log cost function in addition to the Cobb-Douglas function, while the tests for hypotheses were performed using the generalized likelihood-ratio statistic. The results indicated that the trans-log cost function was more suitable for determining the efficiencies in the public transport sector.

Zhang [3] performed studies on analyzing the operating efficiencies and *Service effectiveness* of rail transit organizations in 36 large and medium-sized cities in China for the period between 2010 and 2013 using the SFA. The trans-log cost function was used in this study, which incorporated information on passengers carried by rail in addition to external environmental variables such as the extent of urbanization and the mode share of rail transit. The study indicated that urbanization had a positive influence on improving the operating efficiencies of rail transit, although it resulted in a reduction in the *Service effectiveness*. Also, it was observed that larger cities with more than 10 million population had higher operating efficiencies when compared to smaller cities.

Matulov á and Rejentov á [13] performed investigations on the efficiency of 115 airports in Europe using the DEA and the SFA for the year 2018. Analysis using the SFA was performed with the Cobb-Douglas production function considering input variables such as the number of airport terminals, runways, boarding gates, and aircraft stands, and output variables such as passengers handled, aircraft movements, and cargo handled. The study indicated that there was a strong correlation between the conclusions arrived at based on the SFA and the DEA methods.

The above review of the literature indicates that although there exist a number of studies related to the computation of efficiencies using the SFA method in general since 1977, the application of this approach in the field of public transport has not been adequately explored. Our study builds on these findings by applying SFA to a diverse set of SRTUs in India, encompassing rural, urban, and hilly regions. The present study focuses on the application of the SFA in the analysis of the performance of 31 SRTUs operating in urban, rural, and hilly regions in India. The nine performance indicators used in this study were selected from performance measures classified under *cost efficiency, cost-effectiveness,* and *service-effectiveness* by Fielding et al. [14] for public transport organizations.

3. Theoretical Aspects of Stochastic Frontier Analysis

The SFA method uses a standard production function to determine the efficient frontier. According to Hackman [15], a production function f(x) refers to the maximum output that can be achieved using an input vector $X = (x_1, x_2,..., x_n)$ representing the factors of production. The outputs refer to the number of units of the commodity produced. The maximum efficiency can then be estimated based on the input and output variables. This approach can be used to measure the technical efficiency. The technical efficiency refers to the maximum output that can be produced for a given combination of input factors.

Early SFA models proposed by Aigner et al. [6] and Meeusen and van den Broeck [16] were classified as stochastic frontier models. In these studies, cross-sectional data was used where the values of a number of variables at a particular time period were considered. Pitt and Lee [17] introduced SFA models that utilized panel data, where the values of a number of variables spread over various time periods were used.

Battese and Coelli [7] defined a stochastic production frontier function model for panel data in which technical efficiencies of hypothetical firms were computed using the SFA model. A similar work was performed by Battese and Coelli [8], where it was indicated that the inefficiency effects were stochastic in nature. The expression for the SFA production function is given as follows [7]:

$$Y_{it} = f(x_{it};\beta) . \exp(V_{it} - U_{it}) \tag{1a}$$

and

$$U_{it} = \eta_{it} U_i \tag{1b}$$

where Y_{it} = output of the i^{th} decision-making unit for the

t^{th} period; x_{it} = an input vector of the i^{th} decision-making unit for the t^{th} period; β = a vector of unknown parameters; $f(x_{it};\beta)$ = a suitable cost function of x_{it}, and β; V_{it} = a normally distributed $N(0, \sigma_v^2)$ noise term (or random error) for the t^{th} period; U_{it} = a half normally distributed technical inefficiency term for the positive half denoted as $N^+(0, \sigma_u^2)$ for the t^{th} period; and η_{it} = scalar parameter expressing the time variation of inefficiency.

The cost function can be expressed as [7],

$$f(x_{it};\beta) = \exp(\beta_0)\,(x_{ik})\,\beta_k \tag{1c}$$

where x_{ik} = an input vector of the i^{th} decision-making unit for the kth variable, β_0 = constant or intercept, and β_k = parameter coefficient (or input elasticities) of a k^{th} variable.

The log-transformation of the above function results in a log-linear function that takes the form of a Cobb-Douglas expression given as [4],

$$\ln(Y_{it}) = \beta_0 + \sum\beta_k \ln(x_{it}) + V_i - U_{it} \tag{1d}$$

where β_0 = constant or intercept and β_k = parameter coefficient of k^{th} variable; x_{it} = input value of the i^{th} decision-making unit for the t^{th} time period; V_i = noise term; and U_{it} = a half normally distributed technical inefficiency term for the positive half denoted as $N^+(0, \sigma_u^2)$ for the t^{th} period.

The technical inefficiency term (U_{it}) needs to be positive since it assumes to follow a half-normal distribution with the positive side of the normal [6]. Alternatively, U_i can also follow an exponential distribution [16], a gamma distribution [18], or a truncated normal distribution [19].

The technical efficiencies of decision-making units are calculated by estimating the parameters β_0, β_k (parameter coefficients of input variables), σ^2, γ, and η using the maximum likelihood estimation method, where $\sigma^2 = \sigma_u^2 + \sigma_v^2$; $\gamma = \sigma_u^2/\sigma^2$; σ_u^2 = standard deviation of technical inefficiency; and σ_v^2 = standard deviation of the noise term.

Battese and Coelli [7] observe that technical efficiency can be computed as the ratio of the observed mean production or output to the maximum possible mean production for the most efficient input allocation of resources. The observed output from the SFA approach includes the inefficiency, while in other forms of efficiency measurements, the inefficiency is not specifically computed. Based on studies made by Jondrow et al. [20] and Battese and Coelli [7], the expression for technical efficiency (or *cost efficiency*) was derived by Sami et al. [12] as:

$$\ln(TE_i) = [\beta_0 + \sum\beta_k \ln(x_{it}) + V_i - U_i] / [\beta_0 + \sum\beta_k \ln(x_{it}) + V_i] \tag{1e}$$

Thus,

$$TE_i = e^{-U_i} \tag{1f}$$

The SFA approach can be used to estimate the maximum production for a given production factor.

4. Study Area, Performance Indicators, and Data Collection

4.1. State Road Transport Undertakings (SRTUs)

Indian bus transport organizations operating in the public sector, commonly called SRTUs, provide transport services to trip-makers in rural, urban, and hilly terrains, serving a heterogeneous mix of populations with diverse socio-economic backgrounds. In the years 2015-16, there were 62 SRTUs operated by 24 road transport corporations, 12 public-limited companies, 10 municipal undertakings, and other government departmental undertakings [21] [22]. For the present study, thirty-one SRTUs were selected, considering the need to maintain consistency in the data available and the diversity in services offered to the country's urban, rural, and hilly terrains.

4.2. Identification of Key Performance Indicators (KPIs)

Earlier studies on performance evaluation of public transport organizations were based on individual indicators related to measures of efficiency and measures of effectiveness. Based on a study of the annual performance reports on the functioning of all SRTUs in India by the Central Institute of Road Transport (CIRT), data pertaining to the use of more than 50 performance indicators were reviewed for the period 2010-2017. Out of these, a set of 9 important indicators representing service inputs, service outputs, and service consumption as envisaged in the performance concept model proposed by Fielding et al. [14] were identified for the present study based on investigations made by a number of researchers [5], [11], [12], [23]–[26]. The variables such as total cost, staff strength, fuel consumed, and average fleet operated are examples of service inputs, while the carrying capacity km and effective km are examples of service outputs, and total revenue, passenger-km performed, and passengers carried are examples of service consumption. The *cost-efficiency*, also known as technical efficiency, is computed based on the service inputs and service outputs, whereas the cost-effectiveness is determined based on service inputs and service consumption. Similarly, the *Service effectiveness* is calculated based on service outcomes to service consumption.

4.3. Data Sources

In India, government-sponsored agencies such as the CIRT, Pune, and the *Transport Research Wing* of the MoRTH take responsibility for the performance evaluation of SRTUs. The SRTUs provide CIRT with periodic information on financial and physical performance. The data is scrutinized and compiled by CIRT and is then published in the form of quarterly and annual reports titled ‘State Transport Undertakings Profile and Performance’

[27].

Table 1 provides a summary of the values of nine important performance indicators identified for the present study on 31 SRTUs in India for the period 2010-17.

Table 1. Summary of Performance Indicators of SRTUs for 2010-17

Year	Parameters	Total Cost (TC)	Total Revenue (TR)	Effective km (EKM)	Average Fleet Operated (AFO)	Carrying Capacity km (CKM)	Passenger km (PKM)	Passengers Carried (PC)	Staff Strength (SS)	Fuel Consumed (FC)
2010-11	Mean	123880.1	105538.5	4711.595	3689.742	274631.7	183898.6	8100.364	22460.61	84742.8
	Std.Dev	144028	135801.4	6029.493	4593.055	319833.6	203788.4	9696.285	27180.56	107369.9
	Min	1162.3	231.12	10.3	26	287.8	187.5	1	324	345.25
	Median	106303.9	86438.15	3550.9	3078	228056	134796	4705	17586	66718.67
	Max	646307	614569.4	28958	21701	1462375	973944	46388	120566	456785
2011-12	Mean	22852.77	139417.3	4787.042	3739.290323	262036.9	8217.168	690.8387	182723.4	89632.05
	Std.Dev	27868.28	162709.6	6116.706	4632.2168	303473.1	10212.38	764.3009	207939.5	108744.9
	Min	307	1147.93	8.6	22	239.4	1	0	153.2	273.44
	Median	18214	117816	3740.3	3043	230650.3	4911	485	153630.9	73374.14
	Max	123615	726271.3	28714.9	21411	1433163	50014	3437	1001874	458163
2012-13	Mean	22741.68	157170	4876.327	3825.387	263747.5	7904.706	646.7419	180986.3	93564.54
	Std.Dev	27099.86	179927.3	6277.007	4795.738	307725.5	10299.72	706.3637	206508.1	113146.9
	Min	288	1401.2	7.13	19	192.51	2.74	0	164.78	226.88
	Median	18455	131424.4	3688.48	3050	236693.9	5265.34	417	167087	74508.24
	Max	122287	771990.1	29783	22402	1476933	51675	3078	1017163	481304
2013-14	Mean	31060.48	166030.7	4835.367	3836.196	260368.3	7791.857	649.9032	178128.8	92976.51
	Std.Dev	52016.44	181375.5	5906.514	4605.668	289154.4	10077.57	701.4526	185564.4	109952.9
	Min	276	1225.74	6.5	21	169.52	0.45	0	173.68	208.44
	Median	19128	145125.7	3667.69	3210	234474.6	5356	479	153731.8	74782.68
	Max	267723	744593	26226.18	20423	1299245	50380.25	3154	882461.3	433745.1
2014-15	Mean	21233.87	176125.9	4542.687	3576.877	263747.5	7013.141	553.2581	162564.5	93564.54
	Std.Dev	22134.99	177935.2	4951.121	3774.306	307725.5	7023.668	649.6266	150334.8	112737.7
	Min	286	1360.98	6.5	18	192.51	0.48	0	229.15	226.88
	Median	18412	154469.6	3712.74	3187	236693.9	5440	365	173098.1	74508.24
	Max	107500	764967	20848.56	16702.18	1476933	24556.91	3172	548032.3	481304
2015-16	Mean	20808.32	181171	4547.43	3555.419	253212	6862.841	585.3667	169373.7	90491.99
	Std.Dev	21642.04	180621.4	4970.576	3783.591	238653.6	6852.236	622.4018	163160.7	95340.39
	Min	270	1565.8	6.08	23	192.51	0.43	1	183.11	226.88
	Median	19163	160917.8	3535.23	3237	250415.5	5533.12	369.5	158480.9	83307
	Max	105679	746724.1	21066.38	16981	918189	24561	2920	639059	443747
2016-17	Mean	20230.52	199688.2	4611.677	3566.645	251082	6577.297	537.9032	169272.9	90596.25
	Std.Dev	20863.41	195691.6	5054.224	3847.587	241776.3	6480.501	581.3937	164790.4	94746.21
	Min	260	1493.36	7.08	23	174.17	0.5	0	128	189.26
	Median	17844	174674.3	3785.94	3242	241450.6	5562.03	300	158216	79158
	Max	103043	752070.4	20661.17	16834	895657	24017	2772	619334	436462

5. Result and Discussion

5.1. Formulation of Candidate Models and the Selection of the Best Models Using AIC and BIC

As mentioned in Table 1, the nine KPIs were used to formulate a set of preliminary models for the SFA approach. It may be observed that from the 9 KPIs, it is possible to study a number of combinations of various input-output variables to represent *cost-efficiency*, *cost-effectiveness*, and *Service effectiveness*. Models representing the best combination of KPIs were selected using the *Akaike information criterion* and the *Bayesian information criterion* scores. The AIC and BIC scores represent the relative amount of information lost by a given model with a particular set of independent variables. Lower values of AIC and BIC scores indicate that less information is lost when considering the set of independent variables [5]. This implies that the model is capable of providing a better fit between the dependent and the independent variable. The AIC and the BIC scores can be computed using the following expressions:

$$AIC = 2*k - 2*\log L(model) \tag{2a}$$

$$BIC = k*\ln(N) - 2*\log L(model) \tag{2b}$$

where, k = number of parameters estimated in the model, log L(model) = maximum log-likelihood value of the model obtained as part of the analysis, N = number of observations.

Based on the performance concept model proposed by Fielding et al. [14], five indicators among the nine KPIs could be used to develop *cost-efficiency* models. The KPIs used in this case consisted of two dependent variables (such as carrying capacity km and effective km) and three independent variables (such as total cost, staff employed, and average fleet operated). Thus, eight candidate models were required to be tested for *cost efficiency*.

Similarly, six indicators among the nine KPIs were used to develop *cost-effectiveness* models. The KPIs used in this case consisted of three dependent variables (such as *total revenue*, *passenger-km* performed, and *passengers carried*) and three independent variables (such as *total cost*, *staff strength*, and *average fleet operated*). Thus, twelve candidate models were required to be tested for *cost-effectiveness.*

Additionally, five indicators among the nine KPIs were used to develop *Service effectiveness* models. The KPIs used in this case consisted of three dependent variables (such as *total revenue*, *passenger km* performed, and *passengers carried*) and two independent variables (such as *carrying capacity km*, and *effective km*). Thus, nine candidate models were tested for *Service effectiveness*.

Thus, it was proposed to analyze the suitability of 29 log-linear candidate models consisting of 8 models for evaluating *cost efficiency*, 12 models for evaluation of *cost-effectiveness*, and 9 models for the study of *Service effectiveness* of SRTUs. The statistical soundness of these models was analyzed using the built-in functions "AIC" and "BIC" in R Studio [28]. Table 2 provides details on the formulation of the 29 candidate models, along with details on the AIC and BIC scores. The models with the lowest values of AIC and BIC scores were considered the best models for further analyses using SFA.

Among the models for evaluating cost efficiency, it can be observed that model 8, with effective km as the dependent variable and total cost and average fleet operated as the independent variables, can be selected for further analysis using the SFA approach based on the AIC and BIC values. Similarly, among the models for evaluating *cost-effectiveness*, it can be observed that model 18, with total revenue as the dependent variable and total cost and average fleet operated as the independent variables, can be selected for performance analysis using the SFA approach. Also, among the models for evaluating *service-effectiveness*, it can be observed that model 24, with total revenue as the dependent variable and effective km as the independent variable, was selected for performance analysis using the SFA approach.

Table 2. Preliminary Set of Models Formulated Using SFA and summary of AIC and BIC Scores

Model No.	Independent Variables			Dep. Variable	Proposed Model Structure	AIC	BIC
Cost efficiency Models							
Model 1	TC	SS	AFO	CKM	log(CKM) ~ log(TC)+log(SS)+log(AFO)	23.0134	46.6727
Model 2	TC	SS	AFO	EKM	log(EKM) ~ log(TC)+log(SSSS)+log(AFO)	-441.2809	-417.6216
Model 3	TC	SS	-	CKM	log(CKM) ~ log(TC)+log(SS)	83.0644	103.3438
Model 4	TC	SS	-	EKM	log(EKM) ~ log(TC)+log(SS)	-112.1554	-91.8760
Model 5	SS	AFO	-	CKM	log(CKM) ~ log(AFO) +log(SS)	29.2997	49.5791
Model 6	SS	AFO	-	EKM	log(EKM) ~ log(AFO) +log(SS)	-438.3375	-418.0581
Model 7	AFO	TC	-	CKM	log(CKM) ~ log(AFO) +log(TC)	21.2198	41.4992
Model 8	AFO	TC	-	EKM	log(EKM) ~ log(AFO) +log(TC)	-442.2174	-421.9380
Cost effectiveness Models							
Model 9	TC	SS	AFO	TR	log(TR) ~ log(TC)+log(SS)+log(AFO)	-188.0398	-164.3805
Model 10	TC	SS	AFO	PKM	log(PKM) ~ log(TC)+log(SS)+log(AFO)	234.8730	258.5323
Model 11	TC	SS	AFO	PC	log(PC) ~ log(TC)+log(SS)+log(AFO)	148.5282	172.1875
Model 12	TC	SS	-	TR	log(TR) ~ log(TC)+log(SS)	-121.6278	-101.3484
Model 13	TC	SS	-	PKM	log(PKM) ~ log(TC)+log(SS)	292.2722	312.5516
Model 14	TC	SS	-	PC	log(PC) ~ log(TC)+log(SS)	194.4600	214.7395
Model 15	SS	AFO	-	TR	log(TR) ~ log(AFO) +log(SS)	-141.5905	-121.3112
Model 16	SS	AFO	-	PKM	log(PKM) ~ log(AFO) +log(SS)	234.3836	254.6630
Model 17	SS	AFO	-	PC	log(PC) ~ log(AFO) +log(SS)	147.3530	167.6324
Model 18	AFO	TC	-	TR	log(TR) ~ log(AFO) +log(TC)	-187.8589	-167.5795
Model 19	AFO	TC	-	PKM	log(PKM) ~ log(AFO) +log(TC)	239.2664	259.5457
Model 20	AFO	TC	-	PC	log(PC) ~ log(AFO) +log(TC)	146.6964	166.9758
Service effectiveness Models							
Model 21	CKM	-	-	TR	log(TR) ~ log(CKM)	-1.7232	15.17629
Model 22	CKM	-	-	PKM	log(PKM) ~ log(CKM)	222.0330	238.9325
Model 23	CKM	-	-	PC	log(PC) ~ log(CKM)	196.6552	213.5547
Model 24	EKM	-	-	TR	log(TR) ~ log(EKM)	-178.8612	-161.9617
Model 25	EKM	-	-	PKM	log(PKM) ~ log(EKM)	199.9392	216.8386
Model 26	EKM	-	-	PC	log(PC) ~ log(EKM)	135.4805	152.3800
Model 27	EKM	CKM	-	TR	log(TR) ~ log(EKM)+ log(CKM)	-177.1015	-156.8221
Model 28	EKM	CKM	-	PKM	log(PKM) ~ log(EKM)+ log(CKM)	195.0035	215.2829
Model 29	EKM	CKM	-	PC	log(PC) ~ log(EKM)+ log(CKM)	137.4430	157.7223
CKM = *Carrying Capacity km*			EKM = *Effective km*		TR = *Total Revenue*		
TC = *Total Cost*			AFO = *Average fleet operated*		PKM = *Passenger km*		

5.2. Analysis Using the SFA for the Selected Performance Models

The best models representing *cost-efficiency*, *cost-effectiveness*, and *service-effectiveness* identified as model 8, model 18, and model 24, were then analysed using the SFA approach in the R-programming environment [28]. The results obtained are discussed in the following sections.

5.2.1. Interpretation of Statistical Analyses Performed as Part of SFA for the Best Models

The values of the dependent and independent variables for the best models identified in Table 2 for the 31 SRTUs were given as input as part of the analysis using the frontier module [29] in R-Studio for the SFA. For the best model of *cost-efficiency* identified as model 8, the details on the statistical summary obtained using the summary tools module in R-Studio are provided in Table 3a. In a similar manner, Table 3b and Table 3c provide details on the statistical summaries related to *cost-effectiveness* and *service-effectiveness*, respectively.

In Table 3a, with regard to the analysis of *cost-efficiency* (model 8), the value of the *intercept* of 0.77 for the model is reasonably small, indicating that there is a residual inefficiency that is not explained by the independent variables but needs to be considered in the model. It is also seen that the maximum log-likelihood estimate for the independent variable *average fleet operated* is 0.9 and has a computed p-value of the Z statistic denoted by Pr(>|Z|), which is less than 0.05. This indicates that the variable contributes significantly to the model. Also, the inefficiency term *sigmaSq* with a computed *p-value* less than 0.05 shows that the variation in inefficiency is not significant for the model. Additionally, the *gamma* coefficient with a computed *p-value* less than 0.05 indicates that the inefficiency distribution does not follow a half-normal shape and that it satisfies a fundamental requirement of the SFA model developed. The value of the parameter *time* is -0.01777, which shows that there is a decrease in efficiency scores from 2010 to 2016 which is significant as indicated by the *p-value* of less than 0.05.

In the case of Table 3b, with regard to the analysis of *cost-effectiveness* (model 18), the value of the *intercept* of 1.2 for the model is reasonably small, indicating that there is a residual inefficiency that is not explained by the independent variables but needs to be considered in the model. It is also seen that the maximum log-likelihood estimate for the independent variable *average fleet operated* is 0.44 and has a computed p-value that is less than 0.05. This indicates that the variable contributes significantly to the model. Also, the inefficiency term *sigmaSq* with a computed *p-value* less than 0.05 shows that the variation in inefficiency is not significant. Moreover, the *gamma* coefficient with a computed *p-value* less than 0.05 indicates that the fundamental requirement of the SFA model is satisfied. The value of -0.02 for the parameter *time* indicates that there was a slight decrease in the efficiency scores from 2010 to 2016. However, its computed *p-value* of around 0.07 indicates that this decreasing trend is not significant.

Similarly, with regard to the analysis of *service-effectiveness* (model 24), as provided in Table 3c, the *intercept* of 4.45 for the model is reasonably small, indicating that there is a residual inefficiency that is not explained by the independent variables but needs to be considered in the model. It is also seen that the maximum log-likelihood estimate for the independent variable *effective km* is 0.94 and has a computed p-value that is less than 0.05. This indicates that the variable contributes significantly to the model. Also, the inefficiency term *sigmaSq* with a computed *p-value* less than 0.05 shows that the variation in inefficiency is not significant. Moreover, the *gamma* coefficient with a computed *p-value* less than 0.05 indicates that the fundamental requirement of the SFA model is satisfied. The value of 0.088 for the parameter *time* indicates that there was a slight increase in the efficiency scores from 2010 to 2016. Its computed *p-value* of less than 0.05 indicates that this increasing trend is significant.

Table 3a. Statistical Summary Based on MLE Method: Cost-Efficiency Model

<table>
<tr><td colspan="7">Final maximum likelihood estimates</td></tr>
<tr><td></td><td>Estimate</td><td colspan="2">Std. Error</td><td>Z value</td><td colspan="2">Pr(>|Z|) or p-value</td></tr>
<tr><td>(Intercept)</td><td>0.775336</td><td colspan="2">0.274715</td><td>2.8223</td><td colspan="2">0.004768 **</td></tr>
<tr><td>Log(Average fleet operated)</td><td>0.904888</td><td colspan="2">0.031369</td><td>28.8462</td><td colspan="2">< 2.2e-16 ***</td></tr>
<tr><td>log(Total cost)</td><td>0.060303</td><td colspan="2">0.028083</td><td>2.1473</td><td colspan="2">0.031768 *</td></tr>
<tr><td>sigmaSq</td><td>0.705084</td><td colspan="2">0.182207</td><td>3.8697</td><td colspan="2">0.000109 ***</td></tr>
<tr><td>gamma</td><td>0.99561</td><td colspan="2">0.001264</td><td>787.7957</td><td colspan="2">< 2.2e-16 ***</td></tr>
<tr><td>time</td><td>-0.0177</td><td colspan="2">0.003517</td><td>-5.0319</td><td colspan="2">4.855e-07 ***</td></tr>
<tr><td>Signif. codes:</td><td>0 ‘***’</td><td>0.001 ‘**’</td><td>0.01 ‘*’</td><td>0.05 ‘.’</td><td>0.1 ‘ ’</td><td>1</td></tr>
<tr><td colspan="7">log likelihood value: 227.1087</td></tr>
<tr><td colspan="7">panel data</td></tr>
<tr><td colspan="7">number of cross-sections = 31</td></tr>
<tr><td colspan="7">number of time periods = 7</td></tr>
<tr><td colspan="7">total number of observations = 217</td></tr>
<tr><td colspan="7">thus there are 0 observations not in the panel</td></tr>
<tr><td colspan="7">mean efficiency of each year</td></tr>
<tr><td>2010</td><td>2011</td><td>2012</td><td>2013</td><td>2014</td><td>2015</td><td>2016</td></tr>
<tr><td>0.574387</td><td>0.569425</td><td>0.564441</td><td>0.559435</td><td>0.554408</td><td>0.549361</td><td>0.544295</td></tr>
<tr><td colspan="7">mean efficiency: 0.559393</td></tr>
</table>

Table 3b. Statistical Summary Based on MLE Method: Cost-Effectiveness Model

<table>
<tr><td colspan="7">Final maximum likelihood estimates</td></tr>
<tr><td></td><td>Estimate</td><td colspan="2">Std. Error</td><td>Z value</td><td colspan="2">Pr(>|Z|) or p-value</td></tr>
<tr><td>(Intercept)</td><td>1.206416</td><td colspan="2">0.200872</td><td>6.0059</td><td colspan="2">1.903e-09 ***</td></tr>
<tr><td>log(Average fleet operated)</td><td>0.436964</td><td colspan="2">0.052427</td><td>8.3347</td><td colspan="2">< 2.2e-16 ***</td></tr>
<tr><td>log(Total cost)</td><td>0.599376</td><td colspan="2">0.047407</td><td>12.6432</td><td colspan="2">< 2.2e-16 ***</td></tr>
<tr><td>sigmaSq</td><td>0.238433</td><td colspan="2">0.060777</td><td>3.9231</td><td colspan="2">8.742e-05 ***</td></tr>
<tr><td>gamma</td><td>0.939609</td><td colspan="2">0.016637</td><td>56.4768</td><td colspan="2">< 2.2e-16 ***</td></tr>
<tr><td>time</td><td>-0.022178</td><td colspan="2">0.012300</td><td>-1.8031</td><td colspan="2">0.07138.</td></tr>
<tr><td>Signif. codes:</td><td>0 ‘***’</td><td>0.001 ‘**’</td><td>0.01 ‘*’</td><td>0.05 ‘.’</td><td>0.1 ‘ ’</td><td>1</td></tr>
<tr><td colspan="7">log likelihood value: 99.92943</td></tr>
<tr><td colspan="7">panel data</td></tr>
<tr><td colspan="7">number of cross-sections = 31</td></tr>
<tr><td colspan="7">number of time periods = 7</td></tr>
<tr><td colspan="7">total number of observations = 217</td></tr>
<tr><td colspan="7">thus there are 0 observations not in the panel</td></tr>
<tr><td colspan="7">mean efficiency of each year</td></tr>
<tr><td>2010</td><td>2011</td><td>2012</td><td>2013</td><td>2014</td><td>2015</td><td>2016</td></tr>
<tr><td>0.8161790</td><td>0. 8130397</td><td>0.8098611</td><td>0.806643</td><td>0.8033852</td><td>0. 80008</td><td>0.79675</td></tr>
<tr><td colspan="7">mean efficiency: 0.8065638</td></tr>
</table>

Table 3c. Statistical Summary Based on MLE Method: Service-Effectiveness Model

Final maximum likelihood estimates						
	Estimate	Std. Error		Z value	Pr(>|Z|) or *p-value*	
(Intercept)	4.453173	0.173572		25.6561	< 2.2e-16 ***	
log(Effective km)	0.947931	0.020945		45.2591	< 2.2e-16 ***	
sigmaSq	0.295375	0.102502		2.8817	0.003956 **	
gamma	0.954459	0.017502		54.5355	< 2.2e-16 ***	
time	0.088551	0.009218		9.6066	< 2.2e-16 ***	
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '	1
log likelihood value: 94.43059						
panel data						
number of cross-sections = 31						
number of time periods = 7						
total number of observations = 217						
thus there are 0 observations not in the panel						
mean efficiency of each year						
2010	2011	2012	2013	2014	2015	2016
0.455842	0.484973	0.513665	0.541763	0.569131	0.595655	0.621245
mean efficiency: 0.5403248						

Based on the discussions in Tables 3a, 3b, and 3c with regard to Models 8, 18, and 24, it can be observed that the SFA model can be used effectively in the evaluation of *cost-efficiency*, *cost-effectiveness*, and *service-effectiveness* of public transport organizations. The models incorporate the effects of various factors such as *average fleet operation, effective km, and total cost.* They also explain inherent inefficiencies in the system compared to other performance evaluation approaches.

5.2.2. Computation of Efficiency Scores of SRTUs Based on the SFA Approach

In the next step, it was required to compute the relative efficiencies of the 31 SRTUs using the Frontier package in R Studio for data pertaining to the study period 2010-17. Table 4a provides details on the relative efficiencies for the SRTUs computed using the SFA approach based on the *cost efficiency* model for each year between 2010-17, along with the average scores. Similarly, Table 4b and Table 4c give details on the relative efficiencies and the average scores based on cost-effectiveness and *Service effectiveness*. In the above-mentioned tables, the SRTUs were sorted in descending order with regard to the average scores. In Tables 4a-4c, the SRTUs that constitute 25% of the top-performing organizations are categorized as "Best Performers," as shown in the tables.

Table 4a. Efficiencies of SRTUs Using the SFA Approach for Cost-Efficiency

Sl. No.	SRTU name	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	Average scores	Percentile
1	SETC (TN)	0.9848	0.9846	0.9843	0.9840	0.9837	0.9835	0.9832	*0.9840*	SRTUs performing better than 75% of the organizations
2	TNSTC(VPM)	0.8973	0.8956	0.8938	0.8920	0.8902	0.8884	0.8865	*0.8920*	
3	TNSTC(KUM)	0.8801	0.8781	0.8761	0.8740	0.8719	0.8698	0.8676	*0.8740*	
4	TNSTC(SLM)	0.8636	0.8613	0.8590	0.8567	0.8544	0.8520	0.8495	*0.8566*	
5	TNSTC(MDU)	0.8029	0.7998	0.7966	0.7934	0.7901	0.7868	0.7834	*0.7933*	
6	GSRTC	0.7919	0.7886	0.7852	0.7819	0.7784	0.7750	0.7714	*0.7818*	
7	TNSTC(CBE)	0.7775	0.7740	0.7705	0.7669	0.7633	0.7596	0.7559	*0.7668*	
8	RSRTC	0.7185	0.7143	0.7100	0.7057	0.7013	0.6969	0.6924	*0.7056*	SRTUs performing between 75th and 50th percentiles
9	APSRTC	0.7092	0.7049	0.7005	0.6961	0.6916	0.6871	0.6825	*0.6960*	
10	KnSRTC	0.6774	0.6727	0.6680	0.6632	0.6584	0.6535	0.6485	*0.6631*	
11	UPSRTC	0.6703	0.6655	0.6607	0.6559	0.6509	0.6460	0.6409	*0.6558*	
12	MSRTC	0.6551	0.6502	0.6452	0.6402	0.6351	0.6300	0.6248	*0.6401*	
13	NWKnRTC	0.6432	0.6382	0.6331	0.6279	0.6227	0.6175	0.6122	*0.6278*	
14	NEKnRTC	0.6241	0.6189	0.6136	0.6083	0.6029	0.5975	0.5920	*0.6082*	
15	STHAR	0.6135	0.6082	0.6028	0.5974	0.5919	0.5864	0.5809	*0.5973*	
16	KSRTC	0.5979	0.5925	0.5869	0.5814	0.5758	0.5701	0.5645	*0.5813*	
17	UTC	0.5815	0.5759	0.5703	0.5646	0.5588	0.5531	0.5473	*0.5645*	SRTUs performing between 50th and 25th percentiles
18	MTC (CNI)	0.5576	0.5518	0.5460	0.5401	0.5342	0.5282	0.5223	*0.5400*	
19	OSRTC	0.4830	0.4768	0.4705	0.4642	0.4579	0.4516	0.4452	*0.4642*	
20	KDTC	0.4339	0.4274	0.4210	0.4146	0.4081	0.4016	0.3951	*0.4145*	
21	CHNTU	0.4309	0.4244	0.4180	0.4115	0.4051	0.3986	0.3921	*0.4115*	
22	PMPML	0.4062	0.3997	0.3932	0.3867	0.3802	0.3737	0.3672	*0.3867*	
23	NBSTC	0.4055	0.3990	0.3925	0.3860	0.3795	0.3730	0.3665	*0.3860*	
24	KMTU	0.3958	0.3893	0.3828	0.3763	0.3698	0.3633	0.3568	*0.3763*	
25	BMTC	0.3914	0.3849	0.3784	0.3719	0.3654	0.3589	0.3523	*0.3719*	SRTUs performing poorer less than 25th percentiles
26	AMTS	0.3589	0.3524	0.3459	0.3394	0.3329	0.3265	0.3200	*0.3394*	
27	BEST	0.3507	0.3442	0.3378	0.3313	0.3248	0.3183	0.3119	*0.3313*	
28	DTC	0.3504	0.3439	0.3374	0.3309	0.3244	0.3180	0.3115	*0.3309*	
29	TMTU	0.3237	0.3173	0.3109	0.3044	0.2980	0.2917	0.2853	*0.3045*	
30	MEGTC	0.2815	0.2752	0.2689	0.2627	0.2565	0.2503	0.2442	*0.2627*	
31	MZST	0.1476	0.1426	0.1378	0.1330	0.1283	0.1236	0.1191	*0.1331*	
	Average	*0.5744*	*0.5694*	*0.5644*	*0.5594*	*0.5544*	*0.5493*	*0.5442*		

Table 4b. Efficiencies of SRTUs Using the SFA Approach for Cost-Effectiveness

Sl. No.	SRTU name	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	Average scores	Percentile
1	SETC (TN)	0.9656	0.9649	0.9641	0.9633	0.9625	0.9617	0.9609	*0.9633*	SRTUs performing better than 75% of the organizations
2	KMTU	0.9656	0.9648	0.9640	0.9632	0.9624	0.9616	0.9608	*0.9632*	
3	KDTC	0.9650	0.9642	0.9635	0.9627	0.9619	0.9610	0.9602	*0.9626*	
4	PMPML	0.9485	0.9474	0.9462	0.9451	0.9439	0.9427	0.9415	*0.9450*	
5	KnSRTC	0.9307	0.9292	0.9277	0.9261	0.9245	0.9229	0.9213	*0.9261*	
6	TNSTC(VPM)	0.9279	0.9263	0.9248	0.9232	0.9215	0.9199	0.9182	*0.9231*	
7	OSRTC	0.9208	0.9191	0.9174	0.9156	0.9138	0.9120	0.9101	*0.9156*	
8	UTC	0.9073	0.9054	0.9034	0.9013	0.8992	0.8971	0.8950	*0.9012*	SRTUs performing between 75th and 50th percentiles
9	TNSTC(KUM)	0.9064	0.9044	0.9024	0.9003	0.8982	0.8961	0.8939	*0.9003*	
10	MSRTC	0.9015	0.8994	0.8973	0.8951	0.8929	0.8907	0.8884	*0.8950*	
11	MEGTC	0.8996	0.8975	0.8953	0.8931	0.8909	0.8886	0.8863	*0.8931*	
12	TNSTC(MDU)	0.8989	0.8968	0.8946	0.8924	0.8901	0.8878	0.8855	*0.8923*	
13	NEKnRTC	0.8985	0.8964	0.8942	0.8920	0.8897	0.8874	0.8851	*0.8919*	
14	NWKnRTC	0.8947	0.8925	0.8902	0.8879	0.8856	0.8832	0.8807	*0.8878*	
15	TMTU	0.8929	0.8907	0.8884	0.8861	0.8837	0.8813	0.8788	*0.8860*	
16	GSRTC	0.8909	0.8886	0.8863	0.8839	0.8815	0.8790	0.8765	*0.8838*	
17	TNSTC(SLM)	0.8712	0.8686	0.8659	0.8631	0.8603	0.8574	0.8544	*0.8630*	SRTUs performing between 50th and 25th percentiles
18	MTC (CNI)	0.8695	0.8668	0.8640	0.8612	0.8584	0.8554	0.8525	*0.8611*	
19	UPSRTC	0.8666	0.8638	0.8610	0.8581	0.8552	0.8523	0.8492	*0.8580*	
20	BMTC	0.8509	0.8479	0.8447	0.8416	0.8383	0.8350	0.8317	*0.8414*	
21	TNSTC(CBE)	0.8466	0.8435	0.8403	0.8370	0.8337	0.8304	0.8269	*0.8369*	
22	APSRTC	0.8462	0.8431	0.8399	0.8366	0.8333	0.8299	0.8265	*0.8365*	
23	RSRTC	0.8184	0.8147	0.8110	0.8072	0.8034	0.7995	0.7955	*0.8071*	
24	STHAR	0.7939	0.7898	0.7856	0.7814	0.7771	0.7728	0.7683	*0.7813*	
25	BEST	0.7644	0.7598	0.7551	0.7504	0.7456	0.7407	0.7358	*0.7503*	SRTUs performing poorer less than 25th percentiles
26	KSRTC	0.7546	0.7498	0.7450	0.7401	0.7352	0.7301	0.7250	*0.7400*	
27	CHNTU	0.7267	0.7216	0.7163	0.7110	0.7056	0.7001	0.6946	*0.7109*	
28	NBSTC	0.5494	0.5421	0.5347	0.5273	0.5198	0.5122	0.5046	*0.5272*	
29	AMTS	0.4459	0.4379	0.4299	0.4219	0.4138	0.4057	0.3976	*0.4218*	
30	DTC	0.3926	0.3844	0.3763	0.3681	0.3600	0.3518	0.3437	*0.3681*	
31	MZST	0.1899	0.1829	0.1761	0.1694	0.1628	0.1563	0.1499	*0.1696*	
	Average	*0.816*	*0.813*	*0.810*	*0.807*	*0.803*	*0.800*	*0.797*	0.8160	

Table 4c. Efficiencies of SRTUs Using SFA Approach for Service-Effectiveness

Sl. No.	SRTU name	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	Average scores	Percentile
1	BEST	0.8865	0.8955	0.9039	0.9116	0.9187	0.9253	0.9313	*0.9104*	SRTUs performing better than 75% of the organizations
2	PMPML	0.8334	0.8462	0.8582	0.8693	0.8796	0.8892	0.8981	*0.8677*	
3	TMTU	0.8203	0.8341	0.8469	0.8589	0.8699	0.8802	0.8897	*0.8572*	
4	BMTC	0.6994	0.7208	0.7410	0.7600	0.7778	0.7945	0.8101	*0.7577*	
5	MEGTC	0.5859	0.6130	0.6389	0.6635	0.6870	0.7091	0.7300	*0.6611*	
6	DTC	0.5824	0.6097	0.6357	0.6605	0.6841	0.7064	0.7275	*0.6581*	
7	KDTC	0.5742	0.6018	0.6282	0.6533	0.6773	0.7000	0.7214	*0.6509*	
8	MTC (CNI)	0.5391	0.5680	0.5958	0.6225	0.6480	0.6722	0.6952	*0.6201*	SRTUs performing between 75th and 50th percentiles
9	MSRTC	0.5357	0.5647	0.5927	0.6195	0.6451	0.6695	0.6926	*0.6171*	
10	KMTU	0.4766	0.5074	0.5374	0.5664	0.5943	0.6211	0.6466	*0.5643*	
11	KSRTC	0.4591	0.4904	0.5208	0.5504	0.5789	0.6063	0.6326	*0.5484*	
12	KnSRTC	0.4570	0.4883	0.5189	0.5485	0.5771	0.6046	0.6309	*0.5465*	
13	APSRTC	0.4314	0.4632	0.4944	0.5247	0.5542	0.5826	0.6098	*0.5229*	
14	STHAR	0.4158	0.4478	0.4793	0.5101	0.5400	0.5689	0.5968	*0.5084*	
15	NWKnRTC	0.3972	0.4295	0.4613	0.4925	0.5230	0.5525	0.5809	*0.4910*	
16	CHNTU	0.3958	0.4280	0.4599	0.4912	0.5216	0.5512	0.5797	*0.4896*	
17	NEKnRTC	0.3925	0.4248	0.4567	0.4880	0.5186	0.5482	0.5769	*0.4865*	SRTUs performing between 50th and 25th percentiles
18	RSRTC	0.3867	0.4191	0.4511	0.4825	0.5132	0.5430	0.5719	*0.4811*	
19	UPSRTC	0.3817	0.4141	0.4461	0.4777	0.5085	0.5385	0.5675	*0.4763*	
20	GSRTC	0.3776	0.4100	0.4422	0.4738	0.5047	0.5348	0.5639	*0.4724*	
21	UTC	0.3715	0.4039	0.4361	0.4679	0.4989	0.5292	0.5585	*0.4666*	
22	TNSTC(MDU)	0.3470	0.3795	0.4119	0.4440	0.4756	0.5065	0.5365	*0.4430*	
23	TNSTC(CBE)	0.3420	0.3745	0.4070	0.4392	0.4709	0.5019	0.5320	*0.4382*	
24	TNSTC(VPM)	0.3327	0.3651	0.3976	0.4299	0.4618	0.4930	0.5234	*0.4291*	
25	SETC (TN)	0.3320	0.3645	0.3970	0.4293	0.4611	0.4924	0.5228	*0.4284*	SRTUs performing poorer less than 25th percentiles
26	TNSTC(KUM)	0.3298	0.3623	0.3948	0.4271	0.4590	0.4903	0.5208	*0.4263*	
27	OSRTC	0.3086	0.3409	0.3734	0.4059	0.4381	0.4698	0.5008	*0.4053*	
28	AMTS	0.3076	0.3399	0.3724	0.4049	0.4371	0.4688	0.4999	*0.4044*	
29	TNSTC(SLM)	0.2958	0.3279	0.3604	0.3929	0.4252	0.4572	0.4885	*0.3926*	
30	MZST	0.2706	0.3022	0.3344	0.3669	0.3995	0.4317	0.4636	*0.3670*	
31	NBSTC	0.2654	0.2969	0.3291	0.3615	0.3941	0.4264	0.4583	*0.3617*	
	Average	*0.456*	*0.485*	*0.514*	*0.542*	*0.569*	*0.596*	*0.621*		

5.2.3. Discussions on Best Performing SRTUs Based on Percentile Scores

Interestingly, the best performing SRTUs with regard to *cost efficiency* belong to SRTUs serving in rural areas. These SRTUs include SETC (TN) of the State of Tamil-Nadu, TNSTC serving Villupuram, Kumbakonam, Salem, Madurai, and Coimbatore zones of Tamil-Nadu and GSRTC of the State Gujarat.

Also, the best performing SRTUs with regard to *cost-effectiveness* belong to SRTUs serving rural and urban areas. The urban SRTUs under this category include KMTU and PMPML of Maharashtra, while the rural SRTUs under this category include SETC (TN) and TNSTC (VPM) of Tamil-Nadu, KDTC of Goa and KnSRTC of Karnataka, while the SRTUs serving rural areas include SETC (TN) of Tamil-Nadu.

Moreover, the best performing SRTUs with regard to *Service effectiveness* include BEST, PMPML, and TMTU of Maharashtra, BMTC of Karnataka and DTC of Delhi serving urban areas, and MEGTC of Meghalaya and KDTC serving hilly and rural areas, respectively.

5.2.4. Discussions on Worst Performing SRTUs Based on Percentile Scores

It was observed that AMTS and MZST performed poorly in terms of *cost-efficiency*, *cost-effectiveness*, and *service-effectiveness*. It is also observed that although DTC is considered to perform poorly with regard to *cost-efficiency* and *cost-effectiveness*, it is considered to perform moderately well in terms of *Service effectiveness* with a relative efficiency value of 0.68.

Cost efficiency: The best model for measuring *cost efficiency* was identified as model 8, as explained in Section 5.1, where the independent variables such as total cost and average fleet operated play a major role in influencing the dependent variable, effective km. With regard to *cost efficiency*, it can be observed that MZST of Mizoram and MEGTC of Meghalaya serve hilly areas, and BMTC, AMTU, BEST, DTC, and TMTU serving urban areas are among the poorly performing SRTUs. One of the reasons for the poor performance of SRTUs such as MZST and MEGTC serving hilly regions can be attributed to the fact that the effective km covered is lesser considering the steep terrain. Similar reasons can be attributed to the poor performance of urban SRTUs such as BMTC, AMTU, BEST, DTC, and TMTU, considering the lower effective km operated due to congestion and traffic jams on urban roads. The additional reason for lower levels of performance of SRTUs serving hilly terrains in India can be attributed to higher total costs of operation considering increased cost of fuel, spares, and maintenance, while lower levels of performance of SRTUs serving urban areas can be attributed to higher total costs of operation due to traffic congestion and delays resulting in loss of trips and higher fuel consumption. Additionally, a higher number of fleets operated to satisfy the accessibility requirements of trip-makers, leading to inefficiencies.

Cost effectiveness: The best model for measuring cost-effectiveness was identified as model 18, as explained in Section 5.1, where the independent variables, such as *total cost* and *average fleet operated*, play a major role in influencing the dependent variable, total revenue. The poorly performing SRTUs with regard to *cost-effectiveness* include CHNTU of Punjab, BEST, AMTS of Gujarat and DTC serving urban areas, KSRTC of Kerala and NBSTC of West-Bengal serving rural areas and also MZST serving hilly areas. One of the reasons for the poor performance of SRTUs serving urban areas can be attributed to higher total costs of operation due to traffic congestion and delays resulting in loss of trips and higher fuel consumption. The additional reason for the lower levels of performance of SRTUs serving hilly and rural areas can be attributed to the fact that the total revenue is lesser due to the lower levels of population densities. Additionally, the higher number of fleets operated to satisfy accessibility requirements of trip-makers in hilly and rural areas also leads to inefficiencies.

Service effectiveness: The best model for measuring *Service effectiveness* was identified as model 24 as explained in Section 5.1, where the independent variable effective km plays a major role in influencing the dependent variable, total revenue. The poorly performing SRTUs with regard to *Service effectiveness* include SETC (TN), TNSTC (KUM & SLM zones), OSRTC and NBSTC that serve rural areas, MZSTC that serve hilly regions and also AMTS that serve urban regions. One of the reasons for the poor performance of SRTUs serving rural areas can be attributed to the fact that the total revenue earned is lesser due to the lower levels of population density, as mentioned in the case of analysis for *cost effectiveness*. The additional reason for the lower levels of performance of SRTUs serving hilly regions can be attributed to the fact that the effective km covered is lesser considering the steep terrain in the hilly regions. Additionally, congestion and traffic jams on urban roads also lead to inefficiencies.

From an operator's perspective, maintaining high *cost-efficiency* is essential. Simultaneously, it is crucial to provide adequate accessibility and mobility to passengers to achieve a reasonable level of *Service effectiveness*. Balancing *cost efficiency* and *Service effectiveness* is achievable through cost-effectiveness analysis, which requires determining an appropriate weighting to satisfy both operators and passengers.

5.2.5. Discussions on Performance of SRTUs Based on Efficiency Scores

A. General Discussions on Cost-efficiency

It is observed that GSRTC, RSRTC, SETC(TN), TNSTC(CBE), TNSTC(KUM), TNSTC(MDU), TNSTC(SLM), and TNSTC(VPM) possess cost efficiencies higher than 0.7. Also, it can be observed that SETC(TN) has the highest *cost efficiency* of around 0.9840.

However, it may also be observed that the performance in terms of *cost efficiency* needs to be improved in the cases of OSRTC, AMTS, BEST, BMTC, CHNTU, DTC, KDTC, KMTU, MEGTC, MZST, NBSTC, OSRTC, PMPML, and TMTU that have efficiency scores much lower than 0.5.

The details on the estimates of parameters of *the cost-efficiency* model are provided in Table 4a, as mentioned above. It also gives the mean efficiency of each year in the study period 2010-17 for all the SRTUs. It can be observed that the mean efficiency of each year decreased from 0.574 to 0.544 during the period 2010-17, considering the performance of 31 SRTUs. Although the change in score is not seen to be significant, there is a downward trend in the performance of SRTUs during the period. The reason for such behavior can be attributed to the fact that the rising fuel and operating costs during the period have increased the total cost spent by the SRTUs, while the effective km produced did not improve accordingly. The additional reason for such performance may be due to an increase in the average fleet operated over time to satisfy the rising trip demands.

B. General Discussions on Cost effectiveness

It is observed that KMTU, KDTC, TNSTC(KUM), TNSTC(VPM), UTC, KnSRTC, OSRTC, SETC(TN), and PMPML possess *cost effectiveness* higher than 0.9. Also, it can be observed that the best cost efficient SRTU, SETC(TN), also has the highest *cost effectiveness* of around 0.9633. However, it may also be observed that the performance in terms *of cost-effectiveness needs to be improved in the case of AMTS, DTC, and MZST, which* have efficiency scores much lower than 0.5.

In an analysis related to *cost effectiveness*, it can be observed in Table 4b that the mean efficiency of each year of SRTUs decreased from 0.816 to 0.797 during the period 2010-17. In this case, too, although the change in score is not seen to be significant, there is a downward trend in the performance of SRTUs during the period. However, the values of the *cost effectiveness* scores are seen to be higher than that of the *cost efficiency* scores for the period of study. This implies that, although the SRTUs were poor in producing the effective km using the capital and fleet, they were able to generate fair revenue in the study period 2010-17.

C. General Discussions on Service effectiveness

It is observed that BEST, PMPML, TMTU, and BMTC possess *Service effectiveness* higher than 0.7. Also, it can be observed that the BEST has the highest *Service effectiveness* of around 0.9104. However, it may also be observed that the performance in terms *Service effectiveness* needs to be improved in the case of NWKnRTC, CHNTU, NEKnRTC, RSRTC, UPSRTC, GSRTC, UTC, TNSTC(MDU), TNSTC(CBE), TNSTC(VPM), SETC(TN), TNSTC(KUM), OSRTC, AMTS, TNSTC(SLM), MZST and NBSTC that have efficiency scores much lower than 0.5.

Interestingly, among these SRTUs, it is seen that GSRTC, RSRTC, SETC(TN), TNSTC(CBE), TNSTC(KUM), TNSTC(MDU), TNSTC(SLM), and TNSTC(VPM) show higher performance in terms of *cost efficiency* in operations. This indicates that the quality of service provided by these SRTUs needs to be improved from the point of view of trip-makers.

In analysis related to *Service effectiveness*, it can be observed in Table 4c that the efficiency of each year of SRTUs increased from 0.456 to 0.621 during the period 2010-17. In this case, the change in score is seen to be significant, showing an upward trend in the performance of SRTUs during the period. One of the reasons for such a trend can be attributed to the fact that rising population and trip demand result in more revenue collection by SRTUs.

5.3. Discussion of Findings

Our results indicate that SRTUs serving rural areas exhibit higher efficiency compared to urban and hilly areas. However, studies carried out by [3] in the regions of China indicate urban systems to be more operational-efficient. This discrepancy may be due to differences in population density and traffic congestion levels between China and India.

One key difference in our approach compared to other studies is the use of Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) methods in the identification of variables. These criteria helped us to select the most appropriate models for evaluating cost efficiency, cost-effectiveness, and service effectiveness. This methodical approach ensured that our models were statistically sound and robust, enhancing the reliability of our findings. Previous studies, such as those by [11] [12] and [3], did not employ these criteria, which might explain differences in the identified key performance indicators and overall results.

For instance, our selection process led to the identification of *total cost* and *average fleet operated* as significant variables influencing both cost efficiency and cost-effectiveness, and *effective kilometers* as crucial for service effectiveness. This contrasts with some studies that might have used fewer rigorous criteria for model selection, potentially leading to less precise estimates. Furthermore, the use of the Cobb-Douglas production function in our analysis provided a comprehensive evaluation of the performance of SRTUs across diverse regions, including rural, urban, and hilly areas. The robustness of our model, supported by AIC and BIC, underscores the significant impact of operational and regional factors on public transport efficiency.

The study contributes to the existing literature by providing a comprehensive analysis of Indian SRTUs using SFA. Unlike previous studies [3] that focused on either urban or rural systems, our research encompasses a variety of regions, offering a holistic view of public transport efficiency in a developing country context.

Additionally, our identification of unique challenges faced by SRTUs in hilly areas provides new insights into geographical factors affecting efficiency. Moreover, the application of AIC and BIC methods for model selection sets our study apart, providing a more rigorous and statistically validated approach to performance evaluation.

6. Conclusions

The primary objective of this study was to effectively use a parametric approach, such as Stochastic Frontier Analysis (SFA), in the evaluation of the performance of public transport organizations operating in India. The present study employed nine key performance indicators (KPIs) to evaluate 31 State Road Transport Undertakings (SRTUs) in India over a period of seven years (2010-2017). The nine KPIs were used to develop three categories of performance measurement, which include *cost efficiency*, *cost effectiveness*, and *Service effectiveness*. Statistical analysis, such as Akaike and Bayesian information criteria, were adopted to identify the dependent and independent variables for each category of performance measurement. The use of the maximum likelihood estimation (MLE) in the Stochastic Frontier Analysis (SFA) based analysis assisted in determining the reliability of the independent variables and also provided information on the overall suitability of the models used. The values of the coefficients used can also be used in sensitivity analysis. Later, performance evaluation of SRTUs was carried out using a parametric-based SFA approach.

The best model for measuring *cost efficiency* was identified as model 8, as explained in Section 5.1, where the independent variables, such as *total cost* and *average fleet operated,* play a major role in influencing the dependent variable, effective km. Similarly, the best model for measuring *cost-effectiveness* was identified as model 18, with *total cost* and *average fleet operated* as independent variables and the dependent variable, total revenue. In a similar manner, the best model for measuring Service effectiveness was identified as model 24, where the independent variable *effective km* plays a major role in influencing the dependent variable, *total revenue.*

The study revealed that the best performing SRTUs in terms of *cost efficiency* were those serving rural areas, while those performing well in terms of *cost effectiveness* were a mix of rural and urban SRTUs. The best performing SRTUs in terms of *Service effectiveness* were mostly those serving urban areas, with a few serving hilly and rural areas. However, there were also SRTUs that consistently performed poorly across all three KPIs, including AMTS and MZST, while others had a mixed performance, such as DTC, which performed moderately well in terms of *Service effectiveness* but poorly in terms of *cost efficiency* and *cost effectiveness*.

In general, SRTUs serving hilly regions performed poorly in all three categories of performance evaluation. This can be attributed to the fact that the effective km covered is lesser considering the steep terrain and also the higher total costs of operation considering the increased cost of fuel, spares, and maintenance. Also, total revenue is lesser due to the lower levels of population densities. Similarly, lower levels of performance of SRTUs serving urban areas can be attributed to higher total costs of operation due to traffic congestion and delays resulting in loss of trips and higher fuel consumption. Additionally, a higher number of fleets operated to satisfy accessibility requirements of trip-makers, leading to inefficiencies.

However, from the point of view of the operator, it is required to maintain higher levels of *cost efficiency*, while from the viewpoint of providing higher levels of accessibility and mobility to trip-makers, it is required to maintain a reasonable level of *Service effectiveness*. *Cost effectiveness* can be used as a measure to arrive at a balance between *cost efficiency* and *Service effectiveness*. It is required to determine a weightage that can be applied to satisfy both operators and trip-makers.

The study also found that there was a slight downward trend in the performance of SRTUs in terms of *cost efficiency* and *cost effectiveness* models, although the change in scores was not significant. This suggests that there is room for improvement in the performance of SRTUs in India. The reason for such behavior can be attributed to the fact that the rising fuel and operating costs during the period have increased the total cost spent by the SRTUs, while the effective km produced did not improve accordingly. The additional reason for such performance may be due to an increase in the average fleet operated over time to satisfy the rising trip demands. An increasing trend in the performance related to Service effectiveness can be attributed to the fact that rising population and trip demand result in more revenue collection by SRTUs.

Overall, the findings of this study provide insights into the performance of SRTUs in India and highlight the importance of using KPIs to evaluate and improve their performance. Stochastic Frontier Analysis is a valuable tool for the performance evaluation of public transport organizations when the data related to KPIs are inconsistent and erroneous, as it permits the formulation of a production function that assists in determining the random errors and the inefficiency distinctively. The results can be useful for policymakers and stakeholders in the transport sector to identify areas of improvement and make data-driven decisions to enhance the efficiency, effectiveness, and quality of public transport services in India.

Abbreviations

SFA - *Stochastic Frontier Analysis*
KPI - *Key performance indicator*
AIC - *Akaike's Information Criterion*
BIC - *Bayesian Information Criteria*

SRTU - *State Road Transport Undertaking*
DEA – *Data Envelopment Analysis*
CIRT - *Central Institute of Road Transport*
MoRTH - *Ministry of Road Transport and Highways*
MLE - *maximum likelihood estimatio*n
TC - *Total Cost*
TR - *Total Revenue*
EKM - *Effective km*
AFO – *Average Fleet Operated*
CKM - *Carrying Capacity km*
PKM - *Passenger km*
PC - *Passengers Carried*
SS - *Staff*
FC - *Fuel Consumed*
AMTS - *Ahmedabad municipal transport service*
APSRTC - *Andhra Pradesh State Road Transport Corporation*
BEST - *Brihan Mumbai Electric Supply & Transport Undertaking*
BMTC - *Bengaluru Metropolitan Transport Corporation*
CHNTU - *Chandigarh Transport Undertaking*
DTC - *Delhi Transport Corporation*
GSRTC - *Gujarat State Road Transport Corporation*
STHAR - *State Transport Haryana*
KDTC - *Kadamba Transport Corporation Limited*
KnSRTC- *Karnataka State Road Transport Corporation*
KSRTC - *Kerala State Road Transport Corporation*
KMTU - *Kolhapur Municipal Transport Undertaking*
MSRTC - *Maharashtra State Road Transport Corporation*
MTC - *Meghalaya Transport Corporation*
MTC (CNI) - *Metropolitan Transport Corpn. Ltd. (Chennai)*
MZST - *Mizoram State Transport*
NBSTC - *North Bengal State Transport Corporation*
NEKnRTC - *North Eastern Karnataka Road Transport Corporation*
NWKnRTC - *North Western Karnataka Road Transport Corporation*
OSRTC - *Odisha State Road Transport Corporation*
PMPML - *Pune Mahanagar Parivahan Mahamandal Limited*
RSRTC - *Rajasthan State Road Transport Corporation*
SETC (TN) - *State Express Transport Corpn. Ltd. (Tamil Nadu)*
TMTU - Thane *Municipal Transport Undertaking*
TNSTC (CBE) - *Tamil Nadu State Transport Corpn. Ltd. (Coimbatore)*
TNSTC (KUM) - *Tamil Nadu State Transport Corpn. Ltd. (Kumbakonam)*
TNSTC (MDU) - *Tamil Nadu State Transport Corpn. Ltd. (Madurai)*
TNSTC (SLM) - *Tamil Nadu State Transport Corpn. Ltd. (Salem)*
TNSTC (VPM) - *Tamil Nadu State Transport Corpn. Ltd.(Villupuram)*
UTC - *Uttarakhand Transport Corporation*
UPSRTC - *Uttar Pradesh State Road Transport Corporation*

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