EFFICIENCY AND EFFECTIVENESS STUDIES FOR PERFORMANCE EVALUATION IN PUBLIC TRANSPORT SYSTEMS

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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DECLARATION

by the Ph.D. Research Scholar

I hereby *declare* that the PhD Research Thesis entitled **"EFFICIENCY AND EFFECTIVENESS STUDIES FOR PERFORMANCE EVALUATION IN PUBLIC TRANSPORT SYSTEMS"** which is being submitted to **National Institute of Technology Karnataka Surathkal,** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Transportation Engineering** in the **Department of Civil Engineering,** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

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PRAVEEN KUMAR P

ABSTRACT

Bus-based public transport systems are considered to provide affordable means of transport to trip-makers of urban and rural areas. The use of bus transport modes can help reduce traffic congestion and pollution on urban roads. However, the mode share of travel by public transport has witnessed a steep declined since the last 3 decades especially in the large cities with population of 4-8 million and above 8 million ***(MoUD, 2016)***. The major reasons for the decline in patronage of public transport modes include non-availability of services, inaccessibility, inadequate comfort and convenience, and poor reliability of services offered. Despite the limitations of the public bus transport system, it is still considered to be a viable mode of transport especially for the economically weaker sections of the society.

Public transport undertakings are prone to making losses since these agencies focus on providing mobility to people on commercially viable routes, while providing accessibility and mobility to under-developed remote regions. For example, State Road Transport Undertakings (SRTUs) operating in India accrued a total loss Rs. 113.5 million for the year 2015-16. ***(MoRTH, 2016).*** The increasing cost of fuel and spares, increasing cost of labor, resource crunch on fund allocation in the form of subsidies, the lack of sufficient level of transparency in accounting, the rising trend in the use of private vehicles, coupled with the lack of computational tools for performing advanced in-depth analysis on performance-related aspects have affected the functioning of SRTUs leading to financial losses. In view of the need to satisfy the increasing travel demand of urban trip-makers, it is imperative to rejuvenate and promote public transport systems.

The scope of the present work involves system evaluation of the performance of *State Road Transport Undertakings* (SRTUs) in India, with a special emphasis on micro-level performance evaluation of *Mysore City Transport Division* (MCTD), a part of *Karnataka State Road Transport Corporation* (KnSRTC). The overall approach adopted in this study for performance evaluation of SRTUs is expected to provide the basic framework for fine-tuning the functioning of similar organizations. These approaches will assist in identifying bottlenecks that need to be streamlined for improving the financial and physical performance of transport undertaking.

In the initial phase of the study, a thorough understanding of important performance indicators was attained based on a comprehensive literature review on the use of efficiency and effectiveness measures in transport organizations. This was followed by a questionnaire survey where responses from experts in the field of transport operations, and academicians were elicited in order to rate the importance of various performance criteria in a scale of 1-9. The inputs from the experts were then processed using the AHP and the Fuzzy AHP approaches which gave similar results. Further analyses were performed using another *Multi-Criteria Decision Making* (MCDM) approaches such as, TOPSIS, and Fuzzy-TOPSIS. A total of nine KPIs were identified for further analysis to evaluate performance of SRTUs at system level.

The second phase of the study focused on conducting a system level evaluation of performance of various SRTUs across India with respect to *cost efficiency*, *cost effectiveness*, and *service effectiveness*. Suitable variables that had to be considered to represent the performance in the above-mentioned categories were selected using statistical tools such as the *Akaike's Information Criterion* (AIC), and the *Bayesian Information Criterion* (BIC). The system level analysis of 31 SRTUs operating in Urban, Rural, and Hilly regions of India were carried out using parametric and non-parametric approaches. As part of the parametric approach, the *stochastic frontier analysis* (SFA) method was adopted, while the *Data Envelopment Analysis* (DEA) method was adopted as part of the non-parametric approach. Overall results indicated that SRTUs serving hilly regions performed poorly in all the three categories of performance evaluation.

The third phase of the study involved the analysis of exogenous variables related to vehicle emissions and accidents as part of the performance evaluation using the DEA approach. In this part of the study, the performance of 25 SRTUs were evaluated for various time periods 2004-05, 2009-10, and 2014-15. The results indicate that CO_2-PKM can be effectively used to represent the environmental sustainability of transport organization in the evaluation of SRTUs performance at system level.

In the fourth phase of the study, a micro-level analysis related to 82 bus-routes out of a total of 842 routes operated by *Mysuru City Transport Division* (MCTD), a part of KnSRTC was performed. The QGIS open source software was used to identify the 82 routes based on route-length, and the direction of travel. The parameters representing micro-level performance such as *route-length*, *number of bus-stops*, *revenue* and *passengers carried* for each route, and so on were obtained using *Structured Query Languages* (SQL). The elimination of outliers in the database related to the computation of the journey times was performed using a program written in Python. The important variables to be considered in the micro-level analysis related to performance of bus-routes were identified using the *principal component analysis* (PCA) method, and the *recursive feature elimination* (RFE) approach using RStudio. The variables identified were then used to analyze the performance of 82 routes using the *Data Envelopment Analysis* (DEA), a non-parametric approach implemented using R.

Keywords: *Public Transportation systems, State Road Transport Undertakings, Performance Evaluation, Key Performance Indicators, Multi Criteria Decision Making, Stochastic Frontier Analysis, Data Envelopment Analysis, Bus Route Analysis.*

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LIST OF ABBREVIATIONS

Abbrev.	Description	Abbrev.	Description
SFA	*Stochastic Frontier Analysis*	SRTU	*State Road Transport Undertaking*
KPI	*Key performance indicator*	CIRT	*Central Institute of Road Transport*
AIC	*Akaike's Information Criterion*	MoRTH	*Ministry of Road Transport and Highways*
BIC	*Bayesian Information Criteria*	MCTD	*Mysuru City Transport Division*
DEA	*Data Envelopment Analysis*	AMTS	*Ahmedabad municipal transport service*
MLE	*maximum likelihood estimation*	APSRTC	*Andhra Pradesh State Road Transport Corporation*
MCDM	*Multi-criteria decision-making*	BEST	*Brihan Mumbai Electric Supply & Transport Undertaking*
AHP	*Analytical Hierarchy Process*	BMTC	*Bengaluru Metropolitan Transport Corporation*
TOPSIS	*Technique for Order of Preference by Similarity to Ideal Solution*	CHNTU	*Chandigarh Transport Undertaking*
RFE	*recursive feature elimination*	DTC	*Delhi Transport Corporation*
PCA	*principal component analysis*	GSRTC	*Gujarat State Road Transport Corporation*
DMU	*decision-making unit*	STHAR	*State Transport Haryana*
DRS	*decreasing returns to scale*	KDTC	*Kadamba Transport Corporation Limited*
CRS	*Constant returns to scale*	KnSRTC	*Karnataka State Road Transport Corporation*
IRS	*Increasing returns to scale*	KSRTC	*Kerala State Road Transport Corporation*
SQL	*Sequential Query language*	KMTU	*Kolhapur Municipal Transport Undertaking*
GPS	*Global Positioning system*	MSRTC	*Maharashtra State Road Transport Corporation*
MAD	*Median Absolute Deviation*	MTC	*Meghalaya Transport Corporation*
RMSE	*Root Mean Squared Error*	MTC (CNI)	*Metropolitan Transport Corpn. Ltd. (Chennai)*
MAE	*Mean Absolute Error*	MZST	*Mizoram State Transport*
RMSESD	*standard deviation of the RMSE*	NBSTC	*North Bengal State Transport Corporation*
Rsquared SD	*standard deviation of the Rsquarevalues*	NEKnRTC	*North Eastern Karnataka Road Transport Corporation*
MAESD	*standard deviation of the MAE values*	NWKnRTC	*North Western Karnataka Road Transport Corporation*
ANN	*artificial neural networks*	OSRTC	*Odisha State Road Transport Corporation*
TE	*technical efficiencies*	PMPML	*Pune Mahanagar Parivahan Mahamandal Limited*

Abbrev.	Description	Abbrev.	Description
TGR	*Technical Gap Ratio*	RSRTC	*Rajasthan State Road Transport Corporation*
BTI	*buffer time index*	SETC (TN)	*State Express Transport Corpn. Ltd. (Tamil Nadu)*
PTI	*Planning time index*	TMTU	*Thane Municipal Transport Undertaking*
TTI	*Travel time index*	TNSTC(CBE)	*Tamil Nadu State Transport Corpn. Ltd. (Coimbatore)*
BRCI	*Bus Route Coverage Index*	TNSTC(KUM)	*Tamil Nadu State Transport Corpn. Ltd. (Kumbakonam)*
BCI	*Bus-seating Capacity Index*	TNSTC(MDU)	*Tamil Nadu State Transport Corpn. Ltd. (Madurai)*
TT	*Travel Time*	TNSTC(SLM)	*Tamil Nadu State Transport Corpn. Ltd. (Salem)*
KM	*kilometer*	TNSTC(VPM)	*Tamil Nadu State Transport Corpn. Ltd.(Villupuram)*
TC	*Total Cost*	UTC	*Uttarakhand Transport Corporation*
TR	*Total Revenue*	UPSRTC	*Uttar Pradesh State Road Transport Corporation*
EKM	*Effective kilometer*	TRW	*Transport Research Wing*
CKM	*Carrying Capacity Kilometer*	TM	*transport managers*
PKM	*Passenger Kilometer*	AC	*Academician*
PC	*Passengers Carried*	RS	*Research Scholars*
FC	*Fuel Consumed*	Veh	*vehicle*
TS	*Total Staff*	ITS	*Intelligent Transport System*
SS	*Staff strength*	BMP	*Bannimantap*
EMP	*Number of Employees*	STG	*Satagahalli*
CO_2 - PKM	*Carbon-di-oxide emission per passenger kilometer*	VJN	*Vijayanagar*
ACC_{total}	*total number of Accidents*	KVP	*Kuvempunagar*
AFO	*Average Fleet Operated*	ETM	*Electronic ticket machine*
FS	*Fleet-size*	AVL	*Automatic Vehicle Location*
BoR	*Buses on Road*		

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

India has witnessed rapid urbanization over the past decades, from 25.7% in 1991, to 31.14% in 2011. It may be observed that during 1991 to 2001, the increase in the level of urbanization was 2.1%, while the same during 2001 to 2011 was 3.3% (**MoUD 2016)**. At this rate, the level of urbanization is expected to reach 60% by 2051 as estimated by the Ministry of Urban Development. The increasing travel needs of the burgeoning urban population puts tremendous pressure on the transport infrastructure and services.

According to Census statistics for the year 2011, 377.1 million people in India, which constitutes 31.14% of the total population, reside in urban areas (**MoUD 2016**), a majority of which are dependent on public transport. **Table 1.1** provides details on the mode-share for public transport in major cities of India. However, due to the overwhelming increase in travel demand and the inadequacies of the public transport system, a large number of trip-makers have shifted over to the use of private modes of travel.

Table 1.1 Percentage of Trips by Various Modes of Transport in Major Cities of India

City name	Population in 2011 (million)	Walk	Cycle	Auto-Rickshaw	Public transport	Cars	Two-Wheeler
Mumbai	16.4	28	5	9	44	9	5
Kolkata	13.2	18	12	3	57	7	3
Delhi	12.9	20	12	6	43	14	5
Chennai	6.56	22	6	9	32	9	22
Bengaluru	5.7	28	5	18	26	16	7
Hyderabad	6.34	22	6	7	49	8	8
Ahmedabad	5.41	22	14	5	15	20	24
Pune	3.78	24	8	-	12	10	38

Source: ***NTDPC, 2013***

It may be of interest to note that the percentage of buses among the total registered vehicles in India showed a gradual decline from 11.1% in 1951 to 1.1% in 2011 as shown in **Table 1.2**. Similarly, the mode share of travel by public transport also witnessed a steep decline, especially from 1994, as in **Table 1.3**. Here, it can also be seen that in the case of large cities with populations of 4-8 million and above 8 million, the share of public modes of travel is much below the prescribed desirable levels.

Table 1.2 Total registered vehicles in India and its composition

year	Two Wheelers	Cars, Jeeps & Taxis	Buses	Goods Vehicles	Other Vehicles	Total
	(as % age of total vehicle population)					*(Million)*
1951	8.8	52.0	11.1	26.8	1.3	0.3
1961	13.2	46.6	8.6	25.3	6.3	0.7
1971	30.9	36.6	5.0	18.4	9.1	1.9
1981	48.6	21.5	3.0	10.3	16.6	5.4
1991	66.4	13.8	1.5	6.3	11.9	21.4
2001	70.1	12.8	1.2	5.4	10.5	55.0
2006	72.2	12.9	1.1	4.9	8.8	89.6
2011	71.8	13.6	1.1	5.0	8.5	141.8
2016	73.5	13.1	0.8	4.6	8.1	230.0

Source: ***MoRTH (2018)***

Table 1.3 Public Transport Mode Share in Indian Cities, and the Desirable Modal Split

City population (in Millions)	RITES report, 1994	WSA report, 2007	Desirable Share, National Transport Development Policy Committee, 2013
<0.5	0–22.7	0–15.6	12-15
0.5-1.0	22.7–29.1	0–22.5	15
1.0-2.0	28.1–35.6	0–50.8	20
2.0-4.0	35.6–45.8	0–22.2	33
4.0-8.0	45.8–59.7	0-32.16	38
>8.0	59.7–78.7	35.2–54.0	38

WSA*: Wilmer Smith Associates* RITES*: Rail India Technical and Economic Services*
Source: ***MoUD (2016)***

The major reasons for the decline in patronage of public transport modes among non-captive travellers, in general, include the non-availability of services at the right time, inaccessibility of the destination points, inadequate comfort and convenience, and poor reliability of services offered. The increasing purchase power of the urban middle class, too, has contributed towards higher dependence on personalized nodes of travel, resulting in increased congestion and air pollution. Moreover, the availability of motorized two-wheelers at affordable prices has further resulted in a larger share of urban commuters adopting this mode of travel **(Pucher et al. 2005)**.

The public bus transportation systems have rendered yeomen service to the nation by providing mobility and accessibility at affordable prices for urban and rural trip-makers. Despite the limitations of the public bus transport system, it is still considered to be a viable mode of transport, especially for the economically weaker sections of society. Bus transport systems make effective use of road space by providing mobility to a large number of people at the lowest possible cost. According to data compiled by the **Planning Commission** (**2012**), it is observed a car consumes 6 times more energy than a bus per passenger kilometre, while motorized two-wheelers and three-wheelers consume 2.5 and 4.7 times more energy, respectively. **Woodcock et al. (2009)** observe that it is necessary to maintain public transport services at optimal levels to ensure lesser pollution and congestion as part of the endeavour to provide quality life to urban citizens.

In view of the need to satisfy the increasing travel demand of urban trip-makers, it is imperative to rejuvenate and promote public transport systems. Although the setting up of a more extensive public transportation network and providing services at higher frequencies can mitigate the problems to a limited extent, it may ultimately result in the under-utilization of services. A strategy to adopt more effective methods to monitor and evaluate the performance of public transport services will go a long way in identifying the gaps in the system.

The study of performance evaluation, or in other words, the study of efficiency and effectiveness requires a clear understanding of *service inputs* (such as labour, capital, fuel, etc.), *service outputs* (such as vehicle-hour, vehicle-km, revenue-km, etc.), and *service consumption* (such as, passengers carried, passenger-km, etc.), and the relationship to *cost-efficiency* (service input vs service output), *cost-effectiveness* (service input vs service consumption), and *service effectiveness* (service output vs service consumption). The standard *financial* and *physical* performance indicators used in representing the various aspects of public transport can assist transport managers in determining the strategies to be adopted to operate the services at sustainable levels. These indicators need to be compared with national, and international benchmarks in order to maintain the effective presence of public transport in the country.

In India, public transportation modes other than railways and airways, come under the purview of state/ federal governments. Thus, the bus services in each state are provided and monitored by State Road Transport Undertakings (SRTUs). Private bus-owners, too, are permitted to offer services along designated routes. The financial and physical performance related data are regularly reported by SRTUs to the Central Institute of Road

Transport (CIRT), Pune and *Ministry of Road Transport & Highways* (MoRTH). The data used in this study was primarily obtained from CIRT, Pune.

Analysis of information on existing travel demand, combined with reliable forecasting approaches can help transport planners in evolving strategies for solving complex problems in the public transport sector. The availability of suitable software tools for performing advanced studies can be employed in investigating problems in urban transport. *Multi-criteria decision-making* (*MCDM*) approaches, econometric approaches and Statistical approaches can be employed in the evaluation of the performance of organizations. *MCDM* approaches include the *Analytical Hierarchy Process* (*AHP*) and the *Technique for Order of Preference by Similarity to Ideal Solution* (*TOPSIS*) method. Econometric approaches constitute parametric-based studies using the *Stochastic Frontier Analysis* (*SFA*) approach, and non-parametric-based studies using the *Data Envelopment Analysis* (*DEA*) method. Statistical approaches such as the *principal component analysis* method and the *recursive feature elimination* can be used as an additional tool as part of *MCDM* and *DEA* approaches to derive a smaller set of variables that can effectively explain the variances without significant loss of information.

The scope of the present work involves the identification of *key performance indicators* (KPIs) using PCA, RFE, and MCDM approaches such as AHP and *TOPSIS*. This was followed by performance evaluation using econometric approaches, including the *parametric-based* SFA approach and the *non-parametric-based* DEA method for evaluating the productivity and efficiency of selected SRTUs in India, including *Karnataka State Road Transport Corporation* (KnSRTC). In a similar manner, analyses at the *sub-system* and *micro level* can be performed to estimate the *travel demand* variation at the *route level* in the evaluation of *efficiency and service effectiveness* of transit routes. The study also includes an in-depth analysis of the performance of *Mysuru City Transport Division* (MCTD), an urban-based SRTU at the *micro/route* levels using various analytical tools.

The overall approach adopted in this study for the performance evaluation of SRTUs is expected to provide the basic framework for fine-tuning the functioning of similar organizations. These approaches will assist in identifying bottlenecks that need to be streamlined for improving the financial and physical performance of transport undertakings.

1.2 PROBLEMS AND ISSUES IN MONITORING AND EVALUATION OF PUBLIC TRANSPORT SYSTEMS

Bus-based public transportation in India that provides accessibility and mobility to rural, inter-city, and urban areas is mainly controlled and monitored by state-government/

federal agencies such as SRTUs. The CIRT, Pune collects, compiles, and analyses data on financial and physical performances of SRTUs, and publishes summarized details on a regular basis. The Transport Research Wing of the MoRTH also provides similar details on SRTUs annually. The financial and physical performance indicators used by CIRT are similar to those adopted by international agencies for performance evaluation. These performance indicators can also be used to compare the performance of SRTUs in India, and for benchmarking the performance of SRTUs against international standards.

Monitoring and evaluation of public transportation systems assist in the identification of inadequacies in the system for corrective action. This will help maintain the mode-share of public transport systems at sustainable levels. Urban policies that encourage the use of public transport will attract additional investments in providing the necessary infrastructure.

Urban transport managers use information and data related to the financial and physical performance of public transport systems over time to analyze and identify inefficiencies. This study also aims to provide a clear understanding of key performance indicators in urban transport and the application of mathematical techniques for their analysis. These insights are crucial for developing policies related to subsidies in urban transport, which can attract investments. Consequently, urban transport managers need to adopt a holistic approach to the performance evaluation of public transport systems. This approach should meet societal needs by ensuring last-mile connectivity and enhancing overall mobility.

1.3 BUS TRANSPORT SCENARIO IN INDIA, THE NEED FOR THE PRESENT STUDY

Bus-based public transport systems are considered to provide affordable means of transport to trip-makers of urban and rural areas. The use of bus transport modes can help reduce traffic congestion and pollution on urban roads. In India, State Road Transport Undertakings (SRTUs), established based on the Road Transport Corporation Act 1950, operate bus services along designated travel routes. A total of 54 SRTUs are operated by 24 Road Transport Corporations, 12 Companies, 8 Government Departmental Undertakings, and 10 Municipal Undertakings. Also, the SRTUs provided mobility to 68 million passengers per day as per statistics for 2015-16, which is about 3 times the passengers carried by the Indian Railways (**MoRTH, 2016**). However, most of the SRTUs are running under a loss. Only 7 of the 47 SRTUs that reported details on financial and physical performance for the year 2015-16 are running on profit. These include Bangalore Metropolitan Transport Corporation (BMTC), Himachal-Pradesh Transport Development

Corporation Ltd. (HPTDCL), Kadamba Transport Corporation Ltd. (KTCL), Karnataka State Road Transport Corporation (KnSRTC), Odisha State Road Transport Corporation (OSRTC), Punjab State Bus Stand Management Co. Ltd (PUNBUS), and Uttar Pradesh State Road Transport Corporation (UPSRTC).

In the year 2015-16, the total losses accrued by SRTUs over the years stood at Rs. 113.4978 million (**MoRTH, 2016**). Public transport undertakings are prone to making losses since these agencies focus on providing mobility to people on commercially viable routes, while providing accessibility and mobility to under-developed remote regions. Additionally, these transport undertakings face competition from private bus operators. The increasing cost of fuel and spares, increasing cost of labor, resource crunch on fund allocation in the form of subsidies, the lack of sufficient level of transparency in accounting, the rising trend in the use of private vehicles, coupled with the lack of computational tools for performing advanced in-depth analysis on performance-related aspects have affected the functioning of SRTUs leading to financial losses.

The motivation behind this study is to provide a comprehensive performance evaluation and benchmarking tool for *State Road Transport Undertakings* (SRTUs). By identifying the key performance indicators and utilizing advanced methodologies such as the *Data Envelopment Analysis* (DEA) and the *Stochastic Frontier Analysis* (SFA), the study aims to offer actionable insights for SRTUs to enhance their operational efficiency and effectiveness. The goal is to help these undertakings operate at sustainable levels, either by maximizing output or minimizing input costs, in order to provide reasonably acceptable levels of service without much financial loss. This research will equip the loss making SRTUs with the necessary tools and strategies to achieve a no-profit, no-loss operation model, ensuring better resource utilization and improved service delivery to the public.

There are a number of approaches to benchmark the performance of public transport systems using parametric and non-parametric methods. Parametric approaches include the least-square regression method, the *stochastic frontier analysis* approaches, and other related methods. These methods are adopted when data collection involves randomness and where the chances of committing measurement errors exist, as in the case of data collected through sample surveys, whereas a non-parametric approach such as the DEA method can be adopted where random errors are expected to be the least (**Asmare and Begashaw, 2018**). The objective of the *DEA* approach originally proposed by Charnes et al.

(1978) is to maximize the efficiency of the organization or *decision-making unit* (DMU) based on the measurement of productive efficiency (**Farell, 1957**).

Bus performance assessment can be conducted at three levels - system level, subsystem level, and route level. *System level* evaluations refer to the performance of the bus system as a whole based on data compiled at the depot level all over the administrative area of the SRTUs. The analysis performed at this level assists in the study of trends in the performance of the SRTUs. *Subsystem level* performance evaluations utilize data on performance of buses along various routes under a bus depot, while *route level* evaluations focus on performing micro-level analysis on links served along each route.

1.4 SCOPE AND OBJECTIVES

The scope of the present work focuses on the performance evaluation of *State Road Transport Undertakings* (SRTUs) in India with an in-depth analysis on the performance of Karnataka State Road Transport Corporation (designated as KnSRTC by CIRT). This study involves investigations on the physical and financial performance of SRTUs, the identification of important measures of *efficiency,* and *effectiveness*, and the development of an effective methodology for the performance evaluation of bus transport organizations in India. The study also includes a micro-level/ route level analysis of the performance of the *Mysuru City Transport Division* (MCTD), a part of KnSRTC.

The *first phase* of the present study focuses on performing an in-depth investigation on the use of *measures of efficiency* and *measures of effectiveness* in the performance evaluation of bus transport organizations and the identification of *key performance indicators* (KPI) based on the analysis of responses obtained from experts. In this phase of the study, it was planned to adopt the use of the *MCDM* based approaches such as *AHP*, Fuzzy *AHP*, *TOPSIS,* and *Fuzzy-TOPSIS* methods.

In the *second phase* of the study, it is proposed to compare the performance of various SRTUs in India including KnSRTC using the selected set of performance indicators and to further identify the input and output variables that need to be considered in the analysis using parametric approaches such as the SFA approach and a non-parametric approach such as the *DEA* method.

In the *third phase* of the study, it was also proposed to use important physical and financial performance indicators identified in the literature review to explore the possibilities of using the DEA approach incorporating the use of exogenous variables related to *vehicle emissions* and *accidents*.

The *fourth phase* of the study focuses on performing micro-level/route-level analyses on the MCTD, a part of KnSRTC. This includes the identification of KPIs incorporating the use of the PCA and the RFE implemented using the R/ Python programming language. And performance analysis using a non-parametric-based econometric approach such as the DEA approach implemented using the R/ Python programming language.

The major *objectives* of the present study include the following

1. To comprehensively understand the role and application of financial and physical performance indicators in the evaluation of SRTUs in India.
    a. It was considered appropriate to select relevant *key performance indicators* (KPIs) using MCDM approaches such as the *Analytical Hierarchy Process* (*AHP*) method, and *TOPSIS*.
    b. To integrate statistical methods, including the *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC), for robust selection and comparison of these KPIs across different SRTUs.
2. To compare the performance of various SRTUs in India based on identified KPIs using a parametric approach such as the SFA and a non-parametric approach such as the *DEA* method.
3. It was also proposed to explore the possibilities of using the DEA approach incorporating the use of undesirable/negative variables related to vehicle emissions and accidents in the performance evaluation.
4. To perform subsystem level/route level analyses for *Mysuru City Transport Division* (MCTD), operating under KnSTRC, with emphasis on evaluating *efficiency* in terms of *revenue* and *effectiveness* in terms of *ridership*.
    a. It was considered to utilize the *principal component analysis* (PCA) and the *recursive feature elimination* (RFE) in the identification of the key performance indicators.
    b. To evaluate transit routes using the DEA approach, incorporating factors like *revenue*, *ridership*, and so on.
    c. It was also considered to carry out an in-depth analysis w.r.t *route length* using the *Technical Gap Ratio (*TGR) in the performance evaluation.

1.5 ORGANIZATION OF THE THESIS

Chapter 1 of this thesis provides a general introduction to public transport in India with a brief overview of the current problem scenario and the need for the study. It also provides details on the scope and objectives of the present study with information on various phases of the investigation.

Chapter 2 provides an overview of the literature survey performed on research related to the use of performance measurement indicators in the public transport sector, and the applications of multi-criteria decision making (MCDM) techniques with a special focus on the use of the *AHP*, TOPSIS, and *SFA* approaches in addition to the use of other parametric and non-parametric approaches such as the DEA in performance evaluations in various sectors of economic activity including the transport sector. It also provides details on the methods adopted by various researchers on performance evaluation, along with information on gaps in research that need to be addressed.

Chapter 3 deals with an overview of the theoretical background of the studies related to performance measures used in assessing *efficiency* and effectiveness in the public transport sector, along with the theoretical foundations of MCDM techniques such as *AHP*, *TOPSIS*, and basic concepts related to fuzzy-based decision-making. Details on the use of AIC, and BIC scores and Spearman's rank correlation are also provided in this chapter, along with details on the application of DEA and SFA approaches in performance evaluation.

Chapter 4 provides details on the methodology adopted, a brief description of the study area, and identification of *key performance indicators* (KPIs) based on inputs from experts obtained using a Google-Forms-based questionnaire. This chapter also includes details on the preliminary processing of the responses collected from experts, followed by analysis using the conventional AHP and the Fuzzy AHP, and the conventional TOPSIS and the Fuzzy TOPSIS approach, where a final set of indicators was identified for further analysis.

Chapter 5 provides details on performing analysis using the SFA, where a preliminary set of models were formulated to represent *cost efficiency*, *cost effectiveness,* and *service effectiveness*. Statistical methods such as the AIC and BIC methods in identifying the best models representing *cost efficiency*, *cost effectiveness,* and *service effectiveness*. The SFA approach also incorporates analysis using the *maximum likelihood estimation* (MLE) method to assess the statistical significance of variables used in the models. The performance evaluation and benchmarking of 31 SRTUs in India were then performed.

Chapter 6 provides details on performing analysis using the DEA, where a preliminary set of models were formulated to represent *cost efficiency*, *cost effectiveness,* and *service effectiveness*. Statistical methods such as the AIC and BIC methods in identifying the best models representing *cost efficiency*, *cost effectiveness,* and *service effectiveness*. The performance evaluation and benchmarking of 31 SRTUs in India were then performed.

Chapter 7 provides details on performing analysis based on important physical and financial performance indicators identified in the literature review to explore the possibilities of using the DEA approach incorporating the use of exogenous variables related to vehicle emissions and accidents. The performance evaluation and benchmarking of 25 selected SRTUs in India were then performed.

Chapter 8 provides details on the performance analysis of public transport organizations at the Micro/Route level. This includes the identification of KPIs for route-level analysis using PCA and RFE approaches. Followed by performance evaluation using the DEA approach. It also includes an in-depth analysis performed based on route length using TGR values.

Chapter 9 provides details on the conclusions arrived based on studies performance evaluation of SRTUs at system level and Sub-system/Route level. The chapter also critically draws conclusions on the various approaches, such as AHP, TOPSIS, PCA, and RFE, and analysis using the SFA and DEA approaches. It also includes major findings and scope for future work/ limitations.

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

Public bus transport system in India have provided accessibility and mobility to rural and urban travellers over the last many decades. However, there has been a gradual decline in the ridership by public transport modes. The limitations of public transport modes include poor reliability of services, non-availability of information regarding micro and macro level performance characteristics, increase in travel fares, increasing fuel prices, non-availability of capital, and the increasing cost of manpower deployed. The priorities for improvement of the services need to be clearly defined on a scientific basis based on micro and macro-level performance indicators. Financial and performance indicators can be used to identify deficiencies in the operations of public transport organizations at the system and subsystem levels.

In view of the objectives of the present study, it was considered ideal to have a proper understanding of *key performance indicators* (KPIs), and the application of *Multi-Criteria Decision Making* (MCDM) and Statistical based approaches in the urban transport scenario. It was also proposed to perform a review of literature related to the use of *MCDM approaches such as AHP*, *TOPSIS* and statistical approaches such as *PCA* and *RFE* in the selection of the best criteria for performance evaluation. Additionally, it was considered important to have an overall understanding of parametric and non-parametric techniques adopted in the evaluation of *efficiency* and *effectiveness* of organizations with a special focus on *parametric-based* studies such as the *SFA* approach, and non-parametric methods, such as the DEA approach as part of the present work. This chapter also provides details on DEA-based performance evaluation using variables such as vehicular emissions and accidents.

2.2 REVIEW OF IMPORTANT STUDIES ON THE USE OF *KEY PERFORMANCE INDICATORS*: MEASURES OF *EFFECTIVENESS* AND *EFFICIENCY*

Key performance indicators consist of *measures of efficiency* and *measures of effectiveness* that are widely used by transport managers in evaluating and monitoring the performances of bus transport systems. *Measures of efficiency* are used to derive maximum benefits from minimum input in terms of cost and resources used. *Measures of effectiveness* are used to express the ability of the public transportation system to satisfy the mobility and accessibility needs of passengers. One of the major objectives of transport management is to attain a sustainable balance between the *measures of efficiency* and the *measures of effectiveness* so that the organization makes a reasonable profit.

Fielding et al., (1978) performed studies on the applications of efficiency and effectiveness indicators on bus transport systems. The use of 24 performance indicators were reviewed in this study, based on which 3 efficiency measures, 4 effectiveness measures, and 2 overall indicators were considered to be important. The 3 *measures of efficiency* recommended included *revenue vehicle-hours per employee*, *revenue vehicle-hours per vehicle*, and *operating expenses per revenue vehicle-hour*. The 4 *measures of effectiveness* recommended included *revenue passengers per service area population*, *percentage of population served*, *total passengers per vehicle*, and the *revenue passengers per revenue vehicle-hour*, while the 2 *overall indicators* used were the *operating expenses per passenger*, and the *operating expense per revenue-passenger*, respectively.

With the amendments to the Urban Mass Transportation Act of 1964 in the US, it became necessary for urban transport managements to compile details on performance aspects by all transit managements. This provided the necessary database for **Fielding et al. (1985)** to analyse the suitability of 48 indicators for performance evaluation of a larger group of transit organizations. These indicators were selected in accordance with the framework of the *performance concept model* considering *service input* (labour, capital, fuel, etc.), *service output* (vehicle-hour, vehicle-km, etc.), and *service consumption* (passengers carried, passenger-km, etc.). These are represented by the three corners of a triangle, as shown in **Fig.2.1**.

In the framework for the *performance concept model* in **Fig.2.1**, the corners of the triangle represent *service inputs*, *service outputs*, and *service consumption*. The performance of a public transport system can be evaluated using basic indicators such as the labour costs, capital costs, and fuel costs as part of *service inputs*; the vehicle-hours, vehicle-km, and the capacity-km as part of *service outputs*; and the number of passengers carried, passenger-km, and the operating revenue as part of *service consumption*.

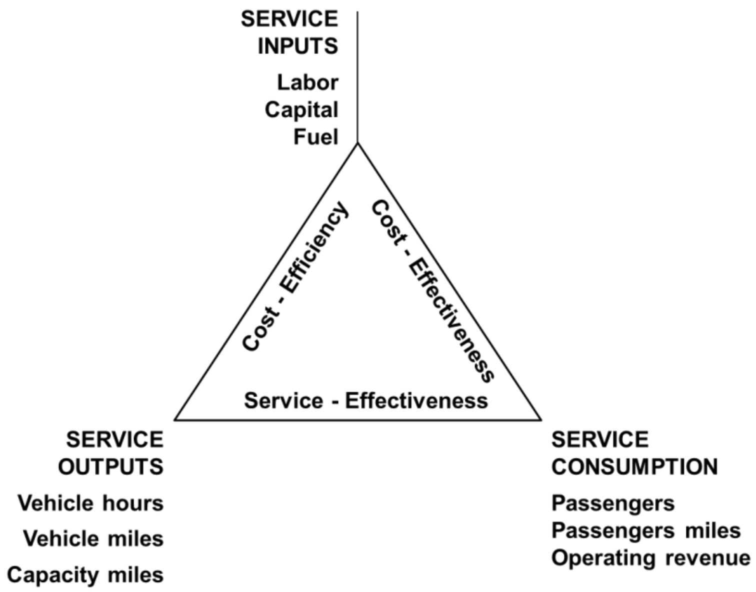

Fig.2.1 The Framework of the Performance Concept Model
(Source: Fielding et al. 1985)

The performance measures, such as labour costs, capital costs, fuel costs, vehicle-hours, vehicle-km, and capacity-km, represent *cost-efficiency* or *technical-efficiency*, while the measures such as labour costs, capital costs, fuel costs, number of passengers carried, passenger-km, and the operating revenue together form *cost-effectiveness*. Also, the measures such as vehicle-hours, vehicle-km, capacity-km, number of passengers carried, passenger-km, operating revenue, and so on represent *service effectiveness*. *cost-efficiency* or *technical-efficiency* thus relates the *service inputs* to the *service outputs*, while *cost-effectiveness* relates *service inputs* to *service consumption*. On the other hand, *service effectiveness* relates the *service outputs* to *service consumption*.

In the above study performed by **Fielding et al. (1985)**, three performance indicators representing the key underlying dimensions of performance evaluation were identified. The indicators such as *revenue vehicle-km per operating expense* (representing *cost-efficiency*), *passengers per revenue vehicle hour* (representing *service-effectiveness*), and the *operating revenue per operating expense* (representing *cost-effectiveness*) were considered to be the most reliable universal measures of performance. Additionally, four more important performance indicators were identified. These include *effective vehicle-hours per traffic employee* (representing *labour-efficiency*), *total vehicle-km per total vehicle* (representing *vehicle-efficiency*), *total vehicle-km per maintenance employee* (representing *maintenance-efficiency*), and *total vehicle km per total accident* (representing safety).

Wright and Thiriez (1987) developed benchmarks for the above-mentioned performance indicators based on studies performed on bus transport services in varies cites in developing countries, including Istanbul, Bangkok, Kingston, Buenos Aires, Bombay, Madras, Coimbatore, Bogota, Colombo, Medellin, Delhi, Lagos, and Abidjan. The benchmarks developed are listed below:

a) Passenger Volume Indicator = Passengers/Bus/Day (1000-1200 for bus capacity of 80) (1200-1500 for bus capacity of 100)
b) Fleet utilization of buses (80-90%)
c) Measure of distance travelled = effective km/bus per day (210-260)
d) Measure of staffing ratio = operating staff/bus (2.2 – 6.1)
e) Measure of accident rates = accidents/ 100,000km.
f) Road mileage lost (%) = (scheduled km. X 100) / kilometres operated by vehicles
g) Measure of cost of service = operating expenses/passenger km (2-5 US Cents)
h) Measure of operating ratio = revenue/operation cost (1.05-1.08)

TCRP (2003) evolved a sequential approach to assist transport authorities in setting up an information system that facilitated performance evaluation. These also include indicators related to transit-users, and benefits to the community. These guidelines developed based on studies performed on transit organizations, proposed the use of 400 performance indicators for decision-making. The performance measures were divided into 10 categories such as those related to transit availability, service delivery, community development, travel-time, safety and security, maintenance and construction, economic development, capacity building, paratransit support, and travel comfort. Transport managements were advised to incorporate suitable performance measures depending on data availability under these categories to satisfy their goals and objectives. Studies on the Nashville Metropolitan Transit Authority (NMTA), Los Angeles County MTA (LACMTA), San Diego Metropolitan Transit Development Board, San Diego Transit, San Diego Trolley, National City Transit, Chula Vista Transit, North County Transit System, and other similar organizations in the US were used in evolving the sequential approach.

Karlaftis (2004) performed investigations on the evaluation of transit system *efficiency* and *effectiveness* and performed studies on developing relationships between them. Data on 256 US transit systems over a five-year period from 1990-94 made available through the National Transit Database (NTD; www.bts.gov) was used in this study. The data included information extracted from the Chicago RTA, Houston Metro, Miami

MDTA, New Orleans RTA, Seattle Metro, and so on. This study focused on the development of three models. The first model focused on the *measurement of efficiency* based on *service inputs* such as the total number of employees, fuel used, and capital expenses, and *service outputs* such as vehicle-miles. The second model focused on the *measurement of effectiveness* based on *service inputs,* as mentioned above, and *service consumption* measured in terms of total annual ridership. The third model dealt with the *measurement of efficiency-cum-effectiveness* based on *service inputs* as mentioned above, *vehicle-miles* (as part of *service outputs*), and *total annual ridership* (as part of *service consumption*).

Eboli and Mazzulla, (2012) performed extensive studies on the application of indicators related to services offered to passengers, including safety, reliability, comfort, cleanliness, customer care, and environmental impact. The studies focused on developing strategies for the measurement of passenger-based indicators in an objective manner based on studies performed in many countries.

LTA Academy (2013), and many similar biannual publications of the Land Transit Authority of Singapore (LTA) provide details on the important performance indicators used in performance evaluation. These indicators include average fleet size, number of routes, average daily vehicle-km, average daily passenger trips, average journey distance (km/passenger-km), public bus fleet per million passengers, average daily public transport trips per person, road density (km/km^2), and the number of stations per km^2.

FDOT (2014) highlighted the importance of a number of performance measures under the following categories:

a) *Ridership indicators*: These include total ridership or ridership by mode or service type, passenger-trips, passenger-miles, a ratio of ridership growth to population growth, a ratio of total passengers to total population (or passengers per capita), and number of trip-makers at park-and-ride terminals.

b) *Availability indicators*: These include total service hours provided versus total hours needed to satisfy public transport travel demand and average days per week that public transport services are available.

c) *Internal cost and efficiency indicators*: These include passengers per vehicle-mile, passengers per vehicle-hour, total operating cost per passenger, operating expense per revenue vehicle-mile, and fuel economy.

Table 2.1 Summary of critical studies on the use of KPIs

Previous studies	Details of study	Variables (KPIs) Considered
Fielding et al. (1985)	Performed pioneering studies on the use of performance indicators using measures of efficiency and effectiveness based on studies in the US.	revenue vehicle-km per operating expense (representing cost-efficiency), passengers per revenue vehicle hour (representing service-effectiveness), and the operating revenue per operating expense (representing cost-effectiveness)
Wright and Thiriez (1987)	Developed benchmarks for the performance indicators based on studies performed on bus transport services in various cities of developing countries	Pass./Bus/Day (1000-2000); Fleet Util (80-90%); Ekm/bus/day (210-260); Staff Ratio (2.2-6.1); Acc. Rate per 100,000km; Road Mileage Lost % Op. Cost Ratio (1.05-1.08)
TCRP (2003)	Proposed the use of 400 performance indicators for the evaluation of Public Transportation Systems operating in the US region.	The performance measures were divided into 10 categories such as those related to transit availability, service delivery, community development, travel-time, safety and security, maintenance and construction, economic development, capacity building, paratransit support, and travel comfort
Karlaftis (2004)	study focused on the development of three models: *measurement of efficiency*, *measurement of effectiveness*, *and efficiency-cum-effectiveness*	***Efficiency:*** *service inputs*: total number of employees, fuel used, and capital expenses, *service outputs:* vehicle-miles. ***Efficiency:*** same as above *service output:* total annual ridership. ***Efficiency:*** *service inputs* total number of employees, fuel used, and capital expenses, *vehicle-miles* (as part of *service outputs*), and *total annual ridership* (as part of *service consumption*).
Eboli and Mazzulla (2012)	Focused on objective measurement of passenger service indicators.	Passenger-based indicators: Safety, reliability, comfort, cleanliness, customer care, environmental impact
LTA Academy (2013)	Evaluation of Public Transportation Systems using performance indicators in Singapore.	average fleet size, number of routes, average daily vehicle-kms, average daily passenger trips, average journey distance (km/passenger-km), public bus fleet per million passengers, average daily public transport trips per person, road density (km/km^2), and the number of stations per km^2.
FDOT (2014)	Comprehensive performance measures for public transportation	Ridership, availability, internal cost and efficiency, quality, asset management, community indicators

d) *Quality indicators*: These include timely performance, rate of injuries and/or fatalities, and other ratings of public transportation systems.

e) *Asset management indicators*: These include details such as the age of the fleet by vehicle type, percentage of the useful life of vehicle remaining, number of mechanical failures per day, the distance between vehicle failures, or frequency of vehicle failures.

f) *Community indicators*: These include the percentage of non–single-occupant vehicle commuters, the number of auto vehicle trips reduced, energy savings, the percentage of fleet vehicles transformed to run on clean or alternative fuels

Daraio et al. (2016) performed a comprehensive review of 127 research articles using *Vos viewer*, a word mapping tool, on studies related to performance evaluation using efficiency and effectiveness indicators in the urban public transport sector. A consolidated list of commonly used performance indicators, in addition to indicators that need to be studied for their effectiveness was prepared. The important performance indicators identified in this study are listed below:

- *Commonly adopted indicators:* These include the number of vehicles, number of employees, fuel consumption, employee-hours of work, price of capital, price of labour, price of fuel, operating expenses, materials costs (tyres, lubricants, etc.), vehicle-km, seat-km or capacity-km, revenue-vehicle-km, passenger-km, number of passengers, and the operating revenue.
- Variables that are not considered either as the input or as the output in efficiency models include *physical characteristics* such as the length of the network, average travel speed, average fleet-age, and the service frequency or headway; socio-demographic *characteristics* such as population density, car ownership, population in the service area, and so on. The study also recommended the use of *externality indicators* such as the number of accidents and emissions.

2.3 MULTI CRITERIA DECISION MAKING TECHNIQUES

In general, *key performance indicators* are generally identified based on a review of the literature. However, MCDM approaches can be adopted to identify KPIs based on literature, standards set by international organizations and recommendations of industry experts. The MCDM approaches are primarily based on their versatility, ease of use, robustness in handling complex data, and the clarity of their outcomes. AHP is often placed at the top due to its comprehensive nature and strong theoretical foundation, while methods like TOPSIS are valued for their practical applicability and clarity in ranking alternatives. The following section provides details on studies related to MCDM approaches such as *AHP* and *TOPSIS*.

2.3.1 Studies on the Application of AHP Approach

Sun (2010) evaluated four notebook computer manufacturing companies based on their performance using fuzzy AHP and fuzzy TOPSIS. The study considered the manufacturing capability, supply chain capability, innovation capability, financial capability, human resource capability, and service quality capability. The opinion of 10 experts was used in the study related to assigning weights using the fuzzy AHP to identify the best performance indicators, followed by the determination of the best performing company using fuzzy TOPSIS.

Velasquez and Hester (2013) performed a review of studies related to the application of eleven MCDM techniques in the decision-making process. The study provided details on the advantages and disadvantages of each of the approaches. The study also indicated that the use of *AHP* and *TOPSIS* is popular in MCDM-based approaches for large organizations.

Cyril et al. (2019) performed studies on a modified approach integrating *AHP* with the goal programming (GP) method for the determination of efficiency in Kerala State Road Transport Corporation (KSRTC). The perspectives of both the operator and the user were considered in the analysis. The weights for 12 important indicators for measuring efficiency were identified based on the *AHP* approach along with the use of penalties as part of the goal programming method. The weights were then assigned to the objective function of the GP problem to find a solution that minimizes the weighted sum of deviations from the goal values. The findings of the study indicated that the operator cost and the staff deployed per schedule were the most important variables to be considered from the operator's perspective, while the safety of travel was most important based on the user’s perspective. The optimal solution indicated that increasing the accessibility, safety, and regularity would increase the number of passengers. Also, decreasing the staff per bus would further reduce the operating cost.

Kumar et al. (2020) evaluated the performance of major public road transport organizations in India using MCDM techniques such as *AHP*, *DEA,* and *VlseKriterijumska Optimizacija Kompromisno Resenje* (*VIKOR*). Also, the increase in productivity was determined using the *Malmquist Productivity Index* (*MPI*). The indicators used for the evaluation of performances were classified into six categories: accident, traffic-revenue, expenses, vehicle operations, manpower operations, and maintenance. These indicators were evaluated for relevance using relative weightage determined with the help of *AHP*. Later on, the Data Envelopment Analysis (*DEA*) was used to compute the efficiency of functional heads of all *Decision-Making Units* (*DMU*). The VIKOR-based approach was then used to assign final ranks to each *DMU*. The performance of each *DMU* was then analysed for two consecutive years using the *Malmquist Productivity Index* (*MPI*).

2.3.2 Studies on Application of the *TOPSIS* Approach

Liu et al. (2006) adopted an MCDM method, such as, *the Technique for Order Preference by Similarity to Ideal Solution (*TOPSIS*)*, to set priorities for rehabilitation in wetland conditions in the Clarence River Catchment, New South Wales. GIS-based information on wetland characteristics, protection measures, and anticipated threats, organized in 13 layers, were used in this study.

Lin et al. (2008) evolved a framework incorporating the use of the *analytical hierarchy process* (AHP) method to identify the relative importance of customer requirements and design characteristics in arriving at the final design solution, followed by the use of TOPSIS to perform benchmarking. These findings indicated that the AHP and TOPSIS could be used in product development.

Awasthi et al. (2011) proposed a *Multi-Criteria Decision Making* (MCDM) approach for the assessment of sustainable urban transportation systems under a *fuzzy* environment in order to incorporate uncertainties. In the *first stage* of performance assessment, criteria related to *sustainability* in transportation were selected, which included the operating costs, safety, security, reliability, air and noise pollution, usage of fossil fuels, travel costs, energy consumption, waste generated, land use, accessibility, mobility, the convenience offered, level of service, and so on. In the *second stage*, information collected from experts in the field of transportation on the selection of criteria for assessment was used in the study. The opinions and the responses were ranked on a linguistic basis. A f*uzzy-based* analysis was then performed using *TOPSIS* to generate aggregate scores for the assessment of sustainability and the selection of the best alternative. The decision-making unit with the highest score was then selected as the best sustainable transportation system. In the *third stage*, a *sensitivity analysis* was performed to analyze the sensitivity of inputs and outputs were analyzed using pair-wise comparisons.

Zyoud et al. (2015) proposed to integrate the use of Fuzzy AHP and Fuzzy TOPSIS for decision making on water loss management in a developing country. The fuzzy AHP approach was initially used to determine the weights for the evaluation criteria, while Fuzzy TOPSIS was used to rank the various options in decision making.

Vasiliki et al. (2018) used the *TOPSIS* approach to choose a suitable spillway for 'Dam Pigi' dam in the district of Kilkis, Northern Greece. Since the criteria for spillway selection were *fuzzy and uncertain* in nature, the authors introduced the concept of AHP that assists in assigning weights to the criteria, based on which *Fuzzy TOPSIS* pairwise computations were performed at a later stage to identify the best spillway. Five types of spillways, including the ogee spillway, shaft spillway, gated spillway, side-channel spillway, and siphon spillway were analyzed as part of the study. The important criteria adopted in the measurement of alternatives included the construction costs, maintenance costs, cost of the foundation, reservoir capacity, discharge capacity, space availability, cost of conveyance of materials, and aesthetics which were determined using literature studies and the opinion of experts. The choices were then sorted using the *Fuzzy TOPSIS* approach to identify the best spillway. This approach using AHP and Fuzzy TOPSIS can be adopted for the evaluation of other organizations using a different set of criteria.

Samet Güner (2018) presented a *two-stage MCDM* approach for bus transit operators to monitor and improve *service quality*. In the *first stage*, a *questionnaire* was designed to obtain details on service quality attributes such as span of service, frequency, capacity, accessibility, network coverage, vehicle occupancy, speed, the ratio of air-conditioned vehicles, availability of direct routes, and so on based on the perspectives of the passengers. The *AHP* method was used to assign the weights, while the *TOPSIS* was used to rank the bus transit routes and to rank the service quality. This study was applied to the Sakarya City Metropolitan Municipality Transportation Bureau (SMMTB), Turkey. The *AHP-TOPSIS* procedure was straightforward and simple to follow. The results obtained were consistent.

Ador et al. (2020) performed studies on the use of Fuzzy AHP and TOPSIS in the selection of the ideal supplier of stones for a Cement Manufacturing Company in Bangladesh. Details on ten factors, including the cost involved, quality, trust, and technology were used to evaluate a set of four different suppliers. The fuzzy AHP approach was found to provide the best solution in a simpler manner when compared to TOPSIS.

2.4 OTHER APPROACHES IN IDENTIFICATION OF KPIs

2.4.1 Studies on *Principal Component Analysis* (PCA) Approach

In order to handle problems associated with an excessive number of input and output data, it is preferred to use the *principal component analysi*s (PCA) method. The PCA approach is capable of analyzing the variance in the data using linear combinations of variables.

Adler and Golany (2001) explored the application of the PCA method along with the DEA approach in studies related to the West European air transport sector. The study focuses on the use of DEA and PCA in identifying the most suitable air transport network. Factors related to the service provided by an airport and the fee charged to the airline are considered in addition to the average passenger per week, the frequency of use, and the airport facilities. The output variables include profitability, average load factor, average delay, and minimum connecting time. A ratio of relative efficiency was then computed for each transport network configuration. The PCA approach was used to aggregate input data due to their excessive number of inputs and outputs. 320 airport network combinations were analyzed in this study. The PCA approach assisted in reducing the number of inputs for subsequent analysis using a *data envelopment analysis* (DEA) approach.

Alder and Yazhesmky (2010) performed studies comparing the variable reduction based on the partial covariance approach and the PCA-DEA approach using the Monte Carlo simulation method. The investigation used simulated data to perform the analysis. The study indicated that the PCA-DEA approach provides consistently more accurate results when compared to other approaches.

Xu and Lin (2016) performed studies based on the PCA approach along with the use of *dynamic programming* (DP) to generate a ranking of indicators to be used in the selection of the most suitable transit projects. Data on transit systems operating in 15 cities in China were in this study. The study indicated that the choice could be obtained based on indicators such as the level of service, the expected income, the expected cost, and the influence of external factors. The analysis showed that the option related to upgrading the existing *bus rapid transit* (BRT) into a *light rail transit* (LRT) system should be given more importance, followed by laying of *mass rail transit* (MRT) routes in the near future.

Naim et al. (2020) performed studies on the performance evaluation of 10 bus transport routes in Chattogram City Corporation (CCC), Bangladesh, using a DEA approach with both measurable and non-measurable quantities. The performance indicators related to *transit users* included inputs related to the *fare, walking distance to the bus stop, waiting time at the bus stop,* and the *journey time* and outputs such as *reliability, comfort, safety and security, fare system,* and so on. The performance indicators related to *transit operators* included inputs related to the *number of stops, daily service time, service frequency, number of staff* and the *operation cost* and outputs such as *ridership* and *passenger km*. The performance indicators related to *transport authorities* included the *accident rate* and *rules and regulations.* The study indicated that the relative efficiency scores in various routes varied based on the priorities of the stakeholders.

Asmeal and Waheed (2020) conducted studies on the use of the DEA approach in the performance evaluation of bus transport organizations in Baghdad at the route level. Details on the *length of the routes*, *number of bus stops*, *speed*, *journey time*, and location of the bus stop were obtained based on a ride check survey, while information on frequency and headway was collected based on a *point check survey*. Information on the level of satisfaction of the transport users was obtained based on a *user opinion survey* spanning 3 days during the morning-peak hours.

Wang et.al (2021) adopted the use of the PCA approach to analyze the combined effect of traffic speed and delay on the efficiency of the road network in Beijing. Factors such as the total delay, the average delay, the delay ratio, the average speed, and the speed ratio were incorporated in the analysis. The first three principal components were found to have larger eigenvalues of up to 92.441% of squared loadings indicating that more than 85% of the variances could be explained. Based on this study, the road links associated with frequent congestion were identified.

Aboul and Elmaraghy (2022) performed studies on a set of criteria used to improve the performance and efficiency of metro services based on standards adopted in 29 countries where the performances were considered better. The PCA approach and the *multiple regression analysis* (MRA) method were used in developing three mathematical equations that could be used to explain the improvement in performance and efficiency. Twenty-eight factors categorized under environmental, demographic, security, technical factors, and so on were used in this study. The PCA based study and the statistical analyses indicated that three main factors could be considered to be highly correlated to the performance of the system.

2.4.2 Studies on Variable Reduction Using *Recursive Feature Elimination* (RFE) Approach

Recursive feature elimination (RFE) is a feature selection algorithm that eliminates the weakest features or variables until it selects the significant features or variables from the dataset. The RFE approach adopts machine learning algorithms such as *linear regression*, *logistic regression*, *random forest (RF) search method*, *support vector machine (SVM)* approach, and so on. In each iteration of computation in the RFE algorithm, it removes the least important feature and tries to fit the model similar to the backward stepwise regression model. Selected studies related to the application of the RFE approach were reviewed as given below.

Yau-Ren Shiau et al. (2015) adopted the application of the RFE to identify 7 key factors out of 17 variables that influenced accidents in Taiwan and ranked the important factors. The traffic accidents were then analyzed using the Fuzzy Robust Principal Component Analysis

(FRPCA), Backpropagation Neural Network (BPNN), and Logistic Regression (LR) methods. Variables related to the road-geometrics and the environment were considered in addition to details on violation of rules and the type of accident. The study indicated that the top 4 variables ranked among the 7 important indicators could be considered for suitable remedial action.

Bahl et al. (2019) performed investigations on the grouping of eleven different types of nanomaterial where the similarities between the Nanomaterial were assessed using the PCA approach followed by the use of the *k-nearest neighbor* approach. Subsequently, the random forests (RFs) were analyzed using a supervised machine-learning method based on the activity class of the nanomaterial. The similarity between various types of nanomaterial was determined based on the correlation of the activity between the nanomaterial. In this study, the RFE was used to determine the important factors that had to be considered in the classification of the nanomaterial. A balanced accuracy of 0.82 was obtained in this study indicating a reasonably good reliability on the result.

One of the applications of the RFE approach was in the medical field where **Riajuliislam et al. (2021)** attempted to predict hypothyroid in the primary stages among patients in Bangladesh. The feature selection technique was used along with diverse classification techniques using a sample size of 512 patients. Feature selection techniques such as the *recursive feature selection* (RFE), *univariate feature selection* (UFS), and the *principal component analysis* (PCA) approach were adopted along with the use of a classification algorithm called *support vector machine* (SVM), the *decision tree*(DT) model, the *random forest* (RF) method, the *logistic regression* (LR) method, and the *naive bayes* (NB) approach in this study. After performing analyses using the above approach, it was found that three out of nine variables were significant. Based on the *accuracy of prediction*, the RFE approach was found reliable in identifying a reliable set of features that could be considered for further studies and investigation.

Lotfi et al. (2022) studied the features affecting the severity of freight train derailments using RFE along with the use of classification algorithms such as the *decision tree*, *random forest*, *support vector machine*, and the *AdaBoost* approaches. The US Rail Accident Database (FRA) with information on derailment accidents from 1999 to 2018 was used in this study. 80% of the data was used to train the classification models, and a 5-fold cross-validation test was performed. The target variable 'freight train derailments on the main lines' was predicted based on nineteen features or independent variables such as month, day of incident, am or pm, cause of incident, speed, and so on. The RFE study indicated that the important factors that caused the accidents were the speed of the train, the train-length, and the ratio of the gross weight of the train to the train length. The classification based on the *decision tree* approach was considered reliable based on indicators such as the *rate of change*, *accuracy*, *precision*, and *recall*.

Saravanan and Abijith (2022) analyzed the flood susceptibility of northeast coastal districts of Tamil Nadu, India, where the RFE algorithm was used to identify the most important variables from among a set of nineteen variables including the slope, aspect, elevation, plan-curvature, profile-curvature, and so on. Machine learning algorithms such as the *GradientBoosting Machine* (GBM), *XGBoost*(XGB), *Rotation Forest* (RTF), S*upport Vector Machine* (SVM), and the *Naïve Bayes* (NB) were then used in the classification of data. Seventeen variables were found to contribute significantly based on the RFE analysis as revealed by the Cohen's Kappa value of 0.6364 and an accuracy of 0.818 in a set of 100 iterations. Among the methods used in classification, the *Gradient Boosting Machine* algorithm was found to perform well based on parameters such as the area under the curve (Receiver Operating characteristics curve).

Sanchez-DelaCruz et al. (2023) performed studies on the classification of vehicular traffic in Medellin, and California with population more than 2 million using the Level of Service (LOS) thresholds specified for urban highways. In this study, the RFE method was employed to determine the important factors affecting traffic flow. This was followed by machine learning algorithms to train and classify the level of traffic congestion. The results obtained were considered reliable.

2.5 STUDIES ON PARAMETRIC AND NON-PARAMETRIC APPROACHES FOR PERFORMANCE EVALUATION OF ORGANIZATIONS

Although performance indicators can be used to identify problems in specific areas of operations, such as employee productivity, fleet utilization, fuel efficiency, and so on, it is required to perform a comprehensive and integrated analysis to identify strategies for the improvement of inefficient organizations. Thus, it is required to adopt the use of *parametric* and *non-parametric* methods that form part of the *frontier-based analysis* approach.

Parametric methods of analysis are adopted when data collection involves randomness as in a sample surveys, and where there are more chances of occurrence of errors in measurement. On the other hand, *non-parametric* methods of analysis are adopted where random-errors in measurement are expected to be the least, such as in the use of data related to financial and operational indicators (**Asmare and Begashaw, 2018**). Parametric methods of analyses include *regression-based* approaches, *stochastic frontier* approaches, and *distribution* *free approaches*, while *non-parametric* approaches include *data envelopment analysis* (DEA) method and the *free disposal* method (**Kumar and Gulati, 2008**). The following sections provide details on selected studies on *parametric* and *non-parametric* approaches for performance evaluation, with special emphasis on *non-parametric* studies since data related to financial and operational aspects are generally used in performance evaluation.

2.5.1 A Brief Review of Studies on Parametric Approaches for Performance Evaluation of Organizations

Aigner et al. (1977) were the first researchers to introduce the stochastic frontier model for cross-sectional data. They were successful in introducing the error term which distinguishes between random noise and inefficiency. The study assumed that inefficiency is Half normally distributed and the noise term is normally distributed. It also applied its model to cross-sectional data from the US. Primary metals industry from 1957-58, as well as the US. Agricultural data of six years (1960-1965).

Merewitz (1977) demonstrated the use of the *regression approach* in measuring efficiency based on the *total cost per vehicle miles* predicted using wages, vehicle miles, seat per bus, operational speed, vehicle age, and so on for bus transport organizations in San Francisco. Benchmarks for statistical cost functions were established to lie between the required tolerance levels based on comparative studies with other similar organizations.

Battese and Coelli (1992) proposed a stochastic frontier model for panel data where the technical inefficiency of the alternatives varies with time. The model incorporates truncated normal distribution for the inefficiency term in the composite error. An empirical application was done on 10 years of data of paddy farmers from an Indian village.

Battese and Coelli (1995) proposed a model for technical inefficiency effects in a *stochastic frontier production function* for *panel* data. The study also incorporates the *time-varying technical inefficiencies.* An empirical application was done on 10 years of data of paddy farmers from an Indian village. The factors like age, years of formal schooling, and years of observation involved were considered for analyzing technical inefficiencies.

Alexandersson et al. (1998) analysed the use of specific indices such as *cost per bus km* and *cost per passenger* for estimating the performance of various bus transport organizations in an unregulated competitive market. In this study, *time series* data for a number of bus transport organizations spread over 24 counties in Sweden from 1987 to

1993 was used. A *regression*-based approach was performed to extract the trend from 168 observations.

Cullinane et al. (2006) 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 similar.

Ottoz et al. (2009) performed studies on the effect of type of ownership on the performance of 65 private bus operators, and 12 public transport organizations in Italy using data compiled during 1998-2002. The overall cost of operation was studied by considering variables such as the cost of labor, materials, and fixed capital. The *translog cost function* developed by *Battese and Coelli (1995)* was used in the analysis. The study revealed that the inefficiency in public bus transport organizations was much higher when compared to privately operated companies.

Karlaftis et al. (2010) conducted investigations on the performance of 15 different European public transport organizations based on the size of operations, and the type of ownership. The study predicted the *efficiency* using the *number of vehicles per kilometre*, and the *effectiveness* using the *number of passengers per kilometre*. The inputs used in this study included the *number of employees*, the *energy or fuel consumed*, and the *capital deployed* (in terms of the total number of vehicles operated). Data pertaining to the period between 1990 and 2000 was used in this study. The study indicated that although most of the organizations operated efficiently, the effectiveness had to be improved considerably.

In Sweden, **Holmgren (2013)** 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. (2013) performed studies on the measurement of technical efficiency of 64 public road transport operators in 18 countries and investigated the degree to which various factors influenced efficiency levels. Based on literature studies, the total operating expenses and the number of employees were considered as input variables, whereas the revenue generated was used as the output variable. A parametric *stochastic frontier approach* (*SFA*) was used to evaluate the data for twelve years from 2000 to 2011. Hypothesis testing was performed using the *generalized likelihood-ratio statistic* in order to select the optimal combination for the production function derived using the Cobb-Douglas method and the *Trans-log* method. The results indicated that the *Trans-log* production model provided the best combination for the production function.

Jarboui et al. (2013) evaluated the technical efficiency of 54 public road transport operators in 18 different countries using data extracted from ‘‘Thomson Financial’’ database for the period between 2000 and 2011. Input variables are *total operating expenses* and the *number of employees*, and *revenue* is used to measure the output. The explanatory variables are investment, operating profit, and firm size. The stochastic parametric approach employed in this study revealed that the level of *technical efficiency* of public road transport organizations ranged between 0.46 and 0.95. The study also indicated that large-scale operators possessed higher technical efficiency. It was also observed that transport operators of developed countries were technically more efficient than their counterparts in developing nations.

Ayadi and Hammami (2015) performed comparative studies on the application of parametric and non-parametric approaches in the evaluation of the efficiency of the public transport system in Tunisia. A *cost efficiency analysis* was conducted on 12 regional transport companies for a period of 10 years from the year 2000. The study focused on *maximizing the production* for a given *fixed cost*. The *parametric* approach based on *SFA* and the *non-parametric approach* based on *DEA* were used in this study. The authors indicated that the productive environment of road transport corporations and the possibility of having errors in the measurement of the variables do not have any significant effect on the evaluation of *cost efficiency*. However, based on the parametric or non-parametric approaches, the Tunisian public transport system was found to be inefficient.

Zhang (2018) performed studies on the *operating efficiency* and *service effectiveness* of public transit in China. The *SFA* with the *trans-log* function was used to evaluate the data from 2010 to 2013 for 36 cities in China. The study also included external environmental factors affecting transport efficiency, such as geography and population characteristics expressed as the ratio of urban built-up area to urban area and rail transit passenger flow parking rate, respectively. The study indicated that urbanization has a positive effect on improving the operating efficiency of public transit. However, the increase in urbanization had a negative effect on service effectiveness.

Matulová and Rejentová (2021) 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 based on the SFA, and the DEA methods.

2.5.2 A Review of Studies on Non-Parametric Approaches for Performance Evaluation of Organizations

Examples of *non-parametric* approaches include the DEA approach, and the *free-disposal hull* approach. The DEA approach involves the use of *efficiency scores* to measure the relative efficiency of performance between various organizations. This approach assists in identifying the basic factors resulting in the loss of efficiency and in the selection of strategies to overcome the inefficiencies. This analysis is performed by 'decomposing' *economic inefficiency* into *technical inefficiency* and *scale inefficiency*.

In the DEA approach, analyses are performed based on measurable actual data collected at regular intervals in an organization and do not involve random measurement errors, as in the case of data obtained through sample surveys. Additionally, in the DEA approach, it is not necessary to assume a *priori functional form* of the cost function as performed in the Cobb-Douglas and Translog production/cost functions (**Banker, 1984**). **Ayadi and Hammami (2015)** provide an example of a *stochastic cost function* that relates operating cost to the output, fixed capital, and the price of input, as in parametric approaches.

The DEA approach can incorporate the use of multiple inputs and outputs in the computation of *efficiency*. The DEA approach can also assist managers in benchmarking the performance of various organizations by facilitating simultaneous comparisons. The various inefficient sectors of operation can be easily identified using the DEA approach, and corrective measures can be taken.

However, one of the limitations of the DEA approach is that it assumes that the data used for analysis does not possess any significant *errors in measurement*. This assumption could at times, lead to unreliable predictions (**Avkiran, 1999**). The following sections provide details on non-parametric approaches for the evaluation of organizations.

2.5.2.1 Efficiency Measurement Using the DEA: A Non-Parametric Approach

The objective of the *DEA* approach, as proposed by **Charnes et al.** (**1978**), focuses on maximizing the efficiency of the organization or *decision-making unit* (DMU) under study. Usually, while formulating the DEA approach, the *normalized* ratio of the selected output to the corresponding input is maximized. This approach was an extension of the methodology proposed by **Farrell** (**1957**) for the measurement of *productive efficiency*.

The *DEA* model can be formulated as an *input-oriented* model, an *output-oriented* model, or even a hybrid combination of both approaches. The original approach adopted by **Charnes et al.** (**1978**) in the CCR model, as it later came to be known, was based on inputs to the *decision-making unit* with a *specific rate of returns* (or *constant returns to scale*). The measure of efficiency obtained using the CCR model is called the *overall technical efficiency* (OTE).

Banker et al. (**1984**) developed an alternative model that came to be known as the BCC model, where the rates of returns could be varied. This approach was known as the *variable returns to scale* approach. The measure of efficiency obtained using the BCC model is called as *pure technical efficiency* (PTE).

Applications of DEA have been used in evaluating the technical efficiencies of banks, financial institutions, educational institutions, judiciary, recreation centres, and hospitals. **Chu et al. (1992)** adopted the DEA approach in evaluating the efficiency and effectiveness of public transit agencies for 48 cities, including metropolitan cities in the US, with populations ranging between 1.4-1.6 million and larger towns and smaller cities of populations ranging between 77,000 and 500,000. The data pertaining to 1985 and 1986 for the above study was obtained from the National Urban Mass Transportation Statistics for 1998. As part of this study, two separate models were developed to evaluate relative efficiency and *relative effectiveness*. In the case of the *relative efficiency model*, the weighted sum of *operations expenses*, *maintenance expenses,* and *general/administrative expenses* were considered as input variables, and, the *revenue vehicle hours* were considered as the output variable. In the case of the *relative effectiveness model*, a weighted sum of *revenue vehicle hours* and selected exogenous variables such as the *population density*, *proportion of households without an automobile,* and *annual financial assistance per passenger* were considered as part of the input variables, while the *passenger trips performed* was used as the output variable.

DEA approaches have later undergone changes to meet the requirements for performing various types of studies. The *chance constraint DEA* (or CCDEA) developed by **Cooper et al., 2002**, was specially designed to handle the *uncertainty in Data* Envelopment Analysis. Additional constraints were used in the formulation of the DEA model assuming that input and output are stochastic in nature and probability distribution function of the data is known in order to eliminate uncertain, incomplete, or imprecise data.

In addition to DEA analyses based on physical and financial characteristics of organizations, it becomes necessary to compare the performance of various organizations based on undesirable outcomes such as emissions from vehicles, accidents, and so on. **McMullen and Noh (2007)** observed that the use of the *DEA* approach alone was not effective in comparing various organizations based on efficiency measures formulated for handling *undesirable vehicle emissions*. The study demonstrated the use of a *directional distance function* approach in addition to the DEA approach to perform benchmarking of 43 bus transport organizations in the US based on data for the year 2000. This study indicated that only five agencies performed better considering physical and financial performance measures, while 22 organizations were found to perform well considering efficiency in reducing vehicle emissions.

Lin and Lan (2009) adopted the use of an improvised DEA approach with two models to address issues related to efficiency. One of the models was used to benchmark performances based on physical and financial performance characteristics, while the second model was used to determine the efficiency based on undesirable outcomes using scores related to the fatality of accidents. Data on 60 bus organizations in Taipei for the period from 2001-06 were used in this study. It was observed that out of the 60 organizations studied, 31 were considered to be efficient, considering accident indices and physical and financial performance characteristics. However, only 16 organizations were found to perform well when the benchmarking was performed based on physical and financial characteristics alone.

Puri and Yadav (2013) adopted the use of **the** *Fuzzy DEA model* with special constraints to handle *uncertain and imprecise data* related to the performance of the State Bank of Patiala (SBOP) in seventeen districts of Punjab State, India. The three inputs used were the *number of employees*, *fixed assets*, and the *total expenses*, and the outputs included the *income from interest*, as well as the *income from other sources*. Among the three inputs, the data pertaining to the *number of employees* and the *total expenses* were not precisely known.

Song and Wang (2014) adopted the *Ratio-DEA decomposition algorithm* to analyze the environmental efficiency of transit services across China from 1992 to 2012. In this study, the *energy consumed in tons per unit million GDP* was considered as an input, while the output included *environmental efficiency variables* such as the *total amount of annual investment for industrial pollution treatment* based on data made available in the China Statistical Yearbook for the study period.

Wang (2019) performed a DEA-based analysis to compare the performance of freight movement for the group of OECD (Organization for Economic Cooperation and Development) countries comprising 37 member countries for the period between 2000-14. The influence of environmental factors such as, *particulate matter* and *carbon dioxide emissions*, and the influence of road accidents on the overall technical efficiency were studied.

Kang et al. (2020) performed studies on the Taipei bus transit system that involved the comparison of performances of 12 bus companies considering *vehicle*, *labor*, and *fuel consumption*, and *vehicle-km* in addition to air pollution emissions using a two-stage network DEA model with DDF. The results indicated that CO_2 emissions also played a significant role in performance evaluations.

2.6 PERFORMANCE EVALUATION OF PUBLIC TRANSPORT ORGANIZATIONS (SRTUs) IN INDIA

A number of studies have been performed in India on the application of physical and financial efficiency indicators in the evaluation of the functioning of SRTUs that provide bus transport facilities for urban and rural areas of the country.

Singh (2000) performed studies using the information on input variables such as network configurations (with special reference to route-length) and cost of operations (including the cost of fuel, maintenance, and labour) in order to model the output variable such as revenue generated. The study adopted the use of the *trans-log cost function*, a parametric approach, to establish the relationships between the inputs and outputs. The studies were performed on 9 SRTUs for the period between 1983-84 and 1996-97. The study provided insight into the reasons for inefficiencies in operations.

Bhagavath (2006) adopted the use of the DEA approach, a non-parametric approach, to determine the physical and financial efficiencies for 44 SRTUs in India for the year 2000-01. A computer program, *DEAP*, developed by Coelli (1996), was used in the computations related to the DEA model. The input variables included the *fleet size*, *average kilometres travelled per bus per day*, and the *cost of operation per bus per day*, while the output variable considered was the *revenue per bus per day*.

Badami & Haider (2007) adopted the use of a disaggregated approach where each of the financial and operational indices was analysed for the relative influence on the transport system for bus transport operations in four metropolitan centers - Chennai, Delhi, Kolkata, and Mumbai), and four secondary cities - Ahmedabad, Kolhapur, Pune, and Thane, over the period 1990–2001.

Agarwal et al. (2010) adopted the use of the DEA approach to determine the three forms of efficiency scores such as the *overall technical efficiency* determined using the CCR model (that considers constant returns to scale), the *pure technical efficiency* determined using the BCC model (that considers variable returns to scale), and the *scale efficiency* (which considered the ratio of the CCR model to the BCC model. The studies were performed on 35 SRTUs for the year 2005-06. It was observed that 14 SRTUs were efficient compared to 21 remaining organizations for the input and output variables considered.

Saxena and Saxena (2010) performed similar studies using the DEA approach for 25 SRTUs in India for the period of 3 years between 2002-05. In this study, the input variables included *fleet size*, *total staff*, *fuel consumption*, and *accidents per lakh kilometers,* while the output variables used included *passenger kilometers*, and *seat kilometres*.

Kumar (2011) performed a *two-stage performance evaluation*, where in the first stage, the DEA was employed to compare the performances of 31 SRTUs in India for the year 2006-07. The input data used consisted of fleet size, total-staff, and fuel and lubricant consumption, while the output variables included revenue bus per day and passenger-km per year. In the second stage, the degree of influence of explanatory variables such as fleet utilization, staff productivity, vehicle productivity, fuel efficiency, and occupancy ratio were examined using the *Tobit* (or *censored regression*) analysis.

Kumar et al. (2013) performed studies on passenger satisfaction measures that included the speed, cost, and comfort of travel in addition to the reliability of transfer to examine the level of service of the multimodal transportation system in New Delhi. The responses to *Stated Preference* (SP) surveys used in this study included 460 random samples collected from 176 female respondents and 284 male respondents.

Vaidya (2014) evaluated the relative performance of 26 SRTUs in India using 19 indicators that were grouped according to operational, financial, and accident-based indicators. Each of the input and output groups were assigned weights as part of the AHP method, which is an MCDM tool. The efficiency scores were then evaluated using the DEA approach for performance comparisons among the SRTUs.

Mulangi et al. (2014) adopted the use of *multivariate analysis* using the *principal component analysis* method for the selection of the ideal set of indicators and performed the system-level comparison of performances at 13 regional centers of KnSRTC for the period between 2004 and 2011. KnSRTC possesses an average total fleet size of approximately 17000 buses distributed across different regions of the State of Karnataka, and are operated by three divisions, namely, KnSRTC, NWKnRTC, and NEKnRTC. The *physical indicators* used in this study include the *number of vehicles*, the *capacity of buses*, *types of buses*, and *fuel consumption*, while the *financial indicators* included the *total effective kilometres travelled*, *load factor*, *total earnings*, *total operating cost*, *number of breakdowns*, and the *number of accidents*.

Agarwal (2016) performed studies on 30 SRTUs in India based on data for 2011-12. The DEA based CCR approach and the BCC approach was used to analyse the performance of the SRTUs. The input data included fleet-size, total-staff, and fuel consumption, while the passenger-km was used as the output. The datasets of the SRTUs were then trained, tested, and validated using a back-propagation-based ANN so as to synchronize with the output attained using the DEA approach. The ANN was found to be useful in predicting the performance of SRTUs, for which the available data was imprecise and approximate.

Pal and Mitra (2016) performed studies on the technical efficiency of 37 SRTUs in India using data pertaining to 2012–13. The *directional distance function* (DDF) was used to analyse both *desirable* and *undesirable outputs* (such as the number of accidents). The DEA was used to evaluate the performance of bus transport undertakings with and without the use of details on the number of accidents. The results were significantly different for the two types of analyses performed. The Tobit model was used to perform the sensitivity analysis to ascertain the importance of factors influencing the efficiency of the organizations.

Singh and Jha (2017) conducted studies using the DEA approach to compare the performances of 15 major SRTUs in India for the period 2003-14. The input variables included *staff employed*, *fuel consumed*, and the *number of vehicles used*, while the output variables included *passenger-km* and *bus-km*. It was observed that a number of smaller and medium-sized SRTUs in the State of West Bengal were less-efficient, while APSRTC, the largest bus transport operator in the world, is the most efficient with higher degrees of effectiveness. The study also indicated that there existed a strong positive correlation between the efficiency and effectiveness of the SRTUs, while there existed a negative relationship between the size of the SRTUs and the returns to scale.

Gadepalli and Rayaprolu (**2020**) performed studies on the measurement of technical efficiencies of SRTUs of 8 major cities of India for a period of 7 years between 2009-16. Three DEA-VRS models were developed to study *consumption efficiency, supply efficiency,* and *revenue efficiency*. The input variables included *buses held, total staff,* and the *total cost*, while the output variables included *effective-km* for *supply-efficiency, passenger-km* for *consumption efficiency,* and *total revenue* for *revenue efficiency*. The influence of various external factors on the efficiency score was analysed using *regression analysis*.

2.7 STUDIES ON THE USE OF PERFORMANCE INDICATORS AND MODIFIED APPROACHES FOR MICRO-LEVEL ANALYSES

Indicators for *measurement of effectiveness* in the transport sector focus on the travel desires and expectations satisfied by the organization. Some of the *measures of efficiency* used in public transport systems include *effective vehicle-hours per traffic employee, total vehicle-km per total vehicle, total vehicle-km per maintenance employee, operating staff/bus, fleet utilization, revenue/operation cost, operating expenses/passenger km, revenue per passenger-km,* and so on. *Measures of effectiveness* in public transport include *vehicle-km, capacity-km, passengers/bus/day, passenger-km, passenger-km/vehicle-km, passengers per vehicle hour, service availability, service reliability,* comfort, cleanliness, safety, fare, and environmental impact. Other indicators include *accidents/ 100,000km, total vehicle km per total accidents,* usage of green and energy-efficient vehicles, and so on. Measures of *efficiency* and *effectiveness* are seen to be employed in micro-level analyses of the functioning of various organizations.

Sheth et al. (2007) performed *route-level* micro-analysis to evaluate 60 bus routes in Virginia, USA using a network-based DEA model. Three models were developed to assess service providers, users, and societal perspectives. The *provider node* model utilized inputs related to headway, service duration, costs, number of intersections, and priority lanes. The *user or passenger-based* model utilized inputs related to the number of accidents, emissions, noise pollution, and resource degradation. The *societal model* based on *environmental variables* utilized inputs related to accessibility, parking space availability, population density, connectivity, and comfort. The output for the *provider node* model included vehicle- miles, service reliability, and average travel time. The output for the *passenger-node/ societal-variable* model included: passenger-mile. The study, based on a number of variables, provided insight into the relationship between the transport provider and the passengers, in addition to external variables.

Barnum et al. (2008) performed *route-level* micro-analysis to evaluate 46 bus routes of a US transit agency using the DEA approach. The model developed included inputs related to seat-kilometre, seat hours, population density, and population, while the output from the model provided details on ridership, span of service, average frequency, maximum frequency, and punctuality. The study indicated that the performance of 20 bus routes could be considered to be efficient, while no appreciable change was recommended for 12 bus routes. Also, 14 bus routes was found to perform at lower efficiency levels.

Lao et al. (2009) performed *route-level* micro-analysis to evaluate 24 fixed bus routes in Monterey County, California, USA, using the DEA approach and the capabilities of *geographic information systems* (GIS). The model developed included inputs related to operation time, round-trip distance, number of bus stops, number of commuters using buses, population older than 65 years of age, and persons with disabilities, while the output from the model provided details on the total number of passengers. In this study, annual data was used for analysis. The study indicated that the performance of 6 bus routes could be considered to be efficient, while in the case of another set of 6 bus routes with scores around 0.6-0.8, it was felt that the performance could be further improved.

Gahlot et al. (2013) developed GIS-based micro-level indices such as *public transit coverage index, ideal stop accessibility index* (ISAI), *actual stop accessibility index* (ASAI), and *stop coverage ratio index* (SCRI) to evaluate the existing public transit network. **Isabello et al. (2014)** performed studies on the use of geo-databased tools to analyse inter-urban public transport services in the Piedmont region of Italy. These tools assist in extracting information on services provided, ridership, overlapping of routes, and financial performance. A web-based database was developed for this purpose, using geo-referenced dynamic maps. The efficiency and effectiveness of various routes were compared to standard values made available in the form of tables.

Georgiadis et al. (2014) used the DEA approach to develop three models to analyse the performance of 60 bus routes in Greece. The first model considered inputs related to route length, span of service, and the number of vehicles deployed. The output provided details on revenue seat- km. The second model also used similar inputs to obtain details on passengers carried. The third model used revenue vehicle-km, and the number of vehicles deployed to estimate the passengers carried. The study indicated that an ideal balance could not be attained considering efficiency and effectiveness, as one or the other could be adversely affected. It was also observed that the DEA approach was effective in identifying less-performing routes where corrective measures could be undertaken.

Tran et al. (2016) conducted studies at the system-level (or macro-level) and at the route level (or micro-level) using the DEA approach for evaluating the performance of a major transit route in Brisbane, which has a total length of 17km with 10 bus stops. The study focused on evaluating the *service effectiveness* of transit routes. The inputs used included the number of services and the travel time, while the output provided details on service punctuality/ reliability (on-time performance), and passenger-km (transit work).

Chepuri et al. (2018) performed studies on *journey time variability* and dependability indexes based on GPS-based bus trip data for a specific bus route in Chennai City, India, using route-level data. *Travel time reliability* indices such as the *planning time index* (PTI), *buffer time index* (BTI), and *buffer time* (BT), as well as other statistical measures, were computed for various time periods. In this study, the *generalized extreme value* (GEV) distribution was found to provide a better fit to the data for bus travel time variability based on the Kolmogorov-Smirnov (KS) test. In the case of data related to the peak hour, the normal distribution was found to fit the data more closely.

Jasti and Ram (2019) performed an analysis of the metro rail network of 425 kilometres for Mumbai city using data for 2017-18. The analysis of performance was performed using 34 indicators grouped under 9 categories. The *AHP-based* MCDM approach was used to assign weights to various performance indicators. The indicators used include the transit availability index, headway, hours of service, and transit service index.

Chen and Fan (2020) proposed the development of a *Travel Time Reliability* (TTR) model using the time series approach for road segments on freeways in Charlotte, North Carolina, USA. The factors considered in the analysis included the travel time of day, day of the week, year, and location of the road section. Data collected from thirty-two road segments of the I-77 southbound freeway for a total length of 19 miles were used in the development of the model. The real-time GPS-based data on travel time and speed obtained from the RITIS web site were used in this study. The study indicated that the *Travel Time Reliability* patterns were distinctly different for different days of the week and for different weather conditions.

Chepuri et al. (2020) performed studies on *travel time reliability* based on GPS-based bus trip data for six bus routes in Mysore City, India, using route-level data. *Travel time reliability* indices such as the *planning time index* (PTI), *travel time index* (TTI), and *buffer time* (BT), as well as other statistical measures, were computed for various time periods. In this study, the *generalized extreme value* (GEV) distribution (with higher *k* values) was found to provide a better fit to the data for bus travel time variability for off-peak hours, while the normal distribution was found to fit the data better for peak hour travel times. The authors also suggested the use of the RBI index which is defined as the difference between PTI and TTI, for modeling *travel time reliability*.

Harsha and Mulangi (2020) analyzed the distribution of travel time for various temporal and spatial scales using *automatic vehicle location* (AVL) data of a selected bus route in Mysore City, India. The travel time data was aggregated into three different temporal scales for 60 minutes, 45 minutes, and 30 minutes and further into different spatial scales based on the distance between the bus stops for performing analyses at the route and segment-level analyses. The study indicated that the *generalized extreme value* (GEV) distribution provided a better and superior fit for trip times at both the route and segment levels.

Table 2.2 provides details on the summary of review of literature related to system level (or macro-level) and route-level (or micro-level) analysis of performance for State Road Transport Undertakings in India.

2.8 SUMMARY

Earlier studies on public transport performance evaluation largely focused on individual measures of efficiency and effectiveness, using frameworks such as the triangular model of service inputs, outputs, and consumption. Benchmarks developed from studies in various global cities provided a theoretical foundation for the present study, which incorporates efficiency and effectiveness indicators from sources like TCRP, FDOT, and LTA. These indicators include aspects related to employee productivity, vehicle efficiency, safety, and additional factors such as comfort, convenience, vehicle emissions, and accidents.

The study adopts a non-parametric approach, specifically DEA, due to its suitability for analyzing data with minimal measurement errors. The DEA methodology, originally applied in the banking sector and later extended to public transport, evaluates performance based on inputs like fuel consumption and outputs like operational revenue. Unlike traditional parametric methods, DEA can handle multiple input-output variables and is deemed more appropriate for comprehensive benchmarking exercises. This approach has been applied in various sectors, including telecommunications and manufacturing, and is recommended for assessing public transport systems' efficiency and effectiveness.

Furthermore, the study explores advanced methodologies like the incorporation of ANN and fuzzy logic to address data imprecision and enhance the DEA model's accuracy. These techniques help estimate missing values and refine performance assessments. Additionally, criteria such as the AIC and BIC are suggested for selecting relevant variables. The study also considers environmental efficiency by including metrics like energy consumption per capita and extends the analysis to a micro-level, focusing on individual bus routes within public transport organizations.

Table 2.3 provides details on the overall summary of review of literature in addition to information on the research gaps that assisted in developing the framework for the present study

CHAPTER 3

THEORETICAL BACKGROUND

3.1 GENERAL

The performance evaluation of bus transport systems has been traditionally conducted based on efficiency and effectiveness indicators. Indicators such as vehicle kilometers, passenger kilometers, and the revenue per passenger kilometer are commonly considered in performance evaluation exercises.

TCRP (2003; 2010) recommends the use of various performance measures and indicators for conducting performance evaluation of public transport systems, and bench-marking based on industry-specific indices and standards. Information on the benchmarks for performance evaluation can be extracted from the following:

- *Internal or external service standards adopted by the bus transport sector, in general, can be obtained based on annual and seasonal reports published by various national-level public transport monitoring authorities.*
- *Internal or external service standards adopted by a set of organizations that operate in similar conditions.*
- *Standards developed by a specific bus transport organization for internal assessment based on historical data and time-series information compiled using annual and seasonal reports. It can include comparisons made based on the best performing years in the past history or analysis of performance trends over the past many years.*

The Key Performance indicators usually include the following (**TCRP, 2003)**:

- *Individual measures of performance*: These include ridership, bus frequency, fleet strength, fleet operated, number of working days lost, number of accidents, number of staff employed, services not performed, and so on.
- *Efficiency and effectiveness ratios*: These include cost per revenue kilometer, occupancy ratio, fleet-utilization ratio, passengers per seat offered, vehicle kilometer per square kilometer, and so on.
- *Use of Other indices*: These include indices that represent the accessibility and availability of transport services that can be formulated using a combination of various

factors such as travel-time index, accessibility index, area serviceability index, population serving index, and so on.

However, it is also recommended that the influence of traditional working styles, accessibility to advanced technology, availability of capital and environmental factors, and operational aspects also need to be considered as part of the performance evaluation for benchmarking.

There are a number of parametric and non-parametric methods used in performance evaluation. *Parametric* methods of analysis such as SFA are adopted when data collection involves randomness, as in sample surveys, and where there are more chances of occurrence of errors in measurement. On the other hand, *non-parametric* methods of analysis such as DEA are adopted where random errors in measurement are expected to be the least, such as in the use of data related to financial and operational indicators.

This chapter provides a theoretical background on the use of key indicators in evaluating the efficiency and effectiveness of public transport organizations. The theoretical foundations related to the parametric-based SFA and non-parametric-based DEA approach are illustrated along with the formulation of the solution approach. This chapter also provides details on the extended DEA model focusing on the need to consider the influence of undesirable outputs, such as pollution, accidents, and so on, in the transport sector as proposed by **Seiford and Zhu (2002)**.

3.2 APPROACHES ADOPTED IN THE SELECTION OF PERFORMANCE INDICATORS

Although there are a number of performance indicators, as summarized in the above section and as compiled in **Table A.1**, it is required to identify the most important set of indicators that are relevant to the bus transport organizations in India in order to perform a proper evaluation of performance.

The selection of key financial and physical performance indicators for the present study was made based on previous studies as reported in ***Chapter 2***, and also based on statistical approaches such as the *Akaike Information Criteria* (AIC) method, *Bayesian Information Criterion* (BIC), Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE). Also, the MCDM-based approaches such as the Analytical Hierarchy Process (AHP) and Fuzzy-based Decision making. Additional considerations on the availability of data with regard to variables referring to undesirable outputs are also likely to be included among the indices used in this study on performance evaluation.

In general, the key indicators for effective performance measurement are selected based on the clarity of information required to be conveyed and the overall *acceptability* of the indicators by the stakeholders. Importance is also given to the *reliability* of the indices used in performance measurement, and the use of a *variety of measures* that assist in undertaking a comprehensive performance measurement. The indicators identified must incorporate sufficient flexibility so as to be adaptable to changing goals of transport undertakings in the near future. **Brown (1996)** describes this phase of the study as "choosing between the vital few measures and the trivial many", and suggests the use of preferably not more than 20 performance indicators. The following subsections provide a brief overview of the approaches adopted in the selection of important indices for performance measurements, such as the *Akaike Information Criteria* (AIC) approach and the AHP method of analysis.

3.2.1 Identification and Selection of Key Performance Indicators Using MCDM-Based Approaches

MCDM is a problem-solving approach that assists in the performance evaluation of alternatives across various conflicting, qualitative, and/or quantitative criteria for a number of *decision-making units* (DMUs). These approaches have evolved a great deal over the past five decades. *MCDM* includes *multi-objective decision making* (MODM) approaches, *multi-attribute decision making* (MADM) approaches, and other related approaches. Some of these techniques have been applied from the beginning of the 1960s.

A number of advanced approaches related to *MCDM* have been developed to address the needs of various fields of interest. *MCDM* approaches presently include applications from the field of *fuzzy-logic,* and *artificial neural networks* (*ANN*). Other approaches related to *MCDM* include *ELECTRE* and *PROMETHEE*.

According to **Khan et al. (2018),** the aim of MCDM approaches is not to recommend the best decision but to assist decision-makers in selecting the best among the shortlisted alternatives or a single alternative that meets their requirements and is consistent with their preferences. *MCDM* approaches assist in obtaining a deeper appreciation of the viewpoint of the decision maker, which could be critically important in effective decision making, especially in the initial stages.

3.2.1.1 Analytical Hierarchy Process (AHP) approach

The *AHP* approach was developed by **Saaty (1980)** for managing a larger set of qualitative and quantitative elements in *multi-attribute decision-making* (*MADM*). This approach considers various aspects of the problem scenario and the *goal*, in addition to the *criteria* used in evaluation, and the presentation of *alternatives* to the managers in a hierarchical fashion. It is a powerful tool that can handle complex problems. Unstructured problems with relationships between various *goals*, *objectives*, and *criteria* too can be solved using this approach by breaking down larger problems into a hierarchy of smaller problems.

Experts in various fields related to performance evaluation are required to respond to a set of questions based on the *criteria*, where pairwise comparisons are made, while the *AHP* generates *priorities* or the *weights* for various *alternatives* based on these pairwise comparisons. The important steps involved in the *AHP* method are described below:

Step 1: Definition of the problem to be solved to derive the rankings of KPIs (Goal)

The *AHP* process begins by defining the *goal* of identification of KPIs for the problem related to the evaluation of performance. The *criteria* (or measurement indices for performance evaluation) used in the analysis must be specified, while a group of experts will provide a pairwise comparison of the importance of each criterion by assigning a suitable rating. The *AHP* then generates a *weight* for each *criterion*. It is possible to evolve alternate strategies (or *alternatives*) for performance improvement of DMUs at a later stage. **Fig.3.1** provides details on the same.

Step 2: Design of a Questionnaire and Obtaining Responses from Experts

Part of the AHP approach is required to develop a questionnaire to elicit information from experts on the ratings that they would provide to the various criteria of performance evaluation. The ratings assigned vary on a scale of 1-9, as in **Table 3.1a**.

The above-mentioned scaling is mainly adopted in rating crisp information for decision-making. However, in order to simulate uncertainties associated with human decision-making, **Buckley (1985)** suggested the use of *fuzzy logic* while computing the weights. *Fuzzy AHP*, an AHP implementation that includes the concept of fuzzy intervals, can be adapted to incorporate the influences of uncertainties in decision-making. A fuzzified rating scale that can be adopted for a triangular membership function is provided in **Table 3.1b**.

Step 3: Preparing a Pairwise Comparison Matrix

A *pairwise comparison matrix* is then generated. Subsequently, based on this matrix, the *AHP* provides weights to the indicators which can later be used to identify *key performance indicators*.

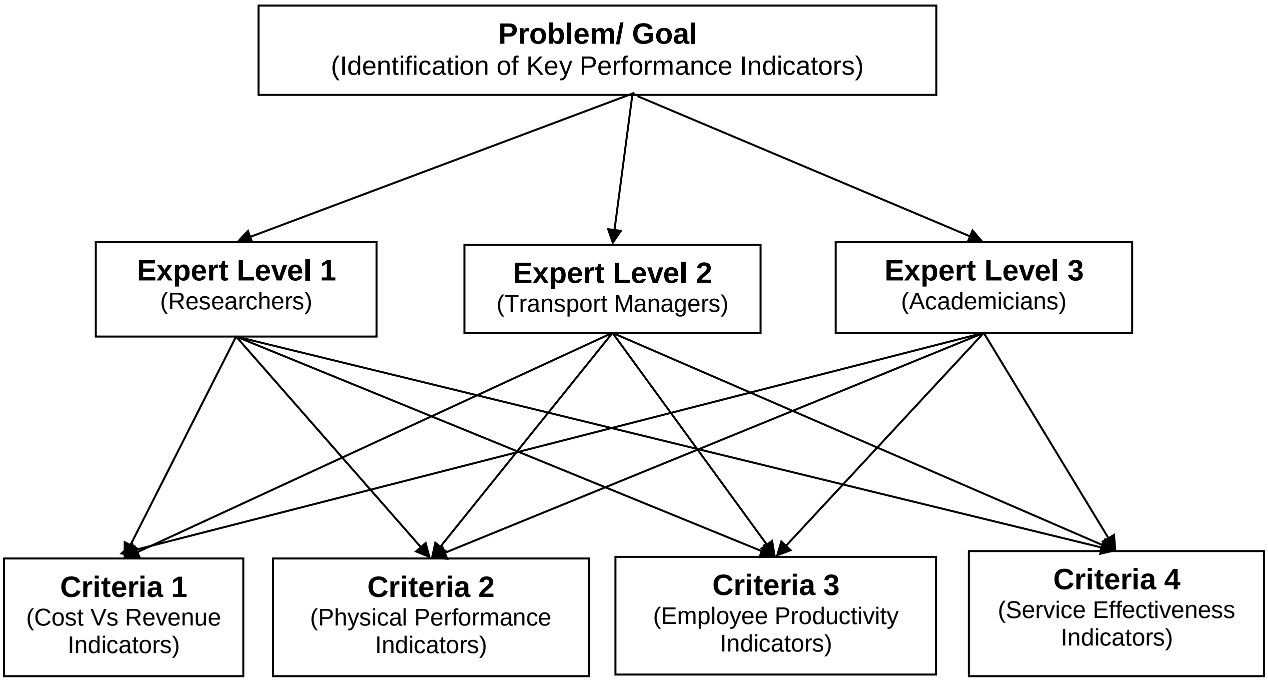

Fig.3.1 Decision-making process in AHP

Table 3.1a Rating Scale to Indicate Relative Importance

Response Indicated	AHP Scale
Equal	1
Moderate	3
Strong	5
Very strong	7
Extremely strong	9
Intermediate values	2
	4
	6
	8

Source: **Kannan et al. (2013)**

Step 4: Obtaining the Rating Scale* for Various *Criteria using AHP

The pairwise comparison matrices computed for each of the experts (using excel by us) is provided as additional input to *R Studio* software. The software then generates weights for each *criterion* using AHP approach.

Table 3.1b Rating Scale that Can be Used in *Fuzzy AHP* for Triangular Membership Functions

Fuzzy Linguistic Scale	AHP Scale	Triangular Fuzzy Scale
Equal	1	(1,1,1)
Moderate	3	(2,3,4)
Strong	5	(4,5,6)
Very strong	7	(6,7,8)
Extremely strong	9	(9,9,9)
Intermediate values	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

Source: **Kannan et al. (2013)**

Step 5: Checking for Consistency of Comparisons **(Saaty, 1980; Alonso and Lamata, 2006)**

In this step, in order to validate the results of the *AHP*, the *consistency ratio* (CR) as expressed below (**Saaty, 1980)** is often used:

$CR = CI / RI$ Eq.3.1

where CI = consistency index = $(\lambda_{max} - n) / (n - 1)$; λ_{max} = maximum eigenvalue of the matrix; n = the number of compared elements; *RI* = *random consistency index* related to the dimension of the matrix for responses for each expert as provided in **Table 3.1c**. It may be observed that the computed values of *consistency ratio* (*CR*) lower than 0.10 imply that the results of the comparison are acceptable.

Table 3.1c Random Consistency Index

Dimension	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.88	1.10	1.24	1.34	1.40	1.45	1.48

Source: **Saaty (1980)**

3.2.1.2 Technique for Order of Preference by Similarity to Ideal Solution (*TOPSIS*)

One of the most widely used multi-criteria decision analysis methods is the TOPSIS method, which was proposed by **Hwang and Yoon (1981),** with further modifications proposed by **Hwang et al. (1993),** and **Yoon and Hwang (1995).** In the TOPSIS approach, the positive ideal solution maximizes the output and minimizes the input, while the negative ideal solution maximizes the input and minimizes the output. The option selected for the improvement of an organization must be such that it is closer to the positive ideal solution. The use of artificial neural networks (ANN) in setting the weights in the analysis using TOPSIS was demonstrated by **Kim et al. (1997)**, while **Chu (2002)**, and **Cha and Jung (2003)** provide information on the application of fuzzy sets in TOPSIS.

Several studies have been performed on the application of the *TOPSIS* technique in various fields related to performance evaluation, supplier selection, tourism destination evaluation, location selection, company evaluation, and ranking the carrier alternatives. The various steps involved in computations related to the *TOPSIS* approach are provided below **(Balioti et al.,2018)**:

Step 1: Construction of the Decision Matrix (D_{n*m}) with input from experts.

Step 2: Computation of the normalized decision matrix construction ($R_k = (r_{ij})_{n\times m}$) using the normalization method expressed as,

$r_{ij} = x_{ij} / [\sum_{i=1}^{m} (x_{ij}^2)]^{1/2}$ Eq. 3.2a

where x_{ij} = Rating provided by experts to each alternative; r_{ij} = Normalized inputs

Step 3: Computation of the weighted normalized decision matrix (V_{ij}) where different weights are assigned to various groups of experts as given below:

$V_{ij} = W_j * r_{ij}$, $j = 1, 2, \dots m$, $i = 1, 2, \dots n$ Eq. 3.2b

where, W_j = weights given to experts; j = number of experts; i = number of criteria.

Step 4: Identification of the *positive ideal solution* (PIS) which refers to the maximum value that represents the best ratings, and the *negative ideal solution* (NIS) which refers to the minimum value that represents the worst ratings for the respective column. The PIS and NIS can be expressed as,

$A^+ = \{(\max v_{ij} \mid j \in J), (\min v_{ij} \mid j \in J'), i = 1,2,3, \dots, m$ Eq. 3.2c

$= \{ V_1^+, V_2^+, V_3^+, \dots, V_n^+ \}$

$A^- = \{(\min v_{ij} \mid j \in J), (\max v_{ij} \mid j \in J'), i = 1,2,3, \dots, m$ Eq. 3.2d

$= \{ V_1^-, V_2^-, V_3^-, \dots, V_n^- \}$

where, A^+ = positive ideal solution; A^- = negative ideal solution; i = the i^{th} criteria in the set of criteria I; j = the j^{th} expert in the set of experts J.

Step 5: Determination of the distance for each option to the PIS and NIS. The ideal separation distance (S_i^+) from the PIS, and the non-ideal separation distance (S_i^-) from the NIS can be computed for various criteria i as given below:

$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_j - v_i^+)^2}$ Eq. 3.2e

where $i = 1, 2, 3, \dots n$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_j - v_i^-\right)^2} \qquad \text{Eq. 3.2f}$$

where i =1, 2, 3, . . . m

Step 6: Computation of the relative proximity (C_i^*) based on the similarity to the best alternative as given below:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \text{ , } 0 < C_i^* < 1,\ i = 1, 2, \ldots, n \qquad \text{Eq. 3.2g}$$

$C_i^* = 1$ if $A_i = A^+$

$C_i^* = 0$ if $A_i = A^-$

Step 7: Ranking of the order of preference of options in the descending order of C_i^* values.

3.2.1.3 Fuzzy-based Decision Making for AHP and TOPSIS Approach:

The use of fuzzy logic in decision making has gained prominence in many fields of engineering and social sciences. **Zadeh (1965)** performed pioneering studies on the concept of *fuzzy sets* and their applications. Decision making in everyday life involves a considerable degree of fuzziness due to the reason that the background information available is rather insufficient or is not very precise. For example, the temperature of a particular day is usually described as too hot, not very warm, slightly cold, and so on without any reference to the actual measurement of the same. Thus, there exists a certain degree of randomness in classifying a particular observation due to the vagueness involved in its measurement. The following are the important steps involved in *fuzzy-based* decision making:

- *Step 1: Identification of the Problem:* In this step, the variables involved, and the criteria used for measurement of a phenomenon are identified, and approaches for the classification of observations are examined.
- *Step 2: Fuzzification:* In this step, the real-life observations are transformed into linguistic descriptions such as *very high, high, medium, low, very low,* and so on.
- *Step 3: Fuzzy inferencing:* This step involves the use of *fuzzy rules* for inferring the state of the observations using *If-Then* conditions.
- *Step 4: Defuzzification:* In this step, the estimated *fuzzy output* is transformed into numerical observations.
- *Step 5: Interpretation and Verification:* This step involves the verification of the fuzzy-based interpretation against the real-life observations.

3.2.2 Spearman's Rank Correlation Coefficient

Spearman's rank correlation coefficient or *Spearman's ρ* (rho) is a statistical measure to test the correlation between two variables. This approach can be applied to both continuous and discrete (or ordinal or counting) variables. The expression for computing *Spearman's ρ* is given as,

$\rho = \text{Cov}\,(rgX, rgY) / (\sigma\, rgX \,.\, \sigma\, rgY)$ Eq. 3.3a

where, Cov (rg$X$, rg$Y$) = covariance of the ranked variables X and Y; rg$X$, and rg$Y$ = ranking applied to variables X and Y respectively; $\sigma\, rgX$, and $\sigma\, rgY$ = standard deviations of the rankings applied to variables X and Y respectively.

Alternatively,

$\rho = 1 - [6\, \Sigma\, d_i^{\,2} / (n\, (n^2\text{-}1))]$ Eq. 3.3b

where, d_i = rg(Xi) – rg(Yi) = difference between the ranks for variables X and Y for observation i; and n = number of observations.

3.2.3 Identification and Selection of Key Performance Indicators Using Statistical Approaches

Selection of *Key performance indicators* using statistical approaches involve evaluating the relationship between input variables and the target variable using statistics. The indicators which possess strongest relationship with the target variable is considered for the selection of the variables.

3.2.3.1 Akaike Information Criteria (AIC)

The *Akaike information criterion* (AIC) approach is a mathematical approach based on the *maximum likelihood* method to determine the degree of fit of the model developed based on filed data collected (**Akaike, 1974**). The value of the AIC estimator is computed as given below based on the number of estimated parameters (K) in the model, and the *maximum likelihood value* (L) of the *likelihood function* for the model:

$\text{AIC} = 2\,K - 2\ln(L)$ Eq. 3.4

The model with the lowest value of the AIC estimator is considered for the selection of key indicators or factors. The best-fit model is that which explains the greatest amount of variations using the least possible number of independent variables.

3.2.3.2 Bayesian Information Criterion (BIC)

The Bayesian information criterion (BIC) (known also as Schwarz Criterion) was developed by the statistician Gideon Schwarz (**Schwarz, 1978**) and is closely related to the

AIC. The *Bayesian Information Criterion* (BIC) approach is similar to the AIC approach, where the degree of fit of a model is measured based on the value of the *maximum likelihood function*. This approach is derived based on *Bayesian probability and inference* and is calculated as follows:

$$\text{BIC} = -2 * L + \ln(N) * K \qquad \text{Eq. 3.5}$$

where L = maximum value of the likelihood function, N = number of examples in the training dataset, and K = number of parameters in the model.

In this approach, the model with the lowest value of the BIC estimator is considered for the selection of key indicators or factors. The best-fit model is that which explains the greatest amount of variations using the least possible number of independent variables.

3.3 *PRINCIPAL COMPONENT ANALYSIS* (PCA) METHOD

The PCA approach attempts to transform data into an *orthogonal linear coordinate system* where the first coordinate (or the principal component) represents the data point with the highest variance. Similarly, the second coordinate (or the second principal component) represents the data with the second highest variance **(Jolliffe, 1986)**. The PCA approach can handle a number of performance indicators which are independent of each other simultaneously in order to obtain a ranking score that can be used by a transit manager. However, it is necessary to obtain a *correlation matrix* or perform a factor analysis before performing the PCA analysis.

The PCA method is an effective tool that can be used as part of analysis of data in various fields of science and engineering. The PCA approach is effective in identifying important variables that influence the functioning of the system under consideration. This approach assists in extracting the required information from a minimum set of variables from a complex dataset with a large number of variables. **Jonathan (2009)** observes that he PCA approach is capable of deriving the required information with minimal effort by reducing a complex dataset to a lower dimension in order to reveal the underlying relationship.

According to **Alberto (2000)**, the PCA approach is considered to be a popular multivariate technique used in ranking correlated variables so as to identify the most effective set of variables called principal components that influence a system. **Hair et al. (2006)** observe that the *first principal component* accounts for a significant amount of data variability, while the succeeding components account for the remaining variability.

The PCA approach assists in identifying groups of variables from among a number of correlated variables to assist in making better and more reliable predictions. The principal components indicate the directions along which the variance is higher. This can be considered to be synonymous with a straight line that explains the maximum possible variance in the data. The PCA is a linear transformation of a given dataset and attempts to fit the dataset to a new coordinate system where the first coordinate gives the highest variance and the subsequent orthogonal coordinate has lower variance. As part of the PCA approach, it is required to obtain the *covariance matrix* of the variables, followed by the computation of the *eigenvalues* for each of the variables. These *eigenvalues* are used to generate the *eigenvectors* based on which the *PCA* values are computed. The *PCA* values provide information on the variance of the data along a particular direction indicated by the *eigenvector*. The *first principal component refers* to the *eigenvector* with the highest *eigenvalue*.

The details on the working of the PCA-based approach are provided below **(Jolliffe, 1986)**

Step 1. The data with R datasets and C variables to be analyzed is compiled in a standard form as follows:

$$U = \begin{vmatrix} U_{11} & U_{12} & \ldots & U_{1C} \\ U_{21} & U_{22} & \ldots & U_{2C} \\ : & : & : & : \\ U_{R1} & U_{R2} & \ldots & U_{RC} \end{vmatrix}$$

where, R >= C. Eq.3.6a

It is then required to transform the original data vector into a standard form where the empirical mean is equal to zero using the following transformation equation:

U' *or* $U'_{RC} = (U_{RC} - U_{RC}^{\sim}) / \sigma_C$ Eq.3.6b

where U'_{RC} = transformed standardized data matrix; U_{RC} = original data comprising R datasets with C variables; $U_{RC}^{\sim}$ = mean of the original data with respect to variable C; σ_C = standard deviation with respect to the variable C; R=number of routes or rows of the dataset, and C=number of variables or columns in the dataset.

Step 2. It is now required to compute the $C \times C$ symmetric (covariance) matrix S as shown below:

$$S = \frac{U'^{T} . U'}{R-1} = \begin{vmatrix} S_{11} & S_{12} & \ldots & S_{1C} \\ S_{21} & S_{22} & \ldots & S_{2C} \\ : & : & : & : \\ S_{C1} & S_{C2} & \ldots & S_{CC} \end{vmatrix}$$

Eq.3.6c

Step 3. Let V be a vector and λ be a scalar quantity that satisfies the following expression:

$S.V = \lambda.V$ Eq.3.6d

Thus,

$S.V - \lambda.V = 0$

$V(S - \lambda.I) = 0$

Since V is a non-zero vector, then

Det $(S - \lambda.I) = 0$. Eq.3.6e

The values of λ computed as $\lambda_1, \lambda_2, \ldots \lambda_C$ (based on the number of variables C) that satisfy the above expression are called *eigenvalues*. On substituting the eigenvalues in place of λ, we can compute the *eigenvectors* ($V = V_1, V_2, \ldots V_C$) as follows:

$$V_1 = \begin{vmatrix} a_{11} \\ a_{12} \\ : \\ a_{1C} \end{vmatrix} \quad V_2 = \begin{vmatrix} a_{21} \\ a_{22} \\ : \\ a_{2C} \end{vmatrix} \begin{matrix} \ldots \\ \ldots \\ : \\ \ldots \end{matrix} \quad V_C = \begin{vmatrix} a_{C1} \\ a_{C2} \\ : \\ a_{CC} \end{vmatrix}$$

Eq.3.6f

Step 4. Based on the *eigenvectors* (V_1, V_2, ... V_C), it is required to compute the principal components Y_1, Y_2, … Y_n of each of the variables using the following expression:

$Y = S.V$ Eq.3.6g

3.3.1 Sample Problem to Demonstrate the PCA Approach in *R Studio*

This section provides details on the procedure adopted in performing the PCA analysis using the *R Studio* package. Here, it is proposed to perform the PCA analysis using details on input variables such as *route length*, *scheduled journey time*, *number of bus stops*, and *number of bus-trips*. It is however, required to obtain a *correlation matrix* before performing a PCA analysis.

Let us consider a simple example in the field of bus transport management, where it is required to perform the PCA analysis for a given dataset named *PCA_Sample_data* in the *R* programming environment. The details of the dataset with information on the input variables such as *route length*, *scheduled journey time*, *number of bus stops*, and *number of bus trips* as given in **Table 3.2a** are interfaced to the *Stats* package using a script (while the information on the output variable *passenger ridership* is provided in the table for information only).

The *Pearson's correlation matrix* for the above datasets was obtained using SPSS software as in **Table 3.2b**. The matrix indicates that the *route length* and the *scheduled time* are mildly and negatively correlated to *ridership*, while the *number of trips* is mildly and directly correlated to *ridership*. However, the *number of stops* is poorly correlated to *ridership*.

The squared loading provides a measure of the proportion of variance of a variable that is captured by a PC (**Jolliffe, 2002**). So, for each variable, the sum of its squared loading across all PCs equals 1. The sum of squared loadings of variables across the selected principal components are then arranged in descending order, and the variables are ranked. The variables *number of trips* and stops are selected for further analysis using the DEA.

3.4 RECURSIVE FEATURE ELIMINATION (RFE) APPROACH

The RFE approach is an algorithm that assists in determining a set of most important factors from a dataset that influence an observed phenomenon. In this approach, the least important factors or variables are systematically eliminated in an iterative manner. The important factors are identified as part of the RFE algorithm using *linear regression*, *logistic regression*, *support vector machine* algorithm, and so on.

Let us assume a set *S* that comprises all variables influencing the phenomenon. In the first iteration, the RFE approach deletes some of the important variables based on an inbuilt algorithm to produce the next set of variables, S_1. Subsequently, in the second iteration, a similar procedure is performed. Thus, it can be seen that the set of important factors S_N identified in the N^{th} iteration will be the least. Hence, the number of variables or factors considered in each iteration can be expressed as $S_N < S_{(N-1)} < S_{(N-2)} \ldots S_3 < S_2 < S_1$. The final set of important factors identified in the set S_N can then be ranked. This approach assists in reducing the *dimensionality* of the dataset so as to improve the performance using the model generated.

The RFE comprises a number of submodules to perform validations at each iteration. One of the approaches adopted is the *cross-validation* technique that can assist in evaluating the performance using a machine learning model by training it on a subset of the data. The *k-fold cross-validation* approach is widely used in various studies. Here, the dataset is randomly divided into *k* subsets of equal size before the validation is performed. This procedure is iterated *k* times, where a different subset is used each time. The average performance of the model is then computed from among the *k* iterations. (**Website: geeksforgeeks and github-RFE**).

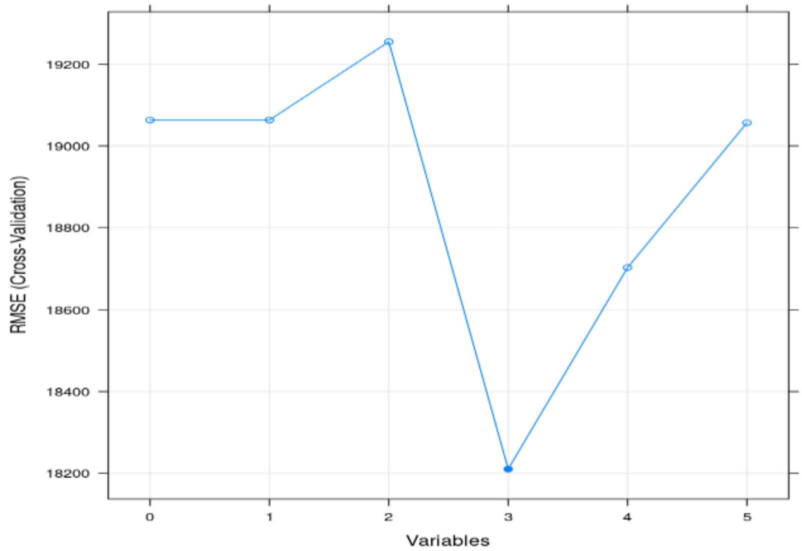

Fig.3.2 Graphical Visualization of RFE Result

From **Table 3.4,** it is evident that the performance of the model improves as the number of variables used increases from 0 to 3. The model with three variables is seen to provide the lowest RMSE and MAE values, indicating a better predictive performance when compared to other models. Additionally, the R-squared value for the three-variable subset is relatively high, indicating a good fit to the data. The *Caret* module in *R* also indicates that the most important variables that can be used are *Frequency*, *Fleet size*, and *Route length*.

3.5 PARAMETRIC AND NON-PARAMETRIC TECHNIQUES IN PERFORMANCE EVALUATION

Measurement of *productive efficiency* commenced with the application of *production theory*, while the later developments related to *performance evaluation* can be attributed to the *frontier theory*. A frontier can be represented graphically by an envelope drawn connecting observations of the most efficient organizations **(Ayadi and Hammami, 2015)**. The frontier can also be drawn assuming a function related to the observations. In the former case, the frontier-based approach is considered to be non-parametric. One of the examples of this approach is the *data envelopment approach* (DEA). In the latter case, the approach is considered to be parametric as demonstrated in the *stochastic frontier analysis* (SFA) approach.

Analyses related to non-parametric approaches can be performed in a deterministic manner based on linear programming techniques. Parametric approaches incorporate the use of econometrics and functions related to cost, revenue, inputs, and outputs, and also include a compound residual term that can be decomposed into a measure of inefficiency, and random noise **(Brons et al. 2005)**.

3.5.1 *Stochastic Frontier Analysis* (SFA): A Parametric Approach

The *stochastic frontier analysis* (SFA) method uses a standard *production function* to determine the *efficient frontier*. In this approach, the *maximum efficiency* is estimated based on the input and output variables. It is mainly used to find *technical efficiency*. *Technical efficiency* (TE) refers to the maximum output that can be produced for a given combination of input factors.

Early SFA models, classified as *stochastic production frontier* models, were introduced by **Aigner et al. (1977)** and **Meeusen and van den Broeck (1977)**. These were specific to *cross-sectional data* where the values of a number of variables at a particular instant of time are used. **Pitt and Lee (1981)** introduced SFA models that utilized *panel data*. *Panel data* refers to the values of a number of variables for a particular period of time.

Battese and Coelli (1992) define a *stochastic production frontier* function model for panel data, in which *technical efficiencies* of firms were computed. Also, the effect of **Battese and Coelli (1995)** proposed a model for estimating *technical inefficiency* in SFA models for panel data. In this model, it was assumed that the inefficiency effects are stochastic, and it permits the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies. According to **Battese and Coelli (1992)**, the expression for the SFA production function can be expressed as,

$$Y_{it} = f(x_{it};\beta)exp(V_{it} - U_{it}) \qquad \text{Eq.3.7a}$$

and

$$U_{it} = \eta_{it}\, U_i \qquad \text{Eq.3.7b}$$

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

Thus, the input vector function can be assumed as,

$$f(x_{it};\beta) = exp(\beta_0)\, \beta_k\, x_{ik}) \qquad \text{Eq.3.7c}$$

where x_{ik} = k^{th} input variable of i^{th} decision-making unit; β_0 = constant or intercept; and β_k = parameter coefficient (or input elasticities) of 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. The *log-linear function* can be expressed as (**Murillo-Zamorano and Vega-Cervera, 2001**):

$ln(Y_{it}) = \beta_0 + \sum\beta_k \, ln(x_{it}) + V_i - U_i$ Eq.3.7d

Where β_0 = constant or intercept and β_k = parameter coefficient of k^{th} variable; x_{ki} = input value of k^{th} variable of i^{th} decision-making unit for the t^{th} time period; V_i = noise term; and U_i = non-negative *technical inefficiency* term.

The *technical inefficiency term* (U_i) needs to be always positive. Hence, it is generally assumed to follow a half-normal distribution with the positive side of the *normal distribution* (**Aigner et al., 1977**). That is $U_i = N^+(0,\sigma^2)$. U_i can also follow an *exponential distribution* (**Meeusen and van den Broeck, 1977**), a *gamma distribution* (**Green, 1980**), or a *truncated normal distribution* (**Stevenson, 1980**).

The technical efficiencies of decision-making units are calculated by estimating the parameters using the *maximum likelihood estimation* method. These parameters include $\boldsymbol{\beta_0}$, $\boldsymbol{\beta_k}$ (parameter coefficients of input variables), $\boldsymbol{\sigma^2}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\eta}$. Where, $\sigma^2 = \sigma_u^2 + \sigma^2_v$ and $\gamma = \sigma_u^2 / \sigma^2$. **Battese and Coelli (1988)** observe that *technical efficiency* (TE) can be computed as the ratio of *observed mean production* or *output* to the *maximum possible mean production* for the most efficient input of resources. The *observed output* from the SFA approach includes the *inefficiency*, while the *maximum possible output* does not consider the *inefficiency* term. Based on studies made by **Jondrow et al. (1982)** and **Battese and Coelli (1988)**, the expression for *technical efficiency* (or *cost efficiency*) was derived by **Sami et al. (2013)** as,

$ln(TE_i) = [\beta_0 + \sum\beta_k \, ln(x_{k,i}) + V_i - U_i] \, / \, [\beta_0 + \sum\beta_k \, ln(x_{k,i}) + V_i]$

Thus,

$TE_i = e^{-U_i}$ Eq.3.7e

The *SFA* approach can be used to estimate maximum production that can be achieved for a given level of existing production factors. It assesses in computing *technical efficiency* level and the factors affecting *technical efficiency*, while the *technical efficiency* can be used to identify the most efficient organizations and the performance measures.

3.5.2 *Data Envelopment Analysis* (DEA): A Non-Parametric Approach

DEA is a non-parametric technique that is widely adopted in the performance evaluation of various organizations. It is also an MCDM technique for measuring the relative efficiency of various organizations that can handle multiple inputs and outputs. The DEA is a *linear programming-based approach* that can assist in determining the best alternative to improve the operation and functioning either by minimizing the inputs, or by maximizing the output based on an efficiency score (**Charnes et al. 1978**).

According to the DEA approach proposed by **Charnes et al. (1978)**, the DEA analysis if formulated considering the ratio between the *output* (or productivity), and the *input* (representing supply variables and resources provided to the system). Since this model was developed by Charnes, Cooper, and Rhodes, it is also known as the CCR model. This *output-oriented* algorithm focuses on maximizing the above-mentioned ratio for the given set of organizations or decision-making units (DMUs). In this approach, it is assumed that the *rate of return* over the period of analysis remains constant. Hence, this approach proposed by **Charnes et al. (1978)**, is also referred to as the *Constant Returns to Scale* (CRS) model. The *measure of efficiency* obtained using the CCR model is called as the *overall technical efficiency* (OTE).

The CCR-DEA model developed by **Charnes et al.** (**1978**) adopts a mathematical programming approach that uses either the "primal" form or "dual" form of the LP problem. The *primal form* is also called as the *multiplier form,* while the *dual form* is called as the *envelopment form*. The DEA is capable of providing solutions to both the primal and the dual forms of the LP problem. In many circumstances, the formulation of the dual problem simplifies complexities due to a higher number of constraints, especially when handling a large number of DMUs. The additional advantage in formulating the dual problem is that the use of slack variables assists in the computation of the amount of reduction of input resources to improve the performance of under-performing DMUs. The following sub-sections provide explanations on the formulation of the primal and the dual LP problems as part of the DEA approach.

3.5.2.1 Formulation of the Primal LP Problem in the DEA Approach

The *primal form* of the LP problem for the q^{th} DMU according to the CCR model proposed by **Charnes et al**. (**1978**) as follows,

Maximize: $\sum_{r=1}^{s} u_r Y_{rq}$ Eq.3.8a

such that,

$\sum_{r=1}^{s} u_r Y_{rq} - \sum_{i=1}^{m} v_i X_{iq} \leq 0$ $\quad q = 1, 2, \ldots, n$ Eq.3.8b

$\sum_{i=1}^{m} v_i X_{iq} = 1$ Eq.3.8c

$u_1, u_2, \ldots u_s \geq 0$ Eq.3.8d

$v_1, v_2, \ldots v_m \geq 0$ Eq.3.8e

where, $\sum_{r=1}^{s} u_r Y_{rq}$ represents the *combined efficiency factor* for the q^{th} decision making unit.

3.5.2.2 Formulation of the Dual LP Problem in the DEA Approach

In the primal LP problem explained in the above section, since the objective function is required to be maximized, the dual problem can be formulated to perform a minimization operation. The solutions to the primal and dual problems will be identical as both represent the same optimal conditions. This approach is adopted in order to simplify complex problems involving large number of DMUs, and where the number of constraints are more in the primal formulation. Moreover, the use of slack variables will provide more insight into the fine-tuning of the operation of the DMUs.

For the primal LP problem formulated above vide **Eq.3.8a** to **Eq.3.8e**, the dual LP problem with slack variables can be formulated as expressed in **Eq.3.9a** to **Eq.3.9d** as demonstrated by **Charnes et al. (1978)**.

Minimize: $\theta - \varepsilon \left(\sum_{r=1}^{s} S^{+}_{r} + \sum_{i=1}^{m} S^{-}_{i}\right)$ Eq.3.9a

Such that,

$\sum_{q=1}^{n} \lambda_q X_{iq} + S^{-}_{i} = \theta X_{iq}$ i = 1, 2, …, m Eq.3.9b

$\sum_{q=1}^{n} \lambda_q Y_{rq} - S^{+}_{r} = Y_{rq}$ r = 1, 2, …, s Eq.3.9c

$\lambda_q, S^{-}_{i}, S^{+}_{r} \geq 0$ Eq.3.9d

where, x_{iq} = amount of input' *i*' used by the q^{th} DMU; y_{rq} = amount of output '*r*' produced by the *q*th DMU; *m* = the number of inputs; *s* = the number of outputs; and *n* = the number of DMUs.

In the above formulation, θ and λ_q (where, q = 1, 2, ... n), are the dual variables of the primal LP problem. Also, S^{-}_{i} and S^{+}_{r} are the "Slack variables" (additional variables) added to the model in order to convert inequality constraints to equality constraints. The *slack variables* indicate the additional increase in outputs (S^{+}_{r}), and/or the decrease in inputs (S^{-}_{i}) required to be implemented for a DMU to become more efficient. 'ε' is a "*Non-Archimedean infinitesimal*" constant which is smaller than any positive real number, and is normally assumed as 10^{-6}.

3.5.2.3 Determination of the Solution to the Dual Form of the LP Problem Using the R Statistical Package in the DEA Approach

The dual form of the LP problem can be solved using the *deaR* submodule of the *R Statistical Package*. The advantage of using the *deaR* submodule is that in addition to the determination of under-performing DMU, it can automatically provide comparisons between one DMU to every other DMU by making use of the open source script contributed by a number of programmers worldwide (**Coll-Serrano et al. 2020**). In order to demonstrate the use of the *deaR* program, the input-oriented basic DEA-CRS model, as proposed by **Charnes et al.** (**1978**) was adopted as the preferred approach in the *deaR* package. This model also incorporates features to estimate the amount of reduction in input variables in addition to estimates of possible extra benefits in outputs that could be achieved when compared to the best performing DMUs. The *deaR* package can also analyze LP problems using the *output-oriented* and *input-cum-output oriented* approaches. Alternatively, the dual form of the LP problem can also be solved using programming platforms such as *Excel*, *VBA*, *MATLAB*, *PYTHON*, and *C++*.

From **Table 3.4c**, it may be observed that the value of λq for DMU 3, when compared to the performance of DMU 1, is 0.1499. Here, it can be seen that the value of λq for DMU 3 when compared to other DMUs, is 0. This indicates that the performance of DMU 3 must be improved by reducing the inputs such as the total cost (X_1), average fleet operated (X_2), and the staff employed (X_3) by a factor of 0.1499 times the values of the corresponding variables X_1, X_2, and X_3 for DMU1. Similar computations can be performed for DMU4. **Table 3.4e** provides details on the optimized target values for the inputs X_1, X_2, and X_3 for DMU 3 and DMU 4. In **Table 3.4c**, if the values of λq for DMU 3 when compared to other DMUs is not zero, then the improvement in performance for DMU 3 can be attained by reducing the inputs by the sum of the product of the λq values and the corresponding input values of the benchmarked organizations. The general expression for the same is given as,

$$X_{iq\text{-}target} = \sum_{q=1}^{n} \lambda_q X_{iq} \qquad \text{Eq.3.10}$$

where, $X_{iq\text{-}target}$ = the target input i for the q^{th} DMU; X_{iq} = actual input i for the q^{th} DMU; and λ_q = dual variables of the primal LP problem.

Alternatively, from **Table 3.4b**, and **Table 3.4d**, it may be observed that the values of the *efficiency scores* (***θ***) for DMU 3 is 0.99754, and the values of the slack variables for the inputs such as the total cost (X_1), the average fleet operated (X_2), and the staff employed (X_3) are 892.84, 0, and 2266.55 respectively. Also, the values of the slack variables for the outputs, such as the total revenue (Y_1), and passenger-km performed (Y_2) are 6251.26 and 0. The improvement in performance for DMU 3 can be summarized as given below:

Step 1: The product of the *efficiency scores* 0.99554 for DMU 3 (obtained from **Table 3.4b**) and the value of the input variable *total cost* (X_1) of 22459.67 (obtained from **Table 3.4a**) is computed as 22359.50.

Step 2: The value of the slack variable (S_i^-) for *total cost* (X_1) of 892.84 is subtracted from the computed value in the above step. This amounts to 21466.66.

Step 3: Similar computations are performed for the other input variables, such as the *average fleet operated*, and the *staff employed*. The results are summarized in **Table 3.4e**. In general, the improvement in performance for a DMU can alternatively be attained for each input variable as the product of efficiency score and the input variable value minus the slack value for the corresponding input. This is expressed as,

$$X_{iq\text{-target}} = (\theta^* X_{iq}) - S_i^{-} \qquad \text{Eq3.11a}$$

where, $X_{iq\text{-target}}$ = the target input *i* for the q^{th} DMU; X_{iq} = actual input *i* for the q^{th} DMU; θ^* = efficiency score of the q^{th} DMU; and S_i^{-} = value of the corresponding input slack variable.

Step 4: For the output variable such as *total revenue* (Y_1), the corresponding value of the slack variable (S_r^{+}) of 6251.26, as in **Table 3.4d,** is added to the existing value of 7532.96 in **Table 3.4a**, to obtain the optimized target value of 13784.22 in **Table 3.4e** for the underperforming *DMU 3*. Similar computations are made for the other output variable, such as *passenger-km performed* (Y_2). The general expression for obtaining the optimized value of the output variables is given as,

$$Y_{rq\text{-target}} = Y_{rq} + S_r^{+} \qquad \text{Eq.3.11b}$$

where, $Y_{rq\text{-target}}$ = target output '*r*' for the q^{th} DMU; Y_{rq} = actual output '*r*' for the q^{th} DMU; and S_r^{+} = value of the corresponding output slack variable.

3.5.3 Formulation of the DEA-BCC Model Considering Variable Returns to Scale (Banker et al., 1985)

The original approach adopted by **Charnes et al. (1978)** in the CCR model, which later became known, was based on inputs to the decision-making unit with a specific rate of returns (or constant returns to scale). **Banker et al. (1984**) developed an alternative model that came to be known as the BCC model, where the rates of returns could be varied. This approach was known as the variable returns to scale approach. The standard formulation of an input-oriented (**Banker et al., 1984**) model is given below:

$$\textit{Minimize: } \theta - \varepsilon \left(\sum_{r=1}^{s} S^{+}_{r} + \sum_{i=1}^{m} S^{-}_{i}\right) \qquad \text{Eq.3.12a}$$

Such that,

$$\sum_{q=1}^{n} \lambda_q X_{iq} + S^{-}_{i} = \theta X_{iq} \qquad i = 1, 2, \ldots, m \qquad \text{Eq.3.12a}$$

$\sum_{q=1}^{n} \lambda_q Y_{rq} - S^+_r = Y_{rq}$ r = 1, 2, …, s Eq.3.12c

$\sum_{q=1}^{n} \lambda_q = 1$ Eq.3.12d

$\lambda_q, S^-_i, S^+_r \geq 0$ Eq.3.12e

where x_{iq} = amount of input 'i' used by the q^{th} DMU; y_{rq} = amount of output 'r' produced by the qth DMU; m = the number of inputs; s = the number of outputs; and n = the number of DMUs.

In the above formulation, θ and λ_q (where, q = 1, 2, ... n), are the dual variables of the primal LP problem. Also, S^-_i and S^+_r is the "Slack variables" (additional variables) added to the model in order to convert inequality constraints to equality constraints. The *slack variables* indicate the additional increase in outputs (S^+_r), and/or the decrease in inputs (S^-_i) required to be implemented for a decision making unit to become more efficient. 'ε' is a "*Non-Archimedean infinitesimal*" constant which is smaller than any positive real number, and is normally assumed as 10^{-6}.

3.5.4 Formulation of the DEA for Undesirable Outputs (Seiford & Zhu, 2002)

The output-oriented and the input-oriented DEA models developed by Charnes et al. (1978) involved the development of the logic for the computation of efficiency of organizations analysed, identification of the best performing set of frontier organizations, and the computation of relative efficiency scores of other organizations. In the output-oriented model, the objective function is formulated to maximise the output for a given set of input values. In the case of input-oriented DEA models, the objective function is formulated to minimize the input of resources required for a given set of output values. However, in the analysis of real-world systems, it is not possible to maximize all output variables, especially when output variables include negative/ undesirable variables such as accident rates, and vehicular emissions as in public transport organizations. The DEA model proposed by **Seiford and Zhu (2002)**, developed based on the BCC model (**Banker et al. 1984**), is essentially a variable-returns-to-scale model that is capable of handling negative variables in the analysis.

The standard formulation of an output-oriented (**Seiford & Zhu, 2002**) model is given below:

$Maximise\ \theta$ Eq.3.13a

Subject to,

$\sum_{q=1}^{n} \lambda_q \cdot X_{iq} + S_i^- = X_{iq}$ $i = 1,2,..,m$ Eq.3.13b

$\sum_{q=1}^{n} \lambda_q \cdot Y_{rq} - S_r^+ = \theta \cdot Y_{rq}$ $r = 1,2,..,s$ Eq.3.13c

$\sum_{q=1}^{n} \lambda_q \cdot \bar{Y}_{tq} - S_t^+ = \theta \cdot \bar{Y}_{tq}$ $\quad t = 1,2,..,k$ Eq.3.13d

$\sum_{q=1}^{n} \lambda_q = 1,$ Eq.3.13e

$\lambda q, S_i^-, S_r^+, S_t^+ \geq 0$ Eq.3.13f

where, θ = efficiency score of the DMU or the organization under consideration which varies between 1 and ∞; λ_q = weight associated with the q^{th} DMU; X_{iq}= amount of input 'i' used by the q^{th} DMU; y_{rq} = amount of desirable output 'r' produced by the q^{th} DMU; $\bar{Y}_{tq}$ = amount of undesirable/ negative output 't' produced by the q^{th} DMU; m = the number of input variables; s = the number of desirable output variables; k = the number of undesirable/ negative output variables and n = the number of DMUs. Also, S_i^-, S_r^+ and S_t^+ are the *Slack/Surplus* variables used in the mathematical formulation. A higher value of θ indicates that the performance of the DMU is lower than that of the efficient DMUs that possess a score of 1.00.

3.6 SUMMARY OF DIFFERENT METHODS AND THEIR ROLE IN THE PRESENT STUDY

The various approaches discussed above are adopted in the study for performance evaluation of public transport systems at different levels. **Fig. 3.3** provides an pictorial representation of the different methods described in this chapter and their role in the current thesis objectives. These approaches will assist in identifying bottlenecks in improving the financial and physical performance of transport undertakings.

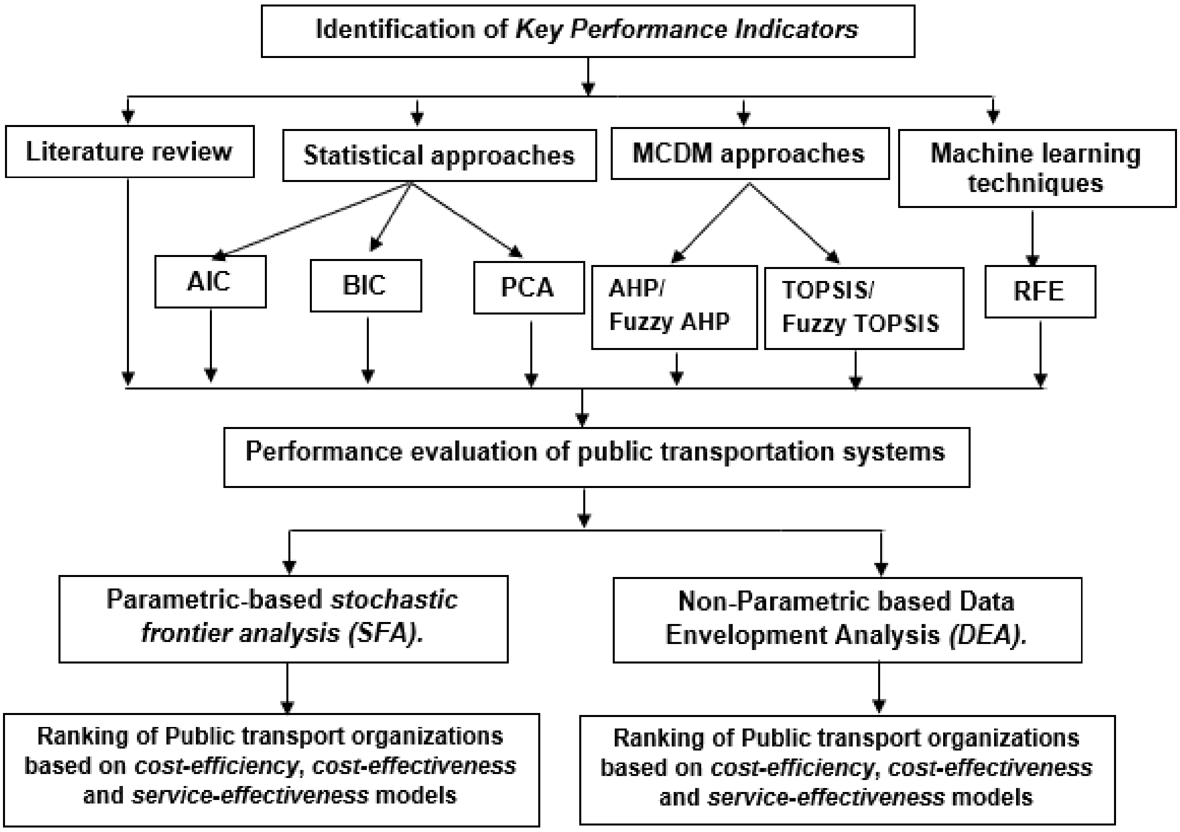

Fig.3.3 Various Approaches Adopted in the Present Study

CHAPTER 4

METHODOLOGY, DETAILS ON THE STUDY AREA, AND IDENTIFICATION OF *KEY PERFORMANCE INDICATORS* USING *MCDM*

4.1 INTRODUCTION

Analyses related to performance evaluation can be performed using *parametric* as well as *non-parametric* approaches. *Parametric* methods are based on econometric techniques that employ functions that relate input and output variables including cost, profit, and production efficiency. These methods include the *Stochastic frontier analysis (SFA)* approach, *thick-frontier* approach, *distribution-free* approach, and *regression-based* (or least-square-based) approach. Non-parametric solution approaches include the *Data Envelopment Analysis (DEA)* approach, *non-parametric regression* approach, and *semi-parametric* regression approach.

The major difference lies in the fact that parametric methods such as *SFA*, including regression models, focus on making inferences based on models that use functional forms in identifying the organizations that constitute the most efficient frontier relating selected input and output variables. Whereas, the DEA–approach is a linear programming-based *non-parametric* approach that can assist in determining the best alternative to improve the operation and functioning either by minimizing the inputs or by maximizing the output based on an efficiency score. (**Kumar and Gulati, 2008**). Additionally, non-parametric methods of analysis are adopted where random errors in measurement are expected to be the least, such as in the use of data related to financial and operational indicators (**Asmare & Begashaw, 2018**).

The present study focuses on the use of the SFA *and* DEA approach in conducting performance evaluation of selected SRTUs in India. In order to conduct a performance evaluation of public transport organizations, it is required to utilize information and data related to the *financial* and *physical* performance of public transport undertakings at various periods of time. As part of this exercise, it is required to obtain a clear understanding of the use of *key performance indicators*. One of the most effective approaches in identifying the *key performance indicators* is the use of MCDM approaches such as *AHP* and *TOPSIS* methods. These MCDM approaches require the opinion of experts in the relevant area of functioning of organizations, which is obtained using a questionnaire survey. The KPIs identified using the MCDM approaches were then planned to be used in the performance evaluation of SRTUs using the SFA and DEA methods. The *efficiencies* and *effectiveness* of SRTUs can be analysed using these approaches.

The present study also focuses on conducting a performance evaluation of selected SRTUs in India using a hybrid-DEA approach considering undesirable/negative variables related to vehicle emissions and accidents. Additionally, it was also proposed to perform analyses at the *sub-system* and *route-level* for MCTD, an urban-based SRTU.

The following section provides details on the framework and overall methodology adopted, a brief description of the study area, and an identification of KPIs based on inputs from experts obtained using a *Google-Forms-based* questionnaire. This chapter also includes details on the preliminary processing of the responses collected from experts, followed by analysis using the *conventional AHP* and the *Fuzzy AHP*, and the *conventional TOPSIS* and the *Fuzzy TOPSIS* approach, where a final set of indicators were identified for further analysis.

4.2 BASIC FRAMEWORK OF THE OVERALL METHODOLOGY ADOPTED

The overall approach adopted in this study for performance evaluation is expected to provide the basic framework for fine-tuning the functioning of SRTUs. These approaches will assist in identifying bottlenecks in improving the financial and physical performance of transport undertakings. **Fig.4.1** provides details on the overall methodology adopted in this study.

The *first phase* of the present study focuses on performing an in-depth investigation on the use of *measures of efficiency* and *measures of effectiveness* in the performance evaluation of bus transport organizations and the identification of KPIs based on the analysis of responses obtained from experts. In this phase of the study, it was planned to adopt the use of the MCDM-based approach such as AHP, Fuzzy AHP, TOPSIS, and Fuzzy-TOPSIS method. In the *second phase* of the study, it is proposed to compare the performance of various SRTUs in India including KnSRTC using the selected set of performance indicators and to further identify the input and output variables that need to be considered in the analysis using parametric approaches such as the SFA approach and the non-parametric approach such as the *DEA* method.

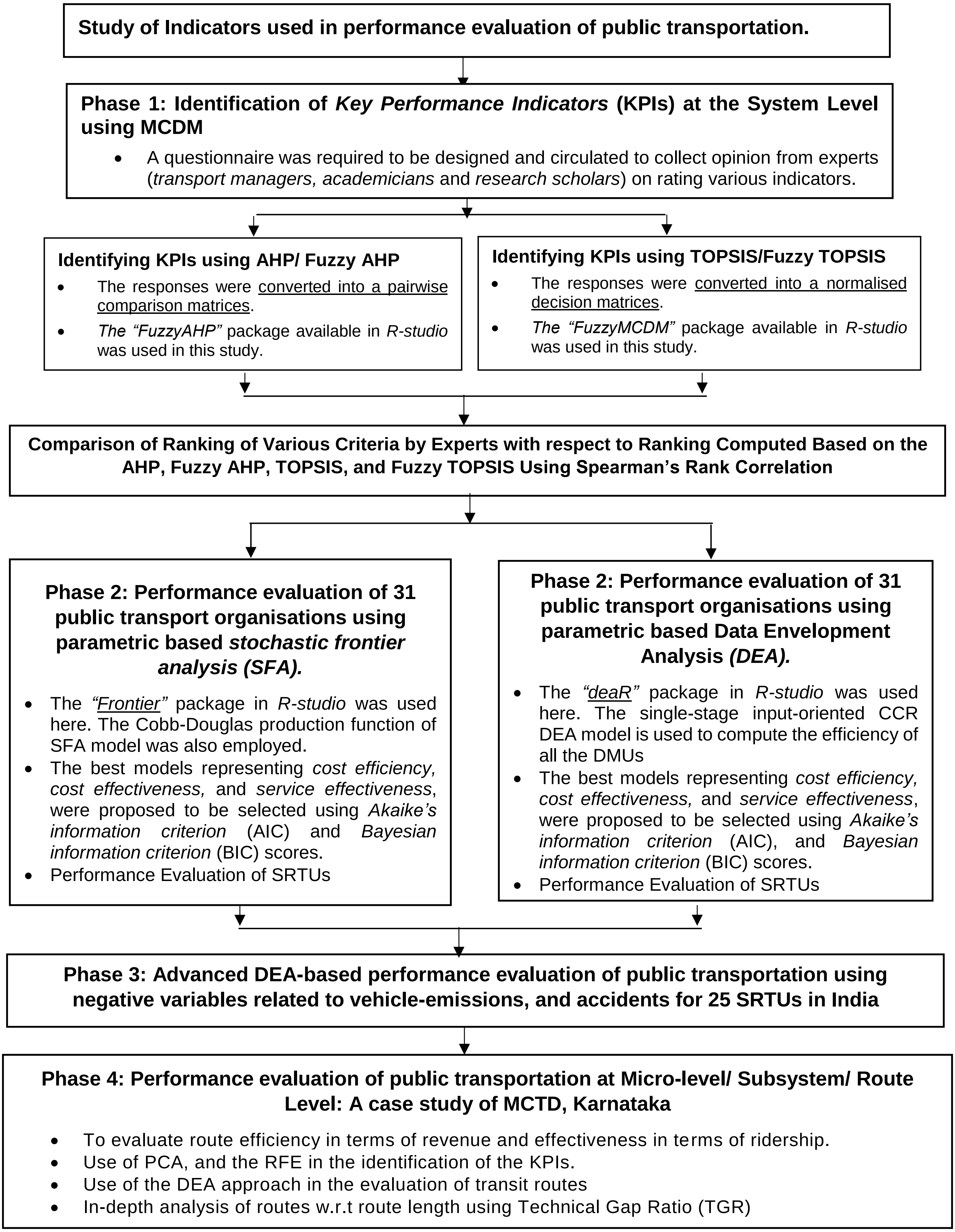

Fig.4.1 Framework of the Overall Methodology

In the *third phase* of the study, it was also proposed to use important physical and financial performance indicators identified in the literature review to explore the possibilities of using the DEA approach incorporating the use of exogenous variables related to vehicle emissions and accidents.

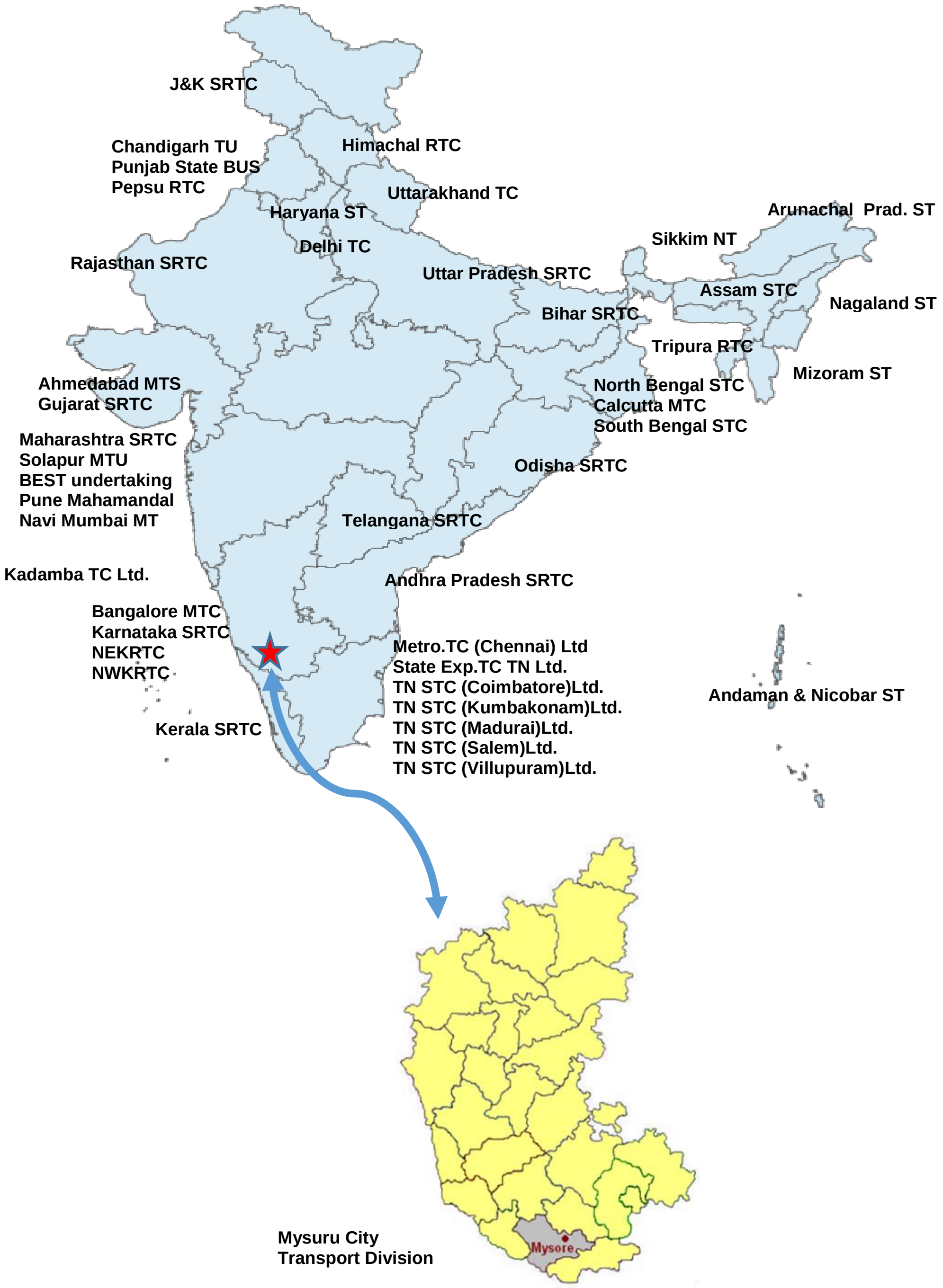

Fig.4.2 Important SRTUs in India and the Area Served by MCTD

The *fourth phase* of the study focuses on performing micro-level/route-level analyses on the MCTD, a part of KnSRTC. This includes the identification of KPIs incorporating the use of the PCA and the RFE implemented using the R/ Python programming language.

And performance analysis using a non-parametric-based econometric approach such as the DEA approach implemented using the R/ Python programming language.

4.3 STUDY AREA CHARACTERISTICS

The present study deals with conducting a performance evaluation of SRTUs in India. Therefore, a brief overview of the SRTUs in India is provided in this section. **Fig.4.2** provides details on the important SRTUs providing passenger transport services in India, and the population area served by MCTD.

4.3.1 State Road Transport Undertakings (SRTUs)

Indian bus transport organizations operating in the public sector, commonly called SRTUs, provide transport services to trip-makers all over India and serve a heterogeneous mix of populations with diverse socio-economic backgrounds. SRTUs were established by the respective State Governments under Section 3 of the Road Transport Corporations Act, 1950. In the year 2020, there were 62 road transport undertakings that operated 150,000 buses to serve 70 million passengers per day. These SRTUs provide safe, economical, and efficient means of transport to urban and rural areas of the country. **(Website: ASRTU_2022).**

Presently, there are 62 SRTUs being operated by 24 Road Transport Corporations, 12 public-limited companies, 10 municipal undertakings, and other Government Departmental Undertakings. The total SRTUs, total fleet size, staff employed, the total passengers served in terms of passengers carried, and the rate of growth in passenger-km for the past decades are given in **Table 4.1**.

The number of SRTUs in India increased from 28 during 1960-61 to 62 during 2009-10. The output produced by the SRTUs increased from around 26 billion passenger-km in 1960-61 to 566 billion passenger-km in 2016-17, registering an increase of around 22 times in a span of five and half decades. It can also be seen that the total fleet strength increased from 18,000 in 1960-61 to 1,49,095 in 2016-17, registering an average annual increase of 3.8%. However, the growth rate in fleet strength from 2000-01 to 2014-15 has not been significant. The overall increase in the fleet strength fleet during this period was found to be only 20,000 buses. In terms of average annual growth rate in fleet size, the SRTUs have registered an increase of only 1.1% from 1990-91 onwards.

Table 4.1 Statistics Related to the Growth of SRTUs Over the Decades

Year →	1960-61	1970-71	1980-81	1990-91	2000-01	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19
Characteristics↓														
Number of SRTUs#	28	32	54	64	63	34*	38*	38*	44*	46*	47*	56*	56*	56*
Total Employ-ment (10^5) #	1.4	2.8	5.7	7.5	7.4	6.72	7.29	7.28	7.62	7.0	7.6	7.4	7.2	7.1
No. of buses held (10^3) *	18	37	78	104	115	130.6	131.8	137.9	140.2	140.5	142.86	149.10	151.88	152.357
Percentage of buses in the country*	32	39	55	33	18	8	7.8	7.6	7.4	7	8	8	8	8
Passenger km performed (10^9)#	26	81	NA	363	434	582	552	536	529	524	540	566	616	599

* MoRTH Road transport year book 2019-10
\# MoRTH Review of performance of SRTUs 2018-19

4.4 INDICATORS USED IN PERFORMANCE EVALUATION AND MONITORING

In India, government-sponsored agencies such as the CIRT, Pune, and the Transport Research Wing of the *Ministry of Road Transport and Highways* (MoRTH) take responsibility for the performance evaluation of SRTUs. The SRTUs provide periodic information on financial and physical performance to CIRT on a regular basis, mainly with regard to capital structure, manpower productivity, fuel efficiency, financial efficiency, operational efficiency, and inventory position. 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.*'

The list of performance indicators commonly used by SRTUs in India is broadly divided into 3 groups, namely, Financial Performance Indicators, Physical Performance Indicators, and Material Performance Indicators.

Financial performance indicators reflect components of cost and revenue, and profit and loss. These indicators refer to the viability of providing transport operations by the bus transport undertaking. These indicators are related to personnel and material costs, taxes, interest, depreciation, revenue, surplus before tax, profit/loss, and percentage return on the capital invested.

Physical performance indicators reflect the characteristics related to service consumption, and service outputs that do not include cost and revenue components. These are categorized into five groups as described below:

- The performance indicators classified in *Categories I* and *II* provide a quick review of the utilization of the fleet and the total capacity of the transport system, respectively. For example, an indicator such as *fleet utilization* classified under *Category I* is computed as the ratio of the fleet on road/ fleet held.

- An indicator such as *occupancy ratio* classified under *Category II* is computed as passenger kilometres/ seat capacity km.

- Indicators classified under *Category III* focus on quality of service provided. For example, the degree of punctuality or regularity in service provided is indicated by the percentage of scheduled trips operated, and the number of lost trips due to vehicle breakdown and other reasons. Indicators related to the level of safety provided were measured in terms of accidents, injuries, and fatalities and also included.

- Indicators classified under *Category IV* and *Category V* are operator-specific and focus on manpower productivity and operational aspects.

- A few other parameters considered in performance evaluation studies related to physical performance include the average age of the fleet, fleet utilization, capacity utilization, manpower productivity, spares, fuel, and tyre performance.

Material performance indicators focus on details related to service consumption in terms of material consumed during the period of operation. Some of these include indicators related to fuel, lubricants, engine oil, tyres, batteries, and spares consumed.

A detailed list of indicators reported by SRTUs on a regular basis to CIRT, Pune, is provided in **Table A.1.**

4.4.1 List of Important Indicators Based on Literature Survey

CIRT publications provide details on a comprehensive list of financial, physical, and material performance indicators used in bus transport organizations in India as listed in **Table A.1**. It is however required to select a meaningful set of indicators that represent *cost efficiency, cost effectiveness* and *service effectiveness* linking *service-inputs, service-consumption,* and *service-outputs* as shown in **Fig.2.1**.

A list of 20 such indicators was selected to assess the performance of SRTUs based on the importance of use in the transport industry, data availability, and data consistency. **Table 4.2** provides details on the selected list of 20 indicators from which the KPIs need to be identified using a suitable MCDM approach.

Table 4.2 List of Important Indicators Considered Based on Literature Review

Sl. no	Indicator	Definition and Formulae
1	**Total Cost** (Rs.)	The total amount of money spent on personnel, materials, taxes, interest and also depreciation is given under total cost.
2	**Total Revenue** (Rs.)	The revenue generated from buses (traffic revenue) and advertisements (non-traffic revenue) together come under the total cost.
3	**Fleet Size** (Num)	The total number of buses held by an organization, including the buses on and off-road, are counted as fleet size.
4	**Buses on Road** (Num):	The number of buses actively serving the people are called buses on road. It is also called as *Buses on Road*/*on-road fleet size*/*Average fleet operated* in the thesis.
5	**Buses off road** (Num)	The number of buses which are not in a condition to run or serve people and are idle or under repair are counted under buses off-road.
6	**Fleet Utilization** (%):	It is defined as the ratio of buses on road (fleet operated) to the total number of buses held (fleet size). *Fleet utilization = (Fleet operated / Fleet size) * 100*
7	**Effective Km** (Num):	The total distance covered by buses, which produced revenue to the organization is called effective kilometers. It is also called as Revenue earning kilometers.
8	**Carrying capacity Km** (Crores):	The product of total carrying capacity of buses (seating + standing) and effective kilometers is called as carrying capacity of an organization. *Carrying capacity Kms = Carrying capacity * Effective kms*
9	**Passenger Km** (Num):	The product of total distance operated and total carrying capacity of an organization is called passenger kilometers. *Passenger kilometers = Total carrying capacity * Total distance operated*
10	**Load Factor** (%):	load factor is defined as total passenger kilometers performed as percentage of total carrying capacity (seats + standing spaces) in the bus. *Load factor = (Total passenger kms / Total carrying capacity) * 100*
11	**Occupancy ratio** (%):	It is defined as total passenger kilometers performed as a percentage of total seats available in the bus. *Occupancy ratio = (Total passenger kms / Total seating capacity kms) * 100*
12	**Passengers carried** (Num):	The total number of passengers carried by the buses.
13	**Fuel consumed** (Kiloliters):	The total number of high-speed diesels consumed in kiloliters.
14	**Number of Accidents** (Num):	The total number of accidents recorded, which includes fatal, major and minor non-fatal number.
15	**Number of Fatal accidents** (Num):	The total number of only fatal accidents.
16	**Accidents per lakh effective Km** (Num):	The ratio of total number of accidents to the effective kilometers in lakhs. *Accidents per lakh eff Kms = Total number of accidents / Effective kilometers (in lakhs)*
17	**Total staff** (Num):	The total number of staff working in an organization. It is also called *No. of employee* or *Staff Strength* in the thesis
18	**Regularity** (%):	The ratio of actual trips operated to the trips scheduled to be operated. *Regularity = (Actual trips operated / Trips to be operated) * 100*
19	**Seating capacity** (Num):	The total seating capacity of a bus.
20	**Number of Breakdowns** (Num):	The total number of times buses have stopped due to mechanical defects and are unable to operate.

4.5 DESIGN AND FORMULATION OF THE QUESTIONNAIRE

The present study focuses on the identification of KPIs using the MCDM approach based on the AHP. In this approach, it is required to collect opinions in the form of ratings from experts in the field of public transportation regarding the degree of importance of the selected list of indicators in performance evaluation. The ratings are performed on a scale ranging between 1 and 9, where a value of **1** corresponds to '*least important'* while a value of **9** corresponds to '*Highly important'*. The inputs from the experts were collected through a survey form created using '*Google Forms*' and circulated to various experts in various SRTUs in India by e-mail. The **questionnaire/ survey form** consisted of two parts:

- The *first part* was designed to collect basic information about the expert with information related to age, qualification, and profession.
- The *second part* included details on approximately 20 shortlisted indicators with a facility for rating each indicator.

Details on *Part 1* and *Part 2* of the questionnaire/ survey are provided in **Table B.1** and **Table B.2**, respectively**.** The experts identified consisted of *bus transport managers* (TM) comprising *depot managers*, *regional transport managers*, *divisional traffic officers*, and *assistant engineers* working in various SRTUs. Additionally, a group of *academicians* (AC) comprising professors and others with knowledge of the functioning of public transport systems and another group consisting of *research scholars* (RS) engaged in conducting research in the field of public transport systems were identified. Each of the respondents belonging to the groups mentioned was required to record their preferences using Google Forms. The links / URLs were shared with the managers for the same.

4.6 COLLECTION OF RESPONSES, AND ANALYSIS FOR THE IDENTIFICATION OF KPIs

The responses were later downloaded in the form of an 'MS Excel spreadsheet for further analysis. The response sheets also provided information on gender, age, highest qualification, and the type of profession. About **18 responses** thus recorded were downloaded. A partial table consisting of the responses collected is presented in **Table 4.3**.

Table 4.3 Responses from Experts Downloaded from Google Forms (Partial)

PART -1					
	Expert No.1	*Expert No.2*	*Expert No.3*	…	*Expert No. N*
1. Gender	Male	Male	Male	….	Male
2. Age	46-60	26-45	46-60	….	18-25
3. Highest Qualification	Post Graduate and above	Post Graduate and above	Post Graduate and above	….	Post Graduate and above
4. Profession	Academician	Academician	Manager of a Transport Organisation	….	Research scholar
PART -2					
1. Total Cost (Personnel Cost + Material Cost + Taxes/Interest + Misc)	7	8	9	….	7
2. Total Revenue (Traffic Revenue + Subsidy + Non-Traffic Revenue)	7	9	9	….	5
3. Fleet size (Total Buses held)	6	7	9	….	8
4. Buses on Road (Fleet Operated)	8	7	9	….	7
5. Buses off Road (Non-Operating buses)	6	7	9	….	3
6. Fleet Utilization	8	6	9	….	8
7. Effective Km (Revenue Earning Kms)	9	9	9	….	7
8. Carrying Capacity Km	6	9	9	….	7
9. Passengers Km	8	8	9	….	7
10. Load Factor	8	8	9	….	8
11. Occupancy Ratio	8	9	9	….	7
12. Passengers Carried	5	9	9	….	6
13. Fuel consumed in Kilo-litres	6	9	9	….	7
14. Number of Accidents	6	5	9	….	2
15. Number of Fatal accidents	6	5	9	….	2
16. Accidents per Lakh Effective Km	8	5	9	….	2
17. Total Staff	9	7	9	….	7
18. Regularity	7	8	5	….	8
19. Seating Capacity of a bus	4	8	5	….	7
20. Number of breakdowns	5	6	1	….	2

4.6.1 Analysis and Identification of KPIs Using the Conventional *AHP*

The *AHP* process begins by defining the *goal* as the identification of KPIs for performance evaluation. Subsequently, the 20 selected lists of indicators identified in the previous section in **Table 4.2** were designated as *criteria* for measurement (or indices for performance evaluation) in the present study. **Fig.4.3** provides a flowchart describing the process involved in identifying the KPIs using the *AHP* method.

The responses received from each expert are used to generate *pairwise comparison matrices* for each expert in *MS Excel*. The sample of a *pairwise comparison matrix* for *Expert No. 1* is provided in **Table 4.4**. The abbreviations C1, C2, …C20 stand for *criteria 1, criteria 2, … criteria 20* (representing the selected list of indicators 1-20). Similarly, pairwise comparison matrices for all the experts are generated and saved in a '*.csv*' file format.

Table 4.4 Pairwise Comparison Matrix for *Expert No. 1* (Partial)

	C1	**C2**	**C3**	**C4**	**…**	**C19**	**C20**
C1	1	1	1.166667	0.875	…	1.75	1.4
C2	1	1	1.166667	0.875	…	1.75	1.4
C3	0.857143	0.857143	1	0.75	…	1.5	1.2
C4							
…	…	…	…	…	…	…	…
C19							
C20	0.714286	0.714286	0.833333	0.625	…	1.25	1

In order to implement the *AHP* in *R-studio*, a script in the *FuzzyAHP* package of *R studio* software is executed. It may be observed that both the conventional *AHP* and the *FuzzyAHP* analyses can be implemented using the *FuzzyAHP* package. The pairwise comparison matrix obtained in the form of a *.csv* file mentioned earlier is provided as input to the program. The *FuzzyAHP* program then computes the weightage of the indicators for each of the experts in the form of three output files for the three categories of experts.

It is then possible to compute the average of the weights for various categories of experts, such as *transport managers*, *academicians*, and *research scholars*, for each of the indices, and the corresponding rankings can be obtained. The weights for each category of experts and the rankings are shown in **Table 4.5**.

4.6.2 Analysis and Identification of KPIs Using *Fuzzy-AHP*

Fuzzy AHP is an efficient tool for handling the fuzziness involved in assigning weights (or preferences or judgments) to various criteria (or decision variables or indicators) by the experts. The responses to the questionnaire provided by the experts involve fuzziness. Due to this reason, it was considered ideal to perform further analysis related to the rating of various criteria/ indicators using *Fuzzy-AHP* in order to identify the KPIs.

The responses received from each expert are used to generate three input matrices, one for each expert category, using *MS Excel*. In order to implement the *Fuzzy-AHP* in *R-studio*, a special script in the *FuzzyAHP* package of *R studio* software is executed. The three input matrices obtained in the form of a *.csv* file mentioned earlier are provided as input to the program. The *FuzzyAHP* program then computes the weights and the rankings of the indicators for each of the expert categories in a single output file. See **Table 4.6**.

Table 4.5 Ranking of Criteria (or Indicators) Based on Weights for Each Category of Experts Using *Conventional AHP*

Indicators (criteria) and their Serial Numbers	Transport Managers		Academicians		Research Scholars	
	Weights	Rankings	Weights	Rankings	Weights	Rankings
1. Total Cost	0.05532	6	0.05443	7	0.05849	1
2. Total Revenue	0.05864	4	0.05863	4	0.05748	2
3. Fleet size	0.05103	12	0.04524	14	0.04512	16
4. Buses on Road	0.05355	9	0.05327	8	0.05505	5
5. Buses off Road	0.03341	20	0.03822	19	0.04287	18
6. Fleet Utilization	0.05355	9	0.04897	11	0.04956	12
7. Effective Km	0.06120	1	0.06626	1	0.05397	6
8. Carrying Capacity Km	0.06120	1	0.05717	5	0.05284	7
9. Passengers Km	0.05867	3	0.06250	2	0.05518	4
10. Load Factor	0.05359	7	0.04601	13	0.05168	8
11. Occupancy Ratio	0.05359	7	0.05136	9	0.05056	10
12. Passengers Carried	0.05103	12	0.05551	6	0.05617	3
13. Fuel consumed in Kilo-litres	0.05611	5	0.05006	10	0.04961	11
14. Number of Accidents	0.04086	16	0.03717	20	0.04597	15
15. Number of Fatal accidents	0.04086	16	0.03988	18	0.04696	14
16. Accidents per Lakh Effective Km	0.03577	18	0.04089	17	0.04279	19
17. Total staff	0.04847	14	0.06127	3	0.05165	9
18. Regularity	0.04723	15	0.04707	12	0.04831	13
19. Seating Capacity of a bus	0.05231	11	0.04380	15	0.04388	17
20. Number of breakdowns	0.03361	19	0.04226	16	0.04187	20
Total of weights	**1.0000**		**1.0000**		**1.0000**	

Table 4.6 Output Weights and Ranks Obtained Using *Fuzzy AHP*

Indicators	Transport Managers		Research Scholars		Academicians	
	Weightage	Ranks	Weightage	Ranks	Weightage	Ranks
1. Total Cost	8.101719	6	9.334589	1	7.573346	7
2. Total Revenue	8.630092	3	9.158465	2	8.101719	4
3. Fleet size	7.573346	11	7.221097	16	6.340476	14
4. Buses on Road	7.925595	7	8.806216	4	7.397222	8
5. Buses off Road	5.107605	19	6.868849	18	5.459854	19
6. Fleet Utilization	7.925595	7	7.925595	11	6.868849	11
7. Effective Km	8.982341	1	8.630092	6	9.158465	1
8. Carrying Capacity Km	8.982341	1	8.453968	7	7.925595	5
9. Passengers Km	8.630092	3	8.806216	4	8.630092	2
10. Load Factor	7.925595	7	8.277843	8	6.5166	13
11. Occupancy Ratio	7.925595	7	8.101719	10	7.221097	9
12. Passengers Carried	7.573346	11	8.982341	3	7.74947	6

13. Fuel consumed in Kilo-litres	8.277843	5	7.925595	12	7.044973	10
14. Number of Accidents	6.164351	16	7.397222	15	5.28373	20
15. Number of Fatal accidents	6.164351	16	7.573346	14	5.635978	18
16. Accidents per Lakh Effective Km	5.459854	18	6.868849	18	5.812103	17
17. Total staff	7.221097	14	8.277843	8	8.453968	3
18. Regularity	6.868849	15	7.74947	13	6.692724	12
19. Seating Capacity of a bus	7.573346	11	7.044973	17	6.164351	15
20. Number of breakdowns	4.755357	20	6.692724	20	5.988227	16

4.6.3 Analysis and Identification of KPIs Using Conventional *TOPSIS*

The *Technique for Order Preference by Similarity to Ideal Solution* (*TOPSIS*) is a method based on choosing the best alternative, where the distance between the ideal (or best) solution, and the existing solution is the least, and where the distance between the worst possible solution and the existing solution is the longest **(Hwang and Yoon, 1981).**

The *TOPSIS* process commences with the definition of the *goal* related to the identification of KPIs for performance evaluation. **Fig.4.4** provides a flowchart describing the process involved in identifying the KPIs using the *TOPSIS* method.

The 20 selected list of indicators identified in the previous chapter in **Table 4.2** were designated as *criteria for measurement* (or indices for performance evaluation) in the present study. The responses received from each category of experts were then used to generate the *decision matrix* using *MS Excel*. The sample of a *decision matrix* of responses for 6 experts belonging to *transport manager (TM)* category is provided in **Table 4.7**. The abbreviations C1, C2, … C20 stand for *criteria 1*, *criteria 2*, … *criteria 20* (representing the selected list of indicators 1-20), while E1, E2, E3, E4, E5 and E6 stand for six experts from the category of *transport managers (TM)*. Similarly, *decision matrices* for the other two categories of experts such as *academicians* (AC), and *research scholars* (RS) was also generated and saved in '.*csv*' file format.

Table 4.7 Decision Matrix for *Transport Managers* (*Partial*)

	E1	**E2**	**E3**	**E4**	**E5**	**E6**
C1	8	7	8	7	8	8
C2	9	8	8	7	9	8
C3	9	8	7	6	7	6
C4	9	8	7	6	8	7
…	…	…	…	…	…	…
C19	5	6	8	7	9	8
C20	1	2	7	6	6	5

In order to implement the *TOPSIS* in *R-studio*, a script comprising functions available in the *MCDM* package of *R studio* software is executed. The *decision matrix* obtained for each category of experts in the form of a *.csv* file mentioned earlier is provided as input to the program. The *MCDM* program then computes the average weightage and the ranking for each criterion (or indicator) for each category of experts (such as *transport managers, academicians,* and *research scholars*) in the form of three output files. **Table 4.8** provides the final output in a consolidated form.

4.6.4 Analysis and Identification of KPIs Using *Fuzzy-TOPSIS*

Fuzzy TOPSIS is an efficient tool for handling the fuzziness involved in assigning weights (or preferences or judgments) to various criteria (or decision variables or indicators) by the experts. The responses to the questionnaire provided by the experts involve fuzziness. Due to this reason, it was considered ideal to perform the analysis related to rating of various criteria/ indicators using *Fuzzy-TOPSIS* in order to identify the KPIs.

4.6.4.1 Classification of Observations into Fuzzy Set Categories and Determination of Overlaps

The present study considered a rating system to evaluate the performance of transport organizations. The experts were required to give responses regarding the degree of importance or weightage ranging between 1 and 9 to a set of criteria/ indicators, with 1 representing the least importance and 9 representing the highest importance. Since decision-making related to such exercises involves a certain degree of fuzziness, the rating may include analysis using the fuzzy-logic approach. The *FuzzyMCDM* package was used to perform the related analysis. The fuzzy sets were defined using triangular fuzzy sets as represented with overlaps in **Fig.4.5** as proposed by **Gumus (2009)**.

Table 4.8 Weights and Ranking Computed by the conventional *TOPSIS* Method

	Transport Managers		**Academicians**		**Research Scholars**	
Indicators (criteria)	**Weight**	**Rankin**	**Weight**	**Rankin**	**Weights**	**Rankin**
1. Total Cost	0.852	6	0.699	6	0.905	1
2. Total Revenue	0.902	3	0.78	4	0.872	2
3. Fleet size	0.731	12	0.473	13	0.454	14
4. Buses on Road	0.786	7	0.643	8	0.759	5
5. Buses off Road	0.43	19	0.263	19	0.366	18
6. Fleet Utilization	0.786	8	0.53	10	0.587	12
7. Effective Km	1	1	1	1	0.744	6
8. Carrying Capacity Km	1	2	0.715	5	0.682	7
9. Passengers Km	0.902	4	0.877	2	0.778	4
10. Load Factor	0.785	9	0.476	12	0.669	8
11. Occupancy Ratio	0.785	10	0.59	9	0.633	10

12. Passengers Carried	0.731	13	0.684	7	0.826	3
13. Fuel consumed in Kilo-litres	0.859	5	0.515	11	0.612	11
14. Number of Accidents	0.527	16	0.245	20	0.448	15
15. Number of Fatal accidents	0.527	17	0.307	18	0.445	16
16. Accidents per Lakh Eff. Km	0.459	18	0.36	17	0.349	19
17. Total Staff	0.671	14	0.86	3	0.657	9
18. Regularity	0.662	15	0.449	15	0.507	13
19. Seating Capacity of a bus	0.741	11	0.465	14	0.375	17
20. Number of breakdowns	0.382	20	0.366	16	0.347	20

Here, fuzzy-sets (1,2,3), (2,3,4), (3,4,5), (4,5,6), (5,6,7), (6,7,8), (7,8,9) and (8,9,10) are represented by triangles OM_2X_2, $X_1M_3X_3$, $X_2M_4X_4$, $X_3M_5X_5$, $X_4M_6X_6$, $X_5M_7X_7$, $X_6M_8X_8$ and $X_7M_9X_9$ respectively and M_1, M_2, M_3, M_4, M_5, M_6, M_7, M_8, and M_9 represents the nine basic linguistic terms varying between "*Extremely low importance*" and "*Extremely high importance"* as described in **Table 4.9**.

Table 4.9 Fuzzy Set Categories, and Linguistic Scale to Convert Fuzzy Ratings to Triangular Fuzzy Ratings (*Gumus, 2009)*

Fuzzy Number	Linguistic Terms	Triangular Fuzzy Members
1	Extremely low importance	(1, 1, 1)
2	Very low importance	(1, 2, 3)
3	Low importance	(2, 3, 4)
4	Fairly low importance	(3, 4, 5)
5	Average importance	(4, 5, 6)
6	Fairly high importance	(5, 6, 7)
7	High importance	(6, 7, 8)
8	Very high importance	(7, 8, 9)
9	Extremely high importance	(9, 9,9)

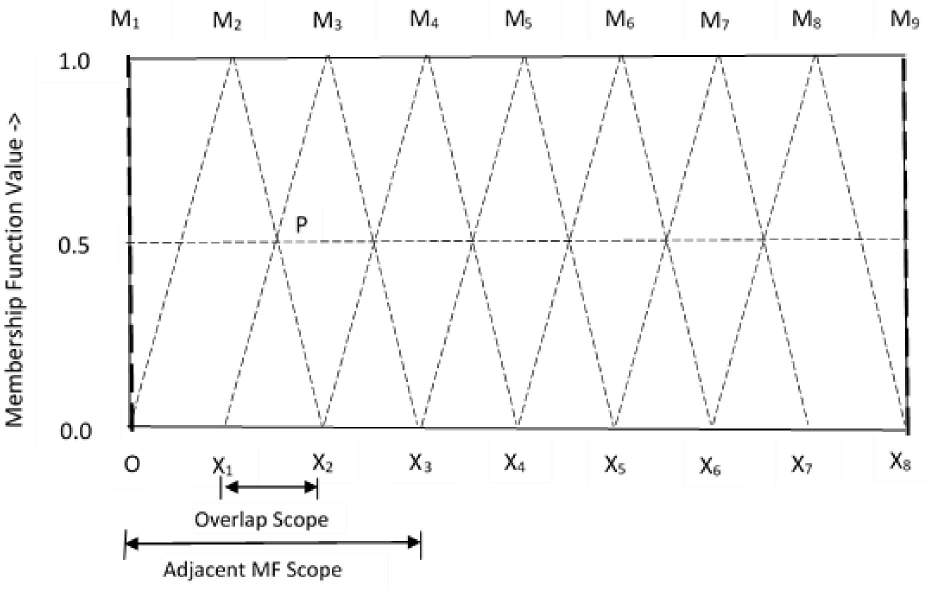

Fig.4.5 Representation of Fuzzy Sets with Overlaps for the Responses

The above diagram as in **Fig.4.5** represents the fuzzy triangular sets for the present study. Here, the region enclosed by triangle X_1PX_2 represents the *overlap region*. The *overlap scope* refers to the base X_1X_2 of triangle X_1PX_2 that represents the region between the two intersecting fuzzy sets where fuzziness is involved. The *adjacent MF scope (or adjacent membership function scope)* refers to the base OX_3 of the entire region encompassed by the two fuzzy sets OM_2X_2, and $X_1M_3X_3$. The *overlap ratio* for the present study can be computed from **Eq.4.1** for the 7 categories of fuzzy sets as 0.33. The overlap ratio complies with the overlapping criteria proposed by **Helm and Hahsler (2007)** and **Kalpana and Kumar (2011)**.

The responses received from experts ranging from 1-9 were then required to be represented in the form of triangular fuzzy members in order to create the *fuzzy decision matrix*. For example, a response of 5 given by an expert may represented as "(4,5,6)". Similarly, response 9 may represented as "(9,9,9)", and response 1 may represented as "(1,1,1)" according to the values provided in **Table 4.9**. The *fuzzy decision matrix* was created using *MS Excel*, and the file was saved in the .csv format. A sample of a *fuzzy decision matrix* of responses for 6 experts belonging to TM category is provided in **Table 4.10.** Similarly, *fuzzy decision matrix* of responses for other categories of experts belonging to AC and RS category are obtained and are provided in **Table C.10.**

Table 4.10 Input to *Fuzzy* TOPSIS: Fuzzy Decision Matrix for *Transport Managers* (*Partial*)

Indicator	E1			E2			E3			E4			E5			E6		
C1	7	8	9	6	7	8	7	8	9	6	7	8	7	8	9	7	8	9
C2	9	9	9	7	8	9	7	8	9	6	7	8	8	9	10	7	8	9
C3	9	9	9	7	8	9	6	7	8	5	6	7	6	7	8	5	6	7
C4	9	9	9	7	8	9	6	7	8	5	6	7	7	8	9	6	7	8
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
C18	4	5	6	5	6	7	6	7	8	5	6	7	7	8	9	6	7	8
C19	4	5	6	5	6	7	7	8	9	6	7	8	9	9	9	7	8	9
C20	1	1	1	1	2	3	6	7	8	5	6	7	5	6	7	4	5	6

Table 4.11 Weights and Ranking Computed using *Fuzzy TOPSIS*

	Transport Managers		Academicians		Research Scholars	
Indicators (criteria)	**Weight**	**Rank**	**Weight**	**Rank**	**Weights**	**Rank**
1. Total Cost	0.855	6	0.736	5	0.920	1
2. Total Revenue	0.907	3	0.803	4	0.888	2
3. Fleet size	0.735	12	0.502	12	0.483	14
4. Buses on Road	0.790	7	0.680	8	0.779	5
5. Buses off Road	0.433	19	0.283	19	0.386	18
6. Fleet Utilization	0.790	8	0.563	10	0.615	12
7. Effective Km	0.998	1	1.032	1	0.770	6
8. Carrying Capacity Km	0.998	2	0.731	6	0.698	8

9. Passengers Km	0.904	4	0.901	2	0.797	4
10. Load Factor	0.788	9	0.499	13	0.699	7
11. Occupancy Ratio	0.788	10	0.618	9	0.664	10
12. Passengers Carried	0.735	13	0.723	7	0.851	3
13. Fuel consumed in Kilo-litres	0.862	5	0.541	11	0.648	11
14. Number of Accidents	0.530	16	0.265	20	0.475	15
15. Number of Fatal accidents	0.530	17	0.330	18	0.448	16
16. Accidents per Lakh Effective Km	0.463	18	0.384	17	0.371	19
17. Total Staff	0.674	14	0.885	3	0.681	9
18. Regularity	0.667	15	0.477	15	0.524	13
19. Seating Capacity of a bus	0.743	11	0.494	14	0.392	17
20. Number of breakdowns	0.387	20	0.391	16	0.368	20

In order to implement the Fuzzy *TOPSIS* in *R-studio*, a script comprising functions available in the *FuzzyMCDM* package is executed. The fuzzy *decision matrix* obtained for each category of experts in the form of a *.csv* file mentioned earlier is provided as input to the program. The *FuzzyMCDM* program then computes the average weightage for each category of experts and computes the ranking for each indicator. **Table 4.11** provides the final output in a consolidated form.

4.7 FINALIZATION OF THE BEST KPIs USING *AHP* AND *FUZZY-AHP*

To identify the best KPIs, the results from analyses using the *Conventional AHP, Conventional TOPSIS, Fuzzy-AHP,* and the *Fuzzy-TOPSIS* need to be compared with respect to the actual ratings assigned based on the average weights of indices for Transport Manager, Academicians, and Research Scholars as shown in **Table 4.12a**, **Table 4.12b**, and **Table 4.12c**.

Table 4.12a Actual Ratings and Ranks of *Transport Managers*

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Consolidated ratings	Ranking
C1	8	7	8	7	8	8	7.667	6
C2	9	8	8	7	9	8	8.167	3
C3	9	8	7	6	7	6	7.167	11
C4	9	8	7	6	8	7	7.500	7
C5	9	8	4	3	2	3	4.833	19
C6	9	8	7	6	8	7	7.500	7
C7	9	8	9	8	9	8	8.500	1
C8	9	8	9	8	9	8	8.500	1
C9	9	8	9	8	8	7	8.167	3
C10	9	8	8	7	7	6	7.500	7
C11	9	8	8	7	7	6	7.500	7
C12	9	8	7	6	7	6	7.167	11
C13	9	8	8	7	8	7	7.833	5
C14	9	8	5	4	5	4	5.833	16
C15	9	8	5	4	5	4	5.833	16
C16	9	8	4	3	4	3	5.167	18
C17	9	8	6	5	7	6	6.833	14
C18	5	6	7	6	8	7	6.500	15

C19	5	6	8	7	9	8	7.167	11
C20	1	2	7	6	6	5	4.500	20

Table 4.12b Actual Ratings and Ranks of *Academicians*

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Consolidated ratings	Ranking
C1	7	8	6	7	8	7	7.167	7
C2	7	9	6	7	8	9	7.667	4
C3	6	7	5	6	7	5	6.000	14
C4	8	6	7	8	7	6	7.000	8
C5	6	7	5	7	4	2	5.167	19
C6	8	7	7	6	7	4	6.500	11
C7	9	9	8	8	9	9	8.667	1
C8	6	9	5	7	9	9	7.500	5
C9	8	8	7	8	9	9	8.167	2
C10	5	9	4	6	8	5	6.167	13
C11	6	9	5	7	8	6	6.833	9
C12	8	8	7	8	7	6	7.333	6
C13	9	7	8	7	6	3	6.667	10
C14	6	5	5	7	5	2	5.000	20
C15	6	5	5	8	5	3	5.333	18
C16	8	5	7	8	4	1	5.500	17
C17	8	9	7	7	8	9	8.000	3
C18	7	8	6	7	7	3	6.333	12
C19	4	8	3	6	8	6	5.833	15
C20	5	6	4	8	7	4	5.667	16

Table 4.12c Actual Ratings and Ranks of *Research Scholars*

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Consolidated ratings	Ranking
C1	9	9	9	8	9	9	8.833	1
C2	9	9	8	8	9	9	8.667	2
C3	6	6	7	8	8	6	6.833	16
C4	8	9	9	8	7	9	8.333	4
C5	5	5	7	7	7	8	6.500	18
C6	8	6	9	8	7	7	7.500	11
C7	8	8	9	8	9	7	8.167	6
C8	7	7	9	7	9	9	8.000	7
C9	9	9	9	7	8	8	8.333	4
C10	7	8	9	7	8	8	7.833	8
C11	7	8	9	7	8	7	7.667	10
C12	8	9	9	8	9	8	8.500	3
C13	7	8	7	8	8	7	7.500	11
C14	5	8	8	8	7	6	7.000	15
C15	4	9	8	8	5	9	7.167	14
C16	5	6	7	8	7	6	6.500	18
C17	7	9	9	7	8	7	7.833	8
C18	7	6	9	9	6	7	7.333	13
C19	6	8	7	9	4	6	6.667	17
C20	6	7	6	7	6	6	6.333	20

The *Spearman's rank correlation* method is adopted to compare the rankings generated using the *MCDM* approaches with respect to the actual rankings. **Table 4.13a**, **Table 4.13b**, and **Table 4.13c** provide details on the same for the expert categories *transport managers*, *academicians*, and *research scholars*, respectively.

Based on the comparison of actual rankings, with respect to the rankings assigned based on the *Conventional AHP* and the *Fuzzy AHP*, it can be said that both approaches provide predictions of rankings very similar to that of actual rankings. This is indicated by the *Spearman's Correlation Coefficient ρ* (Rho) value, which is almost equal to 1.00 for both approaches, with *p-values* lesser than 0.01. In the present study, the predicted rankings obtained based on the *Fuzzy AHP* approach were adopted for identifying the best KPIs to be considered for the next level of analysis using the SFA approach.

It is now required to obtain a common ranking based on the rankings computed for the three categories of experts. The common ranking is computed by assuming a weightage of 50%, 35%, and 15% for weights assigned by TM, AC, and RS, respectively.

Table 4.13a Computation of Spearman's Correlation Coefficient *ρ* for *Conventional AHP* and *Fuzzy AHP*: *Transport Managers*

Criteria (Indicators)	Actual Ranking (a)	*AHP* based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 AHP	*Fuzzy-AHP* based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-AHP
1. Total Cost	6	6	0	0	6	0	0
2. Total Revenue	3	4	-1	1	3	0	0
3. Fleet size	11	12	-1	1	11	0	0
4. Buses on Road	7	9	-2	4	7	0	0
5. Buses off Road	19	20	-1	1	19	0	0
6. Fleet Utilization	7	9	-2	4	7	0	0
7. Effective Kilometres	1	1	0	0	1	0	0
8. Carrying Capacity Km	1	1	0	0	1	0	0
9. Passengers Km	3	3	0	0	3	0	0
10. Load Factor	7	7	0	0	7	0	0
11. Occupancy Ratio	7	7	0	0	7	0	0
12. Passengers Carried	11	12	-1	1	11	0	0
13. Fuel consumed	5	5	0	0	5	0	0
14. Number of Accidents	16	16	0	0	16	0	0
15. Number of Fatal accidents	16	16	0	0	16	0	0
16. Accidents per Lakh Effective Km	18	18	0	0	18	0	0
17. Total staff	14	14	0	0	14	0	0
18. Regularity	15	15	0	0	15	0	0
19. Seating Capacity of a bus	11	11	0	0	11	0	0
20. Number of breakdowns	20	19	1	1	20	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.990226; n=20; Degree of freedom = n-2=18; p-value = 1 – *ρ* = 0.009774			*ρ* = 1- {(6Σd2)/[n(n2-1)]} = 1.00000; n=20; Degree of freedom = n-2=18; p-value = 1 – *ρ* = 0.0000		

Table 4.13b Computation of Spearman's Correlation Coefficient *ρ* for *Conventional AHP* and *Fuzzy AHP*: *Academicians*

Criteria (Indicators)	Actual Ranking (a)	AHP based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 AHP	Fuzzy-AHP based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-AHP
1. Total Cost	7	7	0	0	7	0	0
2. Total Revenue	4	4	0	0	4	0	0
3. Fleet size	14	14	0	0	14	0	0
4. Buses on Road	8	8	0	0	8	0	0
5. Buses off Road	19	19	0	0	19	0	0
6. Fleet Utilization	11	11	0	0	11	0	0
7. Effective Kilometres	1	1	0	0	1	0	0
8. Carrying Capacity Km	5	5	0	0	5	0	0
9. Passengers Km	2	2	0	0	2	0	0
10. Load Factor	13	13	0	0	13	0	0
11. Occupancy Ratio	9	9	0	0	9	0	0
12. Passengers Carried	6	6	0	0	6	0	0
13. Fuel consumed	10	10	0	0	10	0	0
14. Number of Accidents	20	20	0	0	20	0	0
15. Number of Fatal accidents	18	18	0	0	18	0	0
16. Accidents per Lakh Effective Km	17	17	0	0	17	0	0
17. Total staff	3	3	0	0	3	0	0
18. Regularity	12	12	0	0	12	0	0
19. Seating Capacity of a bus	15	15	0	0	15	0	0
20. Number of breakdowns	16	16	0	0	16	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 1.0000; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0			ρ = 1- {(6Σd2)/[n(n2-1)]} = 1.0000; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0		

Table 4.13c *Computation* of Spearman's Correlation Coefficient ρ for *Conventional AHP* and *Fuzzy AHP*: *Research Scholars*

Criteria (Indicators)	Actual Ranking (a)	AHP based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 AHP	Fuzzy-AHP based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-AHP
1. Total Cost	1	1	0	0	1	0	0
2. Total Revenue	2	2	0	0	2	0	0
3. Fleet size	16	16	0	0	16	0	0
4. Buses on Road	4	5	-1	1	4	0	0
5. Buses off Road	18	18	0	0	18	0	0
6. Fleet Utilization	11	12	-1	1	11	0	0
7. Effective Kilometres	6	6	0	0	6	0	0
8. Carrying Capacity Km	7	7	0	0	7	0	0
9. Passengers Km	4	4	0	0	4	0	0
10. Load Factor	8	8	0	0	8	0	0

11. Occupancy Ratio	10	10	0	0	10	0	0
12. Passengers Carried	3	3	0	0	3	0	0
13. Fuel consumed	11	11	0	0	11	0	0
14. Number of Accidents	15	15	0	0	15	0	0
15. Number of Fatal accidents	14	14	0	0	14	0	0
16. Accidents per Lakh Effective Km	18	19	-1	1	18	0	0
17. Total staff	8	9	-1	1	8	0	0
18. Regularity	13	13	0	0	13	0	0
19. Seating Capacity of a bus	17	17	0	0	17	0	0
20. Number of breakdowns	20	20	0	0	20	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.996992; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.003008			ρ = 1- {(6Σd2)/[n(n2-1)]} = 1.0000; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.00000		

Table 4.14 provides details on common rankings by various categories of experts for various criteria adopted for performance evaluation. Based on the results compiled above, the top nine indicators were considered for further analysis using the SFA approach explained in the next chapter.

Table 4.14 The Final List of Rankings from *Fuzzy AHP* for Further Analysis of Performance Evaluation

Indicators	**Ranking using Fuzzy AHP**
Effective Kilometers	1
Passengers Kilometers	2
Total Revenue	3
Carrying Capacity Kilometers	4
Total Cost	5
Total Staff	6
Fuel Consumed in Kilo-liters	7
Buses on Road	8
Passengers Carried	9
Fleet Utilization	10
Load Factor	11
Fleet size	12
Occupancy Ratio	13
Number of Fatal accidents	14
Regularity	15
Number of Accidents	16
Seating Capacity of a bus	17
Accidents per Lakh Effective Kilometers	18
Buses off Road	19
Number of breakdowns	20

This is indicated by the *Spearman's Correlation Coefficient* ρ (Rho) value, which is almost equal to 1.00 for both approaches, with *p-values* lesser than 0.01. In the present study, the predicted rankings obtained based on the *Fuzzy AHP* approach were adopted for identifying the best KPIs to be considered for the next level of performance evaluation using the SFA and DEA approach.

4.8 FINALIZATION OF THE BEST KPIs USING *TOPSIS* AND *FUZZY-TOPSIS*

The *Spearman's rank correlation coefficient* method is adopted to compare the rankings generated using the *Conventional TOPSIS* and the *Fuzzy-TOPSIS* with respect to the actual rankings. **Table 4.15a**, **Table 4.15b**, and **Table 4.15c** provide details on the same for the expert categories *Transport Managers*, *Academicians*, and *Research Scholars*, respectively.

Based on the comparison of actual rankings, with respect to the rankings assigned based on the *Conventional TOPSIS* and the *Fuzzy TOPSIS*, it can be said that both approaches provide predictions of rankings very similar to that of actual rankings. This is indicated by the *Spearman's Correlation Coefficient ρ* (Rho) value, which is very close to 1.00 for both the approaches, with *p-values* lesser than 0.02, but in all the cases, the *Conventional TOPSIS* approach is either equal or gave better results than *Fuzzy TOPSIS*. In the present study, the predicted rankings obtained based on the *Conventional TOPSIS* approach were adopted for identifying the best KPIs to be considered for the next level of analysis.

Table 4.15a Computation of Spearman's Correlation Coefficient *ρ* for *Conventional TOPSIS* and *Fuzzy TOPSIS*: *Transport Managers*

Criteria (Indicators)	Actual Ranking (a)	*TOPSIS* based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 TOPSIS	*Fuzzy-TOPSIS* based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-TOPSIS
1. Total Cost	6	6	0	0	6	0	0
2. Total Revenue	3	3	0	0	3	0	0
3. Fleet size	11	12	-1	1	12	-1	1
4. Buses on Road	7	7	0	0	7	0	0
5. Buses off Road	19	19	0	0	19	0	0
6. Fleet Utilization	7	8	-1	1	8	-1	1
7. Effective kms	1	1	0	0	1	0	0
8. Carrying Capacity Km	1	2	-1	1	2	-1	1
9. Passengers Km	3	4	-1	1	4	-1	1
10. Load Factor	7	9	-2	4	9	-2	4
11. Occupancy Ratio	7	10	-3	9	10	-3	9
12. Passengers Carried	11	13	-2	4	13	-2	4
13. Fuel consumed	5	5	0	0	5	0	0
14. Number of Accidents	16	16	0	0	16	0	0
15. Number of Fatal accidents	16	17	-1	1	17	-1	1
16. Acc. per Lakh Eff. Km	18	18	0	0	18	0	0
17. Total staff	14	14	0	0	14	0	0

18. Regularity	15	15	0	0	15	0	0
19. Seating Capacity of a bus	11	11	0	0	11	0	0
20. Number of breakdowns	20	20	0	0	20	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.983458; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.016541			ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.983458; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.016541		

Table 4.15b Computation of Spearman's Correlation Coefficient ρ for *Conventional TOPSIS* and *Fuzzy TOPSIS*: *Academicians*

Criteria (Indicators)	Actual Ranking (a)	*TOPSIS* based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 TOPSIS	*Fuzzy-TOPSIS* based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-TOPSIS
1. Total Cost	7	6	1	1	5	2	4
2. Total Revenue	4	4	0	0	4	0	0
3. Fleet size	14	13	1	1	12	2	4
4. Buses on Road	8	8	0	0	8	0	0
5. Buses off Road	19	19	0	0	19	0	0
6. Fleet Utilization	11	10	1	1	10	1	1
7. Effective Kms	1	1	0	0	1	0	0
8. Carrying Capacity Km	5	5	0	0	6	-1	1
9. Passengers Km	2	2	0	0	2	0	0
10. Load Factor	13	12	1	1	13	0	0
11. Occupancy Ratio	9	9	0	0	9	0	0
12. Passengers Carried	6	7	-1	1	7	-1	1
13. Fuel consumed	10	11	-1	1	11	-1	1
14. Number of Accidents	20	20	0	0	20	0	0
15. Number of Fatal accidents	18	18	0	0	18	0	0
16. Acc. per Lakh Eff. Km	17	17	0	0	17	0	0
17. Total staff	3	3	0	0	3	0	0
18. Regularity	12	15	-3	9	15	-3	9
19. Seating Capacity of a bus	15	14	1	1	14	1	1
20. Number of breakdowns	16	16	0	0	16	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.98797; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.012030			ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.983459; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.016541		

Table 4.15c Computation of Spearman's Correlation Coefficient ρ for *Conventional TOPSIS* and *Fuzzy TOPSIS*: *Research Scholars*

Criteria (Indicators)	Actual Ranking (a)	*TOPSIS* based Ranking (b)	Absolute Difference Between Ranks d=|a-b|	d^2 TOPSIS	*Fuzzy-TOPSIS* based Ranking (b')	Absolute Difference Between Ranks d'=|a-b'|	d'^2 F-TOPSIS
1. Total Cost	1	1	0	0	1	0	0
2. Total Revenue	2	2	0	0	2	0	0
3. Fleet size	16	14	2	4	14	2	4
4. Buses on Road	4	5	-1	1	5	-1	1
5. Buses off Road	18	18	0	0	18	0	0
6. Fleet Utilization	11	12	-1	1	12	-1	1
7. Effective Kms	6	6	0	0	6	0	0
8. Carrying Capacity Km	7	7	0	0	8	-1	1
9. Passengers Km	4	4	0	0	4	0	0
10. Load Factor	8	8	0	0	7	1	1
11. Occupancy Ratio	10	10	0	0	10	0	0
12. Passengers Carried	3	3	0	0	3	0	0
13. Fuel consumed	11	11	0	0	11	0	0
14. Number of Accidents	15	15	0	0	15	0	0
15. Number of Fatal accidents	14	16	-2	4	16	-2	4
16. Acc. per Lakh Eff. Km	18	19	-1	1	19	-1	1
17. Total staff	8	9	-1	1	9	-1	1
18. Regularity	13	13	0	0	13	0	0
19. Seating Capacity of a bus	17	17	0	0	17	0	0
20. Number of breakdowns	20	20	0	0	20	0	0
		ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.990977; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.009023			ρ = 1- {(6Σd2)/[n(n2-1)]} = 0.989474; n=20; Degree of freedom = n-2=18; p-value = 1 – ρ = 0.010526		

It is now required to obtain a common ranking based on the rankings computed for the three categories of experts. The common ranking is computed by assuming a weightage of 50%, 35%, and 15% for weights assigned by *transport managers*, *academicians*, and *research scholars* respectively. **Table 4.16** provides details on common rankings and the consolidated weights for various categories of experts.

Table 4.16: The Final List of Rankings from *TOPSIS* for Further Analysis

Indicators	Final Consolidated Weights	Ranking using TOPSIS
Effective Km	0.9616	1
Passengers Km	0.87465	2
Total Revenue	0.8548	3
Carrying Capacity Km	0.85255	4
Total Cost	0.8064	5
Total staff	0.73505	6
Buses on Road	0.7319	7
Passengers Carried	0.7288	8
Fuel consumed	0.70155	9
Occupancy Ratio	0.69395	10
Fleet Utilization	0.66655	11

Load Factor	0.65945	12
Fleet size	0.59915	13
Seating Capacity of a bus	0.5895	14
Regularity	0.5642	15
Number of Fatal accidents	0.4377	16
Number of Accidents	0.41645	17
Accidents per Lakh Effective Km	0.40785	18
Number of breakdowns	0.37115	19
Buses off Road	0.36195	20

4.9 FINAL KPIs SELECTED FOR FURTHER STUDIES

The top nine indicators were finalized based on their consistent rankings across both methods, as given in **Table 4.14** and **Table 4.16.** It was observed that while the rankings for the top nine indicators were stable and largely congruent, the rankings for indicators from the 10th position onwards exhibited variability in the order of ranking with regard to analysis using Fuzzy AHP and TOPSIS as in **Table 4.14** and **4.16.** This consistency among the top nine indicators suggests their fundamental importance in capturing the key aspects of performance in public transport systems.

Additionally, the top 9 KPIs identified align well with the theoretical framework proposed by **Fielding et al. (1985).** The selected nine indicators include: *Effective Kilometers, Passenger Kilometers, Total Revenue, Carrying Capacity Kilometers, Total Cost, Total Staff, Buses on Road, Passengers Carried,* and *Fuel Consumed.*

4.10 SUMMARY OF RESULTS RELATED TO IDENTIFICATION OF *KPIs* USING *MCDM* TECHNIQUES

A list of 20 indicators, as in **Table 4.2**, were shortlisted from CIRT publications for performance assessment of SRTUs based on the importance of use in the transport industry, data availability, and data consistency. The study focuses on the identification of KPIs using MCDM approaches such as the *conventional-AHP* and the *fuzzy-AHP*, *conventional-TOPSIS,* and the *fuzzy-TOPSIS,* followed by performance evaluation using a parametric SFA approach and non-parametric DEA approach.

In order to identify the *KPIs*, it was required to obtain responses from three categories of experts such as, *Transport managers*, A*cademicians,* and *Research Scholars*. The relative weights assigned by the experts to various performance indicators were obtained using *Google Forms*, and the preliminary processing files were generated.

- The ranks of indicators computed using the *conventional-AHP* & *fuzzy-AHP* methods and

Conventional TOPSIS & *Fuzzy-TOPSIS* were compared using the *Spearman's rank correlation coefficient* method with respect to the consolidated ratings assigned by the three categories of experts such as *Transport Managers, Academicians,* and *Research Scholars*.

- In the analysis, it was found that the *Spearman's Correlation Coefficient ρ* (Rho) was very close to 1.00, and the *p-values* were lesser than 0.02 for both approaches, indicating that both approaches provided rankings very similar to that of the actual rankings.
- Although the outcomes of both approaches are similar, the results of fuzzy-AHP were considered in the identification of *KPIs* in order to consider the uncertainties involved in decision-making, which is expected to be handled by analysis using the *fuzzy-AHP*.
- In most of the analyses performed using the *Conventional TOPSIS* approach, it was found that the rankings generated were closer to the actual rankings recorded by the experts. In the case of analyses performed using the *Fuzzy TOPSIS* approach, there were slight differences in rankings. Therefore, the results of *TOPSIS* were considered in the identification of *KPIs*
- The final list of nine *KPIs* with the consolidated weights is provided in **Table 4.14** and **Table 4.16**. The nine indicators, including *effective km, passengers km, total revenue, carrying capacity km, total cost, total staff, fuel consumed in kiloliters, buses on the road,* and *passengers carried*, were then used in the performance evaluation.

CHAPTER 5

PERFORMANCE EVALUATION OF *SRTUs* USING PARAMETRIC BASED *SFA* APPROACH

5.1 INTRODUCTION

The *key performance indicators* (KPIs) to be used for performance evaluation of *state road transport undertakings* (SRTUs) were identified using *multi-criteria decision-making* (MCDM) based approaches such as the *analytical hierarchy process* (AHP), the *Fuzzy-AHP*, *TOPSIS*, and *Fuzzy TOPSIS* as discussed in Chapter 4. Though there were minor differences in the order of ranking of the indicators, the top 9 indicators remained the same in all the analyses as provided in **Table 4.14** and **Table 4.16**. The nine *key performance indicators* (KPIs) include *effective km* (EKM), *passenger-km* (PKM), *total revenue* (TR), *carrying capacity km* (CKM), *total cost* (TC), *total staff* (TS), *average fleet operated* (AFO), *passengers carried* (PC), and *fuel consumed* (FC) were subjected to further analysis. The different combinations of variables were evaluated using statistical methods such as AIC and BIC and were adopted in the performance evaluation of SRTUs using the SFA method, a parametric-based approach, as discussed in this chapter. The dataset pertaining to these indicators for the time period 2010-17 compiled from various sources was used in this study.

The following section provides details on a summary of important data pertaining to SRTUs, preliminary formulation of *SFA* models for evaluation of *cost efficiency*, *cost* *effectiveness* and *service effectiveness* of SRTUs, selection of the best representative models, and performance evaluation of SRTUs.

5.2 DATA DESCRIPTION

The present study focuses on performing benchmarking exercises using the SFA approach with regard to 31 selected SRTUS in India. **Table 5.1** provides details on the selected set of SRTUs considered in this study. Annual data on 9 key performance indicators for the 31 SRTUs for the period 2009-10 to 2016-17 based on reports submitted to the *Central Institute of Road Transport* (CIRT), Pune, and the *Transport Research Wing* (*TRW*) of the *Ministry of Road Transport and Highway*s (*MoRTH*) are provided in **Table D.1**. A major part of the data obtained using *.pdf* files provided by CIRT, Pune, were recompiled in spreadsheet format in *MS* Excel.

Table 5.1 Selected SRTUs Considered in the Performance Evaluation Using Identified *KPIs*

SL.No	Name of SRTU	Abbreviation	Category
1	Ahmedabad municipal transport service	AMTS	Urban
2	Andhra Pradesh State Road Transport Corporation	APSRTC	Rural
3	Brihan Mumbai Electric Supply & Transport Undertaking	BEST	Urban
4	Bengaluru Metropolitan Transport Corporation	BMTC	Urban
5	Chandigarh Transport Undertaking	CHNTU	Urban
6	Delhi Transport Corporation	DTC	Urban
7	Gujarat State Road Transport Corporation	GSRTC	Rural
8	State Transport Haryana	STHAR	Rural
9	Kadamba Transport Corporation Limited	KDTC	Rural
10	Karnataka State Road Transport Corporation	KnSRTC	Rural
11	Kerala State Road Transport Corporation	KSRTC	Rural
12	Kolhapur Municipal Transport Undertaking	KMTU	Urban
13	Maharashtra State Road Transport Corporation	MSRTC	Rural
14	Meghalaya Transport Corporation	MEGTC	Hilly
15	Metropolitan Transport Corpn. Ltd. (Chennai)	MTC (CNI)	Urban
16	Mizoram State Transport	MZST	Hilly
17	North Bengal State Transport Corporation	NBSTC	Rural
18	North Eastern Karnataka Road Transport Corporation	NEKnRTC	Rural
19	North Western Karnataka Road Transport Corporation	NWKnRTC	Rural
20	Odisha State Road Transport Corporation	OSRTC	Rural
21	Pune Mahanagar Parivahan Mahamandal Limited	PMPML	Urban
22	Rajasthan State Road Transport Corporation	RSRTC	Rural
23	State Express Transport Corpn. Ltd. (Tamil Nadu)	SETC (TN)	Rural
24	Thane Municipal Transport Undertaking	TMTU	Urban
25	Tamil Nadu State Transport Corpn. Ltd. (Coimbatore)	TNSTC(CBE)	Rural

26	Tamil Nadu State Transport Corpn. Ltd. (Kumbakonam)	TNSTC(KUM)	Rural
27	Tamil Nadu State Transport Corpn. Ltd. (Madurai)	TNSTC(MDU)	Rural
28	Tamil Nadu State Transport Corpn. Ltd. (Salem)	TNSTC(SLM)	Rural
29	Tamil Nadu State Transport Corpn. Ltd.(Villupuram)	TNSTC(VPM)	Rural
30	Uttarakhand Transport Corporation	UTC	Hilly
31	Uttar Pradesh State Road Transport Corporation	UPSRTC	Rural

5.3 MODEL SELECTION AND PERFORMANCE EVALUATION USING PARAMETRIC BASED *SFA* APPROACH

The selected nine KPIs can be divided into three main categories based on the *performance concept model* as proposed by **Fielding et al. (1985)**. This include:

Service inputs*: total cost* (TC), *total staff* (TS), *fuel consumed* (FC), and *average fleet operated* (AFO).

Service outputs*: carrying capacity kms* (CKM) and *effective kms* (EKM).

Service consumption*: total revenue* (TR), *passenger kms* (PKM) performed, and *passengers carried* (PC).

In the next step, it was required to formulate a set of preliminary models using the SFA approach, and the best models were selected using the *Akaike information criterion* (AIC) and the *Bayesian information criterion* (BIC) scores.

5.3.1 Preliminary Formulation of Models Using *SFA*, and Selection of the Best Models Using *AIC* and *BIC* Scores

According to the performance concept model, ***cost-efficiency*** is computed based on the *service inputs* and *service outputs*. Thus, variables related to *service inputs* (such as TC, TS, FC, and AFO) and the variables related to *service outputs* (CKM and EKM), were used to develop a combination of **8 distinct models**.

Similarly, ***cost-effectiveness*** is computed based on the *service inputs* and *service consumption*. Thus, variables related to *service inputs* (such as TC, TS, FC, and AFO) and the variables related to *service consumption* (such as TR, PKM, and PC) were used to develop **12 models**.

Also, service-effectiveness is computed based on the *service outputs* and *service consumption*. Thus, variables related to *service outputs* (such as CKM and EKM) and the variables related to *service consumption* (such as TR, PKM, and PC) were used to develop **9 models.**

Thus, a total of **29 log-linear models** were developed based on the performance concept model proposed by **Fielding et al. (1985)**. These are summarized in **Table 5.2.** In this exercise, models based on *Fuel consumed* (FC) were omitted as fuel consumption was found to be highly correlated to the *average fleet operated* (AFO) as revealed in the initial screening of models using the SPSS software.

The *frontier* package in *R Studio* and the *SFA function* were used to formulate 29 *log-linear* models comprising 8 models for evaluating the *cost efficiency*, 12 models for evaluation of *cost effectiveness*, and 9 models for *service effectiveness* of SRTUs. Each of these models was then proposed to be tested for statistical soundness using the built-in function "AIC and BIC" in *R Studio*, which can be used to compute the consolidated average values of AIC and the BIC for the entire seven-year data for the model formulated. The details on AIC and BIC were discussed in Chapter 3 (Theoretical Background).

Table 5.2 provides details on the formulation of the 29 preliminary models and the results of AIC and BIC approaches as part of the SFA approach using *R Studio* software. The model with the lowest AIC and BIC scores is considered the best model (**Ayadi and Hammami, 2015)**. Here, it may be observed that the *time-effect* option is set to TRUE in the script used in computing the AIC and BIC scores in order to consider temporal variations in inefficiencies.

Table 5.2 Summary of AIC and BIC Scores for the Preliminary Set of Models Tested as part of computations for SFA

Model No.	Independent Variables Used			Dependent Variables	AIC	BIC
Cost Efficiency Models						
Model 1	TC	TS	AFO	CKM	23.01339547	46.67267694
Model 2	TC	TS	AFO	EKM	-441.280871	-417.6215899
Model 3	TC	TS	-	CKM	83.06446432	103.3438484
Model 4	TC	TS	-	EKM	-112.155421	-91.87603711
Model 5	TS	AFO	-	CKM	29.2997171	49.57910123
Model 6	TS	AFO	-	EKM	-438.337478	-418.0580943
Model 7	AFO	TC	-	CKM	21.2197752	41.49915932
Model 8	**AFO**	**TC**	**-**	**EKM**	**-442.217358**	**-421.9379746**
Cost Effectiveness Models						
Model 9	TC	TS	AFO	TR	-188.039811	-164.3805298
Model 10	TC	TS	AFO	PKM	234.8730164	258.5322979
Model 11	TC	TS	AFO	PC	148.5281704	172.1874518
Model 12	TC	TS	-	TR	-121.627762	-101.3483787
Model 13	TC	TS	-	PKM	292.2722009	312.551585
Model 14	TC	TS	-	PC	194.4600935	214.7394776
Model 15	TS	AFO	-	TR	-141.590463	-121.3110794
Model 16	TS	AFO	-	PKM	234.3835709	254.6629551
Model 17	TS	AFO	-	PC	147.3530447	167.6324288
Model 18	**AFO**	**TC**	**-**	**TR**	**-187.858862**	**-167.5794787**
Model 19	AFO	TC	-	PKM	239.2663601	259.5457443
Model 20	AFO	TC	-	PC	146.6964419	166.9758261

Service Effectiveness Models						
Model 21	CKM	-	-	TR	-1.72319909	15.17628767
Model 22	CKM	-	-	PKM	222.0329882	238.9324749
Model 23	CKM	-	-	PC	196.6551725	213.5546592
Model 24	**EKM**	**-**	**-**	**TR**	**-178.861182**	**-161.9616952**
Model 25	EKM	-	-	PKM	199.9391513	216.838638
Model 26	EKM	-	-	PC	135.4805116	152.3799984
Model 27	EKM	CKM	-	TR	-177.101496	-156.8221118
Model 28	EKM	CKM	-	PKM	195.0035274	215.2829116
Model 29	EKM	CKM	-	PC	137.4429765	157.7223607

Note:
CKM = Carrying Capacity km EKM = Effective km PKM = passenger kilometer
TC = Total Cost TS = Total Staff AFO = Average fleet operated
TR = Total Revenue PC = Passenger Carried

Among the models for evaluating the *cost efficiency*, it can be observed that *model 8*, with *effective km* operated as the dependent variable and *total cost* and *average fleet operated* as the independent variables, can be selected for further performance analysis using the *SFA* approach based on 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* covered as the independent variable, was selected for performance analysis using the *SFA* approach. Thus, the best models representing *cost efficiency*, *cost effectiveness,* and *service effectiveness* were identified as *model 8*, *model 18*, and *model 24* based on the *AIC* and *BIC* scores.

5.3.2. Statistical Significance of the Independent Variables in Selected *SFA* Models

In order to assess the reliability of the three best log-linear models finalized using the AIC and BIC scores for measuring *cost efficiency*, *cost effectiveness,* and *service effectiveness,* it was proposed to perform analysis using the *maximum likelihood estimation* (MLE) method using an additional script as part of the *Frontier* package in *R Studio*.

The coefficients of the *independent variables* in the models were thus estimated using the *Frontier* package for modeling using *SFA*. The statistical estimates of these coefficients are provided in **Table 5.3a**, **Table 5.3b**, and **Table 5.3c** for the *cost efficiency* model, *cost effectiveness* model, and *service effectiveness* model, respectively.

Table 5.3a Statistical Summary Based on MLE Method: *Cost Efficiency* Model

Final maximum likelihood estimates

	Estimate	**Std. Error**	**Z value**	**Pr(>|Z|)** or *p-value*		
(Intercept)	0.775336	0.274715	2.8223	0.004768 **		
Log(Average fleet operated)	0.904888	0.031369	28.8462	< 2.2e-16 ***		
log(Total cost)	0.060303	0.028083	2.1473	0.031768 *		
sigmaSq	0.705084	0.182207	3.8697	0.000109 ***		
gamma	0.99561	0.001264	787.7957	< 2.2e-16 ***		
time	-0.0177	0.003517	-5.0319	4.855e-07 ***		
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '	1
log likelihood value: 227.1087						
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
0.574387	0.569425	0.564441	0.559435	0.554408	0.549361	0.544295
mean efficiency: 0.559393						

The *cost efficiency* model (*model 8*) comprises *effective km* as the dependent variable, and the *average fleet operated* and *total cost* as the independent variables. From **Table 5.3a**, it can be observed that based on the *maximum likelihood estimation* (MLE) method, the coefficient for *average fleet operated* is 0.904888. The Z statistic is computed, and the computed *p value* denoted as **Pr(>|Z|)** which indicates the level of significance is much lesser than 0.05, indicating that the coefficient for the variable *average fleet operated* is significant. A similar observation can be made in the case of the variable *total cost,* which has a coefficient value of 0.0603. Thus, the use of the variables *average fleet operated*, and the *total cost* in *model 8* for *cost efficiency* is justified.

Table 5.3b Statistical Summary Based on MLE Method: *Cost Effectiveness* Model

Final maximum likelihood estimates						
	Estimate	**Std. Error**	**Z value**	**Pr(>|Z|)** or *p-value*		
(Intercept)	1.206416	0.200872	6.0059	1.903e-09 ***		
log(Average fleet operated)	0.436964	0.052427	8.3347	< 2.2e-16 ***		
log(Total cost)	0.599376	0.047407	12.6432	< 2.2e-16 ***		
sigmaSq	0.238433	0.060777	3.9231	8.742e-05 ***		
gamma	0.939609	0.016637	56.4768	< 2.2e-16 ***		
time	-0.022178	0.012300	-1.8031	0.07138 .		
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '	1
log likelihood value: 99.92943						
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
0.8161790	0. 8130397	0.8098611	0.806643	0.8033852	0. 80008	0.79675
mean efficiency: 0.8065638						

The *cost effectiveness* model (*model 18*) comprises *total revenue* as the dependent variable and the *average fleet operated* and *total cost* as the independent variables. From **Table 5.3b**, it can be observed that based on the *maximum likelihood estimation* (MLE) method, the coefficient for *average fleet operated* is 0.436964. Here too, it can be seen that the Z statistic is computed and that the computed *p value* denoted as **Pr(>|Z|)** indicates the level of significance is much lesser than 0.05, indicating that the coefficient for the variable *average fleet operated* is significant. A similar observation can be made in the case of the variable *total cost*, which has a coefficient value of 0.599376. Thus, the use of the variables *average fleet operated* and the *total cost* in *model 18* for *cost effectiveness* is justified.

The *service effectiveness* model (*model 24*) comprises *total revenue* as the dependent variable and the *effective km* as the independent variable. From **Table 5.3c**, it can be observed that based on the *maximum likelihood estimation* (MLE) method, the coefficient for *effective km* is 0.947931. Here too, it can be seen that the Z statistic is computed and that the computed *p-value* denoted as **Pr(>|Z|)** indicates the level of significance is much lesser than 0.05, indicating that the coefficient for the variable *effective km* is significant. Thus, the use of the variable *effective km* in *model 24* for *service effectiveness* is justified.

Table 5.3c 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						

It was observed, based on the *maximum likelihood estimation* (MLE) method, that the coefficients of the independent variables were significant with p-values lower than 0.05 in the case of the *cost efficiency* model, *cost effectiveness* model, and *service effectiveness* model.

5.3.3 Computation of Efficiency Scores of SRTUs Using the SFA Approach

In the next step, it was required to use an additional script as part of the *Frontier* package in *R Studio* software to compute the relative efficiencies of the 31 SRTUs for the study period 2010-17. **Table 5.4a**, **Table 5.4b**, and **Table 5.4c** provide details on the relative efficiencies computed using the *SFA* approach considering *cost efficiency*, *cost* effectiveness, and *service effectiveness*. The efficiencies were calculated using data compiled in **Table D.1** used as input in the *Frontier* package.

Table 5.4a Efficiencies of SRTUs Using SFA Approach for *Cost Efficiency*

Sl. No.	SRTU name	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
1	Ahmedabad M T Corpn.	0.359	0.352	0.346	0.339	0.333	0.326	0.320
2	Andhra Pradesh SRTC	0.709	0.705	0.701	0.696	0.692	0.687	0.682
3	B.E.S.T. Undertaking	0.351	0.344	0.338	0.331	0.325	0.318	0.312
4	Bangalore Metropolitan TC (BMTC)	0.391	0.385	0.378	0.372	0.365	0.359	0.352
5	Chandigarh TU	0.431	0.424	0.418	0.412	0.405	0.399	0.392
6	Delhi TC	0.350	0.344	0.337	0.331	0.324	0.318	0.312
7	Gujarat SRTC	0.792	0.789	0.785	0.782	0.778	0.775	0.771
8	Haryana ST	0.614	0.608	0.603	0.597	0.592	0.586	0.581
9	Kadamba TC Ltd.	0.434	0.427	0.421	0.415	0.408	0.402	0.395
10	Karnataka SRTC	0.677	0.673	0.668	0.663	0.658	0.653	0.649
11	Kerala SRTC	0.598	0.592	0.587	0.581	0.576	0.570	0.564
12	Kolhapur MTU	0.396	0.389	0.383	0.376	0.370	0.363	0.357
13	Maharashtra SRTC	0.655	0.650	0.645	0.640	0.635	0.630	0.625
14	Meghalaya STC	0.281	0.275	0.269	0.263	0.256	0.250	0.244
15	Metro.TC (Chennai) Ltd.	0.558	0.552	0.546	0.540	0.534	0.528	0.522
16	Mizoram ST	0.148	0.143	0.138	0.133	0.128	0.124	0.119
17	North Bengal STC	0.405	0.399	0.393	0.386	0.380	0.373	0.366
18	North Eastern Karnataka RTC	0.624	0.619	0.614	0.608	0.603	0.597	0.592
19	North Western Karnataka RTC	0.643	0.638	0.633	0.628	0.623	0.617	0.612
20	OSRTC	0.483	0.477	0.471	0.464	0.458	0.452	0.445
21	Pune Mahamandal	0.406	0.400	0.393	0.387	0.380	0.374	0.367
22	Rajasthan SRTC	0.718	0.714	0.710	0.706	0.701	0.697	0.692
23	State Exp.TC TN Ltd.	0.985	0.985	0.984	0.984	0.984	0.983	0.983
24	Thane MTU	0.324	0.317	0.311	0.304	0.298	0.292	0.285
25	TN STC (Coimbatore)Ltd.	0.777	0.774	0.770	0.767	0.763	0.760	0.756
26	TN STC (Kumbakonam)Ltd.	0.880	0.878	0.876	0.874	0.872	0.870	0.868
27	TN STC (Madurai)Ltd.	0.803	0.800	0.797	0.793	0.790	0.787	0.783
28	TN STC (Salem)Ltd.	0.864	0.861	0.859	0.857	0.854	0.852	0.850
29	TN STC (Villupuram) Ltd.	0.897	0.896	0.894	0.892	0.890	0.888	0.887
30	UTC	0.582	0.576	0.570	0.565	0.559	0.553	0.547
31	Uttar Pradesh SRTC	0.670	0.666	0.661	0.656	0.651	0.646	0.641

Table 5.4b Efficiencies of SRTUs Using SFA Approach for *Cost Effectiveness*

Sl. No.	SRTU name	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
1	Ahmedabad M T Corpn.	0.446	0.438	0.430	0.422	0.414	0.406	0.398
2	Andhra Pradesh SRTC	0.846	0.843	0.840	0.837	0.833	0.830	0.826
3	B.E.S.T. Undertaking	0.764	0.760	0.755	0.750	0.746	0.741	0.736
4	Bangalore Metropolitan TC (BMTC)	0.851	0.848	0.845	0.842	0.838	0.835	0.832
5	Chandigarh TU	0.727	0.722	0.716	0.711	0.706	0.700	0.695
6	Delhi TC	0.393	0.384	0.376	0.368	0.360	0.352	0.344
7	Gujarat SRTC	0.891	0.889	0.886	0.884	0.882	0.879	0.877
8	Haryana ST	0.794	0.790	0.786	0.781	0.777	0.773	0.768
9	Kadamba TC Ltd.	0.965	0.964	0.963	0.963	0.962	0.961	0.960
10	Karnataka SRTC	0.931	0.929	0.928	0.926	0.925	0.923	0.921
11	Kerala SRTC	0.755	0.750	0.745	0.740	0.735	0.730	0.725
12	Kolhapur MTU	0.966	0.965	0.964	0.963	0.962	0.962	0.961
13	Maharashtra SRTC	0.901	0.899	0.897	0.895	0.893	0.891	0.888
14	Meghalaya STC	0.900	0.897	0.895	0.893	0.891	0.889	0.886
15	Metro.TC (Chennai) Ltd.	0.869	0.867	0.864	0.861	0.858	0.855	0.852
16	Mizoram ST	0.190	0.183	0.176	0.169	0.163	0.156	0.150
17	North Bengal STC	0.549	0.542	0.535	0.527	0.520	0.512	0.505
18	North Eastern Karnataka RTC	0.899	0.896	0.894	0.892	0.890	0.887	0.885
19	North Western Karnataka RTC	0.895	0.892	0.890	0.888	0.886	0.883	0.881
20	OSRTC	0.921	0.919	0.917	0.916	0.914	0.912	0.910
21	Pune Mahamandal	0.948	0.947	0.946	0.945	0.944	0.943	0.941
22	Rajasthan SRTC	0.818	0.815	0.811	0.807	0.803	0.799	0.796
23	State Exp.TC TN Ltd.	0.966	0.965	0.964	0.963	0.963	0.962	0.961
24	Thane MTU	0.893	0.891	0.888	0.886	0.884	0.881	0.879
25	TN STC (Coimbatore)Ltd.	0.847	0.843	0.840	0.837	0.834	0.830	0.827
26	TN STC (Kumbakonam)Ltd.	0.906	0.904	0.902	0.900	0.898	0.896	0.894
27	TN STC (Madurai)Ltd.	0.899	0.897	0.895	0.892	0.890	0.888	0.885
28	TN STC (Salem)Ltd.	0.871	0.869	0.866	0.863	0.860	0.857	0.854
29	TN STC (Villupuram) Ltd.	0.928	0.926	0.925	0.923	0.922	0.920	0.918
30	UTC	0.907	0.905	0.903	0.901	0.899	0.897	0.895
31	Uttar Pradesh SRTC	0.867	0.864	0.861	0.858	0.855	0.852	0.849

Table 5.4c 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
1	Ahmedabad M T Corpn.	0.308	0.340	0.372	0.405	0.437	0.469	0.500
2	Andhra Pradesh SRTC	0.431	0.463	0.494	0.525	0.554	0.583	0.610
3	B.E.S.T. Undertaking	0.887	0.896	0.904	0.912	0.919	0.925	0.931
4	Bangalore Metropolitan TC (BMTC)	0.699	0.721	0.741	0.760	0.778	0.795	0.810
5	Chandigarh TU	0.396	0.428	0.460	0.491	0.522	0.551	0.580
6	Delhi TC	0.582	0.610	0.636	0.661	0.684	0.706	0.728
7	Gujarat SRTC	0.378	0.410	0.442	0.474	0.505	0.535	0.564
8	Haryana ST	0.416	0.448	0.479	0.510	0.540	0.569	0.597
9	Kadamba TC Ltd.	0.574	0.602	0.628	0.653	0.677	0.700	0.721
10	Karnataka SRTC	0.457	0.488	0.519	0.548	0.577	0.605	0.631
11	Kerala SRTC	0.459	0.490	0.521	0.550	0.579	0.606	0.633
12	Kolhapur MTU	0.477	0.507	0.537	0.566	0.594	0.621	0.647
13	Maharashtra SRTC	0.536	0.565	0.593	0.619	0.645	0.669	0.693
14	Meghalaya STC	0.586	0.613	0.639	0.664	0.687	0.709	0.730
15	Metro.TC (Chennai) Ltd.	0.539	0.568	0.596	0.623	0.648	0.672	0.695
16	Mizoram ST	0.271	0.302	0.334	0.367	0.399	0.432	0.464
17	North Bengal STC	0.265	0.297	0.329	0.362	0.394	0.426	0.458
18	North Eastern Karnataka RTC	0.392	0.425	0.457	0.488	0.519	0.548	0.577

19	North Western Karnataka RTC	0.397	0.429	0.461	0.493	0.523	0.552	0.581
20	OSRTC	0.309	0.341	0.373	0.406	0.438	0.470	0.501
21	Pune Mahamandal	0.833	0.846	0.858	0.869	0.880	0.889	0.898
22	Rajasthan SRTC	0.387	0.419	0.451	0.483	0.513	0.543	0.572
23	State Exp.TC TN Ltd.	0.332	0.364	0.397	0.429	0.461	0.492	0.523
24	Thane MTU	0.820	0.834	0.847	0.859	0.870	0.880	0.890
25	TN STC (Coimbatore)Ltd.	0.342	0.375	0.407	0.439	0.471	0.502	0.532
26	TN STC (Kumbakonam)Ltd.	0.330	0.362	0.395	0.427	0.459	0.490	0.521
27	TN STC (Madurai)Ltd.	0.347	0.379	0.412	0.444	0.476	0.507	0.537
28	TN STC (Salem)Ltd.	0.296	0.328	0.360	0.393	0.425	0.457	0.489
29	TN STC (Villupuram) Ltd.	0.333	0.365	0.398	0.430	0.462	0.493	0.523
30	UTC	0.371	0.404	0.436	0.468	0.499	0.529	0.558
31	Uttar Pradesh SRTC	0.382	0.414	0.446	0.478	0.509	0.538	0.567

The average of the efficiencies for each of the SRTUs over the period of study 2010-17 was then computed with respect to *cost efficiency*, *cost effectiveness*, and *service effectiveness* based on information available from **Table 5.4a**, **Table 5.4b**, and **Table 5.4c**. The average values of the efficiencies for the SRTUs were then sorted in decreasing order of *cost efficiency, cost effectiveness,* and *service effectiveness,* respectively. The SRTUs that perform better than 75% of the organizations are first identified and listed, as shown in the initial part of **Table 5.5**. Also, SRTUs performing between the 75th and 50th percentiles and SRTUs performing between the 50^{th} and 25^{th} percentiles are listed subsequently. This is followed by SRTUs performing poorer than 75% of the organizations.

Table 5.5 Classification of SRTUs into Quartiles Based on SFA Efficiency Scores: 2010-17

Rank	Quartile class (%)	Percentile of SRTUs (%)	Cost Efficiency		Cost Effectiveness		Service Effectiveness	
			SRTU	Sorted efficiency	SRTU	Sorted efficiency	SRTU	Sorted efficiency
1	SRTUs performing better than 75% of the organi-zations	100.00	SETC (TN)	0.9840	SETC (TN)	0.9633	BEST	0.9104
2		96.77	TNSTC(VPM)	0.8920	KMTU	0.9632	PMPML	0.8677
3		93.55	TNSTC(KUM)	0.8740	KDTC	0.9626	TMTU	0.8572
4		90.32	TNSTC(SLM)	0.8566	PMPML	0.9450	BMTC	0.7577
5		87.10	TNSTC(MDU)	0.7933	KnSRTC	0.9261	MEGTC	0.6611
6		83.87	GSRTC	0.7818	TNSTC(VPM)	0.9231	DTC	0.6581
7		80.65	TNSTC(CBE)	0.7668	OSRTC	0.9156	KDTC	0.6509
8	SRTUs performing between 75^{th} and 50^{th} percentiles (0.7 to 0.57)	77.42	RSRTC	0.7056	UTC	0.9012	MTC (CNI)	0.6201
9		74.19	APSRTC	0.6960	TNSTC(KUM)	0.9003	MSRTC	0.6171
10		70.97	KnSRTC	0.6631	MSRTC	0.8950	KMTU	0.5643
11		67.74	UPSRTC	0.6558	MEGTC	0.8931	KSRTC	0.5484
12		64.52	MSRTC	0.6401	TNSTC(MDU)	0.8923	KnSRTC	0.5465
13		61.29	NWKnRTC	0.6278	NEKnRTC	0.8919	APSRTC	0.5229
14		58.06	NEKnRTC	0.6082	NWKnRTC	0.8878	STHAR	0.5084
15		54.84	STHAR	0.5973	TMTU	0.8860	NWKnRTC	0.4910

16		51.61	KSRTC	0.5813	GSRTC	0.8838	CHNTU	0.4896
17	SRTUs performing between 50th and 25th percentiles	48.39	UTC	0.5645	TNSTC(SLM)	0.8630	NEKnRTC	0.4865
18		45.16	MTC (CNI)	0.5400	MTC (CNI)	0.8611	RSRTC	0.4811
19		41.94	OSRTC	0.4642	UPSRTC	0.8580	UPSRTC	0.4763
20		38.71	KDTC	0.4145	BMTC	0.8414	GSRTC	0.4724
21		35.48	CHNTU	0.4115	TNSTC(CBE)	0.8369	UTC	0.4666
22		32.26	PMPML	0.3867	APSRTC	0.8365	TNSTC(MDU)	0.4430
23		29.03	NBSTC	0.3860	RSRTC	0.8071	TNSTC(CBE)	0.4382
24		25.81	KMTU	0.3763	STHAR	0.7813	TNSTC(VPM)	0.4291
25	SRTUs performing poorer than 75% of the organi-zations	22.58	BMTC	0.3719	BEST	0.7503	SETC (TN)	0.4284
26		19.35	AMTS	0.3394	KSRTC	0.7400	TNSTC(KUM)	0.4263
27		16.13	BEST	0.3313	CHNTU	0.7109	OSRTC	0.4053
28		12.90	DTC	0.3309	NBSTC	0.5272	AMTS	0.4044
29		9.68	TMTU	0.3045	AMTS	0.4218	TNSTC(SLM)	0.3926
30		6.45	MEGTC	0.2627	DTC	0.3681	MZST	0.3670
31		3.23	MZST	0.1331	MZST	0.1696	NBSTC	0.3617

5.3.3.1 Discussions on Best Performing SRTUs Based on Percentile Scores for 2010-17

Interestingly, the *best performing SRTUs* with percentile values higher than 75 with regard to *cost efficiency* belong to SRTUs serving **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. The SETC (TN) serving rural areas of Tamil-Nadu maintains its first position in *cost efficiency* as well as *cost effectiveness* category.

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, while MEGTC of Meghalaya and KDTC serve **hilly and rural areas,** respectively.

5.3.3.2 Discussions on Worst Performing SRTUs Based on Percentile Scores for 2010-17

It was observed that AMTS, and MZST performed *poorly* with regard to *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 5.3, 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 of 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, the higher number of fleets operated to satisfy the accessibility requirements of trip-makers leads to inefficiencies

Cost Effectiveness**:** The best model for measuring *cost effectiveness* was identified as *model 18* as explained in Section 5.3, 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 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 lead to inefficiencies.

Service Effectiveness**:** The best model for measuring *service effectiveness* was identified as *model 24*, as explained in Section 5.3, 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, and 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

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.

5.3.3.3 Discussions on Performance of SRTUs Based on Efficiency Scores for 2010-17

Based on information compiled in **Table 5.4a**, **Table 5.4b**, and **Table 5.4c**, the average efficiencies with regard to *cost efficiency*, *cost effectiveness,* and *service effectiveness* for each of the SRTUs can be as shown graphically in **Fig.5.1a**, **Fig.5.1b**, and **Fig.5.1c**.

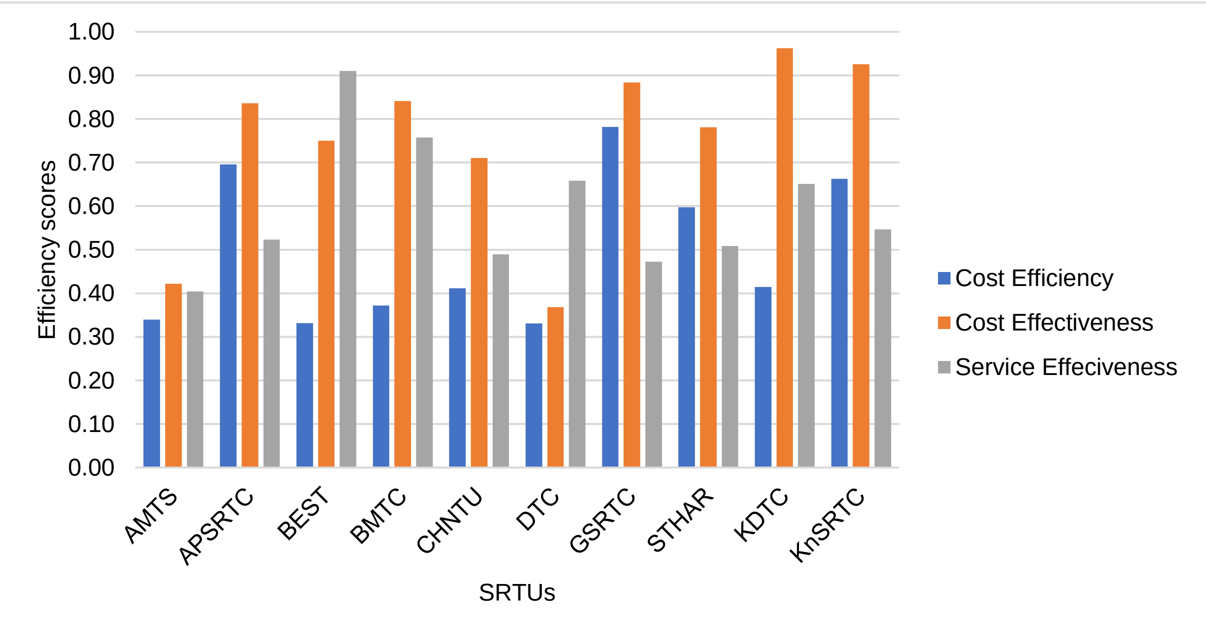

Fig.5.1a Graphical Representation of Average *SFA* Efficiencies for SRTUs 1-10: 2010-17

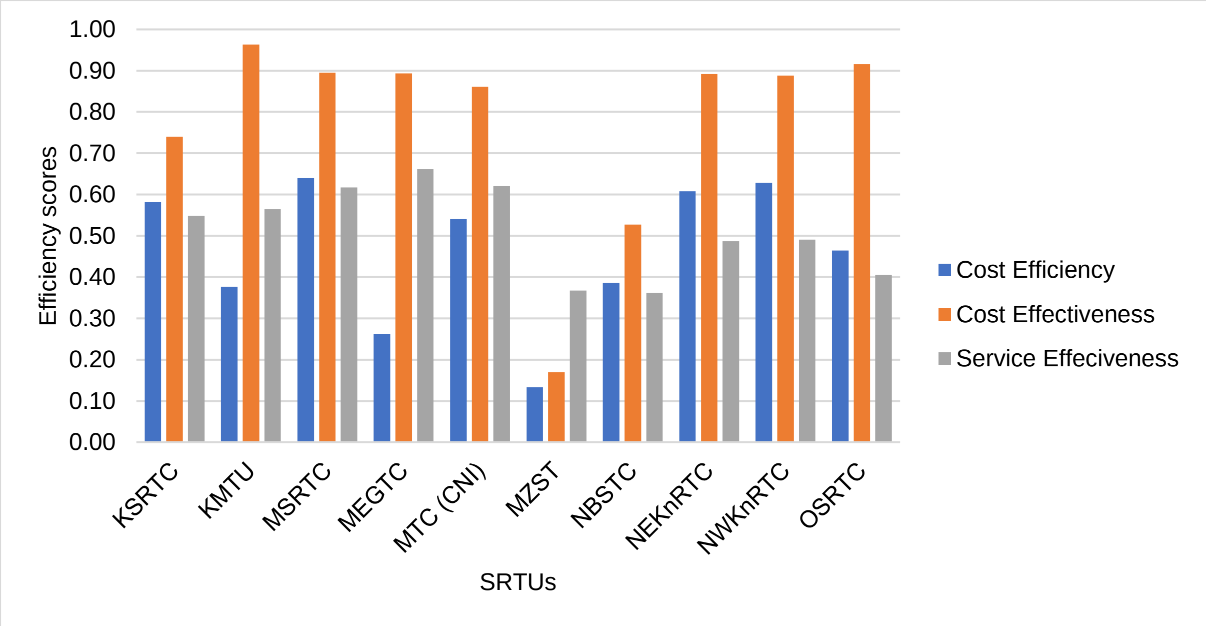

Fig.5.1b Graphical Representation of Average *SFA* Efficiencies for SRTUs 11-20: 2010-17

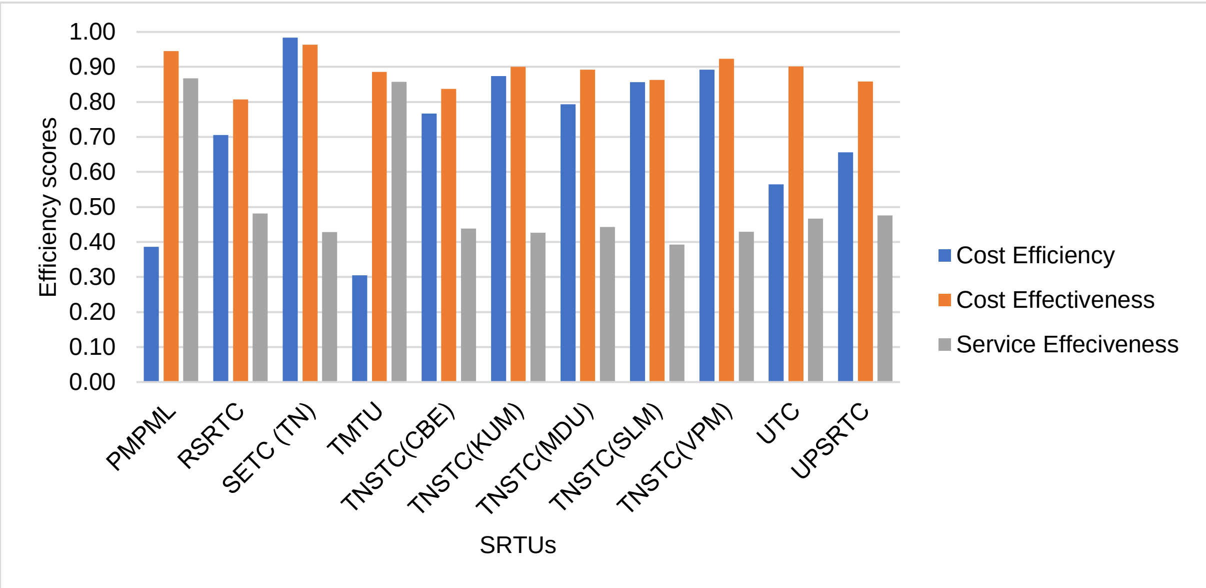

Fig.5.1c Graphical Representation of Average *SFA* Efficiencies for SRTUs 21-31: 2010-17

In the above-mentioned figures, it may be observed that although urban SRTUs such as BEST, BMTC, PMPML, and TMTU possess lower *cost efficiencies*, the *cost effectiveness* and *service effectiveness* of these organizations are quite higher at efficiency levels of more than 0.70. This is due to the reason that SRTUs that operate in urban areas are affected by traffic delays due to congestion and traffic blocks. In the case of KDTC, although it is considered to serve rural areas of the State of Goa, it also connects numerous smaller cities of the state, and is also affected by traffic congestion to a large extent.

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 case 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 *cost efficiency* model are provided in **Table 5.3a,** 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.

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 *cost effectiveness* need to be improved in the case of AMTS, DTC, and MZST that have efficiency scores much lower than 0.5.

In the analysis related to *cost effectiveness*, it can be observed in **Table 5.3b** that the *mean efficiency of each year* of SRTUs decreased from 0.816 to 0.797 during the period 2010-17. In this case, 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.

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 the analysis related to *service effectiveness*, it can be observed in **Table 5.3c** 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.

5.3.3.4 Discussions on Performance of SRTUs Based on Efficiency Scores for 2016-17

An overview of **Table 5.5** indicates that SETC(TN), with an efficiency score of 0.98 can be considered as the best organization with regard to *cost efficiency*. Similarly, SETC(TN), KMTU, and KDTC, with efficiency scores higher than 0.96, can be considered the best organizations with regard to *cost effectiveness*. Also, BEST, with an efficiency score of 0.91, can be considered as a model with regard to *service effectiveness*. In the case of the remaining SRTUs that have *efficiency scores* lesser than 0.9, suitable corrective measures may be suggested to improve the performance indices.

Interpretation of SFA Results for BMTC: Cost Efficiency

The interpretations of the output generated using the *SFA* approach for *cost efficiency* can be explained using a simple example considering the performance of BMTC, an organization that serves Bangalore city in the State of Karnataka. In order to improve the existing performance, it is required to enhance the output or minimize the inputs.

In analysis related to *cost efficiency*, the increase in output can be estimated based on *effective km per bus* for the efficient SRTU such as SETC(TN) using **Eq.5.1a**, and computing the proportionate improvement required or *target effective km* for the inefficient SRTU such as BMTC using **Eq.5.1b**.

Effective km/bus for the efficient SRTU = Effective km/ Average fleet operated Eq.5.1a

*Target Effective km for inefficient SRTU = Effective km/bus for the efficient SRTU * Average fleet operated by the inefficient SRTU* Eq.5.1b

According to **Table 5.4a**, SETC(TN) which has an efficiency score of 0.938, is considered the best performing SRTU in the year 2016-17. This organization was found to have performed an effective km of 2332.53 lakh km with a fleet size of 1058 buses, as mentioned in **Table D.2**. The *effective km operated per bus* for this organization is thus computed as 0.2205 Mi. Km per bus using **Eq.5.1a**.

In the case of an inefficient SRTU such as BMTC with an efficiency score of 0.352 for the year 2016-17 (as mentioned in **Table 5.4a**), the targeted value of *effective km* to be achieved can be computed as 1230.17 Mi. Km using **Eq.5.1b**. This implies that BMTC can be considered to operate in a *cost-efficient* manner if it can be ensured that the *effective km per bus* is maintained at 0.2205 Mi. Km per bus. In other words, the target value of the *total effective km operated* by BMTC must be close to 1230.17 Mi. Km to achieve *cost efficiency*.

Interpretation of SFA Results for BEST: Cost Effectiveness

The interpretations of the output generated using the *SFA* approach for *cost effectiveness* can be explained using a simple example considering the performance of BEST, an organization that serves Mumbai city in the State of Maharashtra.

In analysis related to *cost effectiveness,* the increase in output can be estimated based on *total revenue per bus* for the efficient SRTU, such as KMTU, using **Eq.5.2a**, and computing the proportionate improvement required or *target total revenue* for the inefficient SRTU, such as BEST using **Eq.5.2b**.

Total revenue/bus for the efficient SRTU = Total revenue / Average fleet operated Eq.5.2a

*Target Total revenue for inefficient SRTU = Total revenue/bus for the efficient SRTU * Average fleet operated by the inefficient SRTU* Eq.5.2b

According to **Table 5.4b**, KMTU, which has an efficiency score of 0.961, is considered the best performing SRTU in the year 2016-17. This organization was found to have generated a *total revenue* of 460.271 Mi. Rupees with a fleet size of 107 buses, as mentioned in **Table**

D.2. The *total revenue per bus* for this organization is thus computed as 4.301 Mi. Rupees per bus using **Eq.5.2a**.

In the case of an inefficient SRTU such as BEST with an efficiency score of 0.736 for the year 2016-17 (as mentioned in **Table 5.4b**) the targeted value of *total revenue* to be earned can be computed as 14.05 Bi. Rupees using **Eq.5.2b**. This implies that BEST can be considered to operate in a *cost-effective* manner if it can be ensured that the *total revenue per bus* is maintained at 4.301 Mi. Rupees per bus. In other words, the target value of the *total revenue* generated by BEST must be close to 14.05 Bi. Rupees achieve *cost effectiveness*.

Interpretation of SFA Results for SETC(TN): Service Effectiveness

The interpretations of the output generated using the *SFA* approach for *service effectiveness* can be explained using a simple example considering the performance of SETC(TN), an organization that serves the State of Tamil Nadu.

In analysis related to *service effectiveness*, the increase in output can be estimated based on *total revenue per effective km* for the efficient SRTU, such as BEST, using **Eq.5.3a**, and computing the proportionate improvement required or *target total revenue* for the inefficient SRTU, such as SETC(TN) using **Eq.5.3b**.

Total revenue/Effective km for the efficient SRTU = Total revenue / Effective km Eq.5.3a

Target Total revenue for inefficient SRTU = Total revenue/Effective km for efficient SRTU x Effective km produced by the inefficient SRTU Eq.5.3b

According to **Table 5.4c**, BEST, which has an efficiency score of 0.931, is considered as the best performing SRTU in the year 2016-17. This organization was found to have generated a *total revenue* of 12.955 Bi. Rupees with an *effective km* of 213.56 Mi. Km as mentioned in **Table D.2**. The *total revenue per effective km* for this organization is thus computed as 60.662 rupees per *effective km* using **Eq.5.3a**.

In the case of an inefficient SRTU such as SETC(TN) with an efficiency score of 0.523 for the year 2016-17 (as mentioned in **Table 5.4c**), the targeted value of *total revenue* to be earned can be computed as 14.15 Bi. Rupees using **Eq.5.3b**. This implies that SETC(TN) can be considered to operate in a *service-effective* manner if it can be ensured that the *total revenue per effective km* is maintained at 60.662 rupees per *effective km*. In other words, the target value of the *total revenue* generated by SETC(TN) must be close to 14.15 billion Rupees to achieve *service effectiveness*.

5.4 SUMMARY OF RESULTS RELATED TO PERFORMANCE EVALUATION OF *SRTUs* BASED ON *SFA* APPROACH

5.4.1 *SFA* Models Selection Using AIC and BIC

The datasets pertaining to the time period 2010-17 for the nine *KPIs* for 31 SRTUs were used in performing the analysis. A total of 29 models were developed in the preliminary stage of performance evaluation using the *SFA* approach, comprising 8 models for evaluating the *cost efficiency*, 12 models for evaluation of *cost effectiveness*, and 9 models for *service effectiveness* of SRTUs. These 29 models were then tested for statistical soundness using the *Akaike information criterion* (AIC) and the *Bayesian information criterion* (BIC) for the entire seven-year data for the model formulated using *AIC* and *BIC* functions in *R Studio*.

- Among the models for evaluating the *cost efficiency*, it was observed that *model 8* with *effective km* operated as the dependent variable and *total cost* and *average fleet operated* as the independent variables was selected for performance analysis using the *SFA* approach.
- Among the models for evaluating the *cost effectiveness*, it was observed that *model 18* with *total revenue* as the dependent variable and *total cost* and *average fleet operated* as the independent variables was selected for performance analysis using the *SFA* approach.
- Among the models for evaluating the *service effectiveness*, it was observed that *model 24* with *total revenue* as the dependent variable, and *effective km* covered as the independent variable was selected for performance analysis using the *SFA* approach.

5.4.2 Performance Evaluation Using *SFA*

In order to assess the reliability of the three best models selected for analysis using the SFA, further analysis using the *maximum likelihood estimation* (MLE) method was performed on *model 8*, *model 18*, and *model 24* representing *cost efficiency*, *cost effectiveness*, and *service effectiveness*. It was observed based on the MLE method that the coefficients of the independent variables were significant with p-values lower than 0.05 in the case of the *cost efficiency* model, *cost effectiveness* model, and the *service effectiveness* model indicating that the use of the independent variables in the models are justified.

Further, the relative efficiencies of the 31 SRTUs based on the three models representing *cost efficiency*, *cost effectiveness*, and *service effectiveness* considering performance related data for the period 2010-17 were computed. The observations made based on the average relative efficiencies for the SRTUs for the period 2010-17 are as follows:

- The *best performing SRTUs* with regard to *cost efficiency* belong to SRTUs serving 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.
- 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.
- 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, while MEGTC of Meghalaya and KDTC serving hilly and rural areas respectively
- With regard to *cost efficiency,* it was observed that MZST of Mizoram, and MEGTC of Meghalaya that serve *hilly areas,* and BMTC, AMTU, BEST, DTC and TMTU serving *urban areas* are among the *poorly performing SRTUs*.
- The *poorly performing SRTUs* with regard to *cost effectiveness* include CHNTU of Punjab, BEST, AMTS of Gujarat and DTC serving *urban areas,* and KSRTC of Kerala and NBSTC of West-Bengal serving *rural areas* and also MZST serving *hilly areas*.
- The *poorly performing SRTUs* with regard to *service effectiveness* include SETC (TN), TNSTC (KUM & SLM zones), OSRTC and NBSTC that serve rural areas, and MZSTC that serve hilly region and also AMTS that serve urban regions.

Based on the *annual average efficiencies* of all SRTUs with regard to *cost efficiency, cost effectiveness,* and *service effectiveness* for each of the year in the study period 2010-17, following conclusions were made.

- It was 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 was not seen to be significant, there was a downward trend in performance of SRTUs during the period.
- In analysis related to *cost effectiveness*, it was observed 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 was not seen to be significant, there was a downward trend in performance of SRTUs during the period. However, the values of the *cost effectiveness* scores were seen to be higher than that of the *cost efficiency* scores for the period of study.

- In analysis related to *service effectiveness*, it was observed 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 was seen to be significant, showing an upward trend in performance of SRTUs during the period.

CHAPTER 6

PERFORMANCE EVALUATION OF SRTUs USING PARAMETRIC BASED *DEA* APPROACH

6.1 INTRODUCTION

The *key performance indicators* (*KPIs*) to be used for performance evaluation of *state road transport undertakings* (*SRTUs*) were identified using *multi-criteria decision-making* (*MCDM*) based approaches such as the *analytical hierarchy process* (*AHP*), the *Fuzzy-AHP*, *TOPSIS,* and *Fuzzy TOPSIS* as discussed in Chapter 4.

Though there were minor differences in the order of ranking of the indicators, the top 9 indicators remained the same in all the analyses as provided in **Table 4.14** and **Table 4.16**. The nine KPIs include *effective km* (EKM), *passengers km* (PKM), *total revenue* (TR), *carrying capacity km* (CKM), *total cost* (TC), *staff strength* (SS), *average fleet operated* (AFO), *passengers carried* (PC), and *fuel consumed* (FC) were subjected to further analysis. The different combinations of variables were evaluated using statistical methods such as AIC and BIC and were adopted in the performance evaluation of SRTUs using the DEA method, a non-parametric-based approach as discussed in this chapter. The dataset pertaining to these indicators for the time period 2010-17 compiled from various sources was used in this study.

The following section provides details on a summary of important data pertaining to SRTUs, preliminary formulation of *DEA* models for evaluation of *cost efficiency*, *cost effectiveness* and *service effectiveness* of SRTUs, selection of the best representative models, and performance evaluation of SRTUs.

6.2 DATA DESCRIPTION

The present study focuses on performing benchmarking exercises using the DEA approach with regard to 31 selected SRTUS in India. **Table 5.1,** provided in Chapter 5, gives details on the selected set of SRTUs considered in this study. Also, information on annual data on 9 key performance indicators for the 31 SRTUs for the period 2009-10 to 2016-17 are provided in **Table D.1,** as mentioned in the previous chapter.

6.3 MODEL SELECTION AND PERFORMANCE EVALUATIONS OF SRTUs USING *DEA* APPROACH

According to the *performance concept model*, the selected nine KPIs are divided into three main categories: *service inputs, service outputs, and service consumption*. The variables such as *total cost*, *staff strength*, *fuel consumed*, and *average fleet operated* are examples of *service inputs*; *carrying capacity km* and *effective km* are examples of *service outputs*; and *total revenue*, *passenger km*, and *passengers carried* are examples of *service consumption*. The *cost-efficiency,* also known as *technical efficiency*, is the link between *service inputs* and *service outputs,* whereas the *cost-effectiveness* is the link between *service inputs* and *service consumption*. *Service effectiveness*, on the other hand, links *service outcomes* to *service consumption*.

In the next step, it was required to formulate a set of preliminary models using the DEA approach, and the best models were selected using the AIC and BIC scores. In the analysis of *cost efficiency*, the models developed consisted of *dependent variables* such as the *effective km,* and the *carrying capacity km.* The *independent variables* were then selected from the remaining set of *KPIs*. Similarly, in the case of analysis related to *cost effectiveness*, the *dependent variables* considered were *total revenue*, *passenger km performed*, and *passengers carried*. Also, in the case of analysis related to *service effectiveness*, the *dependent variables* considered were *total revenue*, *passenger km performed*, and *passengers carried*.

6.3.1 Preliminary Formulation of Models and Selection of the Best Models Using *AIC* and *BIC* Scores as Part of *DEA*

A total of 3 models for evaluating *cost efficiency*, 7 models for evaluation of *cost effectiveness*, and 21 models for *service effectiveness* were proposed, comprising 31 models that were selected based on various permutations and combinations of dependent variables and independent variables to be tested. Here too, *Fuel consumed* (FC) was omitted from these models as it correlates with the *average fleet operated* (AFO). The built-in *lm* function in *R Studio* was used to formulate the 31 linear models. Each of these models was then proposed to be tested for statistical soundness using the *Akaike information criterion* (AIC) and the *Bayesian information criterion* (BIC) using the built-in function “AIC and BIC” in *R Studio*. The details on AIC and BIC were discussed in Chapter 3 (Theoretical Background).

A total of 31 preliminary models were analysed for interdependence using AIC and BIC approaches. The average values of the AIC and BIC scores were then computed. **Table 6.1** provides details on all 31 preliminary models analysed using AIC and BIC scores using *R Studio* software. The model with the least AIC and BIC scores is considered the best model (**Ayadi and Hammami, 2015)**.

Among the models for evaluating *cost efficiency*, it can be observed that *model 2* with *effective km operated* as the dependent variable and *total cost, staff strength*, and *average fleet operated* as the independent variables, can be selected for performance analysis using the *DEA* approach based on AIC and BIC values.

Table 6.1 Summary of AIC and BIC Scores for the Preliminary Set of Models Tested as Part of Computations for DEA Using *R Studio*

Model No.	Independent Variables	Dependent Variables	Average AIC	Average BIC
Cost Efficiency Models				
Model 1:	TC, SS & AFO	CKM	796.86	804.04
Model 2:	**TC, SS & AFO**	**EKM**	**565.27**	**572.56**
Model 3:	TC, SS & AFO	CKM & EKM	803.93	811.11
Cost Effectiveness Models				
Model 4:	TC, SS & AFO	TR	663.25	670.42
Model 5:	TC, SS & AFO	PKM	753.48	760.65
Model 6:	**TC, SS & AFO**	**PC**	**583.98**	**595.65**
Model 7:	TC, SS & AFO	TR + PKM	759.70	766.87
Model 8:	TC, SS & AFO	TR + PC	660.10	708.07
Model 9:	TC, SS & AFO	PKM + PC	754.91	762.08
Model 10:	TC, SS & AFO	TR + PC + PKM	760.67	767.84
Service Effectiveness Models				
Model 11:	CKM	TR	727.72	732.02
Model 12:	CKM	PKM	720.06	724.36
Model 13:	CKM	PC	595.05	599.35
Model 14:	CKM	TR + PKM	755.21	759.52
Model 15:	CKM	TR + PC	730.37	734.67
Model 16:	CKM	PKM + PC	723.31	727.61
Model 17:	CKM	TR + PC + PKM	757.33	761.64
Model 18:	EKM	TR	702.17	706.47
Model 19:	EKM	PKM	731.95	736.25
Model 20:	EKM	PC	597.66	601.96
Model 21:	EKM	TR + PKM	738.73	743.03
Model 22:	EKM	TR + PC	707.38	711.68
Model 23:	EKM	PKM + PC	735.40	739.71
Model 24:	EKM	TR + PC + PKM	743.06	747.37
Model 25:	EKM + CKM	TR	701.94	707.68
Model 26:	EKM + CKM	PKM	717.94	723.68
Model 27:	**EKM + CKM**	**PC**	**596.68**	**602.42**
Model 28:	EKM + CKM	TR + PKM	734.80	740.54
Model 29:	EKM + CKM	TR + PC	707.92	713.66
Model 30:	EKM + CKM	PKM + PC	721.66	727.39
Model 31:	EKM + CKM	TR + PC + PKM	739.20	744.94

TC: Total Cost; SS: Staff Strength; EKM: Effective Km
AFO: Avg. Fleet Operated; CKM: Carrying Capacity km; PC: Passenger Carried
TR: Total Revenue; PKM: Passenger km

Similarly, among the models for evaluating the *cost effectiveness,* it can be observed that *model 6* with *passenger carried* as the dependent variable and *total cost, staff strength,* and *average fleet operated* as the independent variables can be selected for performance analysis using the *DEA* approach.

Also, among the models for evaluating the *service effectiveness*, it can be observed that *model 27*, with *passenger carried* as the dependent variable and *effective km* and *carrying capacity km* covered as the independent variable, was selected for performance analysis using the DEA approach.

6.3.2 Computation of Efficiency Scores of SRTUs Using the DEA Approach

In the previous step, the best models representing *cost efficiency*, *cost effectiveness,* and *service effectiveness* were identified as *model 2*, *model 6*, and *model 27*. Based on the best models identified using the average AIC and BIC scores as described in the previous section, it is possible to compute the efficiency of the 31 selected SRTUs as part of the DEA approach.

The computations related to the DEA analysis can be performed using the "*deaR*" open-source package supported by the *R* programming environment. This package can handle classical formulations of DEA models in addition to fuzzy-based DEA models. In the present study, the *input-oriented CCR model* was adopted, where the algorithm minimizes the quantity used as input. The optimized values of λ_q coefficients can then be computed using the "*deaR*" package for the dependent and independent variables. **Table 6.2a**, **Table 6.2b**, and **Table 6.2c** provide details on the relative efficiencies computed based on analyses for *cost efficiency*, *cost* effectiveness, and *service effectiveness*. The relative efficiencies were calculated using data compiled in **Table D.1**which was used as input in the *deaR* package.

Table 6.2a Efficiencies of SRTUs Using DEA Approach for Cost Efficiency

DMU	Cost Efficiencies						
	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
AMTS	0.44807	0.42918	0.4067	0.40565	0.43453	0.40559	0.40597
APSRTC	0.86419	0.87803	0.91388	0.96187	0.87709	0.83637	0.84338
BEST	0.34655	0.35041	0.35598	0.34516	0.33656	0.31038	0.32078
BMTC	0.66193	0.655	0.59585	0.60529	0.5692	0.39727	0.50446
CHNTU	0.61929	0.60908	0.56049	0.56139	0.53929	0.63868	0.55096
DTC	0.30201	0.32958	0.34766	0.35912	0.31193	0.31586	0.32974
GSRTC	0.87339	0.86658	0.89642	0.93357	1	1	1
STHAR	0.71332	0.73555	0.7363	0.74806	0.76207	0.72629	0.72501
KDTC	0.57014	0.55931	0.54136	0.53155	0.53149	0.51963	0.53525
KnSRTC	0.85019	0.88748	0.86971	0.90943	0.8673	0.84077	0.84346
KSRTC	0.66295	0.67439	0.62722	0.67479	0.64762	0.57907	0.57357
KMTU	0.65191	0.62508	0.6552	0.72088	0.65098	0.50233	0.49401
MSRTC	0.74712	0.79988	0.7498	0.77288	0.7769	0.74677	0.78008

MEGTC	0.39145	0.39028	0.3169	0.46493	0.45879	0.43306	0.54514
MTC (CNI)	0.60937	0.6299	0.63145	0.65104	0.63934	0.56787	0.57371
MZST	0.18701	0.17643	0.17137	0.13997	0.164	0.11921	0.13963
NBSTC	0.42553	0.48327	0.55471	0.58329	0.58284	0.67868	0.7062
NEKnRTC	0.9235	0.94973	0.90521	0.92501	0.87187	0.83037	0.87556
NWKnRTC	0.85947	0.90253	0.89684	0.92911	0.92163	0.88766	0.89373
OSRTC	1	1	1	1	1	1	0.99589
PMPML	0.47058	0.48954	0.45143	0.4495	0.42404	0.38617	0.39572
RSRTC	0.89034	0.91249	0.89053	0.88015	0.89503	0.83713	0.79416
SETC (TN)	1	1	1	1	1	1	1
TMTU	0.36471	0.37358	0.37714	0.37603	0.34769	0.32796	0.3012
TNSTC(CBE)	0.86935	0.87365	0.88755	0.89579	0.86789	0.8661	0.85942
TNSTC(KUM)	1	1	0.98661	0.98854	0.9794	0.97732	0.95712
TNSTC(MDU)	1	0.91151	0.90199	0.9415	0.92699	0.89381	0.93832
TNSTC(SLM)	0.99342	1	1	0.99667	0.93703	1	0.97881
TNSTC(VPM)	1	1	1	1	1	0.9977	1
UTC	0.85028	0.87642	0.86314	0.94502	0.87033	0.79736	0.77121
UPSRTC	0.96709	1	1	1	1	1	1

Table 6.2b Efficiencies of SRTUs Using DEA Approach for *Cost Effectiveness*

DMU	Cost Effectiveness						
	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
AMTS	0.71627	0.73992	0.59174	0.51384	0.56678	0.66462	0.74561
APSRTC	0.44656	0.45324	0.56649	0.57349	0.52225	0.54157	0.60076
BEST	0.59282	0.56482	0.64506	0.61862	0.59092	0.55626	0.59728
BMTC	0.7287	0.73505	0.75548	0.71923	0.739	0.85511	0.82921
CHNTU	0.42146	0.43295	0.46868	0.44482	0.31659	0.3836	0.39968
DTC	0.38148	0.48616	0.41936	0.3641	0.60083	0.61619	0.61252
GSRTC	0.2301	0.22731	0.27929	0.2663	0.27422	0.27702	0.29546
STHAR	0.2893	0.30491	0.31993	0.31812	0.35699	0.36118	0.37198
KDTC	0.17682	0.17273	0.21691	0.20924	0.23382	0.24884	0.23913
KnSRTC	0.27397	0.27252	0.3473	0.35887	0.37771	0.3808	0.3742
KSRTC	0.43708	0.44257	0.44285	0.43941	0.42204	0.41928	0.42121
KMTU	0.45669	0.64616	0.54476	0.5233	0.50181	0.47731	0.32672
MSRTC	0.29078	0.30828	0.3498	0.31585	0.31793	0.33316	0.30112
MEGTC	0.02929	0.02289	0.01832	0.02552	0.02472	0.02387	0.02896
MTC (CNI)	1	1	1	1	1	1	1
MZST	0.00488	0.007	0.04849	0.00381	0.00469	0.0034	0.0041
NBSTC	0.1834	0.2142	0.29112	0.32253	0.37141	0.53506	0.45178
NEKnRTC	0.31098	0.31425	0.35131	0.33686	0.36971	0.33866	0.34892
NWKnRTC	0.37868	0.427	0.47699	0.47354	0.49026	0.57945	0.49472
OSRTC	0.05966	0.07229	0.09959	0.10443	0.14611	0.08386	0.08194
PMPML	0.59052	0.60165	0.6384	0.58292	0.60715	0.51673	0.53774
RSRTC	0.18918	0.17597	0.21162	0.21514	0.2426	0.24739	0.25263
SETC (TN)	0.04571	0.04282	0.0463	0.05175	0.05381	0.05521	0.06016
TMTU	0.64866	0.70455	0.79539	0.6273	0.57322	0.56774	0.45475
TNSTC(CBE)	0.66834	0.61275	0.69814	0.62536	0.6616	0.66404	0.67395
TNSTC(KUM)	0.6152	0.60407	0.64382	0.61458	0.64486	0.64571	0.63107
TNSTC(MDU)	1	0.59453	0.6045	0.59351	0.61515	0.59528	0.57265
TNSTC(SLM)	0.63261	0.62815	0.60286	0.56003	0.54218	0.56271	0.58253
TNSTC(VPM)	0.57639	0.51287	0.51059	0.49426	0.52101	0.52562	0.4913
UTC	0.02889	0.09304	0.12198	0.4905	0.07056	0.09868	0.09106
UPSRTC	0.17826	0.1953	0.25838	0.14647	0.30402	0.33748	0.34028

Table 6.2c Efficiencies of SRTUs Using DEA Approach for *Service Effectiveness*

DMU	Service Effectiveness						
	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
AMTS	0.91532	1	0.81152	0.71725	0.90358	0.86743	1
APSRTC	0.3169	0.34043	0.3632	0.39308	0.27334	0.34606	0.36139
BEST	0.96581	0.92948	0.90229	0.98485	0.9718	0.88266	1
BMTC	0.58999	0.58763	0.64727	0.73477	0.89108	1	0.88278
CHNTU	0.35844	0.3634	0.37365	0.35116	0.35057	0.33771	0.32751
DTC	0.62923	0.9139	0.54311	0.56811	0.95851	1	1
GSRTC	0.13968	0.1375	0.13997	0.14975	0.16963	0.16795	0.17884
STHAR	0.22011	0.23242	0.22242	0.21573	0.30322	0.22812	0.23158
KDTC	0.16452	0.17671	0.25544	0.21314	0.38577	0.23712	0.24883
KnSRTC	0.1782	0.17997	0.1991	0.19222	0.28302	0.21431	0.22458
KSRTC	0.37671	0.37749	0.45432	0.42632	0.54471	0.37395	0.37664
KMTU	0.43725	0.58204	0.48716	0.52292	0.47441	0.61705	0.46978
MSRTC	0.2236	0.28116	0.30597	0.27402	0.37884	0.31259	0.26703
MEGTC	0.07603	0.05985	0.05317	0.04448	0.09769	0.05671	0.059
MTC (CNI)	0.95471	0.92889	0.86506	0.96414	1	0.94928	1
MZST	0.0295	0.04075	0.28579	0.02198	0.03411	0.0261	0.03379
NBSTC	0.23521	0.29897	0.34528	0.36271	0.51681	0.44368	0.41095
NEKnRTC	0.1798	0.17646	0.18291	0.20381	0.23889	0.20393	0.21729
NWKnRTC	0.28174	0.29427	0.30287	0.29198	0.41842	0.28065	0.29706
OSRTC	0.02539	0.0274	0.0314	0.03972	0.04602	0.04345	0.04931
PMPML	0.71739	0.70853	0.7732	1	0.98325	0.78477	0.83666
RSRTC	0.11308	0.10636	0.11003	0.11765	0.166	0.13688	0.1343
SETC (TN)	0.03505	0.02949	0.02935	0.02701	0.04328	0.03202	0.03356
TMTU	1	1	1	1	0.96505	0.83325	0.85437
TNSTC(CBE)	0.3912	0.36024	0.34031	0.37315	0.38301	0.35062	0.38786
TNSTC(KUM)	0.32867	0.3173	0.29365	0.33307	0.38267	0.33887	0.35572
TNSTC(MDU)	0.4005	0.32978	0.29746	0.33086	0.33389	0.28998	0.31379
TNSTC(SLM)	0.32276	0.31917	0.27061	0.29617	0.32255	0.27657	0.30718
TNSTC(VPM)	0.29873	0.27105	0.24507	0.27063	0.30864	0.26056	0.2594
UTC	0.02119	0.06364	0.06411	0.23233	0.08837	0.0599	0.06029
UPSRTC	0.09427	0.08958	0.10324	0.0951	0.14056	0.1133	0.10307

The above-mentioned output files are then copied into a spreadsheet for further analysis and interpretation. The average of the efficiencies for each of the SRTUs over the period of study was computed with respect to *cost efficiency*, *cost effectiveness,* and *service effectiveness*. The average values of the efficiencies for the SRTUs were then sorted in decreasing order of *cost efficiency*, *cost effectiveness*, and *service effectiveness,* respectively. The SRTUs that perform better than 75% of the organizations are first identified and listed as shown in the initial part of **Table 6.3**. Also, SRTUs performing between the 75th and 50th percentiles and SRTUs performing between the 50th and 25th percentiles are listed subsequently. This is followed by SRTUs performing poorer than 75% of the organizations.

Table 6.3 Classification of SRTUs into Quartiles Based on DEA-Efficiency Scores: 2010-17

Rank		Percentile (%)	Cost Efficiency		Cost Effectiveness		Service Effectiveness	
			SRTU	Sorted efficiency	SRTU	Sorted efficiency	SRTU	Sorted efficiency
1	SRTUs performing better than 75% of the organi-zations	100.00	SETC (TN)	1.0000	MTC (CNI)	1.0000	MTC (CNI)	0.9517
2		96.77	TNSTC(VPM)	0.9997	BMTC	0.7660	TMTU	0.9504
3		93.55	OSRTC	0.9994	TNSTC(CBE)	0.6577	BEST	0.9481
4		90.32	UPSRTC	0.9953	TNSTC(MDU)	0.6537	AMTS	0.8879
5		87.10	TNSTC(SLM)	0.9866	AMTS	0.6484	PMPML	0.8291
6		83.87	TNSTC(KUM)	0.9841	TNSTC(KUM)	0.6285	DTC	0.8018
7		80.65	GSRTC	0.9386	TMTU	0.6245	BMTC	0.7619
8	SRTUs performing between 75th and 50th percentiles	77.42	TNSTC(MDU)	0.9306	BEST	0.5951	KMTU	0.5129
9		74.19	NWKnRTC	0.8987	TNSTC(SLM)	0.5873	KSRTC	0.4186
10		70.97	NEKnRTC	0.8973	PMPML	0.5822	NBSTC	0.3734
11		67.74	APSRTC	0.8821	APSRTC	0.5292	TNSTC(CBE)	0.3695
12		64.52	TNSTC(CBE)	0.8743	TNSTC(VPM)	0.5189	CHNTU	0.3518
13		61.29	RSRTC	0.8714	DTC	0.4972	APSRTC	0.3421
14		58.06	KnSRTC	0.8669	KMTU	0.4967	TNSTC(KUM)	0.3357
15		54.84	UTC	0.8534	NWKnRTC	0.4744	TNSTC(MDU)	0.3280
16		51.61	MSRTC	0.7676	KSRTC	0.4321	NWKnRTC	0.3096
17	SRTUs performing between 50th and 25th percentiles	48.39	STHAR	0.7352	CHNTU	0.4097	TNSTC(SLM)	0.3021
18		45.16	KSRTC	0.6342	KnSRTC	0.3408	MSRTC	0.2919
19		41.94	MTC (CNI)	0.6147	NEKnRTC	0.3387	TNSTC(VPM)	0.2734
20		38.71	KMTU	0.6143	NBSTC	0.3385	KDTC	0.2402
21		35.48	CHNTU	0.5827	STHAR	0.3318	STHAR	0.2362
22		32.26	NBSTC	0.5735	MSRTC	0.3167	KnSRTC	0.2102
23		29.03	BMTC	0.5699	GSRTC	0.2642	NEKnRTC	0.2004
24		25.81	KDTC	0.5412	UPSRTC	0.2515	GSRTC	0.1548
25	SRTUs performing poorer than 75% of the organi-zations	22.58	PMPML	0.4381	RSRTC	0.2192	RSRTC	0.1263
26		19.35	MEGTC	0.4287	KDTC	0.2139	UPSRTC	0.1056
27		16.13	AMTS	0.4194	UTC	0.1421	UTC	0.0843
28		12.90	TMTU	0.3526	OSRTC	0.0926	MZST	0.0674
29		9.68	BEST	0.3380	SETC (TN)	0.0508	MEGTC	0.0638
30		6.45	DTC	0.3280	MEGTC	0.0248	OSRTC	0.0375
31		3.23	MZST	0.1568	MZST	0.0109	SETC (TN)	0.0328

The average efficiencies for each of the SRTUs can be represented graphically as shown in **Fig.6.1a**, **Fig.6.1b**, and **Fig.6.1c**.

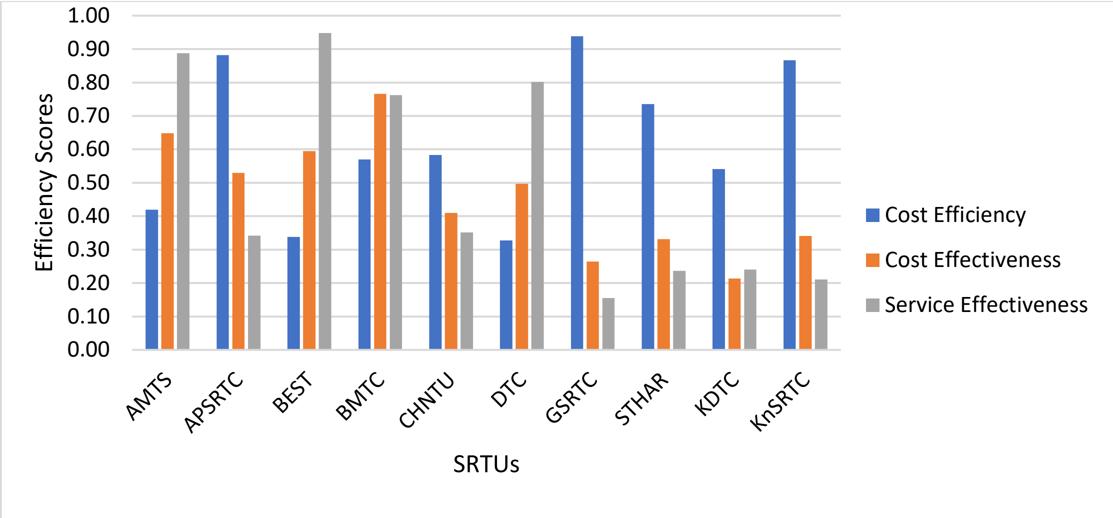

Fig.6.1a Graphical Representation of Average *DEA* Efficiencies for SRTUs 1-10: 2010-17

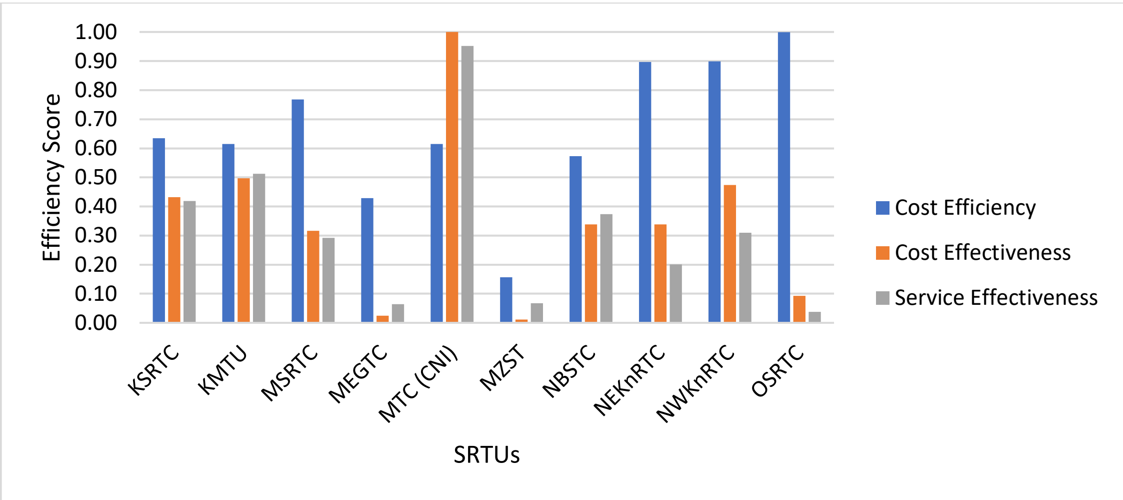

Fig.6.1b Graphical Representation of Average *DEA* Efficiencies for SRTUs 11-20: 2010-17

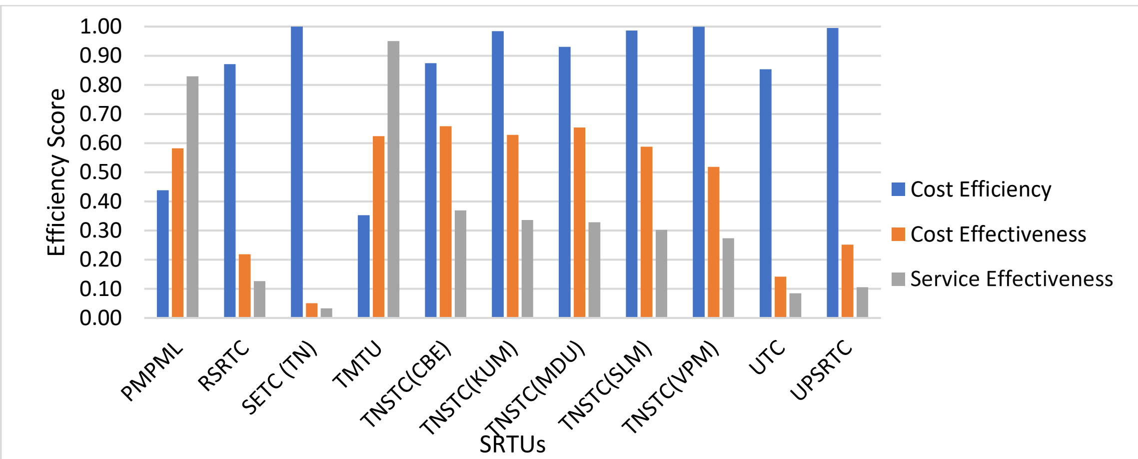

Fig.6.1c Graphical Representation of Average *DEA* Efficiencies for SRTUs 21-31: 2010-17

6.3.2.1 Discussions on Best Performing SRTUs Based on Percentile Score for 2010-17

Interestingly, the *best performing SRTUs* with percentile values higher than 75 with regard to *cost efficiency* belong to SRTUs serving rural areas. These SRTUs include SETC (TN) of the State of Tamil-Nadu, TNSTC serving Villupuram, Kumbakonam, and Salem, zones of Tamil-Nadu, UPSRTC of the State of Uttar Pradesh, OSRTC of the State of Orissa, and GSRTC of the State of 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 MTC(CNI) of Tamil-Nadu, BMTC of Karnataka, AMTS of Gujarat, and TMTU of Maharashtra, while the rural SRTUs under this category include TNSTC(KUM), TNSTC(CBE), and TNSTC(MDU) serving the State of Tamil-Nadu.

Additionally, the *best performing SRTUs* with regard to *service effectiveness* belong to SRTUs serving urban areas. These include MTC(CNI) of Tamil-Nadu, TMTU, BEST, and PMPML of Maharashtra, AMTS of Gujarat, DTC of Delhi, and BMTC of Karnataka respectively.

MTC(CNI) serving Chennai urban area maintains its first position in *cost effectiveness* as well as *service effectiveness* category.

6.3.2.2 Discussions on Worst Performing SRTUs Based on Performance Data for 2010-17

It was observed that OSRTC was one of the *poorly performing* SRTUs with regard to *cost effectiveness* as well as *service effectiveness*. However, with regard to *cost efficiency*, OSRTC can be said to perform better than 75 percent of the SRTUs.

Cost Efficiency**:** The best model for measuring *cost efficiency* was identified as *model 2* as explained in Section 6.3, where the independent variables such as *total cost* (TC), *staff strength* (SS), and *average fleet operated* (AFO) play a major role in influencing the dependent variable, *effective km*. With regard *cost efficiency*, it can be observed that MZST of Mizoram, and MEGTC of Meghalaya serve hilly areas, and DTC, AMTS, BEST, PMPML, 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 DTC, AMTS, BEST, PMPML, 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 of 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 and a higher deployment of staff per bus also lead to inefficiencies.

Cost Effectiveness**:** The best model for measuring *cost effectiveness* was identified as *model 6* as explained in Section 6.3, where the independent variables such as *total cost* (TC), *staff strength* (SS), and *average fleet operated* (AFO) play a major role in influencing the dependent variable, *passenger carried* (PC). The *poorly performing SRTUs* with regard to *cost effectiveness* include SETC(TN), OSRTC, RSRTC, and KDTC serve rural areas, and UTC, MZSTC, and MEGTC serve hilly areas. One of the reasons for the poor performance of SRTUs serving rural areas and hilly regions can be attributed to the fact that the *passengers carried* is lesser due to the lower levels of population densities. The additional reason for the lower levels of performance of SRTUs serving hilly terrains of India can be attributed to higher total costs of operation considering the increased cost of fuel, spares, and maintenance. Additionally, a higher number of fleets operated to satisfy accessibility requirements of trip-makers in rural areas and higher deployment of staff per bus also lead to inefficiencies.

Service Effectiveness**:** The best model for measuring *service effectiveness* was identified as *model* 27, as explained in Section 6.3, where the independent variables, such as *effective km* (EKM) and *carrying capacity km* (CKM), play a major role in influencing the dependent variable, *passenger carried* (PC). The *poorly performing* SRTUs with regard to *service effectiveness* include SETC (TN), OSRTC, UPSRTC, and RSRTC, which serve rural areas, and UTC, MEGTC, and MZSTC, which serve hilly regions. One of the reasons for the poor performance of SRTUs serving rural areas and hilly regions can be attributed to the fact that the *passenger carried* is lesser due to the lower levels of population densities, as mentioned in the case of analysis for *cost effectiveness*. The additional reason for the lower levels of performance of SRTUs serving hilly terrains of India can be attributed to the higher levels of *carrying capacity* offered by the SRTUs. Hence, it is recommended that buses of lower carrying capacities be operated at higher frequencies in rural areas as well as hilly areas. This strategy will also reduce the staff bus ratio and will result in increased distances operated.

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.

6.3.2.3 Discussions on Performance of SRTUs Based on 2016-17 Data: Cost Efficiency

4 SRTUs with *efficiency scores* equal to 1.00 were considered to be the most efficient SRTUs when compared to the performance of 31 SRTUs for the year 2016-17 in the DEA-based analysis with regard to *cost efficiency*. These four SRTUs together constitute the *peer group* or the *efficient frontier* organizations in DEA terminology for performance evaluation and benchmarking of other SRTUs. These SRTUs can also be considered to set the criteria for performance with regard to best practices to be adopted for effective resource utilization. The four exemplary SRTUs that constitute the peer group with regard to *cost efficiency* include:

- Gujarat State Road Transport Corporation (GSRTC);
- State Express Transport Corporation Ltd. (Tamil Nadu);
- Tamil Nadu State Transport Corporation Ltd. Villupuram (*TNSTC-VPM*); and
- Uttar Pradesh State Road Transport Corporation (*UPSRTC*).

The remaining 27 SRTUs have an *efficiency score* of lesser than 1, indicating that the performance of these SRTUs can be further improved with regard to *cost efficiency*. **Fig. 6.2** provides details on *cost efficiency* scores of various SRTUs with comparisons to the most *efficient frontier DMUS* or SRTUs.

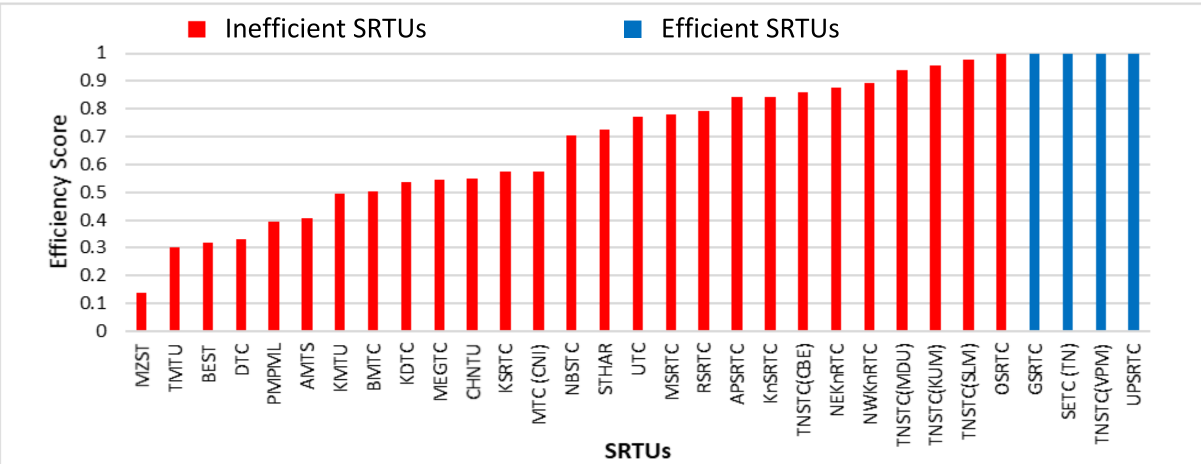

Fig.6.2 Details on *Cost Efficiency* Scores of Various SRTUs with Comparisons to the Most Efficient Frontier DMUs: 2016-17

Interpretation of DEA Results for APSRTC: Approach 1

The interpretations of the output generated using the DEA approach can be explained using a simple example considering the performance of APSRTC, an SRTU serving rural areas in the State of Andhra Pradesh. The *efficiency score* for APSRTC is obtained as 0.8434 as in **Table 6.2a**. Also, **Appendix E** provides a detailed output on comparison of each SRTU with respect to the other along with the values of λ_q. Here, it can be seen that the performance of APSRTC can be compared with the benchmark performances of GSRTC, SETC-TN, and *UPSRTC* with λ_q values of 0.754, 1.9345, and 0.2937, respectively. Thus, the λ_q *sum* value of APSRTC of 2.9822 was obtained as in **Table 6.4**. Since the λ_q *sum* value for APSRTC is greater than 1.0, the SRTU can be said to operate at *decreasing returns to scale* (DRS) according to **Banker et al.** (1984) and **Seiford and Zhu** (1999)**.**

Table 6.4 Efficiency Scores and Return to Scale Based on DEA: Cost Efficiency Model 2016-17

Sl. No	SRTU*	Eff. score	'λ_q' sum	RTS	Sl. No	SRTU*	Eff. score	'λ_q' sum	RTS
1	AMTS	0.4060	0.1255	IRS	17	NBSTC	0.7062	0.0534	IRS
2	**APSRTC**	**0.8434**	**2.9822**	**DRS**	18	NEKnRTC	0.8756	0.4518	IRS
3	BEST	0.3208	0.6430	IRS	19	NWKnRTC	0.8937	0.5450	IRS
4	BMTC	0.5045	0.3915	IRS	20	OSRTC	0.9959	0.0316	IRS
5	CHNTU	0.5510	0.0731	IRS	21	PMPML	0.3957	0.2935	IRS
6	DTC	0.3297	1.1055	DRS	22	RSRTC	0.7942	1.8563	DRS
7	GSRTC	1.0000	1.0000	CRS	23	SETC (TN)	1.0000	1.0000	CRS
8	STHAR	0.7250	1.0644	DRS	24	TMTU	0.3012	0.0417	IRS
9	KDTC	0.5353	0.0402	IRS	25	TNSTC(CBE)	0.8594	0.8224	IRS
10	**KnSRTC**	**0.8435**	**0.9892**	**IRS**	26	TNSTC(KUM)	0.9571	1.2841	DRS
11	KSRTC	0.5736	2.2745	DRS	27	TNSTC(MDU)	0.9383	0.9778	IRS
12	KMTU	0.4940	0.0086	IRS	28	TNSTC(SLM)	0.9788	0.6725	IRS
13	MSRTC	0.7801	1.9237	DRS	29	TNSTC(VPM)	1.0000	1.0000	CRS
14	MEGTC	0.5451	0.0027	IRS	30	UTC	0.7712	0.1248	IRS
15	MTC (CNI)	0.5737	0.5409	IRS	31	UPSRTC	1.0000	1.0000	CRS
16	MZST	0.1396	0.0030	IRS					

* The full names of the SRTUs are provided in TABLE III.
RTS – Returns to Scale; CRS-Constant Returns to Scale; IRS-Increasing Returns to Scale; and DRS-Decreasing Returns to Scale

Usually, during short-term periods, such as during certain seasons of the year, organizations may seem to operate at *increasing returns-to-scale* (IRS) or at *decreasing returns-to-scale* (DRS). Organizations that undergo *decreasing returns to scale* experience rising average costs, while organizations with *increasing returns to scale* are characterized by reduction in average costs.

However, according to micro-economic theory, it is required for organizations to operate at a *constant return to scale* (CRS), ensuring productivity over long periods by minimizing costs and maximizing revenues (**Gelles and Mitchell 1996**). This implies that in the long run, the organizations are expected to operate at a *constant return to scale* (CRS) by either expanding the services or by curtailing unprofitable services so as to compete with other similar firms.

In order to improve the performance of APSRTC, the targeted *total cost* (TC) of this SRTU must be equal to the sum of 0.754 x TC for GSRTC, 1.9345 x TC for SETC-TN, and 0.2937 x TC for *UPSRTC*. Based on **Table D.2,** mentioned in the appendix that provides details on *total cost* (TC) incurred by the SRTUs during the study period, it can be said that the performance of APSRTC with regard to *cost efficiency* computed using *model 2* can be improved by focusing on reducing the targeted *total cost* (TC) of this SRTU by a value equal to the sum of 0.754 x TC for GSRTC, 1.9345 x TC for SETC-TN, and 0.2937 x TC for *UPSRTC* which amounts to 509,432.69 units in place of the existing value of 604,034.93 units. **Table 6.4** provides details on the output generated as part of the '*deaR* program.

In a similar way, the reductions in input of resources such as the *average fleet operated* (AFO) and the *staff strength* (SS) must be computed. Thus, it can be said that the performance of APSRTC with regard to *cost efficiency* can be improved by reducing the input of resources. This can be attained by the sum of the product of the λ_q values and the corresponding input values of the benchmarked organizations for the variables considered, such as *total cost* (TC), *staff strength* (SS), and *average fleet operated* (AFO) as mentioned in *model 2*. The targeted value of the input of a particular resource can be expressed as,

$$X_{iq\text{-}target} = \sum\nolimits^{n}_{q=1} \lambda_q X_{iq} \qquad \text{Eq.6.1a}$$

where, $X_{iq\text{-}target}$ = the target input i for the q^{th} DMU, X_{iq} = actual input i for the q^{th} DMU; and λ_q = dual variables of the primal LP problem.

Interpretation of DEA Results for KnSRTC: Approach 2

The interpretations of the output generated using the DEA approach can also be explained using an alternative approach based on the efficiency scores and the values of slack variables. This approach can be demonstrated considering the performance of KnSRTC, an SRTU serving rural areas in the State of Karnataka.

The *efficiency score* for *KnSRTC* is obtained as 0.8435 as in **Table 6.2a**. The λ_q *sum* value of *KnSRTC* was computed based on the benchmark performances of GSRTC, SETC-TN, and *UPSRTC* with λ_q values of 0.755, 0.1274 and 0.1068 respectively, since based on **Table E.2**, the performance of *KnSRTC* can be compared to the benchmark performances of GSRTC, SETC-TN, and *UPSRTC*. Thus, the λ_q *sum* value of *KnSRTC* was obtained as of 0.9892 in **Table 6.4**. Since the λ_q *sum* value for *KnSRTC* is lesser than 1.0, the SRTU can be said to operate at *increasing returns to scale* (IRS) according to **Banker et al.** (1984) and **Seiford and Zhu** (1999)**.**

For the existing *efficiency score* of 0.8435 for *KnSRTC*, the improvement in performance can be achieved by reducing the inputs by 15.65% (obtained as 100*[1-0.8435]). In other words, the targeted *total cost* (TC) of this SRTU can be proportionally reduced to 0.1565 times the existing value of TC of 334890.4 units for *KnSRTC* (as in column TC of **Table D.2**) minus the value of 0.00 for the value of the corresponding slack variable (as in column 2 of **Table E.1**). Thus, the computed target value of *total cost* (TC) for *KnSRTC* will be 282466.9583 units as shown in column Total Cost of **Table E.3**.

In a similar manner, the inputs for *cost efficiency* model, such as the *average fleet operated* (AFO) and the *staff strength* (SS), must be reduced to 6273.662177 and 31777.38942, respectively. Thus, the improvement in performance for *KnSRTC* can be attained for each input variable as the product of the efficiency score and the input variable value minus the slack value for the corresponding input. This is expressed as,

$$X_{iq\text{-}target} = (\theta^* X_{iq}) - S^{-}_{i} \qquad \text{Eq.6.1b}$$

where, $X_{iq\text{-}target}$ = the target input i for the q^{th} DMU, X_{iq} = actual input i for the q^{th} DMU; θ^* = efficiency score of the q^{th} DMU; and S^{-}_{i} = value of the corresponding input slack variable.

In the case of output variables, it is required to add the slack value for the corresponding output. This is expressed as,

$$Y_{rq\text{-}target} = Y_{rq} + S^{+}_{r} \qquad \text{Eq.6.1c}$$

where, $Y_{rq\text{-}target}$ = target output 'r' for the q^{th} DMU; Y_{rq} = actual output 'r' for the q^{th} DMU; and S^{+}_{r} = value of the corresponding output slack variable.

In the case of *GSRTC*, the efficiency score is 1.0 and the λ_q *sum* value is 1.0 as observed in **Table 6.4** for the *cost efficiency* model. Since the λ_q *sum* value is equal to 1.0, the SRTU is said to operate at *constant return to scale* (CRS) according to **Banker et al.** (1984) and **Seiford and Zhu** (1999)**.**

Out of the twenty seven SRTUs that operate at lower efficiencies with regards to cost efficiency model, it is found that twenty SRTUs are operating at *increasing returns to scale* (IRS), while seven SRTUs are found to operate at *decreasing returns to scale* (DRS). Since the twenty SRTUs are operating at increasing returns to scale (IRS), it can be said that the scale of operations of these SRTUs can be further expanded. On the other hand, the seven SRTUs that are seen to operate at *decreasing returns to scale* (DRS) can be made more efficient by curtailing services offered to unproductive routes.

Additionally, using information compiled in **Table E.2** based on output of lambda values for SRTUS analysed using the DEA approach, it can be seen that GSRTC or Gujarat State Road Transport Corporation can be considered as a benchmark organization for comparison of efficiencies of seventeen comparatively inefficient SRTUs.

Similarly, SETC(TN), TNSTC(VPM), and UPSRTC can be considered as benchmarks for comparison of efficiencies of 16, 11, and 7 other SRTUs. **Fig. 6.3** provides a graphical representation of the ranking of the most efficient SRTUs based on the referenced benchmarks.

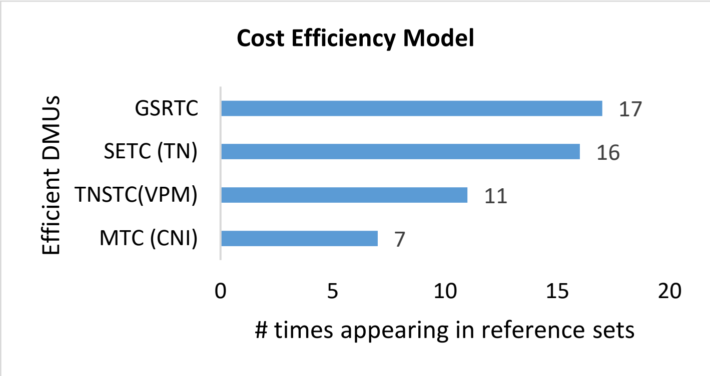

Fig.6.3 Ranking of Efficient SRTUs Based on Referenced Benchmarks: *Cost Efficiency* model for 2016-17

6.3.2.4 Discussions on Performance of SRTUs Based on 2016-17 Data: Cost Effectiveness

Only one SRTU with *efficiency score* equal to 1.00 was considered to be the most efficient SRTU when compared to the performance of 31 SRTUs for the year 2016-17 in the DEA based analysis with regard to *cost effectiveness*. This SRTU represents the *peer group* or the *efficient frontier* organization in DEA terminology for performance evaluation and benchmarking of other SRTUs. This SRTU can also be considered to set the criteria for performance with regard to best practices to be adopted for effective resource utilization. The only best example of SRTUs that can be considered as the peer group with regards to *cost effectiveness* is given below:

- Metropolitan Transport Corpn. Ltd.-Chennai (MTC-CNI)

The remaining 30 SRTUs have an *efficiency score* of lesser than 1, indicating that the performance of these SRTUs can be further improved with regard to *cost effectiveness.* **Fig. 6.4** provides details on *cost effectiveness* scores of various SRTUs with comparisons to the most *efficient frontier DMU* or SRTU.

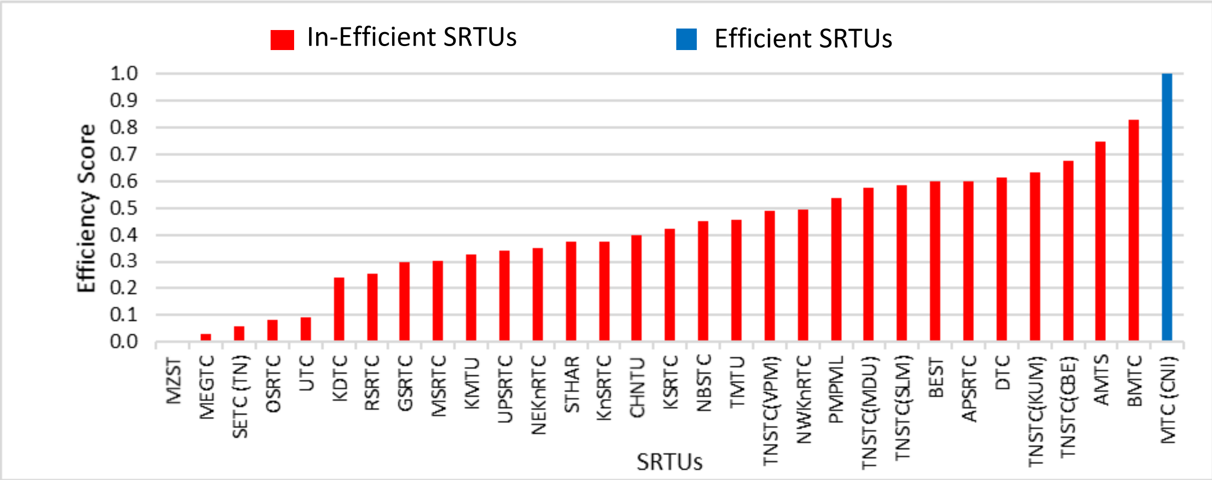

Fig.6.4 Details on *Cost Effectiveness* Scores of Various SRTUs with Comparisons to the Most Efficient Frontier DMUs: 2016-17

Additionally, using information compiled in **Table E.5** based on the output of lambda values for SRTUS analysed using the DEA approach, it can be seen that MTC(CNI) or Metropolitan Transport Corporation Ltd., Chennai can be considered as a benchmark for comparison of efficiencies of twenty-nine comparatively inefficient SRTUs. **Fig. 6.5** provides a graphical representation of the ranking of the most efficient SRTU based on the referenced benchmarks.

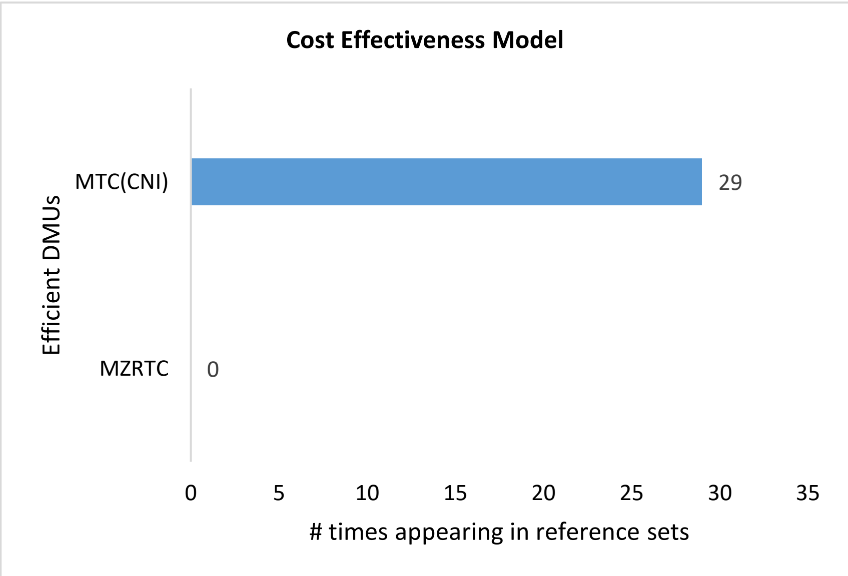

Fig.6.5 Ranking of Efficient SRTUs Based on Referenced Benchmarks for Cost Effectiveness model 2016-17

6.3.2.5 Discussions on Performance of SRTUs Based on 2016-17 Data: Service Effectiveness

4 SRTUs with *efficiency scores* equal to 1.00 were considered to be the most efficient SRTUs when compared to the performance of 31 SRTUs for the year 2016-17 in the DEA based analysis with regard to *service effectiveness*. These four SRTUs together constitute the *peer group* or the *efficient frontier* organizations in DEA terminology for performance evaluation and benchmarking of other SRTUs. These SRTUs can also be considered to set the criteria for performance with regard to best practices to be adopted for effective resource utilization. The four exemplary SRTUs that constitute the peer group with regard to *service effectiveness* include:

- Metropolitan Transport Corporation Ltd.-Chennai (MTC-CNI);
- Delhi Transport Corporation (DTC);
- Brihan Mumbai Electric Supply & Transport Undertaking (BEST); and
- Ahmedabad Municipal Transport Service (AMTS)

The remaining 27 SRTUs have an *efficiency score* of less than 1, indicating that the performance of these SRTUs can be further improved with regard to *service effectiveness*. **Fig. 6.6** provides details on *service effectiveness* scores of various SRTUs with comparisons to the most *efficient frontier DMUs* or SRTUs.

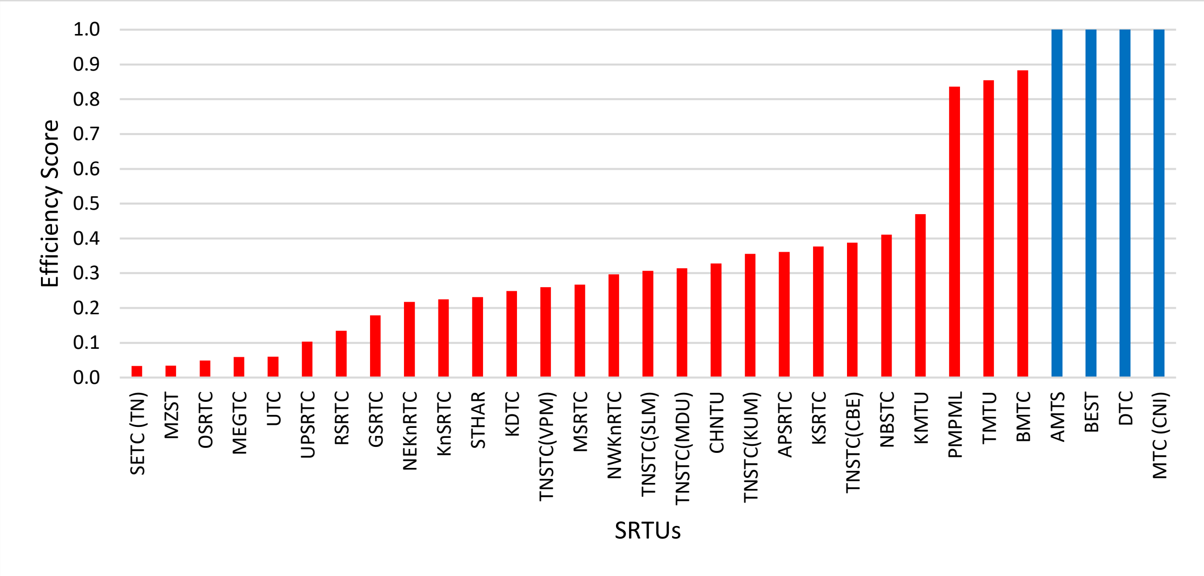

Fig.6.6 Details on *Service Effectiveness* Scores of Various SRTUs with Comparisons to the Most Efficient Frontier DMUs: 2016-17

Additionally, using information compiled in **Table E.8** based on the output of lambda values for SRTUS analysed using the DEA approach, it can be seen that DTC – Delhi Transport Corporation can be considered as a benchmark for comparison of efficiencies of twenty-nine comparatively inefficient SRTUs.

Similarly, AMTC, BEST, and MTC(CNI) can be considered as benchmarks for comparison of efficiencies of 15, 11, and 2 other SRTUs. **Fig. 6.7** provides a graphical representation of the ranking of the most efficient SRTU based on the referenced benchmarks.

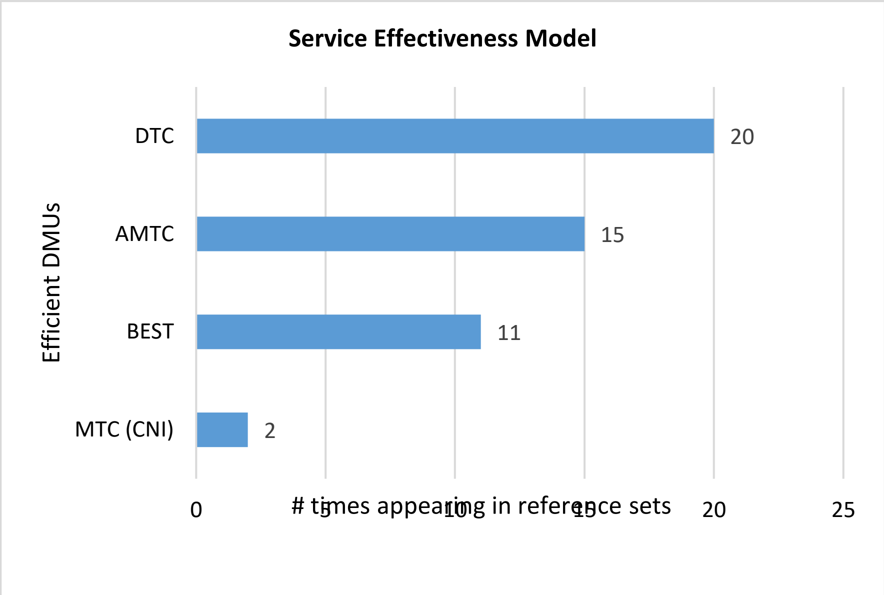

Fig.6.7 Ranking of Efficient SRTUs Based on Referenced Benchmarks for *Service Effectiveness* model 2016-17

6.4 SUMMARY OF RESULTS RELATED TO PERFORMANCE EVALUATION OF SRTUs USING *DEA*

6.4.1 *DEA* Models Selection Using AIC and BIC

A set of 31 preliminary models, including 3 models representing *cost efficiency*, 7 models for *cost effectiveness*, and 21 models for *service effectiveness* were developed as in **Table 5.3c** using the top nine indicators identified using TOPSIS. The best models capable of representing *cost efficiency*, *cost effectiveness*, and *service effectiveness* were identified using the AIC and BIC scores. These three models were then subjected to analysis using the DEA.

- **Best Model representing Cost Efficiency:** *Model 2*, with effective km operated as the dependent variable and total cost, staff strength, and average fleet operated as the independent variables, was selected for performance analysis using the *DEA* approach.
- **Best Model Representing Cost Effectiveness:** *Model 6, with passenger carried as the*

dependent variable and total cost, staff strength, and average fleet operated as the independent variables, was selected for performance analysis using the *DEA* approach.

- **Best Model Representing *Service Effectiveness:*** *Model 27, with passenger carried as the dependent variable and effective km and carrying capacity km covered as the independent variable,* was selected for performance analysis using the *DEA* approach.

6.4.2 Performance Evaluation Using DEA

The DEA analysis was then performed using the best models representing *cost efficiency*, *cost effectiveness*, and *service effectiveness* based on data on 31 State Road Transport Undertakings (SRTUs) operating in India for the seven-year period between 2010-11 and 2016-17. The primary *input-oriented DEA model* with *constant returns to scale* was adopted in the analysis.

The output obtained on efficiency scores for various SRTUs for the period 2010-17 using the DEA were then compiled into various ranges of quartiles for studies based on *cost efficiency*, *cost effectiveness*, and *service effectiveness* as given in **Table 5.5**. The following conclusions were arrived at based on this analysis:

- The *best performing SRTUs* with percentile values higher than 75 with regard to *cost efficiency* belong to SRTUs serving rural areas. These SRTUs include SETC (TN) of the State of Tamil-Nadu, TNSTC serving Villupuram, Kumbakonam, and Salem, zones of Tamil-Nadu, UPSRTC of the State of Uttar Pradesh, OSRTC of the State of Orissa, and GSRTC of the State of Gujarat.
- The *best performing SRTUs* with regard to *cost effectiveness* belong to SRTUs serving rural and urban areas. The urban SRTUs under this category include MTC(CNI) of Tamil-Nadu, BMTC of Karnataka, AMTS of Gujarat, and TMTU of Maharashtra, while the rural SRTUs under this category include TNSTC(KUM), TNSTC(CBE), and TNSTC(MDU) serving the State of Tamil-Nadu.
- The *best performing SRTUs* with regard to *service effectiveness* belong to SRTUs serving urban areas. These include MTC(CNI) of Tamil-Nadu, TMTU, BEST, and PMPML of Maharashtra, AMTS of Gujarat, DTC of Delhi, and BMTC of Karnataka, respectively.
- The *poorly performing SRTUs* with regard to *cost efficiency,* include MZST of Mizoram, and MEGTC of Meghalaya that serve hilly areas, and DTC, AMTS, BEST, PMPML and TMTU serving urban areas are among

- The *poorly performing SRTUs* with regard to *cost effectiveness include SETC(TN), OSRTC, RSRTC, and KDTC, which serve rural areas, and UTC, MZSTC, and MEGTC, which* serve hilly areas.
- The *poorly performing SRTUs* with regard to *service effectiveness* include SETC (TN), OSRTC, UPSRTC, and RSRTC, which serve rural areas, and UTC, MEGTC, and MZSTC, which serve hilly regions.

CHAPTER 7

PERFORMANCE EVALUATION OF SRTUs USING THE *DEA* APPROACH CONSIDERING UNDESIRABLE VARIABLES

7.1 INTRODUCTION

Environmental pollution due to vehicular emissions and accidents reflects upon the sustainability and social responsibility of transport organizations. However, it is also necessary to attain higher levels of performance by ensuring higher transit ridership measured in terms of *passenger km* or *passengers carried per day*. Thus, it would be advantageous to include details related to vehicular emission and accident rates in addition to information on indicators related to operational and financial efficiency. Therefore, the present study incorporates the use of a hybrid output-oriented DEA approach developed by Seiford and Zhu in 2002 to handle undesirable/negative output variables such as annual Carbon-di-oxide (CO_2) emitted per *passenger-km*, and total accidents per year in addition to overall productivity. The DEA based approach also possesses the advantage that it can perform a benchmarking of various efficiency and effectiveness indicators for bus transport organizations. The hybrid DEA approach described in this study can provide the basic framework for transport managers in the analysis of the influence of positive and negative variables to the transit system. Transport organizations can adopt similar approaches in performance evaluation and benchmarking considering sustainability, and social responsibility along with efficiency.

The following sections provide details on the description of the data used in the present study, along with a methodology for the estimation of one of the undesirable/negative variables related to vehicle emissions measured in terms of CO_2 Emissions. The details on the formulation of the DEA incorporating undesirable/negative output variables, as proposed by Seiford and Zhu (2002) is also provided along with the different models of analyses.

7.2 DESCRIPTION OF DATA USED IN THE ANALYSIS

The data pertaining to the physical and financial performance of SRTUs obtained from both CIRT, Pune, and Transport Research wing of the MoRTH were used in this study. Data pertaining to different time periods such as 2004-05, and 2009-10, in addition to the latest published data for 2014-15 for 25 selected SRTUs were analyzed so as to incorporate changes that have taken place in bus transport organizations over the years. The selection of SRTUs for analysis was performed considering the need to maintain consistency in data available and the diversity in services offered to urban, rural, and hilly terrains of the country. Among the SRTUs selected for analysis in this study, 7 SRTUs provide services to urban areas, while 15 and 3 SRTUs cater to the needs of rural and hilly areas. **Table 7.1** provides details on the same.

Table 7.1 Description of SRTUs Considered in the hybrid-DEA Based Performance Evaluation Considering Negative Variables.

Sl no.	SRTUs	Abbreviation	Service Category
1	Ahmedabad municipal transport service	AMTS	Urban Services
2	Brihan Mumbai Electric Supply & Transport Undertaking	BEST	Urban Services
3	Bengaluru Metropolitan Transport Corporation	BMTC	Urban Services
4	Calcutta State Transport Corporation	CSTC	Urban Services
5	Chandigarh Transport Undertaking	CHNTU	Urban Services
6	Delhi Transport Corporation	DTC	Urban Services
7	State Transport Haryana	STHAR	Rural & regional services
8	Maharashtra State Road Transport Corporation	MSRTC	Rural & regional services
9	Meghalaya Transport Corporation	MEGTC	Hilly region
10	Metropolitan Transport Corpn. Ltd. (Chennai)	MTC (CNI)	Urban Services
11	Mizoram State Transport	MZST	Hilly region
12	Nagaland State Transport	NGST	Hilly region
13	North Bengal State Transport Corporation	NBSTC	Rural & regional services
14	North Eastern Karnataka Road Transport Corporation	NEKnRTC	Rural & regional services
15	North Western Karnataka Road Transport Corporation	NWKnRTC	Rural & regional services
16	Odisha State Road Transport Corporation	OSRTC	Rural & regional services
17	State Transport Punjab Roadways	STPJB	Rural & regional services
18	Rajasthan State Road Transport Corporation	RSRTC	Rural & regional services
19	State Express Transport Corpn. Ltd. (Tamil Nadu)	SETC (TN)	Rural & regional services
20	Tamil Nadu State Transport Corpn. Ltd. (Coimbatore)	TNSTC (CBE)	Rural & regional services
21	Tamil Nadu State Transport Corpn. Ltd. (Kumbakonam)	TNSTC (KUM)	Rural & regional services
22	Tamil Nadu State Transport Corpn. Ltd. (Madurai)	TNSTC (MDU)	Rural & regional services
23	Tamil Nadu State Transport Corpn. Ltd. (Salem)	TNSTC (SLM)	Rural & regional services
24	Tamil Nadu State Transport Corpn. Ltd.(Villupuram)	TNSTC (VPM)	Rural & regional services
25	Uttar Pradesh State Road Transport Corporation	UPSRTC	Rural & regional services

The variables considered in the study include, three input variables such as *total cost (TC), number of employees (EMP),* and *on-road Fleet-size* ($FS_{on\text{-}road}$) representing service inputs related to capital, labour, and energy-resource consumed as recommended in fundamental studies on performance indicators by **Fielding et al. (1985).** The output variables considered include *effective kilometre performed* (EKM) as part of service output in addition to *passenger kilometre performed* (PKM) and *total revenue* (TR) as part of service consumption as in the framework of transit performance concept model developed by Fielding et al. (1985). It was also proposed to incorporate the influence of negative/ undesirable variables such as *Carbon-di-oxide emission per passenger kilometre* (CO_2-PKM) and *total number of Accidents* (ACC_{total}) per annum in the present study of performance evaluation.

Table 7.2 provides a statistical summary of the input and output variables considered in the present study, while **Table F.1, Table F.2, and Table F.2** provide a glimpse of the actual data compiled for various SRTUs for the year 2004-05, 2009-10, and 2014-15, respectively.

Table 7.2 A Statistical Summary of Input and Output Variables Considered in the Study

Year	Statistical measure	TC ·(105)	FSon-road	EMP	TR ·(105)	PKM ·(105)	EKM ·(105)
2004-05	Minimum:	860.1	28	379	127.6	14.3	12.93
	Median:	47441.9	2291	15910	41832.3	108193.7	2517.24
	Mean:	55153.6	2539	17522	49668.5	117820.1	3081.52
	Maximum:	339663.0	15229	102231	326345.0	514125.7	17976.31
	Std. dev.:	67727.36	3083.76	20549.11	64698.03	115712.81	3692.81
2009-10	Minimum:	970	32	344	197.1	156.3	9.22
	Median:	86741	2958	18038	72276.0	131253.4	3329.29
	Mean:	87966	2902	18401	71742.2	146499.4	3649.93
	Maximum:	420642	15039	101138	434164.0	533655.0	18473.15
	Std. dev.:	93986.92	3217.92	20289.97	88433.34	114173.8	4093.53
2014-15	Minimum:	1361	18	286	231.4	229.2	6.5
	Median:	146414	3061	18259	111321.1	154800.5	3514.7
	Mean:	157084	3110	18634	124168.0	139158.6	3833.9
	Maximum:	764967	16702	107500	725866.0	523753.8	20848.6
	Std. dev.:	174571.4	3601.29	21823.47	151623.8	129556.3	4535.31

Accidents and Emissions play an important role in ensuring the safety and sustainability of transport services. However, since information on vehicle emissions and the amount of pollution caused is not directly available from SRTUs in India, it was planned to compute the same in this study in terms of CO_2-PKM carried based on studies performed by **Ramachandra et al. (2015).** Information regarding accident rates available from CIRT, Pune, was also used in this study.

7.3 ESTIMATION OF CARBON-DI-OXIDE (CO_2) EMISSIONS FOR *SRTUs* IN INDIA

The estimation of CO_2 emissions can be performed using a top-down approach where emissions are computed for each transport unit based on total pollutants emitted by the transport sector, whereas, in a bottom-up approach, the emission of pollutants by an organization or activity sector is computed based on emission rate per bus. In the present study, the bottom-up approach is adopted in computing the total CO_2 emitted by the transport organization under study. This is performed using the following expression:

$$E_i = \sum(Veh_j \cdot D_j) \cdot (E_{i,j,km}) \qquad \text{Eq.7.1a}$$

where E_i = emission of the pollutant 'i'; Veh_j = number of vehicles of type 'j'; D_j = distance travelled in a year by a single vehicle of type 'j'; and E_{ijkm} = emission factor for pollutant 'i' for vehicle-type 'j' per 'km' driven.

Information on *emission factor* (E_{ijkm}) for CO_2 emitted for buses per 'km' driven is assumed as 567.03gm per km as suggested by Ramachandra et al. (2015). However, in the present work, it was proposed to use the *emission per passenger-km performed* so as to ensure a balanced computation of vehicular emissions by various types of transport organizations in a region. The expression for estimation of CO_2-PKM is given as:

$$E_{CO_2} = \frac{(Veh_j) \cdot (D_j) \cdot (E_{CO2,j,km})}{passengers\ kilometers\ performed} \qquad \text{Eq.7.1b}$$

where, E_{CO_2} = emission of the pollutant 'CO_2'; Veh_j = number of vehicles of type 'j'; D_j = distance travelled in a year by a single vehicle of type 'j'; and $E_{CO2,j,km}$ = emission factor for pollutant 'CO_2' for vehicle-type 'j' per 'km' driven.

Alternatively,

$$E_{CO_2} = \frac{(D) \cdot (E_{CO2,km})}{passengers\ kilometers\ performed} \qquad \text{Eq.7.1c}$$

where, E_{CO_2}= emission of the pollutant 'CO_2'; D = total revenue distance travelled in a year by all buses on road in the SRTU; and $E_{CO_2,km}$ = emission factor for pollutant 'CO_2' for buses per 'km' driven. **Table F.1, Table F.2, and Table F.3 in Appendix F** provide details on the data compiled for selected SRTUs in India with information on the number of accidents and CO_2-PKM for 2004-05, 2009-10, and 2014-15, respectively.

7.4 Types of Seiford and Zhu (2002) Based DEA Models Analysed in the Present Study

Based on a review of the literature performed in Chapter 2, availability of data, and the need to incorporate the influence of negative variables, it was deemed appropriate to use the DEA models proposed by **Seiford and Zhu (2002)** in the present study. The standard formulation of an output-oriented model is given below:

$Maximise\ \theta$ Eq.7.2a

Subject to,

$\sum_{q=1}^{n} \lambda_q \cdot X_{iq} + S_i^- = X_{iq}$ $i = 1,2,..,m$ Eq.7. 2b

$\sum_{q=1}^{n} \lambda_q \cdot Y_{rq} - S_r^+ = \theta \cdot Y_{rq}$ $r = 1,2,..,s$ Eq.7. 2c

$\sum_{q=1}^{n} \lambda_q \cdot \bar{Y}_{tq} - S_t^+ = \theta \cdot \bar{Y}_{tq}$ $t = 1,2,..,k$ Eq.7.2d

$\sum_{q=1}^{n} \lambda_q = 1,$ Eq.7.2e

$\lambda q\ , S_i^-, S_r^+, S_t^+ \geq 0$ Eq.7.2f

where θ = efficiency score of the DMU or the organization under consideration, which varies between 1 and ∞; λ_q = weight associated with the q^{th} DMU; X_{iq}= amount of input 'i' used by the q^{th} DMU; y_{rq} = amount of desirable output 'r' produced by the q^{th} DMU; $\bar{Y}_{tq}$ = amount of undesirable/ negative output 't' produced by the q^{th} DMU; m = the number of input variables; s = the number of desirable output variables; k = the number of undesirable/ negative output variables, and n = the number of DMUs. Also, S_i^-, $S_r^+$and S_t^+ are the *Slack/Surplus* variables used in the mathematical formulation. A higher value of θ indicates that the performance of the DMU is lower than that of the efficient DMUs that possess a score of 1.00.

Based on the results obtained using the analysis related to the DEA output-oriented model, it is possible to determine the improvements that can be made for each DMU by decreasing the input variables for the inefficient DMU and/or by increasing the output variables.

The constraint equation given in Eq.2(b) can be transformed and expressed for the input variables as:

$X_{iq-target} = X_{iq} - S_i^- = \sum_{q=1}^{n} \lambda_q \cdot X_{iq-ref}$ Eq.7.3a

where, $X_{iq-target}$ = target value of input 'i' for the q^{th} DMU; X_{iq} = actual value of input 'i' for the inefficient q^{th} DMU; S_i^-= value of the corresponding input slack/surplus variable; X_{iq-ref} = value of the input variable 'i' for the referenced efficient q^{th} DMU; and λ_q= corresponding weight associated with the referenced DMU.

Considering the changes to the input variables that can be performed, the value of the input variable of the inefficient DMU can be decreased by reducing the value of the slack variable (S_i^-) provided as part of the second term in Eq.7.3a. Alternatively, it is possible to decrease the value of the input variable by making changes to the third term ($\sum_{q=1}^{n} \lambda_q X_{iq-ref}$)

in Eq.7.3(a) where $\lambda_q$represents the weight associated with the referenced DMU which is more efficient; and X_{iq-ref}represents the input variable for the reference DMU.

The constraint equation given in Eq.7.2(c) and Eq.7.2(d) can be transformed and expressed for the desirable and undesirable outputs, respectively as:

$$Y_{rq-target} = \theta \cdot Y_{rq} + S_r^+ = \sum_{q=1}^{n} \lambda_q \cdot Y_{rq-ref} \qquad r = 1,2,..,s \qquad \text{Eq.7.3b}$$

$$\bar{Y}_{tq-target} = \theta \cdot Y_{tq} + S_t^+ = \sum_{q=1}^{n} \lambda_q \cdot \bar{Y}_{tq-ref} \qquad t = 1,2,..,k \qquad \text{Eq.7.3c}$$

where, $Y_{rq\text{-}target}$ = target value of desirable output 'r' for the q^{th} DMU; θ = efficiency score of the DMU; Y_{rq} = actual value of output 'r' for the inefficient q^{th} DMU; S_r^+ = value of the corresponding output slack/surplus variable; Y_{rq-ref} = value of the output variable 'r' for the referenced efficient q^{th} DMU; λ_q= corresponding weight associated with the referenced DMU;

$\bar{Y}_{tq-target}$ = target value of undesirable output 't' for the q^{th} DMU; Y_{tq} = actual value of undesirable output 't' for the inefficient q^{th} DMU; S_t^+= value of the corresponding undesirable output slack variable; and $\bar{Y}_{tq-ref}$ = value of the undesirable output variable 't' for the referenced efficient q^{th} DMU.

Considering the changes to the output variables that can be performed, the value of the output variable of the inefficient DMU can be increased by enhancing the value of the output variable (Y_{rq}) proportionately by θ, followed by the addition of a slack variable (S_r^+) as part of the second term in Eq.7.3(b). Alternatively, it is possible to increase the value of the output variable by making changes to the third term ($\sum_{q=1}^{n} \lambda_q \cdot Y_{rq-ref}$) in Eq.7.3(b) where $\lambda_q$represents the weight associated with the referenced DMU, which is more efficient; and Y_{rq-ref}represents the output variable for the reference DMU.

Also, considering the changes to the undesirable output variables that can be performed, the value of the undesirable output variable of the inefficient DMU can be increased by enhancing the value of the undesirable output variable (Y_{tq}) proportionately by θ, followed by the addition of a slack variable (S_t^+) as part of the second term in Eq.7.3(c). Alternatively, it is possible to increase the value of the undesirable output variable by making changes to the third term ($\sum_{q=1}^{n} \lambda_q \cdot \bar{Y}_{tq-ref}$) in Eq. 7.3(c) where $\lambda_q$represents the weight associated with the referenced DMU, which is more efficient; and $\bar{Y}_{tq-ref}$represents the undesirable output variable for the reference DMU. **Table 7.3** provides details on the different types of **Seiford and Zhu (2002)** based DEA models analysed in the present study.

Table 7.3 Types of Seiford and Zhu (2002) Based DEA Models Analysed

Model no	Model details	Input/output	Variable	abbreviation
Model 1	Overall Productivity (Efficiency and Effectiveness)	Input	Total cost	TC
			On-road fleet-size	$FS_{on\text{-}road}$
			Number of Employees	EMP
		Output	Total Revenue	TR
			Passenger kilometer Performed	PKM
			Effective kilometer Performed	EKM
Model 2	Environment & Safety (sustainability & social responsibility criteria)	Input	Total cost	TC
			On-road fleet-size	$FS_{on\text{-}road}$
			Number of Employees	EMP
		Output - Desirable	Total Revenue	TR
			Passenger kilometer Performed	PKM
			Effective kilometer Performed	EKM
		Output - Undesirable	Carbon-di-oxide emission per passenger kilometer	CO_2 -PKM
			total number of Accidents	ACC_{total}
Model 3	Eco-Efficiency (sustainability criteria)	Input	Total cost	TC
			On-road fleet-size	$FS_{on\text{-}road}$
			Number of Employees	EMP
		Output - Desirable	Total Revenue	TR
			Passenger kilometer Performed	PKM
			Effective kilometer Performed	EKM
		Output - Undesirable	Carbon-di-oxide emission per passenger kilometer	CO_2 -PKM
Model 4	Safety-Efficiency (social responsibility)	Input	Total cost	TC
			On-road fleet-size	$FS_{on\text{-}road}$
			Number of Employees	EMP
		Output - Desirable	Total Revenue	TR
			Passenger kilometer Performed	PKM
			Effective kilometer Performed	EKM
		Output - Undesirable	total number of Accidents	ACC_{total}

Model 1 was formulated to evaluate the efficiency and effectiveness of transport organizations based on input variables representing the TC, EMP, and $FS_{on\text{-}road}$, and output variables such as TR, PKM, and EKM as per recommendations made by various literature (**Fielding et al., 1985; Gadepalli & Rayaprolu, 2020; Karlaftis, 2004**).

Model 2 considers the influence of negative variables, such as vehicular emissions in terms of CO_2-PKM and ACC_{total}, on the efficiency of the SRTUs considering sustainability and social responsibility criteria.

Model 3 was formulated to evaluate the influence of the negative variable such as *vehicular emissions* in terms of CO_2-PKM, on the efficiency of SRTUs considering sustainability in addition to overall productivity. Similarly, Model 4 was formulated to evaluate the influence of the negative variable, such as ACC_{total}, on the efficiency of SRTUs considering social responsibility criteria.

As part of performance evaluation using the DEA method, it is required to satisfy the following condition for the number of DMUs (N_{DMU}) selected for the analysis in order to ensure reliable predictions (**Cooper et al., 2007**):

$N_{DMU} >= 3\ (Var_{Inp} + Var_{Out})$, or

$N_{DMU} >= Var_{Inp}\ .\ Var_{Out}$

where, Var_{Inp} = total input variables; and Var_{Out} = total output variables;

The above-mentioned conditions were fulfilled in the present study by considering details of 25 DMUs.

7.5. RESULTS OF ANALYSIS PERFORMED AND DISCUSSIONS

In the analysis related to Model 1 proposed to be analyzed for performance evaluation of 25 SRTUs in India, the input variables considered were TC, EMP, and $FS_{on\text{-}road}$, while the output variables considered were TR, PKM, and EKM, as explained in **Table 7.3**. The influence of the negative/ undesirable outputs, such as CO_2-PKM, and the ACC_{total} were not considered in this study. The analysis was performed using the output-oriented DEA model that operates on variable returns to scale. The "*deaR*" package available as part of *R Studio* GPL software was used in performing the related computations. The *deaR* program was formulated by **Coll-Serrano et al. (2020).**

In the results obtained from the analysis of *Model 1* based on data analyzed for the year 2004-05, it was observed, as summarized in column 3 of Table 6.4, that the efficiency scores for the SRTUs varied between 1 and 2.0775 with an average value of 1.1869. Based on the analysis assuming an output-oriented model, it can be said that the SRTUs with efficiency scores higher than 1.0 need to increase the outputs by about 18.69% (computed as 100 x [1.1869–1]) while keeping the input at the existing levels. Similar interpretations and insights can be obtained based on efficiency scores summarized in **Table 7.4.**

In the analysis related to *Model 2*, the input variables considered were TC, EMP, and $FS_{on\text{-}road}$, while the output variables considered include TR, PKM, and EKM in addition to the negative/ undesirable outputs such as CO_2-PKM, and the ACC_{total} as summarized in **Table 7.3**. The results obtained for analysis of data for the year 2004-05, as summarized in column 4 of **Table 7.4,** indicate that the efficiency scores for the SRTUs varied between 1 and 1.0011 with an average value of 1.0001. This indicates that when the two negative/ undesirable outputs, such as CO_2-PKM, and the ACC_{total} were considered together in addition to other variables, the difference in performance between the SRTUs did not show much difference. This is because almost all SRTUs performed in a similar manner when considering the combined effect of the two negative outputs. Hence, it was proposed to analyze the influence of each of the negative/ undesirable outputs separately as in *Model 3* and in *Model 4*.

Table 7.4 Distribution of Efficiency Scores of SRTUs Categorised Based on Type of Service

***(1)* Sl. no.**	***(2)* SRTUs**	**2004-05**				**2009-10**				**2014-15**			
		(3) Model1	***(4) Model2***	***(5) Model3***	***(6) Model4***	***(7) Model1***	***(8) Model2***	***(9) Model3***	***(10) Model4***	***(11) Model1***	***(12) Model2***	***(13) Model3***	***(14) Model4***
1	AMTS	1.6308	1.0011	1.0011	1.0616	1.9149	1.0187	1.0187	1.2268	2.2538	1.0182	1.0182	1.1494
2	BEST	1	1	1	1	1.2125	1	1.0055	1.1056	1.1679	1.0050	1.0082	1.0555
3	BMTC	1	1	1	1	1	1	1	1	1.0137	1	1	1
4	CSTC	2.0775	1.0011	1.0021	1.0213	2.3981	1	1	1.0334	2.8287	1.0178	1.0178	1.0561
5	CHNTU	1	1	1	1	1.1308	1	1	1.0179	1.5002	1.0059	1.0059	1.0301
6	DTC	1.7629	1.0001	1.0016	1.0519	1.6960	1	1.0117	1	1.7776	1	1.0032	1
7	MTC (CNI)	1.0938	1	1	1.0938	1.0894	1	1	1.0894	1.0734	1	1	1.0734
Avg. of Urban SRTUs		**1.3664**	**1.0003**	**1.0007**	**1.0326**	**1.4917**	**1.0027**	**1.0052**	**1.0676**	**1.6593**	**1.0067**	**1.0076**	**1.0521**
1	STHAR	1.0239	1	1.0026	1	1.1216	1	1.0158	1	1.1593	1	1.0061	1
2	MSRTC	1	1	1	1	1	1	1	1	1	1	1	1
3	NBSTC	2.0566	1.0009	1.0021	1.0179	2.1583	1	1.0215	1	1.6886	1.0122	1.0162	1.0143
4	NEKnRTC	1	1	1	1	1.0504	1.0196	1.0241	1.0297	1	1	1	1
5	NWKnRTC	1.0200	1	1.0011	1	1.0561	1.0175	1.0195	1.0491	1.0024	1	1.0023	1
6	OSRTC	1	1	1	1	1	1	1	1	1	1	1	1
7	STPJB	1.5765	1	1.0033	1	2.4755	1	2.4755	1	1.4398	1	1.4398	1
8	RSRTC	1	1	1	1	1	1	1	1	1.0109	1	1.0020	1
9	SETC (TN)	1	1	1	1	1	1	1	1	1	1	1	1
10	TNSTC (CBE)	1.0242	1.0001	1.0001	1.0242	1.1124	1	1	1.0616	1.0854	1	1.0007	1.0282
11	TNSTC (KUM)	1	1	1	1	1.0153	1	1.0038	1	1.0167	1.0001	1.0016	1.0001
12	TNSTC (MDU)	1	1	1	1	1	1	1	1	1.0452	1	1.0017	1
13	TNSTC (SLM)	1.0090	1	1	1	1.0057	1	1	1	1.0646	1	1.0029	1
14	TNSTC (VPM)		1	1	1	1	1	1	1	1	1	1	1
15	UPSRTC	1	1	1	1	1	1	1	1	1	1	1	1
Avg. of Rural & regional SRTUs		**1.1140**	**1.0001**	**1.0006**	**1.00281**	**1.1997**	**1.0025**	**1.1040**	**1.0094**	**1.1009**	**1.0008**	**1.0316**	**1.0028**
1	MEGTC	1	1	1	1	1	1	1	1	1	1	1	1
2	MZST	1	1	1	1	1	1	1	1	1	1	1	1
3	NGST	1.3963	1	1.3963	1	2.3737	1	1.0009	1	2.6982	1	1.0200	1
Avg. of Hilly region SRTUs		**1.1321**	**1.0000**	**1.1321**	**1.0000**	**1.4579**	**1.0000**	**1.0003**	**1.0000**	**1.5661**	**1.0000**	**1.0067**	**1.0000**
Avg. of ALL SRTUs		**1.1869**	**1.0001**	**1.0164**	**1.0108**	**1.3124**	**1.0022**	**1.0639**	**1.0245**	**1.3131**	**1.0024**	**1.0219**	**1.0163**

Column 5 in **Table 7.4** provides details on results obtained for analysis of Model 3 based on data analyzed for the year 2004-05, where the use of a negative/ undesirable output such as CO_2-PKM was considered along with other variables. Here, the efficiency scores varied significantly among SRTUs between 1 and 1.3963, with an average value of 1.0164. The results indicate that vehicular emissions measured in terms of CO_2-PKM can be reduced by improving fuel consumption, possibly by incorporating the use of bio-fuels, by upgrading the quality of existing fuel consumed, and by adopting the use of CNG and electric-powered vehicles. Additionally, an increase in passengers carried per bus can further result in an improvement in the performance of SRTUs.

Similarly, column 6 in **Table 7.4** provides details on results obtained for analysis of Model 4 based on data analyzed for the year 2004-05, where the use of a negative/ undesirable output such as the ACC_{total} was considered along with other variables. Here, the efficiency scores varied moderately among SRTUs between 1 and 1.0938, with an average value of 1.0108. However, in view of the need to reduce accidents, considering the social responsibility of transport organizations, it is necessary to adopt strategies for reducing accidents by providing proper training to drivers and by adopting the use of speed-governors to limit vehicle speeds. Moreover, accidents while boarding and alighting of passengers can be reduced by providing dedicated bus lanes with merging zones near bus stops.

Considering the performance of SRTUs for analysis based on Models 1, 2, 3, and 4 together for the year 2004-05, it can be inferred from **Table 7.4** that out of a total of 25 SRTUs, 14 SRTUs are found to be efficient ($\theta = 1$). Among these 14 efficient SRTUs, 3 SRTUs operate in urban areas, while another set of 9 SRTUs serve the rural sector. The remaining 2 efficient SRTUs cater to the transport needs of passengers belonging to hilly regions.

Also, considering the performance of SRTUs for analysis based on Models 1, 2, 3, and 4 together for the year 2009-10, it can be observed from **Table 7.4** that 10 SRTUs are efficient with efficiency scores equal to 1.0. Out of these, 1 SRTU operates in urban areas, while another set of 7 SRTUs operates in the rural sector. The remaining 2 efficient SRTUs provide services to hilly regions.

Similarly, considering the performance of SRTUs for analysis based on Models 1, 2, 3, and 4 together for the year 2014-15, it can be observed from **Table 7.4** that 8 SRTUs are found to be efficient ($\theta = 1$). Out of these, 6 SRTUs operate in rural sector, while another set of 2 SRTUs operates in the hilly regions. There are no efficient SRTUs that provide services to urban areas.

The efficient SRTUs with efficiency scores equal to 1.0 for Models 1, 2, 3, and 4 are highlighted in **Table 7.4**. Here, it can be seen that MSRTC, OSRTC, SETC(TN), TNSTC(VMP), and UPSRTC operating in rural areas displayed exemplary performance levels at higher efficiencies across all the study periods 2004-05, 2009-10, 2014-15. Also, MEGTC, and MZST operating in hilly regions performed consistently well across all the study periods considered.

The five worst performing SRTUs with efficiency scores higher than 1.0 for Models 1,2, 3, and 4 considered together across all the study periods 2004-05, 2009-10, 2014-15 are identified as AMTS, CSTC, DTC, NBSTC, and STPJB.

7.5.1 Improving the Worst Performing Organization STPJB Based on the Results of the DEA Approach

This section provides a detailed explanation of identifying the strategies required to be adopted in improving the functioning of STPJB, one of the SRTUs with the worst performance ratings for the study period 2014-15. It is observed that the efficiency of STPJB is very low (at an efficiency score of 1.4398) for Model 3 when compared to the performance of 25 SRTUs selected in the present study. The analysis was performed for the output-oriented BCC model (Banker et al., 1984) that operates on variable returns to scale. This section demonstrates the manner in which the results can be interpreted, considering the increase in outputs or the reduction in inputs, based on the analysis of Model 3.

The actual values of input variables ($X_{i\text{-actual}}$), and output variables ($Y_{i\text{-actual}}$) related to STPJB were extracted from **Table F.2** and recompiled as in **Table 7.5** for the analysis period 2014-15 pertaining to Model 3.

Table 7.5 Actual Values of Inputs & Outputs for the Inefficient Organization STPJB and the Related Benchmarked Efficient SRTUs for the Year 2014-15 (Extracted from Table E.3)

	$X_{iq\text{-existing}}$			$Y_{rq\text{- existing}}$			$\bar{Y}_{tq-existing}$	
	TC_{ex}·(10^5)	**EMP_{ex}**	**$FS_{on\text{-}road\text{-}ex}$**	**TR_{ex}·(10^5)**	**PKM_{ex}·(10^5)**	**EKM_{ex}·(10^5)**	**CO_2-PKM_{ex}**	**$ACC_{total\text{-}ex}$**
MEGTC	1360.98	286	42	1179.95	399.09	22.58	32.08	0
STPJB	*27759.11*	*4252*	*420*	*16540*	*295.73*	*295.73*	*567.03*	*3*
SETC (TN)	78693.05	6997	1011	65749.16	77551.5	2226.15	16.28	354
TNSTC (VPM)	177126.83	22573	3352	161852.37	293359.86	6037.99	11.67	1091

The output from the DEA analysis obtained using the "*deaR*" package developed by Coll-Serrano et al. (2020) provides details related to coefficients of the input and output variables (or lambda values), the values of the slack (or surplus) for input and output variables, and the targets to be achieved at higher efficiencies. The details pertaining to STPJB are highlighted in the output tables **Table 7.6a** (the table of efficiency scores θ), ***Table***

7.6b (the table of slack values S_i^-, S_r^+ and S_t^+), ***Table 7.6c*** (the table of target values $X_{i\text{-target}}$, and $Y_{i\text{-target}}$), and *Table 6d* (the table of coefficients λ).

Table 7.6a Model 3 Efficiency Scores (θ) for the Year 2014-15 (partial data)

Sl no.	SRTU	Eff. Score
1	AMTS	1.0182
-	-	-
17	MEGTC	1
21	STPJB	1.4398
24	SETC (TN)	1
27	TNSTC (VPM)	1
-	-	-

Table 7.6a indicates that based on the analysis conducted using *Model 3*, the performance of STPJB can be improved by increasing the outputs by 43.98% (computed as, 100 · [1.4398-1.00]). However, the actual values of reduction in input variables, and the increase in output variables can be computed based on Eq.7.3(a), Eq.7.3(b), and Eq.7.3(c). The related computations to improve the performance of STPJB considering data for 2014-15 are explained below.

The reduction in the input variables of STPJB can be determined based on the second term $(X_{iq} - S_i^-)$ in **Eq.7.3(a).** For example, the target number of employees (Emp_{tar}) of STPJB should be an existing value of employees (EMP_{ex}) of 4252 units (as shown in *Table 7.5*) minus the value of 1375.25 units for the slack variable Emp (as shown in **Table 7.6b).** This computes to a target value of 2876.75 units of EMP_{tar} for STPJB, as shown in **Table 7.6c**. In a similar manner, the reductions in other input variables can be implemented so as to achieve the target input values for the total cost (TC_{tar}), and the on-road fleet size ($FS_{on\text{-}road\text{-}tar}$) for the inefficient organization, STPJB.

Table 7.6b Model 3 Slack Values for the Year 2014-15 (Partial data)

	Values of Slack Variables for Inputs (S_i^-)			Values of Slack Variables for Outputs (S_r^+)			S_t^+
DMU	**TC · (10^5)**	**EMP**	**$FS_{on\text{-}road}$**	**TR· (10^5)**	**PKM · (10^5)**	**EKM · (10^5)**	**CO_2-PKM**
-	-	-	-	-	-	-	-
MEGTC	0	0	0	0	0	0	0
STPJB	0	1375.25	0	0	31324.05	391.93	539.2422
SETC (TN)	5.377E-05	7.266E-06	0	0	0.0001746	1.682E-06	2.666E-06
TNSTC (VPM)	0	1.0560E-08	-5.9096E-10	1.1597E-07	1.56176E-06	1.58341E-08	4.18E-09
-	-	-	-	-	-	-	-

St+ = Values of Slack Variable for the undesirable/ negative output

Table 7.6c Targets Generated by the DEA Model 3 for the 2014-15 (Partial data)

	$X_{i\text{-target}}$			$Y_{i\text{-target}}$			$\bar{Y}_{t-target}$
DMU	$TC_{tar}\cdot(10^5)$	EMP_{tar}	$FS_{on\text{-}road\text{-}tar}$	$TR_{tar}\cdot(10^5)$	$PKM_{tar}\cdot(10^5)$	$EKM_{tar}\cdot(10^5)$	$CO_2\text{-}PKM_{tar}$
-	-	-	-	-	-	-	-
MEGTC	1360.98	286	42	1179.95	399.09	22.58	32.082
STPJB	27759.11	2876.75	420	23814.6	31749.85	817.724	27.348
SETC (TN)	78693.05	6997	1011	65749.16	77551.5	2226.15	16.28
TNSTC (VPM)	177126.8	22573	3352	161852.4	293359.9	6037.99	11.671
-	-	-	-	-	-	-	-

Additionally, it is required to increase the output variables of STPJB based on the third term ($\sum_{q=1}^{n}\lambda_q\cdot Y_{rq-ref}$) in **Eq.7.3(b)** where $\lambda_q$represents the weight associated with the referenced efficient SRTU (used as a benchmark), and Y_{rq-ref} is the existing value of the referenced efficient SRTUs. **Table 7.6d** provides partial data of the output obtained for values of λ_q. Here, it can be seen that for STPJB, the referenced efficient SRTUs used as benchmark are MEGTC, SETC(TN), and TNSTC(VPM) with values 0.7129, 0.2445, and 0.0426 respectively. It may be observed that the details on the existing values of output variables ($Y_{rq-existing}$) for the referenced efficient SRTUs (used as a benchmark) were already provided in Table 7.5. The target total revenue (TRtar) of 23814.60 units for STPJB, as in Table 7.6c, can be achieved as the sum of 0.7129 x TR_{ex} for MEGTC, 0.2445 x TR_{ex} for SETC(TN), and 0.0426 x TR_{ex} for TNSTC(VPM) in place of the existing value (TR_{ex}) of 16540 units as shown in Table 7.5. In a similar manner, the increase in other output variables can be implemented so as to achieve the target output values for the passenger-km performed (PKM_{tar}), and the effective-km performed (EKMtar) for the inefficient organization, STPJB.

The decrease in the undesirable/ negative output variables of STPJB can be obtained based on the third term ($\sum_{q=1}^{n}\lambda_q\cdot\bar{Y}_{tq-ref}$) **in Eq.7.3(c)** where λ_q represents the weight associated with the referenced efficient SRTU (used as a benchmark), as in Table 6.6d, and $\bar{Y}_{tq-ref}$ is represented by the existing value $\bar{Y}_{tq-existing}$ as in Table 7.5. For example, the target CO2 emission per passenger-km (CO_2-PKM_{ex}) as in Table 7.6c should be equal to the sum of (0.7129 · CO_2-PKM_{ex}) for MEGTC, (0.2445 · CO_2-PKM_{ex}) for SETC(TN), and (0.0426 · CO2-PKM_{ex}) for TNSTC(VPM) which in turn is equal to 27.348 units as shown in Table 7.6c as opposed to the actual value of 567.03 units as shown in Table 7.5.

Moreover, the decrease in the undesirable/ negative output variables of STPJB can be obtained based on the third term ($\sum_{q=1}^{n}\lambda_q\cdot\bar{Y}_{tq-ref}$) in **Eq.7.3(c)** where $\lambda_q$represents the weight associated with the referenced efficient SRTU (used as a benchmark), and $\bar{Y}_{tq-ref}$ is the existing value of the referenced efficient SRTUs. Table 7.6d provides values of λ_q (partial data of output generated by DEA analysis) and Table 7.5 provides details on the existing values of output variables ($Y_{rq-existing}$) for the referenced efficient SRTUs (used as a benchmark).

The target CO_2 emission per passenger-km (CO_2-PKM_{tar}) of 27.34 units for STPJB as in Table 7.6c can be achieved as the sum of (0.7129 · CO2-PKM_{ex}) for MEGTC, (0.2445 · CO2-PKM_{ex}) for SETC(TN), and (0.0426 · CO_2-PKM_{ex}) for TNSTC(VPM) in place of the existing value (CO_2-PKM_{ex}) of 567.03 units as shown in Table 7.5.

Table 7.6d Summary of λ Values and the Reference SRTUs for the Year 2014-15 (Partial data)

	MEGTC	MSRTC	MZST	SETC(TN)	TNSTC(VPM)	UPSRTC
-	-	-	-	-	-	-
MEGTC	1	0	0	0	0	0
STPJB	0.7129	0	0	0.2445	0.0426	0
SETC (TN)	0	0	0	1	0	0
TNSTC (VPM)	0	0	0	0	1	0
-	-	-	-	-	-	-

Similar computations for other models can be made using the output generated by the *deaR* package. As part of analysis using Model 4, it may be observed that the organization AMTS was found to be inefficient with regard to total number of accidents as in Table 7.4. The computations for reduction in accidents can be performed in a similar manner as explained above.

7.6 SUMMARY OF RESULT RELATED TO *DEA* BASED PERFORMANCE EVALUATIONS OF *SRTUs* CONSIDERING NEGATIVE VARIABLES

The main focus of the present work was on demonstrating the capability of a hybrid output-oriented DEA approach developed by Seiford and Zhu (2002) approach in performance evaluation considering the additional influence of negative variables such as annual CO_2-PKM, and the total accidents per year. The study was performed based on data made available for the year 2004-05, 2009-10 and 2014-15 in order to evaluate performance of 25 SRTUs in India. Four models were evaluated:

Model 1 was formulated to evaluate the efficiency and effectiveness of transport organizations based on input variables representing the *total cost, number of employees, on-road fleet-size* and output variables such as *total revenue, passenger kilometer performed* and *effective kilometer performed*. *Model 2* considers the influence of negative variables such as vehicular-emissions in terms of *Carbon-di-oxide per passenger kilometer performed*, and *total accidents*, on the efficiency of the SRTUs considering sustainability, and social responsibility criteria. *Model 3* and *Model 4* was formulated to evaluate the influence of individual negative variable such as *Carbon-di-oxide per passenger kilometer performed* and *total accidents,* respectively.

Model 1: The results indicate that the efficiency scores for the SRTUs varied significantly between 1 and 2.0775 with an average value of 1.1869 for the year 2004-05. Similar variations in performance efficiency between 1 and 2.4755 were observed for analysis based on data for year 2009-10, where the average efficiency score was found to be 1.3124. Also, for the year 2014-15, the performance of SRTUs varied between 1 and 2.8287 with an average value of 1.3131. This indicated that the overall performance of SRTUs decreased over the years.

Model 2: It may be observed that no significant conclusion can be arrived at based on *model 2*, where the influence of both undesirable outputs such as vehicular emissions and accidents were considered.

Model 3: The results indicate that the efficiency scores for the SRTUs varied moderately between 1 and 1.3963 with an average value of 1.0164 for the year 2004-05. Similar variations in performance efficiency between 1 and 2.4755 were observed for analysis based on data for year 2009-10, where the average efficiency score was found to be 1.0639. Also, for the year 2014-15, the performance of SRTUs varied between 1 and 1.4398 with an average value of 1.0219. This indicated that the overall performance of SRTUs remained almost stable.

Model 4: In the case of analysis using *model 4* where undesirable effects due to accidents were considered, it was observed that most SRTUs performed at par. This implies that the accident rate in most of the SRTUs are almost same with minor variations.

In view of the above, it was considered ideal to study the performance of organizations with respect to model 1 and model 3.

CHAPTER 8

PERFORMANCE EVALUATION OF PUBLIC TRANSPORT ORGANIZATION AT ROUTE LEVEL – A CASE STUDY OF *MCTD* OPERATIONS

8.1 INTRODUCTION

Bus performance assessment can be conducted at three levels - system level, subsystem level, and route level. *System level* evaluations refer to the performance of the bus system as a whole based on data compiled at the depot-level all over the administrative area of the SRTUs. The analysis performed at this level assists in the study of trends in the performance of the SRTUs. *Subsystem level* performance evaluations utilize data on performance of buses along various routes under a bus-depot, while *route level* evaluations focus on performing micro-level analysis on links served along each bus route.

The identification of KPIs in the analysis of public transport organizations at route level depends on the availability of reliable data. The identification of indicators includes statistical approaches such as *correlation analysis*, *Principal component analysis*. However, a more pragmatic approach would select indicators based on how they affect a performance evaluation of public transport organizations. One such technique is *recursive feature elimination (RFE),* which reduces model complexity by removing insignificant variables one by one until the optimal number is reached. On the other hand, the DEA approach is one of the most popular *non-parametric* methods where a standard production function is used in identifying the organizations that constitute the most efficient frontier. The approach can also be used to perform micro/ route level analyses in a bus depot, as demonstrated in this study.

The present study involves the identification of KPIs using the *correlation method*, the *PCA* method, and the *RFE* method. Subsequently, a non-parametric approach such as the *DEA* is adopted in the study of the ***efficiency*** and ***effectiveness*** of bus transport services such as the Mysore City Transport Division (MCTD) operating under Karnataka State Road Transport Undertaking (KnSRTC) at the micro/route level. This was followed by an in-depth analysis using *Technical Gap Ratio* (TGR) for the selected routes.

8.2 STUDY AREA CHARACTERISTICS

A number of bus transport operators existed in a number of cities in India even prior to the 1940s. The Road transport Corporation Act was passed by the Government of India in 1950 to regulate the functioning of the then existing road transport undertakings. The State transport organizations in Gujarat and Maharashtra adopted the Act in 1950, while the State of Mysore adopted the same in 1958. The State of Kerala adopted the same in 1965, followed by other transport organizations in various other states and union territories of India.

8.2.1 Mysuru City

Mysore is a city in the southern part of Karnataka located at about 140km southwest of Bangalore. Mysore city is a heritage city that attracts a large number of tourists from all over the world. It is considered a satellite city of Bangalore and supports a flourishing IT industry.

Public transportation services in Mysuru are offered by MCTD, part of KnSRTC. MCTD was one of the few selected SRTUs to implement the *Intelligent Transport System* (ITS) utilizing funding made available from the World Bank. In view of the high level of availability of digital data on the movement of public transport services, it was considered ideal to focus on micro/ route-level performance evaluation of MCTD so as to explore opportunities to improve the efficiency and effectiveness of services provided. **Fig.8.1a** provides details on the location of the State of Karnataka in India, along with the precise location of Mysore city.

8.2.2 Physical Characteristics of Mysuru: *Demography*

Mysore is the administrative seat of Mysore district, one of the largest districts in the State of Karnataka, India. It is located at 12° 18′ 26″ north latitudes and 76° 38′ 59″ east longitudes. It is the second-largest urban agglomeration in the state of Karnataka, with a population of 1.2 million. The city has a road network of 1182km, radial pattern with arterials originating from the center of the city (**MoUD, 2016**).

The urban area of Mysore City corporation is divided into 65 wards encompassing 88.459 sq. km. The map of Mysuru city with all 65 wards is shown in **Fig.4.1b**. The total population of Mysuru city is 920,550, with 461,042 men and 459,508 women, making it Karnataka's third most populous city (**Census, 2011**). The Mysore urban agglomeration comprises a population of 1,060,120 people, with 497,132 men and 493,762 women, and has a population density of 6,910.5 per square kilometer. However, subsequently, the boundaries of the 65 wards were further revised by Mysore City Corporation in 2018. In this study, the previous ward map that conforms to Census 2011 was used.

8.2.3 Traffic and Transportation Characteristics for Mysuru City

The city is well connected to the rest of India by a National Highway NH-212, and the State Highways SH-17, SH-33, SH-86, and SH-88. The total length of the road network is about 1176 kilometers, including roads maintained by the Corporation, the Public Works Department, and the *National Highway Authority of India* (NHAI). The urban area has a road density of 8.58 km per square kilometer and a road length of 1.45 km per 1000 people.

Buses operated by KnSRTC under MCTD provide public transport services to the city. The city bus stand is located close to the heart of the urban area, providing accessibility to various city activity centers. The MCTD operates a fleet of about 500 buses from 4 bus depots in the city. The modal share of bus transport in Mysore is 42.2%, whereas the share of motorized two-wheelers and cars stands at 23.3% and 16.2%, respectively **(ITS DPR- Mysore, 2011)**. MCTD operations are supported by a comprehensive ITS system with GPS-based *Automatic Vehicle Location* and tracking of *real-time passenger movement*, providing details on passengers carried at each stage, and bus-stops served with digital signage **(Website: Mitra-KSRTC)**.

8.3 BRIEF DESCRIPTION OF METHODOLOGY FOR THE PRESENT STUDY

This section provides details on the methodology adopted, where investigations of performance analysis at the micro/route level for selected routes in the MCTD bus transport organization are part of the present study. **Fig 8.2** provides a flowchart that illustrates the step-by-step procedure adopted.

The preliminary phase of this study was focused on performing studies on the study area, followed by a review of the literature on the indicators generally used in performance evaluation at the micro/ route-level analysis for public transport systems. A set of selected indicators were then identified that could be used in performance analysis.

8.4 DATA RELATED TO KEY PERFORMANCE INDICATORS

8.4.1 Indicators Used in Performance Evaluation and Monitoring for Micro\ Route-Level Analysis

The MCTD transport organization maintains details on the movement of buses, and information on ticket sales for each route and for each trip. The information collected using the ITS and ETM can be effectively used in performing micro/ route-level evaluation of routes.

The list of performance indicators commonly used by SRTUs in India and abroad can be categorized based on the *geographic characteristics of the routes*, *quality of service provided* *by the routes*, *physical measures* (such as the *number of buses), operating expenses*, *service supply* (such as *vehicle-kilometers*), *service consumption* (such as the *number of passengers*), *quality of services offered by the route* (such as *service reliability*, and *vehicle speed*), *revenue earned by the route* (such as *operating revenue*, and *income*) and other factors (such as *environmental factors, accidents, parking facilities, traffic conditions, availability of bus-lanes*). **Table 8.1a** provides a list of indicators used by various organizations based on data compiled by **Karim and Fouad (2018)** and other researchers. The list of input and output variables identified for the present study are listed in **Table 8.1b**.

Table 8.1a List of Micro-Level Indicators Used by Various Organizations

INPUT INDICATORS	
Category I: Geographic Characteristics of the Routes	
• Transfer between routes • Route length • Number of bus stops per route • Number of intersections# • Location of bus stops# • Stops of median bus lanes/ total bus stops*	Karim and Fouad (2018) Asmeal and Waheed (2020) # Hahn et.al. (2013)*
Category II: Quality of Service Provided by the Routes	
• Service reliability • Waiting time • Travel Time or journey speed* • Frequency • Delay* • No. of transfers# • Route-directness# • Walking distance to bus stop$ • Buffer time index@ • Planning time index@ • Travel time index@ • On time performance@	Karim and Fouad (2018) Naim et.al (2020)$ Asmeal and Waheed (2020)# Hahn et al. (2013) * Chepuri et al. (2018)@
Category III: Physical Measures	
• Number of buses or Fleet size	Karim and Fouad (2018) Asmeal and Waheed (2020) Fielding et al. (1985)
Category IV: Operating Expenses	
• Operating Cost • Fuel Cost • Total transportation cost*	Karim and Fouad (2018) Fielding et al. (1985) Hahn et.al. (2013) *
OUTPUT VARIABLES	
Category I: Service Supply	
• Vehicle kilometers • Vehicle hour • Span of service# • Service hour	Karim and Fouad (2018); Fielding et al. (1985) Asmeal and Waheed (2020) # Hahn et.al. (2013)
Category II: Service Consumption	

• Passenger kilometers/ unlinked passenger trips • Number of passengers or ridership • Load factor	Karim and Fouad (2018); Fielding et al. (1985) Asmeal and Waheed (2020) Hahn et.al. (2013)
Category III: Quality of Services Offered by the Route	
• Service reliability • Vehicle speed	Karim and Fouad (2018) Naim et.al (2020) Fielding et al. (1985)
Category IV: Revenue Earned by the Route	
• Operating revenue or income	Karim and Fouad (2018) Fielding et al. (1985)
OTHER INPUT/ OUTPUT VARIABLES	
Category V: Other Variables	
• Environmental factors (including population density, parking, traffic density, number of bus-lanes, and so on) • Externalities (accidents, emissions, and so on) • Safety, Comfort, Cleanliness[$] • Compressed natural gas (CNG) vehicles/ Total fleet-size of vehicles* • Population* • Number of registered vehicles • Cost of air pollutants emitted*	Karim and Fouad (2018); Naim et.al (2020)[$] Hahn et.al. (2013)*

Table 8.1b List of Micro-Level Indicators Selected for the Present Study

INPUT INDICATORS
Category I: Geographic Characteristics of the Routes
• Route length • Number of stops per route • Stop Spacing
Category II: Quality of Service Provided by the Routes
• Scheduled travel time • Number of Trips or Frequency • Service hours • Buffer time index • Planning time index • Travel time index • Delay time
OUTPUT VARIABLES
Category I: Service Consumption
• Number of passengers or *ridership* per route
• Operating revenue/ or income

8.4.2 Data Collection

It was proposed to obtain data related to vehicle operation and passenger movement for the performance evaluation of MCTD, a subsidiary of KnSRTC. In this connection, it may be observed that MCTD implemented the ITS utilizing funds made available through the **World bank** to facilitate the monitoring of operations of bus services. The databases such as *its_myq* and *etm-data* were collected from the MCTD for the duration spanning from 17th to 24th January 2020 as part of the present study.

8.4.3 Data processing

The data for analysis was acquired from the MITRAS (Mysuru Intelligent TRAnsport System) database server maintained by MCTD and was imported to a local server using SQL (Sequential Query Language). Two types of data were acquired: the ITS data and the ETM data. The ITS database consists of the AVL database, which can be categorized as Big Data, in addition to the Simplified Data, which comprises information on buses, routes, schedules, and bus stops. The AVL database comprises information on positional data obtained through GPS for various bus trips. The ETM data comprises other information related to ticket details of passengers boarding the buses.

To assess bus performance, a thorough grasp of each aspect of the databases was required. The SQL based ITS database and the Excel-based ETM database were then sorted to meet the set of objectives. The raw data in these directories were sorted using MySQL, an open-source *relational database management system* (RDBMS). The sorted SQL database was then stored in the MySQL working directory for the present study.

The data extracted in the MySQL directory was then converted into MS Excel format to perform further analysis. The database was the further trimmed to eliminate unwanted data.

8.4.4 Selection of the Routes

In the process of selecting routes for various depots such as VJN, BMP, STG, and KVP, a strategic approach called stratified random sampling was employed. The goal was to ensure that the selected routes represented different lengths and covered the main travel directions in Mysore city.

The present study focuses on performing investigations related to performance evaluation at the micro/ route-level for selected bus-routes of MCTD, one of the important urban SRTUs in India. **Table 8.2** provides details on the selected set of 82 routes considered in this study.

CHAPTER 9

CONCLUSION

9.1 GENERAL

Bus-based public transport systems, if managed efficiently, can cater to the needs of the burgeoning population. Thus, it is essential to evaluate the existing transport systems using a reliable performance evaluation technique which can eventually help in enhancing the transit service delivery to their trusted passengers. In this connection, the present study focuses on the identification of KPIs using an MCDM approach, followed by the performance evaluation of state road transport undertakings (SRTUs) of India using the parametric *SFA* approach and non-parametric *DEA* approach. The study also focuses on evaluating the performance of SRTUs considering negative variables in the DEA approach and route level performance evaluation using DEA for a case study of Mysuru City Transport Division.

The following chapter consists of a summary of conclusions based on the results obtained in the previous chapters, major contributions, and scope for future studies.

9.2 CONCLUSION BASED ON IDENTIFICATION OF *KPIs* USING *MCDM* TECHNIQUES

The study began with the identification of 20 performance indicators from CIRT publications, deemed important for assessing the performance of *State Road Transport Undertakings* (SRTUs). These indicators were scrutinized using *Multi-Criteria Decision Making* (MCDM) techniques, including *conventional-AHP*, fu*zzy-AHP*, *conventional-TOPSIS,* and *fuzzy-TOPSIS*.

- Experts from three groups—*Transport Managers*, *Academicians*, and *Research Scholars*—provided their input via Google Forms, which was essential in assigning weights to these indicators. The ranks of indicators computed using the *conventional-AHP* & *fuzzy-AHP* methods and *Conventional TOPSIS* & *Fuzzy-TOPSIS* were compared using *Spearman's rank correlation coefficient* method with respect to the actual average ratings assigned.

- The fuzzy-AHP method emerged as particularly useful due to its capability to handle the uncertainties inherent in decision-making processes, leading to a more nuanced and reliable set of KPIs.

- The final list of nine *KPIs* with the consolidated weights are provided in **Table 4.14**. The nine indicators, including *effective km*, *passengers km*, *total revenue*, *carrying capacity km*, *total cost*, *total staff*, *fuel consumed in kiloliters*, *buses on road*, and *passengers carried* were then used in the performance evaluation.

9.3 CONCLUSION BASED ON RESULTS OF PERFORMANCE EVALUATION OF *SRTUs* BASED ON *SFA* APPROACH

The *Stochastic Frontier Analysis* (SFA) was employed to evaluate the performance of 31 SRTUs over a period from 2010 to 2017. The selection of models was guided by statistical measures such as the *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC), ensuring the robustness of the analysis.

- ***Cost Efficiency***: The model focusing on *effective km* operated, with *total cost* and *average fleet* as independent variables, highlighted that **rural SRTUs** such as those in Tamil Nadu and Gujarat were generally **more *cost-efficient***.
- ***Cost Effectiveness:*** Here, *total revenue* was the dependent variable, with *total cost* and *average fleet* as independent variables. The results showed that a **mix of rural and urban SRTUs**, including those in Maharashtra and Tamil Nadu, **performed well.**
- ***Service Effectiveness:*** The analysis used *total revenue* as the dependent variable and *effective km* as the independent variable. **Urban SRTUs** in cities like Mumbai, Delhi, and Bangalore showed **strong service effectiveness**, likely due to better infrastructure and resource allocation.
- The study found a slight **downward trend in *cost efficiency* and *cost effectiveness* scores** over the years, while ***service effectiveness* showed a noticeable improvement**, indicating better service delivery and customer satisfaction in urban areas.

9.4 CONCLUSIONS ON PERFORMANCE EVALUATION OF SRTUs USING *DEA* APPROACH

The *Data Envelopment Analysis* (DEA) was employed to evaluate the performance of 31 SRTUs over a period from 2010 to 2017 based on *cost efficiency*, *cost effectiveness*, and *service effectiveness* as given in **Table 5.5**. The selection of models was guided by statistical measures such as the *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC), ensuring the robustness of the analysis.

- ***Cost Efficiency:*** The model with *effective km operated* as the dependent variable *and total cost, staff strength,* and *average fleet operated* as the independent variables revealed that SRTUs serving rural areas had higher efficiency scores.
- ***Cost Effectiveness*****:** The model with *passenger carried* as the dependent variable and *total cost, staff strength,* and *average fleet operated* as the independent variables demonstrated that both rural and urban SRTUs could achieve high efficiency, though urban areas often had higher operational complexities.
- ***Service Effectiveness:*** The Model with *passenger carried* as the dependent variable, and *effective km and carrying capacity km covered* as the independent variable showed that urban SRTUs generally performed better in providing effective service.
- The DEA results underscored the disparity between *rural* and *urban* SRTUs, with *rural* SRTUs often excelling in *cost-related efficiencies*, while *urban* SRTUs were better in *service effectiveness*, highlighting the different challenges and strengths in these areas.

9.5 CONCLUSIONS ON *DEA* BASED PERFORMANCE EVALUATIONS OF SRTUs CONSIDERING UNDESIRABLE VARIABLES

The main focus was to demonstrate the capability of a hybrid output-oriented DEA approach in performance evaluation considering the additional influence of negative variables such as annual *carbon dioxide per passenger kilometer performed* (CO_2-PKM*)* and the *total accidents per year*. The study was performed based on data made available for the year 2004-05, 2009-10 and 2014-15 in order to evaluate performance of 25 SRTUs in India. Four models were evaluated:

- *Model 1* was formulated to evaluate the efficiency and effectiveness of transport organizations based on input variables representing the *total cost, number of employees, on-road fleet size, and output variables such as total revenue, passenger-kilometer performed,* and *effective kilometer performed*. From the analysis, it was found that the overall performance of SRTUs decreased over the years.
- *Model 2* considers the influence of negative variables, such as vehicular emissions in terms of CO_2-PKM, and total accidents, on the efficiency of the SRTUs considering sustainability and social responsibility criteria. It may be observed that no significant conclusion can be arrived at based on *model 2*.
- *Model 3* considers the influence of only CO_2-PKM, and the results indicated that the overall

performance of SRTUs remained almost stable.

- *Model 4* was formulated to evaluate the influence of *total accidents* alone, and it was observed that most SRTUs performed at par. This implies that the accident rate in most of the SRTUs is almost the same with minor variations.

9.6. CONCLUSIONS ON *DEA* BASED PERFORMANCE EVALUATIONS AT MICRO/ROUTE LEVEL – A CASE OF *MCTD* OPERATIONS

The *KPIs* to be used for the performance evaluation of *MCTD routes* were identified using the *correlation*, the *PCA*, and the RFE methods. The summary of the results is given in **section 8.8** in Chapter 8.

- **Travel Time Reliability Measures:** The *level of variability* in the efficiency scores was *moderate* across all the correlation-based DEA analyses, PCA-based DEA analyses, and RFE-based DEA analyses.
- **Service Availability Measures:** The *level of variability* in the efficiency scores was *inconsistent* across all three DEA analyses. The correlation-based DEA analysis showed a *moderate level of variability.* while, the efficiency scores varied *significantly* for the PCA-based DEA analysis, which suggests that the *level of variability* is *higher.* For the RFE-based DEA analysis, the *level of variability* in efficiency scores was *lower.*
- The **Technical Gap Ratio (TGR)** analysis further confirmed that routes with shorter distances performed slightly better in efficiency measures compared to longer routes. This could be due to the more manageable logistics and operational control in shorter routes.

9.7 LIMITATIONS AND FUTURE SCOPE OF WORK

The limitations of this study include the following:

- It is possible to perform performance evaluations separately for SRTUs serving *urban*, *rural,* and *hilly* areas. Differentiating SRTUs by these geographical areas could provide more nuanced insights into their operational challenges and performance metrics.
- The study did not explore the use of various other MCDM approaches, such as the PROMETHEE and the VIKOR, in the identification of KPIs. Also, the potential incorporation of *Artificial Neural Networks* (ANNs) for identifying frontier organizations and performing benchmarking exercises could provide slightly a

different result.

- The applications of time-series analyses can also be incorporated in order to forecast the performance of transport organizations. Incorporating time-series methodologies could help in understanding trends over time and provide a more dynamic analysis of performance metrics.
- Further temporal-based analysis could be performed for peak and off-peak traffic hours for various routes for micro/route level analysis

These limitations highlight areas for future research and the potential for more refined analyses that could offer deeper insights into the performance of public transport systems. The focus on specific methodologies and areas was a deliberate choice to align with the study's primary objectives and scope, but these acknowledged limitations provide avenues for expanding the research in subsequent studies.

9.8 MAJOR CONTRIBUTION OF THE STUDY

The major contributions of the work include the following:

- The present study enabled the identification of *key performance indicators* (KPIs) in the performance evaluation of public transport organizations with regard to *cost efficiency*, *cost effectiveness*, and *service effectiveness* using *multi-criteria decision-making* (MCDM) approaches such as the Fuzzy-AHP, and the conventional AHP, Fuzzy-TOPSIS, and the conventional TOPSIS.
- The SFA approach provided reasonable assistance in estimating the targeted increase in output required to be implemented in order to achieve higher efficiencies. Parametric approaches are suitable in studies where measurement errors are more or for missing datasets. The use of the *maximum likelihood estimation* (MLE) method in the test for reliability of the independent variables as part of the SFA analysis also provided information on the overall suitability of the models used.
- DEA, a non-parametric technique, was found to be effective in providing the relative efficiency of different organizations considering multiple inputs and output variables for the period of study. The provision for analysis using slack variables in DEA provides better capabilities to transport managers in improving operational efficiency. The results of the study can be interesting for policy-makers and transport company managers.
- The present study also demonstrates the capability of a hybrid output-oriented DEA

approach developed by **Seiford and Zhu (2002)** approach in performance evaluation considering the additional influence of negative variables such as annual CO_2-PKM, and the total accidents per year that address safety and environmental concerns related to sustainability.

- The present study provided the framework for the identification of *key performance indicators* (KPIs) at the sub-system/micro/router level based on analysis using the correlation method, the PCA method, and the RFE method.
- DEA can be effectively adopted in the analysis of various routes as part of micro-level analysis. The DEA analysis was also performed for three subgroups of routes classified based on route length. The tests using the TGR permitted a cross-sectional analysis of the performance of routes based on the route length.

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BOOK-CHAPTER

3. Kumar, Praveen., George, Varghese., and Mulangi, Raviraj H. (2022) *Exploring the Application of Data Envelopment Analysis in the Evaluation of Public Transport Organizations*, in Nandagiri, et al. (Eds.) **Lecture Notes on Civil Engineering: Sustainability Trends in Civil Engineering**, Vol.99, Compiled based on Select Proc. Intl. Conf. CTCS 2020 (Intl. Conf. on Civil Engineering Trends and Challenges for Sustainability), as part of Intl. Conf. on Emerging Trends in Engineering (ICETE) Org. by NMAM Institute of Technology, Karkala, held at Nitte, India, 22-23 Dec 2020. Pub. Springer Nature, Singapore, ISBN 978-981-16-2825-2, Scopus Indexed. Cover: https://www.springer.com/in/book/9789811628252