STUDY ON THE FACTORS GOVERNING THE TRAVEL TIME RELIABILITY OF PUBLIC BUS TRANSPORT SYSTEM

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

By

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DECLARATION

I hereby *declare* that the Research Thesis entitled "Study on the Factors Governing the Travel Time Reliability of Public Bus Transport System" which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy in 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

This is to certify that the Research Thesis entitled "Study on the Factors Governing the Travel Time Reliability of Public Bus Transport System" submitted by Harsha M M (Register Number: 177001CV004) as the record of the research work carried out by him, is accepted as the *Research Thesis submission* in partial fulfillment of the requirements for the award of degree of Doctor of philosophy.

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I dedicate this thesis to my Amma

ABSTRACT

Travel time reliability is the key aspect that indicates the quality of urban public transit service. The reliability is the most preferred parameter by the passengers to decide whether or not to choose the public transit mode of transport. Several factors can affect travel time reliability of the public transit system and it is necessary to understand the impact of these factors on travel time reliability of public transit system. Hence, the present research work aims to study the factors governing travel time reliability of the public bus transport system. Mysore is one of the largest cities in Karnataka state whose transit system has been considered in the present research work, since it generates the Automatic Vehicle Location (AVL) data through the Intelligent Transport System (ITS) infrastructure for public transit. Data collected for the research work comprises of AVL data from Mysore ITS and side friction data collected from study sections using videography method. Mysore city transit vehicles are equipped with the GPS units which provide the Automatic Vehicle Location (AVL) and other trip details of the respective buses. This AVL data has been used to extract travel time of bus routes and segments. The field data extracted from videography includes, side friction elements, traffic volume, and travel time of public bus transit at two different road sections (divided and undivided) during weekdays and weekends. This data is utilised in studying the impact of side friction on travel time reliability of the public transit system.

Roadside friction is one of the critical factors which hinders the movement of traffic. The impact of different types of friction elements on travel time depends on their static and dynamic characteristics, as well as the position of friction elements on the carriageway. The data collected at two side friction locations of Mysore city has been used to analyse the impact of side friction on travel time reliability of public transit system. The data have been categorized as static and dynamic side frictions. An approach has been proposed to represent different types of side friction elements with a single index called Side Friction Index (SFI) using relative weight analysis. Travel time reliability is represented using measures such as Buffer Time Index (BTI), Planning Time Index (PTI), Travel Time Index (TTI) and Reliable Buffer Index (RBI). The impact of side friction on travel time reliability was found to be sensitive to traffic volume, and hence the thresholds for different traffic volume levels have been

determined using K-means clustering method. The impact of side friction on reliability measures at different traffic volume levels has been studied and found to have a non-linear (exponential) relationship. The impact of SFI has been observed to be higher on TTI and PTI in comparison with BTI. The outcomes from this study show that the impact of side friction on TTI and PTI is sensitive to traffic volume, especially at higher traffic volume level and impact of side friction on BTI is least at medium traffic volume level. The inference from this research work shows that the impact of side friction elements varies with respect to the type of road (divided and undivided), traffic volume levels, different days of week (weekday and weekend), and different time periods of day.

Travel time variability (TTV) plays a significant role in analysing the reliability of the public transit system. Therefore, this study attempts to analyse travel time variability of the public transit system with the help of AVL data of buses collected from the Mysore ITS. The travel time data are analysed at different temporal aggregation levels corresponding to different Departure Time Windows for peak and off-peak periods. Travel time variability is also influenced by the presence of intersections, bus stops and other geometric and traffic characteristics. Hence, the segment level analysis has been carried out taking into consider the presence of bus stops, intersections and land-use type. AVL data collected from Mysore ITS are used to evaluate travel time distributions with respect to temporal aggregations (peak period, off-peak period, 60 minutes, 30 minutes and 15 minutes) and spatial aggregations (route level and segment level). The distribution fitting process has been carried out using EasyFit software, which estimates the distribution parameters using maximum likelihood estimation (MLE) method. The Kolmogorov-Smirnov (KS) test for goodness of fit has been used to evaluate the fitting of each distribution. The performance of each selected distribution has been evaluated in terms of accuracy and robustness. The results of both route and segment level analysis show that the Generalised Extreme Value (GEV) distribution is superior in describing travel time variability of public transit. The accuracy and robustness of GEV distribution are higher than that of other distributions and also the performance of GEV distribution in the case of signalised intersections and land use type shows the fitting ability and versatility of GEV distribution. Hence, GEV

distribution has been considered as the descriptor of travel time variability of the public transit system. Travel time reliability measures, TTI, PTI and BTI of four bus routes are determined using GEV distribution and reliability of these routes have been evaluated. The reliability measures of the study routes indicate that the reliability of public transit is lower during peak hours.

Understanding the factors causing unreliability of the public transit system is necessary for the improvement of system's reliability. In this study, the reliability of the system has been modelled considering three travel time reliability measures. The Multiple Linear Regression (MLR) method has been adopted to model the three travel time reliability measures (Average Travel Time (ATT), Planning Time (PT) and Buffer Time (BT)) as the dependent variables and independent variables selected are corresponding to five important factors affecting the measures related to travel time: segment length, bus stops, intersections, land-use and peak/off-peak time period. The results of this study show that length of the segment has a higher impact on all the three reliability measures. The average delay has a higher standardised coefficient value than standard deviation (SD) of delay in the case of ATT and PT. In BT model, SD of delay is more than average delay, which shows that variation in bus stop delay leads to a higher buffer time. The presence of intersection in the segments and Central Business District (CBD)/commercial land-use segments are found to have lesser travel time reliability. Level of service (LOS) is a quantitative stratification of a performance measure or a measure that represents the quality of service. The LOS of bus routes are determined based on travel time reliability such as TTI, PTI and BTI. K-means clustering method has been applied to the segment level travel time data of four bus routes to determine LOS thresholds. Initially, globally accepted six clusters for LOS (A to F) have been considered and cluster validation has been conducted using silhouette analysis. The results of cluster validation show that clusters have reasonable structures and six clusters can be used to determine the LOS thresholds based on these reliability measures. Finally, recommendations have been put forward based on the outcomes of the research work to improve the reliability of the public transit system.

Keywords: Travel time reliability, Public transit system, Intelligent Transport System (ITS), Roadside frictions, Travel time distributions.

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LIST OF ABBREVIATIONS

APC	Automatic Passenger Count
ATT	Average Travel Time
AVL	Automatic Vehicle Location
BRTS	Bus Rapid Transit System
BT	Buffer Time
BTI	Buffer Time Index
CBD	Central Business District
COV	Coefficient of Variation
DTW	Departure Time Windows
GEV	Generalised Extreme Value
GIS	Geographic Information System
GMM	Gaussian Mixture Model
GPS	Global Positioning System
HCM	Highway Capacity Manual
ITS	Intelligent Transportation System
KS	Kolmogorov Smirnov
KSRTC	Karnataka State Road Transport Corporation
LCV	Light Commercial Vehicle
LOS	Level of Service
MLR	Multiple Linear Regression
MUDA	Mysore Urban Development Authority
PT	Planning Time
PTI	Planning Time Index
RBI	Reliable Buffer Index
RCI	Recurrent Congestion Index
SD	Standard Deviation
SFI	Side Friction Index
SQL	Sequential Query Language
TSP	Transit Signal Priority

TT	Travel Time
TTI	Travel Time Index
TTR	Travel Time Reliability
TTV	Travel Time Variability
VMU	Vehicle Mounted Unit

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Transportation system is one of the essential components involved in the development of a civilization. Among different types of transportation modes, road transport is the most common one, providing door to door service. Road transport system in developing economies like India is composed of different vehicle categories such as, car, three-wheeler, two-wheeler, light commercial vehicle (LCV), bus, heavy vehicle etc. All these vehicles are sharing the same roadway space, except in the case of dedicated lanes.

Urbanisation has become a vital part of the growth of Indian economy. More and more agglomeration of people in urban places has led to rapid growth in the urbanization. Figure 1.1 (Planning Commission, Government of India) shows that around 31.14% of the total population of India are living in urban areas. There is steady growth in the proportion of urban population to total population in India and the proportion of urban population is expected to reach 37% of the total population in 2021 (Statistical Year Book India 2018). The other significant factors in the Indian economy, influencing the road transport system are, automobile manufacturing industries and vehicle ownership. The data regarding vehicle numbers in India are collected from MORTH Annual Report- 2017. Figure 1.2 depicts the variation in vehicle population from the year 1951 to 2015. The vehicle population has increased from 0.3 million (1951) to 210 million (2015). A drastic change in vehicle ownership can be observed, starting from 2001. From the year 2001, the private vehicles have been increasing at an average growth rate higher than 9%. In 2015, the vehicle population in India has reached 210 million and the vehicle composition of past years from 1951 to 2015 is as shown in Figure 1.3 (MORTH Annual Report, 2017). The vehicle population of 2 wheelers is more than 70% in 2015 and the next highest proportion is of cars, jeeps and taxis. The increase in vehicle population along with inadequate road infrastructure in urban areas of India is the major cause behind traffic congestion (Chakrabartty and Gupta 2014). Traffic congestion in Indian cities can be considered as an economical as well as a social impediment. As mentioned above, inadequate infrastructure and private vehicle ownership are the major factors contributing greatly to traffic congestion in urban areas. Providing adequate infrastructure is not a better solution as the availability of space in urban areas for the expansion of roads is very less. One of the significant alternative solutions for combating traffic congestion is to promote the utilisation of public transportation in place of private vehicles, which also helps in the reduction of environmental pollution, increase in fuel efficiency and health benefits. Hence it is imperative that the urban public transit agencies must concentrate on sustainable transport systems to increase the modal share of public transport.

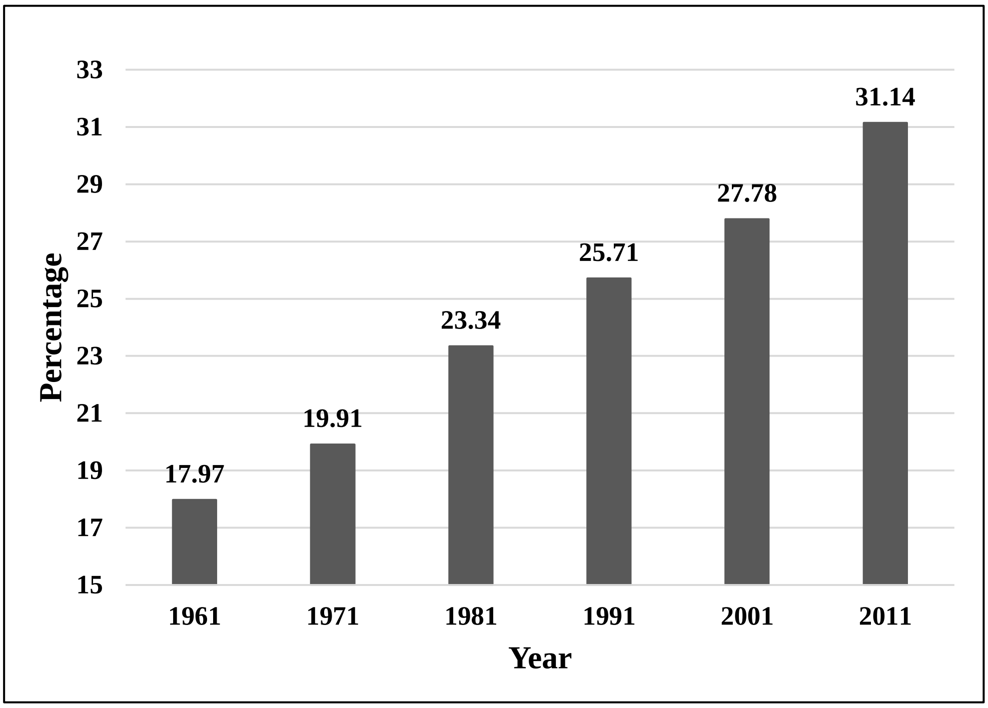


Figure 1.1. Proportion of Urban Population to Total Population (Planning Commission, Govt of India)

1.2 PUBLIC TRANSPORT SYSTEM

Public transportation system comprises of different kinds of facilities such as metro, suburban trains, monorails, bus transit system, etc. Among them, bus transit system is considered as the most economical and preferable public transit system in terms of connectivity between the origin and destination of the commuters and economical perspective. Other public transit systems like metro, monorail and suburban trains require more infrastructure and financial aid. The public transportation modal share of major cities of India is shown in Figure 1.4. Mumbai city has the highest usage of public transportation fallowed by Delhi, Bangalore and Chennai. In the case of bus transit system existing road space can be utilised by implementing the latest electronics, communication and information technologies and upgrading the existing road infrastructure. Bus public transit system has the share of almost 90% in the public transit systems of the Indian cities (Priyanka and Pawan 2014). Therefore, bus public transit system could be considered as one of the potential solutions in reducing urban traffic congestion.

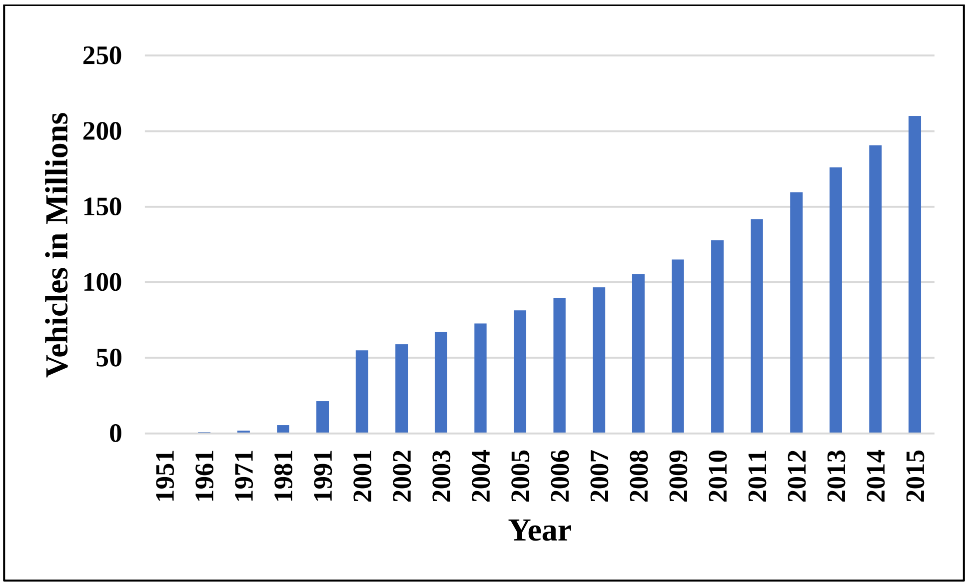


Figure 1.2. Vehicle Population in Past Years (Annual Report, MORTH, 2017)

(Note: From now onwards, the term "public transit system" has been used in place of "bus public transit system" in the following sections of the thesis)

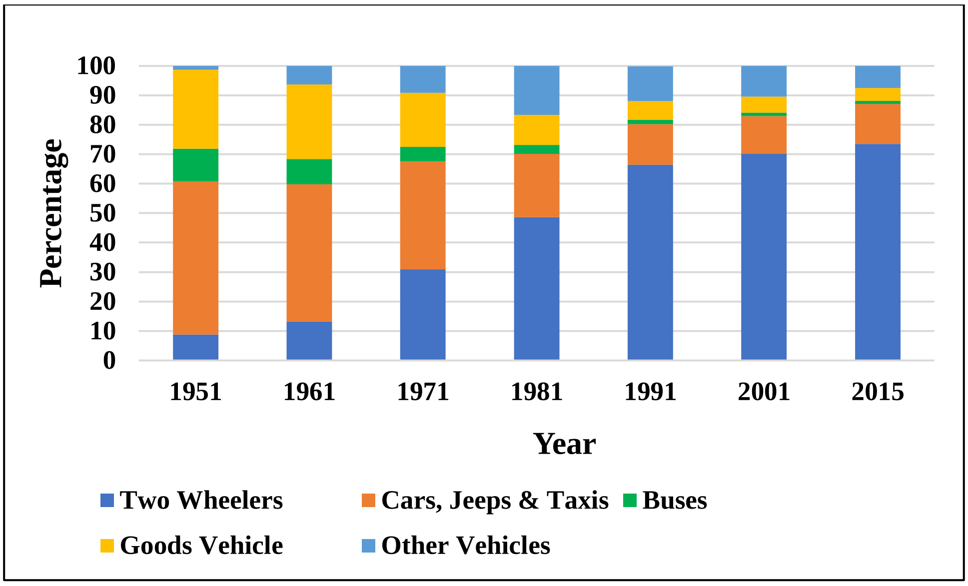


Figure 1.3. Vehicle Composition in Past Years (Annual Report, MORTH, 2017)

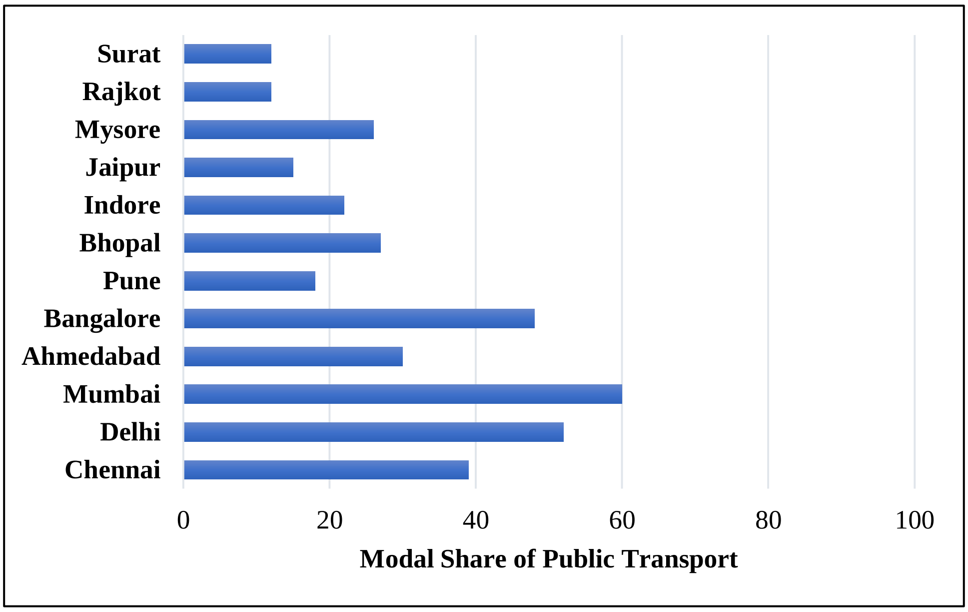


Figure 1.4 Modal Share of Public Transport (Pai, M. 2010)

The performance of the public transit system is very important as it influences the modal share. The performance of the system depends on reliability of service provided by the transit agencies, which influences the attractiveness of service, operating costs and overall efficiency of the system. Transit agencies have put substantial effort in incorporating the advanced technologies which can improve the service reliability. In recent years, some of the urban transit agencies in India have shown interest in implementing strategies regarding advanced technologies like, Bus Rapid Transit System (BRTS), Intelligent Transportation System (ITS), Bus Feeder System, etc. The concept of BRTS evolved with a view to provide separate lanes for buses for unobstructed movement. The implementation of BRTS started in India in 2005 supported by the JNNURM scheme. BRTS was first implemented during 2006, in two cities of Maharashtra, Pune and Pimpri-Chinchwad, and was known as Rainbow BRTS. At present, BRTS is operating in 14 cities of India and in 9 cities it is at the planning stage. The BRTS in Bhopal city is the largest one in India, where as the Ahmedabad BRTS is known to be the best BRTS with a global recognition. The implementation of these advanced technologies all over the country are in rapid progress under the Smart City projects. In 2015, Prime Minister Narendra Modi launched the 100 Smart Cities Mission in India ("Prime Minister launches Smart Cities, AMRUT, Urban Housing Missions", Press Information Bureau, 25 June 2015), with a budget allocation of ₹98,000 crore approved by the cabinet. The Ministry of Urban Development (MoUD) presented a smart city challenge for the selection of the cities for the area-based development under the smart city mission. The cities were evaluated based on the competition between cities at state level and states at national level challenge. The mission also had an alliance with the other programs introduced by the Indian government such as, Digital India, Heritage City Development and Augmentation Yojana (HRIDAY), Atal Mission for Rejuvenation and Urban Transformation (AMRUT), Make in India, skill development, Swachh Bharat Mission, etc., including the infrastructure of the development of education, health and culture. The idea of smart city is comprised of an urban area with advanced and sustainable infrastructure, communication systems and commercial feasibility. The integration of well-connected public transit systems is one of the major features of smart cities. The smart city programs are conceptualized with the development of public transit systems that promote the different modal choices among the travellers and thus ensuring efficient mobility in urban areas.

Studies on traveller’s response show that the travellers usually give more importance to the decrease in reliability than the increase in average travel time (Lam and Small, 2001). Schedule constraints in public transit systems demands the passengers to adjust their departure timings, which makes the concept of reliability a more important aspect for public transit systems than in case of private vehicles (Bates et al. 2001). Enhancing the reliability of the transit system is the need of the hour for both passengers and the transit agency. An unreliable transit route may struggle to attract potential ridership and face depletion in financial support over the time. The increase in unreliability affects the perceived waiting time of passengers and ultimately impacts on the modal choice decisions of passengers and operating cost of the system, which further increase the traffic congestion, fuel consumption, emission and travellers' dependency on private vehicles. For the transit scheduling team, transit travel time is more important since, increase in travel time variation leads to the addition of layover time or slack time to the existing transit schedules.

1.3 RELIABILITY OF THE SYSTEM

The reliability of any system is the probability of service provided by it in performing an appropriate function under a given condition for a specific time span (hourly, daily, monthly or yearly). The function of the system reliability can be analysed in terms of capacity reliability (Chen et al. 2002), connectivity reliability (Bell and Iida 1997), service reliability (Leong et al. 2016) or travel time reliability (Ng and Waller 2010). The impact of reliability on the efficiency of the system gives rise to the need for the study of reliability measures to identify and develop the consistent reliability measures. These measures are useful in identifying and measuring the causes of unreliability and in proposing suitable recommendation strategies to increase the reliability of the system. In previous studies, reliability has been addressed in different ways such as, on-time performance (Nakanishi 1997; Kittelson & Associates et al. 2003; Camus et al. 2005), travel time variability and reliability (Kaparias et al. 2008); waiting time (Trompet et al. 2011), and few researchers have made use of integrated measures considering different service attributes.

1.3.1 Travel Time Variability (TTV)

Travel time variability can be considered as the measure of performance, as it reflects the reliability of travel time. The reduction in travel time variability is more valued by the passengers since, it decreases the anxiety and stress due to unreliability and also it reduces the uncertainty in taking decisions regarding departure time and route choice (Bates et al. 2001; Van Oort 2011). Travel time distributions characterise the pattern and nature of travel time variability. Studies on travel time distribution have been done previously with travel time data of traffic and public transit data. The normal distribution (Ma et al. 2016) can be used to characterise the travel time but, some researches showed that the travel time data is positively skewed (Richardson and Taylor 1978) and may follow lognormal distribution which is mostly used in traffic studies (Clark and Watling 2005; Sumalee et al. 2006; Hollander and Liu 2008). Other distributions reported in the literatures include, gamma (Polus 1979), log-logistic (Chu 2010), Burr (Susilawati et al. 2013), Weibull (Al-Deek and Emam 2006) and some advanced distributions like Gaussian Mixture Model (GMM) model (Ma et al. 2016). Even though there is significant research conducted previously on travel time distribution, the outcomes of these studies are not consistent. A research work carried out in Indian conditions suggests Generalised Extreme Value (GEV) distributions (Chepuri et al. 2018b) better describes the travel time data. The results of these studies are mainly based on the evaluation approaches and data sets utilised. The data set refers to quantity (different seasons), type (method of data collection) and other factors. The evaluation approach also affects the outcome of the study such as temporal and spatial aggregation of travel time data. The other characteristics such as, passenger demand, passenger behaviour and transit driver behaviour are unique in India compared to other heterogeneous traffic systems like in China. Hence, this study is focussed on analysing the travel time distributions with different temporal and spatial aggregations of travel time for Indian conditions.

1.3.2 Travel Time Reliability (TTR)

Travel time reliability can be measured by the metrics generated using travel time distribution (Figure 1.5) and these measures have a good technical background, with a simple meaning to understand. Travel time during the days facing high delays is compared with average delays to measure the TTR. The important measures which have been recommended for TTR (Federal Highway Administration 2006) are: 90^{th} or 95^{th} percentile travel time, Planning time/Planning time index, Buffer time/Buffer time index, and Travel time index. Travel time reliability can also be explained using travel time variability measures like coefficient of variation and standard deviation. These measures are difficult to understand by a daily commuter and difficult to correlate them to the daily commuting experience.

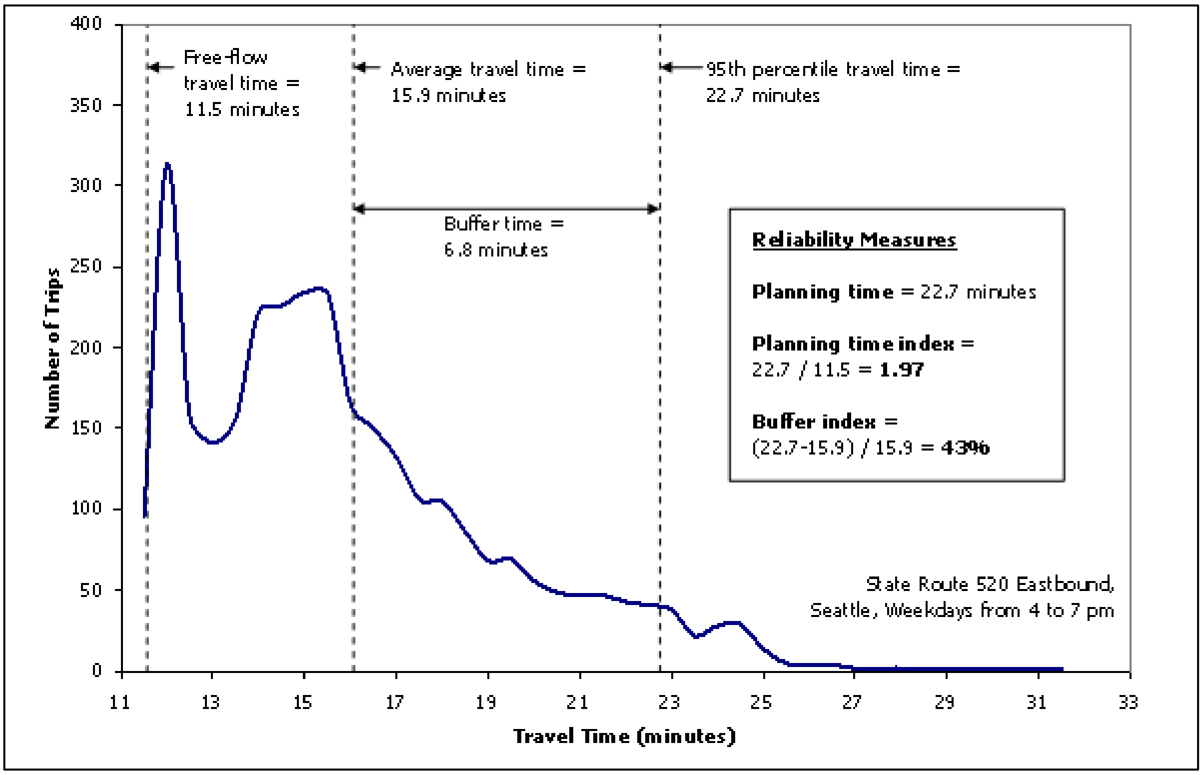


Figure 1.5. Frequency Distribution Curve (FHWA, 2006)

1.3.3 Factors Affecting Travel Time Reliability

There are various forms of sources, which induce variability in travel time and they are grouped into following categories (Kwon et al. 2011),

- Traffic incidents: Traffic incidents are nothing but the events occurring on the roads such as crashes and other unplanned incidents, which cause obstructions to the flow of traffic. These incidents give rise to the variability in travel time.
- Work zone activity: Sometimes there are chances of construction works taking place on a part of the roadway. These repair and maintenance works result in the reduction of actual width of roadway and becomes a source of producing factors affecting the travel time variability.
- Weather: The vehicular speed is affected by the changes and adverseness in weather conditions such as rain, fog, smog, snowfall, etc. Hence, these changes in environmental conditions, become one of the causes of time delays.
- Fluctuations in demand: It is well known that the traffic demand will not be constant and it varies from day-to-day, monthly and seasonally. When this variability becomes higher and not managed properly, it induces travel time variability.
- Special events: Events such as rallies, strikes and festivals cause changes in the traffic demand as well as act as temporary blockages of roadways. The changes occurred due to those special reasons can also be the cause of travel time variability.
- Traffic-control devices: Controlling devices like poorly timed signals and railroad grade crossings leads to disruption of traffic flow and thus creates variability in travel times.
- Inadequate base capacity: Roadways are designed to accommodate certain capacity. Many a times, it is not possible to achieve this designed capacity, due to factors such as, inadequate shoulder width, on-street parking, movement of pedestrians on the roadway, presence of street vendors, curbside bus stops, etc. This reduction in capacity of roadway infrastructure induces variation in travel time.

From the sources mentioned above, the recurring events such as fluctuations in traffic demand, the effect of traffic control devices and inadequate base capacity of roadways were observed to have impact on the travel time variability of public transit especially in Indian conditions of traffic flow (Chandra et al. 2017). Fluctuation in traffic demand refers to the variation in traffic flow with time. For example, number of vehicles moving on a road stretch is higher during peak hours than the other times of the day. Similarly, the traffic flow during weekends might be lesser than that on weekdays. Travel time variation is also the result of such variations in the flow of traffic.

Traffic control devices such as traffic signals at intersections are also the major sources of travel time variability. In India, most of the traffic signals have fixed time durations of red, green and amber timings. At an intersection where the arrival rate of vehicles is not always similar to the one for which the signal was designed, the vehicles may experience unnecessary delays. Along with delay, there is a variability in delays experienced by the traffic which leads to travel time variation. The base capacity of roadway decreases due to several factors such as, inadequate shoulder width, on-street parking, movement of pedestrians on the roadway, presence of street vendors work zone activity, etc. Most of these factors can be grouped together and collectively called as road side frictions. Capacity reduction due to the effect of these side friction elements is not constant and the interactions between these elements with traffic leads to travel time variation.

At bus stops, the boarding and alighting of passengers from public transit takes place. The movement of passengers varies according to variation in passenger demand of that route. Also, the time taken by the passengers to alight or board the bus varies based on factors such as age of the passenger, density of passengers inside and outside the bus, and physical characteristics of the bus (number of doors, width of the door, height of the footboard, etc.) (Currie et al. 2012). The time of stoppage of buses at bus stops, known as dwell time, varies due to the above-mentioned factors. This variability in dwell time of public transit creates variation in travel time.

1.4 LEVEL OF SERVICE

Level of service (LOS) is the measure of service quality offered by systems such as highways using the quantitative categorization of performance measures describing that system. The concept of LOS was first introduced in the highway capacity manual (HCM) in 1965 (Charles et al. 1965). Six levels of service, ranging from A to F have been defined by the HCM for measuring the service offered by the road. Average travel speed, density at highways, percentage of time spent following, are some of the service measures describing the LOS according to the HCM (HCM 2010). None of these measures can capture travel time variability. But the LOS of a roadway, the delay experienced by the commuters and the travel time on that road are interrelated factors and the traffic conditions can be illustrated better, when they are associated with each other. The use of TTR in the evaluation of performance of road network with varying travel demand has not been fully explored for its suitability in mixed traffic conditions like in India, even though the concept is briefly discussed in the Indo HCM (Bharti et al. 2018; Chandra et al. 2017; Chepuri et al. 2018a; Chepuri et al. 2018b). Detailed research needs to be conducted, especially in Indian traffic conditions, to understand the concept of TTR in measuring the quality of service offered by the transportation system.

1.5 NEED FOR THE STUDY

The expeditious growth in urbanisation has increased the transportation demand, especially in the case of road transport, which is causing a substantial increase in vehicle population on urban roads of India. The inadequate and improper road infrastructure and increase in vehicular population are the major components leading to increase in traffic volume, road side friction due to pedestrian movements, road side vendors, on-street parking, etc., The increase in traffic volume demands a greater road capacity but, the presence of side frictions and inadequate road width, decrease in the road capacity, which are the primary elements in creating congestion problems. The speed of vehicles reduces due to congestion on urban roads which in turn gives rise to the delay for both public transit and other vehicles and thereby increases the travel time. Some of the delays most frequently faced by the public transit vehicles are the delays at bus stops and intersections. The amount of delay and its variability caused by road side frictions, variation in delay due to congestion, passenger demand at bus stops and intersections, are responsible for the reduction in attractiveness of public transit. In other words, the reliability of the public transit declines, which influences the modal share of the public transit by shifting from public transit to other modes and results in more number of private vehicles moving on the road. This process continues and builds a complex chain like formation called vicious cycle. Hence, modal share of public transit system can be boosted by increasing the reliability of this system. This can be achieved by analysing the factors affecting the reliability of public transit such as side friction, delay variability of public transit vehicles at the intersection and bus stop, etc., and implementing the measures suggested by outcomes of such analysis.

1.6 OBJECTIVES OF THE STUDY

The main aim of the present research is to study the factors governing travel time reliability of the public bus transport system.

To achieve the main aim of the study, four specific objectives have been formulated,

- To determine the impact of road side frictions on the travel time of public bus transport system.
- To analyse the effect of temporal and spatial aggregation of travel time on the travel time variability of public transit.
- To analyse the factors affecting travel time reliability of public transit.
- To determine the LOS of bus routes based on travel time reliability.

1.7 SCOPE OF THE STUDY

The scope of the research work is to study travel time reliability of public transit systems for Indian traffic conditions utilising the travel time data of Mysore ITS. The Mysore city transit has adopted ITS infrastructure in 2012. This includes the system providing the real time information to passengers about public transit trips collected by GPS units installed in buses. Hence, Mysore city transit has been considered as the case study in this research work. The reliability of a system is a significant measure in evaluating the performance of the system. In the public transit systems, reliability is the most preferred parameter by the passengers to decide whether or not to choose the public transit mode of transport. Further, there are several factors which impact TTR of public transit systems. The most important factors among them were found to be: travel time variability, traffic characteristics, road side frictions, land use characteristics, bus stops, intersections, etc. Travel time variability is the basic parameter to evaluate the TTR. Statistical distributions are used to explain the travel time variability better (Sumalee et al. 2013). Literature suggests that the travel time variability will not follow the same distribution at all the conditions and it varies with the temporal and spatial conditions. Therefore, travel time data of four bus routes are analysed using statistical distributions in route and segment levels. Automatic Vehicle Location (AVL) data of Mysore ITS pertaining to four bus routes have been analysed in this study. The performance of each distribution is analysed to understand the efficiency of these distributions in explaining the travel time variability. Since road side friction activities have their impact on TTR, the data from two urban roads of Mysore city have been analysed to determine the impact of side friction activities on TTR of public transit system. Two road sections of length 100 m are selected for the side friction study, which are free from the effect of bus stop and intersections. The other common factors affecting TTR of public transit system are investigated using segment level travel time data, data related to length of each segment, bus stop delay, intersections, land-use and peak hours. The service offered by the transport system is very important in attracting the road users towards public transit system. Therefore, the present research work has a significant scope in determining LOS of bus routes based on travel time reliability. The study makes use of segment level travel time data to determine LOS thresholds with respect to different TTR measures.

1.8 ORGANIZATION OF THE THESIS

The thesis is composed of six chapters and the organisation of the thesis are briefly explained as below,

Chapter 1 consists of introduction to the present study including the importance of public transport system and its reliability. It also provides explanation on the travel time variability, travel time reliability, factors affecting travel time reliability and concept of Level of Service (LOS). The major objective of the study, the scope of the study and major contributions of the research work have been stated in this chapter.

Chapter 2 provides the review of literatures relevant to previous research works on the concept of travel time variability and reliability. The chapter also reviews the literature related to road side friction, TTR modelling and level of service based on the reliability concept. The summary of the literature and the research gaps identified have been presented in this chapter.

Chapter 3 consists of the details regarding the study area which is Mysore city in Karnataka, India equipped with intelligent city transit system. The description of the study area in terms of major trip attractions, road network, land use and traffic states has been provided. The details regarding the components of Mysore ITS are also discussed in this chapter.

Chapter 4 describes the step-by-step process involved in data collection and processing in the present study. The travel time data collected from the Mysore ITS and side friction data collected from the videography method have been discussed in this chapter. The chapter presents the detailed methodology and framework developed to achieve the objectives of the study. The research methodology adopted to study the impact of side friction on TTR, modelling travel time variability of the public transit system using probability distributions, modelling of factors affecting TTR of public transit and level of service based on TTR have been described in this chapter

Chapter 5 discusses the results obtained from the analysis carried out to achieve the objectives of the study. The results of the study of impact of side friction on TTR of the study are discussed. The detailed discussion of the results of modelling travel time variability considering spatial and temporal aggregation are provided. Finally, the results of modelling of TTR and Level of Service have been presented and discussed in this chapter.

Chapter 6 concludes the thesis based on the results obtained along with the summary of the research work. The significant findings of the study of impact of side friction on TTR, travel time variability analysis, TTR modelling and LOS have been summarized. The recommendations based on the outcomes of the present study and the scope for further work are also stated in the chapter.

1.9 MAJOR CONTRIBUTIONS OF THE RESEARCH WORK

The primary objective of this study is to analyse the factors governing travel time reliability of public bus transit system. A comprehensive literature survey has been conducted to identify the factors affecting TTR of public transit system especially in Indian traffic condition. The impact of different factors on TTR of public transit system are analysed. The travel time variability of public transit system is studied and modelled using travel time distributions, with respect to different temporal and spatial aggregations. Finally, LOS of urban bus routes are determined based on TTR measures. The major contributions of the research work are,

- An effective method for quantifying the different side friction elements is presented. This methodology considers both static and dynamic characteristics of side friction elements and these elements are quantitatively represented by an index known as Side Friction Index (SFI).
- The traffic volume levels are determined using K-Means clustering and the impact of side friction on TTR are analysed with respect to each of the traffic volume levels.
- Daily variations of public transit travel time have been analysed using probability distributions and their performance has been evaluated at both route level and segment level. The impact of temporal aggregation on the descriptive statistics of travel time distribution has been analysed by aggregating the data into 15 min, 30 min, hourly and peak/off-peak periods. The spatial aggregation has been done by considering direction of movement, route level and segment level (based on the intermediate bus stops). The performance of seven distributions is evaluated with respect to the above-mentioned spatial aggregations.
- The segments with signalised intersections and different land-use types are analysed separately to evaluate the adaptability of each distribution. The performance of each distribution has been evaluated in terms of accuracy and robustness, which shows the fitting ability and versatility of the distributions.
- Travel time of four bus routes of Mysore city have been utilised for the determination of LOS of transit routes based on TTR measures. K-Means clustering method has been adopted to develop six levels of LOS based on TTR measures.

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

In this chapter, the review of existing literature related to TTV, TTR, road side friction, TTR modelling, concept of TTR in defining the LOS have been presented in separate sections. The limitations and gaps in the previous studies are explained at the end of the chapter.

2.1.1 Travel Time Variability

Travel time variability (TTV) is very significant in analysing the reliability of the public transit system. The quantification of the reliability of public transit system is usually done with the travel time as the reliability measure. Travel time distributions characterise the pattern and nature of travel time variability. Better understanding of the travel time distribution is imperative in the analysis of TTR and examining the causes for unreliability of public transit system (Sumalee et al. 2013). Travel time distribution is considered as a significant input in the discrete choice models, microsimulation of the transit system, time table design and travel time predictions (Mazloumi et al. 2010). Understanding of TTV helps the operators of public transit in optimising the cost and performance during routing and scheduling of buses, by defining an optimal slack time (Kimpel et al. 2004). The existing studies related TTV are reviewed in this section.

Taylor (1982) analysed the TTV of two public transit modes, i.e., bus and underground metro. The data of travel time were collected from the observers moving in transit for a period of fifteen days. The study validated the relationship between degree of variability and level of congestion (travel speed) in the network.

Fu and Hellinga (2000) studied the delay variability at signalised intersections. Randomly distributed vehicle arrivals and the vehicle headway were simulated following negative exponential distribution with a minimum headway of one second, to obtain the data for the study. The delay variability has been calibrated based on the uniform and overflow delay components. Calibrated delay was used for quantifying the level of service at the signalised intersection.

Study on travel time variability and its causes was conducted by **Li et al. (2006)**. The study utilised the automatic vehicle identification data collected on a 14 km study stretch in October 2003. In this study, investigations on travel time distributions were carried out with different time windows. The three types of variability such as Vehicle to vehicle variability, supply related variability and capacity related variability has been analysed. Multiple linear regression was considered to understand the effect of day to day variation, within day variation, weather conditions and incident occurrence on the travel time variability by using morning and afternoon peak data. The results show that as the time window reduced, the travel time distributions tends towards normal distribution. Vehicle to vehicle variability is contributing 50% in explaining the off peak and morning variability. Demand is contributing more in the morning peak and factors like weather and incident have major contribution in the afternoon peak variability.

Mazloumi et al. (2010) carried out a study on travel time variability of public transit of GPS data of the 27 km circumferential route. Different travel time distributions were analysed in different Departure Time Windows (DTWs). The linear regression technique was used to analyse the factors affecting the TTV. The travel time distribution tends towards normal distribution for shorter DTWs as per the observations from this study. For longer DTWs, normal distribution is appropriate for peak condition and lognormal is more suitable for off-peak conditions.

A study on characterization of travel time variability in the networks was carried out by **Mahmassani et al. (2012)**. The simulation data and real data sample were used for calibration and validation respectively. In this study, the relationship between mean travel time per unit length and standard deviation of travel time per mile has been tested with multilevel or multidimensional approach considering four levels, i.e., origin-destination, network, link and path. The model was calibrated and validated with sample real world data. This study shows that the standard deviation of travel time per mile is representative statistic for the TTV. A linear relationship has been achieved between these parameters.

Susilawati et al. (2013) made use of GPS data of buses (as probe vehicles) for two routes with 180 runs and 67 runs respectively. The maximum likelihood estimation method and Kolmogorov-Smirnov (KS) test were used in this study to investigate the travel time distributions of route level and link level. The outcome of this study suggests that lognormal, Weibull and Gamma distributions are not able to fully represent the data and Burr distribution is significant with respect to performance, mathematical tractability and flexibility.

Kieu et al. (2014) made use of one-year AVL data of public transit in Brisbane to identify the distribution of travel time. The seven-step approach has been proposed to identify the travel time distribution and Hartigan Dip test has been incorporated to check the bimodality of travel time distributions. The results show that lognormal distribution can be considered as the descriptor for the daily TTV.

Feng et al. (2015) studied the combined effects of traffic conditions, location of bus stops, signalised intersections on bus travel time and its quantification. The data used for the study was collected from March to May at a study stretch in Portland. The study location consists of length 4 miles with average headway of 15 minutes in a mid-day and 6-7 minutes in the morning. The study stretch contains 12 signalised intersections (120sec cycle length) and 22 bus stops with 21 stop to stop segments. Linear regression technique along with elimination method was used to find out the effects of individual variable. The results show that travel distance, skipping a stop and red delay have more impact on the TTV.

Ma et al. (2016) analysed the influence of spatial and temporal aggregation of travel time on components of travel time and also evaluated the performance of other distribution models using Anderson–Darling (AD) test. Results show that the Gaussian Mixture Model (GMM) model is superior to other models with 95% results having AD value more than 0.7, with respect to robustness, accuracy and explanatory power.

Ma et al. (2017a) carried out a study on characterization of trip level pace variability using GPS data of taxis. The study includes 8 periods of data from 2013 to 2015 having 7-day GPS data of 5131 zones. The two new models with time and distance corrected pace variable (TCPV and DCPV) have been introduced to overcome the heteroscedasticity in the linear regression. These models along with the ordinary linear model have been tested for the consistency over time (different time period data) and space (different zones) using hypothesis testing. Based on this study, the TCPV model was found to be the best fit and is consistent over time and space.

Rahman et al. (2018) proposed the analysis of different travel time distributions using six months data collected for a period of three hours of peak traffic on weekdays. In this study, the characteristics of travel time variations of public bus transit with pseudo horizons were presented in terms of different statistical measures. The probability distributions and their shape measured the form and extent of variability with pseudo horizons. The different distributions were ranked for various pseudo horizons in order to identify the cut off points. The identified distributions were then used for bus travel time estimation. The results show that the bus travel times were best fitted by log normal distribution when pseudo horizon is below 8 kms and normal distribution when the pseudo horizon is above 8 kms.

2.1.2 Travel Time Reliability

Transit service reliability is a measure of the quality of service offered by the public transit systems (Mazloumi et al. 2010) and it also evaluates the system performance better at different traffic conditions over a time and space (Chepuri et al. 2018b). The idea of comparing the travel time with that of travellers' expectations forms the basis of travel time reliability (Small 1982). The transport systems probably fail to attract potential travellers when the service provided by the routes becomes unreliable (Ma et al. 2016). The important measures which have been recommended for travel time reliability (Federal Highway Administration 2006) are: 90th or 95th percentile travel time, Planning time/Planning time index, Travel time index, and Buffer time/Buffer time index.

90^{th} or 95^{th} Percentile Travel Time: This is one of the simplest TTR measure which depicts the severity of delay when there are heavy travels taking place. This measure is easy to understand for the daily commuters having well known about their trips.

Travel Time Index (TTI): Travel time index is one of the significant reliability measures which helps in monitoring the average congestion. Travel time index indicates the mean additional travel time required during peak hours in comparison with non-peak hours of traffic. Travel time index is obtained by using Equation 2.1.

$$TTI = \frac{Average\ Travel\ Time}{Free\ Flow\ Travel\ Time} \tag{2.1}$$

Planning Time Index (PTI): Planning time index illustrates the total travel time which has to be planned on the inclusion of sufficient buffer time. This measure compares the nearly the worst case travel time with respect to the travel time during free-flow. It is useful in terms of comparing the worst-case travel time to the average congestion scenario (TTI) on a similar numerical scale. Planning time index is given by Equation 2.2.

$$PTI = \frac{95th\ Percentile\ Travel\ Time}{Free\ Flow\ Travel\ Time} \tag{2.2}$$

Buffer Time Index (BTI): Buffer time index indicates the extra buffer time (or time cushion) that is added to the average travel time by most of the travellers for the timely arrival during the trip planning. The unexpected delays are managed by this extra time. This measure is expressed in percentage and calculated by Equation 2.3. Unlike planning time index, the buffer time index also includes the unexpected delay along with the typical delay.

$$BTI = \frac{(95th\ Percentile\ Travel\ Time - Average\ Travel\ Time)}{Average\ Travel\ Time} * 100 \tag{2.3}$$

Several other reliability measures are also proposed by previous studies to describe travel time reliability. This section reviews the previous studies relevant to travel time reliability.

Gaver (1968) worked on embedding travel time variability concept in the utility maximization model. This concept is based on the result that the travellers start earlier than the time they would start when there is no variability in travel time, by the selection of “slack” time. A similar concept was discussed by Knight 1974 which suggests that travellers choose a safety margin before departing from their origin.

Turnquist (1974) discussed four strategies to increase reliability such as the strategies for holding the vehicles, reduced number of bus stops, pre-emption in signals and a restricted right-of-way provision. It was found that vehicle-holding, signal pre-emption and exclusive right-of-way are more suitable for low frequency, medium frequency and high frequency bus routes respectively.

Noland and Small (1995) extended the previous models of time-of-day choice for commuting to examine the impact of uncertainty in travel times. They studied the effect of recurring congestion on the daily TTV separately. The expected cost due to delay in schedules can also be predicted using their model. This model has been developed based on the changed schedule of the trip and the reaction of the commuter for the same.

Bates et al. (2001) presented the overview of reliability-based valuation on the utility function and travel time variability. It has been used for the rail service punctuality test. The study was conducted using the responses from the questionnaire survey. Based on the results of this survey which was carried out on passengers, the punctuality of the service is the most rated parameter.

Chen et al. (2003) used 30 second loop detector data collected for 65 weekdays. The study mainly aims at proving the travel time measures like mean, standard deviation and 90^{th} percentile travel time can be used to describe the LOS of the particular service. The outcome of this study shows that 90th percentile is a good parameter to combine mean and standard deviation and providing prior information about incidents increases reliability of travel.

Yin et al. (2004) conducted investigations on the reliability of transit services considering the interaction between the route choice behaviour of commuters and performance of the network. The reliability of transit service was described in three different ways in the views of transit service administrators, operators and commuters as, reliability in schedules, reliability in waiting time and system-level reliability of travel time. These estimates of reliability were quantified using the Monte Carlo simulation method. A case study on the effect of Bus Rapid Transit (BRT) system on the reliability of transit service was undertaken utilising the developed simulation method.

Oh and Chung (2006) carried out a study on calculation of travel time variability. The study used 30 sec loop detector station data divided into 5 min interval collected for a period from March 2001 to February 2002, where more than 250 loop detectors were used for data collection from 10 zones. The mean, standard deviation and co-efficient of variance were used in the determination of daily variation, variation in a day and route level variations in travel time. This study also incorporates section and route-based data into GIS to manage and visualise the variability.

Lyman and Bertini (2008) used data of corridors collected for three years, having 10 seconds time step. Three reliability measures such as, planning time index, travel time index and buffer time index were used for prioritising the freeway corridors for further improvement. Some trends were observed in variation in reliability with respect to morning peak. By using volume and buffer index, the cluster of the corridors which needs prior consideration for improvement of the corridors were identified.

A study was carried out on the effect of traffic flow on the TTV of freeway corridors by **Tu et al. (2007)**. Four data sets from dual loop detectors which contains two data sets of 15km and 17.3 km stretch for 12 hours and another two data sets from 7.1km and 15.5km stretches for 2 weeks were used for the study. This paper studied the impact of inflow on TTV by defining 3 zones of traffic flow level namely, Fluent traffic region (free flow), Transition traffic region (free, synchronized and congested flow) and Capacity traffic region (high flow and high speed). There are two critical flow levels λ_1 and λ_2 creating three regions in speed flow relationship. The Travel time variability below λ_1 and above λ_2 is mainly due to the capacity (supply) variation. Overall study states that among demand (inflow) and supply (capacity), capacity is the one which is more dominant variable in the variability of travel time.

Mazloumi et al. (2008) carried out a case study in Melbourne on causes for unreliability of travel time. The study used the travel time data from 3351 complete vehicle trips of week day extracted from AVL data. The linear regression with the minimum least square method has been incorporated in this study. The selection of independent variables has been done by backward stepwise selection method, where the procedure starts with considering all the variables and eliminating insignificant variables by an iterative process until there is no chance to eliminate any variables. The variable length of corridor, delay indicating both early and late arrival, number of signalised intersections and bus stops were considered as independent variables and 90th and 10th percentile as dependent variables. The results show that R square value is 0.66 and the addition of average travel time variable as independent variable increased the R square value to 0.88.

Chen et al. (2009) analysed the reliability of bus service at network, route and stop levels. 30 bus routes, 6 circular lines, one BRT line were considered for data collection, 396 surveyors recorded boarding and arrival time along with occupancy of buses at each stop manually. Three parameters, i.e., Punctuality index based on routes (PIR), Evenness index based on stops (EIS) and Deviation index based on stops (DIS) were proposed to evaluate the reliability at route, network and stop level. The effects of headway distance, length of the route, restricted lanes, and distance from a stop to the origin terminal, on service reliability have been considered. The results of the analysis show that PIR > DIS > EIS and as route length increases the effect of all 3 parameters increases but DIS alone increases and EIS decreases for longer headways. The relationship between stop to origin distance is uneven after 30 km and the EIS tends to be low whereas the EIS remarkably shows fluctuation. The provision of restricted bus lanes increases the service reliability considerably.

Islam and Vandebona (2010) considered stochastic simulation using data from 5 bus stops which was simulated for analysing the reliability of public transit. A simulation model has been developed to estimate the effect of dispatch headway variation and bus size limit on the average passenger waiting time. It was known from the study that the distribution of waiting time gets widened with an increase in headway and a decrease in capacity of bus. As the capacity of bus decreases, the probability of passengers moving to other modes becomes usual.

In the research work carried out by **Moghaddam et al. (2011)**, data from AVL, APC and data from travel forecasting model have been used in developing models to predict mean and standard deviation (SD) of travel times. Two models have been developed by considering the average number of alighting and boarding, segment length, signals present in that segment, signals present between Origin-Destination path and the weighted average of V/C ratio for that O-D path and validated by comparing actual mean and SD of data collected.

Alvarez and Hadi (2012) studied time variant travel time distributions based on the reliability aspect using ITS data. The data was obtained from a corridor of 6.5 miles length, consisting of six lanes with two lanes of toll road updated the system for every 20 seconds. Variation of parameters (median, standard deviation, skewness and kurtosis) of distribution of travel time by the time of the day has been considered. The sensitivity of reliability matrices (Buffer Index (BI) Failure/On-Time Performance, 95th Planning Time Index, 80th Percentile Travel Time Index Skew Statistics, Misery Index) has been analysed with finer level (15 min) of aggregation and the length of the data required for the better understanding of variability has been explained. 95th, 80th and Misery Index is sensitive to change in congestion level, but Buffer Index shows insensitivity and hence metrics should be adopted carefully during reliability analysis. The study confirms that at least one-year data is must for encapsulating all the variation.

Wei Feng from Portland State University presented his work on bus TTR analysis at stop level and segment level (**Feng et al. 2015**). The combined effect of signal timings, location of bus stops, intersections and conditions of traffic on the variability of stop-to-stop segments, was analysed in this study. The data of AVL, APC, intersection traffic count and signal phase log data were collected from different sources and analysed using multiple linear regression. Intersection delay is the major factor which is linearly associated with the red phase signal timings, as per the outcomes of this study.

An et al. (2014) used agent-based simulation for measuring the reliability of public transit systems which considered perception of route level commuters. They developed two indicators, i.e., perceived passenger time and reliability index. Results claim that the effect of passenger demand on reliability of public transit services can be effectively quantified by the developed indicators.

Ma et al. (2015) modelled bus TTR using AVL data and smart card system revealing the demand and supply status of public transit. The data from two routes, one with 12 scheduled stops having 7.8 km stretch and another with 13 scheduled stops having 31 km stretch, was collected from various means such as AVL systems, traffic signal, passenger smart cards and meteorological department. The main objective of the research was to identify and quantify the underlying factors (planning, operational and environmental) that affect TTR at the link level of various types of roads in the form of 3 different dependent variables (Buffer Time, Average Travel Time and Coefficient of Variance of TT). Development of a new index named Recurrent Congestion Index (RCI) was done for representing the traffic congestion and applied in the modelling. The seemingly unrelated regression equations (SURE) method has been used to identify the cross-equation correlation between different models. It was observed that the RCI has significant effect on the dependent variables and there is a cross equation correlation present between different models. SURE model estimators were found to be more efficient than the OLS models. The Demand and Supply concept can be applied to find out TTR in the form of on-time performance and headway regularity. These models can also be expanded to network and route levels.

Diab et al. (2015) conducted a review on strategies for improving the public bus transit. The passenger perspectives on the bus service reliability and change in their perception for the adjustment in the transit service was one part of the conducted review. The other part of the review consists of studies on plans and goals of transit agencies regarding transit service reliability, the strategies used by them in improving reliability and their impact.

Glick and Figliozzi (2017) in their work described a novel methodology for the estimation of traffic and transit TTR indices and confidence levels at segment level as well as corridor level. The data used were collected for three weeks on weekdays with a time step of 5 seconds. The percentile of travel speeds and confidence intervals with respect to it were determined using the formulae given in this study. 85^{th} speed percentiles were utilized as a novel approach for identification of intersections having lesser performance and corridor sections. Speed variability index and speed difference were proposed for identification of low performing sections in peak or/and non-peak hours. Visualization and identification of problematic intersections and segments having delay along the stretch of a corridor was done with this new approach.

A study was carried out to analyse the bus route reliability by **Hu and Shalaby (2017)**. The study utilised AVL data collected for five weeks, traffic volume count for 8 hours and pedestrian counts. Regression analysis was used as a means for achieving the main aim of this work to analyse the relationship between influential factors of reliability of transit and speed. Coefficient of variation of travel time was calculated with dependent 19 independent variables. At route level, factors related to poor performance such as traffic volume, peak hours, transfer stops at subway and signal density at intersections were considered. Factors such as lesser reliability and lower speed were noted in the segments having a higher number of alighting and boarding commuters, higher density of intersections with signals, stopping density, length of the segment, and the segments at the end of the routes, were considered at the segment level. Likewise, intersection density, stopping density also has its effect on speed and TTV.

Yu et al. (2017) studied the travel time estimation and the uncertainties associated with travel time using loop detector data of weekdays collected from 8 AM to 7 PM, August 2013 to December 2014 on a road stretch of 4.1 mile. In this study, the accelerated failure time survival models were considered to estimate the travel time of the bus and to capture the uncertainty related to time of travel that could not be modelled in the case of Linear regression. Both the model results were calibrated and validated. Both linear model and survival (log logistics) models of travel time estimation results are acceptable but in the case of uncertainty consideration, the survival model outperforms the linear model.

Chepuri et al. (2018b) studied different types of travel time distribution by considering various temporal aggregation of travel time such as an hour of the day and a day of the week and also made an attempt to define the LOS of route based on suitable reliability measures for Indian conditions. The outcome of this research shows that Generalised Extreme Value (GEV) distribution as the best fit for travel time. The Buffer time and 95^{th} percentile travel time were adopted in generating the LOS of bus route.

A case study on the analysis of reliability of travel time of bus routes was carried out by **Ji et al. (2018)** using bus Automatic Vehicle Location (AVL) data. Two bus routes of Shanghai city, one in the urban and the other one in the suburban area were considered for the study. They came up with few indices such as buffer time index, deviation index, punctuality index etc., in order to quantify the TTV. The results obtained from the study show that the effect of peak hours is more on reliability of travel time and buffer time in off peak hours increases with increase in bus stop spacing. It was also concluded that the stability in travel time of buses in the suburban area was more than urban area.

2.1.3 Road side Friction

Travel time reliability of public transit depends on many factors such as road geometrics, traffic volume, intersection delays, passenger demand, and also roadside activities. The roadside activities on urban roads include on-street parking, roadside vendors, bus stops, and pedestrian movements. The inadequacy of off-street parking and certain benefits of on-street parking creates a tendency among the road users to park their vehicles on-street. Parking and unparking manoeuvres induce complex interactions between the traffic movement and the parking/unparking vehicles (Biswas et al. 2017). On many of the urban roads, pedestrians tend to use curb lane due to improper footpath design and the presence of vendors on the footpath. These roadside elements obstruct the through-traffic, including transit vehicles, and reduce vehicle speed (Biswas et al. 2017). A review on the previous research works on road side friction has been provided in this section.

Chiguma (2007) presented the analysis of effects of side friction on urban roads. Dar-es-salaam case study has been presented. The data regarding traffic, side friction and road geometrics were collected both by manual and video graphic techniques. The study was conducted at both macroscopic (combined effect), microscopic (individual effect) levels. The outcomes of the study showed a reduction of 8% in speed in two lane - two way road, and 2% in four lane - two way roads has been observed due to the presence of side friction.

Portilla et al. (2009) studied the impact of manoeuvre of parking vehicles and badly parked vehicle on travel time/journey time of vehicles on two lane roads. It was analysed by incorporating the M/M/∞ queuing model and this model has been validated by microsimulation model. Microsimulation results show that the reduction in road capacity of 6%, 10% and 16% for 10, 20 and 30 parking manoeuvres and increase in journey time of other commuters by 57 to 107% because of bad parking vehicles for 15 to 30 min. The degree of error between journey times generated by microsimulation and queuing model was found to be lesser than 5% when the link traffic is at 60-70% of capacity but, degree of error was 14% for all the cases of different manoeuvre.

Hidayati et al. (2012) carried out a study in Indonesia on impact of road side activities. In this study, side friction total score was calculated based on the side friction frequency, weight factor and length of side friction (SF). The side friction total score was then used in the determination of SF factor and Impact of SF is analysed with respect to flow, speed, composition and total score around the morning peak hour. The results of this study show that there is reduction in speed of all the vehicles before the zone of school safety and also there is a significant reduction in the car speeds at the zone of school safety during school opening time.

Guo et al. (2012a) conducted a study to analyse the effect of side friction on traffic flow by developing a Nagel-Schreckenberg cellular automata simulation model. This model was used to describe the interaction between the manoeuvres of on-street parked vehicles and vehicular flow. The Monte Carlo simulation has been adopted to numerical simulation of different scenarios of on-street parking with different type of parameters.

Guo et al. (2012b) conducted a research work to analyse the influential factors related to curbside parking such as effective lane width, the number of parking manoeuvres and occupancy on the travel time and proposed a proportional hazard-based duration model. The outcome of this study indicates that the effect of parking and unparking freuency and manoeuvres, conflict of travel and occupancy on travel time is positive and that of effective lane width is negative. Among them, conflict in traveling and effective width of lane were said to be significant factors.

Ye and Chen (2013) analysed the impact of curb-side parking on the performance of nonmotorized vehicles by developing a proportional hazard-based duration model. The study was conducted in China and collected the data regarding parking manoeuvre, number of bicycles and e-bikes on bicycle lane by conducting videography during morning peak hours, i.e., 7:00 - 9:00 AM and evening peak hours, i.e., 4.30 - 7:00 PM. The significant factors related to curb side parking considered are effective width of bicycle lane, double parking, outbound and inbound manoeuvres of parking/parked vehicles, time influence rate and load and unload activities. The study results show that the travel speed of nonmotorized vehicles is significantly affected by curbside parking. Results also suggest that travel speed is negatively affected by inbound and outbound manoeuvres and positively affected by effective lane width of bicycle lane.

Wang et al. (2013) analysed the interruption caused by the manoeuvring of parked/parking vehicles in and out of the parking space on the traffic flow. The influence coefficient was established by the formula deduction method and provided the road capacity model for curb side parking.

The study of mixed flow behaviour under the influence of side frictions was studied by **Patel and Joshi (2014)**. Two separate roads from two cities of India have been considered with four hours of videography data. The comparison of the capacity of two roads was done by fundamental diagram. 57% reduction in capacity and 14% reduction in speed was observed from the study.

Pal and Roy (2016) studied the effect of road side frictions on LOS of rural roads along with speed of travel. The traffic flow data and speed data collected by videography technique and side friction data collected in market area were used. The objectives of study aimed at estimation of the road side friction Index and its effect on LOS and speed of travel (free speed and standard deviation of spot speeds). From the outcomes of the study, it was observed that there was a 25% speed reduction and LOS of E achieved in place of LOS C for the same volume of traffic.

Salini et al. (2016) analysed the impact of side frictions on urban arterials using parking, pedestrians and bus stops data at Thiruvananthapuram, Bengaluru and Mumbai. The study aimed at analysing the effect of side friction on speed by multiple linear regression method and developed combined index considering effect of parking, pedestrians and bus by using weighted index method. It was found from the study that the Bus stops are causing more reduction in speed compare to other factors.

Gao et al. (2016) used two types of modelling approach to assess the impact of double parking on mean travel time. M/M/∞ queueing model and micro-simulation models were used in the analysis. The study utilised the combined data obtained from parking violation and data from video recordings. The efficiency of the two models was compared and M/M/∞ queueing model was found to be more appropriate in describing the effect of double parking on average travel time for larger urban networks. With respect to congested conditions, micro-simulation models were more powerful in evaluating the effect of explanatory variables.

Chen et al. (2017) carried out a simulation-based study on the effect of parking operations of traffic by using cellular automaton. Cellular Automaton model was developed and calibrated to understand the interaction between bicycle and vehicles. The delay has been analysed by considering the two types of scenarios namely, frictional and blocking scenarios. Density of bicycle, vehicle traffic and parking space occupancy were found to be affecting the vehicular delays.

Rao et al. (2017) evaluated the effect of road side frictions on road capacity in Delhi. Total of 12 sections were selected for data collection, among which two ideal sections, three bus stops on curb side, five segments having on-street parking facilities and two bus bays were considered. Speed reduction and influential length were determined as a result of capacity reduction with respect to dwell time, bus bay and on-street parking facilities. Results of the study showed a speed reduction of 49-57% due to bus bay, 45-67% because of on-street parking. 10-53% reduction in capacity at bus bay and bus stops and 28-63% due to on-street parking.

The traffic stream in the presence of on-street parking was simulated by **Małecki (2018).** The drivers' behaviour was modelled on the basis of cellular automata and a multi-agent system. A random discrete model was considered to know the impact of behaviours of various drivers on capacity of road during parking process. The results obtained showed that the motorists' patience had a positive impact on road traffic, which would give rise to lane changing behaviour.

Cao et al. (2011) investigated the effects of curb parking on the traffic flow at the Central Business District (CBD) especially in medium-sized cities and developed acceleration and deceleration models. The following speed was obtained using a car following model. The study indicated that the location of parking is a significant factor to be considered during the construction of parking lots in CBDs. The model can be helpful in analysing traffic having the curb parking space as a measure.

A study on measurement of the impact of modal conflicts on reliability of transit system was conducted by **Wickland and Sall (2014)**. A data-driven methodology was applied for the purpose and for the comparison of alternative solutions based on their reliability. The reliability during the disagreement of choice between Bus Rapid Transit (BRT) and other transport modes are quantified.

The impacts of on-street parking facility on the service rates of the nearby intersections were studied by **Cao et al. (2016)** conducted research to analyse how the nearby intersections were affected by on-street parking. The resulting disturbance by the parking process was analysed on the basis of hydrodynamic theory. The v/c ratio when reached values greater than 1 indicated a problematic situation creating oversaturated conditions at the intersections even in the absence of parking movement.

Kladeftiras and Antoniou (2013) evaluated the effect of double-parking on traffic as well as the environmental conditions using simulation. The particular patterns of double-parking and their effect on traffic conditions were analysed. A reduction in average speed and increase in delay was observed due to the parking process. The simulation results showed that by putting limitations on double-parking, the speed could be improved by 10-15% and the delay could be decreased by 15-20%. The simulation conducted for a case study in Athens calculated the reduction in emissions and saved lost time.

A study was conducted by **Gulivindala and Meher (2018)** to estimate the static and dynamic side frictions using multiple linear regression. Four roadways with side frictions in the city of Warangal were the study sections and the data was obtained during morning peak and evening peak hours. The impact of traffic volume and side friction on the speed of traffic was collectively evaluated. The side frictions when less had weaker effect on speed of traffic and the outcomes indicated a reduction of 9% in stream speed due to side frictions.

2.1.4 Travel Time Reliability Modelling

The understanding of the factors causing unreliability of the public transit system is significant in improving the system's reliability. There are different factors inducing unreliability such as, weather, work-zone activity, traffic incidents, fluctuation in traffic demand, control devices, special events, etc., (Kwon et al. 2011). The understanding of these factors is required to evaluate TTR of the system. This section reviews the previous studies related to TTR and its models, considering different factors of unreliability.

Abkowitz and Engelstein (1983) developed the empirical models of running time deviation and mean running time of transit system, using MLR. The independent variables considered are link distance, signalised intersections, bus stops, peak and off-peak, boarding passengers, alighting passengers and direction of transit movement. The study results show that link distance, number of barding passengers, number of alighting passengers and signalised intersection have stronger influence on the running time characteristics.

Strathman et al. (2002) utilised the AVL and APC data Tri-Met's BDS to model the bus running times considering distance, lifts, bus stops, peak hour and off-peak hour details including Early morning and late evening, type of service (feeder, crosstown and express), number of boarding and alighting commuters, headway, summer and operator details as the exploratory variable. The study results show that each extra mile requires extra 206 seconds, morning peak hours are having less running time than midday trips, feeder service has less running time than crosstown and radial service and headway and summer season are found to be significant.

Kimpel et al. (2005) analysed the running time of bus, on time performance and wait time for passengers in TriMet public transit system to understand the effectiveness of Transit Signal Priority (TSP). Regression analysis has been conducted considering schedule run time, stops made in the journey, lift usage, operator experience, delay at terminal, period of pre/post TSP implementation and peak hour details as the exploratory variable. The study results show that benefits of TSP implementation are not consistent with respect to different routes, time period and across performance measures.

Mazloumi et al. (2010) studied the TTV considering the factors contributions to describe the SD and T_{90}-T_{10}. This study utilised the data of GPS equipped buses of

Melbourne city and modelled SD and T_{90}-T_{10} using MLR. The length of segments, number of signals, number of bus stops, average delay, SD of delay, land-use and rain details are considered as the exploratory variables and different models are developed for morning, inter and evening peak hours, and off-peak hours. The results of this study show that SD model has greater R^2 value than T_{90}-T_{10} model. Land-use, segments length and signals are found to have significant impact.

El-Geneidy et al. (2011) analysed the reliability of a bus route connecting two suburbs of Minneapolis, United States using APC data. The data has been analysed in two levels namely trip pattern and time point segment level. The MLR technique has been adopted considering run time, deviation in run time, coefficient of variation (COV) of run time and headway deviation as the dependent parameter and distance, scheduled stops, Actual stops, peak hour details, driver experience, headway delay and passenger details as independent variable. The results of the study show that most of the independent parameters are significant in describing run time and headway deviation. The AM peak, average passenger load, headway delay and driver experience found to not significant with respect to run time deviation. Distance parameter is found to be having negative impact on the COV of run time.

Diab and El-Geneidy (2012) studied the effectiveness of transit improvement strategies considering the running time as the performance measure. MLR has been carried out considering passenger load, actual stops made, peak hour details, passenger activity, snow details, delay at the start and improvement strategies like smart card implementation, articulated buses, TSP implementation and reserved lanes are considered as the exploratory variables. The results show that smart card and articulated buses have a negative impact on bus running times than TSP and reserved lanes.

Ma et al. (2015) identified and quantified the critical factors defining the TTR using demand and supply data of Brisbane transit system. ATT, BT and COV of travel time were taken as dependent variables and different independent variables corresponding to the segment length, delay at first stop, number of stops, number of boarding, number of alighting, rain, traffic signals, CBD vs non-CBD and congestion. The modelling has been carried out separately for different types of roads, such as arterial roads, motorway roads, busway roads, roads in CBD and others roads using an unrelated regression equation method. The results of the study show that passenger demand, traffic signals and traffic congestion are the important factors of these models.

Ma et al. (2017b) analysed the travel time determinants using quantile regression considering AVL and smart card data. Average speed and COV of speed are considered as dependent variables and planning variables (length, headway, peak and off-peak, direction), operational variables (passenger demand and delay) and environment variables (signals, congestion, rain, CBD, road type) as the independent variables. This case study results show that regression results provide more information about the impacts of these variables on speed and its variability.

Kathuria et al. (2020) developed TTR models to identify the significant variables affecting reliability of the BRTS system. Length of the segment, number of intersections and bus stops, average and SD of delay, peak and off-peak hours, segregated route and land-use are considered as the independent variables in MLR method. SD of travel time and T_{90}-T_{10} are considered as the dependent variables. The results of MLR models show that segregated route, length and number of intersections are having more impact on travel time variability.

2.1.5 Travel Time Reliability and Level of Service

Level of service (LOS) is a measure of the quality of service offered by systems such as highways using the quantitative categorization of performance measures describing that system. Travel time reliability is a significant measure of quality of service offered by the system for transit users. Hence, this has a vital significance in determining the LOS of the system. The existing studies related to LOS, determined based on different service-oriented measures, are reviewed in this section.

Chalumuri et al. (2007) investigated TTR and evaluated the performance of an expressway in Japan. The travel time data obtained from four routes of Han-shin expressway was used for the study. This work quantifies the TTR using existing indices and also their capability in determining the level of congestion on expressways. Results suggest that TTR measures are capable of measuring the congestion variation.

Mehran and Nakamura (2009) proposed a method of estimating the TTR with respect to several factors, i.e., capacity of the road, traffic demand, accidents and weather conditions. Monte Carlo simulation method was used to generate the values of capacity and demand for a time interval of 5 minutes of an entire year and generation of accident data was done randomly based on traffic for an expressway of 9.9 km. The queue length was analysed by shock wave analysis and speed-flow relationships were used to determine travel time values. In this study, buffer index was used to measure the TTR. The application of this study was conducted to evaluate the effect of opening a hard shoulder to traffic on TTR.

A probability-based method of evaluating TTR of urban expressways was presented by **Lei et al. (2014)**. The study was conducted using shockwave theory. The data collected for seven days on Beijing expressway was used for the study. The travel distance at segments having different LOS and travel time distributions were the two parameters estimated with the help of shockwave theory and floating car data respectively. The data was aggregated for 5 min intervals and the distributions derived from the analysis were Generalised Pareto and Generalised Extreme value (GEV) distributions. It was known from the results of the study that it is possible to achieve higher accuracy in prediction of travel time using the model proposed.

Margiotta et al. (2015) analysed reliability as a measure of LOS for freeways present in Florida. This study discusses the four different options of describing TTR LOS and those are: based on the reliability metrics, amount of Vehicle Miles Travelled at certain speed ranges, speed statistic from the distribution of speeds and TTR index.

Patnaik et al. (2016) used DIANA (Divisive Analysis) algorithm to cluster speed data obtained from five urban corridors in Mumbai. The algorithm was applied to differentiate free flow speeds into different classes which were then used to describe the limits of various LOS categories. The speed ranges were determined in percentage of free flow speeds for different categories of LOS and then compared with the speed values given in HCM. The results of the study were satisfactory.

Biswas et al. (2016) introduced an alternative method of percentage reduction in free flow speed to evaluate LOS. A case study was undertaken in Kolkata using 16 hours traffic data on a road segment of a divided six lane urban arterial. A trap length of 60 m was used for the speed data collection. Percentage speed reduction in free flow speed was found to represent the variation in traffic flow and also the state of overall mobility better. K-mean clustering and silhouette methods were used for the analysis and developed the six ranges of LOS.

Zheng et al. (2018) proposed a linear model for describing the relationship between travel time, skewness, standard deviation and few other traffic parameters. The methodology was used to estimate TTR of a corridor in China. Automatic Number Plate Recognition cameras were used as a tool for obtaining the real-world data. The data generated by simulation using delay distribution model were analysed and compared statistically. The results of the study show that the correlation between the standard deviation and average travel time was linear. It was also found that the standard deviation was well explained from traffic characteristics than the skewness.

Mohanty and Dey (2018) proposed a method to compute area occupancy and for the evaluation of traffic performance at the openings of medians. The data for the study was obtained from seven median openings of a six-lane divided road through videography. The data collection was done for around 10 hours which included the peak and off-peak hours of traffic. The method of area occupancy was modified in order to eliminate the drawbacks in earlier techniques. A method of K-mean clustering was used to differentiate the ranges of area occupancy based on different LOS categories.

Bharti et al. (2018) conducted a study on evaluating TTR measures. The data considered in this study was collected from 3 corridors for 8 hours using TrafficMon system. The correlation between the v/c ratio and various measures of TTR such as planning time, planning time index, buffer time and buffer time index, was studied. The K-mean clustering was used to categorize the reliability measures depending on the LOS. The outcomes of the analysis show that the value of travel time for intercity highways is 40-46 sec/km, interrupted corridors is 75-135 sec/km and uninterrupted corridors is 64-80 sec/km for a LOS of B. The planning time was analysed in the similar manner and it was found to be lesser for inter-urban corridors when compared with urban arterial corridors. Evaluation of other reliability measures was also carried out and the values were obtained for different v/c ratios of different types of corridors.

2.2 SUMMARY OF LITERATURE

The review of the previous studies on TTV, TTR, effect of side friction, travel time reliability modelling and LOS are summarised below,

- Travel time variability (TTV) plays a significant role in analysing the reliability of the public transit system. Travel time distributions characterise the pattern and nature of travel time variability. The different probability distributions such as normal, Gamma, Weibull, lognormal, Burr, log-logistic and Generalised Extreme Value (GEV), are suggested as the descriptors of the distribution of travel time in the previous studies on TTV of public transit.
- Analysis of TTR is necessary to perceive the quality of service offered by the public transit system. The researches on TTR of public transit, have analysed TTR with the help of measures such as, mean, SD, COV of travel time, skewness and kurtosis, 95^{th} percentile travel time, Planning Time Index (PTI), Travel Time Index (TTI), Buffer Time (BT), and Buffer Time Index (BTI).
- The different side friction elements are quantified using Area ratio, distance ratio, linear regression methods etc., The factors related to on-street parking and pedestrians such as, parking/unparking manoeuvre, category of vehicles parked, pedestrians crossing/ walking along the road which can have an impact on the traffic movement, were not considered in the previous studies related to TTR of public transit.
- The reliability measures have been modelled considering the different factors affecting the reliability. The reliability measures considered for these studies are, mean running time, running time deviation, on-time performance, passenger waiting time, SD, T_{90}-T_{10}, dwell time, average speed, CV of speed, average travel time, Buffer Time (BT), CV of travel time. The different variables are considered as the determinants of reliability measures such as, length of the segment, peak hour and off-peak hour, intersections, traffic signals, bus stops, average and SD of delay, land-use, passenger demand and rainfall.
- Level of Service (LOS) is a quantitative stratification of performance measures of the system which describe the service quality offered by the system to the users. The important measures used in defining the LOS are traffic density,

average speed and time spent in following for different types of roads. But these measures are not capable of capturing the variability in travel time of public transport system. In recent years, various TTR measures such as ATT, 95th percentile travel time, PTI, BT, BTI, COV of travel time, headway adherence and waiting delay index have been considered in defining LOS of the public transit system. Most of these studies adopted widely used K-Means clustering method for the stratification of different reliability measures to define LOS thresholds.

2.3 GAPS IN THE LITERATURE

From the study of previous research works, very few studies on TTR and TTV in Indian conditions were found and it was observed that most of the aspects in this field are yet to be explored. The following gaps were identified from the review of existing studies:

- Even though there are many researchers who studied and analysed travel time variability in homogeneous traffic condition, the impact of spatial and temporal aggregation on variability of travel time in terms of statistical distribution has not been addressed with respect to performance of the distribution.
- Among the previous works on travel time studies, limited studies were found on TTR of public transportation especially in Indian traffic condition as these studies require huge amount of transit data. The studies conducted so far have not studied the performance of different distributions with respect to different temporal and spatial aggregations.
- On urban roads, the road side activities like on-street parking is an important factor that can impact TTV. The impact of side friction on TTV and TTR has not been investigated in the literature.
- The effect of intersection and bus stops on travel time reliability of public transport system was not analysed in the previous studies conducted in Indian condition.
- The definition of Level of Service (LOS) based on TTR, particularly under heterogeneous traffic of India is yet to be explored in detail.

2.4 SUMMARY

This chapter reviews the research works conducted previously on TTV, TTR, road side friction, travel time reliability modelling and Level of Service. The review of the literature indicates that, the studies on TTV and travel time distributions are very few under mixed traffic conditions (as per Indian context). Also, the travel time variability studies conducted in India did not consider the influence of different temporal and spatial aggregation of travel times on travel time distributions. It was observed that the studies on travel time reliability of public transit under heterogeneous traffic conditions like in India are hardly any. Also, the studies which attempted travel time reliability analysis, have not considered the effect of side friction. The different factors affecting travel time reliability have been analysed using Multiple Linear Regression (MLR) in most of the studies. K-Means clustering method has been adopted in determining the Level of Service as the effective method of grouping the data based on the similar data structure. The present study attempts to address the potential research gaps stated in this chapter using some of the aforementioned modelling techniques.

CHAPTER 3

STUDY AREA

3.1 GENERAL

In this chapter, the study area considered is explained in detail. Mysore city has been considered as the study area for the analysis of travel time reliability of public transit system. Mysore city transit has the Intelligent Transport System (ITS) infrastructure which provides real-time information to passengers about public transit trips and also generates large amount of Automatic Vehicle Location (AVL) data of transit vehicles which have been used for TTR study. The details of Mysore city and Mysore urban public transit system are presented in the following section. The components of Mysore ITS are also discussed in this chapter.

3.2 DESCRIPTION OF STUDY AREA

Mysore city in India, is the study area of the present research work. It is the third-largest city in Karnataka, located in the southern part of the state (Karnataka state is located in the southern part of India). Mysore city is located at a height of 770 m from the mean sea level and lies between north latitude 12° 18′ 26″ and east longitude 76° 38′ 59″. It is spread over an area of 286.05 km^2 and located at the foothills of Chamundi hills. The urban population growth of Mysore city is depicted in the Figure 3.1. The steady growth in the urban population can be observed as 0.23 million in 1950 and increased to 1.21 million in 2020. The growth of population in urban areas shows the magnitude of urbanisation in the Mysore city.

The city is renowned for its tourist attractions and is well facilitated with the medical, educational and industrial amenities. Major activity in the city is tourism, as there are many attractive places in and around the city. Mysore is also well known for Dasara festival, a hallmark of the old Kingdom of Mysore, taking place for ten days annually during early September and October. Mysore city is being visited by tourists from all over the country and other foreign countries also. Around 20 lakh tourists from the country and more than 5 lakh tourists from foreign countries (USA, China, Japan, Korea, Maldives, Srilanka, Italy, Germany, UK, Netherlands and so on) visit the Mysore city annually. It is also renowned for the activities promoting the applications of emerging technologies in the infrastructure development. The major reason for the migration of people from rural area to Mysore city is due to better employment opportunities. The city is well connected with the air, railway and road transportation network with other districts and states.

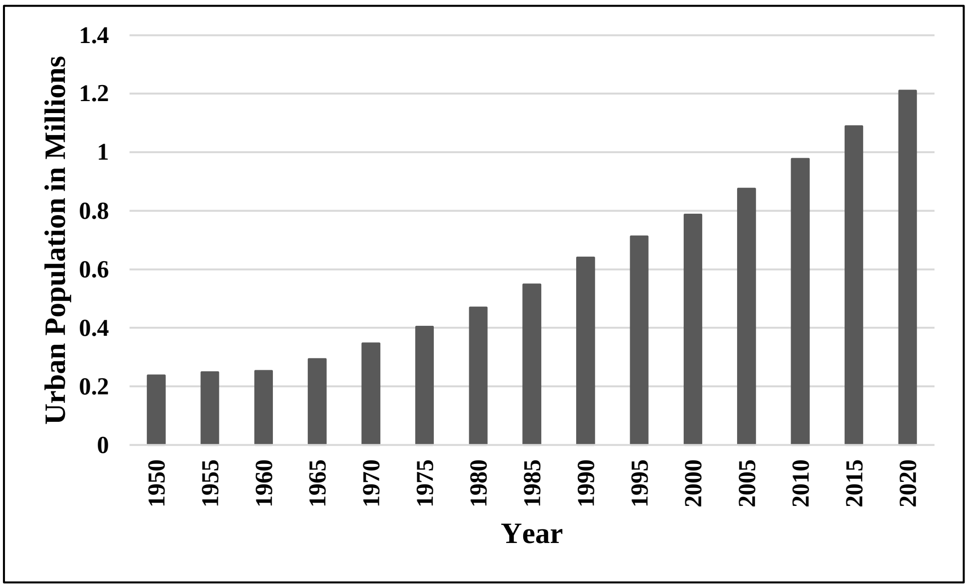


Figure 3.1. Urban population growth of Mysore City (Source: PopulationStat)

3.3 LAND USE AND TRANSPORT

Old city of Mysore spreads around the world-famous Mysore palace which constitutes the CBD and it is the heart of the city. The land use pattern of the city follows its past culture. In 2011, land use pattern data generated reveals that the city has 43.45% of residential areas, 16.10% of roads, 13.22% of industries, 8.41% of public properties, 7.52% of parks, 6.41% of agricultural lands, 2.45% of commercial areas and 1.27% of water bodies.

In Mysore city, arterial roads are generated from CBD area with grid-iron pattern and radial pattern of roads. The arterial roads run from the central palace area and covers up to the outskirts of the city. The road network consists of a system of ring roads which surrounds the city, with the combination of radial major roads connecting these ring roads from the city centre. The ring roads of city consist of inner ring road which is in the CBD, intermediate ring road that connects the residential areas with the commercial areas and the outer ring road which is located in the circumference of the city. The congestion at the centre of the city is controlled by three ring roads which act as by-pass roads for collecting traffic from various parts of those locations. The road network of Mysore city is shown in Figure 3.2.

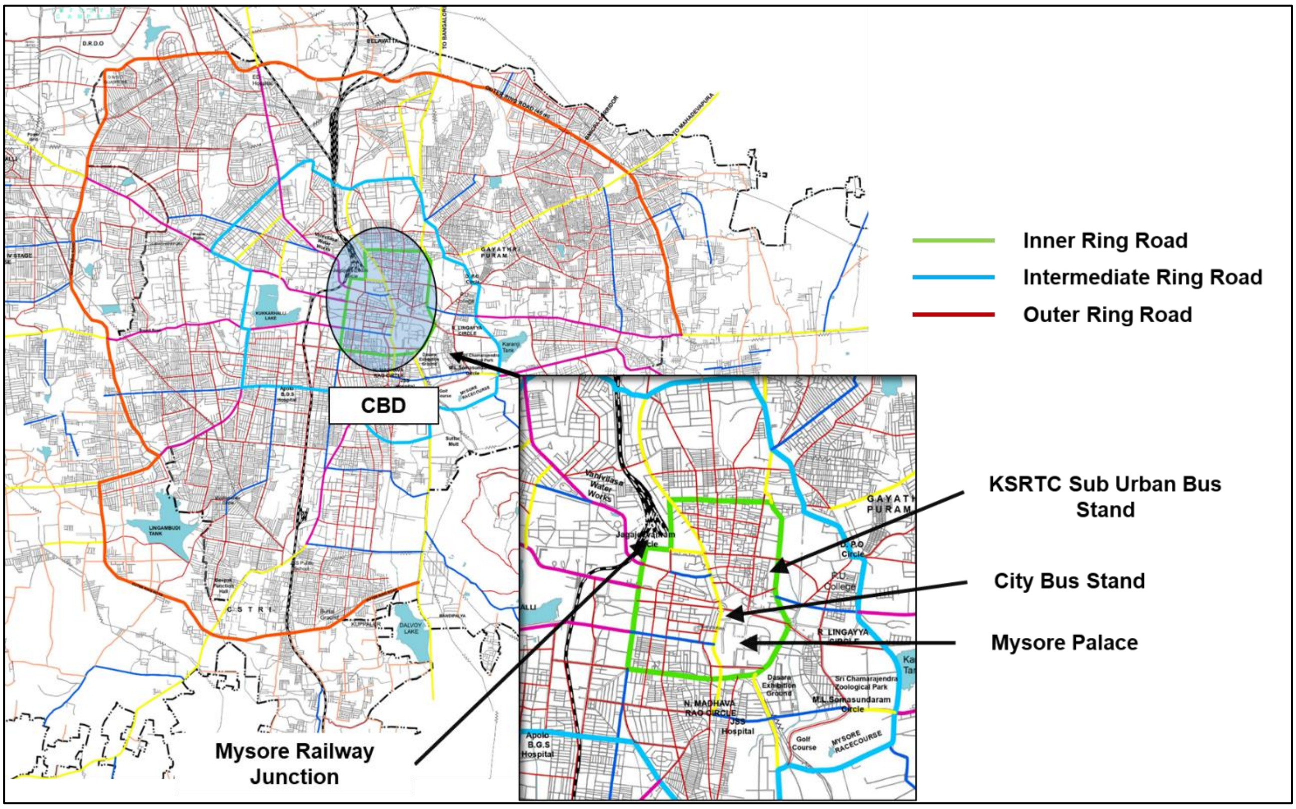


Figure 3.2 Mysore City road network (Mysore Urban Development Authority - MUDA)

The economic wellbeing of any society can be denoted by the status of road network in it. Economic activities are promoted in an urban infrastructural growth with road network as an important factor of consideration. Mysore city has 1.45 km of road length for every 1000 population and has 8.58 km of road density for each square kilometre area. Mysore has 30 signalised intersections among the total of 210 intersections across the city. The parking areas also play significant role in the urban transportation network. They are very important especially in the areas where, commercial activities and public gathering take place, resulting in heavy traffic movement. Almost 22 roads of the city have on-street parking facilities. Local planning Region (LPA) has a note of 8.65 lakhs registered vehicles by 2016 according the Regional Transport Office (RTO). The major proportion of traffic composition consists of two wheelers and cars.

3.4 PUBLIC TRANSIT SYSTEM – MYSORE ITS

The popular mode of public transport in the Mysore city is the bus transit system, which is operated by the Karnataka State Road Transport Corporation (KSRTC) under the control of Mysore City Transport Division (MCTD). There are four major bus depots and ten bus terminals under the MCTD. In the year 2012, MCTD introduced the adoption of Intelligent Transport System for the city buses. The application of Intelligent Transportation System to the public transit services in Mysore was the very first attempt in India to implement the advanced technologies in the transport sector. Sustainable Urban Transport Project (SUTP), Karnataka State Road Transport Corporation (KSRTC), Ministry of Urban Development (MoUD), Global Envirionment Facility (GEF), The Ministry of Environment and Forests, World Bank, United Nations Development Programme and IBI Group are the major stake holders for this project. Mysore being a medium sized city, is expected to grow faster in the near future with more and more transportation demands. Hence, this city was found to be suitable for the application of ITS as a demonstrative project. Mysore ITS operates buses equipped with GPS devices, collecting and process a large amount of data. The implementation of ITS infrastructure in the Mysore city transit has resulted in the reduction of daily km due to proper scheduling, savings in staff cost, savings in cost due to schedule optimisation and increase in the daily commuters up to 3 lakh passengers.

The following paragraph explains briefly about the operation of Mysore ITS. Under this ITS infrastructure, city buses are equipped with the GPS units which provides the location and other details of the trip related to the respective buses. GPS units are installed in more than 500 buses which are maintained by four major bus depots. The major components of the Mysore ITS project are as follows,

- Real Time Passenger Information System: Informing the passengers about the Estimated Time of Arrival (ETA) and Estimated Time of Departure (ETD) (Figure 3.3). ETA boards are provided at bus stops and the bus terminals are equipped with ETD boards.

Figure 3.3 Real Time Passenger Information System

- In-Vehicle display System: Inside the buses, there will be visual LED display boards which displays the real time traffic information from the central control station, regarding the current and next bus stops and other informative messages. Sample picture of in-vehicle display system is shown in Figure 3.4.

Figure 3.4 In-Vehicle display System

- Automated Voice Announcement System: The in-bus voice announcement system helps in passing audible information to the passengers along with the visual information and the important messages to be conveyed to them.
- Central Control Station: The control room is the place where the monitoring of the entire system takes place by the skilled officials. Server room consisting of different servers connected to a main database server, is the heart of the system. The server components are - Communication server, Geographic Information System (GIS) server, Interactive Voice Response Service (IVRS) server, display server, SMS server, application server and commuter portal. The Communication server receives information from the GPS equipment in the bus and application server processes the data and estimates the travel time. GIS server provides the map services and real time positions of buses on maps which helps in searching and tracking a transit vehicle. Display servers help in displaying information at bus stops and terminals. IVRS and SMS servers

Figure 3.5 Central Control Station (City Bus Stand)

provide information regarding bus transit to the commuters on their request through phone calls and SMS services respectively. Central control station of Mysore ITS is located in CBS and a sample picture of control station is shown in Figure 3.5.

- Automatic Vehicle Location System: It consists of GPS device mounted inside the bus called Vehicle Mounted Unit (VMU) and provides the real time vehicle location data of the bus to the server. These units are installed near driver seat as shown in Figure 3.6.

Figure 3.6 Vehicle Mounted Unit (VMU) - GPS

Global Positioning System (GPS) is the most reliable and accurate tool for collecting information regarding the real time location of vehicles. GPS combined with map display techniques such as Geographic Information System (GIS) is used in the collection of data which is helpful in analysing traffic problems. ITS, Mysore make use of GPS and GIS for the effective information of real time vehicle location of public transit buses. The availability of AVL data is best suited for TTR analysis and hence, Mysore city has been considered as the study area. In the next chapter, the AVL data collection and processing techniques have been explained in detail.

3.5 SUMMARY

The details of study area, Mysore city of Karnataka State, India are discussed in this chapter.. The population growth in urban area, trip attraction and the land use characteristics of the city have been discussed. The Mysore city has an area of 286.05 km^2 with urban population of 1.21 million as per the year 2020. The land use characteristics of Mysore city shows that the predominant land use type is residential area, which is about 43% of the total area. The Mysore city transit system has been upgraded by the implementation of Intelligent Transport System (ITS) that consists of in-vehicle display system, automated voice announcement system, real time passenger information system, and central controlling station. For providing the real time passenger information system, Mysore ITS collects the AVL data of buses with the help of GPS units mounted on the buses. Major reason for selecting Mysore as the study area is the availability of AVL data, which is a reliable source for analysing TTR of public transit systems.

CHAPTER 4

DATA COLLECTION AND METHODOLOGY

4.1 GENERAL

This chapter deals with the data collection and methodology adopted to achieve the objectives of the research work. In the current study, mainly two types of data have been utilised: travel time data of bus routes which are collected from Mysore ITS and data related to side friction locations of Mysore city, collected from videography method. The data collection and extraction process are explained in detail in this chapter. The chapter also describes the research framework designed to achieve each of the objectives defined. The methodology formulated to analyse the impact of side friction activities on TTR of public transport system has been presented. The steps followed in investigating the effect of spatial and temporal aggregation on travel time variability are explained. The modelling of TTR involving the data related to bus stop, intersection, land-use, and peak hour details has also been discussed. Finally, the conceptual framework to determine the LOS of bus routes based on TTR has been provided.

4.2 RESEARCH FRAMEWORK

The aim of this research is to study the factors governing TTR of the public bus transport system. The study area considered for this research is Mysore city, Karnataka. The overall research framework for this study is as shown in Figure 4.1. The data used in this study consist of AVL data of Mysore ITS and side friction data collected using videography. The steps involved in the data collection and processing has been explained in the subsequent sections. Among the four specific objectives have been stated in the Section 1.6, the first objective is to find the impact of side friction on TTR of public transit system. The study has been carried out for both divided and undivided urban road sections by considering different types of side friction elements.

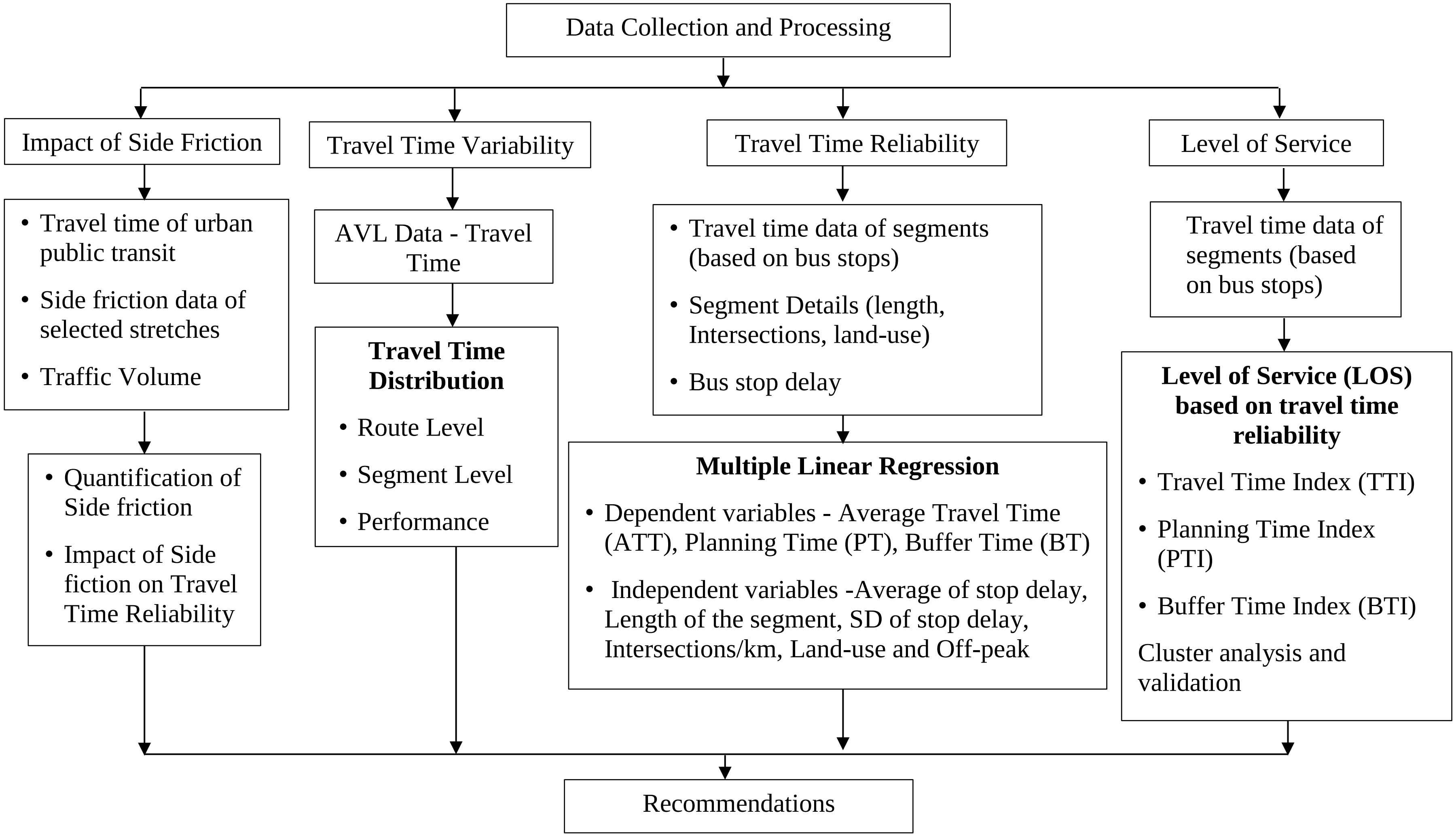


Figure 4.1. Research Framework

The impact of side friction can collectively be affected by both static and dynamic characteristics of side friction elements. Therefore, these static and dynamic side friction elements have been quantified using relative weight analysis and represented by a single index called Side Friction Index (SFI). Then, the impact of side friction on TTR is analysed using SFI. In the second objective, travel time variability of the public transit system has been analysed with the help of Automatic Vehicle Location (AVL) data of buses collected from the Mysore ITS (MITRA). The travel time data are analysed at different temporal aggregation levels corresponding to different DTWs (Departure Time Window) for peak and off-peak periods. The segment level analysis has been carried out considering bus stops, intersections and land-use type. The understanding of the factors causing unreliability of the public transit system is necessary in improving the reliability of that system. The reliability of the system has been modelled considering three TTR measures. The Multiple Linear Regression (MLR) method has been adopted to model the three TTR measures as the dependent variables. The independent variables have been chosen corresponding to five important factors: length of segment, bus stops, intersections, land-use and peak/off-peak time period, which might affect TTR measures. The final objective of this study is to determine the LOS of transit routes based on travel time reliability concept. The segment level data from four bus routes of Mysore city transit have been used to determine the LOS of public transit routes. K-Means clustering method has been adopted to determine the threshold of each LOS levels. The steps involved in the data collection and processing are explained in next section.

4.3 DATA COLLECTION

The implementation of ITS in the Mysore city transit has helped MCTD in reducing the dead kms, unscheduled stoppages, cancellation of kms due to late departure and early arrival(Case study report - MITRA, KSRTC) and bus stop skipping. ITS implementation has elevated the overall performance and efficiency of the Mysore city transit. But the problems of delays in arrival time and daily variation in arrival time, especially in peak hours, have been observed in congested and crowded routes. The potential factors which induce travel time variation are: traffic incidents, work zone activity, weather, fluctuations in demand (bus stop delay), special events, traffic-control devices (Signalised intersections), inadequate base capacity (Side friction activities) (Kwon et al. 2011). Hence, travel time variability has been analysed considering different transit routes and also the factors affecting the travel time reliability such as side friction, bus stops and intersections have been explored in this study. The data required to achieve the objectives and data collection methods have been discussed in this section. The collection and processing of Mysore ITS data and side friction data are explained in detail.

4.3.1 Travel Time Data of Public Transit

Mysore city transit vehicles are equipped with the GPS units which provide the Automatic Vehicle Location (AVL) and other trip details of the respective buses. A large amount of information is collected and stored at every time step. A time step of 10 seconds has been adopted for updating the vehicle's position and other information. The data stored on the server are retrieved using Sequential Query Language (SQL) (Appendix A.1). The information about schedule date, schedule ID, trip ID, longitude, latitude, route ID, and GPS timestamp are included in the retrieved data. The sample AVL data is provided in Table 4.1. The steps involved in the extraction of travel time from SQL language files are given and explained in subsequent paragraphs of Appendix A.2.

The major commercial and tourist activities take place in the central business district (CBD) near the city bus stand (CBS). The major roads are radially located towards the other parts of the city and suburban areas from CBS. Most of the city bus routes originate in the CBS and move towards other parts of the city and sub urban areas. Four transit routes originating from CBS have been considered in the present study, namely BEML (94), JP Nagar (13), Infosys (119) and Yelawala (266) (Figure 4.2). The routes have been selected so that they are comprised of different roadway characteristics, varying traffic and passenger demands. The details of the study routes are provided in Table 4.2. Both to and fro bus movements are considered between each origin and destination pair. The notation 'UP' refers to the trips from CBS to the destination point and 'DOWN' refers to the trips from the origin location to CBS. All the considered routes consist of both divided and undivided road sections. The study routes pass through the road sections with different land-use characteristics, mainly CBD, residential, commercial and industrial. The AVL data of weekdays for a duration of two months (March and April, 2018) have been used in this study.

The raw data obtained from the server has been pre-processed in a sequential order to eliminate outliers and incorrect observations. The predominant error in the data is missing information such as, schedule, route and trip details and duplicated timestamps. The aforementioned errors have been corrected during pre-processing to obtain bus trips with all the details and unique timestamps using the Python language code (Appendix A.3). Then, the GPS data is overlapped on the real-world map using QGIS to ensure the correct positions of the buses with respect to the road networks (Appendix A.5). At the end of this process, the data for the selected routes of the network have been extracted (Appendix A.4).

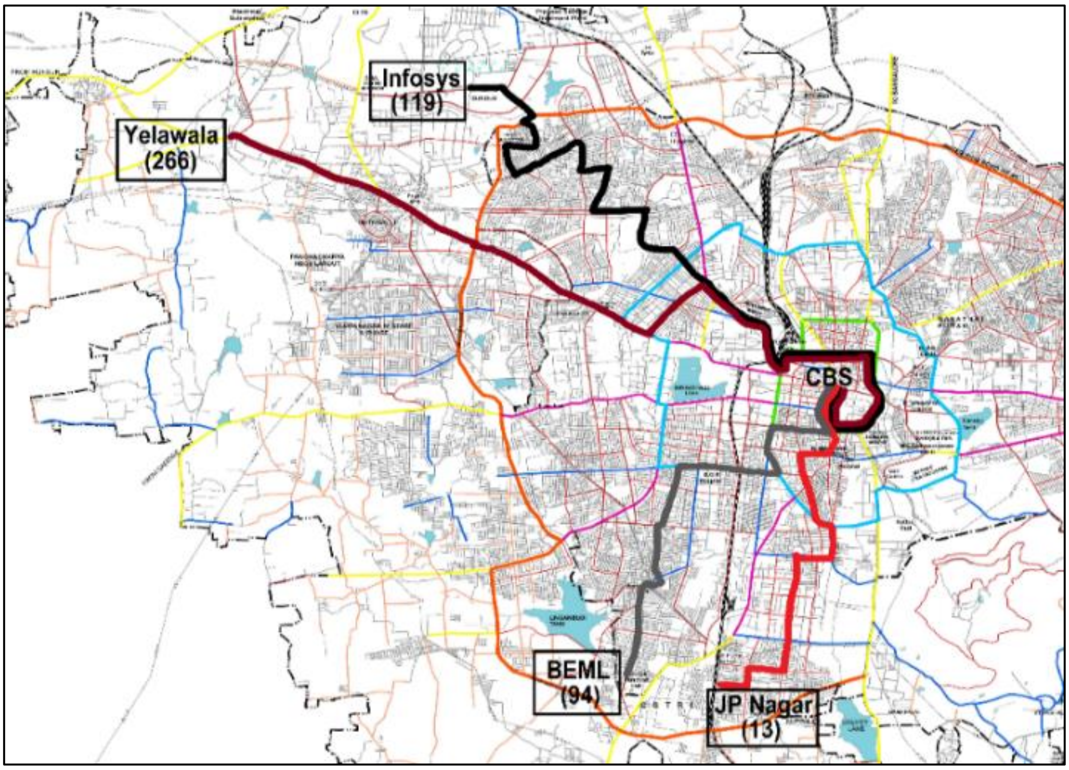


Figure 4.2. Details of the Study Routes (Source: MUDA Mysore)

Table 4.1. Sample AVL data after data processing

bus id	depot id	Schedule id	route id	trip no	latitude	longitude	GPS date	GPS time	altitude	velocity
583	2	77	599	3	12.359	76.542	06-04-2018	09:17:17	824	33
583	2	77	599	3	12.358	76.543	06-04-2018	09:17:27	823	36
583	2	77	599	3	12.357	76.543	06-04-2018	09:17:37	823	39
583	2	77	599	3	12.356	76.544	06-04-2018	09:17:47	823	26
583	2	77	599	3	12.356	76.544	06-04-2018	09:17:57	821	29
583	2	77	599	3	12.355	76.544	06-04-2018	09:18:07	816	40
583	2	77	599	3	12.354	76.545	06-04-2018	09:18:17	812	39
583	2	77	599	3	12.354	76.546	06-04-2018	09:18:27	812	43
583	2	77	599	3	12.353	76.546	06-04-2018	09:18:37	813	44

Table 4.2. Details of transit routes and segments

Route (ID)	Route Length (Km)	Number of Bus stops	Segments with Intersections	Segments with Land-use Type				
				CBD	Commercial	Residential	Open Space	Industrial
BEML (94)	8.42	17	5	3	2	11	-	-
JP Nagar (13)	8.62	18	2	2	1	14	-	-
Infosys (119)	16.52	26	4	5	2	15	1	2
Yelawala(266)	18.46	23	7	5	6	7	4	-

The GPS points existing away from the bus routes (at least 100 m) have been removed which might have been recorded due to the error in the communication system or GPS functionality. The trips with deviations from the designated routes have not been considered for analysis, due to the heterogeneity in route characteristics that may exist. The pre-processed data are then used to compute the travel times. The sample travel time are provided in Appendix A.6. The distance between the GPS points have been calculated by Haversine formula using Equation 4.1, which computes the great circle distance between two points on a sphere. The outliers with undesirable cumulative distance or travel times (very large or very small) have been removed using the Median Absolute Deviation (MAD) technique (Ma et al. 2016).

$$d = 2r \arcsin\left(\sqrt{(sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\, sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right) \tag{4.1}$$

Where,

d – Distance between two GPS points

r – Radius of the earth

φ_1, φ_2 - Latitude of point 1 and latitude of point 2 (radians)

λ_1, λ_2 - Longitude of point 1 and longitude of point 2 (radians)

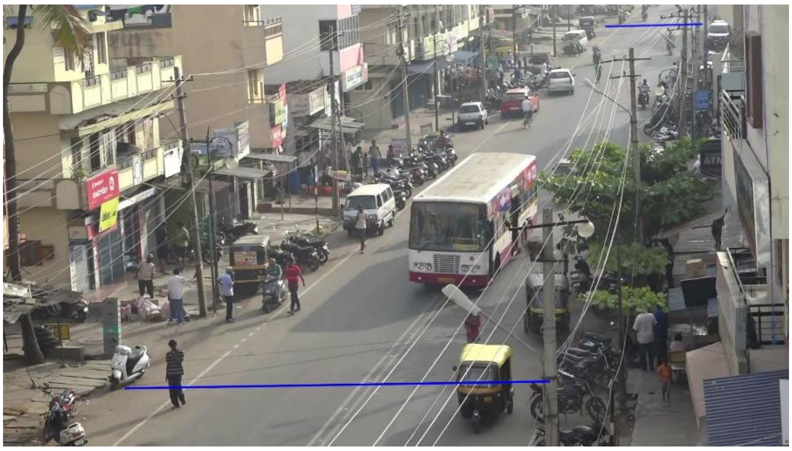
4.3.2 Data of side friction study

The process of data collection and extraction involved in the analysis of impact of side friction on TTR of public transit system are described in this section. Two road sections of Mysore city: a divided road (Chamaraja Double road) and an undivided road (New Kantharaj Urs Road) with significant side friction activities have been considered for the study. In the divided road section, the traffic movement in one of the directions (towards Ramaswamy circle) and the respective side friction elements have been considered for the study. The side friction activities such as on-street parking, pedestrian movements, exist in both the sections, and cross-street entry/exits are present only along the undivided road. The details of both the study sections are tabulated in Table 4.3**.** The study locations are selected in such a manner that, sections are free from the interferences from nearby intersections and bus stops. There is a considerable variation found in the side friction level within the study sections. Figure 4.3 shows the locations of selected study sections and Figure 4.4 shows the sample pictures of undivided and divided roads.

Table 4.3. Details of side friction study sections

Sl. No.	Study Location	Road Type	Carriageway width (m)	Parking width (m)	No. of lanes per direction	Peak Hour Traffic Volume PCU/h	Types of Side Friction
1	New Kantharaj Urs road	Undivided	15.6	2.2	2	5,075	Parked vehicles, pedestrians and cross-street vehicles
2	Chamaraja Double road	Divided	12	2.5	2	2,986	Parked vehicles and pedestrians

Figure 4.3. Side Friction Road Sections (@Google Maps)



(a)

(b)

Figure 4.4. Sample pictures of study locations a) Undivided road b) Divided road

The study aims to analyse the effect of side friction alone on TTR of urban roads. Considering long road stretches (more than 100 meters) in the present study area would make the presence of junctions and bus stops affect the travel time of public transit. Hence, the study has been conducted on mid-block sections of length 100 meters, where the side friction is significantly present and the section is free from the effect of intersections and bus stops. Data collection has been done with the help of videography technique. High clarity video cameras were installed in the vantage points in such a way that it can cover the study stretch. Continuous videography of traffic flow was conducted from 6 AM to 10 PM in the month of January, 2019 to understand the hourly variation of both side friction activities and travel time of public transit. The data has been collected on a weekday and a day during the weekend. Three types of data have been extracted from the video namely, travel time of public bus transit, traffic volume, and side friction data at every 5-minute interval. The classified traffic volume data has been extracted for both the sections. The classified traffic volume is converted into Passenger Car Units using PCU factors (Appendix A.7) provided in IRC: 106 1990. The sample traffic volume data is given in Appendix A.8.

4.3.2.1 Travel Time Data of Public Transit

In this study, the travel time and interactions of side friction with public transit are collected for the urban public transit system. Reference lines have been inserted at the beginning and end of the 100-meters section using video editing software. The time taken by the public transit vehicles to traverse between these lines has been considered as the travel time. The free-flow travel time (FFTT) is collected during early morning hours (5 A.M to 6 A.M) when public transit vehicles can travel with minimum or no impedance.

4.3.2.2 Side Friction Data

The different types of side friction activities are observed on the roadside of the study area. On the selected study stretches, pedestrians crossing the road and walking along the road, different types of parked vehicles, parking/unparking manoeuvres and cross-street entry/exit (undivided road section) movements are the activities observed. These data are extracted from the video. The number of interactions of the aforementioned side friction activities with public transit vehicles have been aggregated for every 5-minute interval (Guo et al. 2012b). The interactions with the vehicles other than the public transit buses are not considered since, this study is mainly focused on investigating the impact of side friction on public transit vehicles.

The parking of vehicles outside the designated parking lane will have a higher impact on the traffic movement, due to the reduction in the road width. Therefore, the entire road width is divided into two strips: Parking strip and middle strip as shown in Figure 4.5 and Figure 4.6. D_e refers to midpoint of edge strip from carriageway edge and D_1,

D_2 ….D_i is the distance to midpoint of strip in which the friction element (i) is present, from carriageway edge. The interaction of public transit vehicles with the vehicles parking outside the parking strip is considered separately. The undivided study stretch has two cross-streets having fewer vehicle movements compared to through traffic flow. The entry/exit from these cross-streets also interrupt the through traffic flow. Hence these cross-street entry/exits are considered as a category of side friction elements.

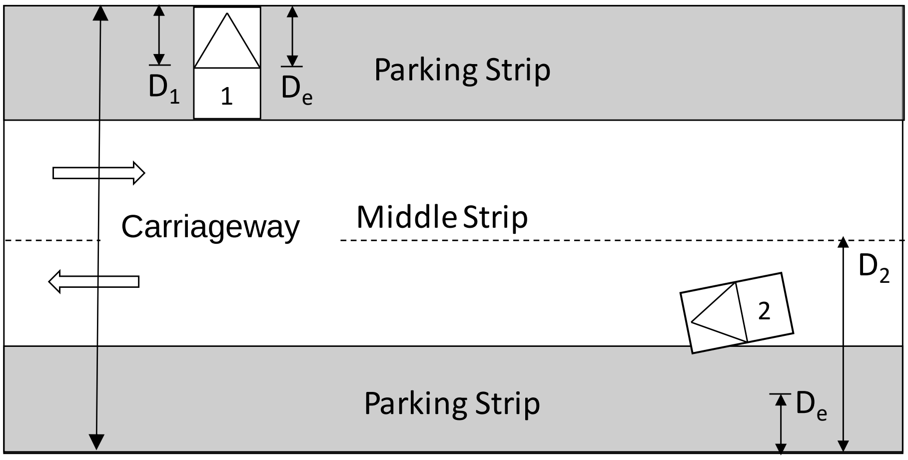


Figure 4.5. Details of parking strip and middle strip of undivided road (Note, 1: Vehicle parked in parking strip and 2: Vehicle parked outside parking strip)

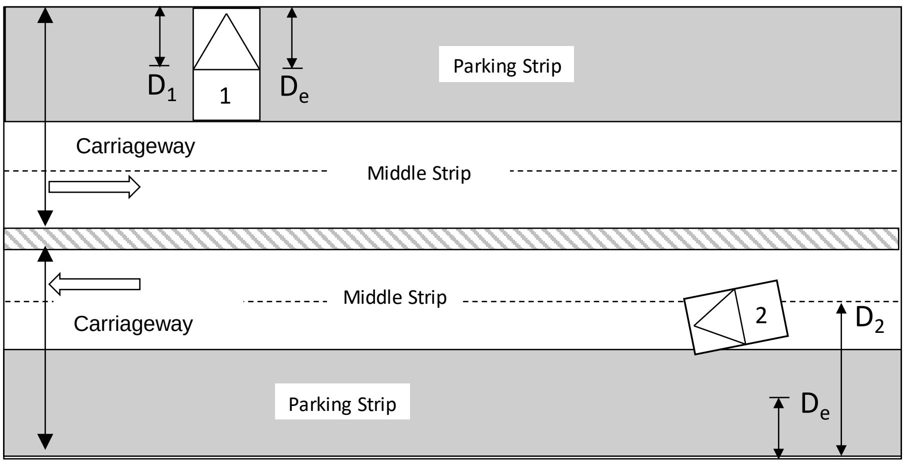


Figure 4.6. Details of parking strip and middle strip of divided road (Note, 1: Vehicle parked in parking strip and 2: Vehicle parked outside parking strip)

4.4 METHODOLOGY

The overall objective of this research work is to study the factors governing travel time reliability of the public bus transport system. The methodology and framework adopted is briefly explained in the Section 4.2 and the research framework is as shown in Figure 4.1. The impact of side friction elements on TTR has been studied with the help of Side Friction Index (SFI). SFI is determined by the quantification of different static and dynamic side friction elements using relative weight analysis. The variability in travel time of public transit has been investigated by considering the influence of temporal and spatial aggregation of travel times on the travel time distributions. TTR modelling has been carried out to analyse the factors affecting TTR measures using Multiple Linear Regression (MLR). Finally, Level of Service (LOS) thresholds of bus routes are defined based on TTR concept using K-Means clustering technique. The methodology followed to achieve each of the objectives have been explained in detail in the subsequent sections.

4.5 IMPACT OF SIDE FRICTION ON TRAVEL TIME RELIABILITY

The methodology adopted to achieve the first objective of the research, i.e., analysis of the impact of side friction on TTR is described in this section, and the framework of this objective is shown in Figure 4.7. The travel time data of urban public transit buses, traffic volume, and side friction data of the selected undivided road and divided road sections are utilised in this study. The different types of side friction elements have been grouped into static and dynamic side frictions. Static side friction is determined based on area ratio and distance ratio (Pal and Roy 2016). Relative weight analysis has been used to quantify the relative importance of dynamic side friction elements along with static side friction and is represented by Side Friction Index (SFI). Travel time reliability is described in terms of reliability measures: TTI, PTI, BTI, and RBI. The hourly variation of TTR measures is analysed with the variation of SFI. K-Means clustering algorithm has been used to find the number of traffic volume levels and their threshold values. Finally, the impact of SFI on TTR indices is analysed separately based on the traffic volume levels. The detailed explanation of the above-mentioned methodology is provided in the subsequent sections.

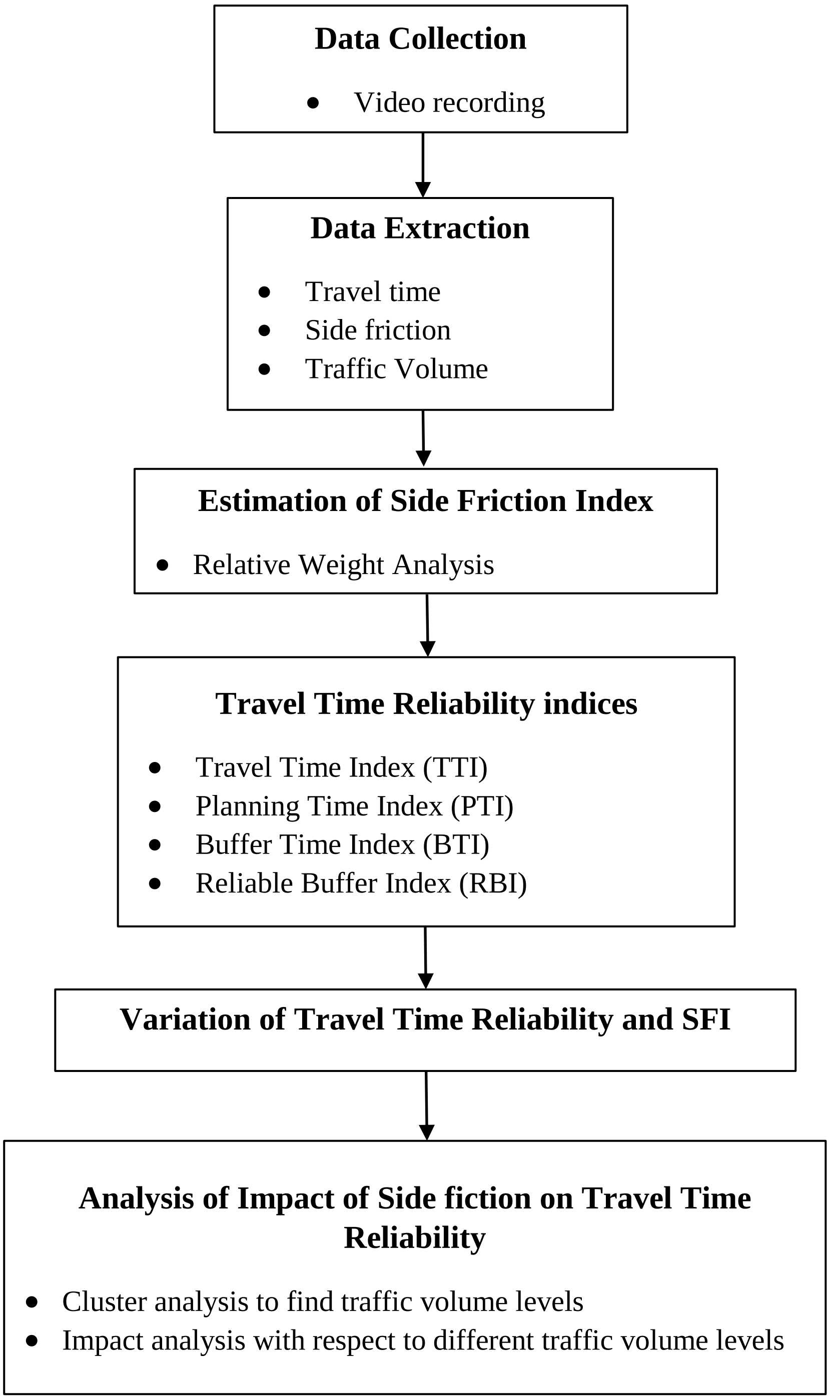


Figure 4.7. Methodological framework for impact of side friction

4.5.1 Side Friction Index

In the present research work, both static and dynamic side friction elements are considered to analyse the effect of side friction activities on TTR of public transit. The side friction index is computed by considering the quantified static side friction and dynamic side friction elements by relative weight analysis. The static side friction has been quantified using area ratio and distance ratio. Static side friction consists of all types of parked vehicles on the parking strip/lane and also the vehicles parked outside the parking lane. Dynamic side friction involves parking and unparking manoeuvres, pedestrian movements (crossing the road and walking along the roadside), and cross-street entry/exits (in the case of the undivided road). The detailed procedure of the quantification of static and dynamic side frictions has been described in the following subsections.

4.5.1.1 Estimation of Static Side Friction

There are different types of side friction elements having different levels of impact on the traffic movement. The impact of different types of friction elements on travel time depends on their static and dynamic characteristics, as well as the position of friction elements on the carriageway. For example, the impact of car standing on the middle of the road would be higher than the pedestrian standing on the edge of the road. In this study, static side friction is estimated based on the area ratio (AR) and distance ratio (DR) (Pal and Roy 2016). Area ratio is determined based on the projected area of side friction element with respect to that of a pedestrian standing on the carriageway edge (Equation 4.2). The projected area of a pedestrian standing on the carriageway edge is considered as a unit of static side friction similar to a passenger car as standard vehicle in vehicular movement.

The impact of side friction is not only dependent on the projected area but also on the position of the friction element with respect to the carriageway edge. Two strips namely; parking strip and middle strip are considered in this study as shown in Figure 4.5 and Figure 4.6. The side friction impact is estimated in terms of distance ratio (DR) using Equation 4.3. DR is the ratio of distance to the midpoint of strip in which the side friction element stands from carriageway edge and the distance to midpoint of edge strip from carriageway edge (Refer to Figure 4.5 and Figure 4.6 for details of DR).

$$Area\ Ratio\ (AR) = \frac{Projected\ area\ of\ side\ friction\ elements\ (Ai)}{Projected\ area\ of\ pedetrian\ (Ap)} \tag{4.2}$$

$$Distance\ Ratio\ (DR) = \frac{Midpoint\ of\ strip\ where\ friction\ element\ is\ present\ from\ carriageway\ edge\ (Di)}{Midpoint\ of\ edge\ strip\ from\ carriageway\ edge\ \ (De)} \tag{4.3}$$

Where $D_i = D_1, D_2, D_3 \ldots\ldots D_n$, n = Total number of parked vehicles

Later, the weight factor (W_i) is determined by adding AR and DR as shown in Table 4.4 and Table 4.5. The scaled weight factors are calculated considering a pedestrian standing on the parking strip as one unit of static side friction (Table 4.6) and examples of calculation of scaled weight factors are given below.

Table 4.4. Calculation of weight factor for the undivided road

Parking Strip					
Friction Element	**Projected area, Ai (m^2)**	**Distance of CW edge from strip midpoint, Di (m)**	**Area ratio AR = Ai/Ap**	**Distance ratio DR = Di/De**	**Weight factor Wi = AR + DR**
Pedestrian	0.5	1.1	1.00	1	2.00
Two-Wheeler	1.2	1.1	2.40	1	3.40
Three-Wheeler	4.48	1.1	8.96	1	9.96
Car	5.36	1.1	10.72	1	11.72
LCV	12.81	1.1	25.62	1	26.62
Middle Strip					
Pedestrian	0.5	7.8	1.00	7.09	8.09
Two-Wheeler	1.2	7.8	2.40	7.09	9.49
Three-Wheeler	4.48	7.8	8.96	7.09	16.05
Car	5.36	7.8	10.72	7.09	17.81
LCV	12.81	7.8	25.62	7.09	32.71

Example 1: Scaled weight factors W_i for pedestrian standing on the parking strip of undivided road – $\frac{weight\ factor\ of\ pedestrian\ standing\ on\ parking\ strip\ (2.00)}{weight\ factor\ of\ pedestrian\ standing\ on\ parking\ strip\ (2.00)} = 1.00$

Example 2: Scaled weight factors W_i for two wheeler parked on the parking strip of undivided road – $\frac{weight\ factor\ of\ two\ wheeler\ parked\ on\ parking\ strip\ (3.40)}{weight\ factor\ of\ pedestrian\ standing\ on\ parking\ strip\ (2.00)} = 1.70$

Table 4.5. Calculation of weight factor for the divided road

Parking Strip					
Friction Element	**Projected area, Ai (m^2)**	**Distance of CW edge from strip midpoint, Di (m)**	**Area ratio AR = Ai/Ap**	**Distance ratio DR = Di/De**	**Weight factor Wi = AR + DR**
Pedestrian	0.5	1.25	1.00	1	2.00
Two-Wheeler	1.2	1.25	2.40	1	3.40
Three-Wheeler	4.48	1.25	8.96	1	9.96
Car	5.36	1.25	10.72	1	11.72
LCV	12.81	1.25	25.62	1	26.62
Middle Strip					
Pedestrian	0.5	6	1.00	4.80	5.80
Two-Wheeler	1.2	6	2.40	4.80	7.20
Three-Wheeler	4.48	6	8.96	4.80	13.76
Car	5.36	6	10.72	4.80	15.52
LCV	12.81	6	25.62	4.80	30.42

Finally, the static side friction is estimated by multiplying the number of each type of static friction element and the scaled factor of respective friction elements using Equation 4.4. The sample calculation of Static Side Friction (SSF) is given in Table 4.7.

$$SSF = \sum W_i N_i \qquad (4.4)$$

Where,

SSF = Static Side Friction

W_i = Scaled weight factors of i_{th} type of side friction elements

N_i = Number of i_{th} type of side friction elements

Table 4.6. Details of scaled weight factors of static side friction

	Undivided road		**Divided road**	
Friction Elements	**Parking strip**	**Middle strip**	**Parking strip**	**Middle strip**
Pedestrian	1	4.05	1	2.90
Two-Wheeler	1.700	4.75	1.700	3.60
Three-Wheeler	4.980	8.03	4.980	6.88
Car	5.860	8.91	5.860	7.76
LCV	13.310	16.36	13.310	15.21

Table 4.7. Sample calculation of Static Side Friction (SSF)

	Edge strip					**Middle strip**				**SSF**
	Pedestrian Standing on Edge strip	**2W**	**3W**	**CAR**	**LCV**	**2W**	**3W**	**CAR**	**LCV**	
Weight factor	1	1.7	4.98	5.86	13.31	4.7	8.03	8.91	16.36	
9.20 AM to 9.25 AM	11	27	1	5	0	3	0	3	0	132.16

4.5.1.2 Estimation of Side Friction Index

The interaction between dynamic side friction elements with the moving vehicles is very complex in nature. The estimation of relative weight/importance of each side friction element is very crucial in the quantification process. Few studies (Chiguma 2007; Gulivindala and Mehar 2018) have adopted standardised regression coefficients of multiple regression in determining the relative contribution of each predictor towards explaining variance in the criterion variable. But, the correlation between predictor variables leads to the underestimation/overestimation of some of the predictors. In this study, both static and dynamic side friction elements are considered to analyse the effect of side friction activities on TTR of public transit. The static side friction (SSF) has been quantified using area ratio and distance ratio as explained in Section 4.5.1.1. Static side friction consists of all types of parked vehicles on the parking strip/lane and also the vehicles parked outside the parking lane. Dynamic side friction involves parking and unparking manoeuvres (PK_UPK), pedestrian movements (crossing the road - PDSCR and walking along the roadside - PDSW), and cross-street entry/exits - CSentry_exit (in the case of the undivided road). The correlation matrix of the above predictor variables along with traffic volume of two study sections is given in Table 4.8 and Table 4.9.

Table 4.8. Correlation matrix of predictor variables for the undivided road

Variable	Traffic Volume	SSF	PK_UPK	CSentry exit	PDSW	PDSCR
Traffic Volume	1	0.310	0.086	0.219	0.087	0.102
SSF	0.310	1	0.136	0.161	0.156	0.180
PK_UPK	0.086	0.136	1	0.509	0.350	0.287
CSentry_exit	0.219	0.161	0.509	1	0.623	0.419
PDSW	0.087	0.156	0.350	0.623	1	0.509
PDSCR	0.102	0.180	0.287	0.419	0.509	1

Table 4.9. Correlation matrix of predictor variables for the divided road

Variable	Traffic Volume	SSF	PK_UPK	PDSW	PDSCR
Traffic Volume	1	0.607	0.188	0.141	0.169
SSF	0.607	1	0.315	0.164	0.258
PK_UPK	0.188	0.315	1	0.425	0.097
PDSW	0.141	0.164	0.425	1	0.079
PDSCR	0.169	0.258	0.097	0.079	1

The resultant correlation matrices for both the locations reveal a certain degree of correlation between the variables. Relative weight analysis is an alternative technique to estimate the relative importance of each independent variables when they are correlated with each other (Johnson 2000). Relative weight analysis is one of the methods which addresses the problem created by correlated independent variables. The independent variables are transformed to their maximally related orthogonal duplicates. Then, the uncorrelated orthogonal duplicates are regressed with the criterion variable to produce standardised regression coefficients. These standardised regression coefficients are then rescaled with respect to original independent variables. The detailed explanation of the determination of the relative weights of independent variables can be found in the previous research works (Johnson 2000; Tonidandel and LeBreton 2015). In the present study, the method of relative weight analysis is adopted to find the relative importance of each independent variable. The travel time is considered as the criterion variable (dependent variable) and traffic volume, static side friction, and dynamic friction elements are considered as independent variables. The data for SSF is obtained from the Table 4.7. The raw relative weights for each predictor variable except traffic volume (since it is not a side friction element) are rescaled in terms of SSF. Finally, SFI is calculated using rescaled relative weights given by Equation 4.5 (Sample SFI calculation is provided in Appendix A.9)

$$SFI = A * SSF + B * PK\_UPK + C * PDSW + D * PDSCR + E * CSentry\_exit \qquad (4.5)$$

Where,

SFI - Side Friction Index

A, B, C, D, E - Rescaled relative weights of predictor variables (Results from relative weight analysis)

SSF – Static Side Friction

PK_UPK – Number of parking and unparking interactions with bus per unit time

PDSW – Number of interactions of bus with pedestrians walking along the road per unit time

PDSCR - Number of interactions of bus with pedestrians crossing the road per unit time

CSentry_exit – Number of interactions of bus with cross-street entry and exit vehicles per unit time

4.5.2 Travel Time Reliability

Travel time reliability is one of the significant parameters in the assessment of public transit performance. In this study, TTR of public transit has been analysed using the reliability indices such as BTI, TTI, and PTI as described by Federal Highway Administration (FHWA, 2006). TTI, PTI and BTI are calculated using Equations 2.1 to 2.3. The definitions of these reliability measures are given in section 2.1.2.

All the reliability measures cannot be used to compare the reliability of different road sections. For example, BTI can only be used to compare the reliability of bus transit at the same road section under different conditions. TTI and PTI consider the effect of FFTT on average travel time and 95th percentile travel time, respectively. These measures can be used to understand the difference in the performance of different road sections. But it is not possible to take into account the effect of both average travel time and 95th travel time simultaneously. Hence, the reliability measure developed by Chepuri et al. (2020) called Reliable Buffer Index (RBI) is used, which considers the effect of both 95th travel time and average travel time together. RBI is calculated using Equation 4.6.

$$RBI = \frac{95th\ Travel\ Time - Average\ Travel\ time}{Free\ Flow\ Travel\ Time} \tag{4.6}$$

The above-mentioned travel time indices have been computed, and their variations throughout the day with respect to that of roadside frictions have been analysed. The side friction levels are not constant throughout the day which depends on the peak hour time periods, types of commercial activities, land use type etc. These variations impart variability in travel time of public transit. Hence, the hourly variation of SFI along with reliability measures BTI, PTI, and TTI have been plotted for both the days of the sections separately. In the present study, both divided and undivided roads are considered and analysed separately due to the difference in the geometrical and traffic characteristics of the sections. Hence, the comparison of the effect of side friction on TTR of transit vehicles is done using RBI considering the travel time data of weekday and weekend separately.

4.5.3 Analysis of Impact of Side Friction on Travel Time Reliability

In this section, the analysis carried out to know the relationship between SFI and travel time indices has been described. The data aggregated for 15 minutes have been used in this analysis to get a sufficient sample size to determine TTR measures, especially PTI and BTI. Initially, the relationship between SFI and reliability indices has been analysed using regression by considering SFI as the independent variable as shown in Figure 4.8 and Figure 4.9 for the divided and undivided road respectively. In the case of the undivided road (Figure 4.8), R^2 value ranges from 0.21 to 0.42. It is in the range of 0.23 to 0.46 in the case of the divided road (Figure 4.9). In both the cases, the relationship between TTR indices and SFI has R^2 value less than 0.5. The lower R^2 value is due to the influence of traffic volume on TTR along with side friction. The traffic volume is one of the important factors which affect travel time. The impact of side friction is mentioned to be positively correlated with traffic volume, in the previous literature (Pal and Roy, 2019). Hence, the traffic volume is also considered in the analysis of impact of side friction on TTR. In order to decide the traffic volume levels and their threshold values based on their similar data structure related to travel time, K-means clustering method has been adopted. K-Means clustering is an algorithm that assigns group labels to the unlabelled data points based on the Euclidian distance from a centroid of the cluster to the data points. This algorithm is effectively used in the previous studies on LOS (Chepuri et al. 2019), side friction (Pal and Roy 2019) and road safety (Shirmohammadi et al. 2019). It is said to be an effective way to determine the threshold values. The first step in the cluster analysis is to decide the optimum number of clusters. The optimum number of clusters can be decided using silhouette analysis, Elbow method, and Gap statistic method. In this study, the optimum number of clusters is decided using the Elbow method as it is one of the commonly used methods (Kehagias et al. 2015; Elsa Shaji et al. 2018). This method decides the optimum number of clusters based on minimizing the variation of data structure within the cluster. The optimum number of clusters is defined by a function called, 'within cluster sum of squares' (WCSS), which is calculated based on the distance between data points and cluster centroids using Equation 4.7. Then, the graph of WCSS and number of clusters is plotted. As the number of clusters increases, the distance between data points and respective cluster centroid (WCSS) decreases. However, the change in WCSS drops as the number of clusters increases. The optimum number of clusters is considered as that point at which change in WCSS is not significant thereafter.

The steps to be followed in this clustering method are as mentioned below,

1. After the selection of k number of clusters, cluster the data points into k clusters and select k data points randomly as cluster centroids.
2. The Euclidean distance has to be calculated between cluster centroids and each data points.
3. If the calculated distance between data point and cluster centroid of other cluster is closer than the assigned one, data point will be shifted to that cluster.
4. Now, there are new data points added to clusters and calculate the mean/centroid of each cluster.

5. Calculate the Euclidean distance between cluster centroid and the data point again with new data points and cluster centroids.
6. Reassign the data points to the closest clusters and repeat the steps until the same data points are assigned to the same clusters in consecutive iterations.

$$WCSS = \sum_{i}^{N}(x_i - C_i)^2 \quad (4.7)$$

Where *N* – number of clusters,

WCSS - within cluster sum of squares

x_i – member of cluster *i*

C_i – centroid of cluster *i*.

The clustering analysis gives the range of different traffic volume levels, according to which the impact of side friction on TTR has been analysed. The results of Elbow method and K-means clustering are discussed in the next chapter.

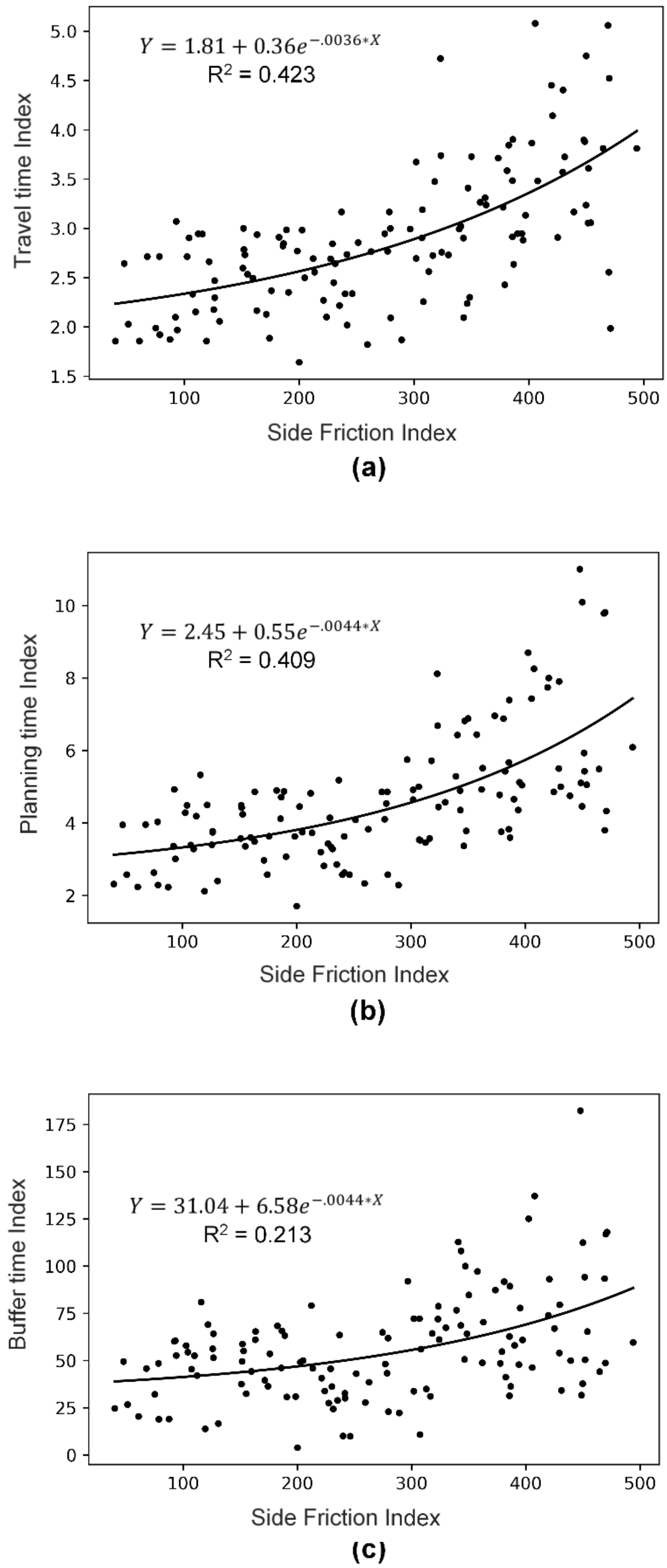
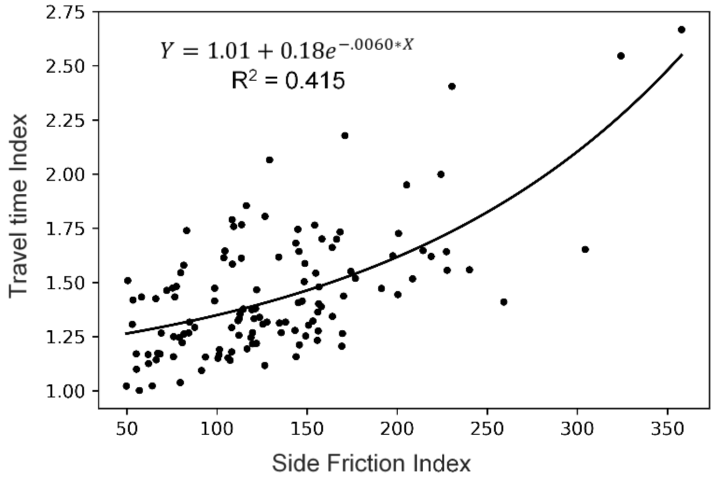


Figure 4.8. Travel Time Reliability vs SFI (Undivided road) a) TTI b) PTI and c) BTI



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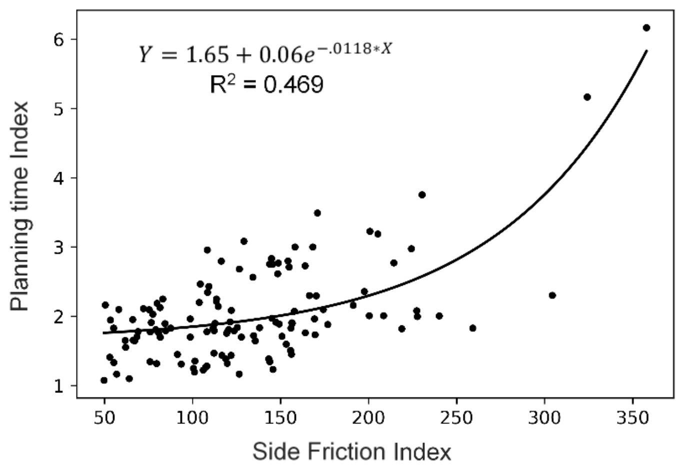

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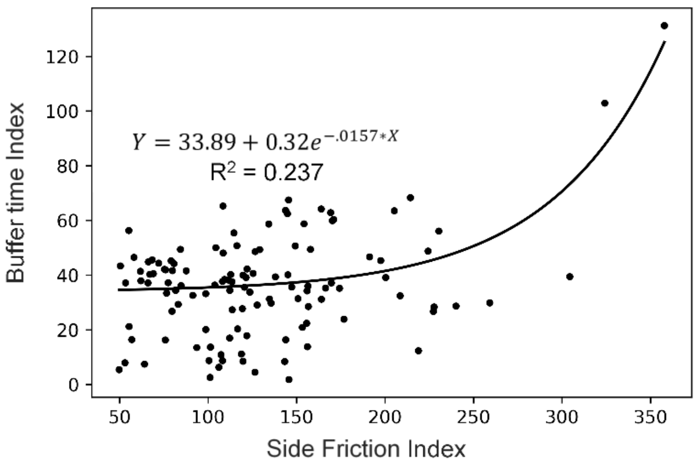

(c)

Figure 4.9. Travel Time Reliability vs SFI (Divided road) a) TTI b) PTI and c) BTI

4.6 TRAVEL TIME VARIABILITY

The second objective of this study is to analyse the effect of spatial and temporal aggregation on travel time variability of public transit using statistical distributions. The framework of methodology of travel time variability study is shown in Figure 4.10. The travel time data for four routes (segment level and route level) have been extracted after processing the data. Three types of aggregation have been considered in this study to analyse travel time variability, namely temporal aggregation, spatial aggregation, and time period components. Different cases are obtained depending on the aggregation of the travel time data for each route based on the temporal aggregation (period, 60 minutes, 30 minutes, and 15 minutes), spatial aggregation (direction, route level and segment level) and time periods (morning peak hour, evening peak hour, afternoon peak hour and off-peak hour). In total, 520 cases for route level and 2528 cases for segment level are generated.

The distribution fitting process has been conducted for each generated case separately. Based on the previous studies of TTV, seven probability distributions have been selected, namely Burr, GEV, Gamma, log-logistic, lognormal, normal and Weibull. The distribution fitting process has been carried out using EasyFit software, which estimates the distribution parameters using maximum likelihood estimation (MLE) method. MLE is the parameter estimation method for probability distribution of a population from its sample, so that the probability or likelihood of obtaining the observed data is most likely.

The Kolmogorov-Smirnov (KS) test for goodness of fit (Rahman et al. 2018; Mazloumi et al. 2010; Chepuri et al. 2020) has been used to evaluate the fitting of each distribution. The distribution can be considered as significantly fitting the observations when the p-value is greater than significance level (0.05) and fails to discard the null hypothesis H_o, which states that the observations come from the distribution considered. The larger KS test p-value implies the better fitting ability of the distributions. All the distributions are ranked based on the significance value in the ascending order with the best fitting distribution ranked as 1.

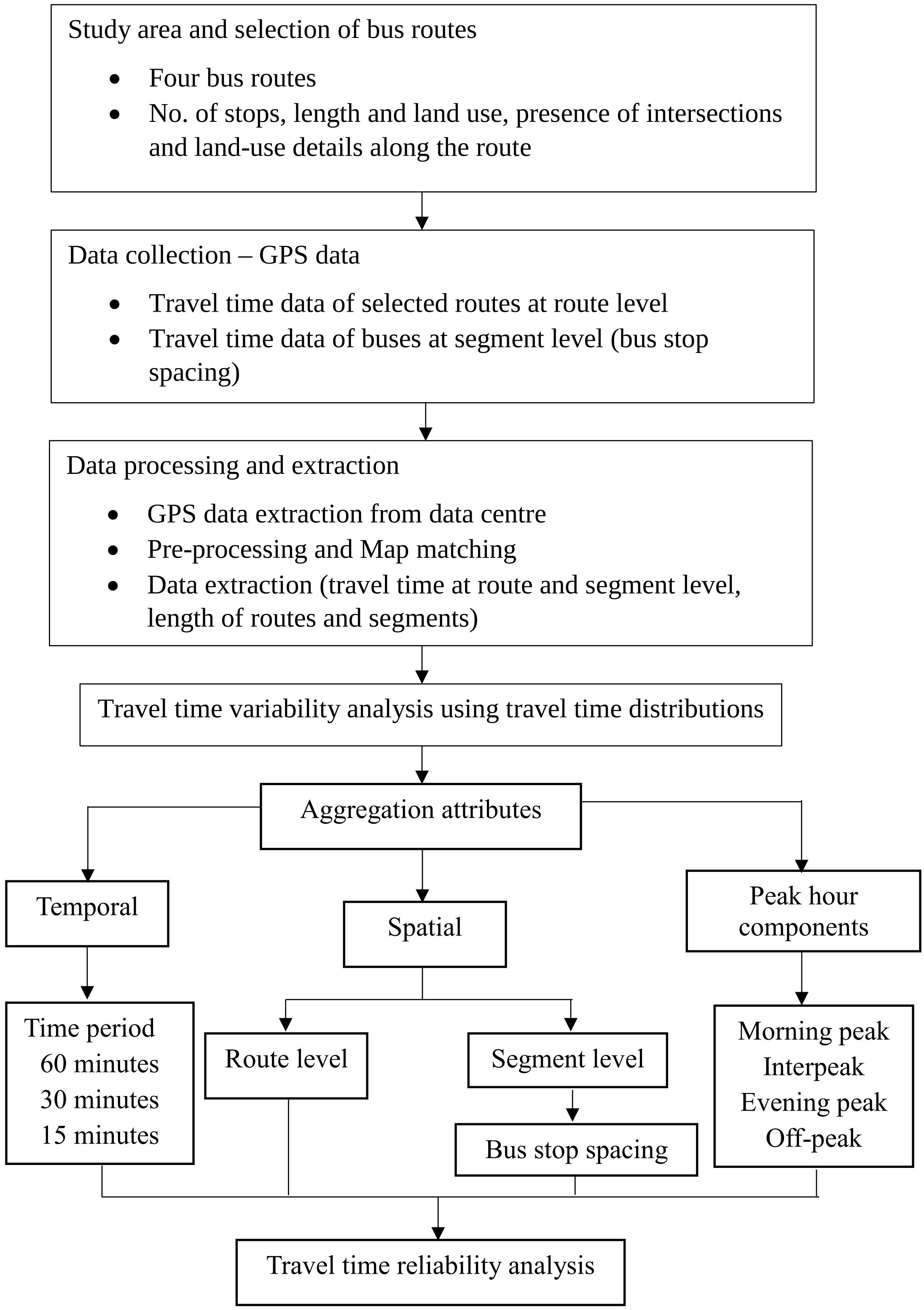

Figure 4.10. Methodological framework for travel time variability

The performance of each selected distribution has been evaluated in terms of accuracy and robustness (Ma et al. 2016). Accuracy describes the fitting ability of distributions with a small error, and it is obtained using the descriptive statistics of KS test p-value and ranks of distribution. Robustness describes the versatility of distributions to model different complex situations with the permissible fitting error. It is computed using number of cases that passes the hypothesis test. The performance of the distributions is also evaluated for the segments that have signalised intersections and different land-use category separately to understand the effectiveness of the distributions under different traffic and land-use conditions.

The statistical measures such as skewness, kurtosis and multimodality have been considered to evaluate the impact of aggregation on travel time variability. For a distribution, kurtosis gives the measure of tailedness and skewness estimates the degree of asymmetry. Multimodality of the travel time data has been investigated using Hartigan dip test. The dip test determines the maximum distinction between empirical distribution function and unimodal distribution function, which minimizes that difference (Hartigan and Hartigan 1985). The data is said to be unimodal distributed if the significance value chosen (0.05) is lesser than the p-value obtained.

The performance of the alternative distributions in fitting travel time data of public transit has been evaluated using survivor function. The survival probability of the distributions with respect to KS test p-value has been analysed using survivor function (Equation 4.8).

$$S(KS\ p-value\ ) = 1 - F(KS\ p-value\ ) \tag{4.8}$$

Where,

S (KS p-value) = Survival function of KS p-value

F (KS p-value) = Cumulative density function of KS p-value

4.7 TRAVEL TIME RELIABILITY MODELLING

The factors affecting the reliability of public transit have been analysed in the third objective of the research. The reliability of the system has been addressed by considering three TTR measures namely; Average Travel Time (ATT), Planning Time (PT) and Buffer Time (BT). The Multiple Linear Regression (MLR) method has been adopted to model the three TTR measures as the dependent variables. The methodological framework of TTR modelling is given in Figure 4.11. Backward stepwise selection process has been adopted for the selection of independent variables. The segment level travel time data of Yelawala route (route no- 266) is considered for TTR modelling. The route-266 is divided into segments based on the bus stops spacing and resulted in 22 segments (Table 4.2). The travel time data of these segments are used to calculate the ATT, PT and BT. The independent/exploratory variables have been selected based on the previous studies. The independent variables selected are corresponding to the factors such as segment length, bus stops, intersections, land-use and peak/off-peak time period, which impact the travel time related measures. In the previous studies, the data regarding the boarding and alighting of passengers are considered to represent the impact of bus stop on TTR. Most of these studies were conducted in the developed countries which have adopted the digital system to collect Automatic Passenger Count (APC). But, in case of the Mysore city transit system the passenger tickets are issued through Electronic Ticketing Machine (ETM), which stores the passenger related data not with respect to each bus stop separately but, stage-wise (each stage consists of two or three bus stops). Hence, the bus stop delay is calculated using GPS data and it is considered as a parameter representing the number of passengers served at each bus stop. The detailed explanation of the bus stop delay extraction is provided in the next sub section. The segments with land-use type CBD/commercial are assigned with the dummy variable 1. The data from 6 AM to 10 PM are used in this study in which the data from 6 AM to 8 AM are considered as off-peak data. Intersections/Junctions are the other important factors which affect TTR and hence, number of signalised intersections and major junctions per km in each segment have been considered as one of the independent variables. The description of all the independent variables considered to motel TTR is given in Table 4.10.

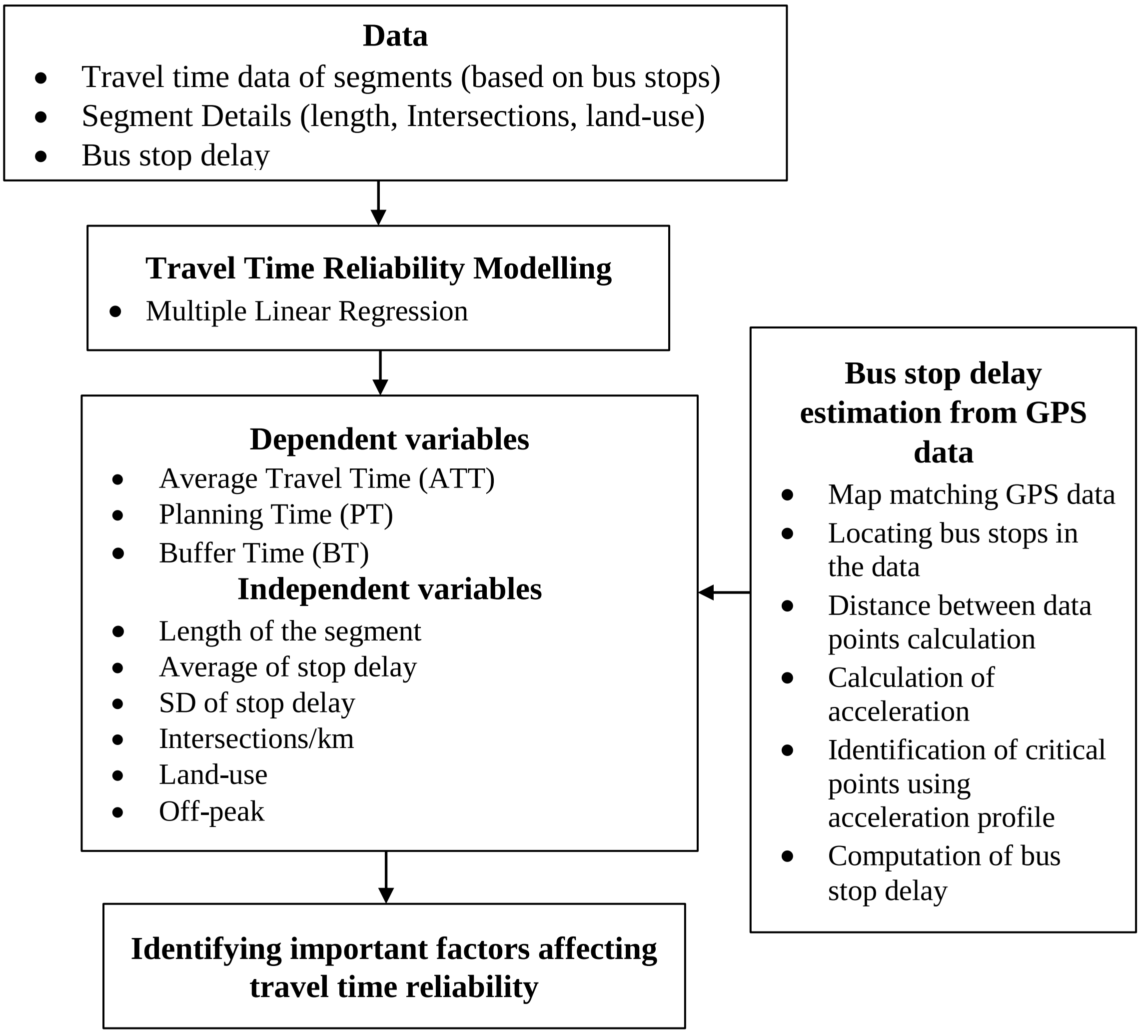

Figure 4.11. Methodological framework for travel time reliability modelling

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Table 4.10. Details of Independent Variable

Independent Variable	**Description**
Length	Length of each segment in meters
Average of stop delay	Average of bus stop delay in seconds
SD of stop delay	Standard deviation of bus stop delays in seconds
Intersections/km	Number of signalised and unsignalized intersections per km
Land-use	1 if segment land-use is CBD/Commercial, else 0
Off-peak	1 for morning off-peak period 6 to 8, else 0

4.7.1 Bus Stop Delay Estimation

The bus stop delay is estimated from GPS data. The estimation of bus stop delay consists of three stages, namely deceleration, stopping and acceleration. The diagrammatic representation of whole process of bus arriving at bus stop is given in Figure 4.12. The difference in travel times when the vehicle trajectory is affected and unaffected by the bus stop is termed as bus stop delay and it can be observed from Figure 4.12. Deceleration delay (t_1 and t_2) corresponding to distance d_1 and d_2 is the initial part in bus stop delay, which is a result of slowing down of vehicle from the normal speed. Next, the vehicle comes to stopped condition at distance d_2 (from t_2 and t_3) which is termed as stopped delay. Then, acceleration delay is defined when the vehicle is getting back to the normal speed (t_3 and t_4), corresponding to distance d_2 and d_3. The critical delay points (t_1 and t_4) have to be identified for computing the bus stop delay components. The components of bus stop delay are shown in Figure 4.13.

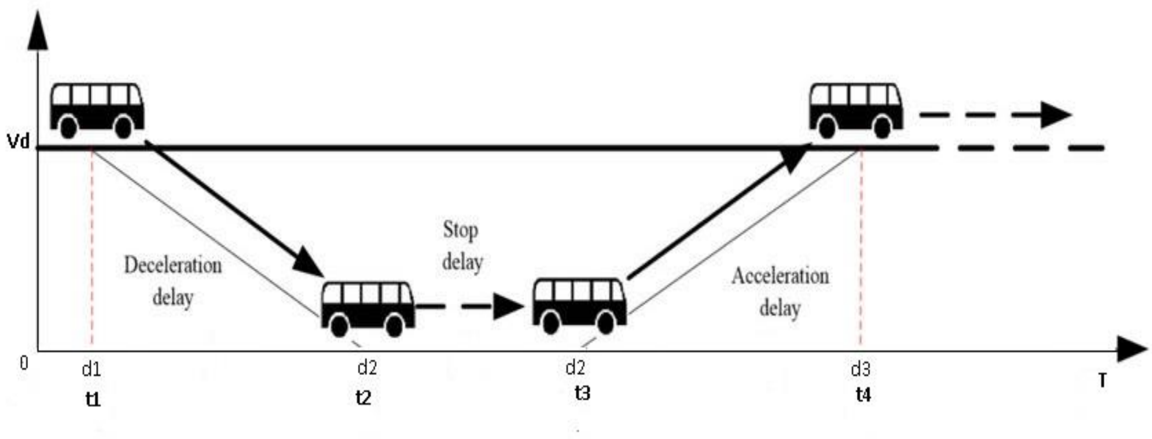


Figure 4.12. Bus arriving process at bus stop (Sarisoy et al. 2016)

The first step is to identify the exact location of bus stops with respect to GPS data which is carried out by matching the GPS data to map using QGIS (Appendix A.10). Then, distance between each GPS data point is calculated using Haversine formula. The distance at which bus stop is located is identified and used in the further stages of delay estimation. After the initial data processing, acceleration values at each GPS data point have been calculated depending on the velocity of the respective data points. The vehicles which have one or more data points with velocity less than 5 kmph

(Mousa 2002) near the upstream of the bus stop are considered as the stopped vehicles and used in further study. The sample speed profile of stopped vehicles are given in Appendix A.11. Then, critical points of total bus stop delay (t_1 and t_4) have been identified using acceleration profile plots of the stopped vehicles (Appendix A.12). The points which initiated the decrease/increase in the acceleration profile at the entrance/exit of the bus stop and reaching zero are known as the critical points (t_1 and t_4 in Figure 4.14) (Ko et al. 2008). In this study, the total bus stop delay is considered. After identifying the critical points, the total delay has been calculated using Equation 4.9.

$$\text{Bus stop delay} = (t_4 - t_1) - \frac{d_3 - d_1}{v_d} \tag{4.9}$$

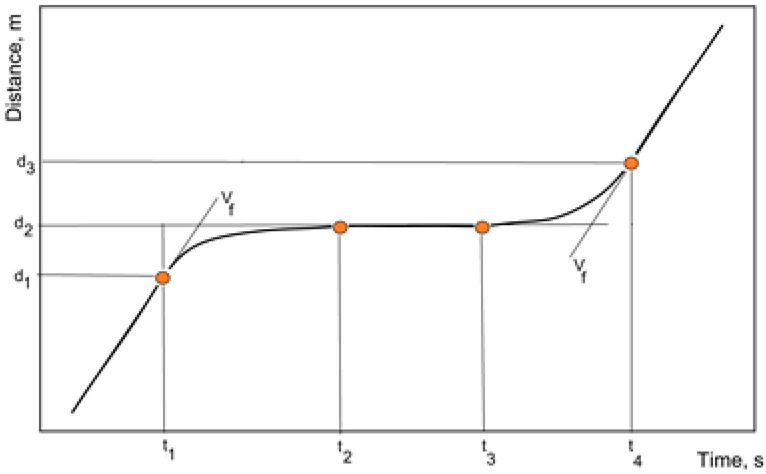


Figure 4.13. Bus stop delay components

The d_1 and d_3 are the distance at which deceleration starts and acceleration ends respectively. The desired speed v_d is taken as 60 kmph based on the free-flow speed. Similar steps have been carried out for delay estimation at all the bus stops on the selected route and used in the modelling of TTR. The sample delay data is given in Appendix A.13. The major limitation of this method is that the accuracy of the estimated delay may decrease when it is applied to a lower resolution GPS data. In this study, GPS data of 10 sec resolution have been used which is quite lower when compared to data with time resolution of l sec or 5 sec and also not of a very low resolution like 30 sec. The GPS data of 10 seconds can be categorized neither as higher resolution nor as lower resolution data. Due to the unavailability of higher resolution GPS data, 10 sec GPS data have been used in this study. In this study, bus stop delay estimation has been used only for TTR modelling. The analysis of efficiency of this delay estimation has the scope for future work.

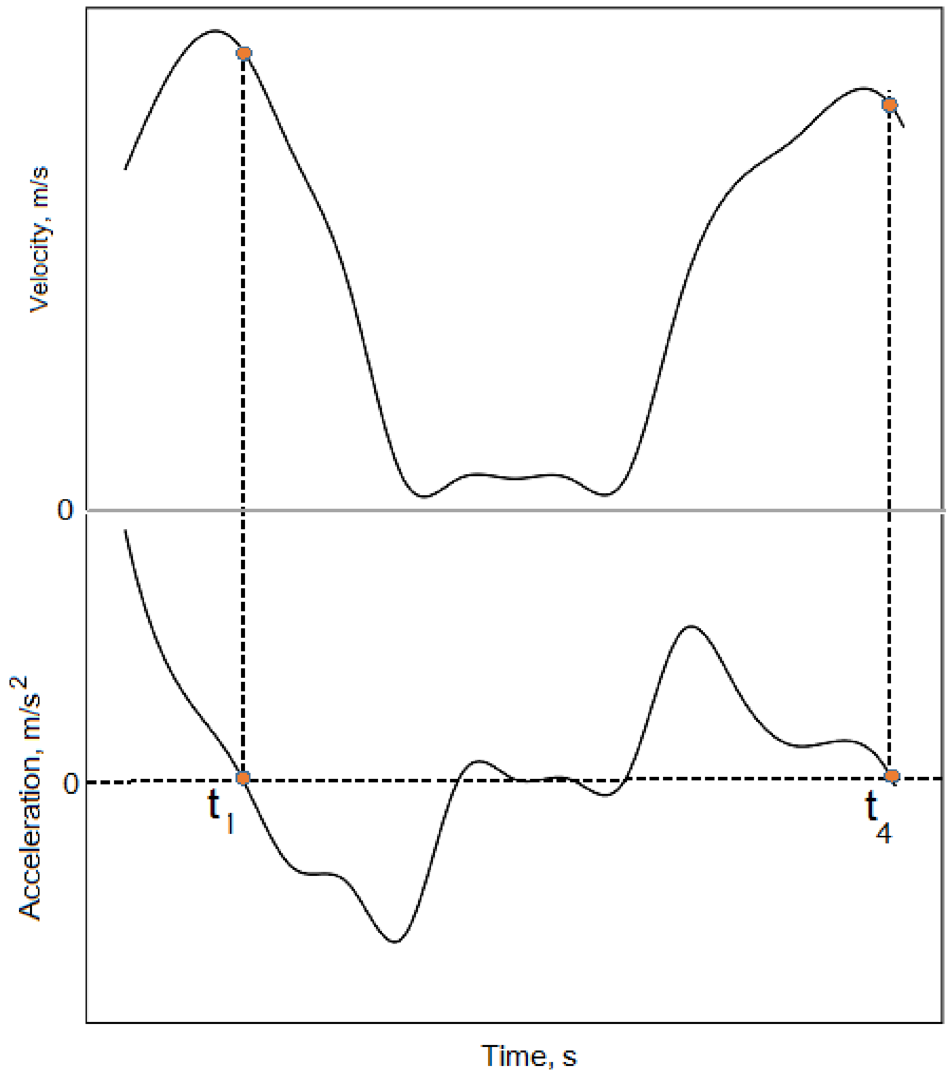


Figure 4.14. Speed and acceleration profile at bus stop

4.8 LEVEL OF SERVICE BASED ON TRAVEL TIME RELIABILITY

Level of service (LOS) is a quantitative stratification of a performance measure or a measure that represents the quality of service. In this study, travel time reliability

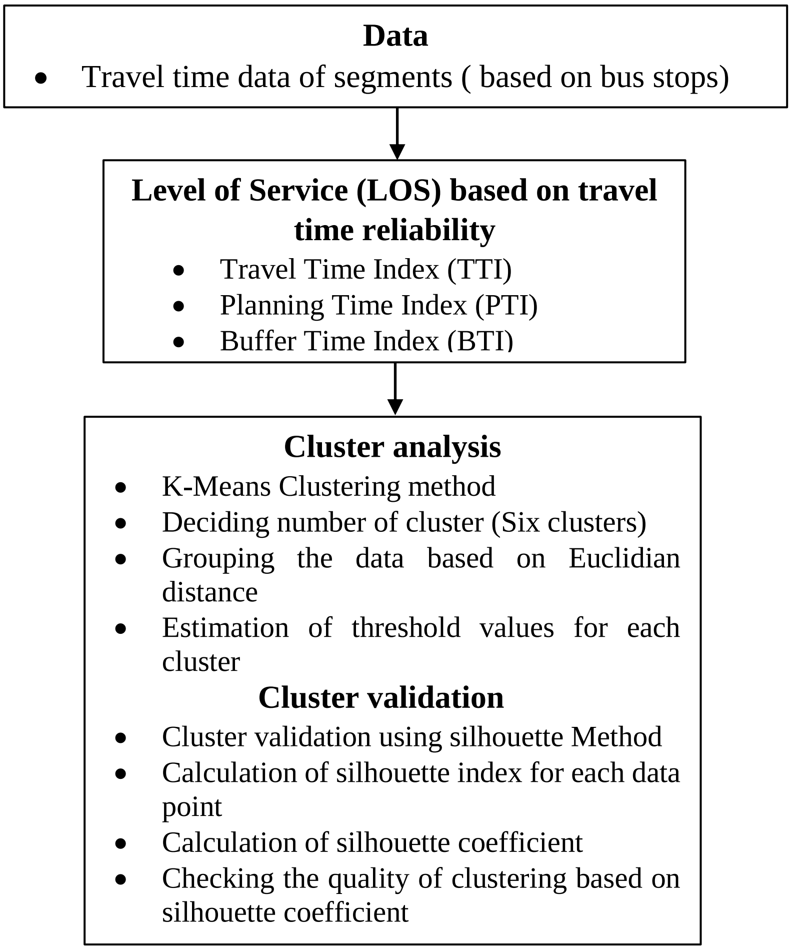


Figure 4.15. Methodological framework for level of service determination

measures such as TTI, PTI and BTI have been considered to determine the LOS thresholds and framework of LOS determination is shown in Figure 4.15. Four transit routes originating from CBS have been considered in the present study, namely BEML (94), JP Nagar (13), Infosys (119) and Yelawala (266) (Figure 4.2). The details of the study bus routes are given in Table 4.2. Travel time reliability measures are calculated for each segment and used in the methodology. K-Means clustering method has been adopted to determine the threshold of each LOS levels. Clustering is the process of grouping the data points based on the data pattern. K-Means clustering is an algorithm that assigns group labels to the unlabelled data points based on the Euclidian distance from a centroid of the cluster to the data points. This algorithm is effectively used in the previous studies on LOS (Chepuri et al. 2019), side friction (Pal and Roy 2019) and road safety (Shirmohammadi et al. 2019). It is said to be an effective way to determine the threshold values. The first step in the cluster analysis is to decide the optimum number of clusters. The globally accepted six service levels such as LOS A to LOS F have been adopted in this study. The steps followed in K-Means clustering method is provided in Section 4.5.3.

After the clustering of data, threshold values for each cluster have been determined. The assumption of optimum number of clusters is need to be validated to check the quality of clusters. Hence, the cluster validation has been conducted using silhouette index (Kathuria et al. 2020). Silhouette analysis helps in interpretation and validation of data consistency within clusters. The silhouette index measures the similarity of a data point to its cluster compared to other clusters. The higher silhouette index represents higher quality of cluster. This graphical method of examining the quality of clusters was introduced by Kaufman and Rousseeuw (2009). The silhouette index for i^{th} data point is calculated using Equation 4.10.

$$S(i) = \frac{V(i) - U(i)}{\max\{U(i), V(i)\}} \tag{4.10}$$

Where,

V(i) is the average dissimilarity of i^{th} data point with other data points of the closest cluster.

U(i) is the average dissimilarity of i^{th} data point with other data points of the same cluster.

The silhouette index can take value from -1 to 1. The silhouette width of each cluster is computed as the average of silhouette index of data points of that cluster. The total silhouette coefficient is calculated as the average of silhouette index of all the data. The silhouette range and the quality of the corresponding cluster are provided in Table 4.11. The results of K-means clustering and silhouette analysis are provided in the next chapter.

Table 4.11. Quality of cluster based on Silhouette Coefficient

Range of Silhouette Coefficient	Cluster Quality
0.71 – 1.0	Strong cluster structure
0.51 – 0.71	Reasonable cluster structure
0.26 – 0.50	Cluster structure is weak
Less than 0.25	No substantial cluster structure

4.9 SUMMARY

This chapter explains in detail, the data collection and processing, methodology adopted to achieve the defined objectives of the present research work. The summary of this chapter is given below,

- Mysore city has been considered as the study area which is the third-largest city in Karnataka, located in the southern part of the state and Karnataka state is located in southern part of India.
- The GPS data of Mysore ITS for the four bus routes have been processed and travel time for both directions have been extracted at route level and segment level.
- Side friction data has been collected at two road stretches (Divided and Undivided road) using videography method. The data related to side friction activities such as pedestrians crossing the road and walking along the road, different types of parked vehicles, parking/unparking manoeuvres and cross-street entry/exit (undivided road section) movements are collected. Along with the above side friction data, traffic volume on both road stretches and travel time data of buses are extracted from the video recordings collected.
- The impact of side friction on TTR has been analysed. Different side friction elements are grouped into Side Friction Index (SFI) and the impact of SFI on TTR measures TTI, PTI, BTI and RBI are evaluated. K-Means clustering method has been adopted to group the traffic volume levels and the impact of SFI on reliability measures are analysed at each traffic volume levels.

- The travel time data obtained from the public transit of Mysore ITS are utilised to evaluate the effect of spatial and temporal aggregation on travel time variability of public transit system. Seven probability distributions have been chosen for the analysis namely, Burr, GEV, Gamma, log-logistic, lognormal, normal and Weibull. Travel time distributions have been analysed with respect to different levels of temporal aggregation (peak period, off-peak period, 60 minutes, 30 minutes and 15 minutes) and spatial aggregation (route level and segment level). The performance of the distributions is evaluated using the Kolmogorov-Smirnov (KS) test in terms of accuracy and robustness. The segment level analysis is also carried out separately for the segments with signalised intersections and different land-use types.
- The factors affecting TTR are modelled using Average Travel Time (ATT), Planning Time (PT) and Buffer Time (BT) as the dependent variable and length of the segment, bus stop delay, intersections, land-use and peak/off-peak time period as the independent variables. The segment travel time data of route-266 is considered in this study which has 22 segments based on the bus stop spacing. Three different models of ATT, PT and BT are developed using MLR method.
- The LOS bus routes are determined based on TTR such as TTI, PTI and BTI. The segment level travel time data of four bus routes have been considered in K-means clustering method to determine LOS thresholds. Initially, globally accepted six clusters for LOS (A to F) have been assumed and cluster validation has been conducted using silhouette analysis.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 GENERAL

The results of the study conducted to achieve the objectives of the present research work are presented and discussed in this chapter. The overall objective of this research work is to analyse the factors affecting TTR of the public transit system and the major findings of the research related to TTR analysis of Mysore ITS have been reported here. The results from the analysis of the first objective, which mainly consists of the quantification of different side friction activities into SFI, variation of TTR measures along with SFI and the impact of SFI on TTR measures with respect to different traffic volume levels have been presented. Since, the travel time variability plays a crucial role in describing the reliability of system, this study evaluates the effect of spatial and temporal aggregations on variations in travel time using travel time distributions along with the performance evaluation of travel time distributions and results are presented in this chapter. This chapter also describes the results of TTR modelling which has been conducted to study the factors causing unreliability using Multiple Linear Regression (MLR) method. The results from the analysis of LOS of public transit system using TTR measures are presented and discussed.

5.2 IMPACT OF SIDE FRICTION ON TRAVEL TIME RELIABILITY

The results from the analysis of the impact of side friction on TTR have been discussed in this section. Firstly, different types of side friction elements (static and dynamic) are quantified into Side Friction Index (SFI) using relative weight analysis. Then, the impact of SFI on TTR has been analysed considering traffic volume levels which have been determined using K-Means clustering method (Section 4.5.3). The results from this study are presented and discussed in the following sub sections.

5.2.1 Side Friction Index

The results of the relative weight analysis are tabulated in Table 5.1. The relative weights of side friction elements have been determined using relative weight analysis (Section 4.5.1.2). The raw relative weights have values ranging from 0.0039 to 0.509 and 0.042 to 0.327 for undivided and divided road sections respectively. In the case of the undivided road, SSF has the highest raw relative weight of 0.509, followed by the traffic volume as the most contributing factor. All the other factors have similar relative weights within the range of 0.039 to 0.061. In the case of the divided road, SSF has a raw relative weight of about 0.327, and traffic volume is the second most contributing factor with raw relative weight of 0.226. Pedestrian crossing the road has a raw relative weight of 0.170 and pedestrian walking along the road and parking/unparking interactions have less raw relative weightages of 0.042 and 0.089, respectively. Traffic volume is not considered in the calculation of rescaled relative weight and SFI, since it is not a side friction element.

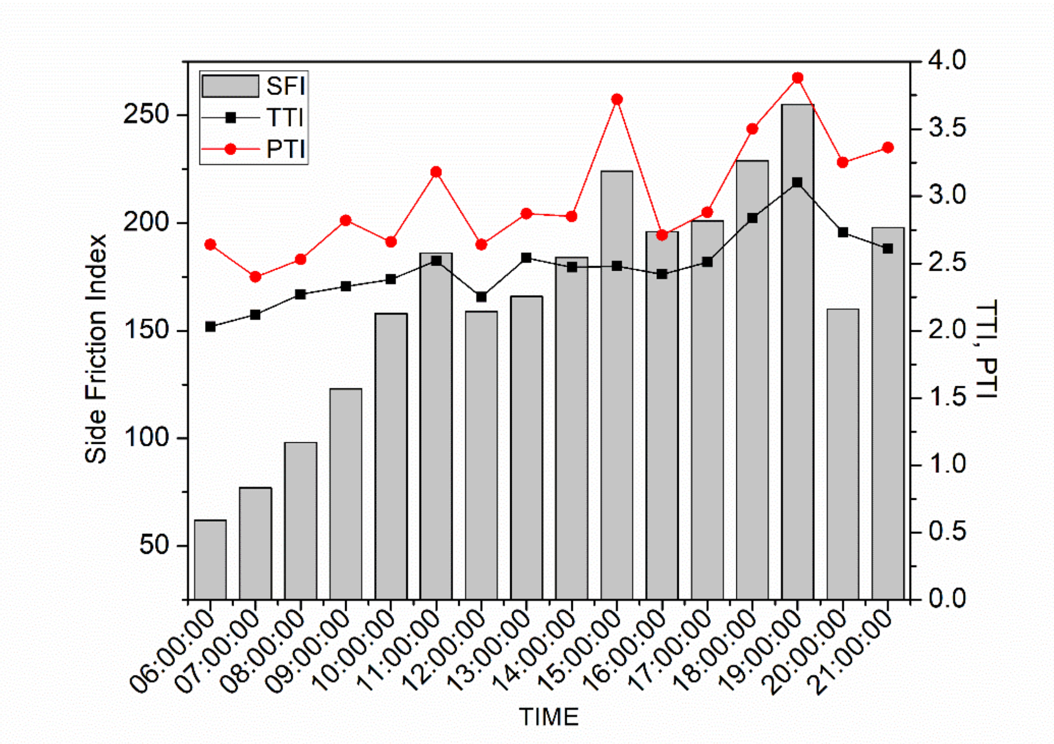
The results of the relative weight analysis (Table 5.1) show that the static side friction (SSF) has a raw relative weight of 0.509 in the undivided road. This suggests that static side friction is the major contributing factor in the variation of travel time. But, in the case of the divided road, it has a raw relative weight of 0.327. The major reason behind the higher relative weight of static side friction in the case of the undivided road is due to the presence of side friction on both sides of the road, which makes the drivers on both sides shift to the centre of the road by reducing their speed. Pedestrian crossing the road has more weightage among dynamic friction elements in the case of both divided and undivided road sections. This indicates that the interruption caused by the pedestrians crossing the road is higher than the other types of dynamic side frictions. The major reason behind this is the tendency of vehicles to shift away from the parking/unparking vehicles and pedestrians walking along the road. But, in the case of a pedestrian crossing the road, the vehicles need to slow down for the safety purpose to avoid collision (Biswas et al. 2021). In both the above cases, vehicles must slow down, but the opportunity to move away from the carriageway edge will not be there when the pedestrians are crossing the road. Hence, its impact is more on the vehicle's speed in comparison with that of other dynamic side friction elements. In both the roads, the dynamic side friction elements have lesser relative weight than that of static side friction. This can be due to the fact that all the public transit buses might not have experienced the obstruction from dynamic side friction characteristics, which is naturally random.

Table 5.1. Results of relative weight analysis

	Undivided road		**Divided road**	
	Raw RW	**Rescaled RW**	**Raw RW**	**Rescaled RW**
Traffic Volume	0.157	-	0.226	-
SSF	0.509	1	0.327	1
PK/UPK	0.039	0.077	0.089	0.271
PDSW	0.048	0.095	0.042	0.128
PDSCR	0.061	0.120	0.170	0.521
CSentry_exit	0.055	0.108	NA	NA
R^2	0.850		0.834	

5.2.2 Travel Time Reliability

The hourly variation of TTI and PTI with SFI is visualised together as shown in Figure 5.1 and Figure 5.2 respectively, because both TTI and PTI measure travel time reliability with respect to free-flow travel time. The hourly variation of BTI with SFI has been plotted separately for a better understanding of the variation as shown in Figure 5.3 and Figure 5.4**.** In the case of undivided road (Figure 5.1), SFI ranges from 61 to 255 for weekday data. The amount of side friction (SFI) is highest during 3 PM and 7 PM and a small peak is observed in the morning around 11 AM. This stretch consists of different kinds of commercial shops and these commercial activities are more in the evening hours on weekdays.



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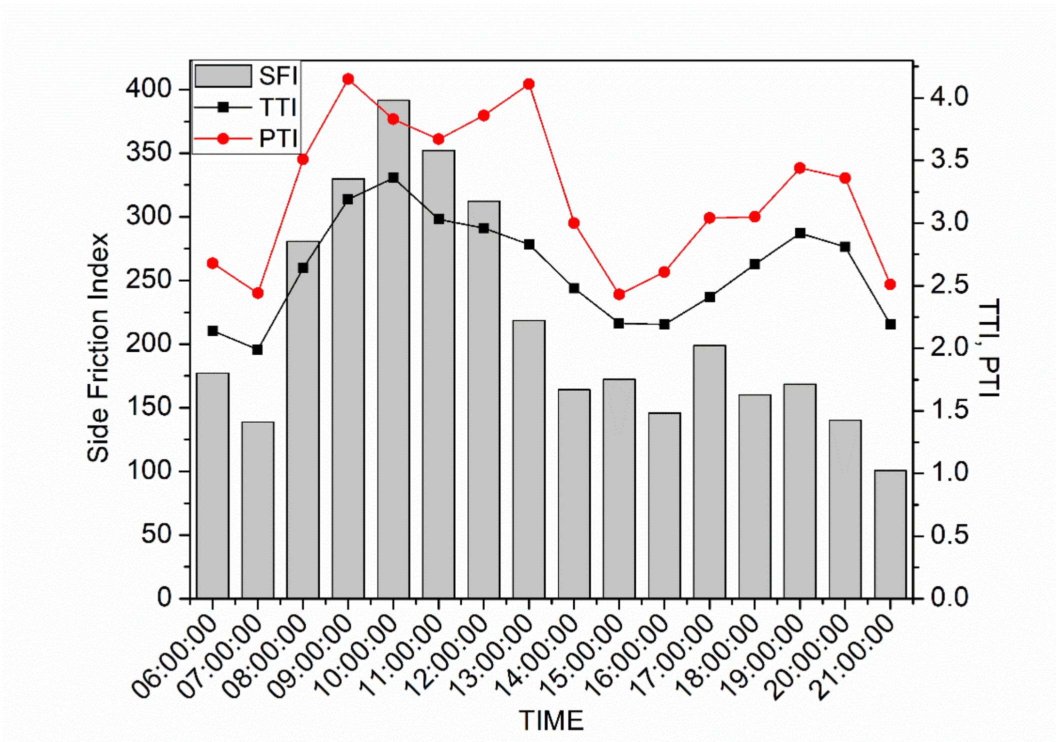
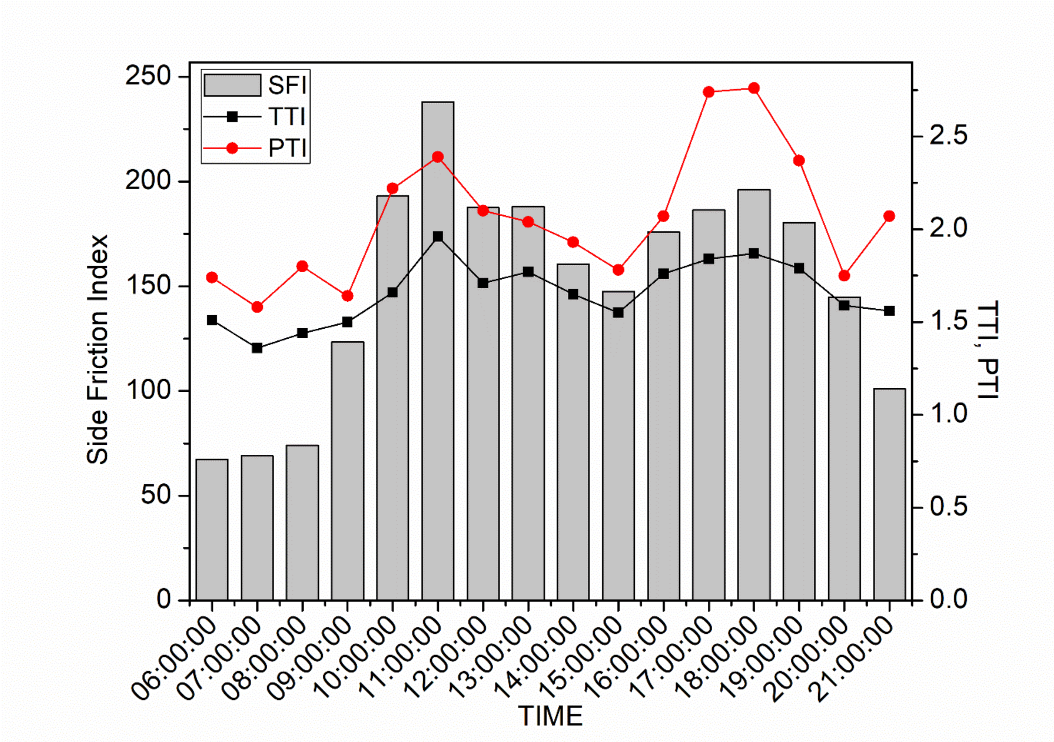


(b)

Figure 5.1. Hourly Variation of TTI, PTI and SFI: a) Weekday of Undivided Road and b) Weekend of Undivided Road



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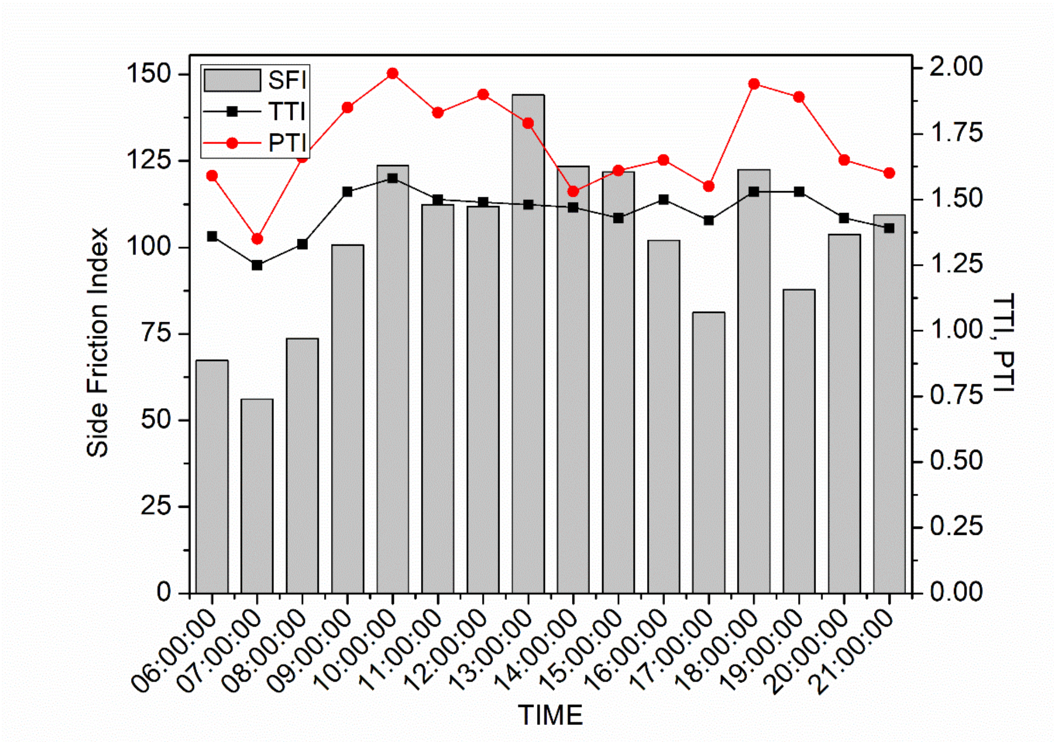


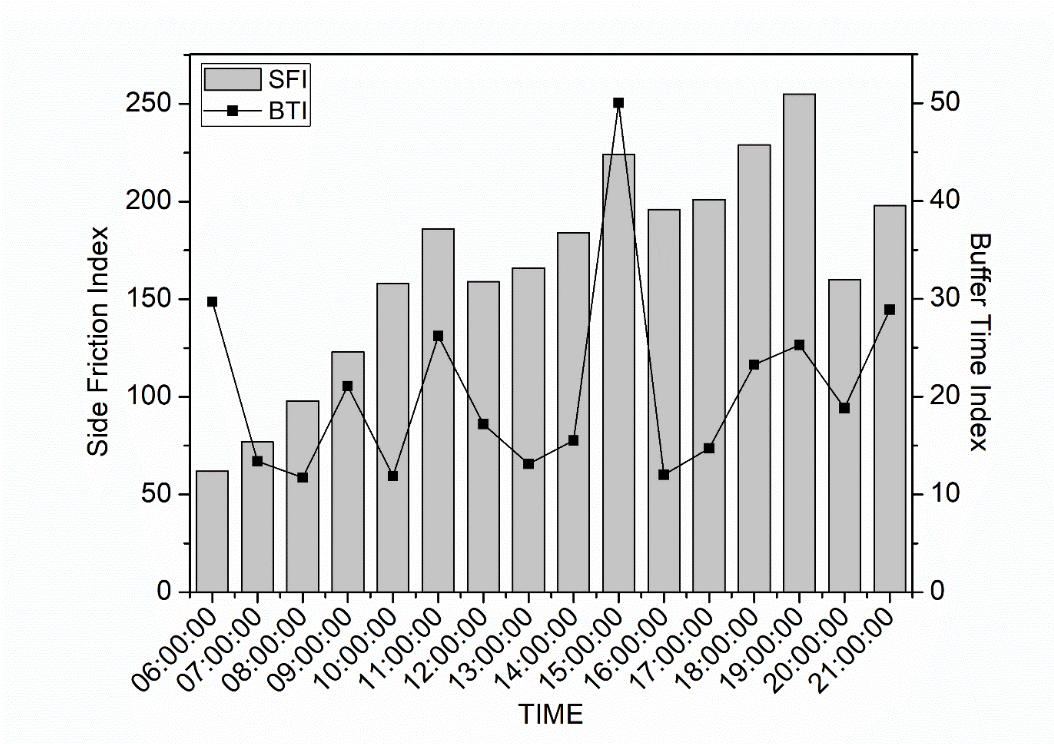
(b)

Figure 5.2. Hourly Variation of TTI, PTI and SFI: a) Weekday of Divided Road and b) Weekend of Divided Road

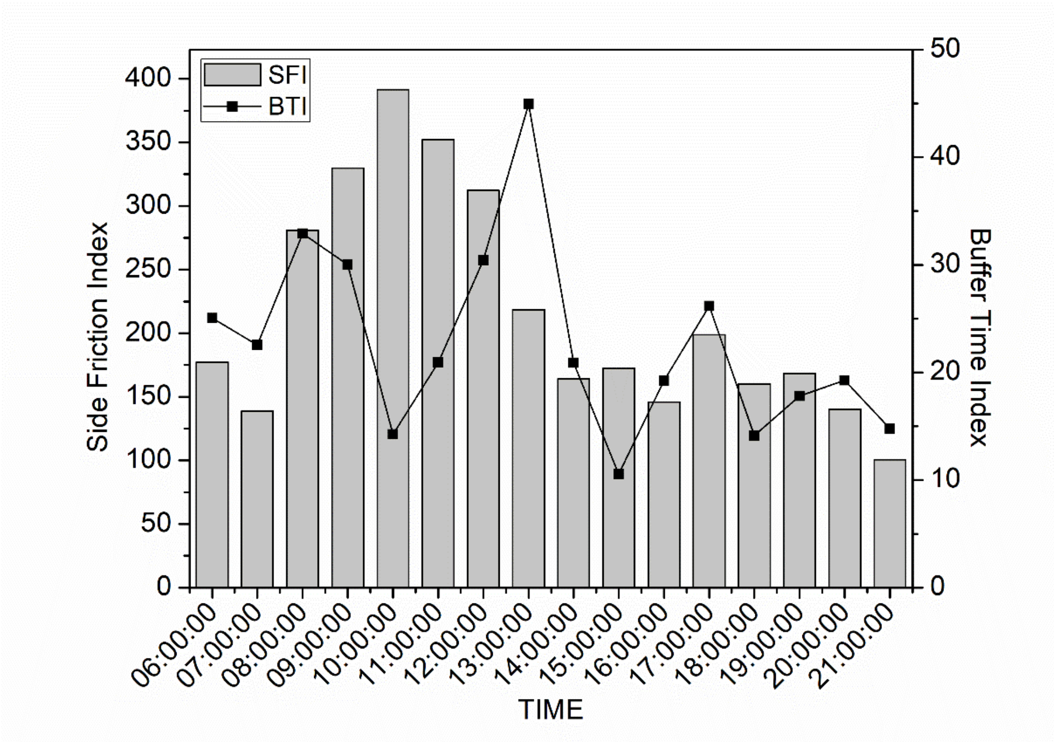
The variation of PTI follows an almost similar trend (Figure 5.1), which ranges from 2.40 to 3.88, being highest during evening around 7 PM. Both SFI and PTI are higher during the same time periods of the day. However, variation in TTI is less as compared to PTI, only two small peaks are observed at 11 AM and 7 PM. In the case of the undivided road on weekend, SFI ranges from 100 to 390 and the side friction (SFI) is found to be higher during morning hours i.e., from 8 AM to 12 PM. TTI and PTI vary in the range between 1.99 to 3.36 and 2.44 to 4.15, respectively. Both TTI and PTI are higher from 8 AM to 1 PM and a small peak is observed during the evening.

The side friction (SFI) activities in the data are lesser at the divided road since, side friction activities on only one side of the roadway are considered. The SFI on divided road (Figure 5.2) ranges from 67 to 237 and 56 to 144 on weekday and weekend respectively. On weekday, SFI is highest at 11 AM with the value of 238 and another peak value of SFI (196) is found at evening 6 PM. At divided road section, TTI and PTI are varying from 1.36 to 1.96 and 1.58 to 2.76 respectively, on weekday. TTI is more in the same time period where the SFI was found to be higher with the value 1.96 at 11 AM and 1.87 at 6 PM. PTI is found to be highest at 5 PM to 6 PM (2.74 and 2.76, respectively). The morning peak in the PTI is observed at 11 AM with the value of 2.39. On weekend, the side friction activities are very less and SFI is highest (144) at 1 PM. Evening peak is observed at 6 PM with the value of 122. The variation in TTI is found to be lesser (ranging from 1.25 to 1.58) than that for PTI (varies from 1.35 to 1.98). But, PTI has two peaks with highest value of 1.98 at 10 AM and evening peak at 6 PM with the value 1.93.

The variation in BTI and SFI of undivided road and divided road with time are plotted separately as shown in Figure 5.3 and Figure 5.4 respectively. In the case of undivided road section (Figure 5.3**)** on weekday, BTI ranges from 11.7 to 50.03 and the highest value (50.03) is observed at 3 PM. BTI is highest at 1 PM with the value 44.93 on weekend. In the case of weekday at divided road, the maximum BTI is observed at 5 PM and 6 PM with the values 48.69 and 47.51, respectively. The BTI varies from 4.17 to 27.79 in the case of the divided road section (Figure 5.4**)** on weekend and has the maximum value of 27.29 at 12 PM. The hourly variation of BTI is slightly different than that of PTI and TTI.

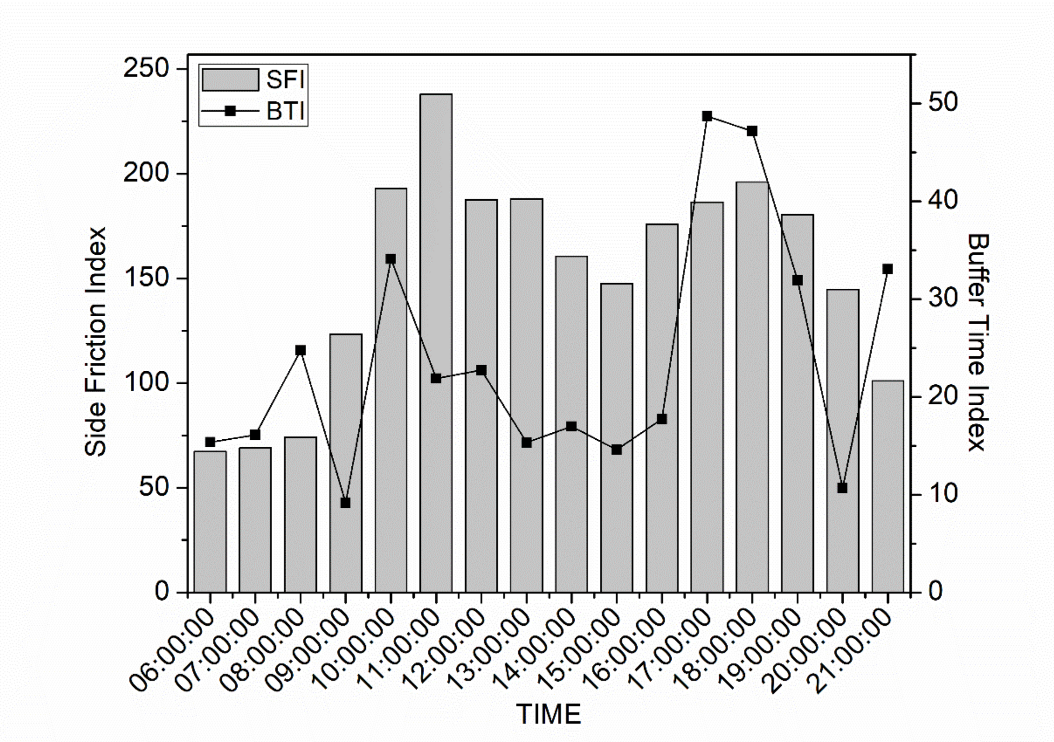


(a)

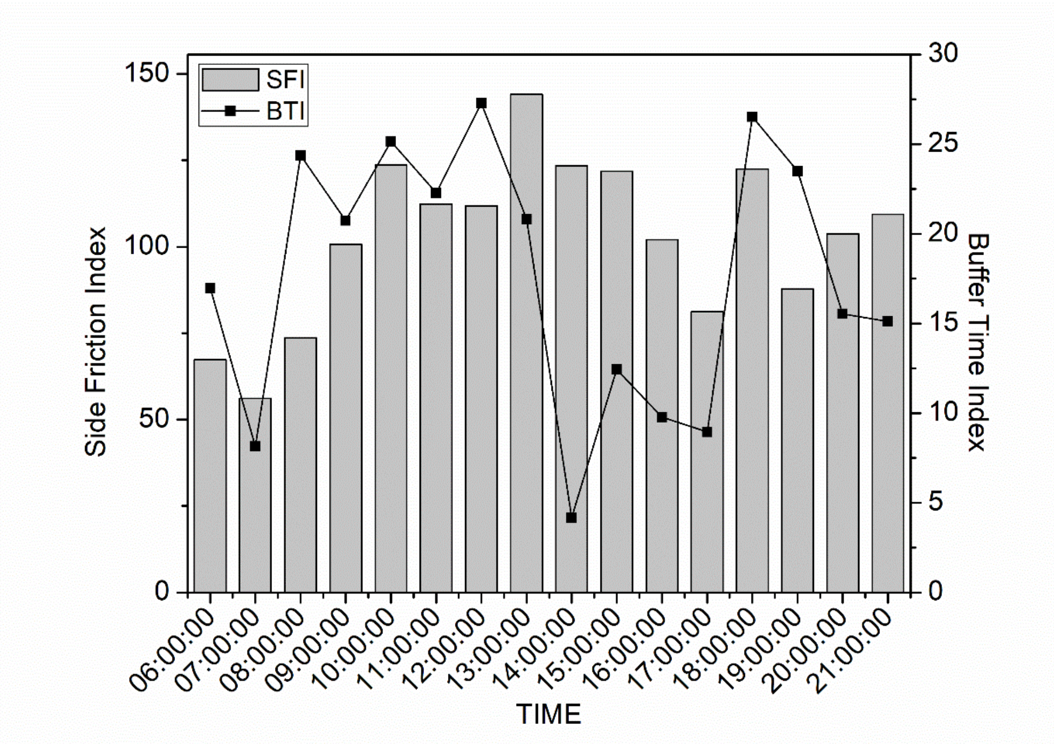


(b)

Figure 5.3. Hourly Variation of BTI and SFI: a) Weekday of Undivided Road and b) Weekend of Undivided Road



(a)

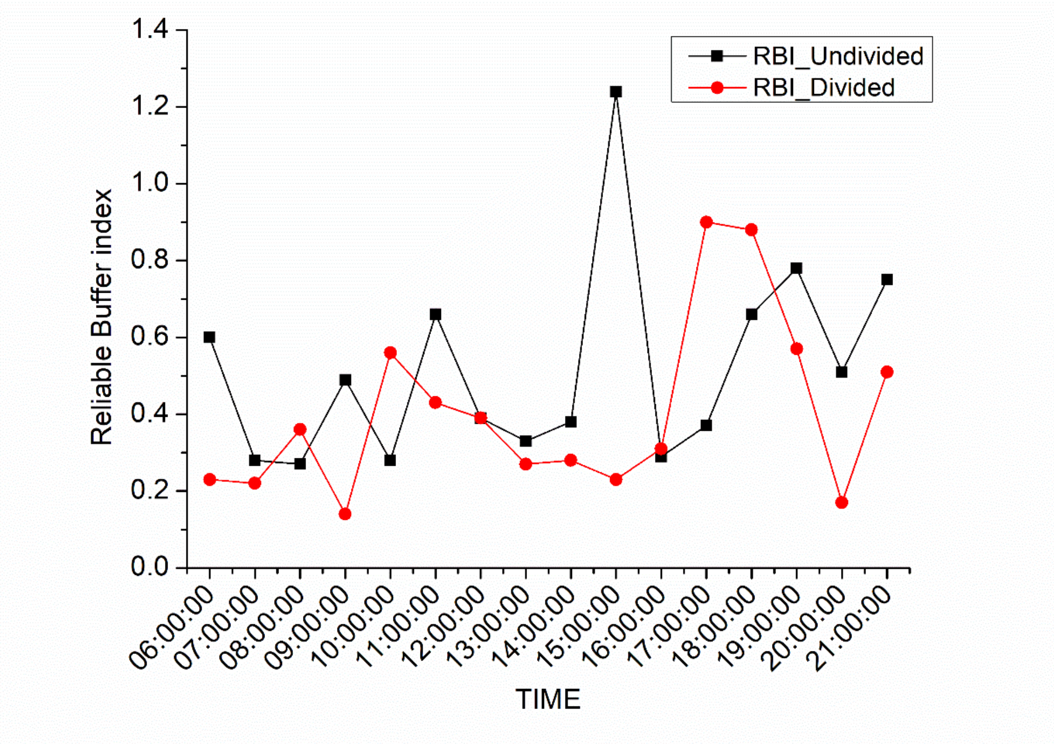


(b)

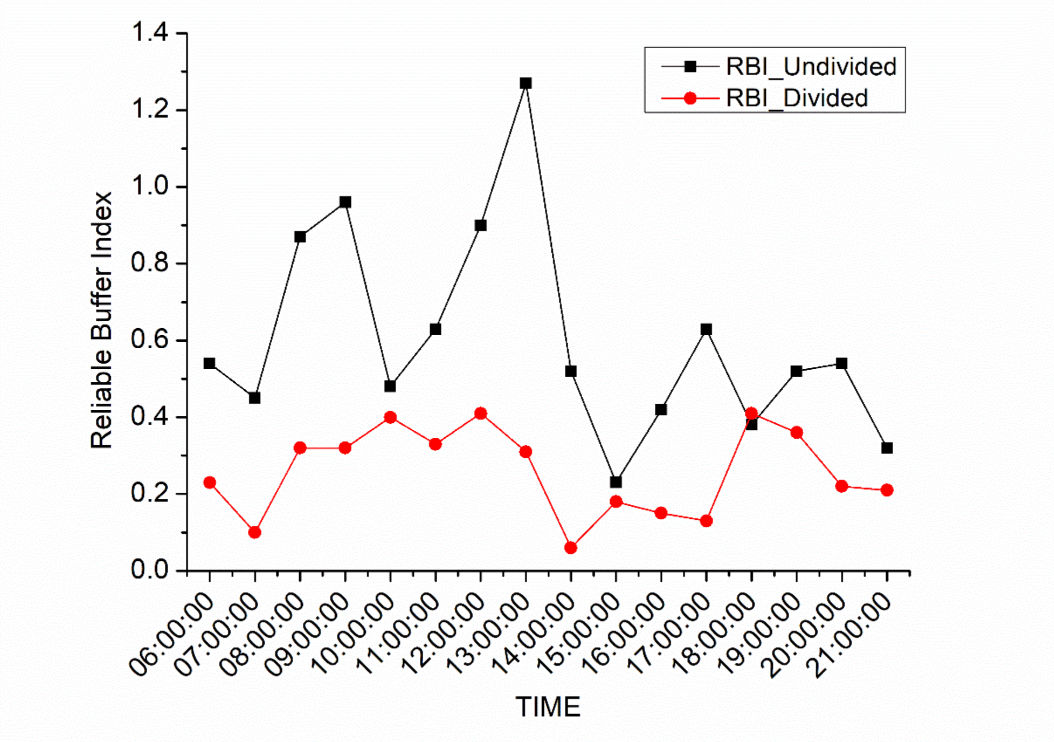
Figure 5.4. Hourly Variation of BTI and SFI: a) Weekday of Divided Road and b) Weekend of Divided Road

The hourly variation of SFI and reliability measures are shown in Figure 5.1 to Figure 5.4. The side friction activities are found to be more on weekend compared to weekday at the undivided road. At the divided road, the side friction activities are observed to be more on weekday than on weekend. The maximum values of PTI and TTI are observed during the same time periods when SFI is observed to be maximum in both the study sections. This suggests that increase in the SFI led to an increase in the average travel time and 95th travel time which in turn increases the values of TTI and PTI respectively. The hourly variation of BTI **(**Figure 5.3 and Figure 5.4**)** shows a slightly different trend than the TTI and PTI. The increase in the SFI will increase the travel time, but does not always increase BTI. This is because, BTI is computed using the difference of 95th percentile travel time and average travel time, with average travel time in the denominator. This situation occurs when most of the buses experience the impact of side friction, which leads to an increase in both 95th percentile travel time and average travel time. This can be observed during 5 PM and 6 PM in the divided road on weekday **(**Figure 5.4**)**. But, during few time periods, BTI has higher values in spite of lower values of SFI e.g., at 1 PM of weekend on the undivided road (Figure 5.3). This is mainly due to the increase in 95th percentile travel time without much increase in average travel time. If only a few buses experienced the obstruction due to side friction, then it leads to an increase in the BTI even when the side friction activities are less.

The comparison of TTR of the two study sections which are geometrically different has been conducted using RBI as shown in Figure 5.5. For weekday data, RBI ranges from 0.23 to 1.24 and 0.06 to 0.897 at undivided and divided road sections, respectively. The maximum RBI at the undivided road is observed at 3 PM (1.24) with the evening peak at 7 PM (0.782). On weekday at divided road, the higher values are observed at 5 PM and 7 PM (0.897 and 0.883, respectively) and the values are lower for the rest of the time periods. In the case of weekend data, RBI is ranging from 0.27 to 1.27 and 0.14 to 0.40 at undivided and divided road respectively. RBI at the undivided road is highest at 1 PM (1.273) and at morning 8 AM and 9 AM, RBI values were found to be 0.869 and 0.959, respectively. RBI values for the divided road on weekend are found to be comparatively lower than that of undivided road, with the highest value being 0.408.



(a)



(b)

Figure 5.5. Hourly variation of RBI of both roads a) weekday and b) weekend

The two road sections (divided and undivided) considered for the study have been compared using RBI, by considering travel time data from weekday and weekend separately. The hourly variation RBI of both sections (Figure 5.5) shows that RBI value is more in the case of the undivided road than the divided road for both weekday and weekend data. On weekend, the reliability of the undivided road is low during morning hours. The side friction activities are more in the morning hours of weekend which plays a significant role in the reduction of reliability of the transit system. RBI values are lower in the case of the divided road during weekends when side friction activities are less. The reliability of the public transit on undivided road is found to be lesser than that of the divided road, due to the impact of side friction from both sides of the road combined with the effect of two-way traffic movement.

5.2.3 Analysis of Impact of Side Friction on Travel Time Reliability

The K-Means cluster analysis has been applied to find the thresholds for traffic volume levels and the elbow method is used to find the number of clusters in traffic volume data. The detailed explanation of K- Means and elbow method is provided in Section 4.5.3. An elbow-like bend is found at the number of clusters equal to three and there is no significant change in WCSS thereafter (Figure 5.6). Hence, the optimum number of clusters is chosen as three.

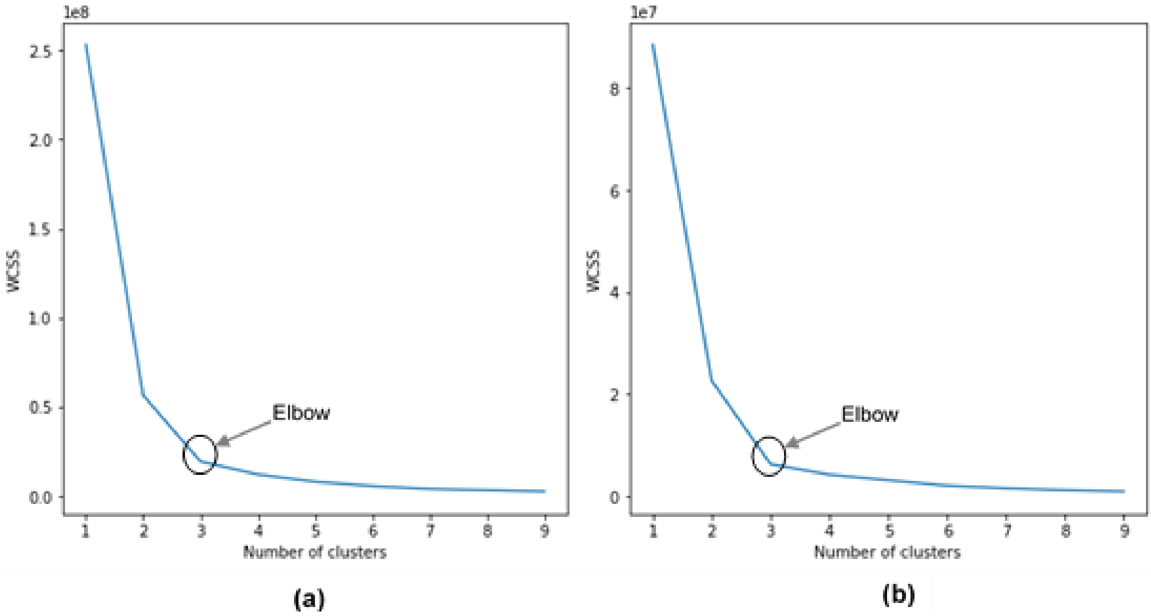
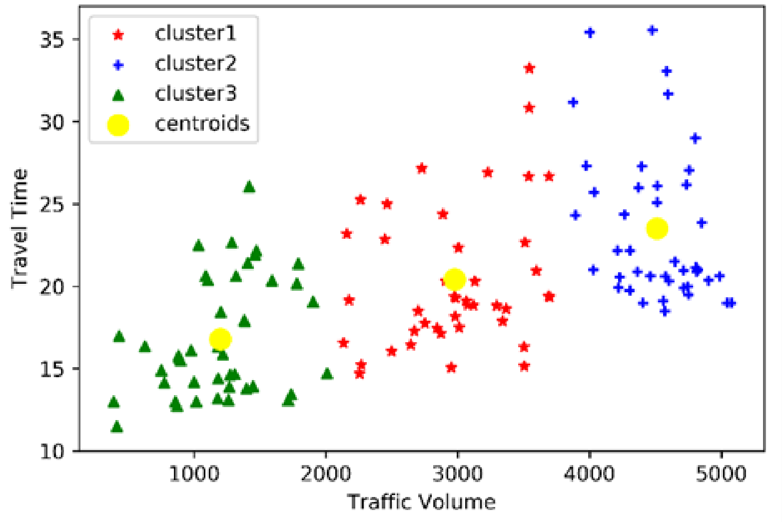
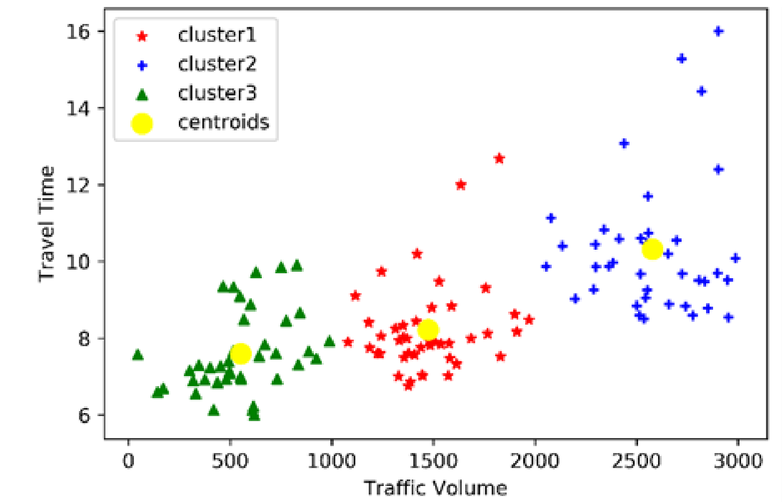


Figure 5.6. Elbow curve to find the no. of clusters in traffic volume data for (a) Divided road and (b) Undivided road

The resulting data clusters for the undivided and divided roads are shown in Figure 5.7. The threshold values of traffic volume levels have been determined by plotting 45° curve with traffic volume data along both x and y-axes (Figure 5.8**)**, which gives the information about the range of each cluster. The threshold values of traffic volume for the undivided and divided roads are given in Table 5.2**.** The traffic volume levels are named as low, medium, and high traffic volume levels.



(a)



(b)

Figure 5.7. Results of cluster analysis for (a) Undivided Road (b) Divided Road

The relationship between SFI and TTR indices for different traffic volume levels is shown in Figure 5.9 and Figure 5.10 for the undivided road and divided road, respectively. The curve fitting has been done using Microsoft Excel. The exponential curve has been found to be the best fit with the highest goodness of fit value. In the case of the undivided road, TTI and PTI have R^2 values ranges 0.59 to 0.83 and 0.60 to 0.88, respectively. But, BTI has poor goodness of fit with R^2 value 0.07 to 0.50. Similar results have been obtained in the case of the divided road. TTI and PTI have the R^2 values in the range of 0.71 to 0.78 and 0.73 to 0.92, respectively. BTI has R^2 values ranging from 0.03 to 0.75. In the case of both the road sections, BTI has lower R^2 values in comparison with that for TTI and PTI, indicating a poor fit.

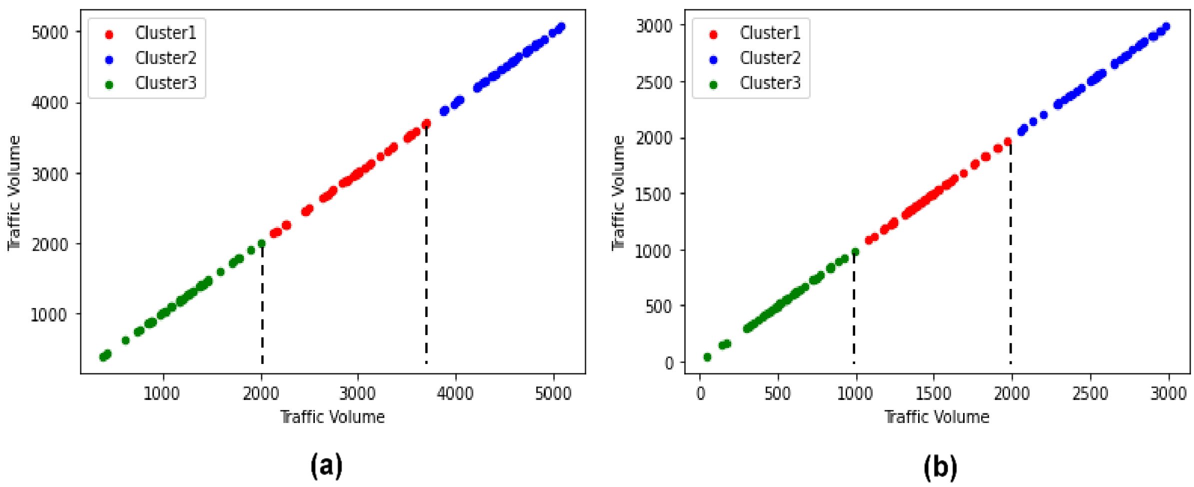


Figure 5.8. Clustered range of traffic volume for (a) Undivided road (b) Divided road

Table 5.2. Threshold values of traffic volume from cluster analysis

Traffic Volume Level	**Undivided road**	**Divided road**
	Volume, PCU/hr	**Volume PCU/hr**
Low	<2010	<990
Medium	2010-3670	990-2000
High	>3670	>2000

The relationship between SFI and reliability metrics has been analysed (Figure 4.8 and Figure 4.9) and found to have less goodness of fit (R^2). The lower values of R^2 are due to the impact of side friction on travel time being sensitive to the change in traffic volume at mid-block sections. On performing K-means clustering analysis, it has been found that the optimum number of different traffic volume levels for the study sections are three (Figure 5.6). The cluster analysis (Section 4.5.3) shows that three traffic volume regimes are present in the study sections with a similar data structure.

From the plots of TTR indices versus SFI for different levels of traffic volume (Figure 5.9 and Figure 5.10), it has been found that the exponential model has a better fit than linear. From this analysis, TTI is observed to increase with the increase in traffic volume levels for the same SFI in both the road sections. It shows that the impact of SFI is higher on the average travel time of public transit, as the traffic volume increases. PTI also has a similar relationship with SFI, in which the PTI values are found to increase with the increasing levels of traffic volume for the same value of side friction. The impact of side friction on PTI is observed to be drastically increasing for high levels of traffic volume in both the sections, which suggests that around 95% of the buses experience a higher impact on TTR when the traffic volume is higher. Both TTI and PTI values are found to be higher for low SFI values when the traffic volume level is high. There is an upward shift found in PTI and TTI for the same SFI with the increase in traffic volume level. These instances are due to the increase in friction between public transit and side friction elements, as the traffic volume increases. In the case of low traffic volume, the increase in PTI and TTI is very less even for higher SFI values. This implies that the higher amount of side friction may not affect the travel time significantly when the traffic volume is less. Because, at lower traffic volume, the drivers can shift to the middle of the road in order to avoid interaction with the side friction elements, which is not possible in the case of higher traffic volume. The relationship between BTI and SFI is different from that of PTI and TTI. In the case of low and high traffic volume levels, there is a small amount of increase in BTI observed with the increasing SFI. But there is no increase in the BTI values with the increase in SFI values in the case of the medium traffic volume. This is due to an increase in both 95th percentile travel time and average travel time in equal proportions, which suggests that the impact of SFI on BTI is less sensitive to traffic volume, especially at medium traffic volume (Figure 5.9 and Figure 5.10**)**.

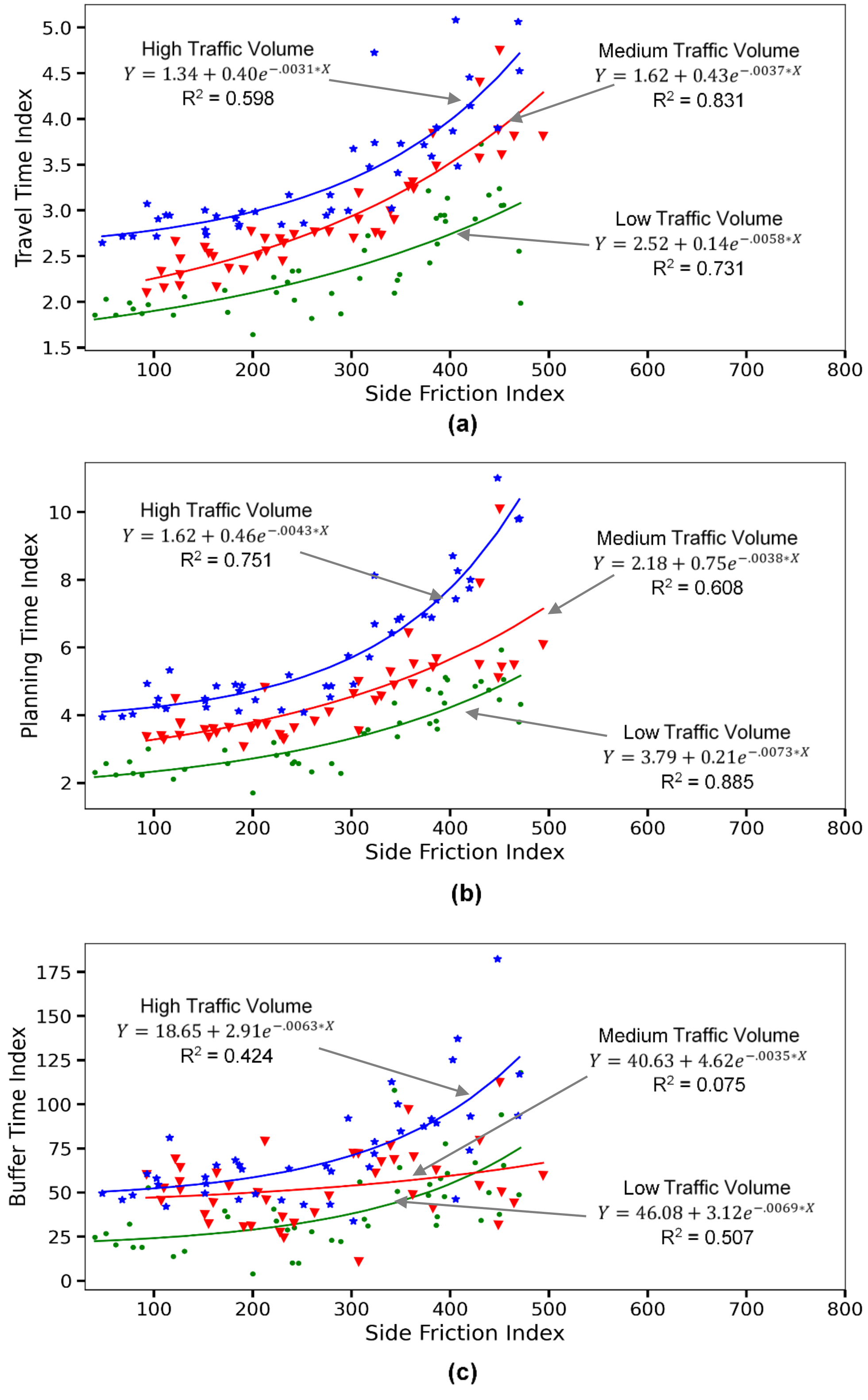
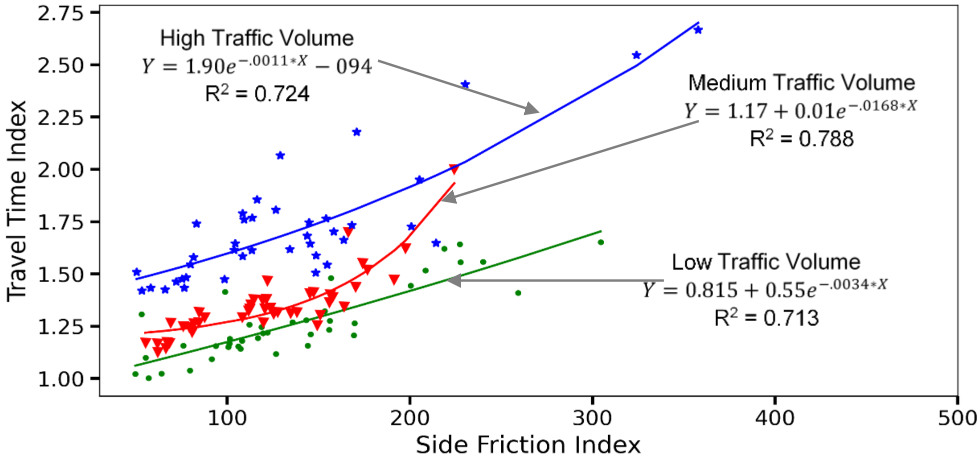
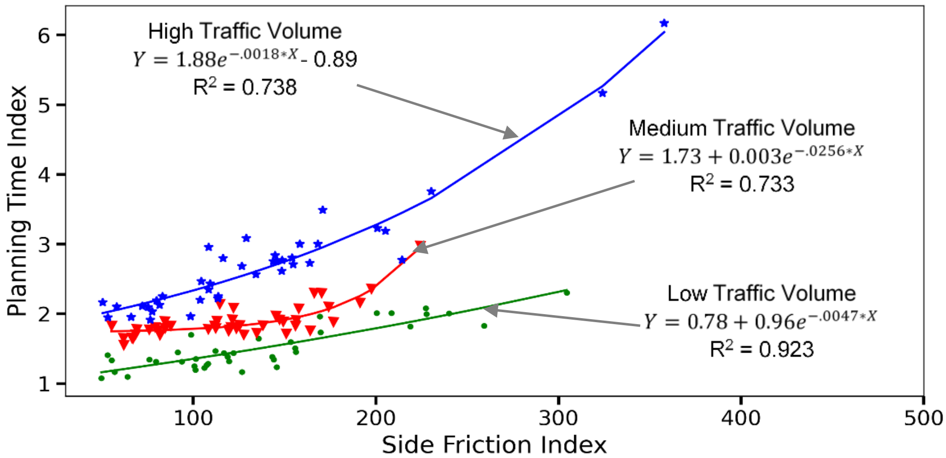


Figure 5.9. Travel Time Reliability vs SFI (Undivided road) a) TTI b) PTI and c) BTI



(a)



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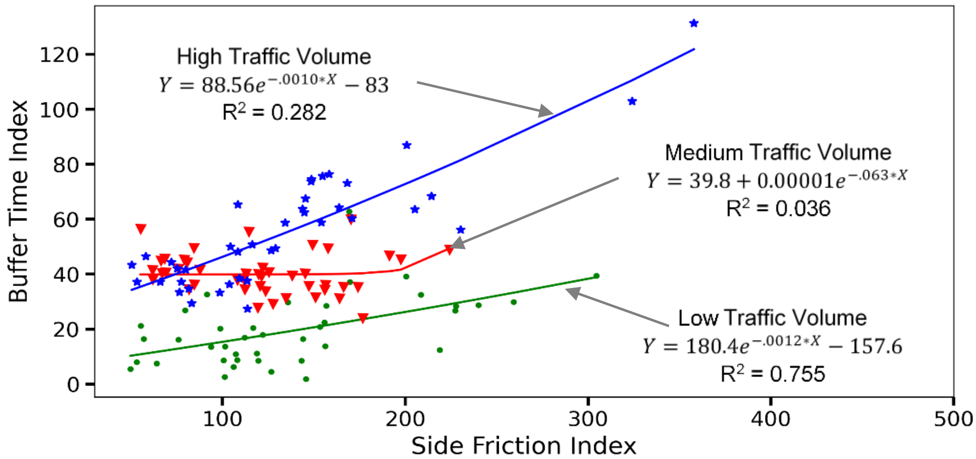


(c)

Figure 5.10. Travel Time Reliability vs SFI (Divided road) a) TTI b) PTI and c) BTI

5.3 TRAVEL TIME VARIABILITY

The outcomes from the study on temporal and spatial aggregation of travel time of Mysore ITS public transit and the performance of distributions at route and segment level have been discussed in this section. The travel time data have been analysed at different temporal aggregation levels corresponding to different DTWs (Departure Time Window) for peak and off-peak periods. Travel time variability is also influenced by the presence of intersections, bus stops and other geometric and traffic characteristics. Hence, the segment level analysis has been carried out considering bus stops, intersections and land-use type. The results from this study are presented and discussed in the following sub sections.

5.3.1 Temporal Aggregation

Travel time variability analysis at route level is conducted considering different temporal aggregations with respect to peak and off-peak periods. Statistical tests for symmetry and multimodality have been carried out (Table 5.3 to Table 5.6). The description of skewness, Kurtosis and Hartigan dip test is provided in Section 4.6. Hartigan dip test shows that the travel time data for most of the aggregation levels are unimodal. The results of skewness for different temporal aggregation indicate that there is a slight decrease in the skewness as the temporal aggregation decreases in few cases and change in skewness values is minimal in most of the cases. The change in the values of Kurtosis is also observed to be less with respect to temporal aggregation. The skewness and kurtosis values are higher in the case of route-266 DOWN compared to the other routes. The resulting skewness and kurtosis values imply that the temporal aggregation has very less impact on the shape of travel time distributions.

5.3.2 Spatial Aggregation

The variability in travel times with variations in passenger demand may not be captured by route level analysis and the travel time distributions may also vary across the segments. Hence to explore further, the routes have been divided into segments on the basis of bus stop positions. The segments are considered from start of the upstream bus stop to start of the downstream bus stop. This results in each segment containing an upstream bus stop. The temporal aggregation of peak/off-peak hour and 60 minutes are considered in the segment level analysis.

The segment level travel time distribution study is carried out to analyse travel time variability inclusive of the delays at bus stops and intersections. The factors such as passenger demand, presence of signals and varying signal timings, type of roads utilisation, land-use, variation in free flow travel time of each segment and geometric characteristics can be different within a route. Hence, the delays due to intersection and bus stops will be more precisely accounted in segment level analysis. Figure 5.11 presents the coefficient of variation (COV) of all the segments (varies from 9.25 % to 35.65 %) for the data from four routes in UP direction. The first 3 segments of all the four routes and segment 4 and 5 of route - 266 are observed to have higher COV values compared to other segments. These segments are located in CBD with higher traffic flow and the presence of signalised intersections impart more variability. The COV values are higher for the other segments, to the reason being the variation in passenger demand and traffic condition. Most of the segments of route-266 are having higher COV than the other route segments. This study stretch is one of the major arterial roads with high traffic volume. Similar to the route level analysis, in most of the segments, travel time data are unimodal.

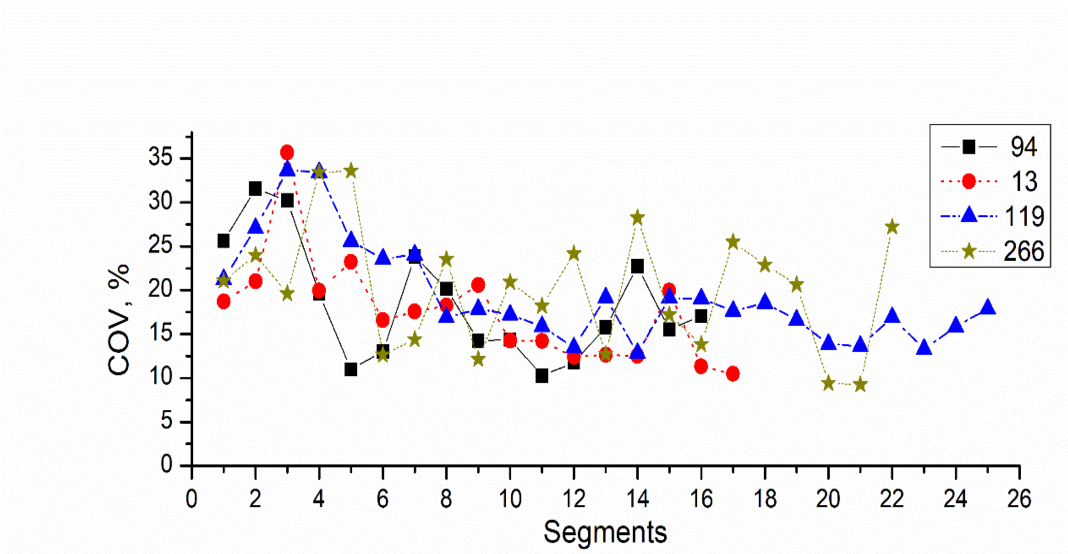


Figure 5.11. Coefficient of Variation of Four Routes

Table 5.3. Travel time descriptive statistics of temporal aggregation – Route 94

Route	Time period	Aggregation level	Sample size	Skewness/SE	Kurtosis/SE	Dip Test P-value
94 UP						
	Morning peak	peak period	312	0.60	0.53	0.17
		60 min	95	0.93	0.81	0.75
		30 min	61	0.74	0.00	0.68
		15 min	40	0.30	0.01	0.79
	Interpeak	peak period	204	3.26	3.70	0.85
		60 min	88	3.63	3.09	0.60
		30 min	59	3.41	4.52	0.83
		15 min	36	4.66	4.07	0.80
	Evening peak	peak period	257	1.43	3.66	0.40
		60 min	93	1.35	3.61	0.80
		30 min	68	2.60	3.54	0.88
		15 min	41	2.24	3.35	0.82
	Off-peak	peak period	101	3.50	3.05	0.02
		60 min	67	3.82	3.10	0.35
		30 min	39	3.34	4.15	0.64
94 DOWN						
	Morning peak	peak period	258	0.16	0.20	0.51
		60 min	101	0.08	0.33	0.72
		30 min	78	0.49	0.94	0.70
		15 min	42	0.40	0.55	0.48
	Interpeak	peak period	191	2.95	4.86	0.50
		60 min	88	1.18	4.51	0.79
		30 min	51	3.09	5.09	0.80
		15 min	36	3.02	5.13	0.74
	Evening peak	peak period	258	2.65	1.68	0.64
		60 min	103	1.84	1.79	0.52
		30 min	69	1.59	1.38	0.36
		15 min	40	2.66	2.23	0.51
	Off-peak	peak period	97	0.51	0.40	0.63
		60 min	58	0.23	0.08	0.94
		30 min	36	0.50	0.65	0.84

Table 5.4. Travel time descriptive statistics of temporal aggregation – Route 13

Route	Time period	Aggregation level	Sample size	Skewness/SE	Kurtosis/SE	Dip Test P-value
13 UP						
	Morning peak	peak period	697	1.48	1.11	0.17
		60 min	191	1.50	0.82	0.48
		30 min	108	7.18	13.17	0.67
		15 min	50	3.33	4.35	0.62
	Interpeak	peak period	460	2.18	2.26	0.24
		60 min	113	2.46	1.93	0.82
		30 min	62	3.74	2.78	0.48
		15 min	38	2.12	2.96	0.62
	Evening peak	peak period	414	2.19	1.32	0.28
		60 min	140	2.11	0.75	0.60
		30 min	64	1.91	1.41	0.59
		15 min	38	1.83	1.94	0.68
	Off-peak	peak period	222	2.22	0.70	0.67
		60 min	134	1.31	0.61	0.82
		30 min	81	1.85	1.71	0.66
		15 min	39	3.70	5.11	0.47
13 DOWN						
	Morning peak	peak period	571	2.32	2.18	0.24
		60 min	143	2.01	2.05	0.66
		30 min	88	2.00	1.71	0.79
		15 min	49	1.73	1.32	0.65
	Interpeak	peak period	363	2.00	2.35	0.67
		60 min	123	1.50	2.66	0.87
		30 min	65	2.76	2.63	0.82
		15 min	45	2.93	4.06	0.74
	Evening peak	peak period	484	3.86	7.70	0.04
		60 min	129	4.15	7.14	0.51
		30 min	77	4.69	7.83	0.61
		15 min	47	4.38	7.06	0.58
	Off-peak	peak period	198	3.99	3.71	0.66
		60 min	121	3.62	1.45	0.72
		30 min	54	3.77	1.02	0.70
		15 min	34	3.50	1.71	0.65

Table 5.5. Travel time descriptive statistics of temporal aggregation – Route 119

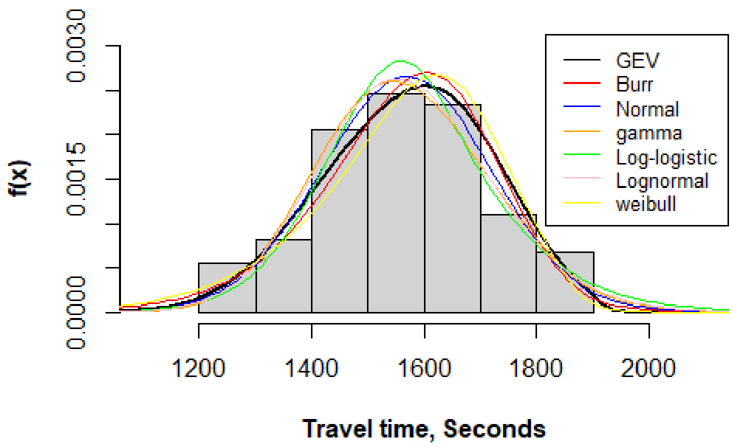
Route	Time period	Aggregation level	Sample size	Skewness/SE	Kurtosis/SE	Dip Test P-value
119 UP						
	Morning peak	peak period	654	1.69	2.18	0.54
		60 min	202	1.09	1.14	0.82
		30 min	119	1.12	1.07	0.74
		15 min	37	0.96	1.09	0.72
	Interpeak	peak period	572	2.82	1.86	0.87
		60 min	115	1.78	1.88	0.51
		30 min	91	1.25	0.69	0.61
		15 min	50	2.50	0.94	0.55
	Evening peak	peak period	354	0.41	1.45	0.87
		60 min	171	0.36	1.56	0.67
		30 min	114	0.80	1.10	0.69
		15 min	56	0.40	0.97	0.73
	Off-peak	peak period	181	0.07	1.35	0.67
		60 min	117	0.54	1.37	0.46
		30 min	44	0.44	1.03	0.52
		15 min	42	0.19	1.00	0.50
119 DOWN						
	Morning peak	peak period	592	2.03	1.38	0.60
		60 min	90	1.33	0.38	0.75
		30 min	74	0.86	0.65	0.72
		15 min	43	0.46	0.13	0.83
	Interpeak	peak period	524	1.82	1.45	0.64
		60 min	161	0.39	1.60	0.61
		30 min	103	0.39	0.90	0.81
		15 min	45	0.46	1.18	0.60
	Evening peak	peak period	390	0.17	0.89	0.96
		60 min	118	0.27	0.68	0.71
		30 min	89	0.17	0.17	0.69
		15 min	40	0.47	0.32	0.58
	Off-peak	peak period	174	3.44	1.13	0.90
		60 min	110	3.91	1.06	0.57
		30 min	65	3.31	0.62	0.63
		15 min	34	2.12	0.25	0.41

Table 5.6. Travel time descriptive statistics of temporal aggregation – Route 266

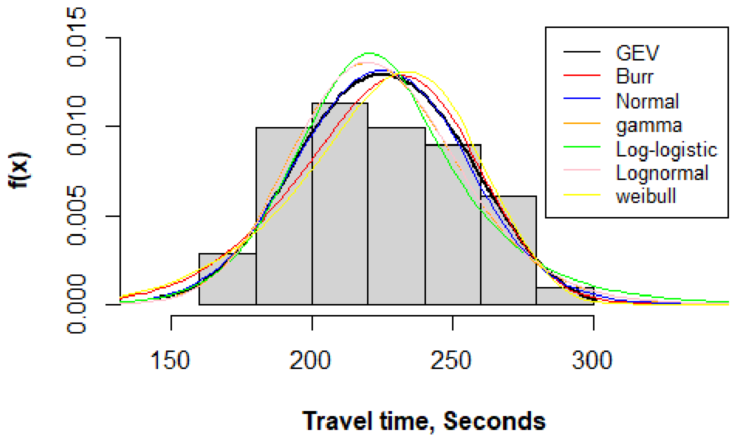
Route	Time period	Aggregation level	Sample size	Skewness/SE	Kurtosis/SE	Dip Test P-value
266 UP						
	Morning peak	peak period	731	2.17	1.05	0.68
		60 min	236	1.31	1.15	0.89
		30 min	96	1.66	1.07	0.68
		15 min	78	1.59	1.71	0.63
	Interpeak	peak period	563	1.85	1.12	0.70
		60 min	182	1.90	0.75	0.92
		30 min	60	2.32	1.70	0.80
		15 min	43	1.96	1.07	0.74
	Evening peak	peak period	418	0.28	1.64	0.03
		60 min	207	0.37	2.74	0.76
		30 min	99	1.72	3.63	0.83
		15 min	69	1.08	4.48	0.87
	Off-peak	peak period	181	3.00	1.69	0.88
		60 min	104	2.48	0.24	0.71
		30 min	60	3.16	0.46	0.59
		15 min	42	3.22	0.85	0.73
266 DOWN						
	Morning peak	peak period	813	4.13	1.41	0.85
		60 min	255	2.36	1.72	0.90
		30 min	132	2.38	1.79	0.78
		15 min	59	2.40	1.20	0.77
	Interpeak	peak period	490	4.32	2.20	0.86
		60 min	71	3.18	2.61	0.55
		30 min	96	2.38	2.71	0.72
		15 min	51	2.24	3.62	0.71
	Evening peak	peak period	431	2.20	2.98	0.66
		60 min	125	2.25	2.52	0.78
		30 min	70	2.56	3.63	0.76
		15 min	42	2.18	2.16	0.64
	Off-peak	peak period	130	7.43	8.44	0.74
		60 min	87	7.51	9.14	0.69
		30 min	62	7.56	16.17	0.81
		15 min	43	6.51	8.93	0.97

5.3.3 Performance Evaluation

The performance of selected distributions in describing travel time variability has been evaluated for different temporal and spatial aggregations. The KS test has been conducted for each aggregation case and p-value of the test has been inspected to appraise the robustness and accuracy of each distribution. The sample probability density function (PDF) plots for route and segment level are shown in Figure 5.12**.**



(a)



(b)

Figure 5.12. Probability density function of distributions a) Route level and b) Segment level

5.3.3.1 Route level

Survivor function of KS test p-value has been utilised to evaluate the performance of the considered distributions. Figure 5.13a shows the plot of p-value along the x-axis and survivor function on the y- axis for route level analysis. The KS test p-values of each distribution are arranged in the ascending order and then survivor function has been determined using Eq. (1). The x-axis of survivor plot shows the KS test p-value which increases from zero to one and the corresponding survival function value is

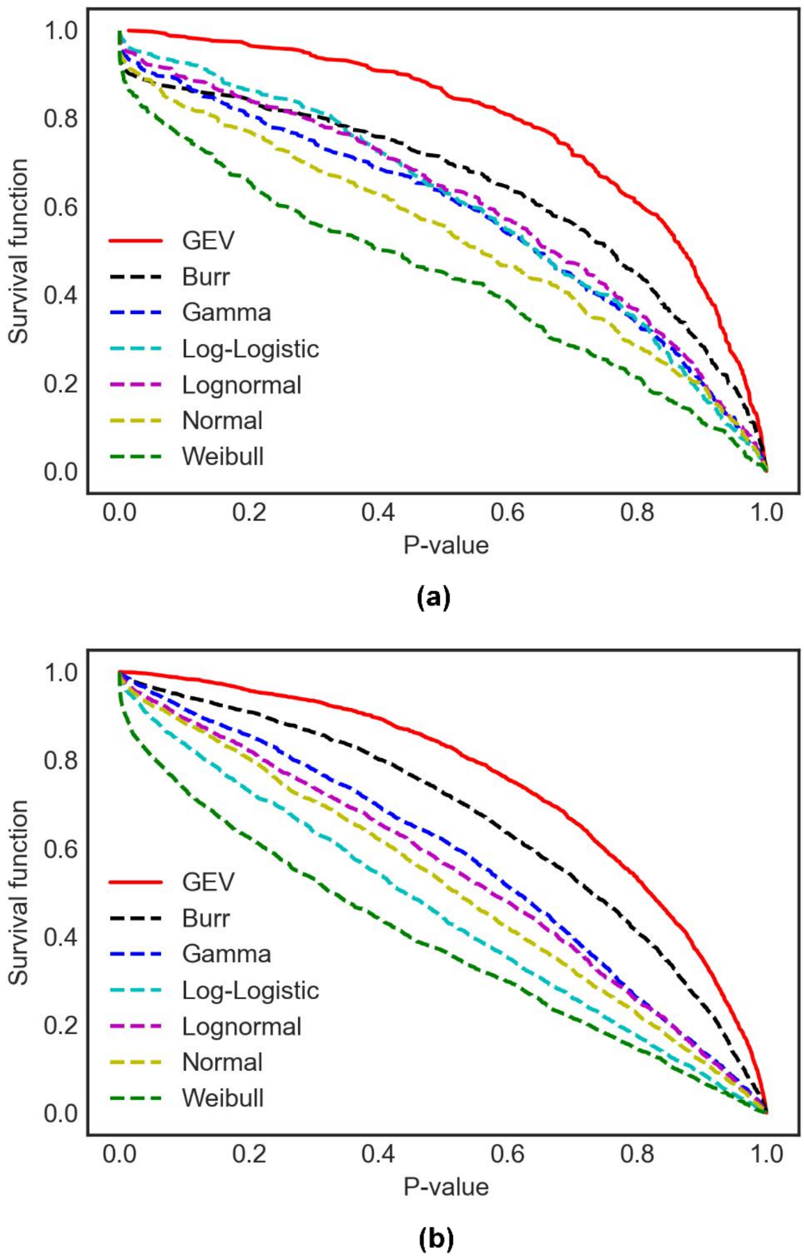


Figure 5.13. Survival Probability a) Route level and b) Segment level

represented by y-axis. Survivor curve shows the probability of each distribution that can perform well with a good fit for specified p-value.

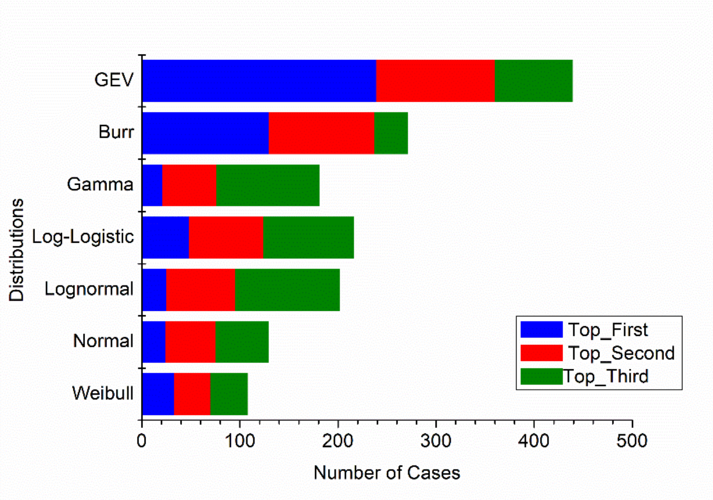
In route level analysis, around 80% cases with GEV distribution fit have KS test p-value more than 0.7, which shows the better performance of GEV than the alternative distributions. The survival curve plot of all the distributions shows that the Weibull distribution has the worst performance with a poor fit, as the survival rate is decreasing faster with the increase in p-value. Gamma, log-logistic, lognormal, and normal distribution have similar performance with gamma having a slightly higher performance than the other three distributions. The performance of GEV and Burr distribution is slightly similar from p-value 0.5 onwards but, the Burr distribution has an initial drop of 10 % at p-value equal to zero. The initial dip in the survival curve of Burr distribution highlights its failure cases, in which Burr distribution was unable to converge to the solution. This failure of Burr distribution will impact the performance of describing travel time variability when applied to real-world conditions, and similar results are observed in the previous studies (Ma et al. 2016).

Table 5.7. Descriptive Summary of KS test p-value and Distributions performance at route level

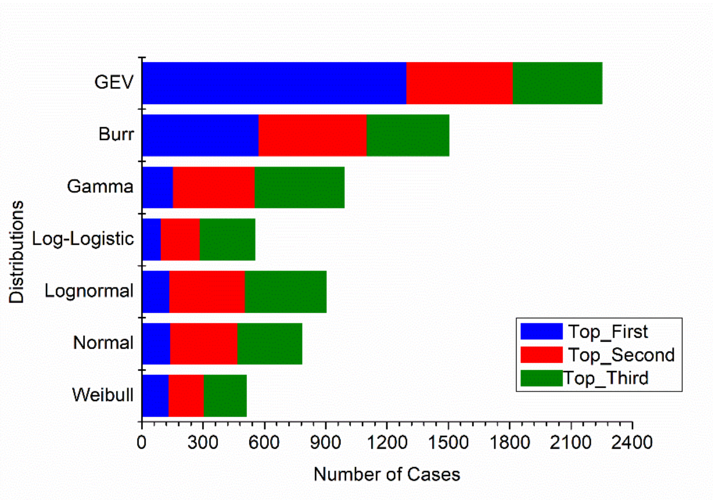
Distributions	Mean of p-value	SD of p-value	Cases_pass	Cases_top3
Burr	0.626	0.345	451	305
GEV	**0.809**	**0.190**	**519**	**360**
Gamma	0.632	0.285	497	98
Log-Logistic	0.627	0.275	500	143
Lognormal	0.649	0.276	502	112
Normal	0.586	0.300	489	105
Weibull	0.482	0.325	453	136

Table 5.7 shows the descriptive summary of KS test p-value for each distribution and the number of cases passed and the number of cases the distribution is in the top 3 positions, based on the p-value. The descriptive summary of p-value shows that GEV

distribution has the highest mean value and lowest SD (standard deviation) value. The total number of cases considered in the route level analysis is 520. GEV distribution passed the KS test in all the 520 cases. This shows the high accuracy and robustness of GEV distribution in modelling travel time variability. Burr distribution has a mean value of p-value of 0.626 with a higher SD of p-value (0.345). Lognormal, log-logistic and Burr distributions have almost similar mean and SD of p-value. Figure 5.14a shows the top 3 fitted distributions and the number of cases. The cases of GEV distribution being in top 3 are almost twice in number compared to the other distributions, except for Burr distribution. Burr distribution has more frequency of being in top 3 positions than log-logistic, gamma, normal, lognormal and Weibull distributions.



(a)



(b)

Figure 5.14. Summary of Top 3 distributions a) Route level and B) Segment level

5.3.3.2 Segment Level

Survival curve in Figure 5.13b shows the survival probability of all the distribution in segment level analysis. The results of the survival function show that GEV distribution has almost same performance at the segment level as that of route level, but the survival rate has decreased especially when the p-value is ranging from 0.3 to 0.8. The survival probability of GEV distribution is better than other distributions despite the reduction in survival rate compared to route level. The initial reduction in survival probability of Burr distribution has been improved in segment level analysis, compared to route level analysis but, it is still lower than GEV distribution.

The descriptive summary of KS test p-value for each distribution and the number of cases passed and the number of cases the distribution is in top 3 position is provided in Table 5.8. The outcomes show that the GEV distribution has highest mean and lowest SD values. In the segment level analysis, total of 2528 cases have been generated. The total number of cases passed and the cases of GEV distribution being in top 3 position are 2515 and 1828 cases, respectively.

Figure 5.14b shows the number of cases of each distribution present in top 3 positions. The figure indicates that the GEV distribution has more number of cases with top first positions compared to the other distributions. Also, the number of cases for which GEV has the top first position is more than the cases of next best fit Burr distribution being in top second position. The performance of log–logistic in segment level analysis is lower when compared to its performance in route level.

The segments have been grouped based on the presence of signalised intersections and the respective land-use type to understand their impact on travel time variability.

Table 5.9 shows the results of descriptive summary of segments with signalised intersection. The Cases pass ratio, Cases top_3 ratio and Cases first ratio have been calculated using Equation 5.1.to Equation 5.3., respectively.

$$\boldsymbol{Cases\ pass\ ratio} = \frac{\boldsymbol{Number\ of\ Cases\ passing\ the\ KS\ test}}{\boldsymbol{Total\ Number\ of\ Cases\ generated}} \qquad \textbf{(5.1)}$$

$$\boldsymbol{Cases\ top3\ ratio} = \frac{\boldsymbol{Number\ of\ Cases\ present\ in\ the\ Top\ 3\ position\ (KS\ test\ p{-}value)}}{\boldsymbol{Total\ Number\ of\ Cases\ generated}} \textbf{(5.2)}$$

$$\boldsymbol{Cases\ first\ ratio} = \frac{\boldsymbol{Number\ of\ Cases\ present\ in\ the\ 1st\ \ position\ (KS\ test\ p{-}value)}}{\boldsymbol{Total\ Number\ of\ Cases\ generated}} \quad \textbf{(5.3)}$$

The results show that the GEV distribution performs better than other distributions with highest mean p-value and lowest SD. Also, GEV has passed the KS test in 99% of the cases and is present in the top 3 and top first in 83 % and 61 % of the cases, respectively, which validates the robustness of GEV distribution. Burr distribution is the second-best in terms of the mean p-value, the number of cases passed and cases being in the top 3 position, but it is less accurate due to higher SD value.

Table 5.8. Descriptive Summary of KS test p-value and Distributions performance at segment level

Distributions	Mean of p-value	SD of p-value	Cases_pass	Cases_top3
Burr	0.659	0.279	2439	1189
GEV	**0.746**	**0.238**	**2515**	**1828**
Gamma	0.569	0.289	2410	669
Log-Logistic	0.455	0.301	2260	550
Lognormal	0.542	0.301	2363	668
Normal	0.511	0.299	2334	662
Weibull	0.386	0.313	2042	789

Table 5.9. Descriptive Summary of KS test p-value and Distributions performance of segments with signalised Intersection

Distributions	Mean of p-value	SD of p-value	Cases pass ratio	Cases top3 ratio	Cases first ratio
Burr	0.587	0.314	92%	48%	16%
GEV	**0.717**	**0.258**	**99%**	**83%**	**61%**
Gamma	0.498	0.300	92%	26%	4%
Log-Logistic	0.401	0.307	84%	27%	4%
Lognormal	0.475	0.312	90%	28%	7%
Normal	0.459	0.306	89%	25%	2%
Weibull	0.406	0.313	84%	31%	5%

The results of the descriptive summary and the number of cases with respect to different land-use type are provided in Table 5.10. The segments are grouped into five groups (CBD, Commercial, Residential, Industrial and Open space) depending on the predominant land-use pattern of the segments. Among the five groups, GEV has a better performance than other distributions in terms of accuracy and robustness. The mean p-value of GEV distribution is highest in the industrial area and lowest in CBD area. The SD of this distribution is highest in the commercial area and lowest in the industrial area. GEV distribution has passed the KS test in 100% of the cases in the industrial, open space and residential area and 99% of the cases in CBD and commercial area. The number of cases GEV is in top 3 position and top first position is found to be highest for GEV distribution. Burr distribution has better performance over the other 5 distributions (except GEV distributions) and Weibull distribution is observed to have a poor performance.

Table 5.10. Descriptive Summary of KS test p-value and Distributions performance of segments with different land-use type

Land-use type	Distributions	Mean of p-value	SD of p-value	Cases pass ratio	Cases top3 ratio	Cases first ratio
CBD						
	Burr	0.624	0.305	95%	49%	18%
	GEV	**0.741**	**0.251**	**99%**	**78%**	**59%**
	Gamma	0.522	0.306	93%	24%	4%
	Log-Logistic	0.447	0.311	86%	26%	4%
	Lognormal	0.515	0.319	91%	30%	6%
	Normal	0.457	0.304	90%	23%	4%
	Weibull	0.373	0.311	79%	35%	5%
Commercial						
	Burr	0.627	0.288	95%	49%	22%
	GEV	**0.701**	**0.256**	**99%**	**73%**	**50%**
	Gamma	0.527	0.291	93%	28%	6%
	Log-Logistic	0.420	0.295	86%	24%	4%
	Lognormal	0.504	0.296	92%	27%	5%
	Normal	0.461	0.308	88%	28%	5%
	Weibull	0.348	0.309	78%	38%	7%
Industrial						
	Burr	0.740	0.226	100%	41%	20%
	GEV	**0.852**	**0.152**	**100%**	**80%**	**63%**
	Gamma	0.616	0.302	98%	13%	2%

	Log-Logistic	0.557	0.314	92%	23%	5%
	Lognormal	0.643	0.310	97%	31%	6%
	Normal	0.520	0.316	95%	20%	2%
	Weibull	0.396	0.320	78%	31%	3%
Open space						
	Burr	0.720	0.232	100%	50%	35%
	GEV	**0.784**	**0.194**	**100%**	**60%**	**41%**
	Gamma	0.617	0.253	99%	21%	9%
	Log-Logistic	0.436	0.290	91%	22%	3%
	Lognormal	0.554	0.283	96%	20%	4%
	Normal	0.637	0.249	100%	32%	6%
	Weibull	0.409	0.311	86%	24%	1%
Residential						
	Burr	0.672	0.271	97%	46%	23%
	GEV	**0.752**	**0.232**	**100%**	**71%**	**49%**
	Gamma	0.590	0.281	96%	28%	7%
	Log-logistic	0.463	0.298	91%	20%	4%
	Lognormal	0.556	0.295	94%	25%	5%
	Normal	0.533	0.292	93%	27%	6%
	Weibull	0.398	0.314	82%	29%	5%

The route and segment level performance of selected distributions have been compared and presented in Table 5.11. The results show that COV of p-value of all the routes increased from route level to segment level, which indicates the complexity of segment travel time than route travel time. The lowest COV of p-values, i.e., 0.190 and 0.319 have been observed for GEV distribution at route level and segment level, respectively. The COV of Weibull distribution has increased from 0.325 to 0.812 from route level to segment level. The ratio of number of passing cases to total cases, has decreased for all the distributions except for Burr and the decrease for GEV distribution is observed to be negligible. The performance of log-logistic, normal, lognormal and gamma distribution is almost same for route and segment level analysis.

The above analysis of travel time distributions implies that the GEV distribution performs well for all the cases (route level and segment level) in comparison with the other distributions. The analysis also describes the robustness and accuracy of the GEV distribution are superior among the distributions examined. The segment level analysis of the distributions considering the presence of signalised intersection and its land-use type shows the effectiveness of GEV distribution in describing travel time variability of public transit under different working environments. Overall, the GEV distribution can be considered as the better descriptor of the public transit travel time variability and is used for the further analysis of TTR of selected transit routes.

Table 5.11. Comparison of distribution performance at route and segment level

	Route Level				Segment Level			
Distributions	COV of p-value	Cases pass ratio	Cases first ratio	Cases top3 ratio	COV of p-value	Cases pass ratio	Cases first ratio	Cases top3 ratio
Burr	0.345	87%	25%	59%	0.424	96%	23%	47%
GEV	**0.190**	**100%**	**46%**	**69%**	**0.319**	**99%**	**51%**	**72%**
Gamma	0.285	96%	4%	19%	0.507	95%	6%	26%
Log-Logistic	0.275	96%	9%	28%	0.662	89%	4%	22%
Lognormal	0.276	97%	5%	22%	0.554	93%	5%	26%
Normal	0.300	94%	5%	20%	0.585	92%	5%	26%
Weibull	0.325	87%	6%	26%	0.812	81%	5%	31%

5.4 TRAVEL TIME RELIABILITY ANALYSIS USING STATISTICAL DISTRIBUTION

Analysis of travel time reliability is necessary to perceive the quality of service offered by the public transit system. The present study conducted on travel time distributions shows the effectiveness of GEV distribution in describing travel time variability. Hence, GEV distribution has been used to analyse TTR of selected transit routes of Mysore city. GEV distribution is beneficial when it comes to mathematical calculations, with the direct computation of percentile values. In this study, the reliability metrics such as TTI, PTI and BTI suggested by Federal Highway Administration (2006) have been adopted to evaluate public transit TTR. The reliability measures TTI, PTI and BTI have been defined in Section 2.1.2 and are calculated using Equations 2.1 to 2.3. These reliability measures are computed using percentile values from the travel time distribution.

GEV distribution is a family of continuous probability distributions developed within extreme value theory. The type of GEV distribution is based on the three parameters: location, scale, and shape. There are three versions of GEV distribution: Type I - Gumbel, Type II – Frechet, and Type III - Reversed Weibull (Papalexiou and Koutsoyiannis 2013). The type of GEV distribution is defined by the shape parameter values: K=0, K>0 and K<0 corresponding to Gumbel, Frechet and Reversed Weibull distributions, respectively.

The probability density function of GEV distribution

$$\boldsymbol{f(x)} = \frac{\mathbf{1}}{\sigma}\ \boldsymbol{e}^{\left(-(\mathbf{1}+\boldsymbol{kZ})^{\frac{-\mathbf{1}}{\boldsymbol{k}}}\right)(\mathbf{1}+\boldsymbol{kz})^{-\mathbf{1}-\frac{\mathbf{1}}{\boldsymbol{k}}}} \qquad k \neq 0 \tag{5.4}$$

The cumulative density function of GEV given by

$$\boldsymbol{F(x)} = \ \boldsymbol{e}^{\left(-(\mathbf{1}+\boldsymbol{kZ})^{\frac{-\mathbf{1}}{\boldsymbol{k}}}\right)} \tag{5.5}$$

Where z = (x- μ)/σ

k = Shape parameter

μ = Location parameter

σ=Scale parameter

The percentile function is derived by solving CDF for x as given below

$$\boldsymbol{x} = \ \boldsymbol{\mu} - \frac{\sigma}{\boldsymbol{k}}\ (\ \mathbf{1} + \mathbf{ln}(\boldsymbol{p})^{-\boldsymbol{k}}) \tag{5.6}$$

Where, p = percentile of travel time

TTR measures - TTI, PTI and BTI have been calculated and analysed for the UP direction of all the routes using Equations 5.4 to 5.6. The free flow travel time has been determined from 5 to 6 AM for each route separately. The variation of these metrics with respect to different time periods of the day for the selected routes has been studied to quantify the reliability of public transit. Figure 5.15 exhibits the variation of reliability measures of study stretches within a day.

The variation of TTI is shown in Figure 5.15a. All the routes are originated from CBS connecting different destinations. Higher the reliability index value, lower will be travel time reliability of public transit. For route-94, TTI is observed to be higher during 9 to 10 AM and being nearly constant for rest of the time periods. Route-13 has lower TTI values during the morning, which showed an increasing trend during afternoon hours and reached maximum value during 7 to 8 PM. TTI values for route-119 are found to have smaller peaks in the morning, afternoon, and evening hours than the other routes. The highest TTI values are observed during 5 to 6 PM and 8 to 9 AM. The route-266 has abrupt variations in TTI with peak values from 10 to 11 AM and 5 to 6 PM. The evening hours have comparatively higher TTI values for most of the routes except for route - 94. TTI values of public transit along routes 266 are higher than the other routes.

Figure 5.15b shows the variation of PTI values throughout the day. PTI values for routes 94 and 119 are observed to have similar variation with highest values during 8 to 9 AM and 6 to 7 PM. For route-13, PTI values reach maximum during 8 to 9 PM. During 10 to 11 AM and 5 to 6 PM, the route-266 has the peak values of PTI. PTI values for all the routes are lower in the morning peak period than in evening peak period.

The variation in BTI for the selected routes is presented in Figure 5.15c. BTI is an indication of extra buffer time that will be considered by the passenger in addition to average travel time during trip planning. Higher BTI value indicates lower travel time reliability. The variation of BTI for route-119 has the peak during 11 to 12 PM with the highest value (55%) among all the routes. It also has a peak in the evening with 35% BTI during 6 to 7 PM. BTI plots for routes 94 and 266 have peaks at morning 8 to 9 AM and 11 AM to 12 PM with a value around 35%. The peak BTI values for route-13 is observed to be during 9 to 10 AM and 2 to 3 PM with a value 22%. During 4 to 5 PM with BTI 35% which is same as that of route-94. BTI values of all the routes are higher during morning and evening peak hours. Among all the routes, routes 266 and 119 are having higher reliability values. This might be due to the variation in delay caused by the presence of more bus stops and intersections.

The inferences from TTR indices give the understanding of public transit reliability along the route. The results from this study imply that the routes have specific time periods of the day with low public transit travel time reliability. The above analysis of TTR is significant in the performance evaluation of public transit. It is helpful in identifying the locations and time durations with a lower TTR of buses, to inspect the influencing factors and proposing measures to improve reliability.

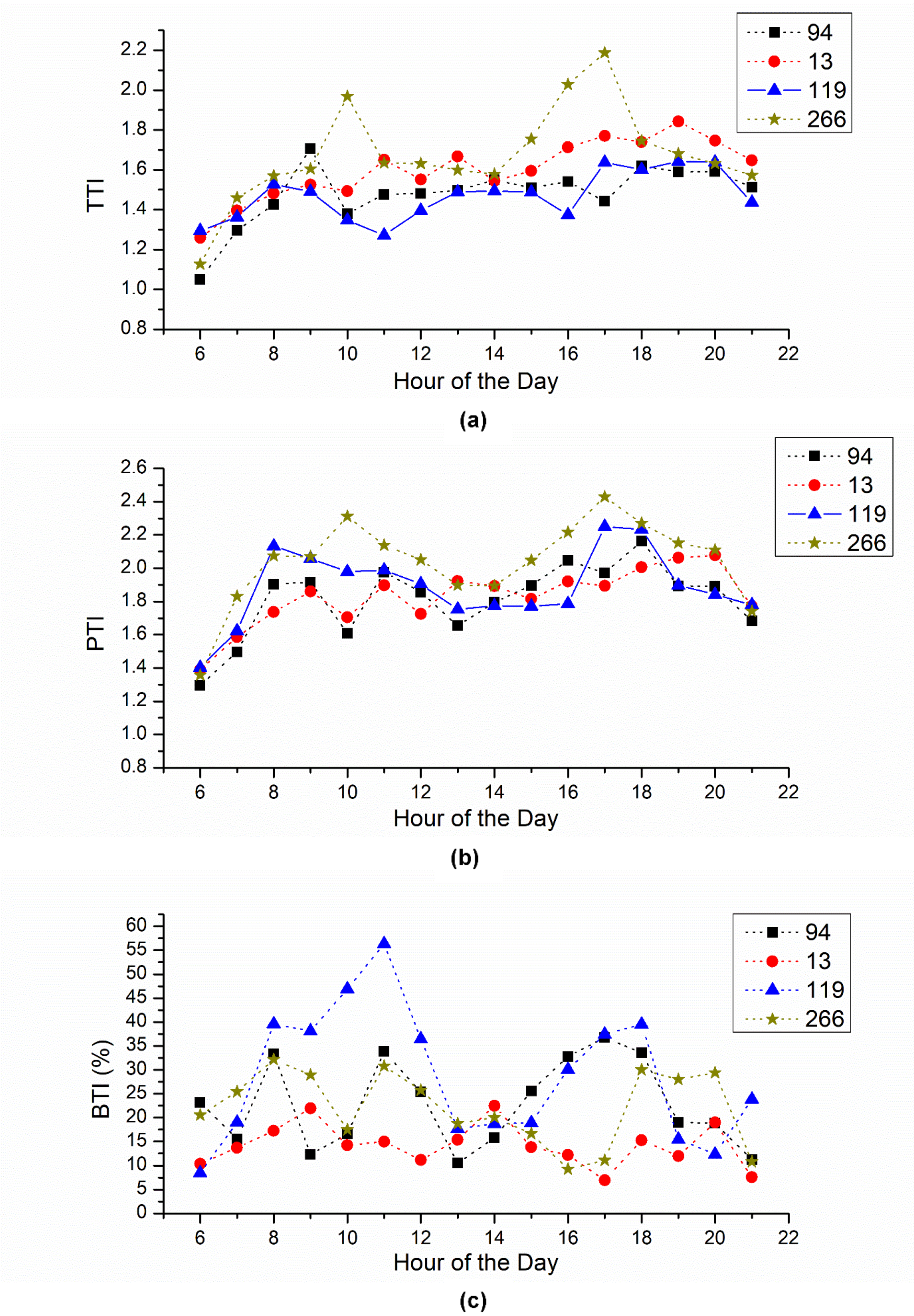


Figure 5.15. Travel Time Reliability of Transit Routes

5.5 TRAVEL TIME RELIABILITY MODELLING

As explained in Section 4.7, TTR is modelled using the MLR method. Three separate models have been developed with average travel time (ATT), Planning Time and Buffer Time as the dependent variables. The selected independent variables are found to explain 76.6%, 64.3% and 33.5% of ATT, PT and BT respectively (Table 5.12 to Table 5.14). The outcomes of ATT model are presented in Table 5.12.

Table 5.12. Travel time reliability model results – Average Travel Time (ATT)

Independent Variable	Coefficients	Standardised Coefficients (Beta)	t -statistics	Significance
Constant	-50.726		-9.856	0.000
Length	0.109	0.653	30.577	0.000
Average of stop delay	0.986	0.291	6.618	0.000
SD of stop delay	1.132	0.207	4.758	0.000
Intersections/km	10.273	0.167	7.285	0.000
Land-use	18.799	0.122	5.354	0.000
Off-peak	-9.575	-0.043	-2.035	0.042
Adjusted $R^2 = 0.766$				

All the independent variables (Table 4.10) except off-peak, showed a positive impact on the ATT and are found significant with a significance level of 0.05. ATT is found to be increasing with the increasing segment length as expected. As the segment length increases, interaction of public transit bus with on-street parking vehicles, pedestrians crossing at midblock and other side friction activity also increases. Length variable acts as a proxy variable for side friction impedance. Both average bus stop delay and SD of bus stop delay have a positive impact on ATT. The presence of intersections is increasing ATT around 10.2 sec and the coefficient of land-use (CBD/Commercial) variable is 18.79. The off-peak variable has the least impact and also a negative impact on ATT, which suggests that ATT is lesser in off-peak hours which is logically true.

The results of PT model are given in Table 5.13. All the variables are contributing to the increase in PT except the off-peak variable which has an opposite effect. In PT model also, length of segment is found to have the largest impact and the off-peak having the least effect on PT. The coefficients of PT model variables are higher than that of ATT model due to the consideration of 95th percentile travel time. All the variables are found to be significant at a significance level of 0.05 or less. Average bus stop delay is having more impact than SD of bus stop delay which can be observed in standardised coefficients. The results of regression show that the variables, intersections/km and land-use, have similar effect on PT as that of ATT.

Table 5.13. Travel time reliability model results – Planning Time (PT)

Independent Variable	Coefficients	Standardised Coefficients (Beta)	t -statistics	Significance
Constant	-60.456		-6.492	0.000
Length	0.133	0.545	20.672	0.000
Average of stop delay	1.282	0.258	4.754	0.000
SD of stop delay	1.848	0.231	4.294	0.000
Intersections/km	15.023	0.167	5.888	0.000
Land-use	31.195	0.138	4.911	0.000
Off-peak	-21.774	-0.067	-2.558	0.011
Adjusted R^2 = 0.643				

Table 5.14 shows the results of BT model. Similar to ATT and PT model, off-peak variable has a negative impact and all other variables have a positive effect on BT. The standardised coefficient of length of segment variable has been found to have decreased drastically in BT model in comparison with the ATT and PT models, but with a positive impact. The major changes in the results of BT are observed with respect to the variables, average bus stop delay and SD of bus stop delay. The SD of bus stop delay has a higher impact on BT than the average bus stop delay. This suggests that the

variation in bus stop delay leads to a higher buffer time, which proves it to be almost as important as the length of segment variable. The coefficient values of intersections/km, land-use and off-peak are similar to those of ATT and PT model, with off-peak having the least but a negative impact on BT.

Table 5.14. Travel time reliability model results – Buffer Time (BT)

Independent Variable	Coefficients	Standardised Coefficients (Beta)	t -statistics	Significance
Constant	-9.730		-2.040	0.042
Length	0.024	0.265	7.365	0.000
Average of stop delay	0.295	0.159	2.139	0.033
SD of stop delay	0.716	0.238	3.248	0.001
Intersections/km	4.750	0.141	3.635	0.000
Land-use	12.396	0.146	3.810	0.000
Off-peak	-12.198	-0.099	-2.798	0.005
Adjusted R^2 = 0.335				

The adjusted R^2 of BT is significantly lower when compared to that of ATT and PTI. These observations are similar to the outcomes reported in the past research works (Ma et al. 2015). The results of TTR models show that the independent variables are significant at 0.05 significance level. The segment length acts as a proxy variable for the traffic movement obstruction caused by the side friction activities and the results suggest that the increasing length of the segment is causing the reduction of public transit reliability. Hence, the bus stop location and the spacing between the stops should be designed properly considering the factors such as passenger demand, land-use, and other physical characteristics of the road. The bus stop delay has a significant impact on TTR measures which can be addressed by maintaining the scheduled departure/arrival timings and the headways in each stop according to passenger demand of the bus stop. The presence of intersections and junctions are also found to be the contributing factor to the reduction in reliability, which can be improved by adopting segregated lanes and transit signal priority systems.

5.6 LEVEL OF SERVICE BASED ON TRAVEL TIME RELIABILITY

The LOS of transit routes has been developed based on TTR measures. As mentioned in the methodology (Section 4.8), six clusters have been considered to define different levels of service and the cluster validation is conducted using silhouette index. Figure 5.16 shows the silhouette plot for reliability measures along with width of silhouette for each cluster. The width of silhouette for almost all the clusters of TTI, PTI and BTI is greater than 0.5. The total silhouette coefficient is calculated as the average of silhouette width of all the clusters and the values of silhouette coefficients are 0.523, 0.538 and 0.572 for TTI, PTI and BTI respectively. The results of silhouette analysis show that clusters formed have reasonable structures and the six LOS measures can be developed based on these reliability measures. The LOS ranges based on reliability measures are determined by the 45^{o} curve with the reliability measures plotted on both the axes (Figure 5.17) and the results are tabulated in Table 5.15. These range of values can be used by transit operators and traffic management system to measure the service offered by the system and also to evaluate the performance of the system periodically.

Table 5.15. Travel time reliability based LOS thresholds

Level of service	TTI	PTI	BTI
LOS A	< 2.42	< 3.14	< 11.40
LOS B	> 2.42 – 2.95	> 3.14 – 3.94	> 11.40 – 22.00
LOS C	> 2.95 -3.47	> 3.94 – 4.71	> 22.00 – 29.16
LOS D	> 3.47 - 4.10	> 4.71 – 5.74	> 29.16 – 38.25
LOS E	> 4.10 – 4.92	> 5.74 – 7.38	> 38.25 – 52.94
LOS F	> 4.92	>7.38	> 52.94

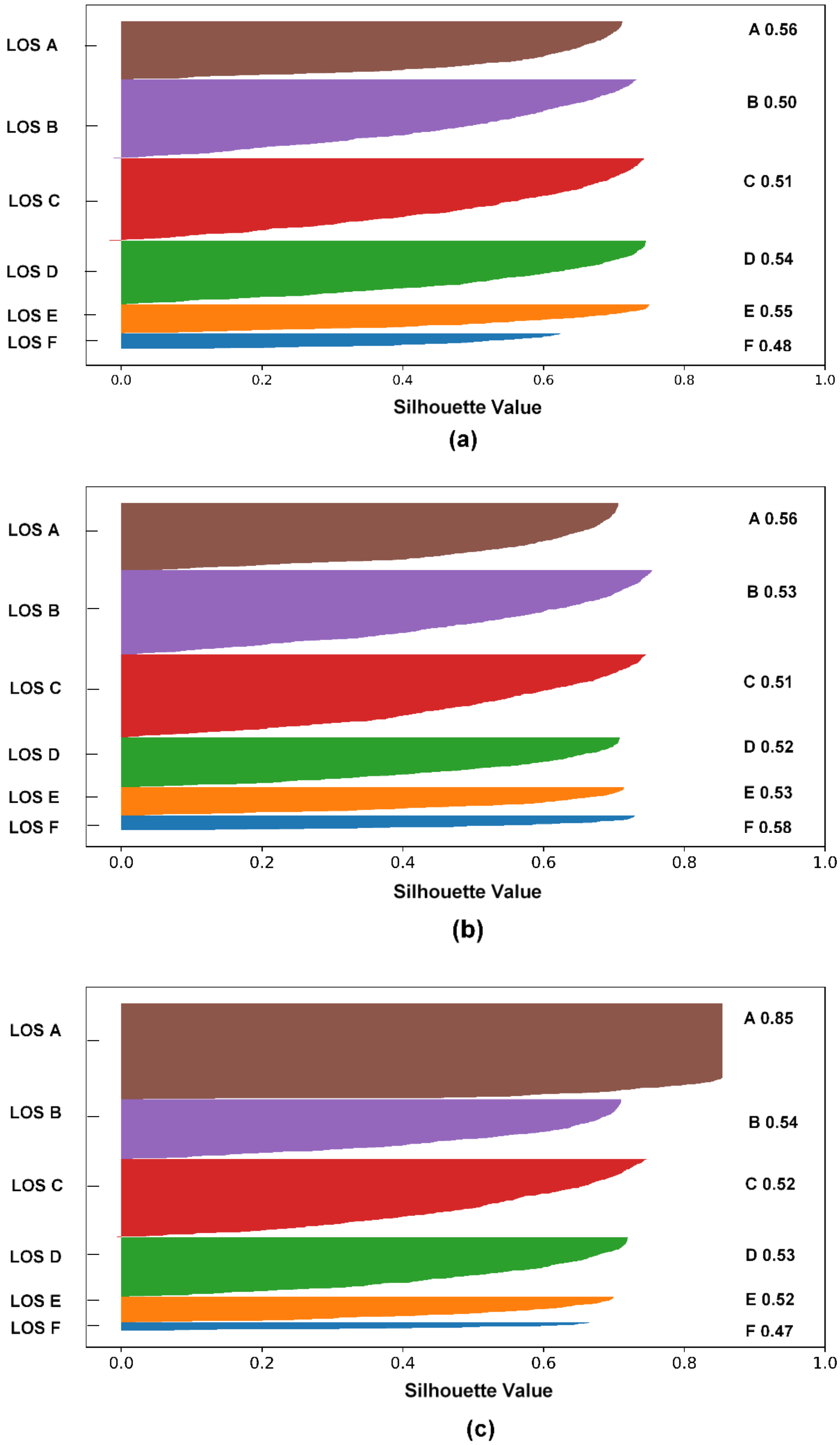


Figure 5.16. Silhouette Plot a) TTI b) PTI and c) BTI

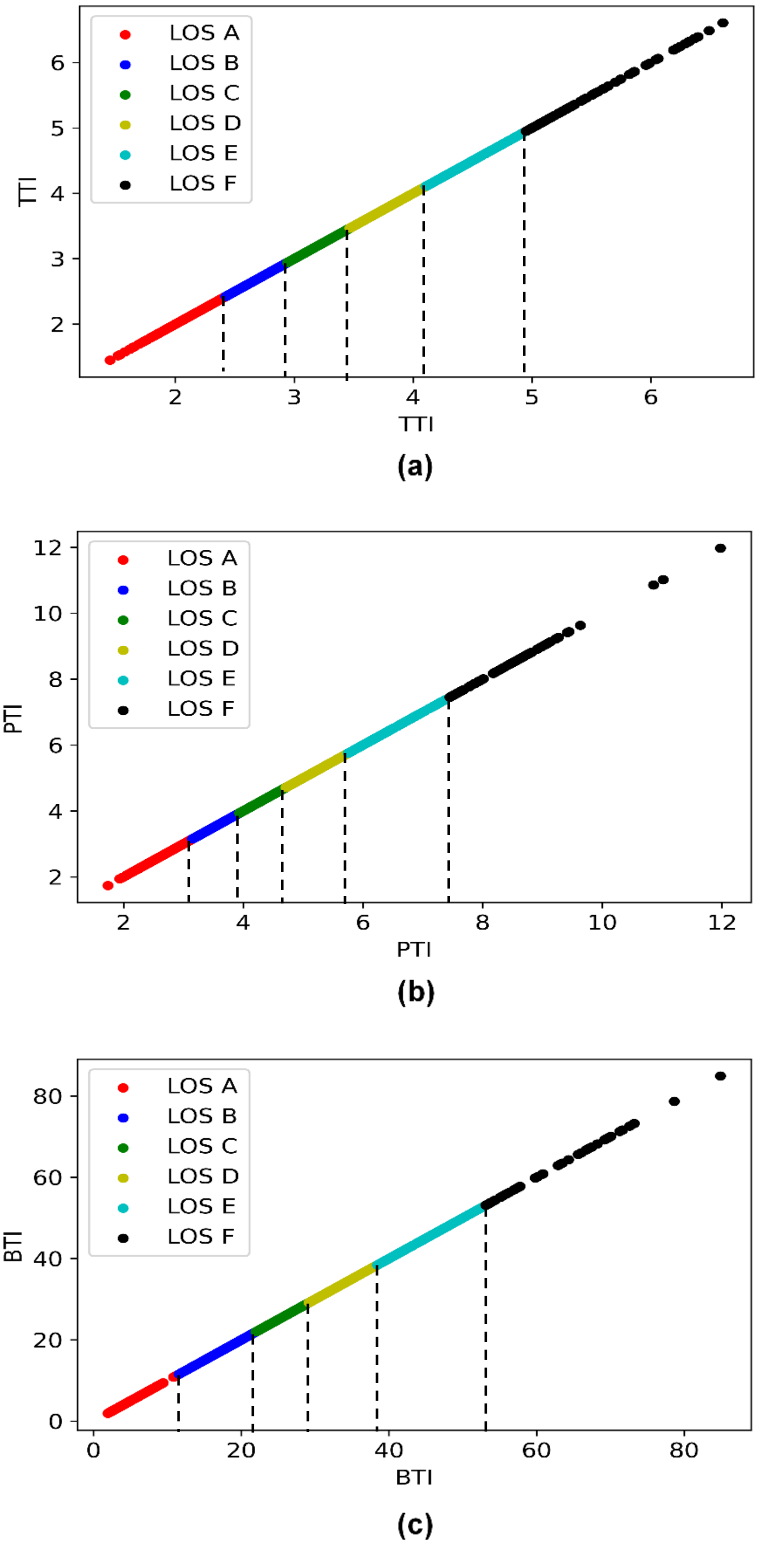


Figure 5.17. Clustered range of reliability measures a) TTI b) PTI and c) BTI

5.7 SUMMARY

This chapter deals with the results and findings of the research work with respect to the objectives defined for the study. The effect of side friction on TTR, effect of spatial and temporal aggregations on travel time variability, TTR models considering the factors affecting reliability of the public transit system, are discussed. Finally, the LOS of bus routes are determined based on TTR and the results are discussed.

- In the quantification of side friction elements, the results of relative weight analysis show that the static side friction has a raw relative weight of 0.509 and 0.327 for undivided and divided roads respectively, which are the highest among all the side friction elements.
- Side friction activities are found to be higher during weekend on the undivided road and on weekday in the case of divided road. The variation of TTI and PTI follow almost similar trend as that of SFI.
- The Impact of SFI on reliability measures are analysed with respect to traffic volume levels and the exponential curve has been found to be the best fit with the maximum goodness of fit value. In the case of the undivided road, TTI and PTI have R^2 values ranging from 0.59 to 0.83 and 0.60 to 0.88, respectively. But, BTI has a least goodness of fit value with R^2 in the range of 0.07 to 0.50. Similar results have been obtained in the case of the divided road. TTI and PTI have the R^2 values ranging from 0.71 to 0.78 and 0.73 to 0.92, respectively. BTI has R^2 values in the range of 0.03 to 0.75. The above results show the impact of SFI on TTI. PTI is sensitive to traffic volume especially at higher traffic volume and the impact is less on BTI at medium traffic volume.
- The effect of temporal and spatial aggregation on travel time variability has been evaluated using travel time distributions. The results of temporal aggregation show that its impact on the shape of the distributions is found to be weak.
- The performance of seven statistical distributions namely Burr, GEV, Gamma, log-logistic, lognormal, normal, and Weibull are evaluated using K S test with respect to route level and segment level. The efficiency of these distributions in describing the travel time variability are studied using survivor function and

also accuracy and robustness of these distributions are analysed with respect to segments having signalised intersections and different land-use types. The results of distribution fitting indicates that the GEV distribution is superior to other distributions in both route and segment levels. The accuracy and robustness of GEV distribution are found to be better in the case of signalised intersections and different land-use types. Travel time reliability of the four routes is analysed using GEV distribution and found that reliability of the routes is lesser during peak hours.

- Travel time reliability modelling has been conducted considering three reliability measures (ATT, PT and BT). Multiple Linear Regression method is adopted to model these reliability measures. The results of this study shows that length of the segment has a higher impact on all the three reliability measures (0.653 in ATT, 0.545 in PT and 0.265 in BT). The average delay has a higher standardised coefficient value than the SD of delay in case of ATT (0.291) and PT (0.258). In BT model, SD of delay (0.238) is more than average delay (0.159) which shows that variation in bus stop delay leads to a higher buffer time. The presence of intersection in the segments and CBD/commercial land-use segments are found to have lesser travel time reliability.
- The LOS of bus routes are determined based on TTR using K-Means clustering method. The LOS thresholds of six clusters which are the globally accepted LOS levels from A to F, are determined with the segment travel time data of four bus routes using K-means clustering method. Finally, the assumed number of clusters are validated using silhouette analysis. The results from silhouette analysis prove that the silhouette values for all the clusters defined are greater than 0.5 and hence the cluster quality is acceptable in all the clusters of three reliability measures. Similar thresholds can be determined to different study areas and it can be used to evaluate the service offered by the transit system in that area.

CHAPTER 6

CONCLUSION

6.1 GENERAL

This chapter provides the conclusions drawn from the results of travel time variability study, analysis of impact of side friction on TTR, modelling of TTR and determination of the LOS of bus routes based on TTR. The conclusions obtained from the each of the objectives are given in the following sections.

6.2 CONCLUSION

The study of travel time variability and reliability is necessary in estimating the quality of service offered by the public transit system. The first objective of this study is to analyse the impact of side friction on travel time reliability of public transit (buses). An effective method to quantify the impact of different types of side friction elements inclusive of both static and dynamic parameters and their representation by Side Friction Index (SFI) has been presented. The impact of different types of side friction on travel time reliability has been analysed using reliability indices such as Travel Time Index (TTI), Planning Time Index (PTI), and Buffer Time Index (BTI). The two road sections (divided and undivided) considered for the study have different types of geometric and traffic characteristics. Hence, reliability indicators of public transit at both the sections have been compared using the Reliability Buffer Index (RBI). The impact of side friction is sensitive to traffic volume levels. Hence, Cluster analysis has been carried out to obtain the threshold values of traffic volume using the K-Means clustering algorithm. The impact of side friction on travel time reliability indices and its sensitivity at different traffic volume levels have been analysed and discussed. Finally, the study concludes that the roadside friction elements have a significant impact on travel time reliability of public transit and the impact varies with respect to the type of road (divided and undivided), volume levels, different days of week (weekday and weekend), and different time periods of day. The major conclusions of this objective are,

- The results of the relative weight analysis used for the quantification of side friction show that the relative importance of static side friction is significant when compared to that of dynamic side friction.
- The hourly variation of reliability measures viz. TTI and PTI, follow similar trends as that of SFI.
- The impact of side friction at different traffic volume levels varies non-linearly (exponential) with respect to travel time reliability.
- The impact of side friction on TTI and PTI is sensitive to traffic volume, especially at higher traffic volume level.
- The impact of side friction on BTI is lower at medium traffic volume level.
- Travel time reliability of public transit is found to be lower in the case of the undivided road than the divided road.

Daily variations of travel time in public transit using probability distributions and the impact of different level of aggregations (temporal and spatial) on travel time variability have been studied to address the second objective of the present study. The AVL data of four transit routes of Mysore City are utilised in this research work. Seven probability distributions have been chosen for the analysis namely, Burr, GEV, Gamma, log-logistic, lognormal, normal and Weibull, based on the previous literature. Travel time distributions have been applied to the data, with respect to different levels of temporal aggregation (peak period, off-peak period, 60 minutes, 30 minutes and 15 minutes) and spatial aggregation (route level and segment level). The performance of the distributions is evaluated using the Kolmogorov-Smirnov (KS) test in terms of accuracy and robustness. The segment level analysis is also carried out separately for the segments with signalised intersections and different land-use types. The results of the study show that the GEV distribution is the best descriptor of travel time variability of public transit and its performance is better in terms of accuracy and robustness. Travel time reliability measures such as TTI, PTI, and BTI have been determined using GEV distribution and the reliability of transit routes has been estimated. The major conclusions of this objective are,

- The impact of temporal aggregation on the shape of travel time distribution is minimum.
- The distribution fitting of Burr, GEV, Gamma, log-logistic, lognormal, normal, and Weibull distributions indicates that the GEV distribution is superior to other distributions in route and segment level analysis.
- The GEV distribution performs well even for the segments with signalised intersections and different land-use types, which shows the effectiveness of GEV distribution in describing travel time variability of public transit under different environments.
- The reliability measures indicate that the reliability of public transit is lower during peak hours for the study routes and also the lower values of reliability is observed for the transit routes with more bus stops and intersections.

The understanding of the factors causing unreliability of the public transit system is significant in improving the system's reliability. Hence, the factors affecting travel time reliability have been analysed. Three TTR measures, Average Travel Time (ATT), Planning Time (PT) and Buffer Time (BT), are considered as the dependent variables. The length of the segment, bus stop delay, intersections, land-use, and peak/off-peak time period are considered as the independent variables for modelling TTR. The segment travel time data of route-266 is considered in this study, which has 22 segments based on the bus stop spacing. Three different models for ATT, PT, and BT are developed using MLR method. The major conclusions from the outcomes are,

- The results of TTR models show that all the independent variables are significantly affecting the TTR (at 0.05% significance level).
- Length of the segment has a greater impact than the other variables in ATT and PT models but, the effect is lesser in the BT model.
- The average bus stop delay is found to affect TTR more than the SD of bus stop delay in ATT and PT models. But, SD of bus stop has a higher impact than the average bus stop delay in BT model.
- Intersections and CBD/commercial land-use have positive impact on all the three dependent factors, which suggests that the increase in number of

intersections and CBD/commercial land-use decreases the travel time reliability of the public transit system.

Travel time reliability is one of the prominent measures of quality of service offered by the system for transit users. The LOS thresholds are determined based on the travel reliability measures such as TTI, PTI and BTI. The segment level data of four bus routes of Mysore city transit have been used in this study. K-Means clustering method has been adopted to determine the threshold of each LOS. The number of clusters has been taken as six which is accepted globally. Six clusters and their threshold values have been determined based on the output of clustering analysis. Finally, cluster validation has been conducted using silhouette analysis. The silhouette value of each cluster is more than 0.5 with respect to all the three reliability measures. The results of cluster validation shows that clusters have reasonable cluster structure and six clusters can be used to determine the LOS thresholds based on these reliability measures.

6.3 RECOMMENDATIONS AND STRATEGIES

- The undivided sections of the road having on-street parking on both the sides have higher impact on travel time reliability of public transit system than the divided road sections. These types of undivided road sections must be avoided in the route allotment process. Otherwise, the side friction activities can be shifted to the minor roads with sufficient road width where public transit buses do not travel and thus the LOS of the road would remain unaffected.
- The mixed type of on-street parking should be avoided as it reduces the effective usage of parking space, which results in reduction of carriageway. The on-street parking facility of cars, auto-rickshaws, LCV, and other bigger vehicles on major roads, must be prohibited as these vehicles occupy larger space. Also, the parking/unparking manoeuvre of these vehicles require more space and time. The pedestrian crossing the road must be restricted by providing zebra crossing.
- Studying the hourly variation of SFI and reliability measures helps in identifying the unreliable hours of a particular day in a week and can be used in the regulation of side friction activity. Similar steps can be followed in identifying the segments with higher SFI.

- The GEV distribution can be utilised to evaluate travel time reliability of transit routes. The routes, segments, and time periods of the day with low reliability can be identified using travel time reliability measures and suitable corrective measures must be applied to improve the reliability.
- The length of the segment or spacing between bus stops has a major impact on travel time reliability. Hence, the spacing between bus stops should be optimised in order to achieve the desired reliability.
- Bus stop delay has a prominent effect on reliability. Hence, the average delay and variation in delay should be decreased by maintaining proper schedules at each bus stop.
- Intersections contribute to the reduction of reliability of the public transit system. Transit signal priority (TSP) is a significant strategy to minimise the travel time delay and its variation.
- Level of service of bus routes can be determined based on travel time reliability measures which helps in identifying the underperforming routes and segments. This measure is significant in assessing the performance of public transit network in providing reliable public transit service.

6.4 SCOPE OF FUTURE WORK

- The performance of the GEV distribution can be used in different studies to evaluate its efficiency in describing travel time variability of public transit and travel time variability of the whole traffic stream as well.
- The concept of travel time reliability can be applied to analyse the performance of public transit system at network level.
- The methodology proposed to evaluate the impact of side friction on travel time reliability can be explored further by considering study locations with different types of side friction elements.
- The efficiency of the bus stop delay estimation can be improved by applying the methodology on the data with higher resolution.
- There is a scope of future work in travel time reliability modelling by considering more comprehensive range of exploratory variables.

- The LOS of bus routes can be determined based on travel time reliability concept for different types of cities with public transit movements all over India, having different geographic and geometric conditions and those LOS thresholds can be used for benchmarking the performance of the public transit system.

APPENDIX

A.1. Sample data of SQL file

```
563,2,5005,80,'2018-04-06',1617,2328,3,NULL,12.262960,76.657150,'2018-04-06 09:31:23',709,37,12,9,'Y','2018-04-06 09:31:24'
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196,7,267,165,NULL,NULL,NULL,NULL,NULL,12.337820,76.622894,'2018-04-06 09:31:22',781,16,88,9,'Y','2018-04-06 09:31:23'
166,1,429,23,NULL,NULL,NULL,NULL,NULL,12.306588,76.652954,'2018-04-06 09:31:22',750,0,260,9,'Y','2018-04-06 09:31:23'
144,3,285,59,NULL,NULL,NULL,NULL,NULL,12.333980,76.692818,'2018-04-06 09:31:22',745,0,316,9,'Y','2018-04-06 09:31:23'
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192,3,709,241,NULL,NULL,NULL,NULL,NULL,12.168081,76.793320,'2018-04-06 09:31:24',652,39,104,9,'Y','2018-04-06 09:31:25'
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```
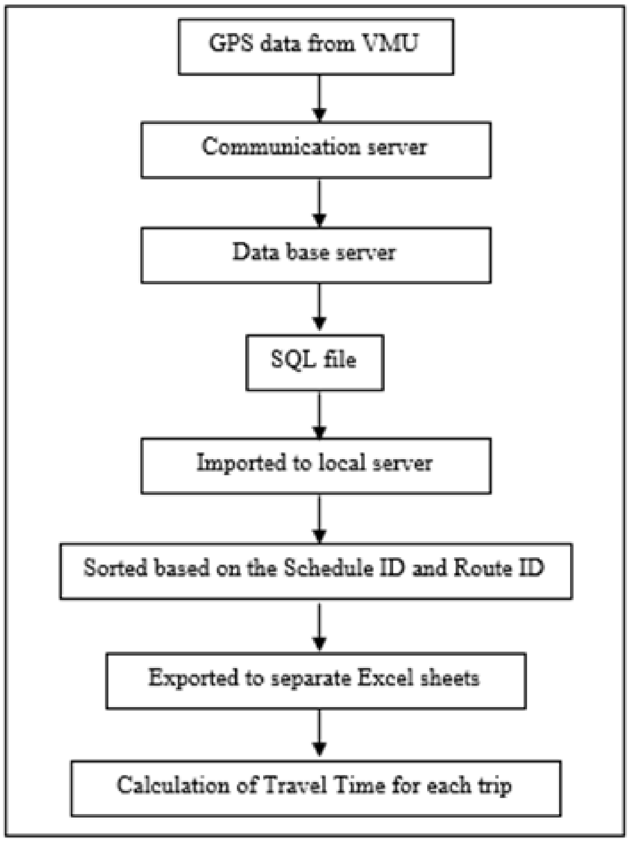

A.2. Flowchart of steps involved in data processing

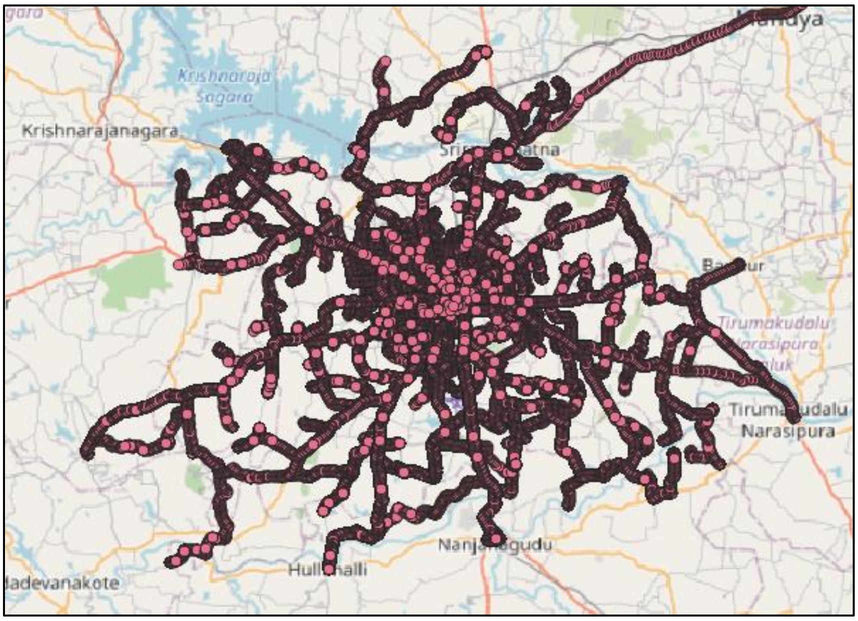


A.3. Python Code used in the data processing

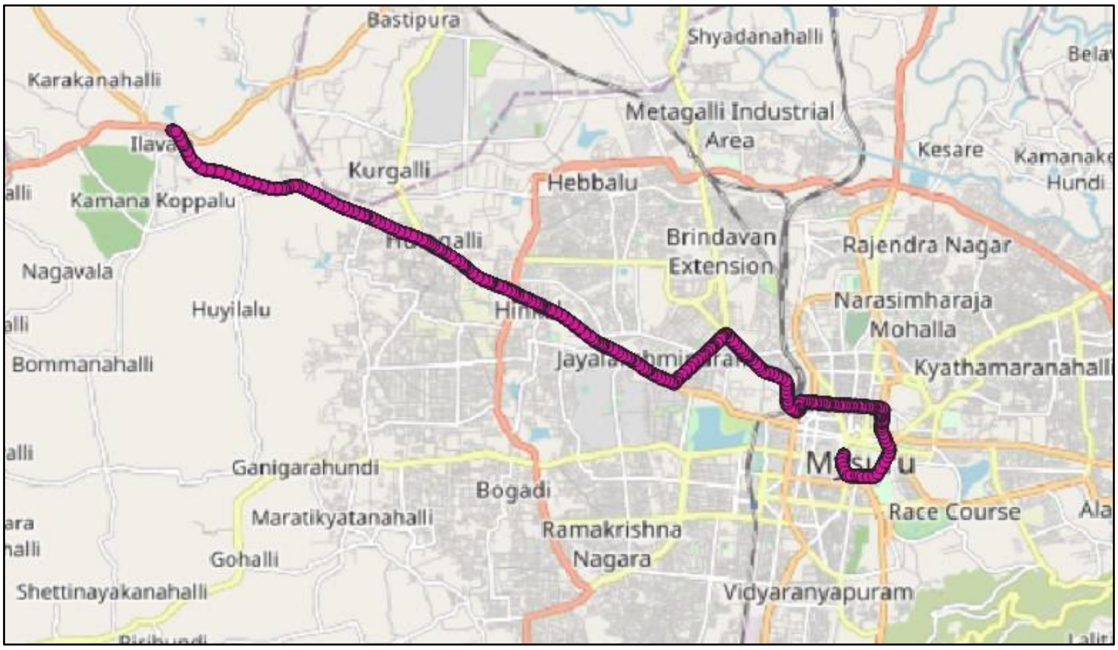
```
import pandas as pd

import numpy as np

df = pd.read_csv('G:\ITS_data\File_name.txt')

#assign header to dataframe

df.columns =
['bus_id','depot_id','vmu_id','vmu_seq_no','schd_dt','schedule_id','route_id','trip_no','d
```

```
irection','latitude','longitude','gps_timestamp','altitude','velocity','direction_angle','track_satellite','gprs_or_gsm_data','record_insert_time']

#delete columns with null value

df.dropna(axis=1, inplace = True)

#delete unwanted columns

df.drop(['vmu_id','vmu_seq_no','schd_dt','direction_angle','track_satellite','gprs_or_gsm_data','record_insert_time' ], axis = 1)

#select required route ID

data = df[data1.trip_no.isin([route IDs])]

#Split Date and Time from GPS timestamp column

data['GPS_date'], data['GPS_time']= data['gps_timestamp'].str.split(' ',1).str

#convert data type to respective data type of columns

data['GPS_date'] = pd.to_datetime(data['GPS_date'])

data['GPS_time'] = pd.to_datetime(data['GPS_time'])

data["schedule_id"]=data.schedule_id.astype(int)

data["route_id"]=data.route_id.astype(int)

data["trip_no"]=data.trip_no.astype(int)

#sort dataframe based on conditions

data.sort_values(['GPS_date','schedule_id','route_id','trip_no','GPS_time'], ascending=[True,True,True,True,True],inplace=True)

#export dataframe to excel file

data.to_excel('G:\ITS_data\Processed_data\File_name.xlsx')
```

A.5. Map matching of AVL data using QGIS



A.4. Sample picture of bus route selection



A.6. Sample hourly travel time data of public transit (in minutes)

6:00 to 7:00	7:00 to 8:00	8:00 to 9:00	9:00 to 10:00	10:00 to 11:00	11:00 to 12:00	12:00 to 13:00	13:00 to 14:00	14:00 to 15:00	15:00 to 16:00	16:00 to 17:00	17:00 to 18:00	18:00 to 19:00	19:00 to 20:00	20:00 to 21:00	21:00 to 22:00
37.67	42.17	44.50	40.00	45.33	49.50	47.67	45.67	50.00	46.00	55.83	55.00	52.00	49.00	42.50	39.10
33.83	44.17	42.17	52.83	48.40	47.67	46.00	42.67	44.00	46.00	55.83	48.00	54.00	49.00	40.83	38.00
38.17	41.33	47.83	46.17	45.83	46.00	51.00	47.33	46.00	42.00	49.50	54.00	46.17	49.83	49.50	43.00
39.67	42.00	39.83	47.17	50.80	51.00	43.33	46.17	46.00	43.00	58.33	48.00	54.50	47.33	41.67	37.33
33.83	36.50	40.83	46.83	45.67	43.33	47.17	43.50	42.00	48.83	53.33	51.00	57.67	55.83	36.67	38.00
39.50	37.50	39.33	42.33	47.60	47.17	44.83	40.17	42.00	52.33	44.67	54.00	51.00	55.00	44.67	33.50
39.00	41.33	41.83	42.50	51.33	44.83	46.00	47.00	43.00	50.50	56.33	53.50	58.33	51.83	40.83	33.00
33.67	43.33	48.33	40.33	51.17	44.17	51.33	46.17	48.83	46.17	56.17	49.00	49.67	43.50	39.50	40.17
35.50	42.83	48.17	42.67	46.33	48.50	46.67	48.33	49.50	52.67	45.50	52.17	50.17	55.83	42.17	42.17
33.50	41.67	42.17	45.50	51.50	46.00	48.17	45.00	49.50	52.67	58.83	53.33	49.33	49.50	35.83	33.50

A.7. PCU Values of IRC 106: 1990

Vehicle Type	Equivalent PCU Factors	
	Percentage Composition of Vehicle type in Traffic Stream	
	5 %	10 % and Above
Two wheelers	0.5	0.75
Passenger cars	1.0	1.0
Auto-rickshaw	1.2	2.0
Light commercial vehicle	1.4	2.0
Truck or bus	2.2	3.7
Agricultural Tractor Trailer	4.0	5.0
Cycle	0.4	0.5
Horse driven vehicle	1.5	2.0
Hand cart	2.0	3.0

A.8. Sample traffic volume data of side friction location (Undivided road)

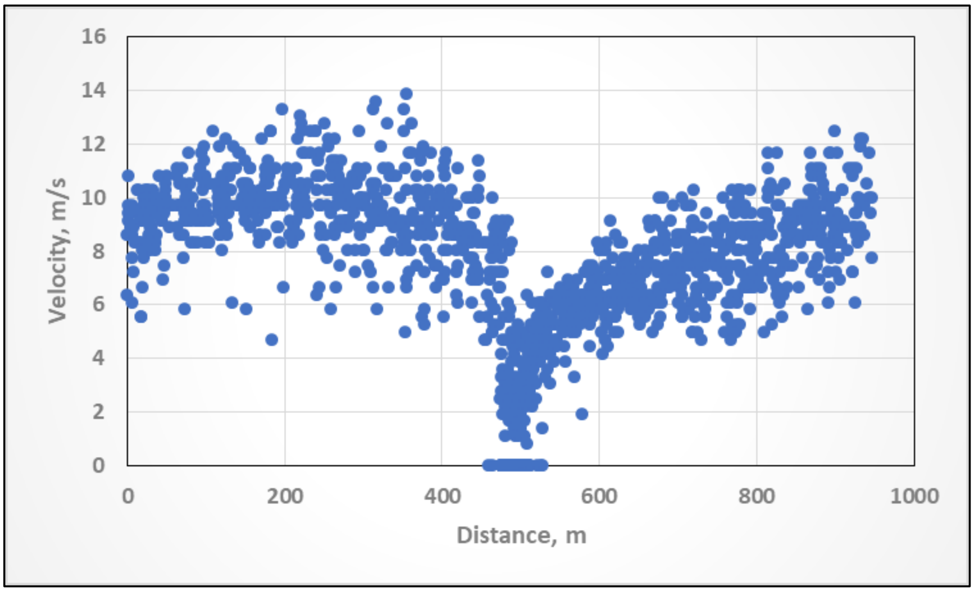
Time	Two Wheeler	Three Wheeler	Car	LCV	Bus	Truck	PCU/5 min	PCU/ Hour
9:00-9:05	125	15	17	1	1	1	147	1759
9:05-9:10	133	26	21	5	0	0	180	2157
9:10-9:15	115	17	23	2	2	0	150	1805
9:15-9:20	123	17	24	3	2	0	159	1906
9:20-9:25	123	23	22	1	3	0	168	2019
9:25-9:30	133	27	26	5	0	0	187	2241

A.9. Sample calculation of Side Friction Index (SFI)

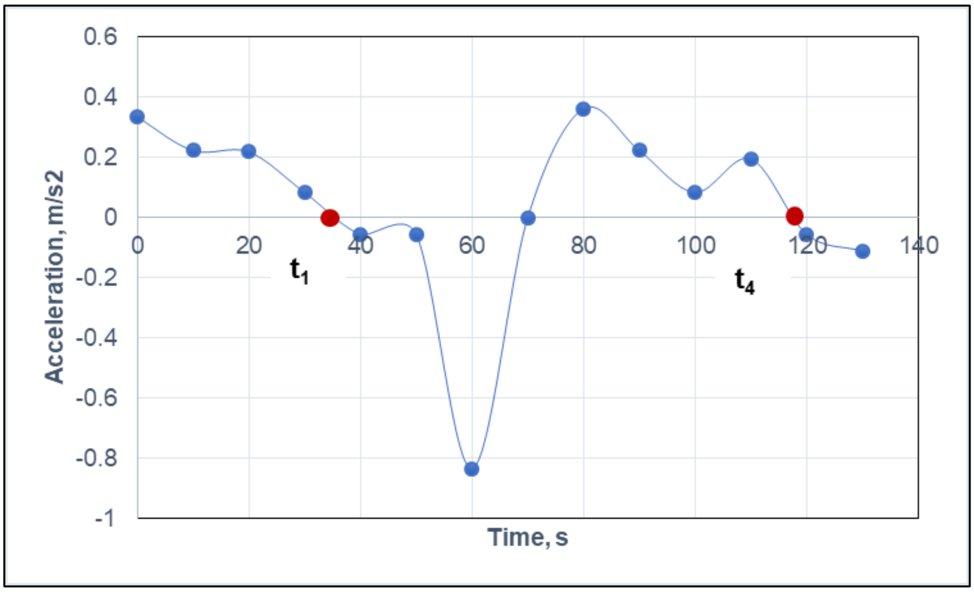
Time	SSF	PK_UPK	CSentry_exit	PDSW	PDSCR	SFI
9.20 AM to 9.25 AM	132.16	0.667	1	4.223	0.889	132.827

A.10. Selection of bus stop in QGIS

A.11. Velocity profile of stopped vehicles



A.12. Sample acceleration profile



A.13 Sample hourly bus stop delay data (in seconds)

6:00 to 7:00	7:00 to 8:00	8:00 to 9:00	9:00 to 10:00	10:00 to 11:00	11:00 to 12:00	12:00 to 13:00	13:00 to 14:00	14:00 to 15:00	15:00 to 16:00	16:00 to 17:00	17:00 to 18:00	18:00 to 19:00	19:00 to 20:00	20:00 to 21:00	21:00 to 22:00
37.91	36.00	25.94	42.91	68.62	95.46	37.68	56.70	72.54	94.41	64.60	120.04	64.93	106.53	78.53	72.06
46.55	30.80	50.39	54.59	109.71	45.85	94.14	108.70	61.01	33.99	25.79	27.49	76.87	31.90	57.11	32.31
58.00	22.09	38.33	62.86	49.52	84.84	39.95	87.37	106.44	31.66	109.28	128.99	89.47	94.49	75.35	42.71
25.28	32.33	52.28	37.02	61.12	87.62	70.77	42.02	118.68	23.34	47.89	71.49	91.99	12.47	54.87	58.55
29.08	47.29	28.57	78.26	28.03	89.33	78.69	74.75	60.62	32.32	25.73	27.57	84.25	79.50	61.95	98.18
18.99	36.64	61.69	21.91	120.05	109.44	42.94	64.39	63.02	69.89	68.71	77.24	132.60	32.06	65.46	46.10
21.97	26.93	36.41	36.93	89.18	33.88	87.54	112.08	82.88	29.06	116.29	62.10	50.50	59.71	57.70	46.81
23.42	48.34	37.81	109.27	86.44	75.58	59.06	87.98	30.67	86.09	33.86	135.43	60.98	30.84	50.55	21.47
23.96	32.88	21.02	14.84	97.99	113.78	80.19	98.51	34.08	23.43	112.69	29.63	54.13	38.72	54.89	27.37
23.98	40.91	31.25	107.09	64.73	33.63	88.03	89.28	46.93	28.89	69.46	168.84	73.09	76.31	28.52	30.58

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LIST OF PUBLICATIONS

Journals

1. Harsha, M. M., and Raviraj H. Mulangi (2021). Impact of Side Friction on Travel Time Reliability of Urban Public Transit. *International Journal of Civil Engineering*, 1-17. **https://doi.org/10.1007/s40999-021-00622-y**
2. Harsha M. M and Raviraj H. Mulangi (2021). "Probability distributions analysis of travel time variability for the public transit system." *International Journal of Transportation Science and Technology.* **https://doi.org/10.1016/j.ijtst.2021.10.006**
3. Harsha M. M, Raviraj H. Mulangi and Vrunda Kulkarni (2021). "Impact assessment of route diversion due to roadworks on traffic congestion using AVL data of public transit." *Journal of Traffic and Transportation Engineering (English Edition)* (**Under Review**).
4. Harsha M. M and Raviraj H. Mulangi (2021). "Delay Variability Analysis of Public Transit using AVL data". *Arabian Journal for Science and Engineering* (**Under Review**).

International Conferences

1. Harsha, M. M., and Raviraj H. Mulangi (2018). "Public Transit Travel Time Analysis Using GPS Data: A Case Study of Mysore ITS." In *3rd International Conference on Communication and Electronics Systems (ICCES)*, IEEE, Coimbatore, India.

2. Harsha, M. M., Raviraj H. Mulangi, and Dinesh Kumar H. D. (2020). "Analysis of Bus Travel Time Variability using Automatic Vehicle Location Data." *In World Conference on Transport Research (WCTR)*, Mumbai, India.

3. Harsha M. M, Raviraj H. Mulangi, Dinesh Kumar H. D and Kishore Kumar M. G. (2020) "Evaluation of Congestion on Urban Roads using Public Transit GPS Data." *In Second ASCE India Conference on Challenges of Resilient and*

Sustainable Infrastructure Development in Emerging Economies (CRSIDE2020), Kolkata, India.

4. Harsha M. M, Raviraj H. Mulangi, Dinesh Kumar H. D and Kishore Kumar M. G. (2020) “Analysis of Passenger Flow using Electronic Ticket Machine Data.” *In 13th International Conference on Transportation Planning and Implementation Methodologies for Developing Countries (TPMDC 2020)*, Mumbai, India.

Conference Proceedings

1. Harsha, M. M., and Raviraj H. Mulangi (2018). “Public Transit Travel Time Analysis Using GPS Data: A Case Study of Mysore ITS.” Proceedings of *3rd International Conference on Communication and Electronics Systems (ICCES)* (pp. 407-411), IEEE, Coimbatore, India. **https://doi.org/10.1109/CESYS.2018.8723923**

2. Harsha, M. M., Raviraj H. Mulangi, and Dinesh Kumar H. D. (2020). “Analysis of Bus Travel Time Variability using Automatic Vehicle Location Data.” *Transportation Research Procedia*, *48*, 3283-3298. **https://doi.org/10.1016/j.trpro.2020.08.123**

BIO DATA

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Academic Profile:

Degree	Year of Completion	Institution	Board	Percentage/ CGPA
Ph.D. (Civil Engineering)	2021	National Institute of Technology Karnataka, Surathkal	Deemed University	7.46
MTECH (Transportation Engineering and Management)	2017	BMS College of Engineering, Bangalore	Visvesvaraya Technological University, Belagavi	82.38 %
BE (Civil Engineering)	2015	Malnad College of Engineering, Hassan	Visvesvaraya Technological University, Belagavi	8.98
PUC (PCMB)	2011	Sri Venkateswara PU College, Hassan	Department of Pre-University Education, Karnataka	77.34 %
SSLC	2009	Sri Venkateswara High School, Hassan	Karnataka Secondary Education Examination Board	73.76 %