Performance Analysis and Route Design of Addis Ababa Public Bus Transport

A dissertation Submitted for the Partial Fulfillments of PhD Degree in Mechanical Engineering, Industrial Engineering Specialization, in the School of Mechanical and Industrial Engineering, Addis Ababa Institute of Technology, Addis Ababa University, Ethiopia

By: Eshetie Berhan

Supervisor: Prof. Daniel Kitaw (PhD)
Co-Supervisor: Prof. Ajith Abraham (PhD)

Addis Ababa, Ethiopia, 2013

ADDIS ABABA UNIVERSITY
ADDIS ABABA INSTITUTE OF TECHNOLOGY (AAIT)
SCHOOL OF MECHANICAL AND INDUSTRIAL ENGINEERING
INDUSTRIAL ENGINEERING CHAIR
ADDIS ABABA, ETHIOPIA

By: Eshetie Berhan (ir.)
School of Mechanical & Industrial Engineering PhD Candidate

____
Signature

____
Date

Co-Supervisor: Prof. Ajith Abraham (PhD)
MIR Labs, Scientific Network for Innovation & Research Excellence, Washington, USA

____
Signature

____
Date

Internal Examiner: Asso. Prof. Tesfaye Dama (PhD)

____
Signature

____
Date

Prof. Young Kyun Kim (PhD)
AAiT Scientific Directory

____
Signature

____
Date

Supervisor: Prof. Daniel Kitaw (PhD)
School of Mechanical & Industrial Engineering, Industrial Engineering Chair

____
Signature

____
Date

Dr. Daniel Tilahun (PhD)
School Head in Mechanical and Industrial Engineering

____
Signature

____
Date

External Examiner: Prof. Carlo Rafele (PhD)

____
Signature

____
Date

Dr.-Ing. Getahun Mekuria (PhD)
AAiT Graduate Program Director and Deputy Scientific Director

____
Signature

____
Date

In memory of my sister

I lovingly dedicate this dissertation to my lovely sister whom I lost her during the beginning of my PhD study. It was very extremely traumatic and painful when I heard your death. I remember you afterwards in every movement of my work. You left fingerprints of grace on our lives. You shant be forgotten.

PhD dissertation

Eshetie Berhan (ir.)
Addis Ababa
P. O. Box: 33033
Addis Ababa, Ethiopia
E-mail: eshetie_ethio@yahoo.com

Prof. Daniel Kitaw (PhD)
Associate Professor and Chair of Industrial Engineering
School of Mechanical and Industrial Engineering
Addis Ababa Institute of Technology
Addis Ababa University
P.O.Box 385, Addis Ababa, Ethiopia
E-mail: danilkitaw@yahoo.com

Prof. Ajith Abraham (Dr.)
Machine Intelligence Research Labs (MIR Labs)
Scientific Network for Innovation and Research Excellence Washington, USA
E-mail: abraham.ajith@gmail.com

Addis Ababa University (AAU)
Addis Ababa institute of Technology (AAiT)
School of Mechanical and Industrial Engineering
Industrial Chiar
Ethiopia

August 20, 2013

Abstract

Anbessa City Bus Service Enterprise (ACBSE) is the only public enterprise that provides transport services in and around the city of Addis Ababa. The transportation service provided by ACBSE is the safest and cheapest as compared with other public transport system in the city. However, due to the rapidly growing mass mobility, high population growth and galloping urbanization in the city of Addis Ababa, providing and improving urban public transport service is becoming highly difficult and the enterprise leaves much to be desired and remains long to go. The enterprise as well as the Ethiopian government has made different interventions to address the problem. Notwithstanding the efforts attempted, the interventions in the short run as well as in the long run could not fully address the problem without efficient utilization and scheduling of buses. Whatever systems are in place as a solution, if there is no efficient use of that system, it may rather create additional problem.

The unbalanced bus scheduling and fixed bus assignment systems currently used by the enterprise contributed its share to the problem of poor service quality, low operational and financial performances. This dissertation, therefore, tries to assess the existing operational and financial performances of the enterprise and develop different models that can improve the performances of the bus scheduling and assignment systems of the enterprise.

To achieve these objectives, the dissertation conducts an extensive literature review related to Vehicle Routing Problem (VRP), urban bus public transport services and different international standards related to urban bus transport. Primary and secondary data related to route performance, bus utilization and scheduling techniques of the enterprise were also collected. Using the data and the observations made, first, different operational and financial performance analysis was made. Then an LP model that can improve the performances of the enterprise was developed. It is a new model in the knowledge of VRP and; was tested and validated using the secondary data collected on 93 routes and 4 operating shifts. At last a new VRP model that can address the stochastic pickup and stochastic delivery of passengers with real simultaneous pickup and delivery services at each passenger location or bus stop was developed and introduced to the literature.

The findings of the study show that the overall operational and financial performances of the enterprise are inadequate as compared with the international standards. The operational performances of the enterprise, namely the Percentage Load Factor (PLF), the Kilometer Per Vehicle Per Day (KPVPD), the numbers of Passengers carried Per Vehicle Per Day (PPVPD), and the Fleet Utilization (FU) are lower than the international standards but with higher fuel consumption to every 100kms (ltrs/100km). The PLF, PPVPD and FU have exhibited slight improvement from time to time. Related to the financial performances, the results show that the enterprise could not recover its operational costs from the traffic revenue or income generated. It operates at a loss even before tax. But the results of the new model show better performances: on the operating costs, bus utilizations, total trips made and distance covered by the enterprise compared with the existing system. The enterprise's performance improvement achieved by the new system on the one hand cut costs to the enterprise and on the other hand improves the service quality to passengers by reducing congestion during peak hours.

The dissertation, further tries to develop a model that can address the stochastic nature of passengers pickup and delivery/drop at each bus stop. Since the LP-model developed improves the existing system does note exhibits breakthrough improvements, a new model was developed if dramatic improvement may be achieved. The model is the first of its kind due to the fact that it addresses real simultaneous stochastic pickup and stochastic delivery of passengers. However, due to limitation of digital road data, the model was not fully tested and implemented. It is only tested

by taking limited data on routes on Merkato terminal. The enterprise is expanding and improving its service from time to time to serve the increasing demand. It serves the people safely at a cheaper fare. In this regard, the enterprise contributes a lot to the economy of the society. However, with regards to quality, performance, and future expansion to regional cities still require extra miles to go. Therefore, based on the findings of the study the following recommendations are forwarded to the enterprise. ACBSE should develop and follow a continuous performance improvement system so as to serve passengers' need with maximum satisfaction and minimize its operating costs. The enterprise should adopt the improved bus assignment system developed in the dissertation so that buses can be assigned based on the demand distribution of passengers for each route at a given shift or operating times and improve its transportation services to the international standards. Further ACBSE, by improving the availability of buses, should also expand its service to regional cities where population and mobility are very high.

Re-designing the new routes based on the stochastic distribution of pickup and delivery of passengers using the proposed model and studying the ticketing services would be research directions that can be addressed in the future.

Eshetie Berhan, June 2013

Acknowledgements

First and foremost, more than anything else, I would like to thank the Almighty God for his indescribable grace and gift.

Next, I would like to thank my supervisor, prof. Dr.-Ing. Daniel Kitaw. I cannot find words to express my gratitude to acknowledge the enthusiastic supervisor prof. Dr. Ing-Daniel Kitaw (PhD) for the valuable guidance and advice. He inspired me greatly to work with him. He was abundantly helpful and offered invaluable assistance, support and guidance from the beginning to the end of the research processes. His willingness to motivate me contributed tremendously to my research. I would like to take also an immense pleasure in thanking him for his guidance and advise like a father, a colleague, a teacher, as an academician and as an Industrial Engineer. It is not often that one finds an advisor and colleague that always finds the time for listening to the little problems and roadblocks that unavoidably crop up in the course of performing research. His technical and editorial advice was essential to the completion of my dissertation and has taught me innumerable lessons and insights on the workings of research in general.

I am truly indebted and thankful to my co-advisor, Professor Ajith Abraham (PhD) and my colleague Dr. Birhanu Beshah (PhD) for their devotion, assistance and constant supervision as well as for providing necessary information regarding my thesis and also for their support in completing my study. It could have not been possible to lift up my research this level without their consistent support.

I owe sincere and earnest thankfulness to Addis Ababa University, Institute of Technology and School of Mechanical and Industrial Engineering for the opportunity I have been given to study my PhD degree and all the support and facilities provided to me. It gives me great pleasure in acknowledging Anbessa City Bus Service

Eshetie Berhan, June 2013

Enterprise (ACBSE) and workers in the enterprise for their support, advise and cooperation during the data collection processes as well as their keen interest towards my research. It is rarely possible to find such an industry to provide all the necessary data and show a strong determination to work together. My special thanks go to Ato Bedilu, Ato Abraham, and Ato Solomon who facilitated and made my data collection processes easier.

I would like to share the credit of my work with my beloved fiancé Mahlet Tesfaye for her continuous encouragement and support from the beginning to the end. Without her perseverance support it would have not been possible to lift up my work to this level.

This dissertation has also been influenced and improved by the inputs of more people than it is possible to list in this acknowledgement. In this regard, I was fortunate enough to have had the support of many people. Therefore I would like to devote the following few lines to express my appreciation to some, if not all of them. My sincere thanks goes to all of my respected families, my mother Asnika Mahlet and my father Birhan Atanaw; to my brothers Malede Birhan and Mastewal Birhan, to all my colleagues Helen Tigabu, Samrawit Gismu, Ayesheshem Awoke, Tayachew Muche, Yilak Sergualem, and all colleagues in the school of Mechanial and Industrial Engineering as well as workers in AAiT to their consistent encouragement and support.

I would like to extend my sincere gratitude to Ato Melku Tezera and Ato Birhanu Tibebu for their professional editorial work and Ato Dejene Mengistu, Edris Sherif and Melkie Mihret who helped me in the data collection processes.

Eshetie Berhan (ir.)

Eshetie Berhan, June 2013

Contents

List of Tables

List of Figures

Chapter 1

Background and Justifications of the Study

1.1 Introduction

Bus transport system provides a versatile form of public transportation with the flexibility to serve a variety of access needs and an unlimited range of locations throughout a metropolitan area [1]. This is because buses travel with a relatively higher degree of safety on urban roadways than other modes of communication by land. Moreover, the infrastructure investments needed to support bus service is substantially lower than the capital costs required for rail system which requires different structural supplements. As a result, bus transport service can be implemented cost-effectively on routes where passengers for rails may not be sufficient or where the capital investment may not be available to implement rail system. But the road transport system must also be considered as it involves multidimensional issues including developing and maintaining infrastructure, vehicles, road safety, impact on human health and the environment, human and institutional capacity building, proper planning and finance [2]. Owing to these reasons, urban public transport systems represent one of the most complex settings of operations for a transport company.

The planning process, in public transportation, consists of different recurrent and complex tasks. It starts at a strategic level by collecting or forecasting the number of passengers at each transfer point [3], which is most of the time fully unknown and adds the complexity of the planning process. However, [3], based on demand matrices (deterministic or stochastic) the infrastructures of the public transportation network could be defined and on these infrastructures planners can establish routes and stop-points for different lines. Though the transportation network is designed based on the consideration of the demand matrix and the infrastructures, in bus scheduling, the time is also another dimension that has to be considered as a factor in the complexity of planning process [1, 4]. A bus network design must include additional time, which is commonly called the transfer time at transfer centers together with in-vehicle and waiting time at bus stops [5].

The problem of bus scheduling should address the task of assigning a number of buses to cover a given set of routes within a given timetable [6]. It also considers some practical requirements such as multiple depots, transfer times, time windows [7, 8], uncertainty of demand [9, 10, 11] and vehicle types and capacity [3]. In many practical transportation or distribution problems, a time window is also associated with each customer or demand, defining a time interval in which the customer should be serviced [12, 13, 14].

The inclusion of all these parameters again contributes to the magnitude and complexity of the scheduling process. The problem of public transport is somewhat more complex than that of traditional network design [15], which is commonly called the Classical Vehicle Routing Problem [16]. The classical Vehicle Routing Problem (VRP) can be represented by models which do not capture the important aspects of real-life transportation parameters such as demand, time, distance, city location, etc which are often stochastic in nature. Most existing VRP models oversimplify the actual system by making different assumptions, e.g. customer demands as deterministic value, although in real application, it may not be possible to know this before designing the routes.

In addition to determining what links to include in the network, the design must include the work of assembling the links into fixed routes, and determining the frequency of service on each route [8]. The result of the network design, then, should cover a set of routes and their frequencies [6].

Transport is one of the key sectors that plays crucial role in the effort to achieve the goals of poverty eradication and sustainable development [2]. The issue of having a sustainable transport in sub-saharan and Eastern Africa attracts the attention of many scholars, senior officials in government, and representative of other international offices [2, 17]. Like of those cities of other developing countries, the transportation service of Anbessa City Bus Service Enterprise (ACBSE) in Addis Ababa faces major challenges. Among others the increasing pressure on public transport (high commuters demand due to population growth and rapid city expansion), inappropriate location of freight and mass transport terminals (poor routing schedules) and poor traffic management system within the city.

ACBSE in Ethiopia has a long history of providing transportation service in and around the city of Addis Ababa since establishment in 1943. It has problems similar to many urban areas in the world, where in most cases, the demand for bus users has resulted in uneven distribution of service over space and time. In order to satisfy the demand, however, it is usually impractical to directly connect all origin-destination pairs with bus routes due to limited economic and social resources [5]. In such cases, a bus transport network with limited accessibility and mobility is effective in serving the demand; and consists of several bus routes and transfer centers which require a complex planning.

Moreover, the transport scheduling system in ACBSE has not be designed well based on consideration of passengers's demand distribution. Owing to this, the enterprise could not be able to satisfy the ever-increasing demand of commuters, which subsequently hampered the mobility and productivity of the people in the city at large and adversely affects the economy of the country to the detriment of the environment.

In order to address these, the dissertation thoroughly studies the existing performance of ACBSE, and then envisages an improvement of its performance on the existing routes using a linear programming method to determine an optimal supply of buses for each route to satisfy the demand. The dissertation also focuses on designing a new route using SVRP based on stochastic passengers Demands (VRPSD) with real simultaneous pick-up and delivery. This situation arises in practice in public bus transport companies like ACBSE which services customers with random occurrence. The dissertation is, therefore; aimed at developing an optimum route for ACBSE using the concept of VRP with Real Simultaneous Pickup and Delivery (VRPSPD) by considering the ever-increasing and stochastic nature of passengers' demand.

1.2 Background of the Study

In Ethiopia, particularly in the city of of Addis Ababa, ACBSE has a long history in providing transportation service. It was established at the end of the Italian invasion in 1943 by collecting vehicles and garage equipment from the invader to serve passengers in Addis Ababa. It was named public transport and was guided by auxiliary staff of the remaining Italian and other foreigners. In December 1954, it was organized into a share company by getting legal personality vested in it by the Ethiopian government. At that time, it had 10 buses to serve the people in Addis Ababa in only four routes. After two years, the numbers of buses were increased to 30 and were able to operate in 14 routes. Again, the company transferred its ownership to a public transport service in the year 1966; and in the year 1973, bought 50 city buses to strengthen its services.

Similarly, during the year 1996 to 2003 the enterprise bought 466 DAF model city buses. As of the year 2011 the enterprise operates 98 routes with an average daily dispatch of 321 buses with three large depot, four bus terminals, 16 checkpoints and

1,400 bus stops throughout the city. According to the report of [18], the city of Addis Ababa is mainly served by ACBSE, minibuses, collective and private taxicabs which account for 6.94%, 34.23% and 6.28% of the modal share respectively. Moreover, in the city, walking accounts for 43.76% (pedestrian), 8.65% the trip are made by private cars and the rest are company provided transport service.

Mass Transport service is a shared passenger transport service, which is available for use by the general public, as distinct from modes such as taxicab, car pooling or hired buses. It is one of the most shared transportation services that facilitate the mobility of the society in any city with less cost and efficient time in the developed world. It serves the public with less amount of fuel, more safety and environmental friendly in comparison to the private and collective small taxies.

Shown in Table 1.1 and the report of [18], the annual operating and fuel costs of private automobile cars in Addis Ababa are 470,746,782 € and 236,640,740 € respectively. While the corresponding costs of ACBSE are 9,470,464 € and 3,391,151 €, which are considerably less than 50%. The annual operating and fuel cost of minibuses are 74,165,698 € and 32,896,709 € respectively, which is nearly 8 times higher than the costs of ACBSE. Hence it can be observed that a huge foreign currency could be saved for the country if ACBSE improved its service and attract passengers that would otherwise use their automobiles or minibuses. Proportionally, ACBSE accounted 1.71% of the operating cost, 1.24% of the fuel cost and 2.29% of the total fuel consumed. But that of private the operating and fuel cost accounts 84.91% and 86.70% respectively and fuel consumption accounts 76.80%.

With regard to safety, as of the year 2010, ACBSE is the safest means of public transport as compared to any other types of motorized transportation service. Out of the total of 7,523 accidents that occurred in the city, 141 of them were due to ACBSE, which accounted 1.87% of the total accident reported. The extent of acci-

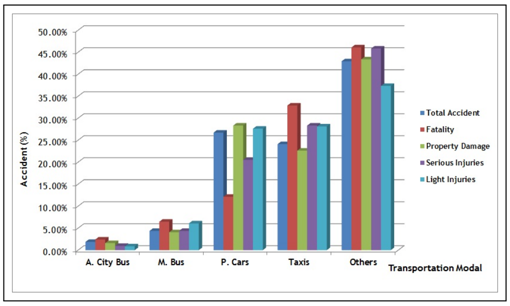

Figure 1.1: Accident & property damage

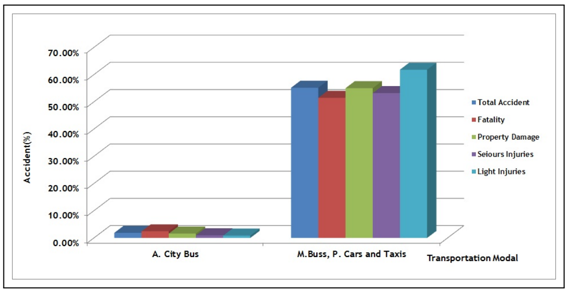

Figure 1.2: ACBSE vs. Other Modal

dent occurrence for ACBSE (i.e. 1.87% of the total accidents) is by far insignificant as compared to other modes of transportation systems (See Figure 1.1 and 1.2).

Table 1.1: Transport modal system by fuel and cost

S/No	Transport modal	Fuel in Litre (%)	Operating cost in € (%)	Fuel cost in € (%)
1	ACBSE	8,867,502(2.29)	9,470,464(1.71)	3,391,151(1.24)
2	Minibus	81,117,478(20.92)	74,165,698(13.38)	32,896,709(12.05)
3	Private Cars	297,856,000(76.80)	470,746,782(84.91)	236,640,740(86.70)
4	Total	387,840,980(100)	554,382,944 (100)	272,928,600 (100)

In order to compare the efficiency of each mode of transportation service, the fuel consumed per passenger has to be evaluated also . Based on this assessment, fuel per passenger for ACBSE stands at 0.087 littre, but for minibuses and private cars fuel per passenger rate are 0.335 littre and 2.353 littre respectively. A recent study in Germany showed that in the year 2008 a single full tank of fuel costs equivalent to a monthly public transport ticket in the city of Berlin [1]. This shows that public mass transport is becoming an important and preferable means of transportation system due to the surging costs of individual traffic and environmental pollution.

Though Anbessa City bus is the cheapest in cost and the safest in accident, it is considered to be inefficient in its service, inconvenient, and most inferior by the people in the city of Addis Ababa as compared to their preference to use of private cars, taxis or minibuses. Moreover, it is mostly used by low income level people; and hence rarely by medium income level people in the city.

1.3 Statements of the Problem

Transportation service is a backbone of the economy of any country. Hence, public transportation plays a major role in the quality of life of individuals as well as the productivity of entire regions in every society [1]. However, providing a reliable, efficient and quality transportation service to the people is a challenging operation to the service provider. In this regard, ACBSE sets a good example. It is the only and sole enterprise in the country that provides public transportation service in Addis Ababa. Since its establishment, the enterprise has passed through many ups and downs to improve and expand its transportation service in general. It has got major improvement so far. However, still, the enterprise could not be able to address the ever-increasing transportation demand in and around the city of Addis Ababa.

Moreover, the frequency and quality of the transportation service still remain unsatisfactory and poor. This is partly due to insufficient fleet of buses being available to meet the demand and the larger distance covered by each route of city buses. Despite the large number of route variations and large number of buses assigned to them, over 70% of the routes have only two to four buses assigned [18], resulting in low service frequency rate that could not satisfy the demand. In order to cope with commuters' demand, the government has made interventions to introduce midi-buses (495 China made Higer buses with a seat capacity of 25 passengers) and encourage private owners to participate in the public transportation. But this could not address fully the high demand rather created high congestion in the mixed traffic system.

In the case of the remaining private modes of public transport such as minibus and taxi, services are provided on selected and heavily populated routes where fleet numbers are larger, at a higher price than that of ACBSE. The interventions made as well as the use of minibuses and taxis as a means of public transport system contribute adversely to congestion and pollution matter rather than solving the high demand.

Though, it is also very difficult to assess the extent and magnitude of air pollution by each mode of transport, it is obvious that mass transportation system has less impact on air pollution than other collective mode of transportation. The volume of gas and fuel consumed indicate the emission they caused by each mode of transportation (See Table 1.1). This includes the sum of the annual emission, expressed in kilograms of Carbon Monoxide (CO), Volatile Hydrocarbons or unburned petrol per diesel (VHC) also called particulate matter (PM) and Nitrous Oxide (NOx). It is evident that the combustion released from a bus with a loading capacity of 100 passengers is nearly the same as volume of combustion emitted by 25 private automobiles or 9 minibuses to transport the same number of passengers [18].

From the investigation made so far, the major challenges of the low capacity and quality transportation service in the city is manifested by:

1. Low availability of buses due to poor maintenance management practice. It is manifested on the overall performance of ACBSE, which is hampered due to low number and technical fitness of most of the vehicles (in which more than 40% the total buses are over 10 years).
2. The service routes are not optimally designed in consideration of availability and number of buses and uncertainty of increasing commuters' demand. At the moment, there is no optimally designed transportation network or route that considers the above factors.
3. The mixed traffic system used in the country (poor utilization of the road infrastructure) causes high traffic jams; resulting in long service time, which is one of the factors that affect the quality of the service. This contributes adversely to the high traffic congestion and environmental pollution. It is

also mainly because 80% of the nationally registered fleet is found in Addis Ababa [18].

Consequently, the bus service system in ACBSE serving the capital city still remains traditional in scheduling, poor in service quality and unable to meet commuters' demand. As it is evident from the Statistical Report of [18, 19], the number of bus user dwellers in and around the city of Addis Ababa has increased dramatically ever before at a rate of 3.8% due to the galloping urbanization and rural exodus. The estimate showed that in the year 2020, 55% of the African population will be living in urban areas, with no exception for Ethiopia and in particular for Addis Ababa where its population is currently estimated to be more than 3.8 millions with 8% annual growth rate [19].

Therefore, unless urgent measures are taken; Addis will face enormous challenges in terms of infrastructure provisions and transportation services. If existing problem continues in this way, the inhabitants with low and medium income will soon be confronted with a serious transportation crisis. As a result, the mobility of the people and subsequently the economic development of the citizen will be greatly affected.

The numbers of private automobile users, as compared to the total population of Addis Ababa which is excepted to be few is paradoxically more in number as compared with the purchasing power of the people however. Nevertheless, traffic congestion, urban sprawl, central city decline, high fuel and operating costs and air pollution are all problems associated with excessive dependence on private automobiles. The need to alleviate such problems has recently fueled a growing demand for efficient and effective mass transport services in the city. Among others, it is evident that the establishment of bus assembly lines in Hibret Machine tools and the railway systems which are considered in the Growth and Transformation Plan (GTP) of the Ethiopian government [20] have, in fact, played an essential role in preserving and revitalizing the downtown areas of major Ethiopian cities. But notwithstanding those efforts, the problem cannot be fully solved and neither can the new changes envisaged be capable of substituting the bus service all in all.

The government has also planned to intervene to reduce the waiting time by 67%, and increase the daily transport supply of Addis Ababa (frequency) by 43% within five years, until 2014/15 [20]. But in themselves, these interventions will not solve the the problems associated with the bus schedule service. In addition to this, it requires proper utilization, high availability and efficient scheduling of buses.

To address the problem, different Linear Programming (LP) models from a mathematical perspective, were designed. Since the general structures and representations remained the same, the LP model representation used for ACBSE is defined based on the following notations and considerations using the concept of graph theory.

Let $G = (V, A, C)$, a complete graph, where:
$V = \{o, \ldots, n\}$ is a set of nodes where node 0 denotes the depot and nodes $1, 2, \ldots, n$ correspond to bus stops where passengers are picked or dropped by a vehicle with capacity of Q.

$A = \{(i, j)i, j \in V, i \neq j\}$ is the set of arcs joining the nodes, as origin-and destination of the routes and,
$C = (c_{ij} : i, j \in V, i \neq j\})$ denotes a non-negative matrix $C \geq 0, \forall_{i,j}, c_{ij} \geq 0$ that denotes the travel cost or distance between node i and j or between origin-destination..

The cost matrix C is symmetric and satisfies the triangular inequality $c_{ij} + c_{ik} \geq c_{ik}, \forall_{i,j,k} \in V$. Moreover, passengers have stochastic nature of arrival, call it demand $d_i, i = 1, \ldots, n$, which are a non-negative discreet random variable but with known probability distribution of $p_{ik} = prob(d_i = d_i^k)$, $k = 0, 1, \ldots, K \leq Q$.

In order to address these issues and to design an optimum transportation network, the dissertation tries to address the following basic research questions.

- How can the quality of the transportation service of ACBSE be improved to attract more passengers?
    1. What is the Operational and financial performances of ACBSE as compared to the international standards?
    2. How to develop a model that can optimally assign buses to the existing routes?
    3. In what way the transportation network of ACBSE can be rerouted to address the current stochastic passengers demand?

1.4 Objectives of the Study

General Objectives

The general objective of the dissertation is to assess the operational and financial performances of the enterprise and design a model that can optimally assign buses to routes so as to improve the quality of the transportation service of ACBSE.

Specific Objectives

The specific objectives of the dissertation are trying to:

1. Assess the current performances of ACBSE as compared to the international standards?
2. Investigate and develop a model that can optimally assign buses to routes and improve the current performances of the enterprise?
3. Reroute the transportation network of ACBSE to serve the current stochastic passengers demand ?

4. Provide appropriate conclusion and recommendations to the enterprise and policy makers so as to improve the services quality and performances of the enterprise.

1.5 Significance of the Study

It is hoped that the findings of this study will benefit ACBSE by minimizing the operating cost, increasing the bus utilization and providing efficient and timely quality service to customers. Subsequently, this will improve the productivity of bus users in the city and also attract middle and higher income level people to use bus as an alternative means of transportation. Moreover, when the bus service in the city improves, the demand obviously will increase at large due to the fact that people who used their private automobiles may instead use bus as alternative. This results in low traffic congestion, minimize car accidents, reduce pollution and decrease the fuel demand of the country. It also minimizes the operating cost of personal automobile users in addition to providing an opportunity for effective and efficient transportation services for the people in Addis Ababa.

Moreover, increasing the mobility of the people at large improves the living standard of the society. The efficient transportation network design also helps the enterprise to expand its routes to include a wider perimeter of suburb areas so as to increase the number of passengers to be served. The findings of the research can also be implemented with no or little or no modification in scheduling of other routes, warehouses and distribution centers for large manufacturing companies as well as pickup and delivery of goods for postal service and banks. It can also be extended in stochastic transportation-inventory network design and other related problems involving one or more supplier and multiple retailers/customers. Finally, the research would also be a good reference materials for those who would be interested in VRP, SVRP and/or SVRPSDP.

1.6 Scope of the Study

The dissertation focuses on the method of developing LP-Model to improve the performances of the existing routes and SVRPSPD to design new routes. It emphasizes the use of SVRP models with simultaneous pickup and delivery to develop an integer linear programming model for ACBSE to schedule its bus service. The design considers the nature and capacity of buses, the stochastic passengers demand with simultaneous pickup and delivery in the development of the models. It also schedules busses based on demand distribution required for ACBSE to serve passengers demand.

1.7 Limitations of the Study

Since the research is highly dependent on secondary data, the inadequacy of sufficient data may limit the reliability of the research findings. Moreover, the financial limitation may affect the real time simulation of the model. The other main constraint which is not included at this time is lack of data on factors such as ticketing, working environments of workers and price controlling systems of the enterprise. The dissertation does not consider the scheduling and controlling of the workforce as well as the ticketing system in ACBSE. However, the limitations do not affect the quality of the research addressed within its scope.

1.8 Organization of the Study

The dissertation is organized into seven chapters. The first chapter gives an overview on the general background and justifications of the problem. The second chapter deals with a literature review of the present problem in VRP, SVRP and SVRPSPD, bus scheduling and its variants with considerations of simultaneous pickup and delivery. The third chapter focus on the research design and methodology to give a clear view on the methodology of the research design used in the dissertation. Chapter four presents the current performances of ACBSE. Chapter five deals with the model development process for improving the existing bus scheduling. Chapter six includes the new model development for ACBSE and its solution. Lastly, chapter seven covers the conclusion and recommendations of the research.

Chapter 2

Literature Review

2.1 Bus Scheduling Techniques

The problem of designing a minimum cost set of routes to serve a collection of customers with a fleet of vehicles is a fundamental challenge in the field of logistics, distribution and transportation [16, 21, 22]. This is because transportation and distribution contribute approximately 20% to the total costs of a product [23]. Therefore, the need for designing an optimal route that can minimize the transportation cost is the challenge and concern of many industries.

In this regard, the fundamental and well-studied routing problem is the Traveling Salesman Problem (TSP), in which a salesman is to visit a set of cities and return to the city he started in. The objective for the TSP is to minimize the total distance traveled by the salesman. VRP is a generalization of the TSP in that the VRP consists in determining m vehicle routes, where a route is a tour that begins at the depot, visits a subset of the customers in a given order and returns to the depot.

The task of designing delivery or pickup routes to service customers in the transport and supply chain is known in the literature as a Vehicle Routing Problem [22]. It was the first time proposed by [24] under the title "Truck dispatching problem" with the objective to design optimum routing of a fleet of gasoline delivery trucks between a bulk terminal and a large number of service stations supplied by the terminal. Often the context is that of delivering goods located at a central depot to customers who have placed orders for such goods, but the area of application of VRP is also so versatile and are used in many areas in real world life.

The VRP is defined by a depot, as a set of geographically dispersed customers with known demands, and a set of vehicles with fixed capacity[21, 25, 26]. All customers must be visited exactly once and the total customer demand of a route must not exceed the vehicle capacity. The objective of the VRP is to minimize the overall distribution costs. In most real-life distribution contexts a number of side constraints complicate the model. These side constraints could for instance be time constraints on the total route time and time windows within which the service must begin.

As it is cited in [27], the VRP also known in the literature as the "vehicle scheduling"(VSP) or "vehicle dispatching" [28] or simply as the "delivery " problem [29] appears very frequently in practical situations not directly related to the physical delivery of goods.

The problem can be considered as a combination of the two well-known optimization problems; the Bin Packing Problem (BPP) and the Travelling Salesman Problem (TSP) [30, 31, 32]. The BPP is described in the following way: Given a finite set of numbers (the item sizes) and a constant K, specifying the capacity of the bin, what is the minimum number of bins needed? [33]

Naturally, all items have to be inside exactly one bin and the total capacity of items in each bin has to be within the capacity limits of the bin. This is known as the best packing version of BPP. The TSP [3] is about a traveling salesman who wants to visit a number of cities. The salesman has to visit each city exactly once, starting and ending in his home town commonly called depot in VRP. The problem is to find the shortest tour through all cities [30]. Relating this to the VRP, customers can be assigned to vehicles by solving BPP and the order in which they are visited can be found by solving TSP. A VRP with single vehicle and infinite capacity is a TSP

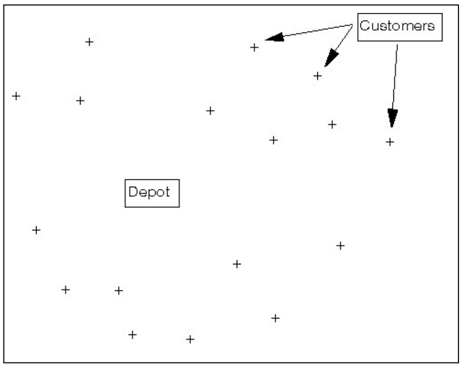

Figure 2.1: VRP inputs

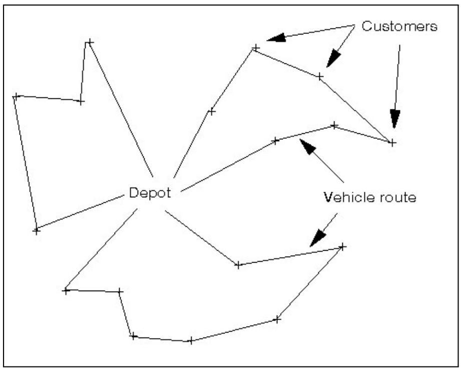

Figure 2.2: VRP outputs

VRP is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or several depots must be determined for a number of geographically dispersed cities or customers [14]. The objective of the VRP is to deliver a set of customers with known demands on minimum-cost [31, 34, 35]. Vehicle routes originate and terminate at a depot. It is one of the most challenging combinatorial optimization task in transportation, distribution and logistics [21]. This problem consists in designing the optimal set of routes for fleet of vehicles in order to serve a given set of customers. Customers are scattered geographically and a fleet of vehicle served them from a depot and return back to the depot [27]. The decision required is to determine the assignment of vehicles and routes that a vehicle will serve. The simplified representation of the input and output of VRP is illustrated in Figure 2.1 and 2.2.

Since both BPP and TSP are the so-called NP-hard problems [36, 33], and since VRP is a combination of the two, it is also NP-hard [37, 31]. It is a combinatorial optimization and integer programming problem seeking to service a number of customers with a fleet of vehicles [24, 13]. VRP is also a well known integer programming problem in which most of them fall into the category of None-Polynomial-Hard or (*NP-Hard*) problems [37]; meaning that the computational effort required to solve this problem increases exponentially with the problem size [38, 39].

Due to increasing utilization of optimization packages, based on Operations Research and Mathematical techniques for effective management of the provision of goods and services in distribution systems [31] in the last decade, VRP has got much attention by many scholars. Even in recent years, with the rapid development of economic globalization and supply chain and transportation system becoming more and more important to the economy, VRP is becoming one of the important research topic in the fields of supply chain and operations research [40, 41].

Moreover, because of the complexity and its practical relevance of VRPs, vast literature is devoted to the study and analysis of Bus Scheduling Problem (BSP) and many optimization models have been proposed [5, 10]. The models tried to achieve optimal or near optimal solutions with a reasonable amount of computational effort [22, 35]. Several extensions for the Vehicle Schedule Problem (VSP) or VRP with different additional requirements were also discussed in the literature over the last fifty years [3, 31, 42]. Among others the existence of one depot [14] or more than one depot [43], a heterogeneous fleet with multiple vehicle types [14] the permission of variable departure times of trips, VRP with deterministic demand which is commonly called classical VRP [7, 14] are the very few examples in the VRP literatures. Whereas VRP with Stochastic Demand (VRPSD) is also one of the major variants of VRP in the literature, but may not be studied well for real world application, due to the fact that the actual demand may differ from the initial estimate [22] and makes the model assumption more complex to solve. But this thesis aimed to design and develop a solution for VRPSD for ACBSE so as to serve the stochastic passengers demand with a minimum cost or distance.

2.2 The Vehicle Routing Problem

In a more general sense, VRP can be defined as a problem of finding the optimal routes of delivery or collection from one or several *depots* to a number of *cities* or *customers* while satisfying some operational constraints, and minimized the global transportation cost [31, 44]. In the well-known VRP, it can also be defined as a set of identical vehicles based at a central depot, is to be optimally routed to supply or serve customers with known demands subject to vehicle capacity constraints [16, 41].

A typical VRP can be described as the problem of designing least cost routes from one depot to a set of geographically scattered points (cities, stores, warehouses, schools, customers etc). The routes must be designed in such a way that each point is visited only once by exactly one vehicle, all routes start and end at the depot, and the total demands of all points on one particular route cannot exceed the capacity of the vehicle. VRP has been practically used in many areas. According to [31] and [44], typical applications of VRP are for instance collection of household waste, gasoline delivery trucks, goods distribution, snowplough, mail delivery, solid waste collection, street cleaning, school bus routing, dial-a-ride systems, transportation of handicapped persons, routing of salespeople, and of maintenance units.

2.3 Assumptions and Constraints in VRP Models

According to [31], the major constraints of VRP are the road network [45], customers, depots, vehicles and drivers. The road network, used for the transportation of goods, is generally described through a graph, whose arcs represent the road sections and whose vertices correspond to the road junctions and to the depot and customer locations. The arcs (and consequently the corresponding graphs) can be directed or undirected, depending on whether they can be traversed in only one direction (for instance, because of the presence of one-way streets, typical of urban or motor way networks) or in both directions, respectively. Each arc is associated with a cost, which generally represents its length, and a travel time, which is possibly dependent on the vehicle type or on the period during which the arc is traversed. The other constraint is the customer. Typical characteristics of customers may be:

- Vertex of the road graph in which the customer is located;
- Amount of goods (demand), possibly of different types, which must be delivered or collected at the customer;
- Periods of the day (time windows) during which the customer can be served (for instance, because of specific periods during which the customer is open or the location can be reached, due to traffic limitations);
- Times required to deliver or collect the goods at the customer location (unloading or loading times, respectively), possibly dependent on the vehicle type; and
- Subset of the available vehicles that can be used to serve the customer (for instance, because of possible access limitations or loading and unloading requirements).

Sometimes, it is not possible to fully satisfy the demand of each customer [9, 46]. In these cases, the amounts to be delivered or collected can be reduced, or a subset of customers can be left unserved, which is commonly called route failure in VRP [21]. To deal with these situations, different priorities, or penalties associated with the partial or total lack of service, can be assigned to the model[22, 31].

The routes performed to serve customers start and end at one or more depots, located at the vertices of the road graph [47]. Each depot is characterized by the number and types of vehicles associated with it and by the global amount of goods it can deal with [41]. Transportation of goods is performed by using a fleet of vehicles whose composition and size can be fixed or can be defined according to the requirements of the customers [45, 48].

The vehicle used in VRP is also one constraint in the model assumptions. According to [31], the vehicles may be characterized as:

- Capacity of the vehicle, expressed as the maximum weight, or volume, or number of pallets, the vehicle can carry;
- Possible subdivision of the vehicle into compartments, each characterized by its capacity and by the types of goods that can be carried;
- Devices available for the loading and unloading operations;
- Subset of arcs of the road graph which can be traversed by the vehicle; and
- Costs associated with utilization of the vehicle (per distance unit, per time unit, per route, etc.).

In most scenarios the least considered constraint is the drivers [31]. The drivers operating the vehicles must also satisfy several constraints laid down by union contracts and company regulations (for instance, working periods during the day, number and duration of breaks during service, maximum duration of driving periods, overtime).

According to [31], several, and often contrasting, objectives can be considered for the vehicle routing problems. Typical objectives can be:

1. Minimization of the global transportation cost, dependent on the global distance traveled (or on the global travel time) and on the fixed costs associated with the used vehicles (and with the corresponding drivers);
2. Minimization of the number of vehicles (or drivers) required to serve all the customers;
3. Balancing of the routes, for travel time and vehicle load;
4. Minimization of the penalties associated with partial service of the customers or any weighted combination of these objectives can be formulated as a model;

The VRP, since it was first introduced by [24]as a generalized problem of TPS, the concept has received much attention in recent years due to the increased importance of determining efficient distribution strategies to reduce operational costs in a distribution system [16, 41, 44]. Since then the concept of VRP is used in many application areas, it is one of the most studied combinatorial optimization problems and is concerned with the optimal design of routes to be used by a fleet of vehicles to serve a set of customers [48]. It concerns the distribution of goods between depots and final customers or users. However such a problem is also called Vehicle Scheduling Problem (VSP). In many articles and literatures, the term VRP and VSP are interchangeably used and they are same. But in this dissertation the term VRP is used consistently. VRP is not only concerned with the delivery and collection of goods but involves also in different real-world application arising from transportation system [31].

Many different VRP mathematical models have been proposed for different problems with the deep study of Routing Problem [40]. More recently, a greater attention has been devoted to more complex variants of the VRP sometimes named ”rich” VRPs, that are closer to the practical distribution problems that VRP models [41] are used to design efficient distribution system that can improve the level of their services [49]. [31] have evidently reported that the use of computerized methods in distribution process produce a substantial savings ranging from 5% to 20%.

2.4 General Model Representation of VRPs

In this section, the definitions and formulation of the classical VRP using graph theories are presented as a basis for the remaining models or other variants of VRP. The classical vehicle routing problem commonly called VRP aims to find a set of routes at a minimal cost (finding the shortest path, minimizing the number of vehicles, etc) beginning and ending the route at the depot, so that the known demand of all nodes are fulfilled [44]. Each node is visited only once, by only one vehicle, and each vehicle has a limited capacity. Some formulations also present constraints on the maximum traveling time [16].

VRP can be modeled as directed or undirected graph depending on the nature of the problem [13, 44]. The undirected graph representation is used for large scales to model the network of a country or regions. Whereas the directed graph representation is used for small scale level in cities and towns. In classical VRP where customers or customer's demand are known in advance and the driving time between the customer and the service time at each customer are also known, it can be defined and formulated in this section [35, 44].

The classical VRP is a generalization of the TSP [24]. A common used definition for the TSP is the following: given a graph with nonnegative arc weights, and a least weight Hamiltonian cycle such that all nodes (customers) are visited at least once. In vehicle routing problem, instead of one salesmen, there are m vehicles with restricted capacities that visit customers having demand. When demand of all customers exceeds the vehicle capacity, two or more vehicles are needed to serve the demand. This implies that in the Capacitated Vehicle Routing Problem (CVRP)there are multiple Hamiltonian cycles such that each Hamiltonian cycle is not exceeding the vehicle capacity. An illustration of VRP with multiple vehicles are shown in Figure 2.3.

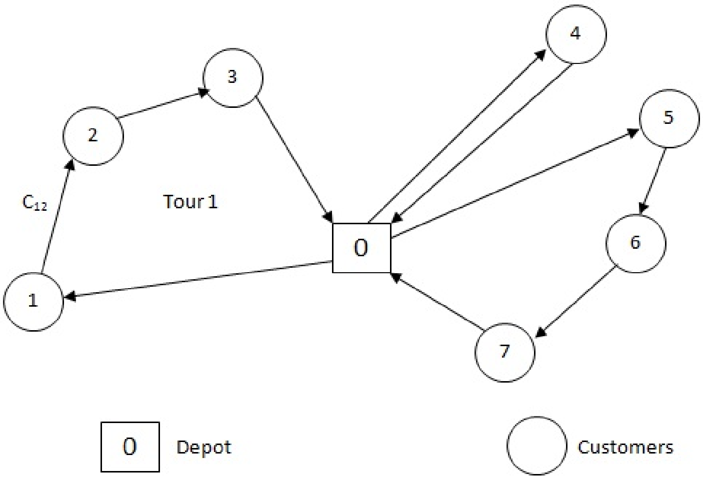

Figure 2.3: More than one tour VRP model

According to [11, 13, 35, 46, 50], the following assumptions are considered in the classical VRP models formulation.

- The vehicle fleet is homogeneous, i.e. each vehicle has an equal capacity of Q.
- Each customer has a positive demand q_i which has to be fully satisfied
- The depot has no demand.
- All customers are served by a single vehicle.

Based on considerations and definition of [8, 13, 35, 48, 51] the general and classical VRP model is defined in a more versatile and detail way as follow. Let $G = (V, A)$ be a directed or asymmetric graph where $V = \{0, \ldots, n\}$ is a set of vertices representing *cities* with the *depot* located at vertex 0, and A is the set of arcs. With every arc $(i, j)i \neq j$ is associated a non negative distance matrix $C = (c_{ij})$. In some context, c_{ij} can be interpreted as a *travel cost* or as a *travel time* [13, 35].

According to [8], when C is symmetrical, it is often convenient to replace A by a set E of undirected edges and it is called symmetric or undirected graph. For undirected graph, let $G = (V, E)$, with set $V = \{0, \ldots, n\}$ is a vertex set. To each edge $e \in E = \{(i, j) : i, j \in V, i < j\}$ is associated with travel cost c_e or c_{ij}. Each vertex $i \in V \setminus \{0\}$ represents a customer having a nonnegative demand q_i, while vertex 0 corresponds to a depot. Assume also a fixed fleet of m identical vehicles, each of capacity Q, is available at the depot.

According to [52], the number of vehicles is either known in advance or treated as a decision variable in many cases. The VRP consists of designing a set of at most K delivery or collection routes such that:

- Each route starts and ends at the depot,
- Each customer is visited exactly once by exactly one vehicle,
- The total demand of each route does not exceed the vehicle capacity, Q,

- The total routing cost is minimized

Having considered the above assumptions, according to [53], a compact and convenient formulation of VRP can be written as:

$$\text{Minimize} \sum_{k} \sum_{i,j} c_{ij} x_{ij}^{k} \tag{2.1}$$

Subject to

$$\sum_{i,j} q_i x_{ij}^{k} \leq Q; k = 1, 2, \ldots, m \tag{2.2}$$

$$x = \lfloor x_{ij}^{k} \rfloor \in S_m \tag{2.3}$$

Where:

c_{ij} = the cost of traveling from i to j
x_{ij}^{k} = 1 if vehicle k travels from i to j and $x_{ij}^{k} = 0$ otherwise
K = the number of vehicles available
S_m = the set of all feasible solutions in the m-traveling salesman problem (m-TSP)
q_i = the amount demanded at location i
Q = the vehicle capacity.

From the above equation it is clear that the VRP is an Integer-Programming (IP) problem. It is also an NP-hard problem and, therefore, practical problem instances cannot be solved to optimality within reasonable time; in fact there are no exact algorithms available that consistently solve problems with more than 50 to 75 customers [31].

In VRP models, a distinction has to be made between symmetric and a-symmetric travel cost/time matrices. In the symmetric case the arc set is usually replaced by an edge set E and given by equation 2.5. Solution approaches can vary significantly between these two cases [51].

$$A = \{(i, j) \mid i \in V, j \in V, i \neq j\} \tag{2.4}$$

$$A = \{(i, j) \mid i \in V, j \in V, i < j\} \tag{2.5}$$

According to [35] a constant vehicle speed is the other common assumption so that distances, travel times and travel costs are considered as synonymous. A solution can be viewed as a set of m cycles sharing a common vertex at the depot. In addition, assume there are K available vehicles based at the depot, where $K_L < K < K_U$; K_L and K_U lower and upper limits of the number of vehicles available in the depot. When $K_L = K_U$, K is said to be *fixed.* When $K_L = 1$ and $K_U = n - 1$, M is said to be free. When K is not fixed, it often makes sense to associate a fixed cost f on the use of a vehicle. The VRP consists of designing a set of least-cost vehicle routes in such a way that some side constraints are satisfied in addition to the above constraints [35, 44].

As it is stated above, in classical VRP, the customers are known in advance and the driving time between the customers and the service times at each customer are also known [35, 54]. The majority of the real world problems are, however, often much more complex than the classical VRP models and the above assumptions.

According to [16] however, in practice, the classical VRP problem is augmented by different constraints or side constraints such as vehicle capacity or time interval in which each customer has to be served [31], revealing the Capacitated Vehicle Routing Problem (CVRP) [37] and the Vehicle Routing Problem with Time Windows (VRPTW) [7, 12, 13, 14, 54]. In the last fifty years many real-world problems have required extended formulation that resulted in the multiple depot VRP [55], periodic VRP, split delivery VRP [10, 50, 56], stochastic VRP [13, 22, 35, 43, 46, 57], VRP with backhauls [31], VRP with pickup and delivering [58] and many others.

VRP models, in any case, whether they are used for public transport or transit, inventory control, as well as distribution centers, they share some common characteristics. They focus on minimization of cost (operating or traveling cost), distance travel, waiting time by considering customer's demand to be serviced (which may be known or unknown), with a given Time (travel time, service time and waiting time), hard or soft window time, as well as capacity of vehicle (limited or unlimited) at different depot single or multiple (bus stops, terminals or depots).

Since VRP is NP-Hard combinatory problem by its nature, in the real world formulation, most of them are limited in the number of buses used, the number of depots, and even the number of routes to be considered in their study. When more assumptions and realities are considered in the model, the problem becomes more complex and solving the model will be impossible. The reason is that, the computational effort required to solve this problem increases exponentially with the problem size [38, 39]. However, this dissertation has assessed some of the variants of VRP which are assumed to be the foundation for the research (VRPSD).

2.5 Variants of VRP

VRP is a well-studied combinatorial optimization problem, and many extensions have been made in order to support decision making under different real-world conditions. To this effect different variants of VRP have evolved from it. VRP and its variants have also been extensively studied in many research areas for more than half a century [3, 24, 42]. Moreover, since the introductions of VRP, there have been many new insights and algorithms developed for the classical or deterministic VRP [7] as well as for natural stochastic and dynamic variations of it [38, 59, 60, 61]. Among others, due to their significant importance for VRPSD for this dissertation, CVRP and SVRP are discussed more in details in sections 2.5.1 and 2.5.2.

The variants of VRP are differed by the inclusion or exclusions of different side constraints. The most common side constraints are restrictions on capacity of vehicle [40], total time, time windows [54], precedence relations between pairs of cities, the number of depots and others [31, 35]. Since VRP is a modified form of TSP, then the relationship among other basic VRP's are also derived from TSP (see Figure 2.4 [51]).

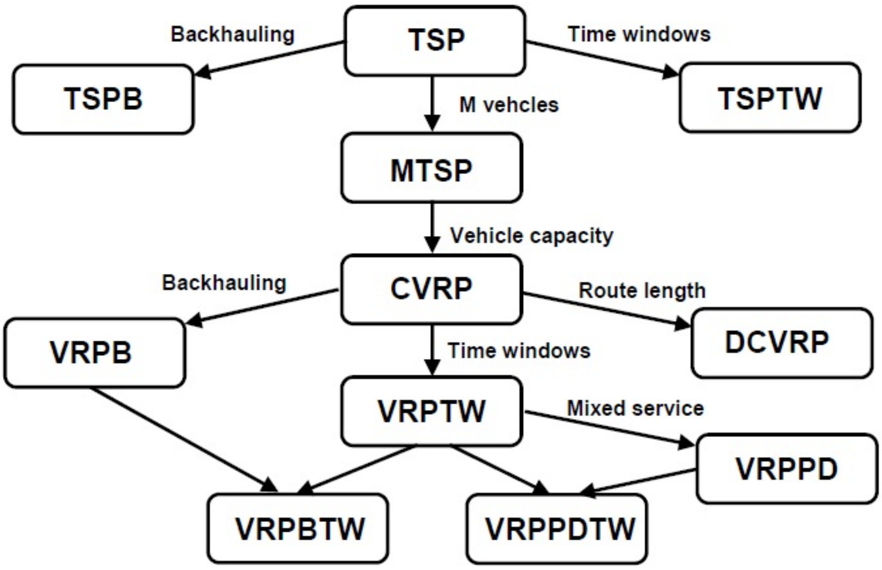

Figure 2.4: Relationships among the basic VRPs

Usually, in real world VRPs, have many side constraints or variants which appear in the model beyond the classical formulation [31]. Moreover, it is possible to drop or add certain assumptions in order to obtain a new VRP and many variants are developed to this effect. Most of them focus on designing a network or vehicle route with minimum operating cost or maximum customer satisfaction. As it has been assessed so far from different literatures, VRP's can be classified in different categories. According to [51, 62], some of the variants of VRP are:

1. The mix-fleet vehicle routing problem (MVRP)
2. The vehicle routing problem with stochastic demands (VRPSD)

3. The multi-depot vehicle routing problem (MDVRP)
4. The vehicle routing problem with backhauls (VRPB)
5. The vehicle routing problem with pick-up and delivery (VRPPD)
6. Capacitated VRP with Pick-up and Deliveries and Time Windows (CVRP-PDTW)
7. Dynamic location-routing problems
8. Split delivery vehicle routing problems with or without window time.
9. The vehicle routing problem with time windows (VRPTW)

The modification, that is of most interest to this dissertation is the VRP with Stochastic Demand (VRPSD) and VRP with limited capacity called Capacitated VRP(CVRP). The detailed description of these problems and models are given in sections 2.5.1 and 2.5.2. However, VRPs have also many classifications and taxonomy in terms of type, scenario, information, and data other characteristics [63].

2.5.1 Capacitated VRP (CVRP)

There exist formulations for both the Capacitated VRP and the un capacitated VRP depending on whether vehicle capacities are considered. The Capacitated VRP (CVRP), as presented for example in [31], is perhaps amongst the most widely researched variations of the problem.

The Capacitated VRP (CVRP) falls into the category of NP-Complete problem, it implies that there is no known solution that can execute in polynomial time. The CVRP is a VRP in which a fixed fleet of delivery vehicle of uniform capacity must service known customer demands for a single commodity from a common depot at minimum transit cost [40]. That is, CVRP is like VRP with the additional constraint that every vehicles must have uniform limited capacity of a single commodity [43]. The objective of the CVRP model is to minimize the vehicle fleet and the sum of travel time, and the total demand of commodities for each route may not exceed the capacity of the vehicle which serves that route. The model will be feasible if the total quantity assigned to each route does not exceed the capacity of the vehicle which services the route.

The general version of VRP is the Capacitated Vehicle Routing Problem (CVRP). The model for CVRP has the following parameters from [64] with little modification on the naming to make consistent with the definition and assumption made section 2.4: According to the model representation of [51, 31, 35], the parameters and decision variables of this model are given below.

The $NP-Hard$ nature of VRP pushes many researchers to use heuristics, however; exact algorithms were also introduced and applied for VRP [35, 44]. In this section the linear Integer Programming (IP) vehicle flow formulation for the asymmetric VRP, which is given by [31] is discussed This model is minimizing the total cost or distance for all vehicles while completely satisfying all demands. The CVRP model is formulated as follow.

Parameters:

c_{ij} = the cost of traveling from node i to node j

q_i = positive demand of customer i

$k = \{1, \ldots, K\}$ the number of vehicles available

Q = the vehicle capacity

Decision variables:

$$x_{ij}^{k} = \begin{cases} 1, & \text{if vehicle } k \text{ travels from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases}$$

The mathematical representation of the model will be:

$$\text{Minimize} \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} c_{ij}x_{ij}^{k} \tag{2.6}$$

Subject to

$$\sum_{j=1}^{n} x_{0j}^{k} = k \tag{2.7}$$

$$\sum_{i=1}^{n} x_{ij}^{k} = 1; i = 1, \ldots, n \tag{2.8}$$

$$\sum_{i=1}^{n} q_{ij}x_{ij}^{k} \leq kQ; k = 1, \ldots, K \tag{2.9}$$

$$\sum_{j=1}^{n} x_{ij}^{k} - \sum_{j=1}^{n} x_{ji}^{k} = 0; i = 1, \ldots, n; k = 1, \ldots, K \tag{2.10}$$

$$x_{ij}^{k} \in \{0, 1\} \forall i, j, k, i \neq j \tag{2.11}$$

$$\tag{2.12}$$

Equation 2.6 is the objective function that minimizes the total cost or distance while constraints 2.7- 2.11 are satisfied. Constraint 2.7 ensures that exactly one vehicles leave the depot, while constraint 2.8 guarantees that exactly one vehicle will visit each node. Constraint 2.9 restricts total demand of each vehicle by its capacity. Constraint 2.10 is describing about entrance and exit flows. Finally equations 2.11 define decision variables.

Each vehicle route is a modified Traveling Salesman problem (TSP) and hence CVRP is a multiple TSP. Capacity of the vehicle is fixed in CVRP so the loading constraint could not be violated in the trip but know customer demand at each vertex or node. However, the CVRP has its own limitation. The two major limitations are the assumption of deterministic demand and limited vehicle capacity. In most real world situations demand is stochastic and impractical to anticipate before arrival in the passenger's location. Due to this reason there are cases where demand exceeds the vehicle capacity. In such cases, route failure will occur and require recourse action.

2.5.2 Stochastic VRP (SVRP)

The classical VRP models usually do not capture an important aspect of real life transportation and distribution-logistic problems. This is due to the fact that several of the problem parameters (demand, time, distance, etc) are often stochastic. Most existing VRP models oversimplify the actual system by assuming system parameter (e.g. customer demands) as deterministic value, although in real application, it may not be possible to know all information about customers before designing routes. Stochastic information occurs and has major impact on how the problem is formulated and how the solution is implemented. As compared to the development in deterministic case, research in Stochastic VRP is rather undeveloped so far.

The Stochastic Vehicle Routing Problem (SVRP) refers to a family of problems, that combine the characteristics of stochastic and integer programs, and are often regarded as computationally intractable [65]. Therefore, only relatively small instances can be solved to optimality and effective heuristics are hard to design and assess. The most common stochastic VRPs are the Vehicle Routing Problem with Stochastic Demands[10, 66], the VRP with Stochastic Customers [43], the VRP with Stochastic Customers and Demands [67] and stochastic service time [68].

VRP in which demand at each location is unknown at the time when the route is designed but follows a known probability distribution, is known as VRP with Stochastic Demands (VRPSD) [9, 11, 46]. Whereas the SVRPs are extensions of the deterministic VRP in which some components are random. Most of the stochastic demand VRP are used to model the uncertainty nature of the demand of a commodity or commuters from several suppliers [69]. According to [52] and [43], the three most common cases which are considered to be random in VRP formulations are:

- **Stochastic customers:** customer i is present with probability ξ_i and absent with probability $1 - \xi_i$;

- **Stochastic demands (to be serviced, say):** the demand p_i and/or d_i of customers i is a random variable;
- **Stochastic times:** the service time of customer i and the travel time t_{ij} of edge ij are random variables, but not the concern of this dissertation.

With respect to their deterministic counterparts, SVRPs are considerably more difficult to solve. Not only is the notion of a solution different, but some of the properties that were valid in a deterministic context no longer hold in the stochastic case [10, 65].

But for this dissertation, VRPSD considers the stochastic nature of the number of passengers available at a given node or vertex at a given time are random. VRPSD and SVRP are consistently used afterwards and these mean VRP with stochastic customer demand and Stochastic VRP respectively. That is, in this dissertation, the presence of the customer is the demand to be serviced.

SVRPs are VRPs where one or several components of the problem are random [57]. In VRP with stochastic demand, vehicle route may adhere to a route duration limit and due to this reason there may be probability that some customer demand may be unserved whatever the fleet size and route [22].

Stochastic VRPs can be formulated and solved in the context of stochastic programming: In two stages for getting a solution to find a solution to SVRP [52]. A first solution is determined before knowing the realizations of the random variables. Then in a second stage, a recourse or corrective action can be taken when the values of the random variables are known. The objective of SVRP is to minimize the vehicle fleet and the sum of travel time needed to supply all customers with random values on each execution for the customers to be served, their demands and/or the service and travel times. Since some data in SVRP are random, it is no longer possible to require that all constraints be satisfied for all realizations of the random variables. So the feasibility condition is up to the decision maker, which may either require the satisfaction of some constraints with a given probability, or the incorporation into the model of corrective actions to be taken when a constraint is violated. The SVRP can be a single vehicle with limited capacity [43] applicable to most companies facing a problem of delivery (collection) to (from) a set of customers with random demand.

2.5.3 SVRP with Simultaneous Pickup and Delivery

The basic version of VRP, Stochastic VRP (SVRP) and/or VRP with stochastic Customer Demand (VRPSD), which were stated above are either a pure pick-up or a pure delivery problems [47]. The pure pick-up or pure delivery types of VRP has been extensively studied in the literatures with many application areas [25, 29, 61] such as waste collection with stochastic demand but only picking. [57] considered, stochastic customers demand with a probability distribution of customer's i demand D_i being discrete and uniform over an interval $\{d_i^{min}, d_i^{max}\}$ with servicing of pick-up [11].

The VRP with delivery and pick-up (VRPDP) is also a well studied in the literature but with the assumption of deterministic demand or with modifications of the classical VRP models for the pickup and for the delivery separately [70]. As it is evident in [44] and the surveying of [71], the problem of VRPDP can be divided into two independent CVRPs [70]; one for the delivery (linehaul) customers and one for the pickup (backhaul) customers, such that some vehicles would be designated to linehaul customers and others to backhaul customers.

On their extensive survey on pickup and delivery problems of VRP models, there are also cases where the delivery and pickup are treated separately as VRP with Divisible Delivery and Pickup [71]. Others such as [58], considered the VRPDP simultaneously, called VRP with Simultaneous Delivery and Pickup (VRPSDP). But the assumption for simultaneous delivery and pickup is performed sequentially in which case the delivery takes place first followed by pickup service by a given vehicle along the route or viceversa.

A similar VRPSDP model and approach was also studied by [72] with consideration of first delivery and then followed by pickup service but named as simultaneous delivery and pickup VRP problem. This assumption is more clearly illustrated by [71] and [72] with a symbol representation and mathematical model. The model illustrates first with symbols ▼ as delivery and second with symbols ▲ as pickup along each route in the work of [72]. Where as in the work of [71] it considered P as a set of backhauls or pickup vertices, $P = \{1, \ldots, n\}$ and D as a set of linehauls or delivery vertices, $D = \{n+1, \ldots, n+\tilde{n}\}$. As it can be seen from this consideration, first the pickup is performed from $\{1, \ldots, n\}$ then followed by the delivery from $\{n+1, \ldots, n+\tilde{n}\}$.

However, the idea of simultaneous delivery and pick up with deterministic demand on the same node (for each client or vertices) was noted on the work of [73] as one alternative in their literature but not modeled and solved. In addition to this drawback previous works on VRPSDP had also limitation on the consideration of demand. In other work of the same authors [74], studied simultaneous pickup and delivery service but deliveries are supplied from a single depot at the beginning of the service followed by pickup loads to be taken to the same depot at the conclusion of the service. Most of the models considered a deterministic demand on both delivery and pickup service except the work of [75] which considered stochastic demand on alternative pickup and delivery services using synthesized data. The dissertation is aiming to address the above limitation by designing a SVRP model that can consider stochastic passengers on the real simultaneous pickup and delivery called SVRPSPD.

2.5.4 Other Variants of VRP

As it has been discussed in previous section, there are many different models or variants of VRP due to the modification made on the classical VRP for practical and academical reasons. Though it is difficult to address all of them one by one, an overall summary of some of the different variants are discussed here.

The other variants of VRP, which is the most commonly studied one [52], is a VRP with Time Windows (VRPTW) [8, 54, 76, 77] and [7]and further restrictions on the routes of the buses [3]. The VRPTW is the same problem that VRP with the additional restriction that in VRPTW a time window (soft or hard time window) is associated with each customer, defining an interval wherein the customer has to be supplied [12, 13, 14, 78] and [12]. The interval at the depot is called the scheduling horizon. This consideration is similar to in the case Capacitated VRP with Pick-up and Deliveries and Time Windows (CVRPPDTW), Multiple Depot VRP with Time Windows (MDVRPTW), Split Delivery VRP with Time Windows (SDVRPTW) and Periodic VRP with Time Windows (PVRPTW) [10, 50, 56].

In the case of Multiple Depot VRP (MDVRP) to satisfy the demands a company may have several depots from which it can serve its customers [79, 80]. If the customers are clustered around depots, then the distribution problem should be modeled as a set of independent VRPs. However, if the customers and the depots are intermingled then a Multi-Depot Vehicle Routing Problem should be solved. A MDVRP requires the assignment of customers to depots [29]. A fleet of vehicles is based at each depot. Each vehicle originated from one depot, service the customers assigned to that depot, and return to the same depot.

In classical VRPs, typically the planning period is a single day. In the case of the Period Vehicle Routing Problem (PVRP), the classical VRP is generalized by extending the planning period to M days. The objective is to minimize the vehicle fleet and the sum of travel time needed to supply all customers. A solution is feasible if all constraints of VRP are satisfied. Furthermore a vehicle may not return to the depot in the same day it departs. Over the M-day period, each customer must be visited at least once.

The other relaxation of VRP is Split Delivery VRP (SDVRP) wherein it is allowed that the same customer can be served by different vehicles if it reduces overall costs [10, 50, 56, 81]. This relaxation is very important if the sizes of the customer orders are as big as the capacity of a vehicle. The objective is to minimize the vehicle fleet and the sum of travel time needed to supply all customers. The problem is feasible if all constraints of VRP are satisfied except that a customer may be supplied by more than one vehicle [21].

Moreover, Inventory Routing Problem (IRP) which is an extension of VRP which integrates routing decisions with inventory control are also other variants of VRP in the literature [8, 81]. Stochastic Transportation-inventory network design problem [82] which considers one supplier multiple retailer and each retailer face uncertain demand and can only be served using a single distribution center (demand not specific) and try to minimize shipment cost with fixed location. In this category, [69] has also developed a stochastic transportation problem with unknown demand of a commodity (homogenous commodity) with shipment from several suppliers.

Multiple use of the vehicles (Multiple use of vehicles VRP, MVRP) [83], a heterogeneous fleet to deliver the orders (Heterogeneous VRP, HVRP) [84] and orders to be satisfied in several days (Periodic VRP, PVRP) [85], constrained capacities of the customers for docking and loading the vehicles (CCVRP), transit restrictions on the roads (road dependant VRP, rdVRP) and depots that can ask for goods to other depots (Depot Demand VRP, DDVRP) [86] are also other variants of VRP.

A rich VRP variant, based on the Dantzigs formulation, is defined in [35] as an Extended Vehicle Routing Problem, which is applied to real transportation problems. However, the extended VRP requires the addition of some restrictions that represent transportation situations and this increased its complexity thus making the computation of an optimum solution through exact algorithms more difficult.

There are different algorithms developed to solve VRPs. In this section exact algorithms proposed in different literatures are summarized in brief.

2.6 Exact Algorithms for VRPs

Exact algorithms try to seek optimal solution to the problems of different class of TSP or VRP [32]. According to [35] exact algorithms are classified into three main categories, namely:

1. Direct tree-search methods
2. Dynamic programming methods
3. Integer linear programming methods

For each of these categories a brief discussion with illustrative examples will be discussed in the following sections.

2.6.1 Direct Tree-Search Methods

Based on partitioning of the edge set E into four subsets, [27] have proposed a formulation using direct tree-search methods for the symmetrical VRP. According to the representation, the four subset edges are E_0, E_1, E_2 and E_3. E_0 are edges that do not belong to the solution, E_1 are those edges forming a $k - degree$ center tree where the depot has degree $k, k = 2m - y$, the third edges E_2 are y edges incident to the depot and the last edges E_3 are $m - y$ edges which are not incident to the depot. The objective of their model is to minimize the cost of the edges selected such that all demand is satisfied.

The model developed by this approach is solved most efficiently by relaxing some of the constraint-set and by introducing Lagrangian multipliers. The model is able to successfully solve several VRP's up to twenty five nodes.

The direct tree-search methods proposed by [27], is further improved by another author [87]. As he proposed instead of finding a $k - degree$ center tree, Fisher redefines the formulation in order to find an $m - tree$ which is a set of $n + m$ arcs that span the complete set of $n + 1$ nodes with degree $2m$ on the depot. He obtained a 98% improvement on the lower bound, which is better than the findings of [27] who obtained 85% improvement.

Branch-and-bound and branch-and-cut algorithms [31] are other algorithms which are the members of direct tree-search algorithms. The former uses a divide and conquer strategy to partition the solution space into subproblems and then optimize individually over each subproblem [88]. It is frequently used to solve all sorts of VRP which are formulated as Mixed Integer Programming (MIP) [51]. The initial solution of the method will be obtained by relaxing the integer property of the constraint and solve the resulting linear program. If you solve the LP relaxation of a pure IP and obtain a solution in which all variables are integers, then the optimal solution to the LP relaxation is also the optimal solution to the IP. Therefore, the optimal value Z_{LP} of the relaxation (in the minimization case) is a lower bound to the optimal value Z_{IP} of the integer linear program, i.e., $Z_{LP} \leq Z_{IP}$ [51, 30].

In Branch and Bound algorithm, suppose that in a given subproblem (call it old subproblem), x_i assumes a fractional value between the integers i and $i + 1$. Then the two newly generated subproblems are: the old subproblem + Constraint $x_i \leq i$ and the old subproblem + Constraint $x_i \geq i + 1$ [30]. However, when the number of constraints, which is growing exponentially with n is too large to solve the linear program, the branch-and-bound method shows deficiency.

Branch-and-cut algorithms are the latest development in the exact solution approaches for the symmetric VRP. The branch-and-cut method can be solved based on a cutting plane technique [30]. This approach tries to resolve the deficiency of the branch-and-bound method and can successfully solve VRP's up to 135 customers[51].

2.6.2 Dynamic Programming Methods

The other exact algorithm to solve VRP is also a dynamic programming methods. Many researchers tried to apply dynamic programming to solve the VRP problem. To this effect [89] modeled the cost as an objective function and the demand, distribution and collection, capacity; and capacity and time window as a recurrence constraints in their exact dynamic programing approach.

Based on this approach, let a state (R, C, i) extended to generate another feasible state (R', C', j). The cost and the resource consumption vector of the new state must be computed and those states for which one or more components of R' exceed the available capacity are fathomed. The cost is initialized at 0 at vertex s and it is updated according to the formula; $C' = C - \lambda_i/2 + c_{ij} - \lambda_j/2$

where $\lambda_i = -\lambda_0$ if $i = s$ and $\lambda_j = -\lambda_0$ if $j = t$. The resource vector R is initialized and updated according to the specific problem at hand. In addition dominance rules are applied in order to delete dominated states. [35] developed a dynamic programing model for VRP by defining $V(S)$ as the cost of a TSP visiting all customers in $S \subseteq V$. Then $f(k, S)$ is defined as the minimum cost of serving all customers in S with k vehicles then:

$$f(k, S) = \begin{cases} V(S), & K = 1 \\ min_{L \subset S \subseteq V} f(K-1, S/L) + V(L) & K > 1 \end{cases}$$

The size of the computation was improved or reduced by adding more other constraints on the capacity of the vehicle.

2.6.3 Integer Linear Programming Methods

Set-partitioning formulation method was used in many VRP models [21, 31]. The idea is simple; they prepared a set J with all feasible routes j. The model is then to select a subset of routes from J such that each customer is visited and the cost of the routes in this subset is minimized. [90] formulated the Generalized VRP as an integer linear programing model with a total number of binary variables $n(n+1)$, which makes the running function $O(n^2)$ binary variables and $O(n^2)$ constraints.

All the above exact algorithms have a draw back due to the fact that so far they have been proved to be successful only for relatively small problem instances. A recent review of some successful exact approaches by [31] concludes that over the past years the largest solvable instances have grown from about 25 customers to over a 100 customers. This means relatively important progress has been made, but problems of reasonable size remain unsolvable. They reported that some Euclidean capacitated VRP instances, even with 75 customers, still remain unsolved. Despite this fact we have seen successful applications in recent studies. But the success of these exact algorithms is that they gave optimal or near optimal solutions in acceptable CPU time.

According to the findings of [35], exact algorithms can only solve relatively small problems, but a number of approximate algorithms have proved very satisfactory. The computational complexity of the VRP has prompted the development of heuristics since the 1970s [28, 91]. The development of heuristics especially in practical VRP cases still comprises a significant research area [35]. Exact solutions have also been developed, however, they can only be applied to vehicle routing problems of limited complexity [23]. Due to these reasons another approach to solve different variants of VRP is developed as a heuristics algorithms. The following section deals with solution algorithms to VRP using heuristic approaches.

2.7 Heuristic Algorithms for VRPs

When using branch-and-bound methods to solve TSPs with many cities or VRPs with many nodes, large amounts of computer time may be required. For this reason, heuristic methods, or heuristics, which quickly lead to a good (but not necessarily optimal) solution to a TSP, are often used to address large problems and require manipulation and operation on massive data sets [31, 92].

A heuristic is a method used to solve a problem by trial and error when an algorithmic approach is impractical. Heuristics often have an intuitive justification [30]. According to [35] and [30], the three different types of heuristics are: the nearest neighbor algorithms, insertion algorithms and tour improvement algorithms which are used to solve CVRPs an dynamic VRP (DVRPs) almost without modifications. Whereas [93] categorized the heuristics algorithms by six non-mutual exclusive categories as decomposition methods, inductive methods, feature extraction (reduction) methods, methods involving model manipulation, constructive and local improvement methods.

However, according to [51, 94] they summarized the above categories into three different classes, namely construction heuristics, decomposition and partitioning heuristics and improvement heuristics. The approach they classify may vary but both classification have common ideas on the description and analysis of these algorithms. Since the classification of [35], are also discussed under the classification of [51, 94], a brief discussion is given based on these classes of heuristics.

2.7.1 Construction Heuristics

It is also called Tour Construction Heuristics (TCH) in many literatures. This class of heuristics gradually constructs solutions by adding nodes or arcs to the solution following a predefined set of rules [51]. The TCH may include the famous Nearest Neighbor Heuristic (NNH) and Insertion Procedures [30, 70]. This was originally developed for the TSP, but can also be used for to solve the VRP. Such algorithms such as Clarke and Wright Savings [35], Christofides' heuristic [35, 94].

The general working principles of nearest neighbor heuristic is described as follow. Let S be the set of all customers that are not routed yet. The TCH algorithms randomly pick a customer as the starting point of the tour. Then it looks in S for the closest node to the starting point. This customer will be added to the route and removed from S. It continues until $S = \emptyset$ and connect the last added node/customer with the starting point and obtains a Hamiltonian cycle (a Hamiltonian cycle is a cycle passing through each node $i \in N$ exactly once). It tends to perform well in the beginning, but while adding the last customers to the tour, some expensive arcs have to be used. Even though it is highly unlikely to find the optimal solution in this way, it is possible to find a reasonable solution in polynomial computation time [30] and [94]. A popular heuristic is to apply the NNH beginning at each city and then take the best tour obtained.

According to [30], cheapest-insertion heuristic (CIH) begins at any city and finds its closest neighbor; it create a sub-tour joining those two cities. Next, replace an arc in the sub-tour say, arc (i, j) by the combination of two arcs(i, k) and (k, j), where k is not in the current sub-tour that will increase the length of the sub-tour by the smallest (or cheapest) amount. Let c_{ij} be the length of arc (i, j). Note that if arc (i, j) is replaced by arcs (i, k) and (k, j), then a length $c_{ik} + c_{kj} - c_{ij}$ is added to the sub-tour. Then continue with this procedure until a tour is obtained.

A similar heuristics based on a constructional principle is the saving heuristic introduced by [25]. This heuristic starts with n tours that all serve a single customer. It selects any node as central depot and labeled as node 1 [94, 95]. Then the cost or distance that can be saved by merging route i and j for each pair i, j are defined as s_{ij} and compute savings $s_{ij} = c_{ii} + c_{1j} - c_{ij}$ for $i, j = 2, 3, \ldots, n$ and $i \neq j$.

2.7.2 Decomposition and Partitioning Heuristics

Decomposition heuristics solves a sequence of smaller sub-problems. The output of the previous sub-problem is used as the input for the next. Partition heuristics are quite similar as they also partition the original problem and solve these sub-problems independently from each other. Some examples of this class of heuristics are cluster first route second heuristic [95], route first cluster second heuristic and petal heuristic [51].

The other decomposition and partitioning heuristics is the sweep heuristic which is a modification of a route-first, cluster second heuristic. It was discussed by [35] and the method is commonly attributed to [28] who gave its name. It uses the Euclidean distance and represent vertices by their polar coordinates (θ_i, ρ_i), where θ_i is the angle and ρ_i is the ray length. Then calculates for each customer the polar coordinate angle with respect to the depot and order them in terms of these angles [35, 95]. After reordering it starts assigning customers to vehicles in such a way that starting with the first customer on the list and keep adding customers to the route while keeping the route feasible. Once this is no longer possible, it finishes the route and starts a new route [51, 35]. A natural extension of the sweep algorithm is to generate several routes, called petals, and make a final selection by solving a set partitioning problem of the form [95].

$$Minimiz : \sum_{k \in s} c_k x_k$$

Subject to

$$\sum_{k \in s} a_{ik} x_k = 1, i = 1, \ldots, n$$
$$x_k \in \{0, 1\}; k \in S$$

Where S is the set of routes, $x_k = 1$ if and only if route k belongs to the solution, a_{ik} is the binary parameter equal to 1 only if vertex i belongs to route k, and c_k is the cost of petal k.

A petal heuristic has a petal like structure. It follows a similar method like the sweep heuristics by assigning polar coordinate angles and reordering them accordingly. In the next step petal lists all feasible routes with a petal like structure. In the last step it solves a linear program to optimality in which they select a set of feasible petal routes (a spanning petal) such that each customer is visited and the total traveled distance is minimized [51].

2.7.3 Improvement Heuristics

This class of heuristics is based on the idea to find improvements on feasible solutions that can be obtained in a different way. In each step the improvement heuristic tries to find an exchange or transfer of customers on the tours that will improve the solution. Improvement heuristics for the VRP operate on each vehicle route taken separately, or on several routes at a time [95]. According to them, in the first case, any improvement heuristic for the TSP can be applied and in the second case, procedures that exploit the multi-route structure of the VRP can be developed.

These branch exchange procedures are important since they illustrate a general approach to heuristics for combinatorial optimization problems. In addition, they have been used to generate excellent solutions to large scale traveling salesman problems in a reasonable amount of time [94].

As it is illustrated in [51], the method follows the following approach. Let there be a solution T with objective value $z(T)$ and any tour T' with length $z(T') < z(T)$. Suppose that these tours differs by k arcs. The algorithm then attempts to find two disjoint set of arcs $X = x_1, \ldots, x_k$ and $Y = y_1, \ldots, y_k$ such that if the arcs of set X are replaced by the elements of set Y , the result is a new tour T' with a lower objective function value. This algorithm is a generalization of the 2-opt and 3-opt algorithms frequently mentioned in the literature [94]. The k-opt heuristic just assumes that the number of arcs that will be interchanged is a variable instead of an input parameter [93].

It has been reported that some heuristics perform better than others, but in general the conventional heuristics which were discussed above do not find acceptable solutions to large VRP models. For this reason the development of metaheuristics is necessary [51].

2.7.4 Metaheuristics

When the conventional methods of solving combinatorial problems are not sufficient, an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space was used. This approach was called modern heuristics and as of recent it is called metaheuristics. There is no commonly agreed definitions for metaheuristics [51, 93].

As of [51, 31, 93] there are about six main types of metaheuristic that have been applied to the VRP: Simulated Annealing (SA), Deterministic Annealing (DA), Tabu Search (TS), Genetic Algorithms (GA), Ant Systems (AS), and Neural Networks

(NN). The first three algorithms start from an initial solution x_1 and move at each iteration t from x_t to a solution x_{t+i} in the neighborhood $N(x_t)$ of x_t, until a stopping condition is satisfied. If $f(x))$ denotes the cost of x, then $f(x_{t+1})$ is not necessarily less than $f(x_t)$; as a result, they warned that, care must be taken to avoid cycling.

GA examines at each step a population of solutions. Each population is derived from the preceding one by combining its best elements and discarding the worst [61]. Ant systems is a constructive approach in which several new solutions are created at each iteration using some of the information gathered at previous iterations [96].

2.8 Different Solution Algorithms for SVRP

VRPSD has been studied alongside more traditional deterministic routing problems since initial work by [29], but has received relatively less attention [21]. As compared to other variants, most recent work focuses on finding fixed, or a priori, tours. However, the challenge in these problems is modeling tour feasibility. In practice, it is impossible if not extremely costly to ensure feasibility of a set of a priori tours for all possible demand realizations. Thus, most models are more flexible and allow some recourse decisions. Usually, the feasibility of the a priori tour set is determined given a fixed recourse policy that specifies the actions to take whenever an infeasibility, or tour failure, occurs during operations [22, 43]. For further details, refer the works of [10, 65]. Modeling and solution approaches for the VRPSD can also be divided into three main research streams:

1. Approaches based on chance constrained models
2. Approaches based on stochastic programming with recourse models and
3. Approaches based on Markov decision models

An early chance-constrained model is proposed by [53]. A similar model using chance constrained is proposed by [66]; uses fewer variables, but requires a homogeneous fleet of vehicles. Each of the above models can be transformed into a deterministic vehicle routing problem under reasonable assumptions. One major deficiency in these models is that although the probability of a failure is constrained, the customer locations of failures (and hence their costs) are ignored [22]. Tours with the same a priori cost and the same failure probability can have significantly different expected costs, depending on the possible failure locations.

By many authors, two stage stochastic programming models have also been proposed for VRPSD, and typically considered the recourse actions such that the second stage cost can be determined without optimization. Such models are denoted a priori optimization models [9, 21, 22]. Many authors assume a penalty cost during route failure. Taking into consideration the location of a tour failure or route failure, the recourse action is for the vehicle to travel to the depot to reload before continuing (i.e., detour-to-depot) [21, 22].

An early exact solution approach for such a priori optimization model was given by [67], where in their considerations, an integer L-shaped method is proposed. [26] and [22] present an improved approach which is capable of handling larger problem instances. An important element of this improved approach is the use of lower bounds at the root node which helps to speed up solution times, such as route duration limit as proposed by [22]. These bounds are calculated under the assumption that the expected value of demand on any tour is less than or equal to the vehicle capacity. Significant effort has also been devoted to the development of heuristics for solving the VRPSD. According to [9, 53] both propose algorithms motivated by the idea underlying the savings heuristic of [25] for the deterministic VRP.

According to the survey made by [35], the exact algorithms for VRP are classified as direct tree search methods, dynamic programing and integer linear programing. The heuristic algorithms for VRP are derived from procedures derived from the TSP [35].

Regarding the heuristics approaches [94], the heuristics algorithms are experimented into three broad classes, namely, tour construction, tour improvement and composite procedures.

Moreover, as it is revised in [31], there are few studies that have been completed on the VRPSD focused on heuristic methods. For instance [29] developed and adapted the [25] savings algorithm to account for stochastic demands. The Clarke Wright algorithms were the first heuristic developed in 1964. A simulated annealing heuristic is studied by [67] described a tabu search algorithm to solve VRPSD, and solved in the sequence of a route-first, cluster-second approach. Moreover, [60] were the first to apply stochastic programming to the VRPSD, and [53] presented formulations for the chance constrained case, where customers are served according to a given probability, and the penalty function case, where each customer is served with the inclusion of a possible recourse cost. [57] used ant colony optimization to solve VRPSD, by modeling the stochastic demand and capacity behavior of the vehicles.

Further stochastic programming formulations have been developed by [9, 11, 26, 46]. But these yielded no exact solutions apart from a special location-routing model, presented a special case of the probabilistic VRP with stochastic demands and deterministic customer presence by [97].

An efficient local search heuristic is presented in [98], and their computational results indicate that the approach compares favorably to the savings-based algorithms. [97] extends local search ideas with a tabu search meta heuristic to find solutions to the a priori model proposed in [67].

The quality of the tabu search is assessed by comparison to results using the exact solution approach for a common set of instances; the tabu search algorithm produced an optimal set of tours in 89.45% of the cases. Furthermore, an average deviation from optimal expected cost of only 0.38% was observed. Note that most of the research on recourse models for the VRPSD focuses on simple recourse policies that are separable by vehicle [47, 99]; an exception is a two-vehicle sharing recourse policy proposed by [100].

Another stream of research on the VRPSD focuses on dynamic operating policies that make decisions each time new information is revealed, rather than relying on static recourse policies. Markov decision models are typically propose; one drawback is that these models require a very large state space, and thus are intractable even for modestly-sized instances. [10, 22] proposes a single-vehicle model where a decision epoch corresponds to the moment the vehicle arrives at a customer location and its demand is revealed.At that point, two possible decisions can be made prior to serving the customer: (i) not to serve the customer and move to another location, or (ii) serve the customer and then move to another location. No solution approach or computational study is presented.

An interesting approach, based on Markov decision models, is presented in [22, 101]. The authors attempt to specify an optimal restocking (or unloading) policy for the vehicle in conjunction with the routing decisions. Under such a policy, the vehicle might restock (or unload) at the depot before a capacity failure actually occurs. Although the optimal policy is quite simple, solving a model that further considers routing decisions is difficult, so heuristic approaches are developed. In related work, [102, 103] extends this idea to a more general re-optimization framework for the VRPSD, where the sequence of remaining customer visits may be changed each time a vehicle serves a customer (and thus receives new information).

2.8.1 Selected Solution Approach for SVRP

The Stochastic Vehicle Routing Problem (SVRP) arises when some of the elements of the problem are stochastic. [43] describe the Probabilistic Vehicle Routing Problem (PVRP) as a standard VRP, but with demands which are probabilistic in nature rather than deterministic. The PVRP is an extremely difficult problem to solve. [47] provides a recursive expression for finding the objective value which is also a very hard problem. Bertsimas also provides bounds and asymptotic analysis and several re-optimization policies for the PVRP.

[43] proposed two different strategies for serving the customers. Under Strategy 1 the vehicle visits all the customers in the same fixed order as under the a-priori sequence. However, the vehicle serves only the customers who require service that day. The total expected distance traveled corresponds to the fixed length of the a-priori route plus the expected length of the additional de-tours originating from visits to the depot when the capacity is exceeded. Using Strategy 2 the customers with no demand are simply skipped. Figure 2.5 shows a simple example of the PVRP in which a vehicle of capacity 2 has to serve 6 potential customers each with a demand of 0 or 1 unit [104].

In the example customer 1 and 3 turn out to have a null demand and while Strategy 2 simply skips these customers Strategy 1 visits all 6 customers. [59] note that these two methods differ with respect to the fact that Strategy 1 models situations in which the demands become known, when the vehicle arrives at the customers, while, for Strategy 2 the actual demand is known before the vehicle arrives at the customer. [97] examine a less restrictive formulation of the PVRP in that it allows for full or split deliveries. The PVRP is solved by finding the routes of minimum expected length. [67] proposed an exact algorithm for the PVRP based on the integer L-shaped method. They solve instances with up to 46 vertices. They also show that stochastic customers are far more complex to handle compared to stochastic demands.

[65] provide an excellent survey paper on the SVRP. Usually, the SVRP's are two-stage recourse problems. In the first stage a planned or a-priori route is designed

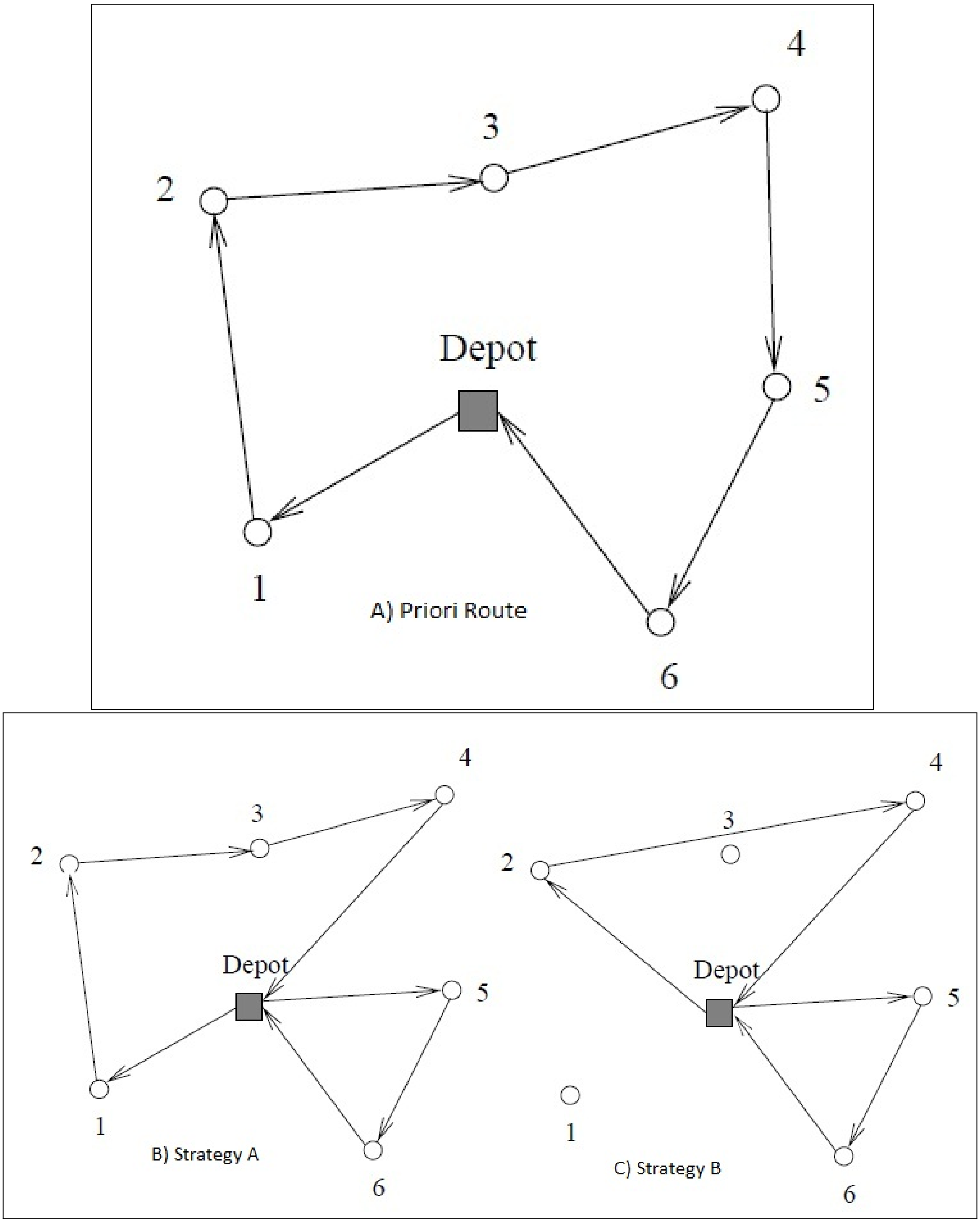

Figure 2.5: (A) The a-priori route; (B) The actual route when Strategy 1 is used & (C) The actual route when Strategy 2 is used

and then a recourse is used in the second stage to accommodate problems like, for instance, exceeded capacity. Usually, the recourse generates a cost or a saving that should be considered when the first stage solution is designed. Gendreau illustrates the two-stage methodology by considering a VRP with stochastic demands.

The first stage solution consists of m vehicle routes visiting each customer exactly once. After the first stage solution has been designed, the actual demands are disclosed. The disclosure implies that the first stage solution becomes infeasible because the total demands of the customers may exceed the vehicle capacity. In this case a simple second stage policy would be to follow the designed routes until the route fails and then return to the depot to unload/replenish and then resume the service of the customers by returning to the customer where the route failed. In this example the recourse action is defined as the cost associated in the return trip to the depot.

Another example of a more clever recourse policy is to return to the depot, whenever the vehicle is near the depot and the residual capacity is below a certain threshold. [10] discuss different recourse policies for this problem. The two basic formulations of stochastic programs are chance constrained programs (CCP) and stochastic programs with recourse (SPR). For the CCP the probability of failure in the first stage is constrained to be below a given threshold. The CCP solution does not take the costs associated with failure into consideration. In the SPR one seeks a first stage solution that minimizes the expected costs of the second stage solution plus the expected costs of the recourse. The SPR approach might seem the most intuitively correct of the two formulations. However, SPR's are often much harder to solve than the CCP's.

2.8.2 Summery

A recent review of some successful exact approaches by [31] shows that over the past years the largest solvable instances have grown from about 25 customers to over a

100 customers. This means relatively important progress has been made, but problems of reasonable size, in the real world environment, remain still unsolvable. As it is evident, the literature showed that Euclidean capacitated VRP instances with 75 customers are still unsolved using the exact algorithms. The Clarke and Wright Algorithm implicitly ignores vehicle fixed cost on fleet size.

Moreover, the use of heuristic search methods helps to find near optimal solutions in polynomial running time. And the heuristics perform better solution (with regard to number of instances and running time) than exact algorithms. However, the conventional heuristics usually do not find optimal solutions (may give good solution). A combination of different heuristics and methaheuristcs are developed to find an acceptable solution to VRP by different researchers. Moreover, from the literature made, it was realized that the stochastic consideration is not limited to customer, demand, and time; rather it includes other side constraints in the SVRP literatures such as road weather conditions, workers' shift and so on. Apart from the findings, there is no previous study that tried to classify and categorize SVRP studies except for some survey in very few areas of focus. Furthermore, based on the systematic review of the articles and the survey conducted, the research has also identified the following gaps in the literature of SVRP which can serve as future study areas.

1. There is no SVRP literature that modeled fully the real world stochastic parameters considered in its study to solve problems using real world data. Nearly, all made an assumption to simplify and tried to fit to a probabilistic model. They tested using synthesis data or previously generated instance or using mathematical proof of lemma, theorem and proposition.
2. Due to the dynamic nature of side constraints in VRP or SVRP, except some open source instances developed by scholars which are modified and used in many literatures, commercial Softwares are not readily available. This highly hinders the strategy to improve the solution methods.
3. Most SVRP studies were conducted on stochastic demand using objective func-

tion of cost minimization and capacitated vehicles with synthesis data, but, in a diversified way to find a solution using exact, heuristic or metha-heuristics techniques. However, SVRP which maximizes vehicle utilization, number of customer to be serviced, revenue earned, and others can be seen as untouched areas in the SVRP literatures.

4. Moreover, there is no VRP model so far that addresses the stochastic nature of demand (pick or drop) with consideration of simultaneous pickup and delivery at a single node.

Chapter 3

Research Design and Methodologies

This chapter tries to present the research design and methodology used in this dissertation. It begins with the general approaches and steps of the research framework. A descriptive and quantitative approach using different data sources are employed in the methodology.

3.1 Research Design

The study addresses the existing transportation service and its performance based on secondary data. Related operation and finance is examined deeply to evaluate the nature of the problem affecting the existing network or routes and number of buses assigned to each route. Based on the existing routes and by considering the number of passengers in each route, an improved model is developed to serve in an optimum way passengers in a given route. The improvement made was analyzed against the current performances of the enterprise. This approach provides an improved solution for ACBSE to serve the passengers' demand within the existing routes without affecting the routes.

Finally, based on considerations of stochastic passengers (pickup and delivery), the distance between the origin-destination of routes, a new model is developed for Merkato Terminal. This is due to the fact that Merkato Terminal serves the majority of the routes and passengers demand. The solution of the new VRP model may propose new routes which may be different from the existing one. If the improvement is significant, ACBSE can adopt it through time to implement the findings of this model. In a real situation, the distances should be the actual milleage travelled by vehicles in the transportation operations. Since the distances can be measured easily on a road map, although this is very time-consuming and could not be undertaken for large applications it is computed by taking the approximate longitude and latitude of origin-destination of each route in Merkato Terminal. This is because the new model is designed to minimize the distance traveled. The overall approach is mapped in the research framework of section 3.2 and illustrated using diagrams in Figure 3.1.

3.2 Research Framework

The research framework of the dissertation is designed based on consideration of the concepts of different theories, VRP/SVRP models and real-world situation in ACBSE. The following assumptions are also considered in designing the research framework is shown in Figure 3.1.

1. The stochastic nature of passengers demand at each route (origin-destination) of Merkato Terminals were captured. This help to model the stochastic arrival of passengers at each Terminal.
2. The number of routes and their characteristics, the number of buses used to transport passengers, the number of passengers per route are collected from the route performance report of ACBSE.
3. The current operational and financial performances of ACBSE were analyzed; and an LP model was developed for the existing system to determine the optimum number of buses for each route and time period or shift.
4. The capacity of the buses (during route selection and assigning of buses) has also been taken under consideration. Each bus can carry an optimum number of passengers so as to make the service attractive. The dissertation considers two types of buses with fixed capacities. Such consideration is called incapacitated vehicle and heterogenous fleet, in which the buses have limited but different capacities.

5. By considering the stochastic nature of passengers a new route was designed with SVRP approach that can take into consideration of real simultaneous pickup and delivery of passengers.

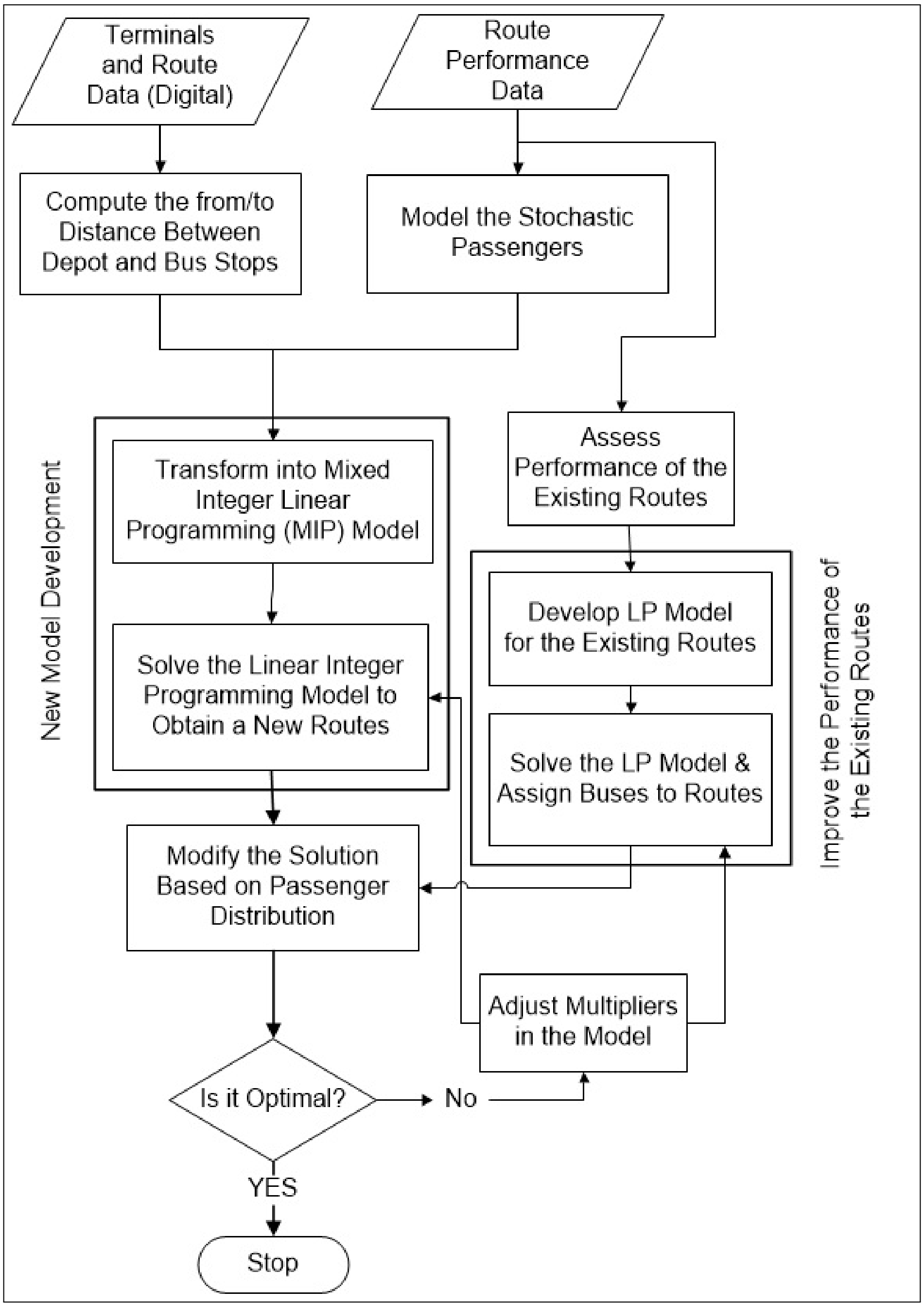

Figure 3.1: Research framework design

3.3 Research Methodologies

The research methodology employed different approaches to achieve its objectives. The following methodologies are used to secure both quantitative and qualitative and/or primary and secondary data. Necessary data are then either collected or simulated depending on their availability. This may include generation of simulation data from the already available data. The different methodologies used in the dissertation are explained below.

3.3.1 Literature Review

In the literature review, different articles, periodicals, proceedings, books, magazines, newsletters, newspapers, web-sites and other materials were surveyed in order to assess the state-of-the-art of transportation problems together with bus scheduling models and different variants of VRPs. The literature review examined different working models and algorithms and modified them to suit the Ethiopian context. For the purpose of this dissertation, the theory of VRP with some of its major variants were also surveyed so as to identify the appropriate model that can best serve the context of ACBSE, such as, nature of demand, vehicle types and the upcoming railway development in the city.

Apart from the literature review, various secondary data which are relevant to the study were also collected in different offices. Some of the major offices contacted are:

- Anbessa City Bus Service Enterprise (to collect data about passengers demand, routes and the number of passengers served at each route for the last five to ten years).
- Addis Ababa Road and Transport Authority (location data for each origin destination on the route of ACBSE).

- Ethiopian Central Statistics Agency (the population size and expected demand of passengers on the city of Addis Ababa).

3.3.2 Primary Data

The primary data are a real-life instance of VRPSD originating from the ACBSE. The data were collected from the different routes, bus stops and depots. The data are collected in 10 selected routes to determine the distribution of alighting and boarding passengers in each bus stops at a given route. The passengers' demand collected for 24 months as a secondary data was fitted to the distribution of the primary data.

Direct involvement and observation at some randomly selected routes, depots and terminals were also made. This helps to triangulate the secondary data with the current nature of demand at each selected bus stops, routes and terminals. Moreover, direct interviews for most frequent bus users, and decision-makers and higher officials in the service and technical personnel of ACBSE were conducted to validate the data that have been collected and gather additional facts and figures.

3.3.3 Secondary Data

In order to test and simulate the models developed, secondary data were collected. The secondary data required are the current routes, the number of passengers served in each route for a period of 19 months from the year 2010/2011 to 2011/2012 (2003 to 2004 E.C.). The variables to be measured in the data collection include:

1. Volume of passengers transported at each route per month
2. The number of Kilometers a bus travels in a month
3. The number of trips a bus travels in a given route in a month's time
4. The amount of revenue or traffic revenue collected per month per route
5. Different costs of the Enterprise during its transport operations for the last two years.

6. In addition to these, the location of each origin-destination of Merkato Terminal was collected from Google Earth. To this effect the latitude and longitude location was collected for the purpose of computing from-to-distance using great circle distance computation.

Moreover, from the secondary data, the peak demand hours in a day was identified and the nature of the distribution of the passengers' demand was also modeled accordingly.

3.3.4 Tools and Methods

Simulation software such as MS-Excel and General Analytical Mathematical solution (GAMS) were used to simulate the demand distribution and to solve the LP models. By giving the simulated demand, alternative solutions were generated. This was done by changing the different parameters of the model as well as the demand for different routes at different times on 58 routes taking Merkato Terminal as depot.

Chapter 4

Performance Analysis of ACBSE

4.1 Introduction

Mass transport facilitates the mobility of the society in any city with less cost and efficient time in the developed world. It provides a public transportation with the flexibility to serve the people with unlimited range of locations from city centers to suburbs. It services the public at a cheaper operating cost, with less amount of fuel, least accident rate and environmental friendly as compared to private cars, small and collective taxicabs [18]. With a motive to provide public transport service ACBSE was started before 70 years after the end of the Italian invasion.

Currently, though the enterprise has a large coverage in and around the city of Addis Ababa, it faces a lot of challenges in providing adequate service. Moreover, in terms of service satisfaction of its customers, the it unfortunately leaves much to be desired and remains long way to go. The problem has got recognition by the Ethiopian government and recently has fueled growing demand for efficient and effective bus transport services in the city.

To address the problem, in the short run as explained in section 1.3, the Ethiopian government has made an intervention by introducing midi-buses and encouraging private owners to participate in the public transportation. Moreover, in the long term, the government has considered the establishment of bus assembly lines and railway systems as a remedies in the Growth and Transformation Plan (GTP) [20]. These will have, in fact, played an essential role in preserving and revitalizing the downtown areas of major Ethiopian cities.

Notwithstanding the efforts made, the interventions in the short run could not address the high demand rather created high congestion in the mixed traffic system. The long run interventions namely, the railway system and increasing the number of buses, however, cannot fully substitute the bus service and address the problems. Expansion of the city roads and increasing the number of buses could not also address the bus scheduling problem without efficient utilization and scheduling of the bus operations. Whatever a system solution in place, if there is no efficient use of that system, it may rather create additional problems. In addition to these, the enterprise has never assessed its performance as related to international standards.

Due to this problem the urban bus systems in Addis Ababa have not been able to keep pace with the rapid and substantial increases in demand over the past decades. Thus the bus service operation of ACBSE requires a continuous performance assessment for efficient scheduling and proper utilization of buses so as to serve the current and forceable customers' demand.

The objective of this chapter is therefore to analyze the existing operational and financial performance of ACBSE so as to come up with a recommendation for mitigating the problems, thereby enabling management to more quickly and accurately enact on those areas that require improvement.

4.2 Current status of ACBSE

Anbessa was originally a private enterprise holding an exclusive franchise for the provision of passenger transport services in the city, but was nationalized in 1982. The federal government now owns the company, but its operations are financially supported by the city. A subsidy is paid for each passenger carried, however this subsidy is being progressively reduced and the city is committed to its eventual elimination which has declined from 26 cents per passenger to 10 cents per passenger. Anbessa has approximately 449 DAF brand buses which were bought in the years $1988 - 1996$ and have given services for more than sixteen years, and most of the 260 Mercedes brand buses are out of major services due to long service years and spare part problems. Those old Mercedes buses are used for special services and school bus service. Its operations are managed from its three depots from Megnegna, Mekanisa and Sheogle. Anbessa currently operates in 110 routes with an average length of 14.6KM, most of which are radial routes to the central business and commercial areas of the city.

ACBSE makes more than 5000 trips daily, with a fleet size of more than 759 operational buses out of which only about 534 of the buses are used for regular service and covers an area with a radius of 45 km from the city center. It serves more than 640,000 passengers daily and travels an average about 78,000 kilometers per day throughout the city. The high mobility of passengers in the city of Addis is mainly because of the concentration of economic activities, educational and social facilities in few city centers.

Currently ACBSE has new brands of Bishoftu buses which are single and articulated types that are about 460 in numbers. As shown in Table 4.1, the total buses available are currently reaching more that 975 buses including non-operational ones. The enterprise currently operates in 110 routes (as of the end of 2012) with an average length of 14.6 kilo meters, most of which are radial routes to the central business and commercial areas of the city. The enterprise fixes the bus capacities larger than the international standard. For example from Table 4.1 Mercedes bus with seat capacity of 30 is considered to transport 100 passengers; with a means it will have a standing capacity of 70 passengers, which is higher than the international standards. Under the column standing the number given in bracket are allowable standing capacity based on the international standards.

Though the enterprise has about 975 buses, due to different reasons only 759 of them are operational. As of the year 2012, on the average, about 5304 buses were available for regular service. Out of the 110 routes, 75%of the routes are operated from four Terminals while about 25% of the total routes operate without terminal. However, this study will consider only 93 routes in which ACBSE operated for more than a decade. Since the enterprise stretched its capacity form 93 routes to 110 routes within a very short period of time, the new routes do not have historical data. Therefore the study considered only the 93 routes in which the enterprise was operating for many years.

Table 4.1: Available buses and their respective capacity

Bus Type	Buses		Capacity		
	Total	Operational	Seating	Standing	Total
Mercedes	55	27	30	70(30)	100
DAF	461	320	30	70(30)	100
Single	350	315	30	70(30)	100
Articulated	109	97	50	100(40)	150
Total	**975**	**759**	140	310	450

4.2.1 Spatial Coverage of ACBSE

Addis Ababa lies at an altitude of over $2,300$ meters above sea level and is located at $9^{o}1^{'}48^{"}$ N and $38^{o}44^{'}24^{"}$ E coordinates. Its population is estimated to be more than 3.6 millions growing at a a rate of 8% [19]. According to [18], by the year 2020, 55% of the African population will be living in urban areas, with no exception for Ethiopia and in particular for Addis Ababa. Spatial coverage shows the ease at which the service of the ACBSE can be reached at different locations. This includes measures such as proximity to the bus routes, number of routes per road segment and route density.

4.2.2 Bus Operations and Route Characteristics

Based on data obtained from the ACBSE and [18], the in-vehicle time average speed of Anbessa City Bus is 16 km/h, which is 40% of the actual operating speed of buses. This is due to road congestion and poor maneuverability of the buses along the road. The average waiting time of passengers was also found to be 45 minutes [20] but according to [18], the waiting time reaches 30-90 minutes. The city bus is working on full time from Monday to Sunday from $6:30am - 20:30pm$.

The enterprise operated in three depots and four terminals. Among the three depots and three major terminals, one depot and one terminal fulfill the facilities to be a depot or terminal. The three depots are Yeka (in the enterprise head office), Sehgole and Mekanissa. Out of the three major terminals namely: Merkato, Legehar, Minilk quare; Merkato terminal is the major one that serves 37 routes followed by Legehar with 19 routes. The enterprise has also 7 minor Terminals for its operations, which are located at Megenagna, Ledeta, Sidist-kilo, Arat-kilo, Ayertena, Mesalemiya and Shromeda. All the buses are dispatched from the depot and scheduled from the terminals. This resulted in a 'negative traffic', that is, empty buses (long dead mileage) for the enterprise which forced to travel long distances in some cases, to get to the origins of their trips. This happened, most of the times, at the beginning and end of the day when empty buses travel from the end point of their last trips to their terminal.

ACBSE has a monopoly exclusive right to provide transportation service with great responsibility to serve the public and improve or upgrade its service to satisfy its passengers' need as well as to cut costs at large. In the country it is the only public enterprise that do not allow to set its service price. It serves the public at a price seated by the city government which is cheaper fare as compared to other modal of transportation in Addis Ababa. At the moment, the enterprise uses two types of buses with a seat capacity of 30 and 50 passengers. As of October 2012, the service is provided from 3 central depots, 4 bus terminals, 110 routes, 16 check points and 1,400 bus stops throughout the city. The number of buses operating are fluctuating due to maintenance and fleet management problems. As of the same year, there are 320 DAF, 27 Mercedes, 315 Bishoftu buses with a seat capacity of 30 passengers and 97 articulated locally assembled buses with a seat capacity of 50 passengers Table 4.1.

As it is evident from the Statistical Report of ECSA (2008) and Africa-Trans (2010) the number of bus user dwellers in and around the city of Addis Ababa has increased from time to time due to the galloping urbanization and rural exodus. The estimate showed by Africa-Trans (2010) in the year 2020, 55% of the African population will be living in urban areas, with no exception for Ethiopia and in particular for Addis Ababa. A similar study made by [105] showed that, by the same year, the population of Addis Ababa will be estimated to be more than 5.5 millions. From the same forecast, the population and bus user dwellers of Addis Ababa by the year 2012 was also estimated as 4 and 3.4 millions respectively. With reference to the bus user dwellers estimated by [105], Addis Ababa has a greater number of population that is 3.6millions with annual growth rate of 3.8% [19].

The bus routes of ACBSE are both radial and tangential, where most of them are radial starting from the center and extending out wards. Due to the increasing demand of the customer, the number of routes and route length served by Anbessa increases from time to time. As reported in Table 4.2, currently the enterprise serves about 110 routes and a total route length of about 1606 KM. Each route has different number of bus stops based on their length which is spaced at a distance of $350 - 500$ meters unless exceptional policy and topographic restriction exists.

The enterprise uses nearly a fixed bus assignment techniques on each route regardless of the demand distribution of passengers at different operation time. The number of buses assigned per route ranges from one bus to 8 buses. Table 4.3 shows the

Table 4.2: Summary of routes and its characteristics

Parameters	Route Length (Km)	Dead Milage (Km)	Travel Time (min)	No. Trips per Route	Number of buses per trip
Minimum	3.80	8.40	20	12	2
Maximum	52.00	67	110	188	8
Average	14.60	19.31	52	61.50	4
Total	1606	1740.44	5728	6764	388

number of buses per route, number of routes and total number of buses.

Table 4.3: The total number of buses by routes (as of 2011)

Number ofbuses per route	Number ofroutes	Total numberof buses
1	1	1
2	42	84
3	16	48
4	15	60
5	4	20
6	9	54
8	6	48
Total	93	315

4.3 Urban Public Bus Performance Analysis

The performance of the existing bus schedule was evaluated based on the following basic parameters, namely, the operating cost based on financial performance, the capacity of the flee to serve the demand, buses utilization and the quality of the transportation service in terms of congestions.

Public bus transport provides an important mobility for the people with in urban area throughout the world. Therefore, improving performances of urban bus service could essentially contribute for improving the quality of the mobility of passengers and productivity of the Enterprise. This is because efficient operation of the urban bus system is contributing to the development of any society [106]. However, as different literatures show, improvement in urban bus system is not an easy task. The difficulty in doing this is because urban bus systems are affected by many overlapping factors.

The performances of a public bus transport systems are affected by several criteria, such as increasing the number of buses, number of bus stops, number of passengers, and changes along roadways [107]. Therefore, the various issues causing inefficient operation of bus services need to be identified and appropriate measures should be formulated to resolve it. As discussed earlier, efficient urban bus systems can play an essential role in reducing urban travel, congestion, air pollution, energy consumption and in the long run it can decrease highway investment and associated impacts [108]. In order to make an improvement on the bus operation, therefore, the performance of the existing bus operation has to be studied well.

Owing to this, performance measurement has become the focus of attention in a variety of public sector. Unfortunately, too little has been done to develop valid operational definitions of performance, or to identify the weaknesses and biases inherent to certain types of performance measures. Among the many other parameters, according to [109] bus and labor productivity, fleet fuel efficiency are used as a measure of performance in the urban bus transport system. However, the consideration of computing these parameters may vary. For example [110] modified the parameters Percentage Load Factor (PLF) using passenger-kilometer per carrying capacity of buses rather than passenger-kilometer per seat capacity; the financial parameter by passenger-kilometer per litter rather than kilometer per litter and the labour productivity by passenger-kilometer per employee per route rather than buses per staff which were used in [109].

Moreover, other performance analysis such as route design, urban bus planning [111], as well as bus and driver schedule [112] which tried to combine bus and driver schedule are other examples in bus scheduling. Some also set standards such as the number of passengers in a given bus [113], the average kilometers per day by urban buses [113, 114]. Others such as [115] evaluated urban bus performance using Data Envelopment Analysis (DEA) based on some selected input (i.e. travel time per round trip, total number of stops, total number of operators, total number of buses) and output (i.e. daily ridership and vehicle-kilometer) variables. Bus performance with Key Performance Indicators (KPI) are also studied by [116] and used Financial, Customer, Learning and Growth, and Business Processes as KPI.

As shown in many literatures, performance is broad term and it depends on how the organization defines it. The methods may differ from one another depending upon their objective, the field they are applied to, the approach they employed, the basis of the metrics, and the data they used.

In this chapter, the performance of ACBSE is evaluated based on two broad performance measurement parameters namely: operational and financial performances. According to [117] there are a wide international variations in geographic, climatic, demographic, political, institutional, economic, environmental, and cultural factors which influence the operation of a transport undertaking. However, for comparison purpose, considering all the above factors would be very difficult to quantify and involve in the performance measurement. Therefore, the standard performance indicators stated from different authors are used for comparison purpose. According to [117], urban buses on all day service will normally operate between 150 and 300 Kms per vehicle per day(KPVPD); but, [114] stated that for a reasonably run urban bus service the average should be in the range of 210 to 260 Kms.

The bus utilization of an urban bus transport can also be computed based on different approach. It can be measured by the number of passengers transported in a given day per bus or the ratio of the number of passengers getting on the bus and passengers capacity of bus [6]. Moreover, the numbers of Passengers carried per vehicle per day (PPVPD) for a city bus with a capacity of 80 to 100 passengers is between 1000 to 1200; the vehicle utilization and the PLF are normally in between 65% to 75% and 80% to 90% respectively. But with regard to fuel consumption they came up with different findings. [117] estimated between 35 and 45 ltrs/100kms for a single-deck bus but in the case [114], the estimate is in between 25 and 55 ltrs/100kms. In addition to these, the expenditure per kilometer on salaries and wages in developing countries with low wage and salary, will generally be between 10% and 40%. Operating surplus or deficit and ratio of operating cost to revenue are expected to be positive and in the range of 1.05:1 [106, 110, 114, 117].

Using the data different performance and financial analysis were made. With regard to performance analysis of bus and fleet utilization,PPVPD, KPVPD, and PLF are used as a measuring parameters. Whereas in the case of financial performance, a much better measure of the actual utilization of buses which is kilometers-litter (fuel efficiency), cost to revenue ratio, profit earned, ratio of revenue to labour cost or fuel cost are used. The comparisons are made in two approaches to assess the performance of the transportation system in ACBSE. This is either by comparing to standards or by measuring and assessing the relative efficiencies if no standards are available [118].

4.4 Data Collection

Both primary and secondary data were used for this research. The primary data was collected through interview with officials of ACBSE which are expected to have high relevancy to the problem. This includes the General manager of ACBSE, Research and Planning Officer, Ticket Daily Service Officer and Financial Officer in ACBSE. The interviews were also conducted thoroughly related to bus scheduling, route design, its performance and challenges faced in the transportation service. Moreover, direct observations were made in different depots, terminal, routes, bus stations and bus stops.

In the secondary source, data related to the number of passengers, number of buses, revenue generated and different expenses to operate the bus services were collected. The kilometer coverage of each route, the tariff charged, the number of working days and the total daily trips made by each bus were also collected from the secondary data. From the data collected the route performance of ACBSE were organized to measure its performance from the year 2010/11 to 2011/12 for about 19 months in 93 routes.

4.5 Data Analysis and Presentation

The result and discussions are organized in two parts for clarity and readability. The first part covers the operational performances then followed by the financial performances.

4.5.1 Operational Performances of ACBSE

The operating performances of ACBSE are evaluated using some performance measuring parameters, namely, PPVPD, fleet utilization, vehicle-kilometers and PLF. In this section, the paper tries to address the extent to which available fleet is utilized by the public. Utilization normally varies between different times of the day (i.e. between peak and off-peak periods), different days of the week, and different times of the year. During peak times, fleet utilization and PLF on urban bus services should normally be between 95% and 100% [117].

In the dissertation the PLF, PPVPD, KPVPD, the fleet utilization and ltr/100kms of ACBSE on daily basis are computed. The findings of the study show that ACBSE has significantly low operational performances in almost all the parameters evaluated as compared to the standards. In order to compare with the standards, a thorough investigation for each performance parameter is required.

The PPVPD is one of the parameters that measure the operational performance of a bus transport company. It is a significant indicator of productivity, which is the number of passengers carried in relation to the capacity of the system. It is measured in terms of the average number of passengers per operating bus per day.

As shown in Figure 4.1, the average PPVPD of ACBSE is found to be 786.63 with Stdv. = 151.59. As compared to the standard, which is 1000 to 1200 with mean of 1100 [114], the performance of ACBSE is significantly low with higher standard deviation. Even the maximum PPVPD of ACBSE(which is Max. = 955.41) in the last 19 months could not attain the standard minimum. Moreover, the data in Figure 4.1 shows the PPVPD is fluctuating from month to month with higher standard deviation. The increase in passengers carried is certainly due to the rapid demand growth, which actually had increased dramatically from month 9 to month 11 and slightly afterwards in the last months.

A further indicator of the productivity of a bus fleet is the total distance traveled by buses in service, i.e., KPVPD. This is usually expressed in terms of average kilometers per operating bus per day. The KPVPD of ACBSE is also reported in Figure 4.1. In this regards, the performance of ACBSE with respect to KPVPD (Mean = 109.32 and Stdv. = 20.42) is significantly low as compared to the range of the standard reported in [114, 117].

The proportion of a bus fleet that can be put into service each day has a direct bearing on the productivity of the system. It has an implication on the effectiveness of bus maintenance, spares and procurement, and stock keeping as well as staff

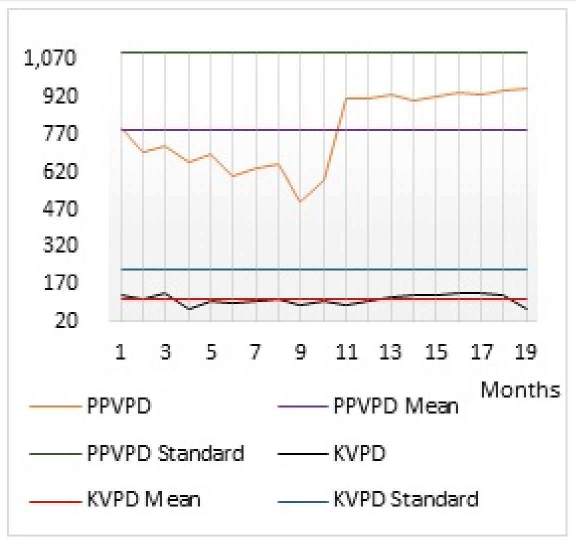

Figure 4.1: PPVPD and KVPD

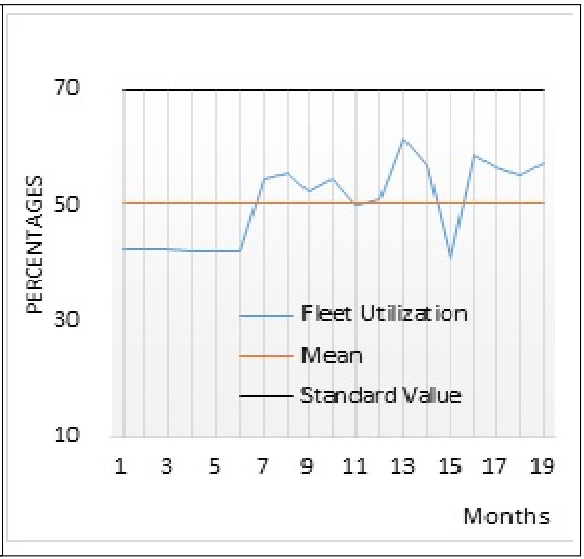

Figure 4.2: Fleet utilization

recruitment and management. Fleet utilization, expressed as a percentage of total fleet, is usually calculated by dividing total buses running during the morning or evening peak period by the total fleet size (excluding buses that are beyond repair). With adequate maintenance and staff management, it should be possible to achieve fleet utilization in between 65% to 75% with mean of 70%. As shown in Figure 4.2, the average fleet utilization of ACBSE is 50.53% of the total available fleet. From the finding, as compared to the standard 70%, ACBSE has very low operational performance with regards to its fleet utilization but has improved with slight fluctuation.

The PLF of ACBSE is also computed and reported in Figure 4.3. It is computed using the ratio of passengers-Kilometer to carrying capacity of buses for the last nineteen months. The PLF, with an average value of 65.33% and shown in Figure 4.3, shows very low performance as compared to the standard stated in [114]. It in fact has been improved slightly in the last nineteen months. In some months the load factor was close to 73.86% showing fair improvement on the average bus loadings, but still low as compared to the standard which is in between 80% and 90% with a mean of 85%.

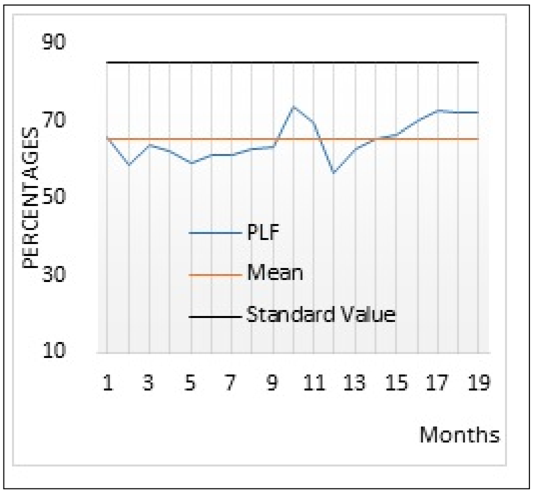

Figure 4.3: Percentage load factor

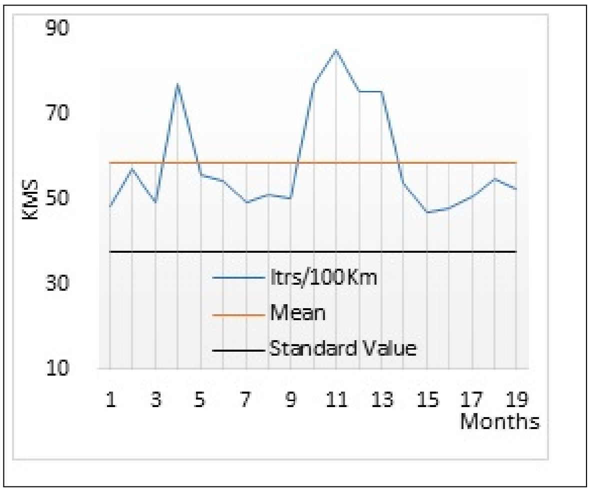

Figure 4.4: Fuel utilization

The other productivity indicator parameter is the fuel consumed in 100Kms covered. The finding is shown in Figure 4.4. It shows that ACBSE consumes an average of 58.36 litters of fuel for every 100Kms. It also exhibits fluctuations from month to month. The overall performance indicates that low range of Kilometers have been covered with high fuel consumption per 100Kms. This may happen due to the large number of old buses that can cover short range of kilometers and consume too much fuel.

4.5.2 Financial Performances of ACBSE

ACBSE is usually working on loss, indicating that the revenue of the enterprise is far lower than its operating costs. The ticket sold for a given trip varies based on the route length and its value is much lower than other fares such as minibus taxi [18]. The public bus operations in Addis Ababa had losses even before tax for the last nineteen months. Based on the interview, such losses had happened almost since its establishment but contributes at large on facilitating the mobility and helping the people in Addis.

As shown in Table 4.4, the consistent losses ranges from 3.852 to 22.42 million

Table 4.4: Financial performance of ACBSE for the last 19-Months

Years	S/No.	Losses (ETB)	Fuel cost: Revenue(%)	Labour: Revenue(%)	Spare Part: Revenue(%)	Total Cost: Revenue	Km/L
2010/11 to 2011/12	1	6,855,072.10	66.44	37.59	28.14	0.69	2.07
	2	6,336,531.85	76.36	35.55	15.84	0.71	1.76
	3	3,852,178.00	63.15	28.76	12.91	0.86	2.14
	4	5,342,081.15	74.11	30.71	10.43	0.78	1.32
	5	6,962,531.85	86.81	35.15	10.51	0.68	1.77
	6	7,138,531.85	85.23	35.43	9.81	0.67	1.81
	7	5,532,210.10	76.62	30.62	7.17	0.79	1.95
	8	5,676,339.15	77.14	31.90	5.25	0.80	1.96
	9	14,033,579.90	81.48	34.29	53.81	0.55	2.04
	10	12,464,582.45	98.64	38.310	19.12	0.59	2.05
	11	7,361,554.80	78.83	29.82	16.68	0.84	2.15
	12	22,014,407.65	77.20	36.40	26.13	0.52	1.30
	13	22,423,467.40	76.40	28.91	17.14	0.55	1.33
	14	13,419,662.10	80.40	28.12	7.23	0.73	1.33
	15	10,863,503.60	75.26	28.83	5.92	0.94	1.73
	16	12,978,214.40	73.84	29.07	5.57	0.66	1.86
	17	5,663,757.70	78.00	26.82	6.35	1.20	2.14
	18	15,170,332.70	41.02	25.00	3.18	1.11	2.09
	19	13,848,498.50	49.42	24.01	4.83	1.16	1.97
Summary	Min	3,852,178.00	41.02	24.01	3.18	0.52	1.30
	Max	22,423,467.40	98.63	38.31	53.81	1.20	2.15
	Mean	10,417,738.80	74.54	31.33	14.00	0.78	1.83
	Stdv	5,503,569.12	12.77	4.24	11.99	0.20	0.30

1USD = 18.62ETB, as of May 14, 2013

Ethiopian Birr with an average losses of 10.42 million Birr. The operations obviously show that the total costs even before taxes consistently exceeded total revenues (mainly from passenger fares or traffic revenue).

The costs of bus services are mainly dependent on local labor, fuel and spare part cost but are also greatly influenced by the efficiency of operations management, road traffic and conditions. The first point to note in ACBSE is that a much higher share of operating costs are recovered through fares or traffic revenue. However, though the traffic revenue improved steadily, the high fuel and labor costs absorbed the large proportion of it. As shown in Table 4.4, the mean proportion of fuel (include Gasoline and Petrol) and labor cost (include Salary and wage, employee benefit and overtime) consumed 74.54% and 31.33% of the total traffic revenue generated. Moreover, on average the spare part also consumed 14.00% of the total revenue. It seems that as compared to labour and fuel, the proportion of spare part cost is relatively low. This is due to the fact that the spare part cost does not include the cost of tyres and tubes, lubricant and tools and materials)

The average proportion of the labour cost is within the ranges of the industry standard. This may be due to the high number of unclassified labour forces with lower cost. In order to be self-sufficient and to avoid the subsidies, revenue should cover costs and show a small surplus to stimulate investment and growth. To meet these requirements, the operating ratio (total revenue divided by operating costs, including depreciation) has to be computed. However, as different development stages and financial methods result in different depreciation of bus assets, the depreciation cost in this study is therefore removed from the operating cost for a fair comparison purpose.

As compared to the standards, the overall financial performances of ACBSE was significantly very low except the last three months. In most of the time the operating ratio was fluctuating and in the last three months showed good recovery. But overall mean shows less than 1 with higher standard deviation (Average = 0.78 and Stdv. = 0.20). Indicates that ACBSE could not recover its operating costs from the traffic revenue.

4.6 Summary

The paper tries to assess the performance of ACBSE using operational and financial performance measurement parameters. From the findings of the study it can be concluded that both the operational and financial performances of the enterprise, as compared to the standard, are relatively low in all of the performance measuring parameters. In the case of operational performance, the enterprise has experienced low operational performance in all the parameter. In the case of PLF though the overall average exhibits very low, it has shown slight improvement from month to month. Similar improvements also observed on PPVPD after month nine.

Moreover, due to arrival of newly assembled buses, the fleet utilization is also decreasing from time to time since all the newly arrived buses are not totally scheduled in the operational fleet. Though there are many new buses in the enterprise, the operational fleet still includes many old buses which have more than 10 years of age. This adversely affects the performances of the enterprise with regard to fuel consumption and distance covered. Moreover, the cost to revenue ratio is less than one most of the time, even after excluding the depreciation cost, indicating that the enterprise is operating at a loss even before tax. Therefore to support and fully utilize the interventions made by the government as well as the enterprise itself, there should be a continuous performance evaluation system that can measure key performance parameters of the bus service based on the international standards. In addition, proper bus scheduling and assignment would also improve the performance of the enterprise.

4.7 Managerial Implications and Future study

It is evident that the low PPVPD resulted from the poor bus scheduling system used in the enterprise. That is a fixed number of buses per route are scheduled in all the operating times. This increases the dead mileage of buses during off-peak and adversely affects the quality of the service during peak hours. The bus utilization during off-peak hours are very low and most of the time buses run empty and incur additional cost without serving passengers. Whereas, in the peak hours buses are forced to carry more passengers than their riding capacity per trip which negatively affects the service quality. Thus balancing the number of buses to be assigned to routes in different time periods based on passengers' demand and setting the bus capacity to standard allowable carrying capacity is required to reduce the costs and also improve service quality and comfort to passengers.

The enterprise should also strategically design a means to replace the old buses with the new ones so that KPVPD and the fuel consumption would be improved significantly. This also would have a subsequent effect on the fleet utilization of the enterprise.

A study shows that making a marginal profit from public bus transport is unlikely. However, as most public bus transport companies do in the rest of the world, ACBSE should also supplement its revenue by other side activities. In this regard ACBSE has an exemplary start up and should be encouraged to generate revenue by providing different services such as maintenance, annual vehicle checking, etc to the public. Though the enterprise is fully responsible to serve the public, it should be given the chance to revise and set its service price from time to time with due consideration of the public.

Furthermore, future research can address the gap observed on bus scheduling and optimum allocation of buses for each route by considering the passengers' demand distribution. Since the operational and the financial performance measuring parameters do not address the level of service quality, future study can address this gap.

Chapter 5

Model Development and Performance Improvement Analysis

5.1 Introduction

Bus scheduling is one of the operations planning process in bus transport that deals with the proper assignment of buses to routes to serve the expected passenger demand. The planning process in public transportation consists of different recurrent and complex tasks. It starts at a strategic level by collecting or forecasting the number of passengers at each transfer point which is most of the time fully unknown and adds to the complexity of the planning process [3].

The decision-making process of bus assignment is however, a trade-off between service quality and operating cost for the bus operating companies. It is because using too many buses incur more operating costs while resulting in good service quality whereas too few buses have opposite effect. As stated in Chapter 4 and Section 4.2, ACBSE currently serves 110 routes that connect different parts of the city using 759 operational buses. The number of passengers show high variability during each time period which requires fluctuating the number of assigned buses in each route. But the enterprise uses mainly a fixed number of buses scheduled per route in its operation throughout the day. This resulted in some buses moving empty while others are being over crowded, which subsequently results in poor performance and service quality. In the dissertation, the bus assignment and scheduling problems faced in ACBSE is modeled and analyzed using Linear Programming (LP). It is used to determine an optimum bus assignment that can improve the existing bus schedule and assignment systems. Thus, this dissertation first focuses to develop a demand oriented LP-Model for the bus routing assignment problems of ACBSE in four operating time periods in a day using 93 selected routes. For simplicity purpose now onwards, the four operating time periods are named as shifts.

As it has been stated on the problem structure in Chapter 4, the performances of ACBSE is relatively low as compared with the international standards. Moreover, the transportation service, in ACBSE, has many challenges to satisfy even the current passengers' demand. Therefore, in this chapter, without altering the existing routes, an LP-model that can solve and optimally satisfy the existing passengers' demand is developed.

5.2 Bus Scheduling System in ACBSE

The existing schedule of ACBSE has many drawbacks as related to bus schedule and the number of buses assigned in each route. The scheduling system currently operates from 6 : 30 am to 20 : 30 pm. The enterprise uses a fixed scheduling system for each route, which means, the number of buses assigned on each route remains fixed regardless of the demand. Of course the number of buses in each route should have been determined based on the demand, but the schedule in ACBSE does not consider the high variability of passengers demand during different working hours and even days. This resulted in some buses moving empty while some others being over crowded resulting in a loss to the enterprise and a bad service to passengers. The enterprise sometimes scheduled additional buses on some routes during peak hours but they do not have recorded data on such types of decisions.

Therefore, for comparison purpose, the fixed number of buses assigned on each route are only considered. A portion of the number of buses and the kilometer they covered per route are shown in Table 5.1. The complete bus scheduling system of ACBSE per route is shown in Appendix-A TableB.1.

Table 5.1: Existing bus assignment system of some selected routes (as of 2011)

Route No.	Origin	Destination	No. of buses	Kms
1	Megenagna	Kara	2	7.7
2	Kore Mekanisa	Addis Ketema	4	11.1
3	Ayer Tena	Minilik Square	8	10.8
4	Kality	Addis Ketema	5	19.4
5	Kore Mekanisa	Minilik Square	3	12.7
6	Kera	Addisu Gebeya	8	9.9
7	Megenagna	Sendafa Beke	2	36.6
8	Semen Gebeya	Addis Ketema	2	9.4
9	Brass clinic	Piassa	2	10.5
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
93	Bole bulbula	Megenaga	2	15.2
Total			321	1349.8

5.3 Data Collection

The data collection was focused only on the first 93 routes. The data collected include route performances, numbers of passenger served, total trips made, revenue collected, operating cost and total distance covered. The data regarding the available facility of ACBSE such as the number of buses both operational and non-operational and their capacity, bus travel time, route length and working hours from the current time tables were also collected. The data were analyzed and organized per shift per route basis for validation purpose. The number of operating shifts, time interval for each shift and the demand proportion per shift are reported in Table 5.2.

Generally with an average fleet of 534 buses, ACBSE transports about $640,000$ passengers per day in 110 routes. In addition to these, peak hour services are operated on 37 routes, and on average a city bus covers about 138 km per day and makes 61.50 trips per day. The enterprise has two types of schedules for its operation in four shift, i.e. peak hour and off-peak hour schedules. These are two peaks and two off-peak shifts during its operation hours (from $6:30am$ to $21:00pm$). The two peaks are: the morning peak from $6:30am - 9:30am$ and after-noon peak from $15:30pm - 19:30pm$. The remaining hours are the off-peak in the morning and the after-noon shift. The time period, the time interval, the duration and the demand proportion of each time period or shift is shown in Table 5.2.

Table 5.2: Bus operation shifts and demand proportion

Time Period	Time Interval	Duration	Demand(%)
Morning Peak (Shift-I)	6:15 - 9:30	3:15	40.00
Morning off-Peak (Shift-II)	9:30 - 15:30	6:00	20.00
Evening Peak (Shift-III)	15:30 - 19:30	4:00	35.00
Evening off-Peak (Shift-IV)	19:30 - 21:00	1:30	5.00

With regard to demand proportion with in the four shifts, the morning peak hour shift serves about 40% of the total of the daily passengers. The second peak-passengers' demand occurs in the evening shift which shares about 35% of total passengers. Unlike the morning peak hour shift, the evening peak hours are relatively less in proportion. The other time periods are the first and the second off-peak shift which occur after the morning peak and the evening peak shift. The last time period is the second off-peak shift, which is from the evening peak hour to the closing time. The percentage share of total daily passengers are 20% and 5% for first off-peak and second off-peak shifts respectively.

In the given shift the demand of passengers on the same route varies from origin to destination based on the route direction. If the route lies from the outer edge of the city to the center of the city, most of the morning peak demand lies on the going trip while in the evening peak the demand is on the returning trip. For example, route number 31 (Legehar to Shiromeda) has high demand in the morning peak along trip from Shromeda to Legehar, while, in the evening peak most of the demand lies on

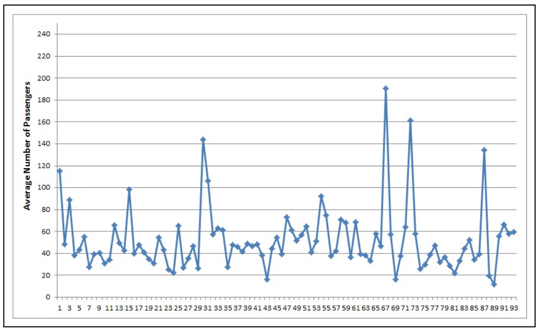

Figure 5.1: Demand distribution

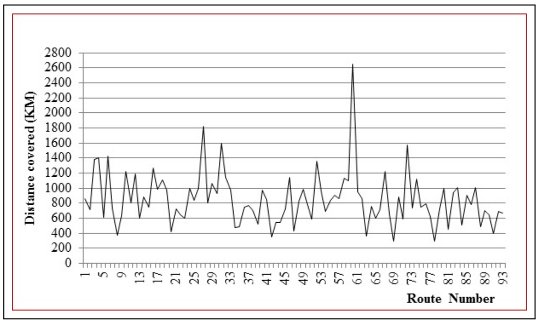

Figure 5.2: Distance coverage

the trip from Legehar to Shromeda. In order to develop the LP model, hourly distribution of demand on each route would have been the major input. However, due to improper data handling by the enterprise determining the distribution of passengers per hour per route was almost impossible. The only available data in the enterprise is the number of passengers transported per month per route. Converting this data into daily passengers per route per hour makes the distribution of the passengers' demand almost constant, which fails to show the actual demand distribution. Due to this reason, the demand distribution per shift are computed.

The average daily passengers demand distribution and kilometer covered for each route are shown in Figure 5.1 and 5.2. The daily demand shows different variations throughout the day from peak to off-peak shifts on each route.

The current schedule of ACBSE shows the total distance coverage is about $78,964$ kilometers and $5,504$ trips per day for the 93 routes. Increasing kilometer covered means increasing service availability if the assignment of buses is based on the demand distribution of a given route, but incurs unnecessary cost if the assignment is not demand oriented. Due to this reason a very close look is required to design and analyze a model that can assign buses optimally and assess the bus utilization of the enterprise.

5.4 Develop the Model

After analyzing the existing bus routing operation systems of ACBSE, an LP-Model was developed to obtain a solution for the bus assignment problems of the enterprise. The LP model developed in this study is easier either for computation or to apply for real problems of bus scheduling. It is a new approach in the literatures of VRP that address the trips made by two types of buses directly in the model based on the demand distribution of passengers in 93 routes and four operating shifts.

5.5 Running the Model

Using the secondary data collected in section 3.1, the LP model was fitted to its input parameters. The model developed was coded and solved using General Algebraic Modeling System (GAMS) optimization software. The GAMS code was running within 0.15 seconds on 3.10G.Hz, Window7 Home Premium, 4GB RAM and core (i5) Dell Personal computer (Optiplex 790-Model). The resulting solution of the LP-model was the number of trips per route per shift for each type of bus. After obtaining the solution, the number of trips was converted into number of buses per route per shift for each type of bus.

5.6 Validating the Model

The LP model was analyzed to identify potential areas of improvement in the bus scheduling and assignment problems of ACBSE. It is also used to assign buses to a given route at a given shift based on the demand distribution of passengers in the four operating shifts for the 93 routes. To validate the findings of the LP-model, its performances were compared with the performances of the existing bus scheduling systems of ACBSE. The validation was made on four performance measuring parameters namely bus utilization, total trips made, total Km covered and different operating costs.

5.7 Model Development

The enterprise is currently operating using four types of buses (DAF, Mercedes, Single Bishoftu and Articulated Bishoftu) but categorized in two based on their seat capacity namely buses with 30 seat capacities (DAF, Mercedes, Single Bishoftu) and buses with 50 seat capacity (Articulated Bishoftu).

For the purpose of the LP-model buses with seat capacity of 30 passengers are labeled as bus *type-I* (but has a total capacity of 60 passengers) and buses with seat capacity of 50 passengers are labeled as bus *type-II* (but a total capacity of 90 passengers). Based on the standard capacity of public bus transportation [113] the maximum recommended capacity of buses with seat capacity of 30 will not exceed 60 passengers and for those buses with seat capacity of 50 will not exceed 90 passengers. The total capacity of each bus type is equal to the seat capacity plus the standing capacity. Fleet *type-I* and bus *type-II* have 600 and 90 buses respectively. Thus the objective function of the LP model is used to determine the optimum trips and mixes of the two types of buses per route per shift.

For the model development, the number of trips per route i per shift j made by bus *type-I* is labeled by "X_{ij}" and by that of bus *type-II* is labeled by "Y_{ij}". The model formulation in this phase is developed as a general model, then later after substituting some parameters, the model is fitted to ACBSE problem.

Definition of terms used in the Model

i = Route number, where i = 1, 2 ,. . . , 93
j = Operating shifts , j = 1, 2, 3 and 4
D_{ij} = Passenger demand of route i at shift j
C_x and C_y = Capacity of fleet type-I and type-II respectively
M_j = Minimum Number of trips required at a given shift j

F_x and F_y = Total available fleets for fleet type-I and bus type-II respectively
T_{ij} = Trip factor, maximum trips a bus can be made on route i per shift j
P_i = Trip proportion for route i computed from demand

The objective of the model is to minimize the total numbers of combined trips made by the two types of buses. That is minimizing $\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij} + Y_{ij})$ by fulfilling different constraints.

The first constraint is to set the overall combined capacity of the two types of buses assigned in route i during shift j should be greater than or equals to the total demand that requires trip in route i at shift j. Mathematically it is expressed as $C_xX_{ij} + C_yY_{ij} \geq D_{ij}$. The other constraints are used to check the total fleet of each type of bus. In this regard, the second and third constraint show that the total trip required by bus of fleet *type-I* and bus of fleet *type-II* should be less than or equal to the total trips available by fleet type-I and fleet type-II respectively. Mathematically they are expressed as: $\sum_{i=1}^{m}\sum_{j=1}^{n} X_{ij} \leq F_x\sum_{i=1}^{m}\sum_{j=1}^{n} T_{ij}; \text{and} \sum_{i=1}^{m}\sum_{j=1}^{n} Y_{ij} \leq F_y\sum_{i=1}^{m}\sum_{j=1}^{n} T_{ij}$.

The other constraint that determines the total minimum number of trips required in every 30 minutes for the 93 routes is given by:$\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij} + Y_{ij}) \geq 93\sum_{j=1}^{n} M_j$. The trip made by bus of fleet *type-I* and bus of fleet *type-II* for route i at shift j should be less than the proportion of the total trip available. It is mathematically expressed as: $X_{ij} \leq P_iT_{ij}F_x; \text{and} Y_{ij} \leq P_iT_{ij}F_y$. The last constraint shows the sum of all the trip proportion equals to one that is $\sum_{i=1}^{m} P_i = 1$.

The general LP-model that determines the optimum number of trips required per route per shift is therefore formulated as follow.

$$\text{Minimize} \quad \sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij}+Y_{ij}) \tag{5.1}$$

Subject to

$$C_xX_{ij}+C_yY_{ij} \geq D_{ij} \tag{5.2}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n}X_{ij} \leq F_x\sum_{i=1}^{m}\sum_{j=1}^{n}T_{ij} \tag{5.3}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n}Y_{ij} \leq F_y\sum_{i=1}^{m}\sum_{j=1}^{n}T_{ij} \tag{5.4}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij}+Y_{ij}) \geq m\sum_{j=1}^{n}M_j \tag{5.5}$$

$$X_{ij} \leq P_iT_{ij}F_x \tag{5.6}$$

$$Y_{ij} \leq P_iT_{ij}F_y \tag{5.7}$$

$$\sum_{i=1}^{m}P_i = 1 \tag{5.8}$$

$$X_{ij}, Y_{ij} \geq= 0 \tag{5.9}$$

The objective function 5.1 is minimizing the total number of buses required. The constraints are: 5.2 the combined capacity of buses assigned to a given route i at a given shift j must equal or exceed the demand of that route during the shift.

Equation 5.3 and 5.4 show the total numbers of buses to be assigned to selected routes must equals or less than the available fleet size; 5.5 the number of buses to be assigned to a given route at a given shift has to be at least equals to the minimum number of buses required per route per shift; 5.6 and 5.7 are the number of buses to be assigned to a given route should not exceed the number of available buses for that route; equation 5.8 ensures the total sum of a probability is always one; and 5.9 is non-negativity constraints.

The model introduces a new approach in including different bus types in a simple LP model. Moreover, it guarantees one round trip for each route in every 30 minutes. It is used for determining the total number of trips required by each type of bus for route i during shift j. But the actual number of buses to be used for the corresponding routes and shifts can be obtained from the total trips.

It also introduces a new approach by including different bus types in a simple LP-model. Moreover, it guarantees one round trip for each route in every 30 minutes. It is used for determining the total number of trips required by each type of bus for route i during shift j. But the actual number of buses to be used for the corresponding routes and shifts can be obtained from the total trips.

The travel time of bus on a given route is the total sum of passenger boarding and alighting time (dwell time), tea and lunch break, acceleration and deceleration at bus stops, traffic light and transfer time between each stop. However, few considerations were also taken into account both in terms of the functionality of the model itself and its output. In particular, the model was run once for all of the four shifts. Although there were different bus sizes considerations in ACBSE, constraint 5.2 includes bus size 60 and 90, which is are taken from the international urban bus standards. The number of buses will be checked to make sure M_j is met for all time slots. The results obtained may be fractional but rounded later into upper integer values.

5.7.1 Minimum Number of Buses

Moreover, some of the parameters need to be defined for clarity. To this effect M_j, T_{ij}, and P_i are explained in detail below. value of us, the minimum number of trips required for a given route i at shift j to meet the maximum allowable waiting time of 30 minutes. It depends on the duration of the time period and maximum allowable waiting time at a given shift.

The value of M_j which is the minimum number of trips required at shift j to meet the maximum allowable waiting time depends on the duration of the time period and maximum allowable waiting time. For example, if a single trip time for a given shift is 30 minutes and the length of the time period is 4 hours for a given shift, then a minimum of 8 trips are required to limit the maximum waiting time of passenger to 30 minutes. This means, there should be at least one bus in every 30 minutes or half an hour for each shift for the quality of the service. The actual minimum number of buses required here is one bus because within a trip time of 30 minutes one bus can make 8 trips during a 4 hour time interval. It is given by:

$$M_j = \frac{\text{Total Duration for shift } j \text{ (Minutes)}}{\text{30 Minutes}} \tag{5.10}$$

Thus using equation 5.10 and the information given in Table 5.2, the value of M_j for the four shifts are computed and reported in Table 5.3.

5.7.2 Trip Factor Analysis

The other parameter that needs to be determined is the trip factor, T_{ij}, which is computed using equation 5.11. This is the minimum number of trips a bus can make on route i at a given shift j. Since the model computes the total trips that are required per route per shift, the trip factor is used to compute the available number of trips per route per shift.

It is the maximum number of trips a bus can make on route i per shift j; this factor is used to get the available number of fleet in terms of trips because the model calculates the total number of trips that is required per route per shift. The actual number of buses is then calculated from the trip factor by determining how many trips a single bus can make at a given time period.

$$T_{ij} = \frac{\text{Total Duration for shift } j \text{ (Minutes)}}{\text{Single trip travel time for route } i} \tag{5.11}$$

By multiplying this trip factor by the available fleet size, that is F_x and F_y, it can help to find the maximum possible trips made by the total available fleet size.

5.7.3 Trip Proportion

The trip proportion required for route i during shift j, P_i, is also determined by equation 5.12. This factor is used to allocate number of trips to route i on shift j from total available trips. It is computed using the following formula.

$$P_i = \frac{\text{Maximum Daily Demand of Route } i}{\text{Total Daily Demand of all Route}} \tag{5.12}$$

D_{ij} is average daily passenger demand of route i during shift j. It is obtained from the secondary data by multiplying the average daily demand of route i by the demand proportion of shift j shown in Table 5.2.

5.8 Solve the Model

The LP model developed is solved based on the average daily demand for the last 19 months in four operating shift time shown in Table 5.2. The daily passengers' demand for the last 19 months was collected and then the average daily passenger' demand of each month was computed per route per shift based on the trip proportion (P_i) of route i, and reported in Table 5.3.

5.8.1 Input Parameter to the Model

To solve the LP-model, the input parameters, which are involved in the model, are need to be determined first. These parameters are either computed or obtained from the secondary data. The sample input parametric values of some routes are reported in Table 5.3.

The inputs are standard passenger carrying capacity of buses, operational number of buses, passenger demand per route per shift (D_{ij}) (computed from the total Demand(TD)), trip factors (T_{ij}) and the minimum number of trips per shift (M_j) and the trip proportion per route (P_{ij}).

Table 5.3: Sample input parameters to the model

Routes	TD	Pi	Shifts (Minimum Trips)				Trip Factor			
			D_{i1} ($M_1 = 7$)	D_{i2} ($M_2 = 12$)	D_{i3} ($M_3 = 8$)	D_{i4} ($M_4 = 3$)	T_{i1}	T_{i2}	T_{i3}	T_{i4}
1	4126	0.014	1650	825	1444	206	7	12	8	3
2	3497	0.012	1399	699	1224	175	4	7	5	2
3	11030	0.038	4412	2206	3860	551	4	7	5	2
4	3029	0.010	1212	606	1060	151	3	5	3	1
5	2442	0.008	977	488	855	122	4	7	4	2
6	9256	0.032	3702	1851	3239	463	4	8	5	2
7	1001	0.003	400	200	350	50	2	4	3	1
8	1446	0.005	578	289	506	72	6	10	7	3
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
91	778	0.003	311	156	272	39	2	4	3	1
92	3836	0.013	1534	767	1342	192	4	8	5	2
93	2029	0.007	812	406	710	101	5	9	6	2

The other inputs are the standard capacity of buses to be considered in the model. The model considers a bus capacity of 60 and 90 passengers for bus *type-I* and bus *type-II* respectively. This capacity is determined based on the international allowable capacity of buses [113] with their dimension and respective seat capacity, although ACBSE currently considers the capacity of buses as 100 passengers and 150 passengers for bus *type-I* and bus *type-II.* The total operational buses in bus *type-I* is 600 (DAF and Single Bishoftu) and that of bus *type-II* is 90 (Articulated) buses. The numbers of operational buses are not only 690, but the rest of the operational buses are kept for backups during failure and for other services such as contract and employee service. Also the 93 routes which are under analysis serve more than 90% of the demand during a day and thus the operational fleet assignment is based on this proportion. After substituting the values of input parameters and constants into the LP model, it can be re-written as:

$$\text{Minimize} \quad \sum_{i=1}^{93}\sum_{j=1}^{4}(X_{ij}+Y_{ij}) \tag{5.13}$$

Subject to

$$60X_{ij}+90Y_{ij} \geq D_{ij} \tag{5.14}$$

$$\sum_{i=1}^{93}\sum_{j=1}^{4}X_{ij} \leq 600\sum_{i=1}^{93}\sum_{j=1}^{4}T_{ij} \tag{5.15}$$

$$\sum_{i=1}^{93}\sum_{j=1}^{4}Y_{ij} \leq 90\sum_{i=1}^{93}\sum_{j=1}^{4}T_{ij} \tag{5.16}$$

$$\sum_{i=1}^{93}\sum_{j=1}^{4}[X_{ij}+Y_{ij}] \geq 93\sum_{j=1}^{n}M_j \tag{5.17}$$

$$X_{ij} \leq 600P_iT_{ij} \tag{5.18}$$

$$Y_{ij} \leq 90P_iT_{ij} \tag{5.19}$$

$$\sum_{i=1}^{m}P_i = 1 \tag{5.20}$$

$$X_{ij}, Y_{ij} \geq= 0 \tag{5.21}$$

5.8.2 Model Outputs

The output of the model shows the total number of trips by the two types of buses required to serve the average demand of each route on a given shift. The sample outputs of the LP model are shown in Table 5.4.

The GAMS Build system has different solvers such as BARON, BDMLP, BENCH, CNOPT, CPLEX, LGO and etc that are capable of solving different varieties of problems. After trying each solver, for reporting purpose, CPLEX solver is chosen to solve the LP model developed above. The LP-model is coded using the GAMS Build system and the piece of the GAMS code is shown below.

Defining Route i and Shift j

Sets i Routes $/1 * 93/$ This sets routes from route 1 to route 93.

j Time periods $/1 * 4/$; Sets shifts from shift 1 to shift 4.

Sample Demand distribution per route per shift

Table $d(i, j)$ demand distribution on route i on time shift j

	1	2	3	4
1	2249	1124	1968	281
2	2249	1124	1968	281
3	2249	1124	1968	281
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
92	1848	924	1617	231
93	1362	681	1192	170

Sample Trip Factors (T_ij)

Table $T(i, j)$ trip factor on route i for time period j

	1	2	3	4
1	7	12	8	3
2	4	7	5	2
3	4	7	5	2
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
92	4	8	5	2
93	5	9	6	2

Minimum Trip Required (M_j)

Parameters M(j) minimum trips required at time period j

/1	7
2	12
3	8
4	3/

Trip Proportion (P_i)

P(i) demand proportion of route *i* from all routes /

1	0.014
2	0.012
3	0.040
.	.
.	.
.	.
92	0.012
93	0.009/;

Decision Variables

$X(i,j)$ Number of Bus type-I for route i during shift j

$Y(i,j)$ Number of Bus type-II for route i during shift j;

Variable Z; For the objective function

Model Equation

---

obj.. Z=e=sum((i,j), X(i,j))+ sum((i,j), Y(i,j));

const1.. sum((i,j), X(i,j))*60 + sum((i,j), Y(i,j))*90 =g= sum((i,j),d(i,j));

const2.. sum((i,j), X(i,j))=l= sum((i,j), T(i,j))*600;

const3.. sum((i,j), Y(i,j))=l= sum((i,j), T(i,j))*90;

const4.. sum((i,j), X(i,j))+ sum((i,j), Y(i,j)) =g= sum(j, M(j));

const5.. sum((i,j), X(i,j))+ sum((i,j), Y(i,j))=l=sum((i,j),T(i,j))*690;

Since bus type-II has greater capacity, priority is given so that demand is to be served by the available capacity of Y for that route to reduce number of bus required and if it is beyond available number of Y for that route then the rest is to be served by available number of X. Thus, based on this assumption the following equation sets the lower bound to values of X and Y, if not since it is minimization it starts from zero and can't display the appropriate mix of X and Y.

$Y.lo(i,j)\$[(d(i,j)/90) \leq (T(i,j)*P(i)*90)] = d(i,j)/90$; lower bound for Y
$Y.lo(i,j)\$[(d(i,j)/90) \geq (P(i)*T(i,j)*90)] = P(i)*T(i,j)*90$;
$X.lo(i,j)\$[(d(i,j)/90) \geq (P(i)*T(i,j)*90)] = (d(i,j)/60) - (P(i)*T(i,j)*90)$; *lower bound for X*
$X.lo(i,j)\$[((d(i,j)/60)-(P(i)*T(i,j)*90)) \geq (P(i)*T(i,j)*600)] = (P(i)*T(i,j)*600)$;

Thus from this the assignment of bus type X depends on assignment of Y and X is assigned for a given route if the expected demand during that time period is beyond the capacity and availability of bus type Y
Model eq / All / ;
Solve eq using lp minimizing Z;
display X.l;
display Y.l;

The outputs of the model are reported by taking the upper integer value. As shown in Table5.4, for examples for route 3, 61 trips by bus *type-I* and 14 trips by bus *type-II* were required for shift one. There are also routes where no trips are required by bus *type-I* in the off-peak shifts. Since the LP model produces number of trips required, the output has to be converted into number of buses required for each route in a given shift. This has to be done by dividing the number of trips from the model output by the trip factor (T_{ij}). The entire solution of the model is reported in Appendix-B TableB.3.

Table 5.4: Number of trips required per route per shift

	Shift 1		Shift 2		Shift 3		Shift 4	
Route No	X_{i1}	Y_{i1}	X_{i2}	Y_{i2}	X_{i3}	Y_{i3}	X_{i4}	Y_{i4}
1	19	9	0	10	14	11	0	3
2	19	5	5	8	15	6	0	2
3	61	14	14	24	48	17	0	7
4	18	3	6	5	15	3	2	1
5	14	3	4	6	12	3	0	2
6	51	12	0	21	41	14	0	6
7	4	1	3	2	6	1	1	1
8	7	3	0	4	6	4	0	1
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
91	4	1	2	2	4	1	1	1
92	21	5	0	9	17	6	0	3
93	11	4	0	5	9	4	0	2
Total	1541	402	174	618	1231	490	18	156

5.8.3 Assigning Buses to Routes

From the output of LP-model, after rounding up, there are about 4,630 total trips required to serve the average daily demand. The actual number of buses required for a given route i during a given shift j depends on the trip factor. That is the number of trips that can be made by each bus type during a given shift. Thus this output need to be transformed to number of buses required for each route per shift based on the possible trips that a bus can make during a given shift j on each route i. From the output of the LP model shown in Table 5.4, the number of trips can be transformed into number of buses using the following steps and equation 5.22

1. The number of buses would proportionally increase or decrease based on the increase or the decrease of trips in each route and shift.

2. Divide the number of trips per route per shift by the trip factors of that route and shift.

$$\text{Number of Buses per Route per Shift} = \frac{(\text{The number of Trips})}{(T_{ij})} \tag{5.22}$$

But, sometimes the output of the LP is small for some routes, so adjusting the actual number of buses is required for such routes to have at least two buses on a given route per shift to allocate them on both ends of the route. That is one on the going trip and the other on the returning trip in every 30 minutes. This is because the demand during a given shift j on each route i lies on both directions of the route. Sample of number of buses per route per shift reported in Table 5.5 and computed for all 93 routes in the same way.

The actual number of buses required for each shift varies and the number of buses required during peak periods is higher than that of off-peak periods. Thus some of the buses that operate during morning peak period have to wait on bus stops until they are required for the evening peak.

Based on these conversion, the entire bus schedule for each route and each time slot is given in Appendix-B TableB.4. But for illustration purpose, the bus schedule for some selected routes is reported in Table 5.5. As shown in the table the total number of buses required in shift1, shfit2, shift3 and shfit4 are 490, 202, 364 and 200 respectively.

5.9 Model Validations

The outputs of the model are then evaluated using different performance measuring parameters. For the validation purpose different comparisons were made between the existing and the LP improved systems. The comparisons made were based on

Table 5.5: Assigning buses to each route

	Shift 1			Shift 2			Shift 3			Shift 4		
Route No.	X_{i1}	Y_{i1}	Total	X_{i1}	Y_{i1}	Total	X_{i1}	Y_{i1}	Total	X_{i1}	Y_{i1}	Total
1	3	1	4	1	1	2	2	1	3	1	1	2
2	5	1	6	1	1	2	3	1	4	1	1	2
3	16	3	19	2	3	5	10	4	14	0	3	3
4	6	1	7	2	1	3	4	1	5	2	0	2
5	4	1	5	1	1	2	3	1	4	1	1	2
6	12	3	15	0	3	3	8	3	11	0	3	3
7	3	0	3	3	0	3	3	0	3	3	0	3
8	2	0	2	2	0	2	2	0	2	2	0	2
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
91	3	0	3	2	0	2	3	0	3	3	0	3
92	5	1	6	1	1	2	3	1	4	1	1	2
93	2	1	3	1	1	2	1	1	2	2	0	2
Total	396	94	490	114	88	202	269	95	364	121	79	200

bus utilizations, distance and trips covered and the different operating costs of the enterprise, and each of them are discussed in the following sections.

5.9.1 Bus Utilization

After assigning buses to each route and each shift, then the improvements achieved by the LP-model were compared with the existing bus utilization of ACBSE. Bus utilization is computed as the ratio of the number of passengers getting on the bus to the passengers carrying capacity. The average daily bus utilization of the existing and the improved systems are shown in Figure 5.3. The findings show that the improved system has better bus utilization than the existing one. The average bus utilization for the improved systems is about 66.33% and for that of the existing systems is 64.26%. The existing systems has a maximum of about 125% daily bus utilization which is very congested to passengers, while the improved system has a maximum utilization of 97%. This shows how the passenger congestion and the service quality are improved in the new systems. Though the average utilization of both of the systems seem close to each other, in the improved system most of the utilization lies in between 60% and 80% whereas, the existing system had unbalanced utilization which sometimes failed below 20% and other times above 120%.

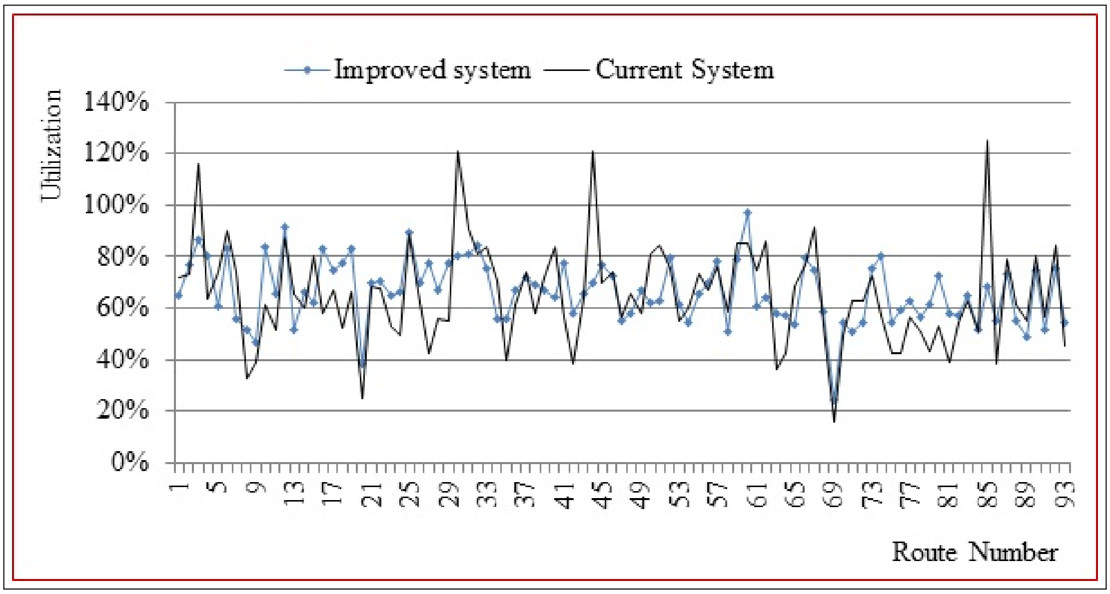

Figure 5.3: Bus utilization of the current and the improved systems

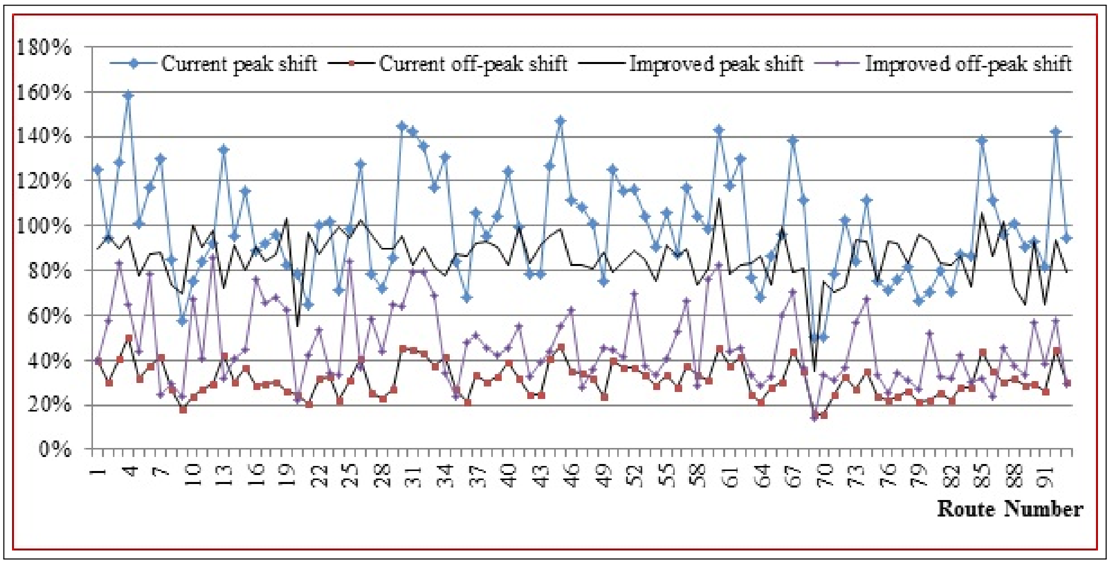

Figure 5.4: Bus utilization of the current and the improved systems by Shift

As shown in Figure 5.4, the bus utilization of the new system has shown significant improvement when the comparison is made on the basis of shift. The improved bus utilization by shift is then 89.8% during morning peak, 51.19% during first off-peak, 82.24% during evening peak and 42.1% during second off-peak periods. The improvement over existing systems, in this case, is 19.75% during first off-peak and 12.15% during the second off-peak. The good bus utilization of the improved system also reduced the passengers' congestions at peak hours, i.e. bus utilization is decreased from 116.1% to 89.8%. Thus the improved system has stable and consistent bus utilization with good service quality. It also indirectly increases the service quality by reducing over crowdedness during peak periods and reduces the operating cost during off-peak periods.

5.9.2 Distance Coverage

Total kilometer covered for route i per day is the sum of kilometer covered during all the four shifts. Figure 5.5 shows the total distance coverage of the current and the improved systems. The distance covered on each shift was computed by multiplying the number of bus assigned to a given route at that shift by the number of trips that can be made by a single bus and by the route length. The total distance covered per day for the improved system is 70,964 kilometers; while for the existing system is about 78,963.7 kilometers per day. This shows a reduction of 10.13% in the daily distance coverage to serve the same number of passengers.

The total daily trips made for the improved system is also computed for each shift by multiplying the number of buses assigned and the number of trips a single bus can make during that shift. The total trips covered for the existing systems were $5,504$ trips per day while $4,630$ for improved systems. This also shows an improvement of 874 trips per day over the existing system. The improved number of trips accounts 15.88% with a 10.13% reduction on the total daily Kilometer. This also improves the availability of buses in addition to the saving on the operating costs.

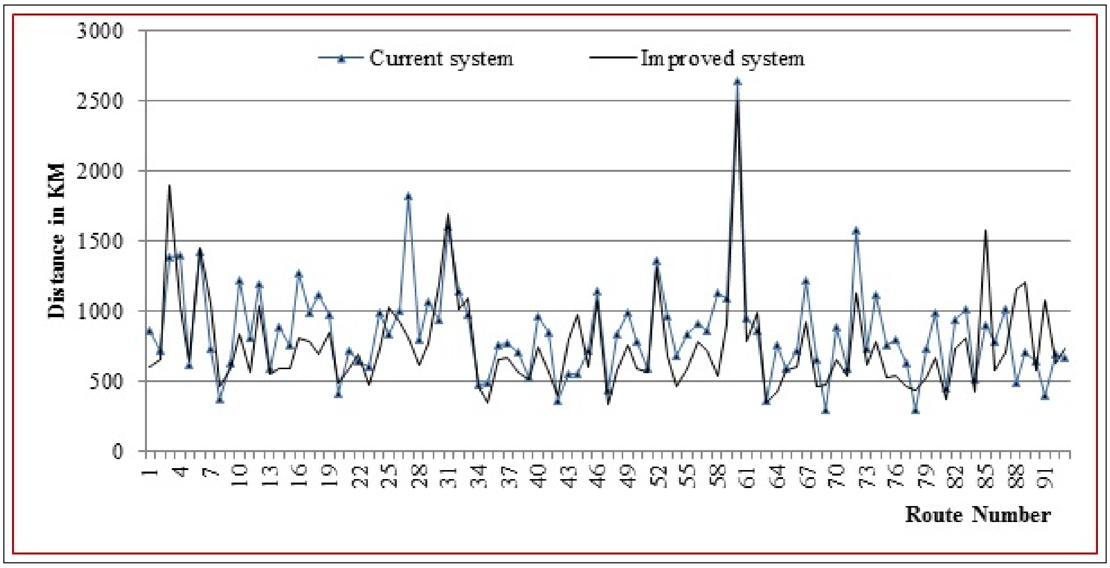

Figure 5.5: Distance coverage of the current and the improved systems

5.9.3 Operating Costs

The improvements made were also validated using the different operating costs of the enterprise. Total daily operating cost for each route is the sum of operating cost for all the shifts. From the comparison shown in Figure 5.6, the finding show that the average daily operating costs for the existing systems is $1,101,283.68 ETB$ while for the improved systems is $949,991.49 ETB$ (1USD = 18.85ETB). This shows a saving of 13.74% per day over the current system. As shown in Figure 5.6, the improvements made by the new systems are achieved nearly in all the operating costs of the enterprise.

As compared to other operating costs, larger saving is observed on gas oil. This also has a strong relation to the total Kilometer and trips covered since the total kilometer and trips covered is improved the gas and oil cost is also improved.

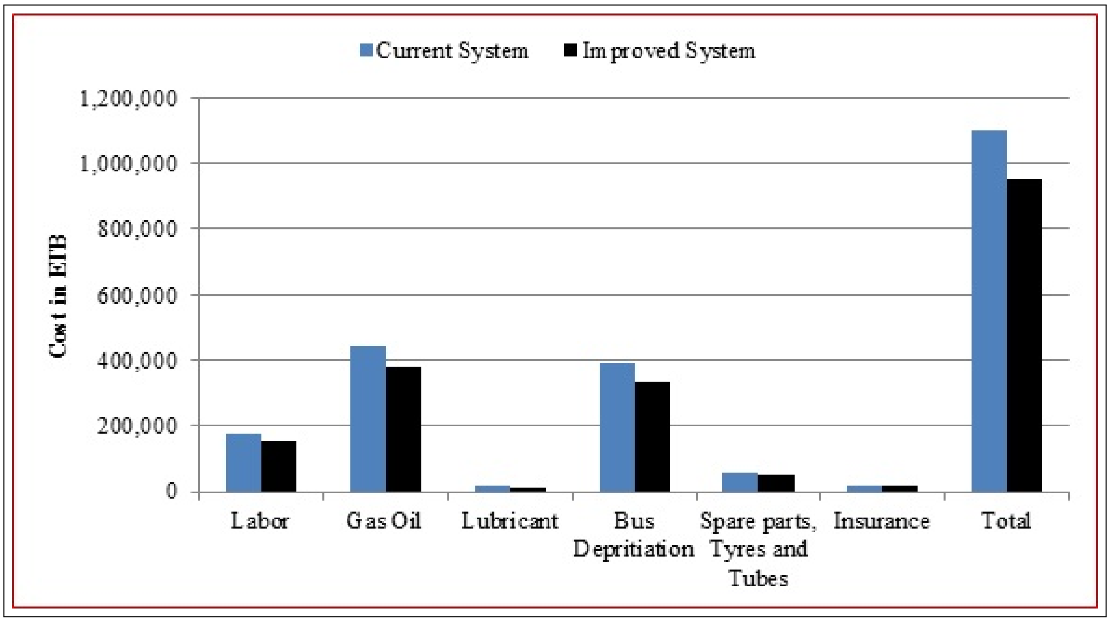

Figure 5.6: The operating costs of the current and the improved systems

5.10 Summary

The findings of the study shows that the current scheduling systems of ACBSE shows low performance on the bus utilization, operating cost and daily trips due to the fixed bus assignment without considering the demand variation. However the new model shows better improvement over the current system nearly with all the above parameters. The current scheduling system has an average utilization of 64.26% while the improved system has 66.33%. Moreover, on shift basis, the new system showed significant improvement over the existing system. The proposed system also shows a saving of 13.74% (151,292.19 ETB) over the current system on the daily bus operating cost. The new system has also a reduction on the total daily Km coverage while improving the total daily trips. Thus the LP model developed can solve the bus scheduling problems in a fastest way and applicable ways. However, due to poor data handling in ACBSE, the model was run based on average demand per shift. If the demand distribution was used per hour per day, the quality of the solution would be improved.

Chapter 6

Reroute Model for ACBSE

The improvement made in Chapter 5, focused to determine the optimum buses required for the existing routes. However, if the demand and distance of all origin-destination would be considered, in the model development process, the solution might have better improvement on the performance of ACBSE. In the previous chapter, a deterministic demand assumption was considered during the LP-model to simplify the model. But practically, passenger arrivals are random in nature. Therefore, in this chapter, using different assumptions the stochastic passengers' demand is evaluated using a Mixed Integer Programming model.

The chapter considerers Stochastic VRP with Simultaneous Pickup and Delivery (SVRPSPD) to develop a new model for ACBSE bus. To develop the mathematical model for the SVRPSPD with simultaneous pickup and delivery, a modification of different models from previous studies were considered. The nature of the stochastic passengers' demand are adopted from [8, 9, 11, 22, 26, 29, 43, 47, 53, 64, 65, 102, 119, 120, 121]; the incapacitated vehicle (limited capacity) from [65, 77, 26]. The simultaneous pick-up and delivery service by a single vehicle along the route is developed by modifying the alternative pickup and delivery service from the work of [58, 73]. This chapter addresses the gap assessed in the literature review in section 2.5.3.

The dissertation improves the deterministic demand with stochastic passengers (on both at pickup and delivery points) from the work of [73, 75]. The reason is that, at each stop except the depot, there are passengers which require ride or drop service. The passengers which ride or loaded at a given node or vertex (which is called bus stop) is considered as a pickup and the passengers which unloaded or alighted from the bus on the same node or vertex is also considered as delivery or dropped. Now onwards the term pickup and delivery is consistently used in the model representations to mean loading and unloading of passengers.

6.1 Model Formulation

The model development is the first of its kind in the consideration of the following points. It considers VRP with real simultaneous pickup and delivery at each bus stop, the pickup and delivery demand at each bus stop is treated as stochastic and random. As far as the knowledge gained, so far from the literatures, this type of VRP is the first variant in its kind. After browsing various literatures [8, 9, 11, 22, 26, 29, 43, 47, 53, 64, 65, 102, 119, 120, 121]considered stochastic passenger demand only in the pickup services. [58, 73] consider the simultaneous pickup and delivery service, but on their research they only considered the pickup and delivery services alternatively not simultaneously but they called it simultaneous pickup and deliver.

In addition to the assumption stated in section 2.5.1, that in the classical VRP, the following assumptions are also considered in the model development.

1. The number of passengers expected to be picked up and dropped are uncertain, but follows a Poisson Probability Distribution.
2. The cumulative number of passengers picked up and delivered along the route will not exceed the vehicle capacity. Moreover, split delivery is not allowed.
3. The fleet consists of homogenous vehicles with limited capacity operating from a single depot.
4. Each vehicle can be used repeatedly within the planning horizon

The mathematical model for SVRP which considered a simultaneous pickup and delivery techniques is modeled as a mixed integer LP problem and is formulated as follows. Let there be a fleet of K vehicles with $k = \{1, 2, \ldots, K\}$ with identical vehicle capacity of Q serving a set of passengers with demand (to be picked or dropped) in passenger's location $V \setminus \{0\}; v_0 =$ depot, each passenger must completely be serviced by a single vehicle. Each vehicle starts from the dept v_0 and picked and/or dropped passengers on node v_i except the depot. Moreover, the first node v_1 is treated as pickup node and the last node before the depot v_n is treated as only dropped node.

Suppose a vehicle starts from the depot v_0 and travels along a certain path until it reaches, node v_n, along the vertices $(v_1, v_2, \ldots, v_n)$ the vehicle will pick and/or drop passengers up to the last node v_n along the path. Let the cumulative number of passengers picked by a vehicle k be represented as C_p and the cumulative number of passengers dropped be C_d along the path on node v_n $(v_1, v_2, \ldots, v_n)$ and these are given by:

$$C_p(V_n) = \sum_{i \in V(0,V_n)} p_i \tag{6.1}$$

$$C_d(V_n) = \sum_{i \in V(0,V_n)} d_i \tag{6.2}$$

Where p_i is the number of passengers picked up at node i and d_i is the number of passengers dropped at the same node i. At the depot, $C_p = C_d = 0$ and the vehicle capacity equals Q, and the path will not become feasible if the cumulative load exceeds the vehicle capacity Q, that is when: $C_d \geq Q$ and $C_p \geq Q$.

Each feasible route will be formed when: $C_d(v_n) \leq Q$ and $C_d(v_{n+1}) \geq Q$ and $C_p(v_n) \leq Q$ and $C_p(v_{n+1}) \geq Q$. The other consideration checks whether the net load of a bus for any consecutive nodes will not exceed the bus capacity after the bus visiting node v_n. Let the net load picked be $L_p(v_n)$ and it is computed as $L_p(v_n) = C_p(v_n) + L_p(v_{n-1}) - C_d(v_n)$.

The solution will be feasible if a vehicle serviced all its demands (picked or dropped) at each node along the path or route without exceeding its capacity. That is the net load in transit between any consecutive nodes or vertices should not exceed the vehicle capacity $(L_p(v_n) \leq Q$. The objective is to determine a route for each vehicle that serves a set of nodes (v_i) such that the total distance traveled is minimized.

To formulate the model of SVRP with simultaneous pickup and delivery as Mixed Integer LP problem, the following notations and definitions are considered.

Notations

V is set of nodes or vertices $V = \{v_0, v_1, v_2, \dots, v_n\}$ treated as bus stops; v_0 = depots
A is set of arcs $(i, j) \in A$
K is number of vehicles $k = \{1, 2, \dots, K\}$
c_{ij} is the distance traversing from node i to node j
p_i is the number of passengers (demand) to be picked at node i, which is a random non-negative integer
d_i is the number of passengers (serviced) to be dropped at node i which is a random non-negative integer
Q the vehicle capacity
n total number of nodes or vertices or bus stops included in the model.

Decision Variables (6.3)

---

y_i^k =The cumulative number of passengers picked by vehicle k when leaving from node i
z_i^k =The number of passengers remaining in vehicle k when leaving from node i
$x_{ij}^k = 1$, if vehicle k travels from node i to node j; 0 otherwise.

Then general model is represented as follow:

$$\text{Minimize} \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij}^{k} \tag{6.4}$$

Subject to

$$\sum_{j=1}^{n} x_{0j}^{k} \leq 1; \tag{6.5}$$

$$\sum_{i=0}^{n} x_{ij}^{k} = 1; \tag{6.6}$$

$$\sum_{i=0}^{n} x_{ij}^{k} - \sum_{i=0}^{n} x_{ji}^{k} = 0; \tag{6.7}$$

$$z_i^k + y_i^k \leq Q; \tag{6.8}$$

$$(z_i^k - d_j - z_j^k) x_{ij}^k = 0; \tag{6.9}$$

$$(y_i^k + p_j - y_j^k) x_{ij}^k = 0; \tag{6.10}$$

$$z_0^k = y_0^k = 0; \tag{6.11}$$

$$z_i^k \geq 0; \tag{6.12}$$

$$y_i^k \geq 0; \tag{6.13}$$

$$x_{ij}^k \in \{0, 1\}; \tag{6.14}$$

$$\forall_k = 1, \ldots, K \quad and \quad i, j = 1, \ldots, n \tag{6.15}$$

The decision variables are given in equation 6.3, equation 6.4 is the objective function to be minimized. Equation 6.5 ensures that each vehicle is used at most once, equation 6.6 indicates that each node has to be visited exactly by one vehicle, equation 6.7 shows that the same vehicle arrives and departs from each node it serves, 6.8 ensures that the load on vehicle k when departing from node i is always less than the vehicle capacity. 6.9 and 6.10 are the transit load constraint, which indicate that when arc (i, j) is traversed by vehicle k, the number of passengers to be dropped by the vehicle has to be decreased by d_j while the number of passengers picked-up has to be increased by p_j. 6.11 ensures that the remaining and the cumulative number of passengers when a vehicle k departs from the depot is always zero; indicates that the vehicle is empty and available with full capacity. Constraints 6.12 and 6.13 are a non-integer and non-negative sign restriction and the last equation 6.14 is an restriction on the non-negative integer value. The lower bound of the model can be estimated with the assumption of a homogenous vehicles with same capacity "Q". The minimum number of vehicles K can be determined as follow:

$$K = max \left\{ \left| \frac{\sum_{i=1}^{V} d_i}{Q} \right|, \left| \frac{\sum_{i=1}^{V} p_i}{Q} \right| \right\} \tag{6.16}$$

6.2 Modifying the New Model

VRPs are commonly known as Non-Polynomial Hard (NP-Hard) models[33, 36, 37]. This is because as the number of variables and input parameters are increased, their complexity increased exponentially. Solving the above model, as it is, would therefore be very complex and demands more resource. It may also not guarantee an optimal solution. Therefore, based on the above assumptions, the model is modified and improved so that it can be solved using heuristics approaches but without losing its generality. The modification made is used to solve the model as a TSP with simultaneous Pick-up and Delivery (TSPSPD), but can also easily be extended to solve SVRP with simultaneous pick-up and delivery using Clarke-Wright algorithm.

To reduce the number of variables, one approach is to reduce the pickup and drop service by one variable. Let $\delta_i = p_i$ - d_i. When $\delta_i \leq 0$, it is only delivery or alighting passengers in node i and will not be considered as demand but used to replenish the capacity of the vehicle by the same amount as $q_i + \delta_i$. When $\delta_i \geq 0$, there is pick-up service or passengers will board the bus and considered as passengers' demand that can deplete the vehicle capacity. At each stage of the computation, the feasibility was checked.

Thus based on this consideration, the above model is modified and shown in equation 6.17 to 6.24. It is modified with the assumptions and considerations stated in section 6.1 and fitted based on the input parameters in Table 6.3 and section 6.4. The explanation of each equation is similar to the previous model except they are modified and reduced.

$$\text{Minimize} \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{j=0}^{n} c_{ij}x_{ij}^{k} \tag{6.17}$$

Subject to

$$\sum_{j=1}^{n} x_{0j}^{k} \leq 1; \tag{6.18}$$

$$\sum_{i=0}^{n} x_{ij}^{k} = 1; \tag{6.19}$$

$$\sum_{i=0}^{n} x_{ij}^{k} - \sum_{i=0}^{n} x_{ji}^{k} = 0; \tag{6.20}$$

$$\sum_{i=0}^{n} \delta_i^k x_{ij}^{k} \leq Q; \tag{6.21}$$

$$\delta_i \geq 0; \tag{6.22}$$

$$x_{ij}^{k} \in \{0,1\}; \tag{6.23}$$

$$\forall_k = 1,\ldots,K \quad and \quad i,j = 1,\ldots,n \tag{6.24}$$

6.3 Modeling the Stochastic Passengers' Demands

The number of passengers picked up at each vertex V are integer-valued random variables with known probability distributions and are denoted by vector $\widetilde{p}(i) \in Z$. Passengers are assumed to be independently distributed. [58] assumed that there is a vector $\underline{p} \in Z$ known such that $\underline{p} \leq \widetilde{p} \leq \overline{p}$ and $\overline{p}(i) > 0$ and $\overline{p}(i) < Q$ for all $i \in V$. Further it can be assumed that there is a positive probability at each demand $\widetilde{p}(i) \geq 0$ that takes every value in the range $[\underline{p}(i),\ \overline{p}(i)]$, then the outcome space $\bigcup$ of demand realizations of p is given by:

$$\bigcup = \{p(i) \in Z : \underline{p} \leq \widetilde{p} \leq \overline{p}\}$$

Finally, for convenience of notation, it can be defined that $\underline{p}(0) = \overline{p}(0) = 0$. Uncertain passengers are assumed to be revealed with certainty at some time immediately prior to or within each operating time. For example, a common assumption is that passengers become known upon the arrival of a vehicle.

But according to [57], two different models were considered and analyzed; namely demand based and capacity based risk modeling. In the demand based modeling individual demand are estimated by using parameter $\gamma = \{0, 1\}$, which determines the risk preferences.

Therefore, the demand used for computing the solutions are computed as $\hat{p} = \gamma p_i^{min} + (1 - \gamma)p_i^{max}$. Similarly, $\hat{d}$ is also computed using the same formula. $\gamma = 0$ clearly implies the risk averse (risk free) case where failure can never occur, while $\gamma = 1$ is the other extreme, which is risk seeking. Moreover, $\gamma = 0.5$ corresponds to computing solutions with the expected demand.

The other model is the capacity based risk modeling approach which is assuming that $\gamma = 0$. Which means the maximum number of passengers may be greater than the vehicle capacity Q. In such cases, the vehicle capacity is modified according to the following consideration. The approach used a parameter $\beta > 0$ that adjusts the vehicle capacity according to the risk preferences of the decision maker. The model characterized by $\hat{Q} = (1 + \beta)Q$, where Q is the actual vehicle capacity and $\hat{Q}$ is the adjusted capacity. In the solution analysis of [57] the worst result is obtained if the risk modeling strategy parameter γ and β reflect risk seeking behavior (i.e. $\gamma > 0.5$ or $\beta > 0.3$) while for the *Monte Carlo* strategy the risk free case, i.e. $\gamma = 0$ or $\beta = 0$, but leads to higher cost.

The stochastic nature of picked and dropped passengers are modeled based on the demand distribution given in section 6.3. According to the simulation run, the demand distribution of the number of passengers picked up and delivered for some nodal points are given below in Table 6.3. The values are computed by taking $\gamma = 0.4$ and $\beta = 0.3$. This consideration is used to minimize the risk that failure can occur in satisfying the demand. Using this value the probability of the number of passengers to be picked-up ($\hat{p_i}$) and dropped ($\hat{d_i}$) is computed from passengers demand data that follow a poison probability distribution. The findings of the demand distribution was validated using primary data collected from 10 different routes at different working time. Then the difference between the number of passengers picked-up and dropped, that is $\delta_i = \hat{p_i}$ - $\hat{d_i}$ is computed and presented in Table 6.3. If $\delta_i \leq 0$ indicating that $\hat{p_i}$ and $\hat{d_i}$ are either the same or there is no passenger picked-up or the expected number of passengers dropped ($\hat{d_i}$) is greater than picked up ($\hat{p_i}$).

6.3.1 Model Fitting

To fit and test the model, some modification have to be made on depot consideration. In this regards, since ACBSE do not provide services from its depot, the terminals which are serving as origin are treated as depot. Further, the remaining origin-destinations are treated as passengers' location points, which is expected to have simultaneous pick-up and delivery services.

The dissertation considered Merkato Terminals as depot and routes that originate and destined at Merkato terminals are treated as passenger point or vertex where picking and dropping passengers are taking place. The demand (pick-up and delivery) along those routes are treated as a random variable that follows a discreet uniform distribution. In the model fitting processes, the following terms are defined and used.

Passengers and depot: $V = \{v_0, v_1, \ldots, v_{58}\}$ is a set of nodes with node v_0 denoting the depot, which is "Merkato" terminal, and nodes $v_1, \ldots, v_{58}$ correspond to the locations of passengers to be picked or dropped. Thess locations are origin-destination points from “Merkato”. It is assumed that all nodes, including the depot, are fully interconnected and there are passengers’ required for both pick-up and drop service except the depot.

Demands: Passengers have stochastic demands (δ_i), which follow a Poison Distributions. Assume further that passengers demands are independent. Actual passengers demand of each location i is only known when the vehicle arrives at passengers location i.

Vehicles and capacity constraint: The vehicle has a limited capacity of Q =70. If the total passengers (the cumulative of the difference between dropped and picked up that is δ_i) exceeds the vehicle capacity, route failure is said to be occurred. But no penalty cost assumed in this case. At each stop when $\delta_i > 0$, which indicates that more number of passengers are picked than dropped; decreasing vehicle capacity, then the vehicle capacity is updated to $Q - \delta_i$ and δ_i becomes the net demand at that node. Whereas when $\delta_i < 0$, which means more number of passengers are dropped than picked; increasing vehicle capacity, then the vehicle capacity is updated to $Q + \delta_i$ and the demand will be zero (see also Table 6.3).

Route: A route must start at the depot, visit a number of passengers (nodes) and return to the depot. A feasible solution to the SVRPSPD is a permutation of the customers $s = (s(1), s(2), \ldots, s(n))$ starting and ending at the depot (that is, $s(1) = s(n) = 0$) and it is called a priori tour. In the model, though in reality it is not exactly true, it assumes there would be roads that can connect from one vertex to the other. This assumption is very important during searching of possible routes that can minimize the total distance.

Distance to be minimized: let $A = (i, j) : i, j \in V, i \neq j$ is the set of arcs joining the nodes and a non-negative matrix $C = \{c_{ij} : i, j \in V, i \neq j\}$ denotes the traveling distances between nodes i and j. Further, assumes the distance matrix C is symmetric and satisfies the triangular inequality. The from-to-distance of a sample of origin-destination are computed from the digital latitude and longitude data using great circle computation and presented in Table 6.3.

6.3.2 Sample Routes to Test the Model

Origin destination routes that depart and end from Merkato terminal(lati. of 9°1'50"N and Longi. of 38°44'15"E) are used in the model validation. The origin-destination points are modified in such a way that they can fit to the model but without losing its information.

The digital data of each origin-destination of Merkato terminal shown in Table 6.1 is collected from Google Earth. the existing routes, 27 origin-destination routes were taken as a sample. Merakto terminal is considered as depot and the other origin-destinations are treated as bus stops where passengers are located. Including the recently added 4 locations, 58 passenger location points are used to simulate the model excluding the depot. Table 6.1 shows the name, latitude and longitude of the 27 routes. Later for the model simulation, they are changed to 54 location points and including the added 4 routes, a total of 59 location points were considered.

Table 6.1: Origin-destination of selected route from Merkato terminal

S/N	Route No	Origin	Latitude	Longitude	Destination	Latitude	Longitude
1	2	Kore Mekanisa	8°58’49”N	38°42’54”E	Addis Ketema	9°2’4”N	38°43’54”E
2	4	Kality	8°56’4”N	38°45’55”E	Addis Ketema	9°2’4”N	38°43’54”E
3	8	Semen Gebeya	9°3’38”N	38°44’11”E	Addis Ketema	9°2’4”N	38°43’54”E
5	13	Bella	9°2’34”N	38°46’56”E	Addis Ketema	9°2’4”N	38°43’54”E
6	15	Megenagna	9°1’10”N	38°48’6”E	Addis Ketema	9°2’4”N	38°43’54”E
7	17	Kuskuam	9°4’40”N	38°45’22”E	Addis Ketema	9°2’4”N	38°43’54”E
8	18	Keranyo	9°0’52”N	38°42’22”E	Addis Ketema	9°2’4”N	38°43’54”E
9	23	Lamberet	9°2’8”N	38°49’41”E	Addis Ketema	9°2’4”N	38°43’54”E
10	24	Burayu	9°4’30”N	38°40’34”E	Addis Ketema	9°2’4”N	38°43’54”E
11	26	Addis Ketema	9°2’4”N	38°43’54”E	Sebeta	8°54’50”N	38°37’47”E
12	28	Asko sansuzi	9°3’54”N	38°41’35”E	Addis Ketema	9°2’4”N	38°43’54”E
13	29	Addisu Sefer	8°57’37”N	38°46’3”E	Addis ketema	9°2’4”N	38°43’54”E
14	30	Sululta	9°6’46”N	38°44’20”E	Addis Ketema	9°2’4”N	38°43’54”E
15	34	Gofa Camp	8°58’0”N	38°44’27”E	Addis Ketema	9°2’4”N	38°43’54”E
16	35	Lafto	8°56’48”N	38°44’36”E	Merkato	9°1’50”N	38°44’15”E
17	39	Bole School	8°59’53”N	38°47’20”E	Addis Ketema	9°1’50”N	38°44’15”E
18	43	Menagesha	9°3’22”N	38°34’5”E	Merkato	9°1’50”N	38°44’15”E
19	44	Legedadi	9°5’18”N	38°55’40”E	Merkato	9°1’50”N	38°44’15”E
20	51	Betel	9°0’15”N	38°41’34”E	Merkato	9°1’50”N	38°44’15”E
21	52	Gerji	8°59’57”N	38°48’49”E	Merkato	9°1’50”N	38°44’15”E
22	65	Merkato	9°1’50”N	38°44’15”E	World Bank	8°59’43”N	38°41’2”E
23	74	Gurd sholla	9°1’22”N	38°50’25”E	Merkato	9°1’50”N	38°44’15”E
24	85	Addis Ketema	9°1’50”N	38°44’15”E	Holeta	9°3’29”N	38°30’4”E
25	88	Addis Ketema	9°1’50”N	38°44’15”E	Chancho	9°18’38”N	38°45’11”E
26	89	Addis Ketema	9°1’50”N	38°44’15”E	Sendafa	9°9’1”N	39°1’16”E
27	91	Legehare	9°0’35”N	38°45’12”E	Tefki	8°50’46”N	38°29’39”E

6.3.3 Data Generation

From the literature review, so far conducted, there is no commonly used benchmark for the SVRPSPD, therefore a new test bed is generated to test the model. It considers 25 sets of randomly generated instances that simulate real problem data from passengers demand distribution of ACBSE collected in 10 selected routes. To fit the data to the model, Merkato terminal is treated as depot and labeled as v_1. The data are used as input parameters for the model.

6.4 Input Parameters to the Model

To run and test the model, different input parameters that have to be substituted to the model are required. These inputs are either collected or generated/computed.

The from-to-distance, the demand realization probability, the demand distributions are computed or generated whereas the longitude and latitude value for each location point v_i is collected from the Google Earth. Each of them are briefly explained and presented in section 6.4.1 and 6.4.2

6.4.1 From-to-Distance

The from-to-distance computational input parameters of each location i is computed by taking the longitude and latitude location of each point using Great Circle distance formula that considers the circular nature of earth. It is computed as:

$d_{ij} = arccos(sin(lat_1) * sin(lat_2) + cos(lat_1) * cost(lat_2) * cost(lon_2 - lon_1)) * R$, where R = earths radius (mean radius = 6,371km).

Table 6.2: From-to-distance matrix (C_{ij})

v_{ij}	1	2	3	4	5	6	7	8	.	.	.	57	58	59
1	0	8	17	7	7	8	1	1	.	.	.	17	20	19
2	8	0	11	7	2	8	9	7	.	.	.	22	14	23
3	17	11	0	11	13	10	18	15	.	.	.	33	20	21
4	7	7	11	0	8	1	8	6	.	.	.	24	21	15
5	7	2	13	8	0	9	8	7	.	.	.	20	14	24
6	8	8	10	1	9	0	10	7	.	.	.	26	22	15
7	1	9	18	8	8	10	0	3	.	.	.	16	21	20
8	1	7	15	6	7	7	3	0	.	.	.	19	20	18
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
57	17	22	33	24	20	26	16	19	.	.	.	0	27	34
58	20	14	20	21	14	22	21	20	.	.	.	27	0	37
59	19	23	21	15	24	15	20	18	.	.	.	34	37	0

Each c_{ij} is defined as the distance from i to j, which can be directly considered as the cost associated to transport passenger including depot 1. Further, it assumes the distance is symmetric, that $c_{ij} = c_{ji}$ and $c_{ii} = 0$. The sample output is shown in Table 6.2. This data is substituted in equation 6.17 in the mathematical model developed in section 6.2.

6.4.2 Stochastic Passengers Demand

The passengers' demand collected in 10 routes of ACBSE are used to fit the demand behavior of passengers in the remaining routes. The snap shot of the demand distribution of passengers picked and dropped along the 10 selected routes were used to fit the demand of the remaining routes. The demand distribution of passengers (roundup values), picked up ($\hat{p_i}$) and passengers dropped ($\hat{d_i}$), the difference between pickup and dropped (δ_i), the demand realization probability, which is computed using the risk modeling strategy parameter (γ), and each digital location point i are reported in Table 6.3. The radian location point shown in Table 6.1 is transformed in to decimal value and are reported in Table 6.3.

Table 6.3: Sample demand distribution and location data

v_i	Location(decimal)		Expected Passengers			Demand
	Longi.	Lati.	$\gamma = 0.4$	$\hat{p_i}$	$\hat{d_i}$	δ_i
1	38.8	9.16	na	na	na	na
2	38.9	9.1	0.22548	18.42	12.12	7
3	38.9	8.94	0.5913	8.35	11.40	0
4	38.8	9.16	0.5913	16.83	11.55	6
5	38.9	9.13	0.5913	8.50	4.29	5
6	38.8	9.04	0.4822	5.58	8.98	0
7	38.8	9.18	0.4822	17.17	8.91	9
8	38.8	9.14	0.4822	17.93	12.94	5
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
57	38.6	9.11	0.6555	14.72	14.93	0
58	39.0	9.13	0.31308	12.42	12.00	1
59	38.8	9.04	0.31308	11.56	4.99	7

Moreover, the model considered a capacitated vehicles with a capacity of 70 passengers which can be used repeatedly during the service horizon. The customers' demand, δ_i, are following Poison Probability Distribution with average arrival rate of $\lambda = 7.397$. The demand distribution of all the 58 customer location points for all the 25 instances are generated using the Poison Probability Distributions. The probability density function is shown in Figure 6.1. It is tested using Chi-Square goodness of fit (GOF) test and found significant with statistic value of 0.15 which is less than the critical value of 0.175 at 5% significant level.

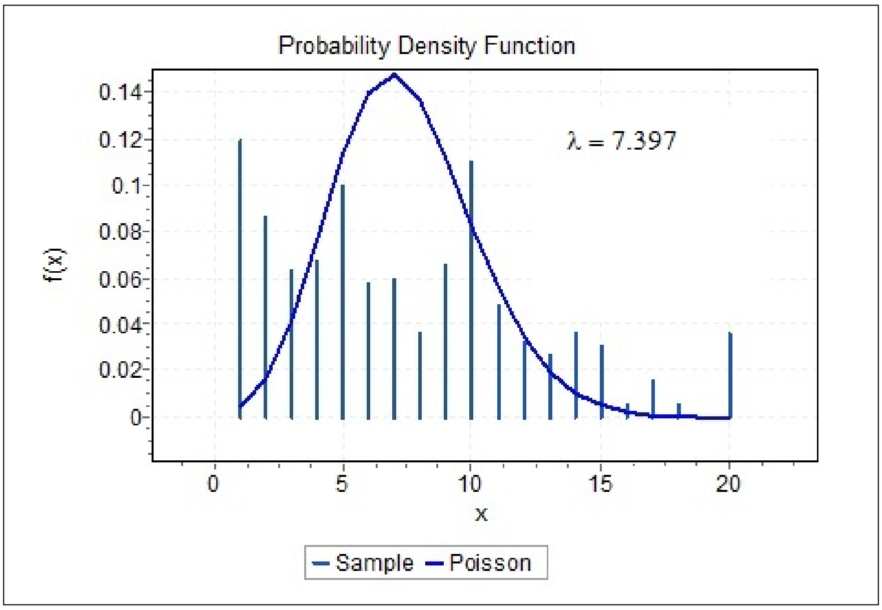

Figure 6.1: Poison PDF of passengers demand distribution

6.5 Solution Approach

A heuristic procedure developed for the classical VRP have been extended to solve SVRPSPD developed above. The heuristics adopted is Clarke-Wright algorithm. The Clarke-Wright algorithm is iteratively repeated for each node as a starting node with the objective of improving the quality of the solution. The following assumptions were considered during solving the model.

- All routes start and end at the node of origin, also known as depot.
- Each node in v_i is visited exactly once by a vehicle.
- The cumulative demand along the route or demand at any node shall never exceed the vehicle capacity Q.

- All vehicles have the same capacity and are stationed at the node of origin.
- Split delivery is not permitted.
- Each vehicle makes exactly one trip.

The task is to determine a route for each vehicle so as to serve a set of nodes such that the total distance traversed is minimal. The initial solution using a Clarke-Wright algorithm is obtained using the following steps:

- Step 1. Select any node as the central depot which we denote as node 1.
- Step 2. Compute savings $s_{ij} = c_{1i} + c_{1j} - c_{ij}$ for i, j = 2, 3 ,. . . , n.
- Step 3. Order the savings from largest to smallest.
- Step 4. Starting at the top of the savings list and moving downward, form larger sub-tours by linking appropriate nodes i and j and determine the net passengers' demand, $L_p(v_n)$, in which the vehicle reaches the maximum load Q. If $L_p(v_n) \leq Q$, the tour is feasible. That is the total cumulative demand $L_p(v_n)$ should be less than or equals to the vehicle capacity Q. Otherwise the model need to define a new tour in which node v_{n+1} will be the starting node and passenger's demand $L_p(v_{n+1})$ takes the first position.
- Step 5. Insert the depot between the first and the last nodes of the tour.
- Step 6. Repeat from step 2 until all passengers are visited.

Since the model developed is new, most of the time, the worst case behavior in such an algorithm is not known . [60] demonstrates, however, that for a sequential version of such an algorithm where at each step selecting the best savings from the last node added to the sub-tour the worst case ratio is bounded by a linear function in $lg(n)$ that is a running time of 5.88. Thus, the Clarke and Wright savings procedure for this model requires on the order of $n^2 lg(n)$ computation, which is about 6164.336 computations in this case. (Note: $lg(n)$ is logarithm function to the base 2).

Using the above approach, the model has solved using Clarke-Wright savings algorithm for vehicle routing problems. It takes input from a text file listing each customer's location (latitude and longitude) and stochastic demand (δ_i) at each location except the depot (demand at depot is zero) 25 times for each instance. It builds vehicle routes that visit every city exactly once and that obey vehicle capacity.

Using the Clarke-Wright savings algorithm, route is constructed by incrementally selecting passengers along the nodes until the cumulative number of passengers reach the vehicle capacity or all customers are visited. Initially each vehicle starts at the depot Merkato (v_1) empty and set passengers included in the tour. The algorithm selects the next customer to visit from the list of feasible locations and the capacity of the vehicle is updated before another location is selected. The vehicle returns to the depot (Merkato) when the capacity constraints of the vehicle is met or when all the passengers at each location are visited. Finally the total minimum distance σCij is computed as the objective function value for the complete route of the vehicle. For each route, the total demand $L_p(v_n)$ and the CPU computation time are also computed. The model is solved using GAMS software and solver CPLEX and run on a Dell Personal Computer with Intel-Pentium corei5 3.1 GHz processor.

6.6 Outputs of the Model

The Clarke-Wright savings algorithm constructs complete tour for the first vehicle prior to the second starting its tour. The procedure continues until all the passenger locations are included in the tours or until all the passengers are visited. As shown in Table 6.4, the first run of the algorithm terminates with 6 possible routes. Since the number of vehicles is not limited, it will be determined by the number of routes formed. The algorithm first solves the problem using the nearest saving heuristic to create sub-cycles that are both drop and pick-up feasible at each node with vehicle capacity $Q = 70$ passengers. This gives the following six routes:

Route 1: $1 \rightarrow 8 \rightarrow 16 \rightarrow 4 \rightarrow 13 \rightarrow 32 \rightarrow 20 \rightarrow 15 \rightarrow 59 \rightarrow 40 \rightarrow 1$.
Distance Traveled = 46.28, Total passenger demand = 61

Route 2: $1 \rightarrow 10 \rightarrow 5 \rightarrow 2 \rightarrow 31 \rightarrow 11 \rightarrow 21 \rightarrow 3 \rightarrow 33 \rightarrow 58 \rightarrow 19 \rightarrow 49 \rightarrow 1$
Distance Traveled = 61.97, Total passenger demand = 70

Route 3: $1 \rightarrow 18 \rightarrow 45 \rightarrow 46 \rightarrow 52 \rightarrow 48 \rightarrow 47 \rightarrow 50 \rightarrow 38 \rightarrow 39 \rightarrow 54 \rightarrow 1$
Distance Traveled = 100.297, Total passenger demand = 62

Route 4: $1 \rightarrow 24 \rightarrow 6 \rightarrow 57 \rightarrow 26 \rightarrow 51 \rightarrow 27 \rightarrow 30 \rightarrow 29 \rightarrow 41 \rightarrow 22 \rightarrow 1$
Distance Traveled = 106.25, Total passenger demand = 69

Route 5: $1 \rightarrow 25 \rightarrow 7 \rightarrow 28 \rightarrow 123 \rightarrow 55 \rightarrow 17 \rightarrow 23 \rightarrow 14 \rightarrow 9 \rightarrow 1$
Distance Traveled = 28.72, Total passenger demand = 44

Route 6: $1 \rightarrow 55 \rightarrow 43 \rightarrow 42 \rightarrow 34 \rightarrow 35 \rightarrow 37 \rightarrow 36 \rightarrow 44 \rightarrow 53 \rightarrow 1$
Distance Traveled = 110.84, Total passenger demand = 52

It was observed that in the above route and data presented in Table 6.4 all the six routes are feasible load in terms of vehicle capacity and can be used as a feasible solution. If route one is considered, the tours are formed from depot 1 and visit the las passenger at location point 40 and returns back to the depot. The overall tour for route or sequence of travel is:

$1 \rightarrow 8 \rightarrow 16 \rightarrow 4 \rightarrow 13 \rightarrow 32 \rightarrow 20 \rightarrow 15 \rightarrow 59 \rightarrow 40 \rightarrow 1$. Along the tour, the vehicle carried 61 passengers and travels a total distance of $46.28Km$. Total passengers demand in each route is less than the vehicle capacity.

Table 6.4: Tabular representation of the first run

Route	Parameter	Route Parameters													Total
1	Tour	1→	8→	16→	4→	13→	32→	20→	15→	59→	40→	1			
	Demand	0	8	5	3	5	9	4	13	14	0				61
	Km	1.38	4.83	.69	.69	.69	2.07	2.76	13.66	8.78	10.73				46.28
2	Tour	1→	10→	5→	2→	31→	11→	21→	3→	33→	58→	19→	49→	1	
	Demand	0	11	5	2	0	0	0	10	9	18	15	0		70
	Km	.69	.69	2.07	.69	3.45	2.07	4.83	9.70	10.21	7.12	7.36	6.82		61.97
3	Tour	1→	18→	45→	46→	52→	48→	47→	50→	38→	39→	54→	1		
	Demand	0	7	1	11	12	6	7	9	1	2				62
	Km	14.06	7.64	6.82	6.82	6.13	5.47	2.04	28.50	6.82	8.36	7.64			100.29
4	Tour	1→	24→	6→	57→	26→	51→	27→	30→	29→	41→	22→	1		
	Demand	0	14	13	6	5	0	12	6	5	6	0			69
	Km	13.81	0	3.45	3.45	6.90	0	25.11	25.6	9	4.83	14.17			106.25
5	Tour	1→	25→	7→	28→	12→	55→	17→	23→	14→	9→	1			
	Demand	0	0	4	2	6	10	0	10	2	10				44
	Km	.69	.69	.69	.69	.69	1.38	2.07	7.97	4.14	9.70				28.72
6	Tour	1→	56→	43→	42→	34→	35→	37→	36→	44→	53→	1			
	Demand	0	0	14	0	8	4	0	14	0	12	0			52
	Km	20.55	27.58	7.13	6.82	6.82	6.82	0	0	20.87	14.25	0			110.84
Summary	Total Distance (Km)														454.36
	Total Passenger Demand														358
	CPU Time														0.55

Similarly, the remaining routes, from route 2 to 6, have similar tour as shown in Table 6.4. From the table the overall summary of a single run shows that the vehicles travel an average distance of 454.36 Km , carried 358 passengers along the route; and the run was performed with 0.55 seconds of CPU time. The illustrative view of the this run is shown in Figure 6.2.

The stochastic passenger demand was run 25 times to address the possible occupancies of passengers. In all the cases, the number of passengers pickup and deliver as well as the net passenger demand at each node was run 25 times and given as an input to the model. The output of this experiment is shown in Table 6.5. The findings show that a minimum and maximum distance covered is 432 and 646. The maximum CPU time recorded is 2.27 seconds which is the worst case, whereas the minimum CPU time is 0.13 seconds. The average performances of the model show that on average 6.48 routes are required to serve passenger demands of 271. with a

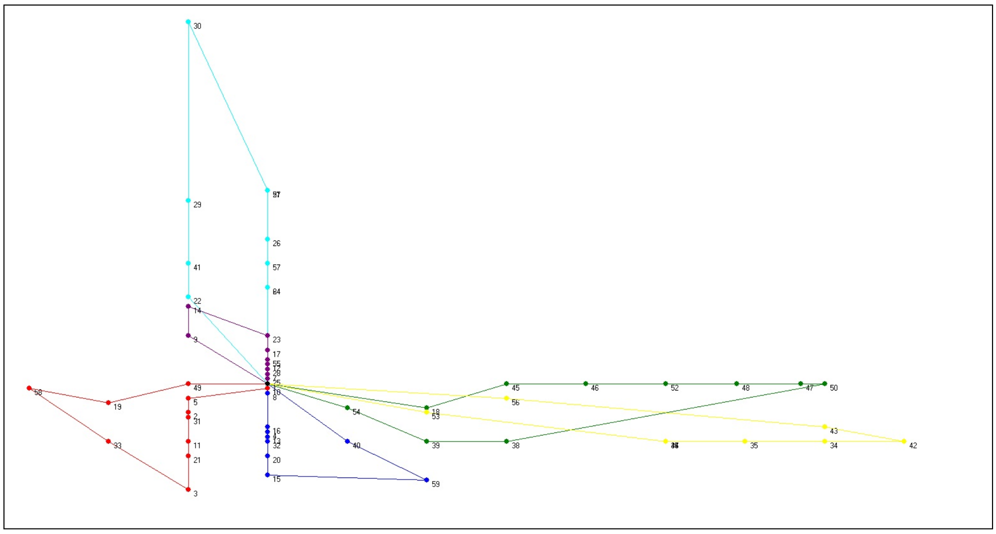

Figure 6.2: Graphical view of the first run

probability occurrence of 0.4356. During this service, the total distance traveled by the six vehicles in a single trip would be $552.92 Km$.

With graphical illustration, the worst and best case is shown in Figure 6.3. This comparison is made based on the total Kilometer coverage, total CPU time of this instance. Since the model is new comparison with previously developed instance is not possible.

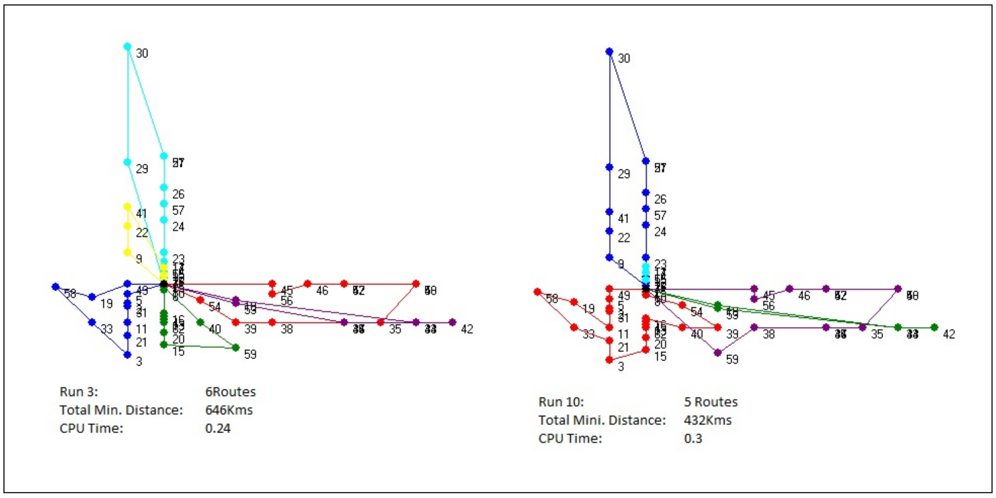

Figure 6.3: Comparison of worst and best solution

Table 6.5: Summary output of the 25 Run

Run	**Total Demand**	**Total Dinstance (Km)**	**Number of Routes**	**CPU Time**
1	358	454	6	0.55
2	427	568	8	0.89
3	298	646	6	0.24
4	285	443	6	0.20
5	285	474	6	0.13
6	286	591	7	0.22
7	285	467	6	0.22
8	285	592	7	0.31
9	284	510	6	0.41
10	217	432	5	0.30
11	217	587	5	0.25
12	257	589	7	2.27
13	237	571	6	0.44
14	275	593	7	0.55
15	234	572	6	0.42
16	277	580	7	0.22
17	326	583	7	0.27
18	258	579	7	0.25
19	263	586	7	0.28
20	242	580	7	0.27
21	179	570	6	0.28
22	289	588	7	0.37
23	271	583	7	0.26
24	244	574	7	0.33
25	268	588	7	0.27
Min	**179**	**432**	**5**	**0.13**
Max	**427**	**646**	**8**	**2.27**
Mean	**271.20**	**552.92**	**6.48**	**0.40**
Stdv	**49.49**	**61.09**	**0.77**	**0.42**

6.7 Summary

The improvement made on Chapter 5 is not a dramatic improvement. The reason is that, the model is developed with the existing routes. It focuses only improvement in bus assignment and its utilization. The initiation to develop a model that can design a new route by taking the stochastic passengers demand and from-to-distance as an input was developed and analyzed.

Due to un availability of continuous digital data and hourly passengers data, it was impossible to test the model in its full capacity as it is complete design in section 5.7. However, by taking the origin-destination of the sample routes of Merkato terminal as passengers location, the model was tested and it generates routes that can be feasible solutions to the model. The findings of the solution show that, the solution achieved at this level is feasible to consider as outputs to the solution space. But validating and testing the accuracy of the solution to the optimum solution is impossible. Moreover, the connected routes in the solution space may not be practical routes that exited in the city. This should be considered as a constraint in future research.

Chapter 7

Conclusion and Recommendations

7.1 Conclusion

Public bus transport is a very complex process in its operation, planning and scheduling. After a thorough literature review related to Vehicle Routing Problems (VRP) and its variances, the dissertation focuses on model development of bus scheduling ACBSE. The dissertation first evaluated the current performances of the enterprise, and then developed a LP-model that could improve the performances without altering the current routes and scheduling systems. It also developed Stochastic VRP model with real Simultaneous Pickup and Delivery (SVRPSPD) that could result in new routes which can be used for re-routing in the future.

From the findings of the study it can be concluded that both the operational and financial performances of the enterprise, as compared with the international standards, are relatively low in most of the performance measuring parameters. In the case of operational performance, the enterprise experienced low performance in all the parameters. In the case of Percentage Load Factor (PLF) though the overall average indications are very low, it shows slight improvement from month to month. Similar improvements are also observed on the Passengers per Vehicle per Day (PPVPD) after month nine.

Though, there are many new buses in the enterprise, the operational fleets still include many old buses which have more than 10 years of age. This adversely contributes to the low performances of the enterprise with regard to fuel consumption, distance and trips covered. Moreover, the revenue to cost ratio is less than one most of the time, even before tax and after excluding the depreciation cost, indicating that the enterprise is operating at a loss even before tax.

In addition to these, the existing scheduling systems of ACBSE has shown low performances on the bus utilization, operating costs, daily trips and distance covered. This is mainly due to the fact that fixed numbers of buses are assigned to routes without considering the variability of demand. However, the operational performances of the LP-model developed have shown better performance improvement over the existing bus scheduling system. It shows better performance improvements on the bus utilization, distance and trips covered.

To this effect, the findings show that the existing bus scheduling system has lower average utilization of buses compared with the improved one by 2.1%. The bus utilization per route per shift also shows significant improvement, from 12% to 17%, over the existing system when the comparison was made based on shift. Moreover, the improved model also results in a 10.13% and 15.88% saving on the total traveled kilometers and trips respectively. In addition to the saving in all the parameters, the improved system also reduces the waiting time, improves the service quality and reduces passenger congestion by scheduling buses based on the international standard bus capacity. It also secures a minimum of one round trip in every 30 minutes for each route to improve the service quality.

With regard to cost, the improved system results in a saving of 13.74% ($151,292.19$ ETB) in the operating costs of the enterprise. This shows that the current bus scheduling and assignment system is also found to be inefficient and could not consider the distribution as well as stochastic nature of passengers' demand.

The dissertation also contributes in the body of knowledge gap by developing two new variants in the VRP literatures. It assessed more than 3000 bibliographical entities and identified articles that are related to VRP. The bibliographical entities were selected from different publications and journals over a period of many years since 1963. From the literature review made, so far, there is no VRP variant that addresses stochastic pickup and delivery service simultaneously at a single service location or point. In this regard, a new model is developed that filled this gap in the literature. Moreover, the LP model developed and used for the purpose of improving the performances of the existing routes has also contributed in the knowledge gap by addressing a heterogeneous fleet with many constraints. Moreover, a structural classification for Stochastic VRP based on eight domains and twenty nine attributes were developed by the researchers.

7.2 Recommendations

Public bus service operations are a very complex decision making environment that tries to balance many but also conflicting objectives. Within such a complex decision making environment and comparatively low infrastructures and facilities ACBSE has strived to fulfill the needs of people in and around the city of Addis Ababa. In this regards, the enterprise is contributing a lot in by facilitating the mobility of low-to-middle income people. It is the safest, cheapest means of transportation in the city as compared to private taxis, minibuses and collective taxis. But the improvements made on the transportation service exhibited so far, the enterprise still needs to go beyond in improving the service quality so that it will attract middle and high income level people in the city. Therefore, based on the major findings of the dissertation, the following major recommendations are forwarded to the enterprise.

- It is evident that the low PPVPD results from the poor bus scheduling system used in the enterprise. That is a fixed number of buses per route are scheduled almost in all the operating times. This increases the dead mileage of buses during off-peak and adversely affects the quality of the service during peak hours. The bus utilization during off-peak hours are very low and most of the time buses run empty and incur additional cost without serving passengers. Whereas, in the peak hours buses are forced to carry more passengers than their riding capacity per trip which negatively affects the service quality and the conditions of the buses. Thus, the enterprise should balance the number of buses scheduled per route per time periods based on passengers' demand distribution.

- To support and fully utilize the interventions made by the government as well as the enterprise itself, ACBSE should develop and use a continuous performance evaluation system that can measure key performance parameters of the bus service based on the international standards.
- In order to improve the service quality, ACBSE should limit the carrying capacity of buses with 30 seat capacity to 60 passengers, and that of 50 seat capacity to 90 passengers based on the international standard allowable carrying capacity buses.
- The enterprise should also strategically design a means to replace the old buses with the new ones so that the Kilometers per Vehicle per Day (KPVPD) and the fuel consumption would be improved. This also would have a subsequent improvement on the availability of buses and result in better fleet utilization and helps to extend its service to regional cities in the future.
- A study shows that making a marginal profit from public bus transport is unlikely. However, as most public bus transport companies do in the rest of the world, ACBSE should also supplement its revenue by other side activities that can generate income. So far, ACBSE has an exemplary start up and should be encouraged to generate revenue by providing different services such: heavy duty vehicle maintenance services, supplementary training for heavy duty vehicle drivers, driving license training, etc to the public.
- The LP-Model developed that addresses a heterogeneous fleet with many con-

straints is simple in terms of its computational analysis and even for implementation. Therefore The enterprise should adopt the new bus assignment system (the LP-Model) so that buses can be assigned based on the demand distribution of passengers for each route at a given shift and can improve its performance.

- The new model that considers the stochastic passengers' distribution in both pickup and delivery services with real simultaneous pickup and delivery should be tested and its computational efficiency can be improved further so that it would be fully implemented to real world problems.

7.3 Future Research Directions

During the overall evolution of the dissertation, some gaps in the areas of VRP are identified and proposed as future directions that can improve the transportation service operations of ACBSE as well the interest of academia. Some of the gaps are:

The LP-Model developed to improve the performances of the existing routes, focuses only improvements without affecting the existing routes and networks used by the enterprise. Due to this reason, some of the improvements achieved are not significant as intended. Re-designing the routes may also bring radical improvement on the performances of the enterprise. In this regard a new model that contributes to the knowledge and addresses the problems of ACBSE was designed and attempted to solve it. However, due to the complexity of the model and un availability of digital route data, it was not possible to solve at its full capacity. The solution attempted was only for academic interest to validate the model. Therefore, future study can fill this gap by collecting digital route data and solve the model at its implementation level for the enterprise.

Moreover, in this study, the interest and satisfaction level of passengers, workers and the ticketing system of the enterprise are not included in any of the attempt. The study focused on model development and improvement only. Further study can address these gaps in the future.

Based on the systematic review previous studies in the field of VRP, the research has also identified the following gaps. There is no SVRP literature that modeled fully the real world stochastic parameters considered in their study to solve problems using real world data. Nearly, all made an assumption to simplify and tried to fit to a probabilistic model. They tested using synthesis data or previously generated instance or using mathematical proof of lemma, theorem and proposition.

Due to the dynamic nature of side constraints in VRP, SVRP, and other variants, except some open source instances developed by some scholars, commercial software are not readily available to solve VRP models. This highly hinders the strategy to improve the solution methods in the field of VRP.

Most SVRP studies were conducted on stochastic demand using objective function of cost minimization and capacitated vehicles with synthesis data. But they were studied in a diversified way to find a solution using exact, heuristic or metha-heuristics techniques. However, SVRP which maximizes vehicle utilization, number of customer to be serviced, revenue earned, and others can be seen as untouched areas in the VRP literatures.

The SVRPSPD model, which is new in the knowledge gap, can be a future study using real and continuous digital data and can be fitted to ACBSE or any other transportation service giving organization.

Bibliography

[1] Borndörfer, R., Martin, G., Jaeger, U.: Planning problems in public transit. Report, ZIB (Sept 2009)

[2] Economic Commision for Africa, E.: Africa review report on transport. Report, United Nations Economic and Social Council, ECA, Addis Ababa, Ethiopia (August 2009)

[3] Stefan, B., Natalia, K.: An overview on vehicle scheduling models. In: Decision Support & Operations Research Lab, University of Paderborn, Warburger, Germany (2009)

[4] Avishai, C.: Methods for creating bus timetables. Transportation Research Part A: General **21**(1) (1987) 59 – 83

[5] Seong, Jae, P.: Bus network scheduling with genetic algorithms and simulation. Master of science thesis, University of Maryland, Department of Civil and Environment Engineering, University of Maryland, College Park (2005)

[6] Savsar, M., Atash, M., Alnaqi, J.: Scheduling and routing of city buses at kuwait public transport company. International Journal of Applied Operational Research **1**(3) (2012) 11–32

[7] Kallehauge, B.: Formulations and exact algorithms for the vehicle routing problem with time window. Journal Computers and Operations Research (2006)

[8] Cordeau, J.F., Laporte, G., Mercier, A.: A unifid tabu search heuristic for vehicle routing problem with time windows. Journal of Operations Research Society **53** (2001) 928–936

[9] Dror, M., P, T.: Stochastic vehicle routing with modified savings algorithm. Journal of Operational Research **23** (1986) 228–235

[10] Dror, M., Trudeau, P.: Savings by split delivery routing. Transportation Science **23** (1989) 141–145

[11] Dror, M.: Modeling vehicle routing with uncertain demands as a stochastic program: Properties of the corresponding solution. European Journal of Operational Research **64**(3) (1993) 432–441

[12] Balakrishnan, N.: Simple heuristics for the vehicle routing problem with soft time windows. Journal of Operations Research Society **44**(3) (1993) 279–287

[13] Xiangyong, L., Peng, T., Leung, S.: Vehicle routing problems withtime windows and stochastic travel and service times: Models and algorithm. Int. Journal of Production Economics **125** (2010) 137–145

[14] Calvete, H.I., Carmen, G., Mara, Jos, O., Beln, Snchez, V.: Vehicle routing problems with soft time windows: an optimization based approach. Journal of Monografas del Seminario Matemtico Garca de Galdeano **31** (2004) 295–304

[15] Guy, D., Mark, D., H.: Chapter 2, Public Transit. In: Operatins Research & MS. Volume 14. Elsevier B.V. (2007) pp. 71–129

[16] Caric, T., Gold, H.: Vehicle routing problem, I-Tech, I-Tech Education and Publishing KG (2008)

[17] UN-Habitat: Promoting sustainable transport solutions for east african cities (sustran east africa). Report inception meetings nairobi kampala addis ababa, UN-HABITAT Sustran East Africa, Addis Ababa, Ethiopia (January 10th-13th 2011)

[18] Africa-Trans: Statistical indicators of public transportaion performance in africa. Report, final version 1.3, International Association of Public Transport (UITP) and African Association of Public Trasnport (UATP) (Appril 2010)

[19] ECSA, E.C.S.A.: Ethiopian centeral statistics agency cesus report. Report, Ethiopian Centeral Statistics Agency, Addis Ababa, Ethiopia (2008)

[20] MoFED, M.o.F..E.D.: Growth and transformation plans (gtp) for the year 2010/11-2014/15. Report, Ministry of Finanace & Economic Development (MoFED), Addis Ababa, Ethiopia (2010)

[21] Clara, N., Rosemary, B., Jeff, L., Robert, S.: A set-partitioning-based model for the stochastic vehicle routing problem. Technical report, Texas State University and Lehigh University, 601 University Drive San Marcos, TX 78666 or 200 W. Packer Ave. Bethlehem, PA 18015 (December 2006)

[22] Christopher, Goodson, J.: Solutions Methedologies for VRP with Stochastic Demand. Dessirtation, Iowa (2010)

[23] Reimann, M., Doerner, K., Hartl, R.: D-ants: Savings based ants divide and conquer the vehicle routing problem. Computers & Operations Research **31**(4) (2003) 563–591

[24] Dantzig, Gilbert, B., Ramser, J., H.: The truck dispatching problem. Journal of Management Science, Management Science **6**(1) (1959) 80–91

[25] Clarke, G., Wright, J.: Scheduling of vehicles from a central depot to a number of delivery points. Operations Research **12** (1964) 568–581

[26] Laporte, G., Louveaux, F., Hamme, v.L.: An integer l-shaped algorithm for the capacitated vehicle routing problem with stochastic demands. Operations Research **50** (2002) 415–423

[27] Christofides, N., Mingozzi, A., Toth, P.: Exact algorithms for the vehicle routing problem, based on spanning tree and shortest path relaxations. Mathematical Programming **20** (1981) 255–282

[28] Gillet, B.E., Miller, L.R.: A heuristic algorqthm for the vehicle dispatch problem. Operations Research **22**(340) (1974)

[29] Tillman, F.A.: The multiple terminal delivery problem with probabilistic demands. Transportation Science **3** (1969) 192–204

[30] Winston, W.: Operations Research: Applications and Algorithms (with CD-ROM and Infotrac). 4th edn. Thomson Brooks/Cole (2003)

[31] Paolo, T., Daniele, V., eds.: The Vehicle Routing Problem. SIAM Monographs on Discrete Mathematics and Applications, Philadelphia, PA, 19104-2688, Society for Industrial and Applied Mathematics, Society for Industrial and Applied Mathematics (2002)

[32] Baldacci, R., Vigo, D., Toth, P.: Exact Solution of the Capacitated Vehicle Routing Problem. John Wiley & Sons, Inc. (2010)

[33] Falkenauer, E.: A hybrid grouping genetic algorithm for bin packing. Journal of Heuristics **2** (1996) 5–30,

[34] Drex, M.: Rich vehicle routing in theory and practice. Technical report lm,, Johannes Gutenberg University (April 2011)

[35] Laporte, G.: The vehicle routing problem: An overview of exact and approximate algorithms. European Journal of Operational Research **59** (1992) 345–358

[36] Wolsey, L.A.: Integer Programming. John Wiley and Sons (1998)

[37] Moses, C., Samir, K., Balaji, R.: Algorithms for capacitated routing. Journal of SIAM Journal on computing **31**(3) (2001) 665–682

[38] Bianchi, L.: Notes on dynamic vehicle routing, the state-of-the-arts. Technical report idsia-05-01, Istituto Dalle Molle di Studi sull'Intelligenza Artificiale, Switzerland (December 2000)

[39] Duncan, T.: Experiment in the use of neighbourhood search techniques for vehicle routing. report, University of Edunbourgh, Artificial Intelligence Application Institute(AIAI)-176 (Jun 1995)

[40] Chenghua, S., Xiaofeng, Z.: Research on model fitting capacity of vehicle routing problem. International Journal of Advancements in Computing Technology(IJACT) **3**(11) (December 2011) 185–193

[41] Roberto, B., Maria, B., Daniele, V.: Routing a heterogeneous fleet of vehicles. Technical report deis or.ingce 2007/1, DEIS, University Bologna, via Venezia 52, 47023 Cesena, Italy (January 2007)

[42] Laporte, G.: Fifty years of vehicle routing. Transportation Science **43**(4) (November 2009 2009) 408–416

[43] Bertsimas, D.: A vehicle routing problem with stochastic demand. Journal of Operations Research **40**(3) (1991) 554–585

[44] Linong, Choong, Y., Wan, Rosmanira, I., Khairuddin, O., Zirour, M.: Vehicle routing problem: Models and solutions. Journal of Quality Measurement and Anlysis **4**(1) (2008) 205–218

[45] Avishai, C.: Optimal multi-vehicle type transit timetabling and vehicle scheduling. Procedia - Social and Behavioral Sciences **20**(0) (2011) 19–30

[46] Dror, M., Laporte, G., Francois, V.L.: Vehicle routing with stochastic demands and restricted failures. Methods and Models of Operations Research **33** (1993) 271–283

[47] Bertsimas, D.: A vehicle routing problem with stochastic demand. Operations Research **40** (1992) 574–585

[48] Baldacci, R., Battarra, M., Vigo, D.: Routing a heterogeneous fleet of vehicles. In Golden, B., Raghavan, S., Wasil, E., eds.: The Vehicle Routing Problem: Latest Advances and New Challenges. Volume 43 of Operations Research/Computer Science Interfaces. Springer US (2008) 3–27

[49] Mariam, F., Ahmed, M., Anouck, G.: Vehicle routing problem instances: Application to multi-uav mission planning. Conference, AIAA Guidance, Navigation, Toronto, Ontario Canada (August 2010)

[50] Dror, M., Laporte, G., P, T.: Vehicle routing with split deliveries. Discrete Applied Mathematics **50** (1994) 229–254

[51] Wouter, J.: Approximate models and solution approaches for the vehicle routing problem with multiple use of vehicles and time windows. Master thesis, Middle East Technical University (June 2008)

[52] Cordeau, J.F., Gendreau, M., Laporte, G., Potvin, J.Y., Semet, F.: A guide to vehicle routing heuristics. Journal of the Operational Research Society **53** (2002) 512–522

[53] Stewart, W.J., Golden, B.L.: Stochastic vehicle routing: a comprehensive approach. European Journal of Operational Research **14** (1983) 371–385

[54] Madsen, O.G., Ravn, F., Rygaard, M.: The vehicle routing problem with time windows part ii: Genetic search. Journal of Computing **8** (1995) 165–172

[55] Antonios, T., Ioannis, M.: Stochastic single vehicle routing with a predefined customer sequence and multiple depot returns. European Journal of Operational Research **197** (2009) 557–571

[56] Dror, M., P, T.: Split delivery routing. Naval Research Logistics **37** (1990) 383–402

[57] Reimann, M.: Analyzing a vehicle routing problem with stochastic demand using ant colony optimization. In: EURO Working Group on Transportation. (2005)

[58] Anbuudayasankar, S., Ganesh, K.: Mixed-integer linear programming for vehicle routing problem with simulatneous delivery and pick-up with maximum

route-length. The International Journal of Applied Management and Technology **6**(1) (2008) 31–52

[59] Bertsimas, D., David, S.l.: A new generation of vehicle routing research: Robust algorithms, addressing uncertainty. Journal of Operations Research **44**(2) (1996) 285–304

[60] Golden, B.L., Stewart, W.J.: Vehicle routing with probabilistic demands. Tenth Annual Symposium on the Interface **503** (1978) 252–259

[61] Ismail, Z., Irhamah: Solving the vehicle routing problem with stochastic demands via hybrid genetic algorithm-tabu search. Journal of Mathematics and Statistics **4**(3) (2008) 161–167

[62] Burak, E., Arif, Volkan, V., Arnold, R.: The vehicle routing problem: A taxonomic review. Computers & Industrial Engineering **57** (2009) 1472–1483

[63] Eksioglu, B., Vural, Arif, V., Reisman, A.: The vehicle routing problem: A taxonomic review. Computers and Industrial Engineering **57**(4) (2009) 1472–1483

[64] Fisher, M.L.: Chapter 1: Vehicle Routing. In: Handbooks of Operations Research and Management Science. Volume 8. (1995) 1–31

[65] Gendreau, M., Laporte, G., Seguin, R.: Stochastic vehicle routing. European Journal of Operational Research **88** (1996a) 3–12

[66] Laporte, G., Louveaux, F., Mercure, H.: Models and exact solutions for a class of stochastic location-routing problems. European Journal of Operational Research **39** (1989) 71–78

[67] Gendreau, M., Laporte, G., Seguin, R.: An exact algorithm for the vehicle routing problem with stochastic demands and customers. Transportation Science **29** (1995) 143–155

[68] Laporte, G., Louveaux, F., Mercure, H.: The vehicle routing problem with stochastic trave ltimes. Transportation Science **26** (1992) 161–170

[69] Williams, A.: A stochastic transportaion problem. Journal of Operations Research **11**(5) (1963) 759–770

[70] Ropke, S., Pisinger, D.: An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. Transportation Science **40**(4) (2006) 455–472

[71] Parragh, S., Doerner, K., Hartl, R.: A survey on pickup and delivery problems. Journal für Betriebswirtschaft **58** (2008) 81–117 10.1007/s11301-008-0036-4.

[72] Kanthavel, K., Prasad, P.S.S., Vignesh, K.P.: Optimization of vehicle routing problem with simultaneous delivery and pickup using nested particle swarm optimization. European Journal of Scientific Research **73**(3) (2012) 331–337

[73] Fermin, Alfredo, T., Roberto, Diéguez, G.: Vehicle routing problem with simultaneous pick-up and delivery service. Operational Research Society of India (OPSEARCH) **39**(1) (2002) 19–34

[74] Fermin, Alfredo, T., Roberto, Diéguez, G.: A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. Operational Research Society of India (OPSEARCH) **33**(1) (2006) 595–619

[75] Wang, Chuanshengand Qiu, Y.: Vehicle routing problem with stochastic demands and simultaneous delivery and pickup based on the cross-entropy method. Advances in Automation and Robotics **2**(LNEE 123) (2011) 55–60

[76] Cordeau, J.F., Laporte, G., Martin, W.P., S., Daniele, V.: Chapter 6: Vehicle Routing. In: Handbook in OR & MS. Volume 14. Elsevier B.V. (2007) pp. 366–427

[77] Kenyon, A.S., P. David, M.: Stochastic vehicle routing with random travel times. Journal of Transportation Science **37**(1) (2003) 69–82

[78] Taillard, E., Badezu, P., Gendreau, M., Guertin, F., J., P.: A tabu search heuristic for the vehicle routing problem with softi time wiindow. Journal of Transportation Science **31**(2) (1997) 170–186

[79] Blanton, J.L., Wainwright, R.L.: Multiple vehicle routing with time and capacity constraints using genetic algorithms. In: ICGA' 93

[80] Mingozzi, A.: An exact algorithm for period and multi-depot vehicle routing problems. report, Department of Mathematics, University of Bologna, Bologna, Italy (2003)

[81] Archetti, C.: The vehicle routing problem with capacity 2 and 3, general distances and multiple customer visits. Operational Research in Land and Resources Manangement **102** (2001)

[82] Chung-Piaw, T., Shen, Z., J.M.: Stochastic transportation-invenotry network design problem. Journal of Operations Research **53**(1) (2005) 48–60

[83] Fleischmann, B.: The vehicle routing problem with multiple use of vehicles. paper, Fachbereigh Wirtschafts wissens chaften, Universitt Hamburg (1990)

[84] Avishai, C.: Public-transport vehicle scheduling with multi vehicle type. Transportation Research Part C: Emerging Technologies **19**(3) (2011) 485–497

[85] Cordeau, J.F.: The vrp with time windows. Technical report cahiers du gerad g-99-13, Ecole des Hautes Etudes Commerciales de Montreal (1999)

[86] Cruz Reyes, L., Delgado Orta, J., Gonzlez Barbosa, J., Torres Jimenez, J., Fraire Huacuja, H., Arraaga Cruz, B.: An ant colony system algorithm to solve routing problems applied to the delivery of bottled products. In An, A., Matwin, S., Ras, Z., Slezak, D., eds.: Foundations of Intelligent Systems. Volume 4994 of Lecture Notes in Computer Science. Springer Berlin / Heidelberg (2008) 329–338

[87] Fisher, M.L.: Optimal solution of vehicle routing problems using minimum k-trees. Operations Research **42** (1994) 626–642

[88] Ropke, S., Cordeau, J.F., Bilbert, L.: Models and branch-and-cut algorithms for pickup and delivery problems with time windows. Networks **49**(4) (2007) 258–272

[89] Giovanni, R., Matteo, S.: Symmetry helps: Bounded bi-directional dynamic programming for the elementary shortest path problem with resource constraints. Discrete Optimization **3** (2006) 255–273

[90] Imdat Kara, T.B.: Integer linear programming formulation of the generalized vehicle routing problem. Report Presented in 5th EURO/INFORMS Joint International Meeting stanbul, Turkey, Baskent University, Dept. of Industrial Engineering, stanbul, Turkey (July 6-10 2003)

[91] Christofides, N., Eilon, S.: An algorithm for the vehicle dispatching problem. Operational Research Quarterly **20** (1969) 309–318

[92] Golden, B.L., Magnanti, T., Nguyen, H.: Implementing vehicle routing algorithms. Networks **7**(2) (1977) 113–148

[93] Haji, Ismail, Z., Irhamah, N., Zaitul, Marlizawati, Z.: The development of heuristic methods based on genetic algorithm (ga) for solving vehicle routing rroblem (vrp). Project Report VOT 74285, The Ministry of Science, Technology and Innovation (MOSTI) (2008)

[94] Golden, B.L., Bodin, L., Doyle, T., Stewart, W.J.: Approximate traveling salesman algorithms. Operations Research **28**(3) (May-Jun 1980) 694–711

[95] Laporte, G., Michel, G., Jean-Yves, P., Frede, S.: Classical and modern heuristics for the vehicle routing problem. International Transactions in Operational Research **5** (2000) 285–300

[96] Jalel, E., Rafaa, M.: The urban bus routing problem in the tunisian case by the hybrid artificial ant colony algorithm. Swarm and Evolutionary Computation **2**(0) (2012) 15 – 24

[97] Gendreau, M., Laporte, G., Seguin, R.: A tabu search heuristic for the vehicle routing problem with stochastic demands and customers. Operations Research **44** (1996b) 469–477

[98] Savelsbergh, M.W., Goetschalckx, M.: A comparison of the efficiency of fixed versus variable vehicle routes. Journal of Business Logistics **16** (1995) 163–187

[99] Bertsimas, D., Simchi-Levi, D.: The new generation of vehicle routing research: robust algorithms addressing uncertainty. Operations Research **44** (1994) 286–304

[100] Ak, A., Erera, A.L.: A paired-vehicle recourse strategy for the vehicle routing problem with stochastic demands. Transportation Science **41** (2007) 222–237

[101] Yang, W.H., Kamlesh, M., Ronald, B.H.: Stochastic vehicle routing problem with restocking. Transportation Science **34** (2000) 99–112

[102] Secomandi, N.: A rollout policy for the vehicle routing problem with stochastic demands. Operations Research **49** (2001) 796–802

[103] Secomandi, N.: Analysis of a rollout approach to sequencing problems with stochastic routing applications. Journal of Heuristics **9** (2003) 321–352

[104] Larsen, A.: The Dynamic Vehicle Routing Problem. Phd thesis, Department of MathematicalModelling (IMM) at the Technical University of Denmark (DTU) (2001)

[105] Gebeyehu, M., Takano, S.e.: Diagnostic evaluation of public transportation mode choice in addis ababa. Journal of Public Transportation **10**(4) (2007) 27–50

[106] Agarwal, P., Singh, A.: Performance improvement of urban bus system: Issues and solutions. International Journal of Engineering Science and Technology **2**(9) (2010) 4759–4766

[107] IIT Madras: Operational Improvements For Buses On Urban Roadways. Proceedings of the International Conference on Best Practices to Relieve Congestion on Mixed Traffic Urban Streets in Developing Countries, Chennai, IIT Madras (2008)

[108] Yu, J.: Transportation Engineering-Introduction To Planning Design and Operation. Elsevier, New York (1982)

[109] CIRT: Performance statistics of state transport undertakings 198990 and 199091. Report, Central Institute of Road Transport, Pune (1992)

[110] Badami, M.G., Haider, M.: An analysis of public bus transit performance in indian cities. Transportation Research Part A: Policy and Practice **41**(10) (2007) 961 – 981

[111] Chua, T.: The planning of urban bus routes and frequencies: A survey. Transportation **12** (1984) 147–172

[112] Valouxis, C., Housos, E.: Combined bus and driver scheduling. Computers & Operations Research **29** (2002) 243–259

[113] TCRP: Transit Capacity and Quality of Service: Part 4 Bus Transit Capacity Manual. Kisttelson and Associates, Inc., Orlando, FL. 2nd edn. (08 2012)

[114] Armstrong-Wright, A., Thiriez, S.: Bus services : reducing costs, raising standards. World Bank, Washington, D.C.: (1987)

[115] Hawas, E.Y., Khan, Md., B., Basu, N.: Evaluating and enhancing the operational performance of public bus systems using gis-based data envelopment analysis. Journal of Public Transportation **15**(2) (2012) 19–44

[116] Randall, R.E., Condry, J., B., Trompet, M.: International bus system benchmarking: Performance measurement development, challenges, and lessons learned. Transportation research board 86th annual meeting, South Kensington Campus, London SW6 2AZ, UK, Imperial College London (2007)

[117] Iles, R.: Public transport in developing countries. Report, Elsevier, Amsterdam (2005)

[118] Hawas, Yaser, E., Khan, Bayzid, M., Basu, N.: Evaluating and enhancing the operational performance of public bus systems using gis-based data envelopment analysis. Journal of Public Transportation **15**(2) (2012) 19–44

[119] Dror, M., Laporte, G., P, T.: Vehicle routing problem with stochastic demands: Properties and solution frameworks. Transportation Sciences **23**(3) (1989) 166–176

[120] Fu, L., Liu, Q., Calamai, P.: Real time optimization model for dynamic stochasitc of transit operations. Journal of Transportation Research Record (1857) 48–55

[121] Chin-Hui, T., Yan, S.: A routing and scheduling framework incorporating real time adjustement for inter-city bus carriers under stochastic trave time and deamnd. Journal of The Chinese Institute of Engineers **30**(4) (2007) 635–649

Appendix A

Major Accomplishments

Major Accomplishment During the PhD Study

Publications

- Eshetie Berhan, Birhanu Beshah and Daniel Kitaw, Performance Analysis on Public Bus Transport of the City of Addis Ababa, International Journal of Computer Information Systems and Industrial Management Applications. ISSN 2150-7988, Volume 5 (2013) pp. 722-728.

- Eshetie Berhan, Dejene Mengistu, Birhanu Beshah and Daniel Kitaw, Modelling and Analysis of Bus Scheduling Systems of Urban Public Bus Transport, Accepted for publication for May 2013 issue in the International Journal of Computer Information Systems and Industrial Management Applications.

- Eshetie Berhan and Daniel Kittaw. (2012). The role of Marketing Information Systems (MKIS) in Service Quality in Ethiopian Industries, South African Journals of Industrial Engineering, Volume 23, Issue 1, Number, 2, pp. 66-76, ISSN: 1012277X.

- Eshetie Berhan, Birhanu Besha and Daniel Kittaw, The Role of Marketing Information Systems (MKIS) in Price Change Decision Making in Ethiopian Industries, International Journal of Science and Advanced Technology, Volume 2 , No 11, November 2012.

- Eshetie Berhan , Birhanu Beshah, Ajith Abraham and Daniel Kitaw Stochastic Vehicle Routing Problem: A Literature Survey, being processed and in progress in the Journal of Information and Knowledge Management

Eshetie Berhan, June 2013

Courses Offered

- Introduction to Statistics for Engineers (Meng 2052)
- Technical Drawing (MEng 1031)
- Entrepreneurship (Meng 5244)
- Research Methodology (MEng 600)
- Production and Operation Management (MEng 6103)
- More than seven Master thesis Co-advising (MEng 7000)
- Eight Plant Design and Erection project Co-advising (MEng 6105)
- Three Total Quality Management project Co-advising (MEng 7101)
- Four Industrial Project Management Co-advising(MEng 6107)

Participation in AAiT and Other Affairs

- Post Graduate Program Leader since December 1, 2012: Assigned by the School of Mechanical and Industrial Engineering
- A member of AAiT's Staff Housing Committee since November 09, 2012: Assignment letter from the Scientific Director (Ref. Number: AAiT/729/2005/12)
- Continuing Education and Extension Program Coordinator of Mechanical Engineering Department (from June 29, 2011): Assignment letter from the department (Ref. Number: ME/669/2003).

Community Services

- Research Assistant and workshop organizer member in Ethiopian Academy of Science (Technology Working Group).

Eshetie Berhan, June 2013

- Provide Short term training for different public, NGO, and other international organization on Advanced Microsoft Project management under Techno-brain since 12-Dec. 2012.
- Provide Short term training for different public, NGO, and other international organization on Advanced Microsoft Project management under Neuro Net Plc since 12-Dec. 2012.

Appendix B

Complete List of Tables

Table B.1: Routes, route length and number of buses assigned

Route No.	Origin	Destination	No. Of buses	K/M
1	Megenagna	Kara	2	7.7
2	Kore Mekanisa	Addis Ketema	4	11.1
3	Ayer Tena	Minilik Square	8	10.8
4	Kality	Addis Ketema	5	19.4
5	Kore Mekanisa	Minilik Square	3	12.7
6	Kera	Semen Addisu Gebeya	8	9.9
7	Megenagna	Sendafa Beke	2	36.6
8	Semen Gebeya	Addis Ketema	2	9.4
9	Brass clinic Bole school	Piassa	2	10.5
10	Kotebe teachers college	Piassa	6	12.7
11	Kolfe mesalemiya	Minilik Hospital	4	10
12	Ferensay film center	Addis Ketema	6	9.9
13	Bella	Addis Ketema	2	9.9
14	Saris Abo	Piassa	3	12.3
15	Megenagna	Addis Ketema	2	10.4
16	Kidane mihret	Addis Ketema	8	7.9
17	Kuskuam	Addis Ketema	6	9.1
18	Keranyo	Addis Ketema	8	7.3
19	Asko	Piassa	4	12.2
19U	Asko mikililand	Piassa	2	9.9
e 20	Dilber	Addis Ketema	2	8.6
21	Fetinoderash	Addis Ketema Piassa	3	8.6
22	Semit	Legehare	4	12.3
23	Lamberet	Addis Ketema	3	12.4
24	Burayu	Degol Square	3	17.7

Table B.1 Ctd'

25	Legehare	Akaki	4	19
25U	Sedest Kilo	Akaki 09	2	22
26	Addis Ketema	Sebeta	3	25.5
27	Legehare	Kaliti	6	11.4
28	Asko sansuzi	Addis Ketema	4	11.1
29	Addisu Sefer	Addis ketema	6	12.7
30	Sululta	Addis Ketema	2	25.8
31	Legehare	Shromeda	8	7.4
32	Hanamariam	Legehare	6	10.6
33	Kotebie Gebriel	Arat killo	5	11.4
34	Gofa Camp	Addis Ketema	2	9.8
35	Lafto	Merkato	2	10
36	Karakore	Legehare	4	11.7
37	Keranyo	Minilik Square	3	12
38	Gofa Camp	Sidest Killo	4	11
39	Bole School	Addis Ketema	3	9.6
40	Kara Alo	Addis Ketema	2	17.9
41	Eyesus	Merkato	5	8.5
42	Megenagna	Bole Legahre	2	9.8
43	Menagesha	Merkato	2	30.2
44	Legedadi	Merkato	2	30.4
45	Legahare	Dilber	4	8.6
46	Gerji	Arat killo	6	11.2
47	Yenegew fre school	Merkato	2	6
48	Bole Mikaeil Square	Minilik Square	2	10.9
49	Ayat CMC	Megenagna	4	8.8
50	Total No 3 round	Megenagna	2	12.1
51	Betel	Merkato	2	10.9
52	Gerji	Merkato	8	14.1
53	Bole	Shromeda	3	11.5
54	Lafto	Legehare	2	9.5
55	Legahare	Ferensay Kella	2	9.5
56	Saris Abo	Shromeda	4	14.2
57	Kara	Legehare	4	14.4
58	Legahare	World Bank	2	12
59	Betel Hospital	Minilik Square	4	11.5
60	Debrezeit	Legehare	6	47.2
61	Ayat CMC	Legehare through Kasanchis	2	15.8

Table B.1 Ctd'

62	Sebeta	Legahare	2	23.8
63	Addis Ketema	Mikililand Building	2	9.1
64	Sidest Killo	Megenagna Gorf ASW	3	9.5
65	Merkato	World Bank	2	11
66	Addis Ketema	Karakore	4	10.5
67	Mekanisa Square ring Road	Legahare	2	10.2
68	Minilik Hospital	Torhayloch Hospital	3	10.2
69	Atena Tera	Kasanchis	2	12.4
70	Kasanchis	Ayer Tena	3	11
71	Gerji Roba Dabo	Bole Urael Balcha	2	10.9
72	Hanamariam	Saris	2	9.6
73	Legehare	Winget school	4	10.2
74	Gurd sholla michael	Merkato through Gh	6	13.3
75	Sidest Killo	kera	4	10.4
76	Megenagna Desalegn Hotel	Saris korki	2	14.7
77	Ayer Tena	Saris Abo	2	13
78	Megenagna	Gofa Camp	2	12.4
79	Arat kilo	Kazanchis summit	2	12.7
80	Semen Gebeya	Megenagna	5	12.4
81	Sidest Killo	Asko	2	10.7
82	Yerer ber	Balcha hospital	3	14.6
83	Ayat CMC	Sidest Killo	3	15.8
84	Kolfe Efoyta Mesalemia	Lagehar	2	9.5
85	Addis Ketema	Holeta	2	45
86	Ayer Tena	Kaliti kelebet menged	2	12.3
87	Kolfe Square Ring road	Ayer Tena	2	10.5
88	Addis Ketema	Chancho	2	40
89	Addis Ketema	Sendafa	2	44
90	Betel Hospital	Legahare	3	10
91	Legehare	Tefki	1	40
92	Hanamariam bridge via ring road	Balcha hospital	3	9.6
93	Bole bulbula Sarisabo via ring Road	Megenaga	2	15.2
Total			321	1349.8

Table B.2: Input Parameters of the LP-Model

Route No.	Pi	Shifts during a day				Time Factor			
		Shift1	Shift2	Shift3	Shift4	T1	T2	T3	T4
1	0.0144	2249	1968	1124	281	7	8	12	3
2	0.0117	1832	1603	916	229	4	5	7	2
3	0.0401	6284	5499	3142	786	4	5	7	2
4	0.0101	1582	1384	791	198	3	3	5	1
5	0.0080	1260	1103	630	158	4	4	7	2
6	0.0306	4784	4186	2392	598	4	5	8	2
7	0.0038	588	514	294	73	2	3	4	1
8	0.0061	958	838	479	120	6	7	10	3
9	0.0091	1424	1246	712	178	6	8	12	3
10	0.0124	1946	1703	973	243	4	5	7	2
11	0.0086	1341	1173	670	168	5	6	9	2
12	0.0267	4185	3662	2092	523	5	6	8	2
13	0.0077	1213	1061	606	152	5	6	8	2
14	0.0080	1260	1103	630	158	4	5	7	2
15	0.0088	1381	1209	691	173	4	5	7	2
16	0.0221	3455	3023	1728	432	5	6	9	2
17	0.0176	2757	2413	1379	345	4	5	8	2
18	0.0204	3190	2792	1595	399	5	6	8	2
19	0.0131	2055	1798	1028	257	5	6	8	2
20	0.0051	792	693	396	99	6	8	12	3
21	0.0155	2432	2128	1216	304	6	8	12	3
22	0.0105	1644	1439	822	206	5	6	9	2
23	0.0048	757	662	378	95	4	5	7	2
24	0.0069	1077	943	539	135	4	4	7	2
25	0.0094	1474	1289	737	184	3	4	6	2
26	0.0053	828	724	414	103	3	3	5	1
27	0.0142	2221	1944	1111	278	3	3	5	1

Table B.2 Ctd'

Route No.	Pi	Shifts during a day				Time Factor			
		Shift1	Shift2	Shift3	Shift4	T1	T2	T3	T4
28	0.0102	1590	1392	795	199	3	4	6	2
29	0.0111	1742	1525	871	218	5	6	9	2
30	0.0083	1297	1135	648	162	4	5	8	2
31	0.0456	7134	6243	3567	892	3	4	6	2
32	0.0188	2936	2569	1468	367	3	4	6	1
33	0.0196	3070	2686	1535	384	7	8	12	3
34	0.0074	1154	1009	577	144	4	5	8	2
35	0.0041	647	566	323	81	4	5	8	2
36	0.0094	1474	1290	737	184	4	5	7	2
37	0.0140	2188	1915	1094	274	4	5	7	2
38	0.0095	1487	1301	743	186	4	5	7	2
39	0.0081	1270	1111	635	159	4	5	7	2
40	0.0074	1154	1009	577	144	4	5	7	2
41	0.0121	1896	1659	948	237	4	5	8	2
42	0.0053	831	727	415	104	3	4	6	1
43	0.0025	386	337	193	48	5	6	9	2
44	0.0055	859	751	429	107	5	6	9	2
45	0.0141	2202	1927	1101	275	2	3	4	1
46	0.0160	2504	2191	1252	313	2	3	4	1
47	0.0079	1237	1082	618	155	5	6	9	2
48	0.0082	1284	1124	642	161	4	5	7	2
49	0.0154	2407	2106	1204	301	6	7	10	3
50	0.0078	1214	1062	607	152	4	5	8	2
51	0.0089	1386	1213	693	173	7	8	12	3
52	0.0166	2598	2273	1299	325	3	4	6	2
53	0.0086	1339	1171	669	167	4	5	7	2
54	0.0077	1198	1048	599	150	3	4	5	1
55	0.0106	1664	1456	832	208	5	6	9	2
56	0.0102	1602	1402	801	200	4	5	7	2
57	0.0086	1349	1180	674	169	5	6	9	2
58	0.0064	1001	876	500	125	4	4	7	2
59	0.0187	2929	2563	1464	366	3	4	6	1
60	0.0144	2258	1976	1129	282	4	5	8	2
61	0.0094	1476	1292	738	185	4	5	7	2
62	0.0059	926	810	463	116	2	3	4	1
63	0.0059	917	802	458	115	3	4	6	2

Table B.2 Ctd’

Route No.	Pi	Shifts during a day				Time Factor			
		Shift1	Shift2	Shift3	Shift4	T1	T2	T3	T4
64	0.0060	938	821	469	117	3	4	6	1
65	0.0076	1183	1035	592	148	4	5	8	2
66	0.0123	1930	1689	965	241	5	6	8	2
67	0.0237	3714	3250	1857	464	4	5	8	2
68	0.0062	977	855	488	122	4	5	7	2
69	0.0021	325	285	163	41	5	6	8	2
70	0.0079	1241	1086	620	155	4	5	7	2
71	0.0071	1112	973	556	139	4	5	8	2
72	0.0218	3406	2980	1703	426	5	6	9	2
73	0.0140	2197	1922	1098	275	4	5	8	2
74	0.0114	1778	1556	889	222	10	12	18	5
75	0.0067	1052	921	526	132	4	5	7	2
76	0.0042	655	573	328	82	3	4	6	2
77	0.0050	780	683	390	98	4	5	8	2
78	0.0045	706	617	353	88	4	5	8	2
79	0.0056	884	774	442	111	4	4	7	2
80	0.0094	1477	1293	739	185	4	4	7	2
81	0.0032	494	432	247	62	5	6	9	2
82	0.0062	970	848	485	121	4	5	7	2
83	0.0077	1212	1060	606	151	4	5	7	2
84	0.0053	835	731	418	104	4	5	7	2
85	0.0051	792	693	396	99	4	5	7	2
86	0.0063	989	865	494	124	5	6	8	2
87	0.0167	2620	2292	1310	327	2	3	4	1
88	0.0025	384	336	192	48	5	6	10	2
89	0.0019	305	267	153	38	6	7	10	3
90	0.0136	2137	1870	1068	267	2	3	4	1
91	0.0043	672	588	336	84	2	3	4	1
92	0.0118	1848	1617	924	231	4	5	7	2
93	0.0087	1362	1192	681	170	2	3	4	1

Table B.3: Number of trips required per route per shift

	Shift 1		Shift 2		Shift 3		Shift 4	
Route No	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II
1	19	9	0	10	14	11	0	3
2	19	5	5	8	15	6	0	2
3	61	14	14	24	48	17	0	7
4	18	3	6	5	15	3	2	1
5	14	3	4	6	12	3	0	2
6	51	12	0	21	41	14	0	6
7	4	1	3	2	6	1	1	1
8	7	3	0	4	6	4	0	1
9	10	4	0	5	7	6	0	2
10	24	6	5	10	19	7	0	3
11	16	5	0	7	12	6	0	2
12	38	12	0	17	30	14	0	5
13	12	4	0	6	10	5	0	2
14	14	4	3	6	11	5	0	2
15	16	4	4	6	13	5	0	2
16	35	11	0	15	27	13	0	4
17	29	7	0	12	23	9	0	3
18	31	9	0	14	24	11	0	4
19	24	7	0	10	19	9	0	3
20	6	3	0	3	5	3	0	1
21	20	6	0	9	16	8	0	3
22	17	4	0	7	14	5	0	2
23	10	3	3	4	9	3	0	1
24	11	2	3	4	9	3	0	1
25	20	4	7	6	17	4	2	2
26	11	2	3	4	9	3	0	2
27	22	7	0	10	17	9	0	3

Table B.3 Ctd'

	Shift 1		Shift 2		Shift 3		Shift 4	
Route No	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II
28	17	4	0	7	13	5	0	2
29	21	4	6	7	17	5	0	2
30	16	3	5	5	13	4	2	1
31	67	32	0	33	50	36	0	9
32	35	8	0	14	27	10	0	4
33	31	7	0	13	25	9	0	4
34	12	3	3	5	10	4	0	2
35	7	2	2	3	6	2	0	1
36	17	4	4	7	13	5	0	2
37	18	4	4	7	14	5	0	2
38	16	4	0	7	12	5	0	2
39	16	4	0	7	13	5	0	2
40	12	2	3	4	10	3	2	1
41	21	7	0	10	17	8	0	3
42	8	3	0	4	6	3	0	1
43	4	1	2	2	5	1	1	1
44	8	2	4	3	9	2	1	1
45	22	7	0	10	18	8	0	3
46	30	7	7	12	24	9	0	3
47	12	5	0	6	10	6	0	2
48	14	3	0	6	11	4	0	2
49	21	11	0	11	16	12	0	3
50	14	3	4	5	12	3	0	2
51	14	4	0	6	11	5	0	2
52	31	5	10	9	25	7	3	2
53	15	5	0	7	12	6	0	2
54	12	3	3	5	10	4	0	2
55	17	5	0	8	14	6	0	2
56	17	4	4	7	14	4	0	2
57	17	3	5	6	13	4	2	1
58	11	3	0	5	9	3	0	2
59	26	6	6	11	20	8	0	3
60	16	3	9	5	20	4	3	2
61	14	3	4	5	11	3	0	2

Table B.3 Ctd'

	Shift 1		Shift 2		Shift 3		Shift 4	
Route No	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II	Bus type-I	Bus type-II
62	12	2	3	4	10	3	2	1
63	8	2	0	3	6	2	0	1
64	11	4	0	5	9	4	0	2
65	13	3	0	6	10	4	0	2
66	20	5	5	8	16	6	0	2
67	27	8	0	12	21	10	0	3
68	12	3	3	5	10	4	0	2
69	3	1	0	2	3	1	0	1
70	14	5	0	6	11	5	0	2
71	11	3	0	5	9	4	0	2
72	21	18	0	13	13	21	0	4
73	20	5	5	8	16	6	0	2
74	21	4	6	7	17	5	0	2
75	13	3	0	5	10	4	0	2
76	8	2	0	3	6	3	0	1
77	9	2	2	4	8	2	0	1
78	8	2	0	4	7	2	0	1
79	9	3	0	4	7	3	0	1
80	17	4	4	7	14	5	0	2
81	7	2	2	3	5	2	0	1
82	13	3	0	6	10	4	0	2
83	15	4	4	6	12	5	0	2
84	9	3	0	4	7	4	0	1
85	8	2	4	3	9	2	1	1
86	9	3	0	4	7	3	0	1
87	20	8	0	9	15	9	0	3
88	4	1	2	2	5	1	1	1
89	3	1	2	1	4	1	1	1
90	19	4	5	7	15	5	0	2
91	4	1	2	2	4	1	1	1
92	21	5	0	9	17	6	0	3
93	4	0	5	9	4	0	2	2
Total	402	174	618	1231	490	18	156	156

Table B.4: Number of buses per route per shift(BT= bus type)

	Shift1			Shift2			Shift3			Shift4		
Route No.	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	Bt-II	Total
1	3	1	4	1	1	2	2	1	3	1	1	2
2	5	1	6	1	1	2	3	1	4	1	1	2
3	16	3	19	2	3	5	10	4	14	0	3	3
4	6	1	7	2	1	3	4	1	5	2	0	2
5	4	1	5	1	1	2	3	1	4	1	1	2
6	12	3	15	0	3	3	8	3	11	0	3	3
7	3	0	3	3	0	3	3	0	3	3	0	3
8	2	0	2	2	0	2	2	0	2	2	0	2
9	1	1	2	2	0	2	1	1	2	2	0	2
10	6	1	7	1	1	2	4	1	5	0	2	2
11	3	1	4	1	1	2	2	1	3	1	1	2
12	8	2	10	0	2	2	5	2	7	0	2	2
13	3	1	4	1	1	2	2	1	3	1	1	2
14	3	1	4	1	1	2	2	1	3	1	1	2
15	4	1	5	1	1	2	3	1	4	1	1	2
16	7	2	9	0	2	2	5	2	7	0	2	2
17	7	2	9	0	2	2	4	2	6	0	2	2
18	7	2	9	0	2	2	4	2	6	0	2	2
19	5	1	6	1	1	2	3	1	4	1	1	2
20	2	0	2	2	0	2	2	0	2	2	0	2
21	4	1	5	1	1	2	2	1	3	2	1	3
22	5	1	6	1	1	2	3	1	4	1	1	2
23	3	1	4	1	1	2	2	0	2	2	0	2
24	3	0	3	2	1	3	2	1	3	2	0	2
25	8	1	9	1	1	2	5	1	6	1	1	2
26	3	0	3	1	1	2	2	1	3	1	1	2
27	5	1	6	1	1	2	3	1	4	1	1	2

Table B.4 Ctd'

	Shift1			Shift2			Shift3			Shift4		
Route No.	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	Bt-II	Total
28	4	1	5	1	1	2	2	1	3	1	1	2
29	6	1	7	1	1	2	4	1	5	1	1	2
30	5	1	6	1	1	2	3	1	4	2	0	2
31	10	5	15	0	3	3	6	5	11	0	3	3
32	8	2	10	0	2	2	5	2	7	0	2	2
33	7	2	9	0	2	2	5	2	7	0	2	2
34	3	1	4	1	1	2	2	1	3	1	1	2
35	2	0	2	2	0	2	2	0	2	2	0	2
36	4	1	5	1	1	2	3	1	4	1	1	2
37	4	1	5	1	1	2	3	1	4	1	1	2
38	4	1	5	1	1	2	2	1	3	1	1	2
39	4	1	5	1	1	2	2	1	3	1	1	2
40	4	1	5	1	1	2	2	1	3	2	0	2
41	4	1	5	1	1	2	3	1	4	1	1	2
42	2	0	2	2	0	2	2	0	2	1	0	1
43	3	0	3	3	0	3	2	0	2	3	0	3
44	4	0	4	1	1	2	3	1	4	3	0	3
45	4	1	5	1	1	2	3	1	4	1	1	2
46	8	2	10	1	2	3	5	2	7	0	2	2
47	2	1	3	1	1	2	1	1	2	1	1	2
48	3	1	4	1	1	2	2	1	3	1	1	2
49	3	2	5	1	1	2	2	1	3	1	1	2
50	4	1	5	1	1	2	3	1	4	1	1	2
51	4	1	5	1	1	2	2	1	3	1	1	2
52	11	2	13	2	2	4	7	2	9	2	1	3
53	3	1	4	1	1	2	2	1	3	1	1	2
54	3	1	4	1	1	2	2	1	3	1	1	2
55	3	1	4	1	1	2	2	1	3	1	1	2
56	5	1	6	1	1	2	3	1	4	1	1	2
57	5	1	6	1	1	2	4	1	5	2	0	2
58	2	1	3	1	1	2	2	1	3	1	1	2
59	7	2	9	1	1	2	4	2	6	1	1	2
60	7	1	8	2	1	3	7	1	8	2	1	3
61	4	1	5	1	1	2	3	1	4	1	1	2

Table B.4 Ctd’

	Shift1			Shift2			Shift3			Shift4		
Route No.	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	BT-II	Total	BT-I	Bt-II	Total
62	4	1	5	1	1	2	2	1	3	2	0	2
63	2	0	2	2	0	2	2	0	2	2	0	2
64	2	1	3	1	1	2	1	1	2	1	1	2
65	3	1	4	1	1	2	2	1	3	1	1	2
66	5	1	6	1	1	2	3	1	4	1	1	2
67	6	2	8	1	1	2	4	2	6	1	1	2
68	3	1	4	1	1	2	2	1	3	1	1	2
69	2	0	2	2	0	2	2	0	2	2	0	2
70	3	1	4	1	1	2	2	1	3	1	1	2
71	3	1	4	1	1	2	2	1	3	1	1	2
72	2	2	4	1	1	2	1	2	3	1	1	2
73	5	1	6	1	1	2	3	1	4	1	1	2
74	6	1	7	1	1	2	4	1	5	1	1	2
75	3	1	4	1	1	2	2	1	3	1	1	2
76	2	0	2	2	0	2	2	0	2	2	0	2
77	2	1	3	2	0	2	2	0	2	2	0	2
78	2	1	3	2	0	2	2	0	2	2	0	2
79	2	0	2	2	0	2	2	0	2	2	0	2
80	4	1	5	1	1	2	3	1	4	1	1	2
81	2	0	2	2	0	2	2	0	2	2	0	2
82	3	1	4	1	1	2	2	1	3	2	1	3
83	4	1	5	1	1	2	2	1	3	1	1	2
84	2	1	3	2	0	2	1	1	2	2	0	2
85	4	0	4	2	1	3	3	1	4	3	1	4
86	2	0	2	2	0	2	2	0	2	2	0	2
87	3	1	4	1	1	2	2	1	3	1	1	2
88	3	0	3	3	0	3	3	0	3	3	0	3
89	3	0	3	3	0	3	3	0	3	3	0	3
90	5	1	6	1	1	2	3	1	4	1	1	2
91	3	0	3	2	0	2	3	0	3	3	0	3
92	5	1	6	1	1	2	3	1	4	1	1	2
93	2	1	3	1	1	2	1	1	2	2	0	2
Total	**396**	**94**	**490**	**114**	**88**	**202**	**269**	**95**	**364**	**121**	**79**	**200**

Table B.5: Longitude and latitude data

V_i	Longi.	Lati.
1	38.8	9.16
2	38.9	9.1
3	38.9	8.94
4	38.8	9.06
5	38.9	9.13
6	38.8	9.04
7	38.8	9.18
8	38.8	9.14
9	38.9	9.26
10	38.8	9.15
11	38.9	9.04
12	38.8	9.2
13	38.8	9.05
14	38.8	9.23
15	38.8	8.97
16	38.8	9.07
17	38.8	9.23
18	38.6	9.11
19	39	9.12
20	38.8	9.01
21	38.9	9
22	38.9	9.34
23	38.8	9.26
24	38.8	9.36
25	38.8	9.17
26	38.8	9.46
27	38.8	9.56

Table B Ctd'

V_i	Longi.	Lati.
28	38.8	9.19
29	38.9	9.54
30	38.9	9.9
31	38.9	9.09
32	38.8	9.04
33	39	9.04
34	38.1	9.04
35	38.2	9.04
36	38.3	9.04
37	38.3	9.04
38	38.5	9.04
39	38.6	9.04
40	38.7	9.04
41	38.9	9.4
42	38	9.04
43	38.1	9.04
44	38.3	9.04
45	38.5	9.16
46	38.4	9.16
47	38.3	9.16
48	38.1	9.16
49	38.9	9.16
50	38.1	9.16
51	38.8	9.56
52	38.3	9.16
53	38.6	9.1
54	38.7	9.11
55	38.8	9.21
56	38.5	9.13
57	38.8	9.41
58	39.1	9.15
59	38.6	8.96