College of Natural and Computational Science

Department of Mathematics

A Thesis

On

Addis Ababa bus transportation problem with optimal schedule

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A Thesis Submitted to the Department of Mathematics in Partial Fulfillment of the Requirements for the Degree of Master of Science in Mathematics (with Specialization in Optimization)

September 2024

Addis Ababa, Ethiopia

Approval

This thesis has been examined and approved as meeting the requirements for the partial fulfillment of Master of Science in mathematics.

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Declaration

I hereby declare that this thesis entitled **"Addis Ababa bus transportation problem with optimal schedule"** has been compiled and organized by **Tsige kinfe Kidanemariam** under the supervision of **Berhanu Guta(Ph.D)** and that it has never been submitted for completion of graduate qualification at any higher learning institution. Any work done by others has been acknowledged and referenced accordingly.

Acknowledgments

First I would like to thank my respectable advisor **Dr. Berhanu Guta** for his unlimited help, suggestions and comments for this thesis report to complete.

Secondly I offer my regards and blessings to all of those who supported me in any respect during the completion of the project specially AA City Education Bureau for its financial support in attending the degree of masters of Science.

Abstract

one of the public company offering transportation services in Addis Ababa is Anbessa City Bus Service Enterprise (ACBSE). The company serves customers on more than 125 routes using a set bus schedule system. However, the company's operational performances are starting to suffer from the present bus assignment and scheduling system. The aim of this study is to use linear programming (LP) to build an optimal bus assignment mechanism. The best number of buses for each route in four shifts is found by developing the LP model following a detailed review of the current bus scheduling system. The performance of the current systems is then used to validate the LP-model's output.
The study's conclusions demonstrated that, in comparison to the current scheduling system, the new model performs better in terms of operational expenses, bus utilization, trips, and distance traveled. The new technology reduces expenses while simultaneously increasing bus utilization and passenger service quality. The authors suggested that the company use the new bus assignment system so that buses could be assigned according to the passenger demand distribution for each route during a certain shift.

Key words:

- ✓ *bus scheduling;*
- ✓ *bus utilization;*
- ✓ *linear programming;*
- ✓ *optimization approaches;*
- ✓ *model validation*

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Introduction

One of the processes used in bus transport operations planning is the bus schedule, which deals with allocating buses to routes in a way that best serves anticipated passenger demand. Public transportation planning entails a variety of intricate, recurring responsibilities. The number of passengers at each transfer point must be gathered or forecasted at the strategic level since this information is frequently completely unknown and increases the complexity of the planning process. Bus assignment decisions are made by weighing the trade-off between operational expenses and service quality for the bus operating businesses. Because utilizing too few buses has the reverse effect of using too many, which results in lower operating costs while maintaining acceptable service quality. According to data gathered from Anbessa City Bus Service Enterprise (ACBSE), as of 2024, the company operated 759 buses to service over 125 routes connecting various regions of the city. The number of passengers varies greatly from time to time, necessitating adjustments to the number of buses allotted to each route. However, the business operates its fleet of buses throughout the day, mostly using a set number of buses scheduled for each route. Because of this, some buses are now moving empty while others are overloaded, which lowers service quality and performance. In addition, there are a number of issues with ACBSE's transportation service, including low bus utilization, unmet passenger demand, and increased operational expenses. This thesis first focuses on developing a demand-oriented linear programming (LP) system to handle the issues of bus assignment & scheduling problems in ACBSE. Within the specialty area of Operations Research, which is part of the larger discipline of Industrial Engineering, LP is a widely recognized technique. Then, utilizing 93 carefully chosen routes, the LP-model is employed to solve and optimally satisfy the current passenger demand throughout each of the four operating hours of the day. In this study, the four operational periods are referred to as shifts for the sake of simplicity. 93 specific routes are used during the day's operating intervals.

Chapter One: Bus scheduling techniques, Vehicle Routing Issues & Modeling

The concept of planning a minimum cost set of transporting routes to serve a group of customers is a fundamental constraint in the field of transport and logistics. Considering that transportation costs make up around 22% of a product's overall cost. Therefore, a number of industries in the field are concerned about the need to create a better route design that can lower the cost of transportation.

The Traveling salesperson Problem (TSP), which asks a salesperson to visit a number of places and then return to the city he began in, is a fundamental and well researched routing model that addresses the aforementioned problems. Reducing the salesman's overall trip distance is the TSP's main goal. A vehicle's route is defined as a tour that starts at the depot, visits a subset of the customers in a specific order, and ends at the depot. This makes the Vehicle Routing Problem (VRP) a generalization of the Traffic Signal Problem (TSP).
To address the above issues, the basic and well-studied routing model is the Traveling Salesman Problem (TSP) in which a salesman is to visit a set of cities & return to the city he started in. The objective of the TSP is to minimize the total distance traveled by the salesman. Vehicle Routing Problem (VRP) is a generalization of the TSP in that the VRP consists of determining m vehicle, 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. "A depot, consisting of a group of geographically dispersed clients with known needs and a group of vehicles with fixed capacity, defines the VRP." Only one visit per department is permitted, and a route's total demand cannot be greater than its vehicle capacity. The overall cost of distribution is what the VRP seeks to minimize. The VRP model is complicated in most real-life distribution scenarios by a multitude of side constraints. These external limitations may include time, such as the entire route duration and the window of time that the service must start. VRP was sometimes referred to as "vehicle dispatching" or "vehicle scheduling" (VSP) in the literature. It regularly shows up in real-world scenarios unrelated to the actual delivery of products.
The Bin Packing Problem (BPP) and the Traveling Salesman Problem (TSP), two well-known optimization issues, are combined to create the VRP problem. The BPP issue asks, "What is the minimum number of bins needed given a finite set of numbers and a constant K, specifying the capacity of the bin?" Logically, all the items have to be inside exactly in 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 is about a traveling salesman who needs to visit several cities. The salesman has to visit each city exactly once, start and end location, commonly called depot in VRP. The issue is to search the shortest tour within all the cities. Connecting this to the

VRP, customers can be allotted to vehicles by solving BPP and the order in which they are visited can be found by solving TSP. A problem known as vehicle routing problem (VRP) involves determining a set of routes for a fleet of vehicles stationed at one or more locations known as a depot for multiple scattered cities or customers. Here, the choice is which cars to allocate and which routes to use in order to maximize their use. The figure below provides a commonly used depiction of the VRP's input & output.

Figure 1: VRP inputs.

Figure 2: VRP output.

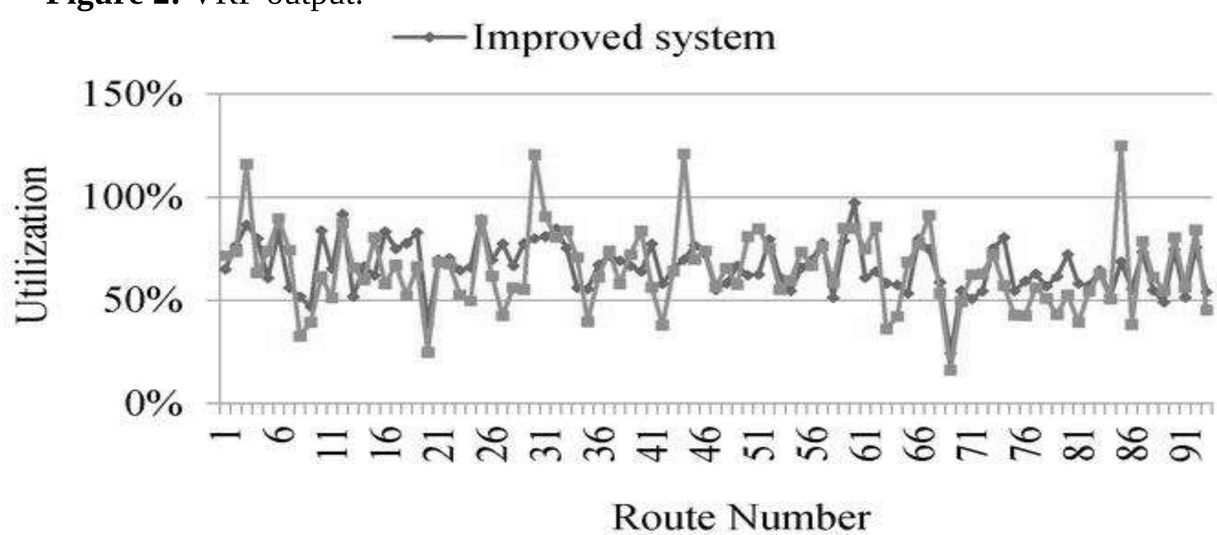

Figure3: Average daily bus utilization; current vs. improved system.

Since both BPP and TSP are the so-called NP-hard problems (nondeterministic polynomial time) and since VRP is combination of the two, it is also NP-hard. Since the last decades, VRP has got much interest from many scholars. Even in recent years, with the rapid advancements of globalization and supply chain systems, VRP is becoming one of the important research topics in the fields. Numerous optimization models have been proposed, and a great deal fracture has been written about the Bus Scheduling Problem (BSP) due to its complexity and importance in applications. The various models that have been developed have attempted to achieve near-optimal answers in a reasonable amount of time and computational effort. Over the past 50 years, there have been numerous requirements-based extensions for the Vehicle Schedule Problem (VSP) or VRP in the literature. Adverse fleet comprising a variety of vehicle types and the availability of one or more depots are only a few instances among many. Permission for journeys with varying departure times, or traditional VRP (variable rate pricing with deterministic demand).

The assignment of timetable buses for each route in the ACBSE's current operations schedule has presented numerous issues. The business has a scheduling system in place that runs from 6:30 to 20:30. as indicated by Table 1 below. The company has a set scheduling method, thus regardless of commuter demand, the number of buses permitted on each route stays the same. In actuality, though, the number of buses on each route ought to have been different and could have been decided upon by looking at the distribution of passenger demand. These methods have caused some buses to go empty while others are packed which causes the business to lose capacity and provides passengers with subpart service.

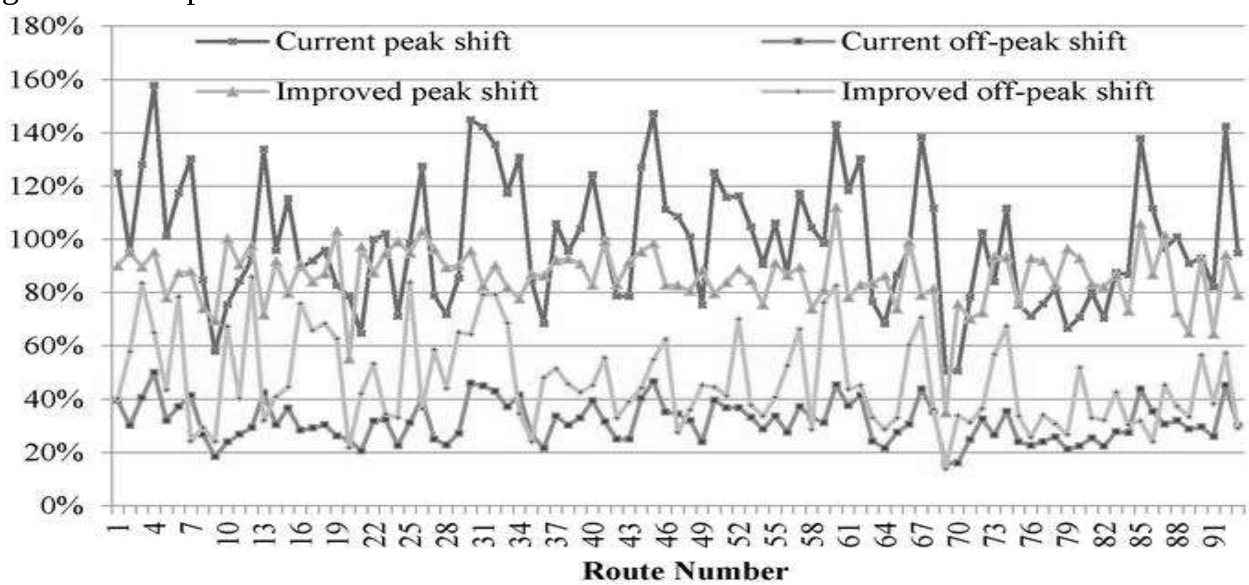

Figure 4: Average bus utilization for peak and off-peak shifts; current vs. improved system.

Route No.	Origin local Name	Destination local Name	No. of busses	Kms
1	Megenagna	Kara	2	7.7
2	Kore Mekanisa	Addis Ketema	4	11.1
3	Ayertena	Minilik Square	8	10.8
4	kaliti	Addis Ketema	5	19.4
93	Bole Bulbula	Megenagna	2	15.2
	Total		**36**	**132.8**

Table 1: The fixed number of busses assigned on selected routes (as of 2024).

The enterprise occasionally involves additional busses on few routes during peak hours to overcome the challenges. Due to the absence of records for such decisions, therefore, in this study, the fixed number of busses assigned on each route is only considered as a basis for benchmarking.

Although there are numerous limitations, the vehicle routing problem has been applied in a variety of settings and contexts. The main limitations are determined by network demand, customer depot locations, vehicle type, and occasionally driver behavior. All of the constraints cannot be met by a single model. Some of the restrictions in this instance can be loosened without sacrificing their universality. In VRP, this type of consumer abandonment is referred to as route failure. In certain cases, the situations can be resolved by imposing new sanctions or priority.

The purpose of the routing operations is to serve customers who choose to start and end at one or more roadside points. Each location or depot is distinguished by the quantity and kind of vehicles parked there as well as by the volume of cargo it is able to handle. Using a fleet of vehicles with a predetermined composition and size based on the needs of the clients, items are transported.

One further restriction in the model's assumptions is the vehicle used in VRP. As per the source, the vehicles can be distinguished based on their capacity, which can be defined as the most weight, volume, or quantity of pallets that the truck is capable of transporting. The drivers are often the least restrictive practice in application areas.

One of the most researched combinatorial optimization issues is vehicle routing problem (VRP), which deals with the best route design for a fleet of vehicles to service a group of clients. VRP is involved in various application areas that arise from the transportation and logistics system in addition to concentrating on the delivery and collection of commodities.

Various VRP models have been created to investigate the Routing Problem in various applications. The most recent one is the one that focuses on more intricate VRP variations that are occasionally referred to as "rich" VRPs. These are employed to create an optimal allocation method that can raise the caliber of their services; they are more akin to the VRP models. According to Toth Paolo and Vigo Daniele, there has been a notable reduction in computational effort, ranging from 5% to 20%, when using automated approaches to solve VRP problems.

VRP can be created as an undirected or directed graph, depending on the circumstances around the issue. In the case of traditional VRP, where the requests of the customers are known ahead of time, together with the driving time to each customer and the service time there. This section can be used to define and formulate it as a general VRP model. According to graph theory, it is named. Let G= (V, A), be an asymmetric graph representing cities or depots located at vertex O, with V=0, 1…, n as vertices, and A=$\{(v_i, v_j); v_i, v_j \in V, i \neq j\}$; A is the set of arcs. In order to describe the generic model of VRP. i=j is connected to a nonnegative distance matrix C=(C_{ij}) in each arc (i, j). It is frequently reasonable to replace A with E when C_{ij} can be interpreted as a journey duration or expense. In order to depict an asymmetric or undirected graph, E is a collection of undirected edges in the graph.

A series of at most K delivery or collection routes that are planned with the depot as the starting and finishing points, and each customer visited exactly once by a single vehicle, make up the common VRP. Each route's overall demand is kept within the vehicle's capacity, and the overall cost of routing is kept at a minimum. Stewart and Golden state that under all of these presumptions, the following compact representation of VRP can be given:

Minimze to $=\sum_{k=1}^{n} C_{ij}\, {x_{ij}}^{k}$ - -- (1)

Under the following conditions: $\sum_{i,j}^{n} q_i\, {x_{ij}}^{k} \leq$Q, k=1,2,3…,n ------(2)

Where:

The price/distance of getting from i to j = C_{ij}.

If vehicle K travels from i to j, then $X^{k}_{ij} = 1$; otherwise, 0;

m = The total number of vehicles available

S_m = The collection of all workable answers in the (m-TSP).

The sum requested at point i is denoted by q_i.

The vehicle's capacity is Q.

The triangular inequality is satisfied by the cost or distance matrix in many practical situations, i.e.,

$C_{ik}+C_{kj}\geq C_{ij}$; $\forall i,j,k\in V$. --(3)

The VRP models require a distinction between symmetric and asymmetric

The approaches to solving these two problems can differ greatly. When

A=(i,j)|i∈V,j∈V,i=j}, -- (4)

A=(i,j)|i∈V,j∈V,i<j} --- (5)

In practice, however, a variety of restrictions or side-constraints improve the general VRP model. The Capacitated Vehicle Routing Problem (CVRP) and the Vehicle Routing Problem with Time Windows (VRPTW) are revealed by the restrictions, which may include things like vehicle capacity or the amount of time that each customer must be served whether they are utilized for distribution and logistics, public transportation, or transit, VRP models have several characteristics in common.

Chapter Two: Information gathering /Data collection

Only the 93 routes that the business has been using for more than ten years were used to acquire the data. The information covers distance traveled, income earned, operational costs, total trips made, number of passengers served each route, and route performances. Additionally, information was gathered regarding the quantity of buses, their capacity, the typical duration of a bus trip, the length of each route, and the hours that they operate. For validation, the data were examined and arranged according to shift and route. Table 2 reports the operational shifts, the time interval for each shift, and the proportion of passengers demanded every shift.

Shift	Time interval	Duration	Demand proportion
Morning peak hours	6:15–9:30	195’	40%
First off-peak hours	9:30–15:30	360’	20%
Evening peak hours	15:30–19:30	240’	35%
Second off-peak hours	19:30–21:00	90’	5%
Total		870’	100%

Table 2: Proportion of demand and length of each shift.

According to its annual report, it operates 534 buses and transports around 640, 000 passengers’ daily over 93 routes. Apart from this, the company travels 138 km and makes 61.50 trips every day.

The enterprise schedules in this study can also be divided into four shifts, or peak hour and off-peak hour schedules. During the services period, there are two peaks and two off-peak times (from 6:30 to 21:00). The morning shifts of 6:30–9:30 and 15:30–19:30 are the peaks, and the morning and afternoon shifts are the off-peaks. Table 2 reports the specifics.

Within the four shifts, the demand share has likewise been distributed. Approximately 40% of the daily passengers are served by the businesses during the morning peak hour. About 35% of all passengers are carried during the evening shift during the second peak in passenger demand. The remaining times are the first and second off-peak shifts, which come after the morning and evening peak shifts, when the demand proportion is allotted at 20% and 5%, respectively.

Chapter Three: Development of Models

After looking into the ACBSE's current operating systems, the researchers created a linear programming (LP) model. The model aids in finding a solution to the enterprise's scheduling issues. In order to handle the demand distribution of passengers on 93 routes throughout the course of four working shifts, the LP model created in this study represents a novel method in the VRP literature. It takes into account the trips taken by two different types of buses.

3.1 Executing the model

Data was fitted to the LP model. The General Algebraic Modeling System (GAMS) optimization software was used to code and execute the model in order to accomplish its goal. In 0.15 seconds, the GAMS algorithm was operating.

3.2 Validation of the model

To find possible areas for improvement in the ACBSE scheduling and assignment problem, the LP model was examined and validated. It is also used to calculate how many buses should be assigned to a route at a given shift in order to accommodate the distribution of passenger demand for each of the 93 routes. By contrasting the present schedule with the enterprise's performances, the outcomes of the LP-model were verified. Four performance measurement parameters namely bus utilization, total trips made, total distance traveled, and various operating costs, were used to validate the results.

Let i be the number of trips per route per shift j made by bus type-I, denoted by $_{Xij}$ and by that of bus type-II, denoted by y_{ij} in order to create the LP model. In this phase, the model is built as a general model, which is subsequently fitted to the ACBSE problem using enterprise data.

Terminology definition:

i=Route number where (i= 1, 2, 3,..., n)

j=shifts, (j = 1, 2,..., m),

D_{ij} = Route i passenger demand at shift j

C_y= bus type-II, and C_x= bus type-I's capacity.

M_j = The least number of trips necessary during a specific shift j

Type-I total busses F_x and type-II busses F_y are equal.

The trip factor, or the most journeys a bus can make on route i during a shift j, is T_{ij}.

P_i is the trip percentage for route i.

Reducing the overall number of trips taken by bus types I & II is the goal. The following represents this goal:

Minimize: $\sum_{j=1}^{m} \sum_{i=1}^{n} \left[x_{ij} + y_{ij}\right]$

but must also adhere to other different restrictions.

Determining the Enterprise's total bus capacity is the first restriction. The two bus types allocated to route i during shift j have the following capacity. This capacity ought to exceed or match the total demand needed by the passengers who must trip on route i during shift j. The formula for it is $C_x x_{ij}+C_y y_{ij} \geq D_{ij}$. To determine the total number of buses for each type of bus, utilize the second and third constraints. In light of this, the total journeys needed by bus types I and II should, respectively, be less than or equal to the total trips made possible by those same types of buses. These can be stated numerically as:

$\sum_{j=1}^{m}\sum_{i=1}^{n} x_{ij} \leq F_x \sum_{j=1}^{m}\sum_{i=1}^{n} T_{ij}$ & $\sum_{j=1}^{m}\sum_{i=1}^{n} y_{ij} \leq F_y \sum_{j=1}^{m}\sum_{i=1}^{n} T_{ij}$

For each of the 93 routes, the fourth restriction will calculate the total minimum number of trips that must be made every 30 minutes.

$\sum_{j=1}^{m}\sum_{i=1}^{n}\left[x_{ij}+y_{ij}\right] \geq 93\sum_{j=1}^{4} M_j$ is the restriction/constraint.

For every route i, the journey taken by bus types I and II during each shift j should likewise be less than the total percentage of the trip that is available. The mathematical expression for this constraint is $X_{ij} \leq F_x P_i T_{ij}$& $y_{ij} \leq F_y P_i T_{ij}$. The last restriction that displays the sum of proportion. It needs to be combined into one.

The formula for this is $\sum_{i=1}^{n} p_i = 1$

The overall LP-model that establishes the ideal number of trips i needed per route per shift j is created as follows after assembling all of the aforementioned restrictions.

Minimize to: $\sum_{j=1}^{m}\sum_{i=1}^{n}\left[x_{ij}+y_{ij}\right]$ ------------------------------------(6)

S.t: $C_x x_{ij} + C_y y_{ij} \geq D_{ij}$ ---(7)

$\sum_{j=1}^{m}\sum_{i=1}^{n} x_{ij} \leq F_x \sum_{j=1}^{m}\sum_{i=1}^{n} T_{ij}$-- (8)

$\sum_{j=1}^{m}\sum_{i=1}^{n} y_{ij} \leq F_y \sum_{j=1}^{m}\sum_{i=1}^{n} T_{ij}$-- (9)

$\sum_{j=1}^{m}\sum_{i=1}^{n}\left[x_{ij}+y_{ij}\right] \geq m\sum_{j=1}^{m}\sum_{i=1}^{n} M_j$------------------------------- (10)

$x_{ij} \leq F_x P_i T_{ij}$ --(11)

$y_{ij} \leq F_y P_i T_{ij}$ --(12)

$\sum_{i=1}^{m} p_i$=1--(13)

$x_{ij}, y_{ij} \geq 0$ --(14)

The intended purpose the total number of busses needed to meet the entire demand will be reduced by using Eq. (6). Limitation the total capacity of the buses assigned to each route i at a particular shift j is shown in Eq. (7). The total number of buses that must be assigned for each route is shown in Equations (8) & (9). Equation (10) indicates that the total number of buses to be assigned on each route each shift must meet the minimum number of buses necessary per route every shift. This means that the total required number of buses must be equal to or less than the total number of buses that the enterprise has available. The number of buses to be assigned to a specific route is found in Equations (11) & (12). Additionally, Eq. (13) ensures that the total amount of probability is 1. Equation 14 shows non negativity restriction.

To maintain a decent service level, this model ensures that each route will receive at least one round trip every thirty minutes. By adding several bus types as a new constraint to a single LP-model, it also advances scientific knowledge.

The model computed the bus travel time on a given route as the total of the bus stop acceleration and deceleration times, passenger boarding and alighting times, and transfer times in between. Nevertheless, the model's functioning and output were not given as much thought. More specifically, each of the four shifts saw a single run of the model. The quantity of buses will be examined to ensure that M_j is satisfied at all times.

3.3 The bare minimum of busses

Furthermore, certain parameters were set for the purpose of understanding and clarity. Among the parameters are P_i, T_{ij}, and M_j. Below is a detailed explanation and illustration of each. The minimum number of visits necessary at shift j to satisfy the maximum permitted waiting time is represented by the value of M_j. For a specific shift in this scenario, a single journey takes 30 minutes during the 4-hour period. at keep passenger wait times at a maximum of 30 minutes throughout a shift, at least 8 trips must be made. This implies that in order to deliver high-quality service, there should be a bus every thirty minutes or such for each shift.

Since a single bus can make eight journeys in a four-hour period in 30 minutes, the real minimum number of buses needed for this approach is just one. Consequently,

$$M_j = \frac{\text{Total Duration for shift j}}{\text{30 minutes}} \text{ --------------------------------------- } (15)$$

Thus, the value of M_j for the four shifts is determined and shown in Table 3 using Eq. (15) and the data supplied in Table 2 above.

Route No.	Demand		Demand ij (D_{ij}) per Shift				Trip factor (T_{ij}) per Shift			
		Pi	D_1 (m_1 = 7)	D_2 (m_2 = 12)	D_3 (m_3 = 8)	D_4 (m_4 = 3)	1	2	3	4
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	11,030	0.038	4412	2206	3860	551	4	7	5	2
4	3029	0.010	1212	606	1060	151	3	5	3	1
93	778	0.003	311	156	272	39	2	4	3	1

Table 3: Input parameters for the LP model for some routes.

3.4 Analysis of trip factors

The trip factor, T_{ij} is the other parameter that needs to be clarified and defined. To compute it, use Equation (16). This figure represents the fewest journeys a bus can make on route i during a specific shift j. The possible number of trips per route per shift is determined by the trip factor, which is derived from the model's computation of the total number of trips required per route every shift.

The trip factor, which determines the maximum number of trips a bus can make on route i during shift j, is used to calculate the total number of journeys that a bus can make. This is due to the fact that the model determines the total number of trips needed for each route throughout a shift. The number of trips a single bus may make in a given period is then set and the actual number of buses is determined from the trip factor.

$$T_{ij} = \frac{\text{Total Duration for Shift j}}{\text{Single trip Travel}} \text{---}(16)$$

The maximum number of trips that the entire number of available busses can make can be found by multiplying the trip factor by the number of buses that are available F_x& F_y

3.5 Proportion of trips

The trip proportion, or P_i, is the other metric that requires explanation. For route i during shift j, it is necessary. P_i is the trip percentage of a specific route ii relative to the total routes provided by Equation (17).

Out of all the possible journeys, P_i is utilized to calculate the number to route i. Based on the percentage of all the routes' total journeys, the number of trips for each route is also calculated. The following equation provides it.

$$P_i = \frac{\text{Daily Demand of rout i}}{\text{Total daily demand of all Routs}} \text{---}17$$

D_{ij} is the final parameter that needs to be explained. During shift j, the average daily passengers on route i are the ones in need of transportation services. It is gathered from the enterprise's secondary data sources. It is reported in Table 2 and is distributed each shifty by multiplying the average daily passenger count of route ii by the demand proportion of shift j.

3.6 Complete the model

The model must then be run in order to produce workable answers. Based on information on the average daily passengers transported over the last 19 months in four shifts, the LP model is solved. After compiling the daily passenger demand for transportation for the previous 19 months, the trip proportion (P_i) of route ii was used to calculate the average daily passenger demand for each month per route per shift. The results are shown in Table 3.

3.7 A parameter entered into the model

Fitting the input data is the initial step in executing and solving the model. In this sense, determining the parameters is a necessary initial step in fitting the LP-model with the input parameters that comprise the model. These variables are either calculated or gathered from the business. Table 3 displays the sample input parametric values.

Standard bus carrying capacity, operational bus count, number of passengers requesting transportation services per route each shift (D_{ij}), trip factors (T_{ij}), minimum number of trips per shift (M_j), and trip proportion per route (P_i) are these input parameters.
Table 3 displays the sample input parametric values for a few routes.
The company uses four different types of buses: DAF, Mercedes, Single, and Rigged Articulated Busses. However, they can be divided into two groups according to the number of seats they can hold. These include one bus (DAF, Mercedes, Single, and Rigged Articulated) that can accommodate 30 passengers and two buses (the articulated one) that can accommodate 50 passengers.
In accordance with the LP-model, buses having a seating capacity of 30 are categorized as bus type-I, although they are capable of carrying 60 people, while buses having a seating capacity of 50 are categorized as bus type-II, although they are capable of carrying 90 passengers. Based on the typical capacity of public bus transportation, the maximum capacity of 60 and 90 passengers respectively. The sum of the seating and standing capacities for each type of bus determines its total capacity. There are a total of 60 type I and 90 type II employees in the firm. As a result, the research's objective function is employed to determine the best routes and combinations of the two bus kinds for each shift.
There are 60 operational buses in bus type I and 90 operational buses in bus type II. Not only are there 690 active buses, but there are still more buses that are preserved for contract and employee service as well as backups in case of breakdown. Additionally, over 90% of the daily demand is served by the 93 routes that are the subject of the analysis; as a result, the operational bus assignment is determined by this percentage. The LP model can be rewritten as follows once the input Parameter and constant values have been entered:

$$\text{Minimize}: \sum_{j=1}^{4}\sum_{i=1}^{93}\left[x_{ij}+y_{ij}\right] \text{-------------------------------} (18)$$

Subject to:

$$60x_{ij}+90y_{ij} \geq D_{ij} \text{---} (19)$$

$$\sum_{j=1}^{4}\sum_{i=1}^{93} x_{ij} \leq 60 * \sum_{j=1}^{4}\sum_{i=1}^{93} T_{ij} \text{--------------------------} (20)$$

$$\sum_{j=1}^{4}\sum_{i=1}^{93} y_{ij} \leq 90 * \sum_{j=1}^{4}\sum_{i=1}^{93} T_{ij} \text{--------------------------} (21)$$

$$\sum_{j=1}^{4}\sum_{i=1}^{93}\left[x_{ij}+y_{ij}\right] \leq 93 * \sum_{j=1}^{4} M_j \text{-------------------------} (22)$$

$$X_{ij} \leq 60 * P_i T_{ij} x_{ij} \leq 60 * P_i T_{ij} \text{--} (23)$$

$$y_{ij} \leq 90 * P_i T_{ij} y_{ij} \leq 90 * P_i T_{ij} \text{--} (24)$$

$$\sum_{i=1}^{93} p_i = 1 \text{--} (25)$$

$$x_{ij}, y_{ij} \geq 0 \text{---} (26)$$

Chapter Four: Model result, Bus routes are assigned& Validations of models

4.1 Bus routes are assigned

To meet the average daily passenger demand, 4627 trips in total are needed, according to the LP-model's output. The trip factor determines the actual number of buses needed for a specific route i during a given shift j. i.e., the total number of journeys each type of bus can make in a particular shift. Therefore, based on the conceivable trips that a bus can make during a given shift j on each route i, the result has to be converted into the number of busses needed for each route per shift. The number of trips can be converted into the number of buses using the LP model's output, which is displayed in Table 3.

Number of bus = $\frac{\text{Number of Buses}}{T_{ij}}$ -- (27)

The output of the LP may be insufficient for some routes, in which case it will be necessary to modify the actual number of buses in order to allocate at least two buses every shift to each route i.e one for the outbound journey and one for the return trip. This is due to the fact that demand exists in both directions along each route i during a given shift j. Table 5 presents a sample of the number of buses per route per shift, which was computed for all 93 routes in the same manner.

Route No.	Shift 1		Shift 2		Shift 3		Shift 4	
	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	3	1	1	1	2	1	1	1
2	5	1	1	1	3	1	1	1
3	16	3	2	3	10	4	0	3
4	6	1	2	1	4	1	2	0
5	4	1	1	1	3	1	1	1
6	12	3	0	3	8	3		
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
91	3	0	2	0	3	0	3	0
92	5	1	1	1	3	1	1	1
93	2	1	1	1	1	1	2	0
Total	396	94	114	88	269	94.8	121	79

Table 5: Number of busses per route per shift.

The findings demonstrated that more buses are really needed during peak hours than during off-peak hours. As a result, certain buses that run during morning rush hour must wait at bus stops until they are needed for evening rush hour. The actual number of buses needed for each shift fluctuates, and during peak hours, more buses are needed than during off-peak hours.

4.2 Model result

The model's output shows how many trips total between the two buses types are required to meet each route's typical demand during a specific shift. Table 4 displays some outputs from the LP model.

Route No.	Shift 1		Shift 2		Shift 3		Shift 4	
	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
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
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

Table 4: Number of trips required per route per shift.

The GAMS build system uses a variety of solvers, including BDMLP, BENCH, and BARON. Replace this text with your section heading, such as CPLEX, LGO, or CNOPT, which can handle a variety of problem types. For reporting purposes, the CPLEX solver is selected to solve the LP model established above after each solver is tried. The GAMS is used to code and program the LP model. The Appendix contains information about this build methodology as well as the GAMS code fragment.

The highest integer number is used to report the model's outputs. For route 3, for instance, Table 4 illustrates that 61 bus type-I trips and 14 bus type-II trips were needed for shift one. Additionally, there are routes where bus type-I journeys during off-peak hours are not necessary. The output of the LP model must be translated into the number of buses needed for each route in a given shift as it generates the number of trips needed. The number of trips from the model output must be divided by the trip factor (T_{ij}) in order to accomplish this.

4.3 Validations of models

Several performance measuring criteria were used to assess the LP-model's results. A variety of comparisons between the current performances and the LP-improved systems were undertaken for validation purposes. This study's comparisons were based on the number of trips taken, the distance traveled, and the various operating expenses of the various businesses. These are covered in detail in the sections that follow.

4.3.1 Bus use

Following conversion and bus assignment to each route and shift, the enhancements made possible by the LP model were contrasted with the current ACBSE bus use. The ratio of the number of passengers carried by the bus to its serviceable capacity was used to compute bus utilization. Figure 3 displays the average daily bus use of the upgraded and current networks. The study's findings demonstrate that the upgraded system outperforms the current one in terms of bus usage.

The enhanced system by this study has demonstrated a maximum bus usage of 97%, whereas the current system has a maximum bus utilization of roughly 125% on a daily basis, which is extremely crowded. This demonstrates how the new approach reduced passenger congestion and enhanced service quality. The enhanced systems have an average bus utilization of roughly 66.33%, which is higher than the 64.26% of the current systems. Although the two systems' average usage appears to be similar, the majority of the enhanced system's utilization falls between 60% & 80%, while the prior system's bus utilization was uneven failing occasionally below 20% & occasionally exceeding 120%. An extensive study of bus use based on shift was conducted, as shown in Figure 4. When compared to the previous system, the upgraded one showed notable improvements, as noted by shift. The increased bus usage by shift is 42.1% in the second off-peak period, 51.19% in the first off-peak, 82.24% in the evening peak, & 89.8% in the morning peak. 19.75% during the first off-peak and 12.15% during the second off-peak are the improvements over the current systems. By decreasing from 116.1% to 89.8%, the bus utilization of the upgraded system also lessened passenger congestion during peak hours. As a result, the enhanced system offers better service quality together with a bus usage that is more steady and regular. By lessening crowding during peak hours and lowering operational costs for the business during off-peak hours, the new model also indirectly raises the quality of service provided to passengers.

4.3.2 Coverage of distance and journey

This section compares the distances that the new system and the current system can cover. The total kilometers driven by buses on route I on a given day are calculated in order to compare this. It is the total number of kilometers traveled throughout the course of the four shifts. The total distance covered by the upgraded and current systems is depicted in Figure 5. The number of buses assigned to a certain route during a shift, the number of trips a single bus may make, and the length of the route were multiplied to get the distance traveled on each shift. Compared to the current system, which covers roughly 78,963 km each day, the enhanced system covers 70,964 km.

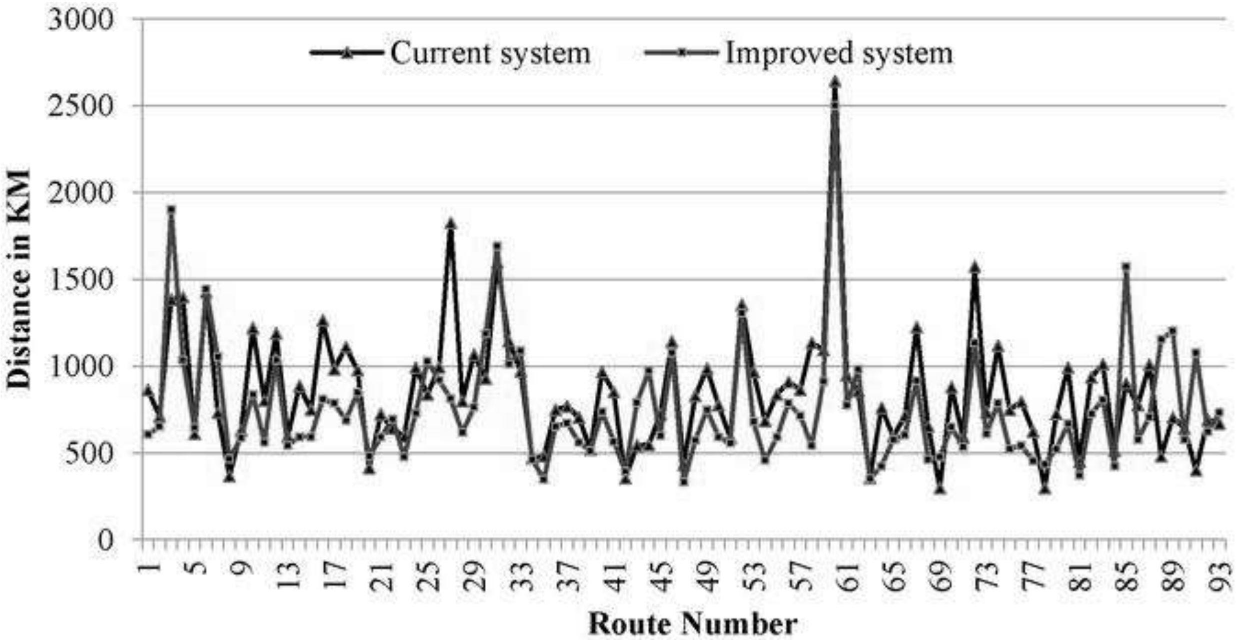

Figure 5: Distance coverage; current vs. improved system.

In this instance, calculating the number of buses allocated by the number of journeys a single bus may make in a given shift yields the total daily trips made for the enhanced system for each shift. 5504 journeys were covered daily by the current systems, compared to 5584 by the upgraded systems. Additionally, this indicates an improvement over the current system of 80 trips every day. A decrease of 10.13% in the daily Kilometer allowed for the rise in trips. This reduces operating expenses and enhances service availability as well.

4.3.3 Costs of operations

In this thesis, the other performance measuring factors were also evaluated using the various operating expenditures of the business. Not to mention, the new model improved things significantly. The entire operating costs for all shifts add up to the enterprise's daily operating cost for each route. Based on a comparative analysis, the study's findings indicate that, as of August 22, 2024, 1 USD = 105.04 ETB (Ethiopian Birr, or ETB) represents an enterprise's average daily running cost for the existing systems, whereas the enhanced systems have an ETB of 949,991. In comparison to the current method, the new system in this read saves around 13.74% every day.

Figure 6 illustrates how the new systems have improved almost every aspect of the business's operational costs when compared to the previous one.

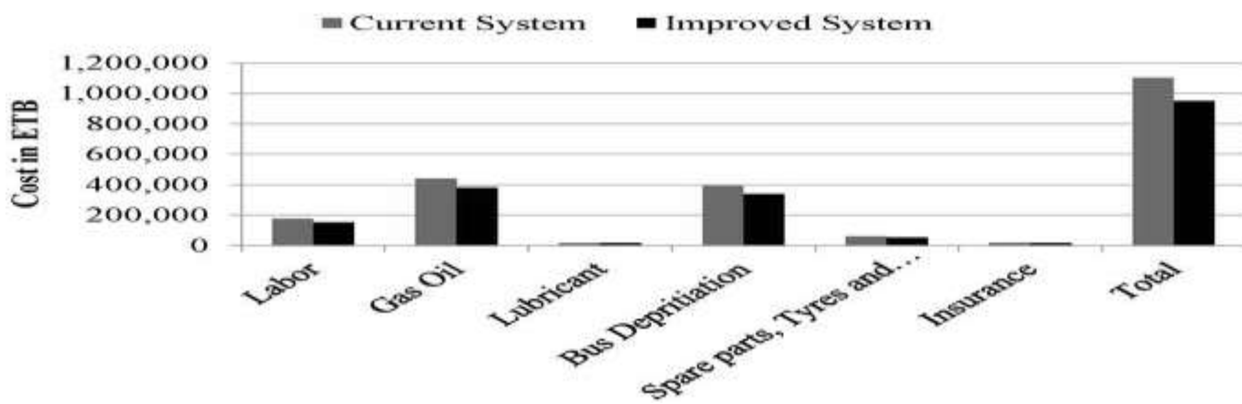

Figure 6: Current vs. improved operating cost.

The savings on gas oil are greater than the savings on all other operational expenditures. There is a close correlation between this reduction and the total kilometers traveled by each bus. This is because the improvement in the total kilometers traveled led to a decrease in the price of gas oil used.

Chapter Five: Overview and Conclusion

The goal of this study was to create a model that would enable ACBSE to operate at peak efficiency. The main conclusions draw the conclusion that the ACBSE's current scheduling methods perform poorly in terms of bus utilization, operational costs, daily trips, and distance traveled. Because the current system assigns a fixed number of buses to routes without taking into account the unpredictability of passenger demand, several modifications have been made. The business had to pay more for this.

Nonetheless, the LP-model's operational performance enhancements have outperformed the current one almost in every one of the performance measurement factors listed above. Furthermore, it can be inferred that the new system has a 2% higher average bus usage than the current bus scheduling and operations system. Additionally, there has been a noticeable boost in bus usage per route every shift compared to the current system.

In terms of savings, the enterprise's operational costs have decreased by 13% (310,124 ETB) as a result of the new model. Additionally, the new model gave the firm 80 extra trips each day and a 10.13% reduction in the overall kilometers traveled. By scheduling buses according to the worldwide standard bus capacity, the enhanced system has not only saved all the parameters but also decreased waiting times, enhanced service quality, and eased passenger congestion. Together with increasing the number of daily journeys, the new approach has also resulted in a notable decrease in the overall kilometers traveled. All of these updates to the LP-Model's new methodology were demonstrated without changing the paths that were previously taken by the enterprise.

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