PROJECT ID: CE/……../…….

"ASSESSMENT OF SCHEDULED BUS OPERATIONS AND ITS FEASIBILITY IN THE CITY OF KIGALI: Case study Line 203"

A DISSERTATION

Submitted by

MIZERO Jules (Reg. No: 221030317)

Under the guidance of

Dr. Alphonse NKURUNZIZA

&

Classio Mendiate

Submitted for the partial fulfillment of the requirements of

MASTER OF SCIENCE DEGREE IN

HIGHWAY ENGINEERING AND MANAGEMENT

JULY, 2025

UNIVERSITY of RWANDA

COLLEGE OF SCIENCE AND TECHNOLOGY

SCHOOL OF ENGINEERING

P.O. Box: 3900 Kigali, Rwanda.

DEPARTMENT OF CIVIL ENVIRONMENTAL AND GEOMATICS ENGINEERING (CEGE)

Declaration

I, MIZERO Jules, with Reg. No 221030317, from University of Rwanda College of Science and Technology, School of Engineering; Department of Civil, Environmental and Geomatics Engineering, Master of Science in Highway Engineering and Management Programme, hereby declare that this thesis/ dissertation is the result of my own work and has not been submitted for any other degree at the University of Rwanda or any other institution or anyone else where he/she had the same purpose.

Name: MIZERO Jules

Signature…………

Date: …24th.../…July…/2025

CERTIFICATION

This Thesis has been submitted with approval from the University supervisor (Main supervisor).

Main Supervisor

Names: Dr Alphonse NKURUNZIZA

Department of Civil, Environmental, and Geomatics Engineering

University of Rwanda, College of Science and Technology

P.O. BOX 3900, KIGALI

Signature: ....   Date: ....25th July 2025............

Co-Supervisor

Names: Dr Classio Joao MENDIATE

Department of Civil, Environmental, and Geomatics Engineering

University of Rwanda, College of Science and Technology

P.O. BOX 3900, KIGALI

Signature: ....Date: ....25th July 2025............

ABSTRACT

The current state of public bus transportation in Kigali, Rwanda. Buses are a crucial mode of transport for a significant portion of the population; however, the existing system largely operates without a formal and consistent timetable. This absence of a scheduled system presents several critical challenges. The scheduled bus operation will solve the problem of long waiting time, Travel time, queues length and increase the Level of services for public transportation. The aim of this research is to assess the scheduled bus operations and feasibility in the city of Kigali by studying the scheduled bus operation of line 203. This study is based on the data conducted from relevant authorities and daily travel demand data. The total of 710 trips for forwards and 710 of backward, Travel demand data was analyzed. to assess the performed of scheduled bus operations at two bus stations punctuality rate was adopted. Analysis using ANOVA and regression showed that deviations were not significantly affected by operator identity, as p-values exceeded the 0.05 significance threshold. Instead, delays and early departures were more commonly associated with time-of-day patterns, especially during late afternoon and evening hours. The findings show 97.7% and 80.6% of on time departures at both Nyanza and CBD and load factor of 53.4% and 58.3% of forward and backward respectively. Researcher also recommend the policies such as formulating regulatory frameworks, traffic congestion measures and implementing dedicated bus lane. From the results from analysis the scheduled bus operation is feasible to be implemented in the City of Kigali.

Keywords: Public transport, load factor, deviation feasibility, forward, backward, research, and Timetable

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

UR: University Of Rwanda

CST: College Of Science and Technology

MININFRA: Ministry of Infrastructure

REG NO: Registration number

Eng.: Engineer

WHO: World Health Organization

RNP: Rwanda National Police

CBD: Central Business District

ANOVA: Analysis of Variance

GIS: Geographic Information System

SPSS: stands for Statistical Package for the Social Sciences

COK: City of Kigali

UMIK: Urban Mobility Improvement in Kigali

DEDICATION

To:

My Family

My supervisors

Eng. box culvert at PK0+270

-Subbase placement BITANGAZA Moise

UMIK Experts Team

My relatives and friends.

My colleagues and workmates.

For your immeasurable love, tolerance, and care.

ACKNOWLEDGEMENT

The realization of this study was made possible by the support and assistance of many people. I want to express my gratitude, particularly to my supervisors Dr. Alphonse NKURUNZIZA and Dr. Classio Mendiate, not only for supervising this work but also and most importantly for providing effective and relevant advice an invaluable atmosphere that enabled me to work confidently and successfully. I am grateful for your very careful and critical reading of my work, as your invaluable comment's suggestions and encouragement.

I thank all, lecturers and staff for organizing, lecturing, accompanying, and making the learning environment so wonderful. Great thanks to my colleagues for spiritual, and moral support to the completion of my studies, and deep gratitude to classmates for their cooperation.

Special thanks to all people who, in one way or another. And I would like to thank the staff of Yahoo Car, Royal Express, City of Kigali, MININFRA and RURA in my survey who have willingly shared their precious time during the process of answering the questionnaire and providing required Information for this thesis. I express my gratitude to the different high learning institutions that allowed and facilitated me to consult their libraries.

To you all, I owe you much but can give you nothing; I just say God bless you.

CHAPTER I. GENERAL INTRODUCTION

1.1 Background

Public transportation is pivotal in the socio-economic development of urban areas like Kigali, Rwanda. Efficient and reliable public transport systems enhance accessibility, alleviate traffic congestion, and improve residents' overall quality of life. A cornerstone of an efficient public transport system is a well-structured and adhered-to timetable [1].

Unscheduled bus services often result in unpredictability and inefficiency[2]. Uncertain arrival and departure schedules cause passengers to lose time and opportunity[3]. This unpredictability can lead to overcrowding, longer travel times, and increased operational costs for both passengers and operators[4]. Additionally, irregular services may contribute to unsafe driving practices among drivers. To meet growing demand, passenger safety may be jeopardized. Furthermore, from an environmental standpoint, inefficient operations can lead to higher fuel consumption and emissions, adversely affecting air quality[5].

Scheduled bus services offer several advantages. They provide passengers with predictability, allowing for better journey planning and reducing travel-related stress. Regular services contribute to optimized route planning, which can help shorten travel times and enhance overall system efficiency[6]. By sticking to schedules, drivers experience less pressure to rush, promoting safer driving practices and potentially decreasing the likelihood of accidents.

1.2 Problem statement

Cities around the world face several challenges in achieving sustainable development, particularly in terms of sustainable mobility[10]. Rapid urbanization in cities across developing countries has led to an increased demand for efficient, reliable, and sustainable public transportation systems. In many African cities, such as Nairobi, Accra, and Lagos, efforts to shift from informal transport modes to regulated, scheduled services have yielded mixed results [11]. Scheduled operations are not reliable or scalable due to issues like irregular service delivery, poor timetable adherence, traffic congestion, and limited passenger data[12]. Cities throughout Africa struggle to match operational realities with planning expectations, even in the face of large investments in cooperative-based models and Bus Rapid Transit (BRT).

Kigali, the capital city of Rwanda, has experienced significant growth in population, economic activities, and urbanization in recent years. This transformation has created an urgent need to enhance the public transport infrastructure, particularly the bus system. Despite the expansion of bus services in Kigali, the city's public transportation system faces challenges related to scheduling, reliability, and passenger satisfaction. A key concern is the feasibility of timetable operations in the City of Kigali. The bus timetable is designed to provide structure and predictability for bus movements within the city, aiming to enhance service efficiency and help passengers plan their journeys. Research indicates that poor bus schedule synchronization, traffic congestion, and inadequate resources can hinder the effectiveness of bus timetables in urban areas[13]. As a result, the existing system in Kigali may not adequately meet the needs of passengers, who often face uncertainty about departure times and fluctuating service quality.

Even though there is evident demand for enhancements, there is an insufficient level of thorough empirical assessment of the operational efficiency of bus line routes. Essential performance metrics such as punctuality, load factors, adherence to scheduled headways, and vehicle utilization are still not quantified. This reflects a gap observed in research concerning developing cities, where dependable metrics are frequently absent unless they are formally assessed. Without hard data, policymakers, operators, and planners lack the basis for targeted operational improvements.

The examination of travel demand trends along the specified Line route is similarly constrained. Recognizing the spatial and temporal aspects of demand, including peak versus off-peak ridership and day-to-day fluctuations in demand, is vital for adapting services to meet the needs of riders. Research conducted in Lagos and Beijing demonstrates how smartcard and GPS data can uncover demand hotspots, peak periods, and variations[14],[15].

Additionally, there is a lack of substantial research regarding the operational difficulties that impact adherence to timetables. In urban areas with mixed traffic conditions, buses face issues such as heavy congestion, delays during boarding, vehicle breakdowns, and shortages of drivers, issues that have been recorded globally [16].

In this study, the researcher has assessed the current scheduled bus operations and their feasibility in the City of Kigali by considering the trip patterns, deviation on planned time and load factor, and key factor influencing scheduled bus operations.

1.3 Research objectives

1.3.1 Main Objective

As the City of Kigali has launched a pilot project for scheduled bus operations on line 203 Nyanza-Downtown, the main Objective of this study is to assess the feasibility of scheduled bus operations in the City of Kigali with a case study of Line 203.

1.3.2 Specific Objectives:

i. To analyze operational performance of the scheduled bus service on Line 203 (Nyanza–Downtown).
ii. To evaluate temporal and operator-based differences in schedule adherence on Line 203.
iii. To recommend policy and regulatory measures that support the expansion of scheduled bus operations in Kigali.

1.4 Relevance of the study

This study is relevant as it supports the City of Kigali's efforts to improve the reliability and efficiency of public transport through scheduled bus operations. By analyzing data from the pilot on Line 203 it provided evidence on the practicality, load factor, and challenges of implementing timetables in the Kigali context. The findings will guided future planning, infrastructure investment, and policy formulation for the citywide expansion of scheduled services.

1.5 The scope of the study

1.5.1 Geographical Scope

The study is restricted to Rwanda's capital, Kigali, which is the main urban location for public transportation. The study focuses on the bus services that run on 203 (Nyanza-Downtown), one of the primary routes that are run by bus networks inside the municipal limits. The demand for travel along the study line route has been examined by the researchers.

1.5.2 Time Scope

The study examined the data collected during the period of January 2025 to February 2025. The data focused on bus operators and transport planners, specifically regarding scheduled bus timetables and operational performance during this period. Data was collected within this timeframe to evaluate and assess the feasibility of scheduled bus operations in the citywide.

1.6 Conceptual framework of assess the feasibility of scheduled bus operation

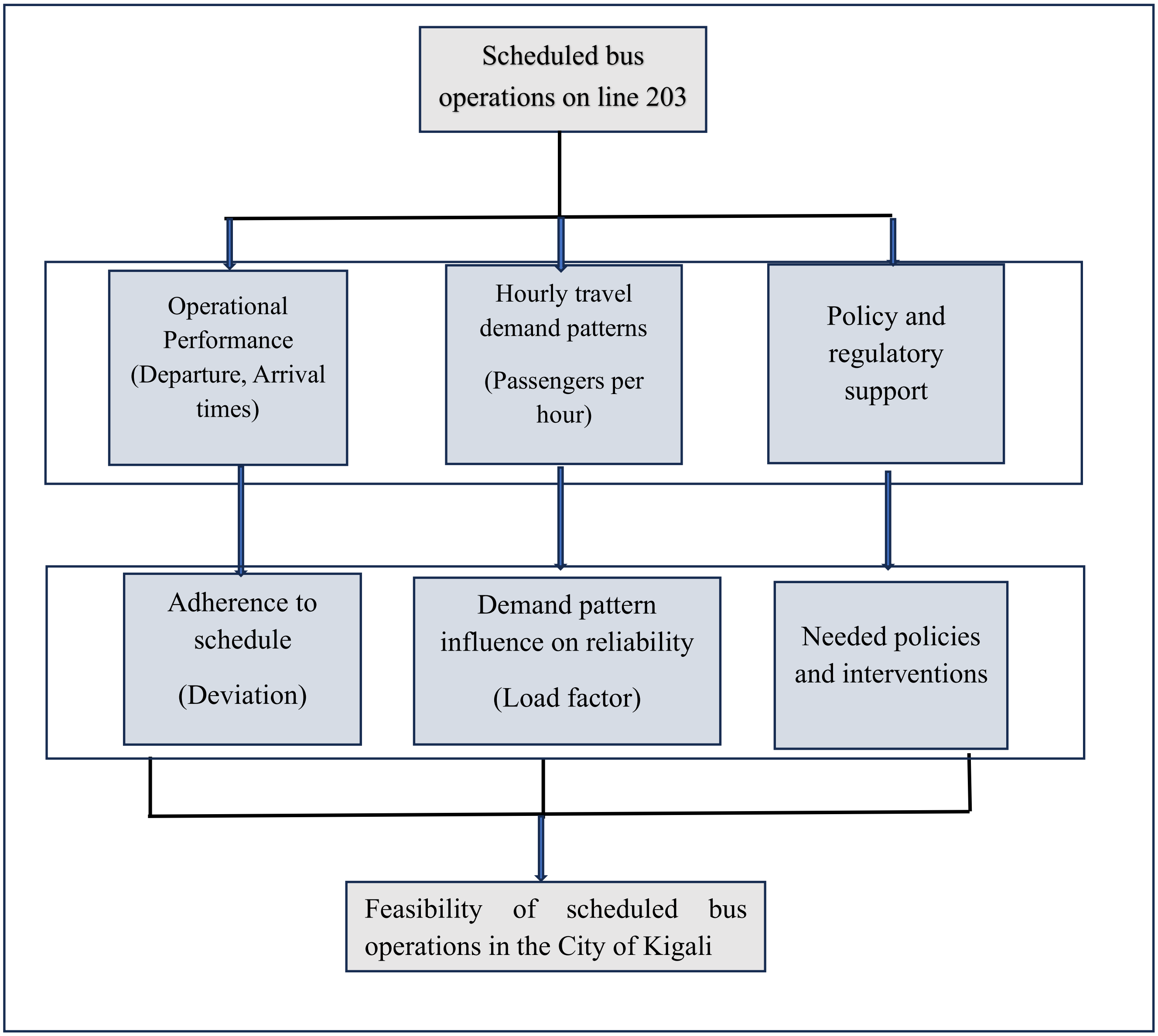

Figure 1: Conceptual framework of assess the feasibility of scheduled bus operation

CHAPTER II. LITERATURE REVIEW

2.1 Introduction

Timetable scheduling plays a vital role in public transport systems, as it determines the frequency and punctuality of services[17]. The main objective of timetable scheduling is to meet transportation demand while ensuring that buses operate at regular intervals, particularly during peak hours. Effective scheduling aims to balance service frequency with available capacity, minimizing waiting times and preventing overcrowding[18].

In many cities, particularly in developing countries, the main challenge is aligning bus timetables with real-time conditions. Delgado and Omar Jorge (2015), point out that without accurate data or real-time monitoring systems, bus schedules often do not reflect the actual operational conditions of the transport network[6]. In Kigali, the lack of comprehensive data on traffic patterns and commuter demand can lead to poorly designed timetables that fail to address peak travel times or fluctuations in demand. Therefore, the challenge is not only to create a timetable but also to ensure it is flexible enough to adapt to varying traffic conditions, passenger flows, and unexpected events such as vehicle breakdowns.

2.2 Punctuality rate

Research on service reliability underscores passenger trust in transit systems—especially punctuality. Reliability is evaluated by the accuracy of arrival/departure times and the percentage of trips operating as scheduled[19], The proposed model is used to analyze 113 runs of a bus route in Xi'an city, China. Real-time GPS data are used to analyze the operation of each run from the origin to the destination stops. The results show that 74.34% of the runs are delayed. When the value of TTD is higher than |0.1|, 64.2% of runs are delayed with bus bunching. [20]

In long-headway services, optimizing the scheduling percentile based on historical trip-time data such as using a 35th percentile choice—minimizes overall delay and waiting time[6].

Modern studies apply statistical and optimization models to minimize average travel time deviations. For example, one control strategy achieved a reduction in average trip-time error from 4.40 to 0.08 minutes, with punctuality improving from 83.3% to 90.5% after schedule optimization[21].

2.3 Deviation and load factor

Bus travel time deviation models incorporate both running time (between stops) and dwell time (at stops), and account for phenomena like bus-bunching to quantify headway variation[20],[22] . These studies often use the coefficient of variation (CV) of headways as a reliability metric lower CV reflects more consistent service and better on-time performance[22].

The load factor (percentage of vehicle capacity utilized) is a key metric linking operational efficiency and passenger comfort. For example, Trans Mamminasata service in Indonesia recorded a highest load factor of just 65%, below the 70% operational standard[23]. Studies show that high load factor coupled with long in-vehicle times significantly reduces passenger comfort perception, underlining its importance in service quality assessments[24].

Innovative models now integrate big data, such as GPS and IC-card information, to dynamically adjust schedules based on time-varying passenger demand. These methods optimize both punctuality and load factor, one Beijing-based study improved passenger numbers by 8.2% via data-driven timetable optimization that considered demand, capacity, and headway constraints[25].

2.4 Service Satisfaction

Passenger acceptance is closely linked to the perceived value and convenience of the service. A study by Lodhi (2014) found that when buses adhere to predictable schedules, passengers are more likely to view the service as efficient, which increases their willingness to use it[26]. Conversely, frequent disruptions and long waiting times lead to dissatisfaction, resulting in a decline in public transport usage.

Operators' acceptance of the timetable is influenced by practical and economic considerations. They must ensure that the timetable provides sufficient flexibility to address operational challenges, such as traffic congestion or unexpected breakdowns, while also remaining within their financial constraints [27]. Operators may resist rigid timetables if they believe the scheduling does not adequately reflect operational realities, leading to inconsistencies in service delivery.

Transportation planning is essential for understanding how bus timetables are designed, implemented, and optimized in urban areas. One of the foundational theories in this field is the Theory of Demand and Supply in Public Transport Systems. This theory explains how service frequency, timetable design, and availability can meet the needs of passengers while considering the operational capacity of service providers[28]. According to the theory, the demand for public transport services is influenced by various factors, including population density, urbanization, and socio-economic conditions. For a bus timetable to be effective and efficient, it must align with transport demand, especially during peak and off-peak hours[28].

2.5 Road Congestion

The second half of the 20th century saw the rapid expansion of the road network in rural and urban areas. In the latter, roads were originally designed for speed and high capacity, but urban growth often occurred at a rate higher than expected. The view was to provide accessibility to cities and regions, with the primary incentive for the expansion of road transport being the provision of high levels of transport supply[29].

Coupled with road congestion, parking is another form of urban congestion, but its effects are different. Parking significantly influences land use, as it consumes large amounts of space. In largely car-dependent cities, this can be very constraining as each economic entity has to provide an amount of parking space proportional to its level of activity. Therefore, parking has become a land use that greatly inflates the demand for space in a largely inefficient way. Land use planning textbooks rarely mention parking congestion and requirements, indicating that the issue has often been neglected and underestimated by urban planners. As in the case of road congestion, cities are often required to provide additional parking space with growing demand to ensure economic development[29].

2.6 Modal Shift

Achieving a modal shift from private transport to public transport, walking, and cycling, is the primary objective of most transport planning city authorities. With the constantly increasing travel demand and the increasingly insufficient private transport infrastructure, public transport in cities presents many advantages, not only in terms of sustainability but also in terms of efficiency. Having greater passenger capacity and a considerably smaller environmental footprint per capita, public transport has become a viable and sustainable alternative to the congested highways of densely populated inner-city areas.

Looking at public transport, the main factors affecting its demand are fares, the quality of service, and the cost of competing modes[30].

2.7 Service reliability

Looking at the supply side, a single vehicle trip is the basis of operations. Vehicle trips are scheduled in time and space resulting in departure and arrival times at all stops along the route from terminal to terminal[31] . In addition to these exact departure times at a stop, the number of trips within a time frame is important. This frequency determines the number of possible departures for passengers per time frame and it determines the headways between successive vehicles[32]. Transit scheduling models traditionally assume deterministic, fixed trip patterns without accounting for dynamic variations. During operations however, actual vehicle trips suffer from disturbances and variations occur, both over the homogeneous periods per day as over longer periods[33].

Unplanned stopping is the stopping of vehicles at a location where no boarding and alighting is enabled, for instance at traffic lights. Eliminating this source completely is the best way to improve public transport reliability[31]. Unfortunately, in urban public transport (bus, tram, and light rail), unplanned stopping occurs and results in both delays and service variability. The main reason is other traffic. Unlike a metro system, which has an exclusive right of way, these systems share parts of the infrastructure, lanes, and junctions with car, bicycle, and even pedestrian traffic. Besides, water traffic may create substantial stopping times as well, due to the openings of bridges.

2.8 Travel time and Waiting time

The first part of passenger travel time (needed for the complete public transport journey) is the access time, which is the time needed between the origin and the departure stop. Often, this part of the journey is on foot and sometimes by bike. At the departure stop, waiting time will occur between the arrival of the passenger and the departure of the vehicle. Two arrival patterns may be distinguished. Passengers may arrive at random or they may plan their arrival according to the schedule. In the latter case, some waiting time at the origin may occur as well. This waiting time is referred to as hidden waiting time and arises due to a discrepancy between the preferred departure time and the available departure time[34].

Researchers have composed a list of elements that affect punctuality to a greater or lesser extent. This list includes aspects such as traffic conditions, distribution of lanes for exclusive or preferential use, the possibility of overtaking, ease of boarding and alighting at bus stops, priority at traffic lights, lane blockages due to special circumstances, trip length, number of stops, intervals between stops, different driving habits, discipline on leaving the terminal and relief shifts, availability of vehicles and drivers, number of passengers, occupation of the buses, uniform demand at each stop, control, and regulation strategy for incident recovery, adapting of timetables, and time spent recovering from incidents[35].

Empirical evidence from East African cities highlights persistent challenges in achieving high punctuality rates, schedule adherence, and balanced load factors in scheduled bus operations. In Kigali, despite formal timetabling across major operators, service reliability remains suboptimal due to traffic congestion, weak regulation, and discretionary driver behavior—which often results in erratic early or late departures and arrivals [36]. Analysis of occupancy rate fluctuations among operators such as Jali, Yahoo car, KBS, and Royal Express reveals significant variability (standard deviations between 0.237 and 0.316), reflecting inconsistent load factors across trips[36].

Although international studies have modeled headway control strategies and reliability interventions[33], this type of analysis has yet to be applied to specific scheduled services like Kigali's Line 203. Objective researcher focused on quantifying headway and frequency performance at the route level, addressing this omission and Cenfri et al. (2023) emphasize leveraging tap-in and GPS data for broad system planning in Kigali, detailed assessments of headway and frequency on individual routes like Line 203 are still absent [37]. This unproved the frequency and headway factor which calls for rigorous operational performance measurement at the route scale.

Research in Lagos demonstrates the value of time-of-day travel demand segmentation for optimizing scheduling [15]. yet such fine-grained demand analysis remains absent for Kigali's bus routes. Research objective targets this by examining temporal and spatial demand along Line 203. National studies and business-model research (e.g., MIC-HUB, 2021) have projected overall demand for Rwanda, but fail to capture temporal spatial variability specific and its influence on scheduled operations to Line 203 [38]. Filling this void will directly support Objectives by uncovering how local demand patterns affect service viability.

Studies in Chennai and Dar es Salaam have applied reliability frameworks such as buffer time index and coefficient of variation to evaluate reliability using GPS data[39], However, these metrics have not been localized to Kigali. Objectives seek to uncover operational constraints affecting timetable reliability in the unique traffic context of Kigali.

While academic discourse proposes various scheduling and regulation strategies[40], there is a lack of empirical adaptation for Kigali's ecosystem driver incentives, fleet mix, resource allocation that support expansion to citywide scheduled services. This study will develop evidence-based recommendations rooted in operational and demand data.

By concentrating on Line 203 (Nyanza–Downtown) and integrating operational performance analysis, load factor variability, punctuality rate, deviation on scheduled time, reliability metrics, and context-sensitive policy interventions, this study fills these critical gaps in the literature.

CHAPTER III. RESEARCH METHODOLOGY

3.1 Study Area

Rwanda, a country in East Africa, is a densely populated country with 13.24 million residents as per the Fith Rwanda |Rwanda Population and Housing Census. Kigali is made up of three districts, Gasabo, Kicukiro, and Nyarugenge. According to the National Institute of Statistics of Rwanda, in the 2018 the population of Kigali stood at approximately 1.5 million [41], with a mean population density of 2391 people/square kilometer with a combined mean road density of 0.093 km/km^2 and an unpaved mean road density of 0.12 km/km^2 [42]. This increase in the number of people in Kigali city has increased the demand for public bus transport. Scheduled bus operations will reduce waiting time and travel time, improve public transport services, and increase customer satisfaction.

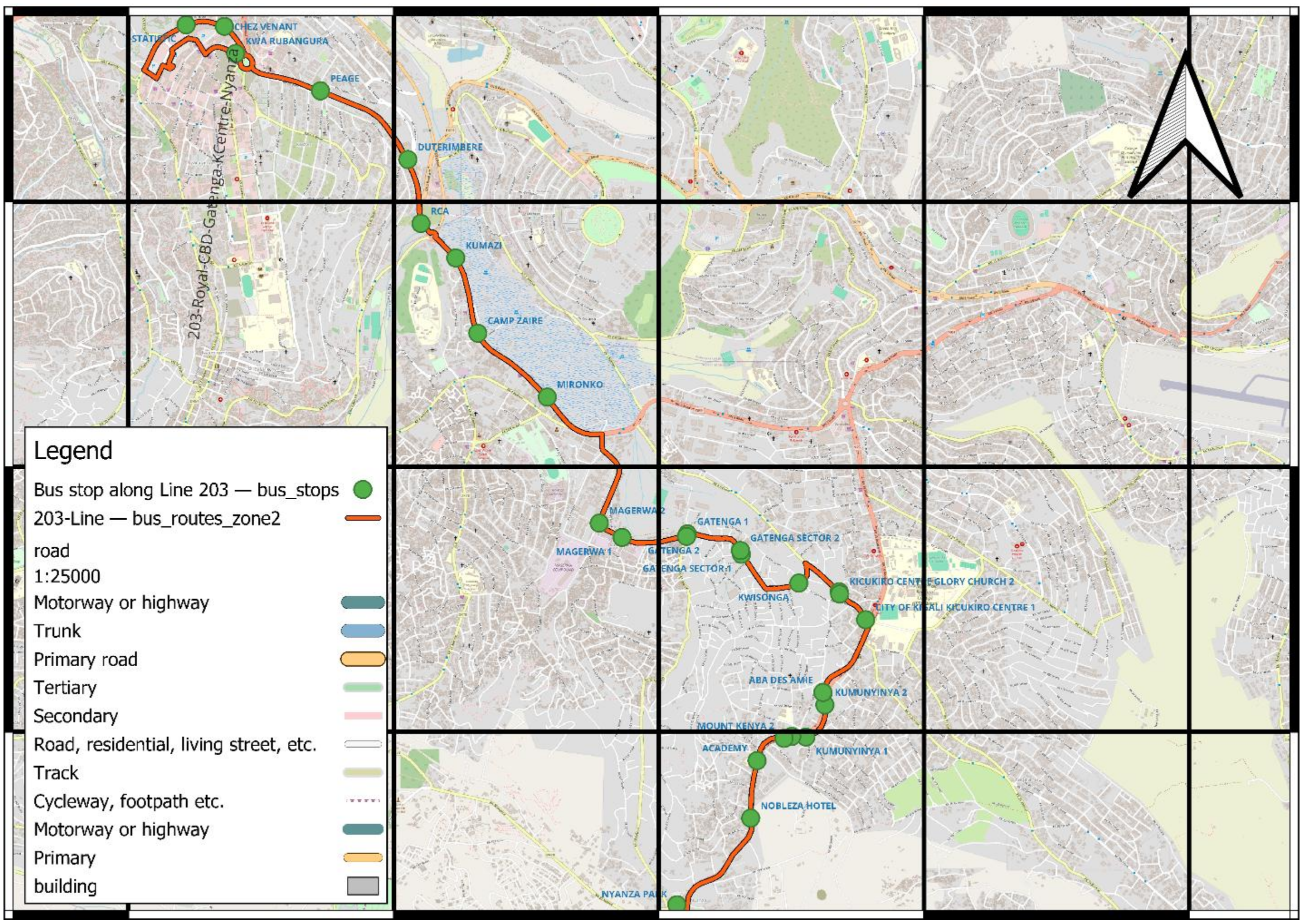

Figure 2:Case Study Location Map

The study focused on Line 203 (Figure 3), a strategic corridor connecting Nyanza bus Terminal and Downtown Terminal. This line was selected due to its inclusion in the pilot project for scheduled bus services, high passenger volumes, and its representation of typical operational conditions in Kigali. The route encompasses residential, commercial, and high-traffic zones, providing a comprehensive view of the operational performance in the current public transport system.

3.1 Research Design

This study included four phases.

- Phase one: Development of Bus Timetable and Driver schedule
- Phase two: Implementation of bus timetable on line 203
- Phase three: Monitoring performance and Data collection
- Phase four: Data analysis, conclusion and recommendation

The main research started on the phase three of monitoring the scheduled bus operations by checking the departure and arrival time, deviation and load factor.

3.2 Method of scheduling bus operations

To develop an efficient and reliable operational timetable for Line 203 (Downtown–Nyanza), a macro-enabled Microsoft Excel application was employed. This tool automates the scheduling process to ensure optimal vehicle utilization, minimize unnecessary deadheading trips, and respect terminal layover constraints. The scheduling method is based on a step-by-step algorithm designed to logically sequence trips and assign vehicles with minimal idle time.

The first step in the scheduling process is to define compatible trips at each terminal Downtown and Nyanza by evaluating the temporal feasibility of linking two successive trips. Two trips, denoted as i and j, are considered compatible if they satisfy the condition $Mk < tsj - tei < 2Dk$, where Mk is the minimum required layover time at terminal k, Dk is the deadhead time from the terminal to the depot, tsj is the start time of trip j, and tei is the end time of trip i. This compatibility condition ensures that sufficient time is available for recovery or repositioning between trips.

The second step of the algorithm applies a restricted First-In-First-Out (FIFO) rule to organize and link compatible trips in chronological order. Beginning with the earliest trip arrival, the algorithm attempts to link each arriving vehicle to the next available compatible departure. If a compatible trip is found, the vehicle is assigned to continue service; if not, it is returned to the depot. Additionally, each vehicle's total assigned route duration is checked against a predefined maximum operating time. If this limit is exceeded, the vehicle is returned to the depot, and the algorithm proceeds to evaluate the next available trip. Once all arrivals have been processed, remaining unlinked departure trips are served by dispatching fresh vehicles from the depot.

Using this algorithm, a detailed timetable for Line 203 was generated. The schedule includes regular departure intervals typically every 10 to 15 minutes during peak periods and ensures that turnaround times at both terminals adhere to required layover and recovery constraints. Trip sequences were optimized so that each vehicle could serve consecutive trips without excessive idle time. For departures that could not be linked to prior arrivals, vehicles were directly assigned from the depot. This systematic scheduling approach contributes to improving service reliability, reducing operational inefficiencies, and facilitating the successful implementation of scheduled bus operations along the selected corridor.

3.1 Data Collection

To meet the general and specific objectives, the data of this study combined the primary data and secondary data. The primary data was collected at the bus terminal, while secondary data was requested from the relevant authority, which are RURA and the Bus operators.

3.1.1.1 Primary data

The data was collected at bus terminals, researcher has conducted information on important metrics such as departure and arrival times, and total journey duration on implemented scheduled bus operations in order to assess operational effectiveness. To ensure comprehensive insights into real-time bus movements.

3.1.1.2 Secondary data

The data on travel demand was requested from the two operators providing transport services on line 203.On peak/off-peak ridership, hourly changes, and the overall number of passengers per trip. The data was gathered in order to comprehend passenger demand. In order to provide a full picture of travel patterns, bus operators were requested to provide detailed data.

3.2 Data Analysis Techniques

MS Excel and SPSS tools were used to analyze conducted data. correlation and regression and Descriptive statistics as mean, median, and standard deviation, was computed for statistical analysis.

Table 1: Deviation category

Deviation Category	**Deviation range on Planned time(min)**
On-Time	-2 to +2
Slightly Delayed	+3 to +6
Delayed	+6 to +10
Significantly Late	> +10
Early Arrivals/Departures	< -2

The Table 1 categorizes bus schedule deviations into defined time ranges to assess punctuality. It identifies on-time performance within ±2 minutes, with increasing levels of delay beyond that. Early departures are those occurring more than 2 minutes before schedule, helping quantify service reliability and pinpoint areas needing operational improvement.

The punctuality rate and average load factor [43], were calculated

- **Punctuality Rate (%)** = (On-time departures / Total scheduled departures) × 100
- **Average Load Factor (%)** = (Passengers carried / Bus seating capacity) × 100

Graphs, tables, and bar charts were generated to utilize visually present trends in travel demand and service dependability, compliance with Planned departure and arrival times. These visual tools enhanced the interpretation of data, making patterns and variations easier to understand and analyze.

Regression model and descriptive statistics analysis were used to evaluate the performance of scheduled bus operation, influence factors and the feasibility of adopting on the large scale.

CHAPTER IV. RESEARCH RESULTS AND DISCUSSION

Results

This chapter section indicates the interpretations of data conducted included with bus headway, service frequency, exactly departure time, Arrival time, total journey durations, punctuality rate and Load factor was collected from site, bus operators, and government officials to assess scheduled bus operations and its feasibility. Also, statistical analysis was done by using IBM SPSS Statistics 20.0 and Q GIS, where the confidence interval is 95%. This section indicates the output results, interpretations and discussion.

4.1 Bus Time table Creation

Before the planning and implementation of the scheduled bus operations, the surveys were conducted before the implementation of pilot project of scheduled bus service with the result of the following headway and frequency of the current operations at both terminals, Downtown and Nyanza.

Table 2: Current headway and frequency at Terminals

From:	Nyanza					
To:	CBD					
5:						
6:	05	33	45	58		**4**
7:	04	11	20	33	48	**5**
8:	03	12	20	33	52	**5**
9:	15	26	47			**3**
10:	00	28	50			**3**
11:	10	44				**2**
12:	11					**1**
13:	19	43				**2**
14:	27	51				**2**
15:	25	58				**2**
16:	10	28	44			**3**
17:	07	30	41			**3**
18:	03	17	31	37	49	**5**
19:	17	32	51			**3**
20:	03	18	20	55		**4**
21:						
22:						
						47

From:	CBD					
To:	Nyanza					
5:						
6:	51					**1**
7:	12	24	39	45	55	**5**
8:	12	32	50			**3**
9:	08	23	48			**3**
10:	10	32	58			**3**
11:	21	38				**2**
12:	04	25	33	37		**4**
13:	52					**1**
14:	24	50				**2**
15:	14	41	58			**3**
16:	26	51				**2**
17:	05	13	20	37	57	**5**
18:	03	15	30	38	49	**5**
19:	14	20	33	47		**4**
20:	04	13	30			**3**
21:						
22:						
						46

The Table 2 presents the weekday bus departure schedule from Nyanza to the CBD, detailing departure times, headways, and frequency per hour. At 6:00, buses depart at 5, 33, 45, and 58 minutes past the hour, with four departures; headways vary from 12 to 15 minutes. At 7:00, five buses depart at 04, 11, 20, 33, and 48 minutes, with headways between 7 and 15 minutes. The 8:00

hour also has five departures at 03, 12, 20, 33, and 52 minutes; headways range from 7 to 19 minutes. At 9:00, buses leave at 15, 26, and 47 minutes with 3 departures and headways of 11 and 21 minutes. The 10:00 hour has three buses at 00, 28, and 50 minutes with headways of 22 and 20 minutes. At 11:00, two buses depart at 10 and 44 minutes (34-minute headway), while at noon, has a single bus at 11 minutes. At 13:00 and 14:00 hours, each has two buses (13:19 and 43 for 13:00, 27 and 51 for 14:00) with a headway of 24 minutes.

At 15:00, two buses depart at 25 and 58 minutes (33-minute headway). The 16:00 hour has three departures at 10, 28, and 44 minutes with headways of 18 and 16 minutes. At 17:00, three buses leave at 07, 30, and 41 minutes, with headways of 23 and 11 minutes. The 18:00 hour shows five departures at 03, 17, 31, 37, and 49 minutes; headways vary between 6 and 14 minutes. At 19:00, three buses leave at 17, 32, and 51 minutes with headways of 15 and 19 minutes. The 20:00 hour has four buses at 03, 18, 20, and 55 minutes with headways from 2 to 35 minutes. No departures occur at 5:00, 21:00, and 22:00. The total frequency between 6:00 and 20:00 is 47 buses.

CBD, At 6:00, there is one bus departing at 6:51. The 7:00 hour has five departures at 7:12, 7:24, 7:39, 7:45, and 7:55, with headways ranging from 6 to 15 minutes. Between 8:00 and 10:59, frequencies are between two to four buses per hour: at 8:00 (7:12, 7:32, 7:50; headways 18 and 18 minutes), 9:00 (9:08, 9:23, 9:48; headways 15 and 25 minutes), and 10:00 (10:10, 10:32, 10:58; headways 22 and 26 minutes). The 11:00 hour has two departures at 11:21 and 11:38, with a headway of 17 minutes. The 12:00 hour shows four buses at 12:04, 12:25, 12:33, and 12:37, headways between 6 and 21 minutes. Some hours have fewer departures such as 13:00 (one bus at 13:52) and 14:00 (two buses at 14:24 and 14:50). 17:00 and 18:00, with five departures each and headways as short as 6 minutes. Later hours show reduced frequency, with no buses at 5:00, 21:00, and 22:00, totaling 46 departures during the day.

4.1.1 Travel time

The results of travel time from Nyanza bus park to CBD terminal and from CBD terminal to Nyanza bus park on weekdays are found and categorized into time ranges with varying travel durations.

Table 3: Bus travel time along line route,

From Downtown to Nyanza				From CBD to Nyanza			
			Travel time				**Travel time**
5:50	~	6:59	45	6:00	~	6:59	35
7:00	~	9:59	50	7:00	~	7:59	40
10:00	~	15:59	45	8:00	~	15:59	45
16:00	~	17:59	50	16:00	~	16:59	50
18:00	~	19:59	45	17:00	~	18:59	55
20:00	~		40	19:00	~	19:59	45
	~			20:00	~		40

The finding shows travel time from Nyanza bus park to CBD terminal, 5:50 AM to 6:59 AM, the travel time is 45 minutes. Between 7:00 AM and 9:59 AM, it increases to 50 minutes. From 10:00 AM to 3:59 PM, it reduces back to 45 minutes. During peak hours from 4:00 PM to 5:59 PM, it again takes 50 minutes. In the evening, from 6:00 PM to 7:59 PM, it drops to 45 minutes, and after 8:00 PM, travel time is 40 minutes.

From CBD Terminal to Nyanza bus park across different time intervals. Travel time is shortest between 6:00–6:59 at 35 minutes, gradually increasing during peak hours. It peaks between 17:00–18:59 with a maximum duration of 55 minutes, Midday travel from 8:00–15:59 averages 45 minutes, while late evening periods (20:00 onward) show a decline to 40 minutes.

4.1.2 The Planned bus time table

After conducting the travel demand, travel time, and determining the peak hours of the day, the bus timetable, trip schedule and driver scheduled created and implemented.

From	Nyanza			From	Downtown		
To	Downtown			To	Nyanza		
5:	50	5am	1	5:		5am	
6:	05 20 30 40 50	6am	5	6:	40 55	6am	2
7:	00 10 20 30 40 50	7am	6	7:	10 20 30 40 50	7am	5
8:	00 10 20 30 45	8am	5	8:	00 10 20 30 40 50	8am	6
9:	00 15 30 45	9am	4	9:	00 15 30 45	9am	4
10:	00 30	10am	2	10:	00 15 30 45	10am	4
11:	00 30	11am	2	11:	00 30	11am	2
12:	00 30	0pm	2	12:	00 30	0pm	2
13:	00 30	1pm	2	13:	00 30	1pm	2
14:	00 30 45	2pm	3	14:	00 30	2pm	2
15:	00 15 30 45	3pm	4	15:	00 30 45	3pm	3
16:	00 15 30 40 50	4pm	5	16:	00 15 30 45	4pm	4
17:	00 10 20 30 40 50	5pm	6	17:	00 10 20 30 40 50	5pm	6
18:	00 10 20 30 40 50	6pm	6	18:	00 10 20 30 40 50	6pm	6
19:	00 10 20 30 45	7pm	5	19:	00 10 20 30 40 50	7pm	6
20:	00 15 30 45	8pm	4	20:	00 15 30 45	8pm	4
21:	00	9pm	1	21:	00 20 40	9pm	3
22:		10pm		22:	00 20	10pm	2
			63				63

Table 4: 203 Bus Timetable

At Nyanza, the first departure is at 6:05 AM, and buses depart frequently during peak hours, 6:00 AM and 8:00 AM, there are 5 to 6 departures per hours. The hours with more demand scheduled to be 4:00 PM and 6:00 PM, with 6 departures each.

At Downtown, buses are planned to start at 6:40 AM, increasing in frequency from 8:00 AM, with 6 departures per hour, which are 8:00, 8:10, 8:20, 8:30, 8:40, and 8:50. Peak periods are also scheduled to be the morning (8–10 AM) and evening (4–6 PM).

4.2 Performance of scheduled bus operations

4.2.1 Deviation on planned departure time at Down town terminal

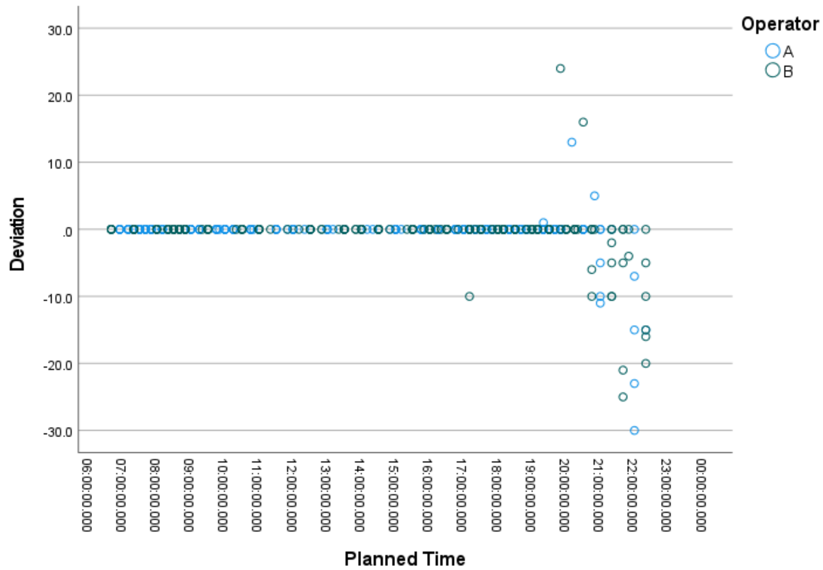

Figure 3: Planned time for departure vs Deviation time at Downtown terminal

Figure 5 shows the deviation from planned departure times for Operators A and B throughout the day. Most buses from both operators maintain punctuality from early morning until 8:00 PM, with deviations close to zero. However, after 8:00 PM, a noticeable pattern of schedule non-adherence emerges. Several buses depart significantly earlier than scheduled, with deviations reaching up to -30 minutes, while a few leave late with deviations exceeding +20 minutes. B operators show more early departures during late evening hours.

4.2.2 Deviation from the planned arrival time at the Downtown terminal

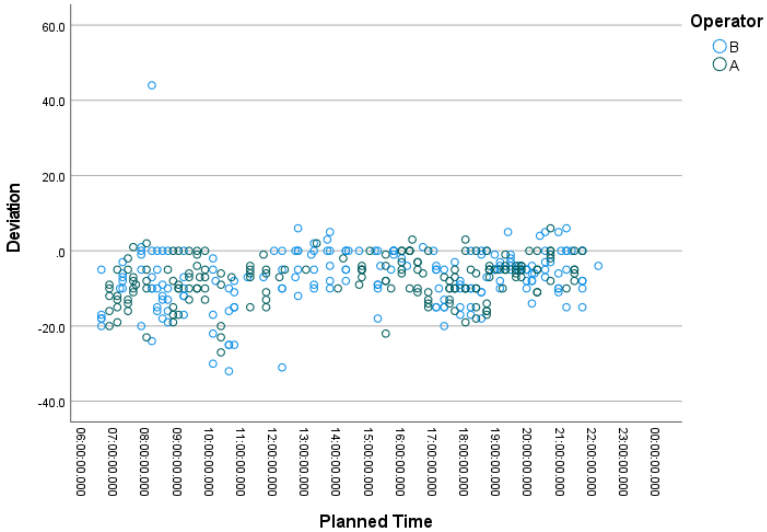

Figure 4: Planned Arrival time Vs Deviation time at Downtown Terminal

The figure 6 above shows the result of deviation as an early arrival, on time and late most buses from both operators arrive slightly earlier than scheduled, with deviations ranging mostly between -20 and 0 minutes during the morning and afternoon hours. Operator A shows more consistent early arrivals compared to Operator B, which shows a slightly wider spread of deviation, including occasional extreme late arrivals by comply with the scheduled timetable.

4.2.3 Deviation from the Planned departure time at Nyanza bus park

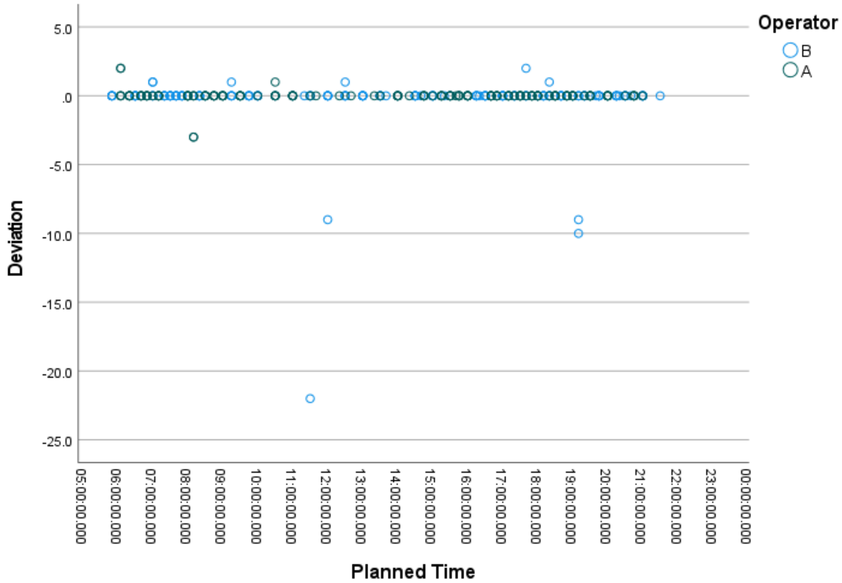

Figure 5: Planned time for departure vs Deviation time at Nyanza bus park

Figure 7 effectively visualizes departure time deviations for two operators, A and B, across various hourly periods. A negative deviation signifies an early departure, while a positive value indicates a late departure. The results indicate that both operators largely adhere to planned schedules, with the majority of departures clustering around the zero that are non-deviations from planned time. Unfortunately, Operator B exhibits several instances of significant early departures, in contrast, Operator A consistently maintains a much tighter adherence to the schedule, the time are in on time window.

4.2.4 Deviation on arrival time at Nyanza bus park

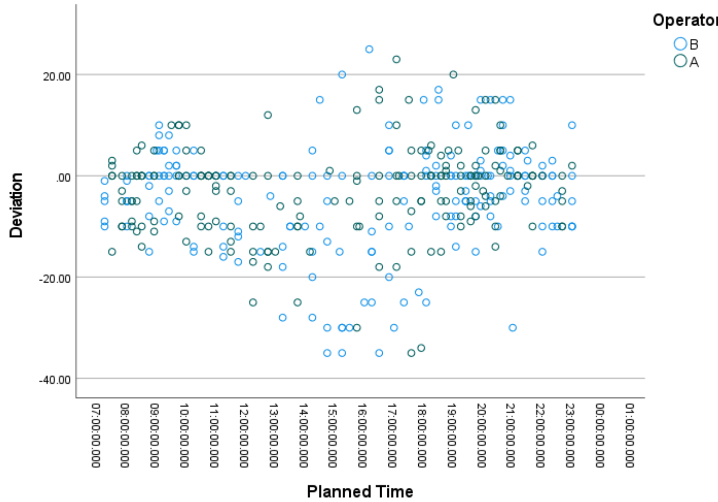

Figure 6: Planned Arrival time Vs Deviation time at Nyanza Bus Park

The results of Figure 8 show notable observations by the broader spread of deviations from scheduled departure times, indicating greater variability in arrivals. Both operators exhibit a mix of early, on-time, and late arrivals. Operator B shows a pronounced tendency towards early arrivals, particularly between 12:00 and 17:00, with some instances exceeding 30 minutes early. Operator A shows a higher frequency of late arrivals, particularly in the late afternoon and early evening (17:00-21:00), with several instances extending beyond 15 minutes late. While both maintain some on-time performance, Operator B's inclination for early arrivals contrasts with Operator A's greater susceptibility to delays.

4.2.5 Load factor

The data collection focused on capturing hourly statistics at two major terminals: Nyanza Bus Park and the CBD Terminal, and along the line. For each terminal, key operational parameters were recorded, including the number of trips per hour, total number of trips, total travel demand (number of passengers), maximum passenger-carrying capacity, and load factor (percentage of seat occupancy). Observations covered the time span from 5:00 a.m. to 10:00 p.m., with each hour treated as an independent interval and other data utilized from RURA with overall line direction passengers. The load factor, in particular, provides insight into how efficiently the available bus capacity was utilized throughout the day.

Table 5: Travel Demand Capacity along line 203

Time		**5:00 - 6:00**	**6:00 - 7:00**	**7:00 - 8:00**	**8:00 - 9:00**	**9:00 - 10:00**	**10:00 - 11:00**	**11:00 - 12:00**	**12:00 - 13:00**	**13:00 - 14:00**	**14:00 - 15:00**	**15:00 - 16:00**	**16:00 - 17:00**	**17:00 - 18:00**	**18:00 - 19:00**	**19:00 - 20:00**	**20:00 - 21:00**	**21:00 - 22:00**
Forward	Number of trips per day	1	5	6	5	4	4	4	4	4	4	4	4	6	6	5	4	1
	Total number of trips	10	50	60	50	40	40	40	40	40	40	40	40	60	60	50	40	10
	Total Travel Demand	493	2632	4473	3318	2058	2004	1505	985	1174	1578	1090	1863	1811	1257	749	817	2
	Max. Capacity	700	3500	4200	3500	2800	2800	2800	2800	2800	2800	2800	2800	4200	4200	3500	2800	700
	Load Factor	70.4	75.2	106.5	94.8	73.5	71.6	53.8	35.2	41.9	56.4	38.9	66.5	43.1	29.9	21.4	29.2	0.3
	Average load factor(%)	**53.4**																
Backward	Number of trips	0	2	5	6	4	4	4	4	4	4	4	4	6	6	6	4	4
	Total number of trips	0	20	50	60	40	40	40	40	40	40	40	40	60	60	60	40	40
	Travel Demand	0	571	1512	911	806	832	997	1019	1243	1437	2028	2832	3784	3280	3682	2618	2188
	Max. Capacity	0	1400	3500	4200	2800	2800	2800	2800	2800	2800	2800	2800	4200	4200	4200	2800	2800
	Load Factor	0	40.8	43.2	21.7	28.8	29.7	35.6	36.4	44.4	51.3	72.4	101.1	90.1	78.1	87.7	93.5	78.1
	Average load factor(%)	**58.3**																

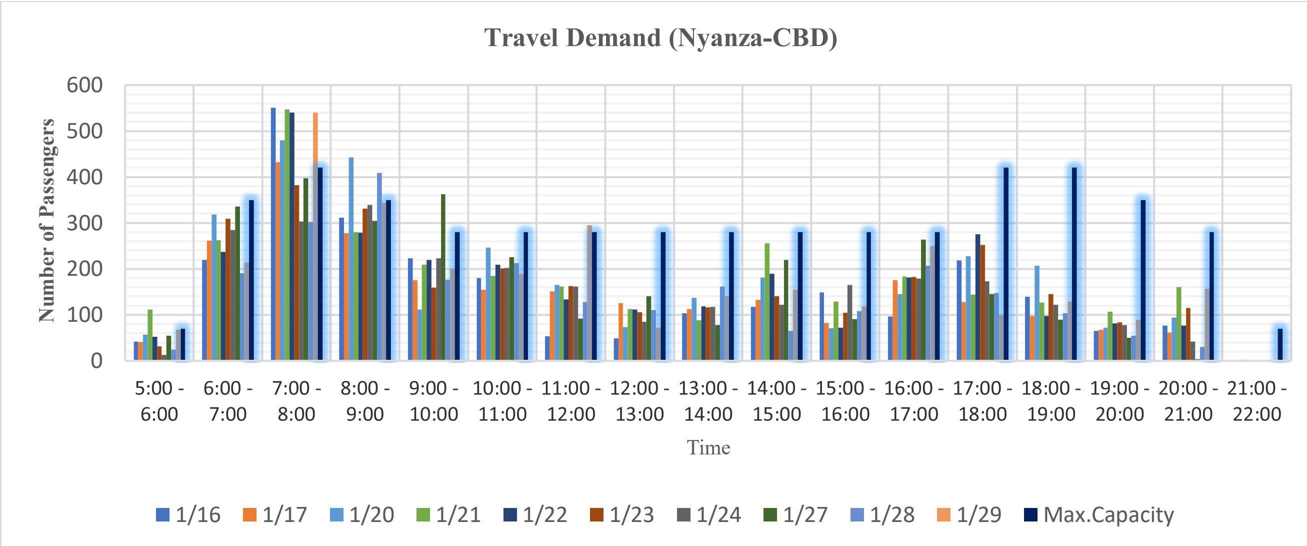

Figure 7: Graph showing comparison of line travel demand and max. bus capacity for Forword direction

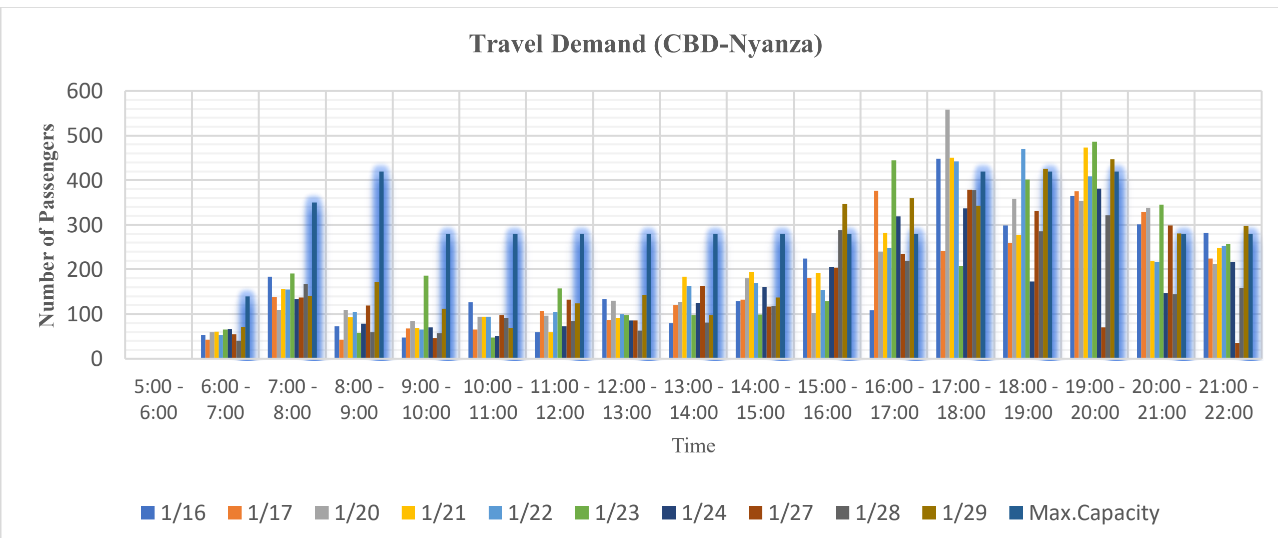

Figure 8: Graph showing comparison of line travel demand and max. bus capacity for backward direction

Forward Direction of line 203 (figure 9), demand and capacity traced a pronounced daily arc that shaped the hourly load-factor profile. The lone pre-dawn trip (5:00–6:00) carried 493 passengers against 700 seats, already filling 70 % of available capacity. Demand then surged: 2,632 passengers at 6:00-7:00 consumed three-quarters of the 3,500 seats, and the morning spike at 7:00-8:00 saw 4,473 riders exceed the 4,200-seat limit, producing the day's highest load factor of 106.5 % and obvious crowding. Although capacity remained robust (3,500 seats) at 8:00-9:00, demand slipped to 3,318 passengers, trimming the load factor to a still-hefty 94.8 %. From mid-morning to early afternoon (9:00-14:00), demand slackened to between 985 and 2,058 passengers, while capacity stayed flat at 2,800 seats; load factors therefore drifted from 73.5 % down to a midday low of 35.2 %. A modest rebound occurred at 15:00-17:00, peaking at 1,863 passengers (66.5 % load) before tapering through the evening. By 19:00-20:00 only 749 Passengers boarded 3,500 seats (21.4 %), and the final departure at 21:00-22:00 carried just two passengers for a negligible 0.3 % load. Across all 17 service windows the system delivered 47,900 seats during study period, of which roughly half were used, yielding an overall average load factor of 53.4 %.

Backward (figure 10) reveals significant fluctuations in bus occupancy levels throughout the day, with a particular focus on the load factor, maximum capacity, and hourly travel demand. During early hours (5:00–6:00), there was no bus operation, resulting in zero travel demand and capacity. Between 6:00–8:00, demand gradually rose to 1,512 passengers at 7:00–8:00, with a load factor of 43.2%, indicating that buses were underutilized despite increased capacity (3,500 seats). From 8:00–13:00, demand remained relatively modest, ranging between 806 and 1,243 passengers per hour, with load factors not exceeding 51.3%, signaling persistent low occupancy. However, a sharp increase in both demand and efficiency was observed from 14:00 onward. Peak demand occurred at 17:00–18:00, reaching 3,784 passengers, exceeding the 4,200-seat capacity with a load factor of 90.1%. The highest load factor (101.1%) was recorded during 16:00–17:00, showing actual overcrowding. Load factors remained above 78% until 21:00, highlighting strong evening utilization. The overall average load factor during the ten days of study survey was 58.3%, reflecting moderate system efficiency.

4.3 Temporal and operator-based Influences on bus time table

This section provides a detailed interpretation of the analysis examining how bus operators and time influence deviations from scheduled departure and arrival times at Downtown Terminal and Nyanza Bus Park. Key findings, statistical implications, and recommendations are presented to guide operational improvements.

4.3.1 Departure at Downtown terminal

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.057[a]	.003	-.034	12.0586	.003	.089	1	27	.768	.722

a. Predictors: (Constant), Operator

b. Dependent Variable: Deviation

Figure 9: Significance of the bus operator on Deviation

As shown in Figure 11, some operators have wider interquartile ranges (IQR), indicating inconsistent performance, while others show tight clustering around the median (more punctual).

the Interquartile Range (IQR) is a measure of statistical dispersion. It tells us how spread out the middle 50% of a dataset is. It's calculated as:

IQR=Q3−Q1

Where:

- Q_1 (1st quartile) = the value below which 25% of the data falls
- Q_3 (3rd quartile) = the value below which 75% of the data falls

the IQR covers the middle 50% of the data (from the 25th to 75th percentile).

Table 6: ANOVA test on planned departure time deviation

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.885	1	12.885	0.089	.768[b]
	Residual	3926.081	27	145.410		
	Total	3938.966	28			
a. Dependent Variable: Deviation						
b. Predictors: (Constant), operator						

Table 6 results of the ANOVA table yielded a p-value of 0.768, which is well above the conventional significance threshold of 0.05. This indicates that, when considered collectively, the bus operators do not have a statistically significant effect on schedule deviations. In other words, the variation in arrival deviations observed among different operators could reasonably be attributed to chance rather than to systematic differences in operator performance

4.3.2 Arrival at the Downtown terminal

Table 7: Regression test on planned arrival deviation at downtown

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-8.479	1.228		-6.904	<.001
	Operator	-.049	.775	-.004	-.064	.949

a. Dependent Variable: Deviation

Table 6 shows a regression analysis that shows a significant intercept of -8.479 ($p < .001$), indicating buses typically arrive 8.5 minutes early, likely due to schedule buffering or terminal efficiency. the operator coefficient (-0.049) is negligible and statistically insignificant ($p = 0.949$), suggesting no impact of operator identity on arrival deviations. The standardized beta (-0.004) further confirms that operator differences explain virtually none of the variance. Overall, arrival patterns appear systematic but unrelated to specific operators.

4.3.3 Departure at Nyanza bus park

Table 8: ANOVA test on planned departure time deviation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.033	1	56.033	1.220	.289[b]
	Residual	596.900	13	45.915		
	Total	652.933	14			

a. Dependent Variable: Deviation

b. Predictors: (Constant), Operator

Analysis of table 7 shows that bus operators do not significantly impact schedule deviations ($F = 1.220$, $p = 0.289$). Only 8.6% of the variance in deviations is explained by operator differences, with the rest likely due to external factors like traffic or time of day. The p-value is much higher than the 0.05 threshold, confirming statistical insignificance. Practical implications suggest that improving punctuality should focus on broader operational factors rather than operator performance.

4.3.4 Arrival at Nyanza

Table 9: ANOVA test on planned arrival time

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	195.091	1	195.091	1.536	.216[b]
	Residual	34796.851	274	126.996		
	Total	34991.942	275			

a. Dependent Variable: Deviation

b. Predictors: (Constant), operator

Analysis at Nyanza Bus Park shows that bus operators have no significant effect on arrival time deviations ($F = 1.536$, $p = 0.216$), with only 0.56% of the variance explained by operator differences. This minimal impact suggests that external factors—such as traffic, route conditions, or time-of-day are the primary causes of delays. The large sample size ($df = 274$) supports the reliability of this finding. Compared to other terminals like Downtown (8.6% variance explained), Nyanza's operator influence is even lower. Future efforts should focus on systemic issues rather than operator performance

4.3.5 Influence of period and load factor on planned operations

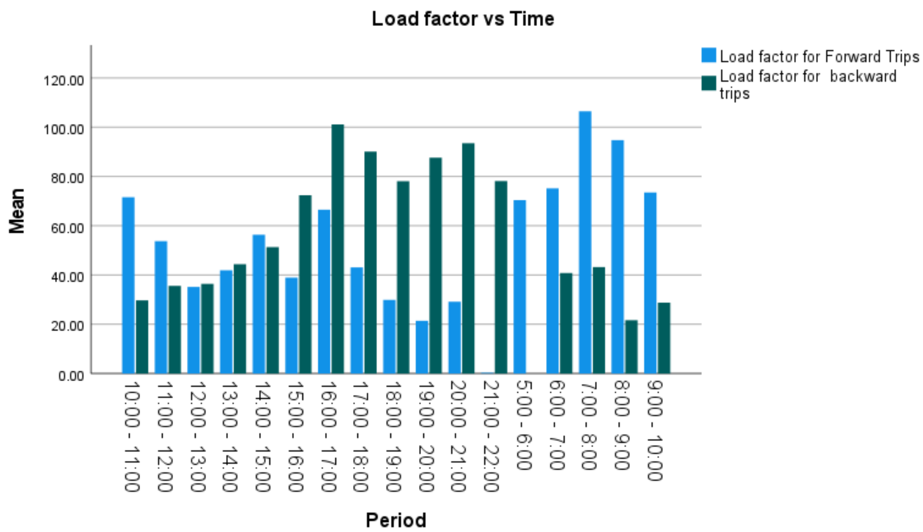

Figure 10: variation of load factor Deviation

Figure 11 shows the average load factors for forward and backward trips across different time periods. Forward trips have higher loads in the morning (10:00-11:00) and evening (18:00–21:00)**,** while backward trips peak in the afternoon (15:00–18:00)**.** This indicates a directional flow of passengers, likely due to daily commuting patterns. The opposite trends support the negative correlation between forward and backward loads.

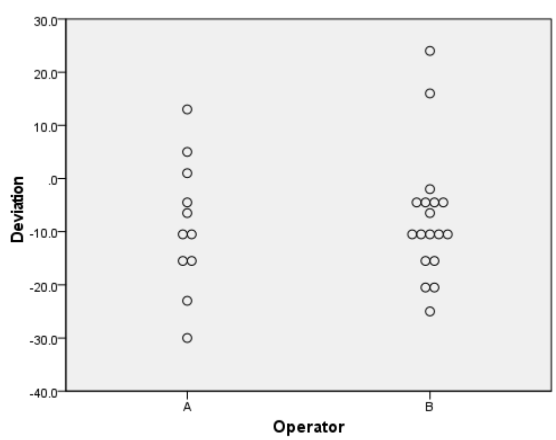

Figure 11: Influence of operator on Deviation of departure time at downtown

Figure 12 is a scatter plot illustrating the deviation of departure times for two different operators, A and B. Operator A. Shows a wider spread of deviation values, ranging from -30 to +15. The deviations are distributed across both positive and negative values, indicating instances where departure times were both earlier and later than scheduled, with a considerable range of variability. Operator B: Shows a narrower spread of deviation values compared to Operator A, primarily clustered around zero deviation, with a few outliers extending to higher positive values This suggests that Operator B generally maintains departure times closer to the schedule, although there are some instances of significant delays.

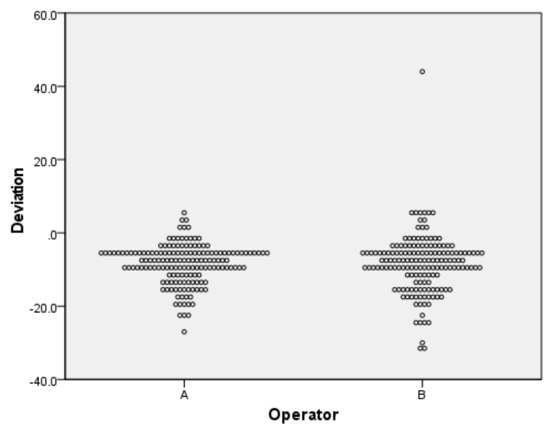

Figure 12: influence of operator on deviation of arrival time at downtown

On Figure 13 Each dot represents an individual arrival time deviation. Operator A shows a tight clustering around zero (approx. -20 to 10), indicating more consistent and less variable arrivals. Operator B displays a wider spread (approx. -30 to 45) with a clear outlier near 45, reflecting higher variability and occasional significant delays.

Table 10: Influence of load factor on Planned time at downtown

Correlations				
		Period	Load factor for Forward Trips	Deviation on Departure time at Downtown terminal
Period	Pearson Correlation	1	.335	-.244
	Sig. (2-tailed)		.188	.345
	N	17	17	17
Load factor for Forward Trips	Pearson Correlation	.335	1	-.076
	Sig. (2-tailed)	.188		.771
	N	17	17	17
Deviation on Departure time at Downtown terminal	Pearson Correlation	-.244	-.076	1
	Sig. (2-tailed)	.345	.771	
	N	17	17	17

The correlation analysis (table 9) shows that the deviation in departure time at the downtown terminal has a weak negative relationship with the period (r = -0.244) and an even weaker negative relationship with the load factor for forward trips (r = -0.076). However, both correlations are not statistically significant, with p-values of 0.345 and 0.771 respectively, indicating that these relationships could be due to chance. This means that neither the time period nor the passenger load has a meaningful influence on the punctuality of departures at the downtown terminal. The low correlation values suggest minimal linear association. In practical terms, fluctuations in scheduling and bus occupancy do not appear to significantly impact how early or late buses leave the downtown terminal. Therefore, other factors be responsible for departure time deviations at this location.

Table 11:Influence of load factor on Arrival time at downtown

Correlations				
		Period	Deviation on Arrival time at Downtown terminal	Load factor for Forward Trips
Period	Pearson Correlation	1	.050	.335
	Sig. (2-tailed)		.850	.188
	N	17	17	17
Deviation on Arrival time at Downtown terminal	Pearson Correlation	.050	1	-.386
	Sig. (2-tailed)	.850		.126
	N	17	17	17
Load factor for Forward Trips	Pearson Correlation	.335	-.386	1
	Sig. (2-tailed)	.188	.126	
	N	17	17	17

The table 10 shows positive correlation (r = 0.050) between the period and arrival time deviation at the downtown terminal, with a high p-value (0.850), indicating no significant relationship. Similarly, the correlation between load factor and arrival time deviation is moderately negative (r = -0.386), suggesting that higher passenger loads might slightly reduce arrival time deviations. However, this relationship is also not statistically significant (p = 0.126). These results imply that neither scheduling period nor load factor has a reliable impact on arrival timing at the downtown

Table 12:Influence of load factor on Departure time at Nyanza

Correlations					
		Period	Load factor for Forward Trips	Deviation on Departure at Nyanza bus park	Load factor for backward trips
Period	Pearson Correlation	1	.335	.406	-.121
	Sig. (2-tailed)		.188	.106	.644
	N	17	17	17	17
Load factor for Forward Trips	Pearson Correlation	.335	1	.101	-.585*
	Sig. (2-tailed)	.188		.700	.014
	N	17	17	17	17
Deviation on Departure at Nyanza bus park	Pearson Correlation	.406	.101	1	.180
	Sig. (2-tailed)	.106	.700		.489
	N	17	17	17	17
Load factor for backward trips	Pearson Correlation	-.121	-.585*	.180	1
	Sig. (2-tailed)	.644	.014	.489	
	N	17	17	17	17
*. Correlation is significant at the 0.05 level (2-tailed).					

The correlation analysis (table 11) for Nyanza bus park indicates that most relationships between period, load factors, and departure deviations are weak and not statistically significant. The deviation in departure time shows a moderate positive correlation with the period (r = 0.406), suggesting potential delays over time, though this is not significant (p = 0.106). The key finding is a significant negative correlation (r = -0.585, p = 0.014) between load factors for forward and backward trips, indicating that higher passenger volumes in one direction are associated with lower volumes in the reverse. Load factors and departure deviations are otherwise weakly related. Overall, passenger load balance between directions is the only notable pattern. The data shows strong evidence that departure times are influenced by load factor.

Table 13: Influence of load factor on planned arrival time at Nyanza

Correlations					
		Period	Load factor for Forward Trips	Load factor for backward trips	Deviation on Arrival at Nyanza bus park
Period	Pearson Correlation	1	.335	-.121	.617**
	Sig. (2-tailed)		.188	.644	.008
	N	17	17	17	17
Load factor for Forward Trips	Pearson Correlation	.335	1	-.585*	.016
	Sig. (2-tailed)	.188		.014	.953
	N	17	17	17	17
Load factor for backward trips	Pearson Correlation	-.121	-.585*	1	-.029
	Sig. (2-tailed)	.644	.014		.911
	N	17	17	17	17
Deviation on Arrival at Nyanza bus park	Pearson Correlation	.617**	.016	-.029	1
	Sig. (2-tailed)	.008	.953	.911	
	N	17	17	17	17
**. Correlation is significant at the 0.01 level (2-tailed).					
*. Correlation is significant at the 0.05 level (2-tailed).					

The correlation analysis table 12 for deviation on arrival at Nyanza bus park reveals two statistically significant relationships. First, there is a strong positive correlation between the period and arrival time deviations ($r = 0.617$, $p = 0.008$), indicating that buses tend to arrive increasingly off-schedule as time progresses. This suggests a deterioration in punctuality during later periods or phases of operation. Second, a significant moderate negative correlation ($r = -0.585$, $p = 0.014$) exists between load factors for forward and backward trips, highlighting a consistent imbalance in passenger flow between directions. However, no significant relationships were found between arrival deviations and load factors, implying that passenger volume does not notably impact schedule adherence. Overall, time-based factors appear more influential on arrival performance than passenger load dynamics.

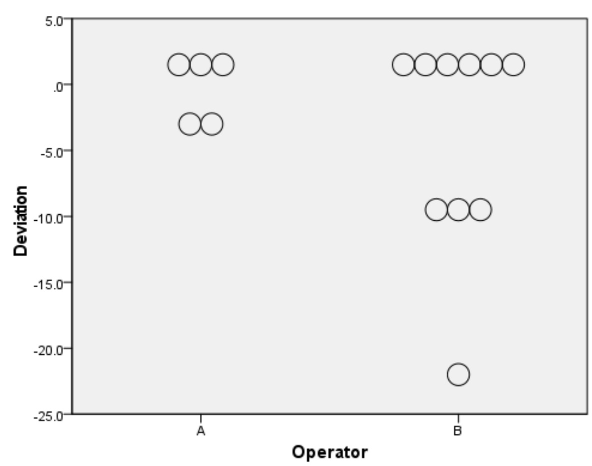

Figure 13:influence of operator on planned departure deviation at Nyanza

The scatterplot figure 14 shows departure time deviations by Operator A and B. Operator A exhibits consistent adherence, with most departures occurring close to the scheduled time, generally within a 0 to -5 minute range. In contrast, Operator B shows greater variability, with several early departures ranging from 0 to -20 minutes. This pattern suggests that Operator B often departs ahead of schedule, potentially inconveniencing passengers. The results indicate that Operator A maintains better schedule discipline compared to Operator B.

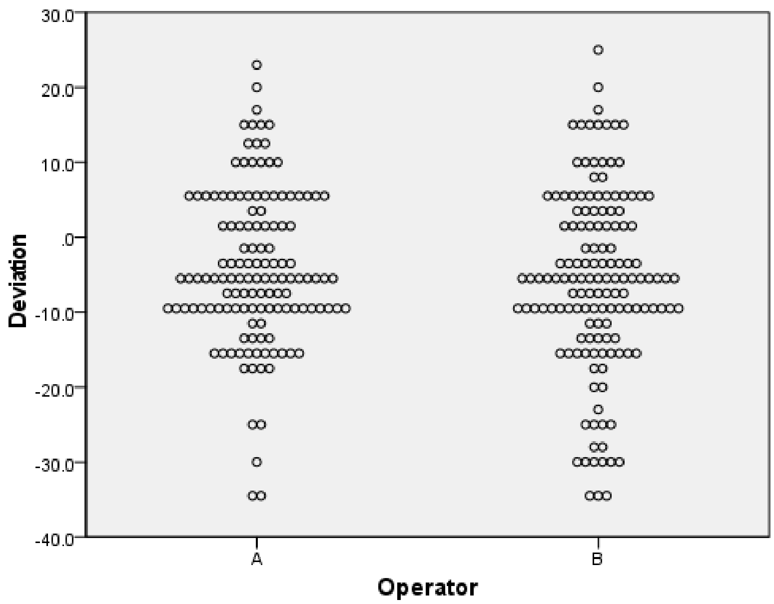

Figure 14: Influence of the operator on planned arrival deviation at Nyanza

The scatterplot displays arrival time deviations for Operators A and B. Both operators show a wide distribution, with deviations ranging from approximately -35 to +25 minutes. The clustering of points around -10 to 0 suggests a general tendency toward early arrivals. Operator A has slightly more extreme early arrivals, while Operator B shows a comparable range but with slightly more late arrivals.

Table 14: Influence of operator on deviation category

		Category														
		Delayed			Early Arrival			On Time			Significantly Late			Slightly Delayed		
		Mean	Table N %	Count	Mean	Table N %	Count	Mean	Table N %	Count	Mean	Table N %	Count	Mean	Table N %	Count
Deviation		9.6	3.3%		-11.5	64.5%		.7	9.4%		15.0	9.1%		4.8	13.8%	
Operator	A			4			84			13			12			19
	B			5			94			13			13			19

The table 14 shows Early Arrival" is the most frequent category, accounting for 64.5% of observations with a mean deviation of -11.5 (indicating early). "Slightly Delayed" follows at 13.8% (mean 4.8), then "On Time" at 9.4% (mean 0.7), and "Significantly Late" at 9.1% (mean 15.0). "Delayed" is the least common at 3.3% (mean 9.6).

Comparing operators, Operator B shows slightly higher counts for "Early Arrival" (94 vs. 84), "Delayed" (5 vs. 4), and "Significantly Late" (13 vs. 12) compared to Operator A. Both operators have identical counts for "On Time" (13) and "Slightly Delayed" (19). This suggests Operator B handles a slightly larger volume of events, exhibiting more early arrivals and a marginal increase in various delayed categories, while their on-time and slightly delayed performance mirrors Operator A's.

4.4 Policy and regulations

Enforceable Performance Contracts for Operators: To improve service reliability, bus operators should be governed by enforceable performance contracts that clearly outline measurable indicators such as punctuality, headway compliance, and passenger load thresholds. These contracts should include incentives for meeting performance standards and penalties for consistent delays and service failures. Such contractual frameworks help standardize expectations and ensure accountability across different operators. It creates a competitive and fair environment where service quality becomes a core metric. Moreover, clear targets motivate operators to optimize vehicle dispatching and crew scheduling.

Centralized Dispatch and Real-Time Monitoring: A centralized dispatch system equipped with real-time GPS tracking would allow transit authorities to monitor bus positions and adjust operations dynamically. This system can respond quickly to traffic delays, reroute buses if necessary, and ensure that headways are maintained. With live data on arrival and departure times, authorities can better manage peak-hour congestion and balance service frequency. This kind of operational control is essential for cities like Kigali, where traffic variability can disrupt scheduled services. It also promotes data-driven decisions, allowing adjustments to be made before passenger dissatisfaction occurs. Operators will also benefit, as dispatchers can provide live feedback to drivers. Ultimately, this ensures more predictable and efficient bus operations.

Staggered Scheduling Based on Peak-Hour Demand; Implementing staggered schedules involves adjusting the frequency of bus services based on time-of-day demand patterns. During peak hours, increasing bus frequency reduces overcrowding and long wait times, while off-peak periods can see slightly reduced service to optimize resources. Data from Line 203 shows high deviation in schedule adherence during rush hours, indicating the need for dynamic scheduling. Staggered scheduling aligns service provision with actual passenger flow, improving both operational efficiency and user satisfaction.

Capacity Building for Operators and Regulators: Continuous training and capacity development are essential for both bus operators and transportation regulators. Drivers and dispatchers should be trained on schedule management, customer service, and crisis response during operational disruptions. Likewise, regulatory bodies need to enhance their capabilities in data analysis, compliance auditing, and performance monitoring. Strengthening institutional capacity ensures that new policies and systems can be effectively implemented and maintained. A well-trained workforce leads to better service delivery and fewer operational errors.

Passenger Information Systems and Feedback Loops: Providing real-time information to passengers enhances transparency and improves the user experience. This includes digital boards at stations, mobile apps showing live bus locations, and estimated arrival/departure times. When passengers are informed, they can plan their journeys better, reducing uncertainty and complaints. In addition, feedback systems such as surveys, SMS platforms, or service hotlines can gather insights on punctuality and satisfaction. Integrating this feedback into performance reviews helps identify gaps and improve services.

Policy Framework for Scheduled Service Expansion; A clear policy framework is necessary to support the long-term expansion of scheduled bus services across Kigali. This includes formalizing the concept of scheduled operations in city transport strategies and integrating it into RURA's regulatory scope. Lessons learned from Line 203 should be codified into guidelines for future corridors, ensuring scalability. The framework should outline how routes are selected, how schedules are developed, and how performance is monitored.

Results and Discussion

The operational performance of Line 203 was evaluated in terms of headway regularity, departure frequency, and punctuality at both Downtown and Nyanza terminals. The planned schedule maintained consistent departure intervals during peak hours of 10 minutes. However, field observations revealed that actual headways varied considerably during off-peak periods, with gaps sometimes exceeding 20 minutes. These inconsistencies not only reduce reliability but can also discourage ridership, particularly when users experience unpredictable wait times. This observation aligns with studies by [44], who concluded that frequency reliability is among the most influential factors affecting public transit user satisfaction. Moreover, early departures, especially during evening hours, undermine the utility of the schedule, as passengers arriving on time might miss the bus. Despite these issues, the overall schedule shows promise, and the integration of real-time monitoring could help align actual operations more closely with the planned timetable. deviations in both departure and arrival times were noted, particularly during late evening periods when some buses left earlier than scheduled by up to 30 minutes or arrived with delays exceeding 20 minutes. Despite these deviations, the majority of trips adhered reasonably well to the planned schedules, indicating a moderate level of schedule reliability. These findings support the feasibility of introducing more structured scheduling practices to enhance predictability and service delivery.

Temporal and operator-based evaluation provided further insights into factors affecting adherence to the bus schedule. Analysis using ANOVA and regression showed that deviations were not significantly affected by operator identity, as p-values exceeded the 0.05 significance threshold. Instead, delays and early departures were more commonly associated with time-of-day patterns, especially during late afternoon and evening hours. These findings are consistent with those of [45], who observed that peak-hour congestion and passenger boarding times significantly influence schedule adherence more than operator behavior. In the case of Line 203, Operator A demonstrated tighter control with lower variability, while Operator B exhibited more instances of early departures. However, neither showed statistically distinct patterns. This suggests that systemic factors such as traffic, passenger flow, and terminal dwell time have a greater effect on service reliability. Improving schedule adherence, therefore, requires a broader operational strategy rather than focusing solely on individual operator performance.

To support the feasibility and long-term success of scheduled bus operations, several policy and regulatory measures are recommended. First, the implementation of enforceable performance contracts can enhance accountability. These contracts should clearly define punctuality thresholds, acceptable headways, and load factor targets. Second, the establishment of a centralized control center equipped with GPS monitoring and dispatch capabilities can help mitigate delays in real-time. Real-time control not only facilitates better scheduling adjustments but also enhances transparency and user confidence. Third, scheduling should be dynamically adapted based on temporal demand, with higher frequencies during peak hours and resource optimization during off-peak periods. Fourth, investments in capacity building particularly for regulatory bodies such as RURA will improve monitoring and data analysis capacities. Lastly, integrating digital passenger information systems and user feedback loops will build trust and responsiveness.

The pilot project on Line 203 has demonstrated that scheduled bus services are both operationally feasible and beneficial to urban mobility in Kigali. The systematic evaluation of headways, frequency, operator impact, and regulatory readiness underscores the importance of structured planning supported by real-time data and enforceable contracts. While variability in service performance was observed, particularly during certain hours of the day, these challenges are not insurmountable. As highlighted in comparable studies, integrating technology with policy reform significantly improves the effectiveness and public perception of scheduled bus operations. This study validates the main objective to assess the feasibility of scheduled services and strongly recommends scaling this model across other city corridors to enhance transit reliability, passenger satisfaction, increase level of services and network efficiency.

CHAPTER V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research systematically evaluated the feasibility and operational performance of scheduled bus operations in the City of Kigali, using Line 203 (Nyanza–Downtown) as a pilot case study. The study was structured around three core objectives: analyzing bus headways and service frequency, assessing schedule adherence based on temporal and operator-related variables, and proposing regulatory and policy interventions for system expansion.

Empirical data, collected from field surveys, operational logs, and institutional reports, were analyzed using statistical tools such as SPSS and GIS. The study revealed irregularities in scheduled adherence, particularly during peak hours and late evening periods, where significant early departures and delays occurred. Analysis of variance (ANOVA) and regression techniques confirmed that operator-related variables were statistically insignificant in explaining these deviations ($p > 0.05$), suggesting that external systemic factors such as traffic congestion, terminal efficiency, and layover logistics are the primary drivers of schedule variability.

Furthermore, load factor analysis revealed a mismatch between scheduled capacity and passenger demand across different time periods. Peak-directional flows in the morning (Nyanza–CBD) and evening (CBD–Nyanza) resulted in overutilization, while midday and off-peak hours exhibited underutilization, indicating inefficient resource allocation. The temporal asymmetry in passenger demand underscores the necessity for adaptive scheduling algorithms and demand-responsive transit planning. The results affirm that scheduled operations are feasible by system-level optimization, operational digitization, and institutional coordination to support scalable and sustainable transit development in the city of Kigali.

5.2 Recommendations

Implement Enforceable Performance Contracts; Develop operator-specific service level agreements incorporating key performance indicators (KPIs) such as punctuality, headway regularity, and vehicle occupancy rates. These contracts should include performance-based incentives and penalties, enabling quantifiable accountability and operational compliance.

Deploy Centralized Dispatch and AVL Systems; Integrate Automatic Vehicle Location (AVL) systems and a real-time Operations Control Center (OCC) to enable dynamic fleet management.

This facilitates adaptive rescheduling, monitors vehicular deviations in real time, and supports incident response planning under variable traffic conditions.

Introduce Demand-Aligned, Time-Responsive Scheduling; Use temporal demand models to restructure timetables based on ridership density per time block. Implement time-of-day frequency optimization and peak-load vehicle assignment strategies to minimize excess capacity and improve vehicle rotation efficiency.

Enhance Human Capital in Operations and Regulation; Establish technical training modules on scheduling algorithms, service quality monitoring, and traffic-responsive control systems for both operators and regulators. Capacity-building will improve operational discipline and regulatory enforcement of scheduled transit norms.

Deploy Intelligent Passenger Information Systems (IPIS); Implement real-time digital signage, journey planning apps, and feedback integration platforms. This fosters user confidence, reduces perceived wait times, and enables transit agencies to calibrate service delivery using passenger sentiment data analytics.

Formulate a Comprehensive Scheduled Services Policy Framework; Institutionalize the scheduled operation model in the city's urban mobility policy, supported by GIS-based corridor planning, operational funding models, performance audit mechanisms, and stakeholder engagement protocols. This framework will guide scalable implementation beyond Line 203.

References

[1] T. Domingo, "The role of transit-oriented development in spatial transformation and sustainable mobility: experience of Jabulani, Soweto," University of Johannesburg (South Africa), 2023.

[2] N. Leng, Z. Liao, and F. Corman, "Role of timetable, rolling stock rescheduling, and information strategies to passengers in public transport disruptions," *Transportation Research Record,* vol. 2674, no. 9, pp. 135-147, 2020.

[3] Z. Li, D. A. Hensher, and J. M. Rose, "Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence," *Transportation research part E: logistics and transportation review,* vol. 46, no. 3, pp. 384-403, 2010.

[4] A. Tirachini, D. A. Hensher, and J. M. Rose, "Crowding in public transport systems: effects on users, operation and implications for the estimation of demand," *Transportation research part A: policy and practice,* vol. 53, pp. 36-52, 2013.

[5] T. Johnson and A. Joshi, "Review of vehicle engine efficiency and emissions," *SAE International Journal of Engines,* vol. 11, no. 6, pp. 1307-1330, 2018.

[6] O. J. Ibarra-Rojas, F. Delgado, R. Giesen, and J. C. Muñoz, "Planning, operation, and control of bus transport systems: A literature review," *Transportation Research Part B: Methodological,* vol. 77, pp. 38-75, 2015.

[7] K. Culotta, V. Fang, F. Habtemichael, and D. Pape, "Does Travel Time Reliability Matter?," United States. Federal Highway Administration. Office of Operations, 2019.

[8] D. Shinar, "Aggressive driving: the contribution of the drivers and the situation," *Transportation Research Part F: traffic psychology and behaviour,* vol. 1, no. 2, pp. 137-160, 1998.

[9] J. Du, F. Qiao, and L. Yu, "Improving bus transit services for disabled individuals: demand clustering, bus assignment, and route optimization," *IEEE Access,* vol. 8, pp. 121564-121571, 2020.

[10] L. A. Guzman, J. Arellana, and V. Alvarez, "Confronting congestion in urban areas: Developing Sustainable Mobility Plans for public and private organizations in Bogotá," *Transportation Research Part A: Policy and Practice,* vol. 134, pp. 321-335, 2020.

[11] D. E. Agbiboa, "How informal transport systems drive African cities," *Current History,* vol. 119, no. 817, pp. 175-181, 2020.

[12] J. Lin, P. Wang, and D. T. Barnum, "A quality control framework for bus schedule reliability," *Transportation Research Part E: Logistics and Transportation Review,* vol. 44, no. 6, pp. 1086-1098, 2008.

[13] D. Kapica, Y. Melnikova, and V. Naumov, "Synchronization in Public Transportation: A Review of Challenges and Techniques," *Future Transportation,* vol. 5, no. 1, p. 6, 2025.

[14] S. Tao, F. Rowe, and H. Shan, "Unveiling the influence of behavioural, built environment and socio-economic features on the spatial and temporal variability of bus use using explainable machine learning," *arXiv preprint arXiv:2403.05545,* 2024.

[15] O. Paul and P. McSharry, "Public Transportation Demand Analysis: A Case Study of Metropolitan Lagos," *arXiv preprint arXiv:2105.11816,* 2021.

[16] S. Nesmachnow, R. Massobrio, S. Guridi, S. Olmedo, and A. Tchernykh, "Big Data Analysis for Travel Time Characterization in Public Transportation Systems," *Sustainability,* vol. 15, no. 19, p. 14561, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/19/14561.

[17] N. Van Oort, *Service reliability and urban public transport design*. Citeseer, 2011.

[18] M. Advani and G. Tiwari, "Review of capacity improvement strategies for bus transit service," *Indian Journal of Transport Management,* vol. 30, no. 4, pp. 363-391, 2006.

[19] M. F. A. Bakar, S. Norhisham, H. Y. Katman, C. M. Fai, N. N. I. M. Azlan, and N. S. S. Samsudin, "Service Quality of Bus Performance in Asia: A Systematic Literature Review and Conceptual Framework," *Sustainability,* vol. 14, no. 13, p. 7998, 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/13/7998.

[20] Y. Zhang, H. Xu, Q.-C. Lu, and X. Fan, "Travel Time Reliability Analysis Considering Bus Bunching: A Case Study in Xi'an, China," *Sustainability,* vol. 14, no. 23, p. 15583, 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/23/15583.

[21] C. Shang, F. Zhu, Y. Xu, X. Liu, and T. Jiang, "Hierarchical Multi-Objective Optimization for Dedicated Bus Punctuality and Supply–Demand Balance Control," *Sensors,* vol. 23, no. 9, p. 4552, 2023.

[22] J. Weng, Y. Wang, J. Huang, and L. Zhang, "Bus operation monitoring oriented public transit travel index system and calculation models," *Advances in Mechanical Engineering,* vol. 5, p. 389825, 2013.

[23] D. Syaifanayah, V. V. Natalia, and A. R. Rasyid, "Public Perception and Preferences on the Bus Service Performance to Encourage Ridership and Shift from Private Vehicle Use," *International Journal of Transport Development and Integration,* vol. 9, no. 1, 2025.

[24] X. Shen, S. Feng, Z. Li, and B. Hu, "Analysis of bus passenger comfort perception based on passenger load factor and in-vehicle time," *SpringerPlus,* vol. 5, no. 1, p. 62, 2016/01/22 2016, doi: 10.1186/s40064-016-1694-7.

[25] H. Ma, X. Li, and H. Yu, "Single bus line timetable optimization with big data: A case study in Beijing," *Information Sciences,* vol. 536, pp. 53-66, 2020/10/01/ 2020, doi: https://doi.org/10.1016/j.ins.2020.03.108.

[26] A. S. Lodhi, A. Jaiswal, and S. N. Sharma, "Assessing bus users satisfaction using discrete choice models: a case of Bhopal," *Innovative Infrastructure Solutions,* vol. 9, no. 11, p. 437, 2024/10/26 2024, doi: 10.1007/s41062-024-01652-w.

[27] D. S. Lai and J. M. Leung, "Real-time rescheduling and disruption management for public transit," *Transportmetrica B: Transport Dynamics,* vol. 6, no. 1, pp. 17-33, 2018.

[28] C. C. Torres, "Modeling and Evaluation of Synchronized Timetables in Public Transport Planning," Universidade do Porto (Portugal), 2024.

[29] K. Zavitsas, I. Kaparias, M. Bell, and M. Tomassini, "Transport problems in cities," *Isis,* vol. 6, no. 05, 2010.

[30] N. Paulley *et al.*, "The demand for public transport: The effects of fares, quality of service, income and car ownership," *Transport Policy,* vol. 13, no. 4, pp. 295-306, 2006/07/01/ 2006, doi: https://doi.org/10.1016/j.tranpol.2005.12.004.

[31] K. Gkiotsalitis, "Bus scheduling considering trip-varying travel times, vehicle availability and capacity," *IET Intelligent Transport Systems,* vol. 14, no. 12, pp. 1594-1605, 2020.

[32] O. Cats, "Regularity-driven bus operation: Principles, implementation and business models," *Transport Policy,* vol. 36, pp. 223-230, 2014.

[33] K. Gkiotsalitis and R. Kumar, "Bus Operations Scheduling Subject to Resource Constraints Using Evolutionary Optimization," *Informatics,* vol. 5, no. 1, p. 9, 2018. [Online]. Available: https://www.mdpi.com/2227-9709/5/1/9.

[34] K. Berdica, "An introduction to road vulnerability: what has been done, is done and should be done," *Transport policy,* vol. 9, no. 2, pp. 117-127, 2002.

[35] M. Salicrú, C. Fleurent, and J. M. Armengol, "Timetable-based operation in urban transport: Run-time optimisation and improvements in the operating process," *Transportation Research Part A: Policy and Practice,* vol. 45, no. 8, pp. 721-740, 2011/10/01/ 2011, doi: https://doi.org/10.1016/j.tra.2011.04.013.

[36] L. Sörensen and J. Schlueter, "How do contract types and incentives influence driver behavior?−An analysis of the Kigali bus network," *Humanities and Social Sciences Communications,* vol. 8, p. 226, 10/08 2021, doi: 10.1057/s41599-021-00896-6.

[37] H. Barmentlo, "Development of a planning support system for public transport rationalization in Kigali, Rwanda," University of Twente, 2012.

[38] A. Rukoro Bizigira, "Assessment of customers' satisfaction for public transport services in Rwanda," University of Rwanda, 2021.

[39] A. Chepuri, J. Ramakrishnan, S. Arkatkar, G. Joshi, and S. S. Pulugurtha, "Examining travel time reliability-based performance indicators for bus routes using GPS-based bus trajectory data in India," *Journal of Transportation Engineering, Part A: Systems,* vol. 144, no. 5, p. 04018012, 2018.

[40] L. Mertens, B. Amberg, and N. Kliewer, "Integrated bus timetabling and scheduling with a mutation-based evolutionary scheme maximizing headway quality and connections," in *Operations Research Forum*, 2024, vol. 5, no. 1: Springer, p. 25.

[41] J. Galuszka *et al.*, "East Africa's policy and stakeholder integration of informal operators in electric mobility transitions—Kigali, Nairobi, Kisumu and Dar es Salaam," *Sustainability,* vol. 13, no. 4, p. 1703, 2021.

[42] V. Manirakiza, L. Mugabe, A. Nsabimana, and M. Nzayirambaho, "City Profile: Kigali, Rwanda," *Environment and Urbanization ASIA,* vol. 10, no. 2, pp. 290-307, 2019.

[43] B. W. Y. Siu and H. K. and Lo, "Punctuality-based route and departure time choice," *Transportmetrica A: Transport Science,* vol. 10, no. 7, pp. 585-621, 2014/08/09 2014, doi: 10.1080/18128602.2012.751681.

[44] J. Soza-Parra, S. Raveau, J. C. Muñoz, and O. Cats, "The underlying effect of public transport reliability on users' satisfaction," *Transportation Research Part A: Policy and Practice,* vol. 126, pp. 83-93, 2019.

[45] Y. Xi, R. Su, Z. Jia, B. Yang, X. Yan, and X. Liu, "Optimization of Departure Time Strategy for Rail Transit Passengers During Early Peak Hours Based on Multi-Agent Simulation," *Available at SSRN 4637753*.

Appendix

Date

Bus Terminal Downtown

Arrival

✓	Planned Time	Actual Time	Job No	Operator	Vehicle Number	Driver
	6:35		1	A		
	6:50		2	B		
	7:05		3	A		
	7:15		4	B		
	7:25		5	A		
	7:35		6	B		
	7:50		7	A		
	8:00		8	A		
	8:10		9	B		
	8:20		10	A		
	8:30		11	B		
	8:40		1	A		
	8:50		2	B		
	9:00		3	A		
	9:10		4	B		
	9:20		5	A		
	9:35		12	B		
	9:50		6	B		
	10:05		7	A		
	10:20		8	A		
	10:35		9	B		
	10:45		1	A		
	11:00		2	B		
	11:15		3	A		
	11:30		4	B		
	11:45		5	A		
	12:00		6	B		
	12:15		7	A		
	12:30		8	A		
	12:45		10	A		
	13:00		11	B		
	13:15		12	B		
	13:30		1	A		
	13:45		2	B		
	14:00		3	A		
	14:15		4	B		
	14:30		13	A		
	14:45		14	B		
	15:00		6	B		
	15:15		12	B		
	15:30		7	A		
	15:45		11	B		
	16:00		3	A		
	16:15		1	A		
	16:30		2	B		
	16:50		4	B		
	17:05		6	B		
	17:20		13	A		
	17:35		14	B		
	17:50		7	A		
	18:00		8	A		
	18:10		9	B		
	18:20		3	A		
	18:30		1	A		
	18:40		2	B		
	18:45		10	A		
	18:55		4	B		
	19:05		12	B		
	19:15		5	A		
	19:25		11	B		
	19:35		6	B		
	19:45		13	A		
	19:55		7	A		
	20:05		14	B		
	20:15		8	A		
	20:30		9	B		
	20:40		10	A		
	20:55		12	B		
	21:10		11	B		
	21:25		13	A		
	21:40		14	B		

Date

Bus Terminal Downtown

Departure

✓	Planned Time	Actual Time	Job No	Operator	Vehicle Number	Driver	No of Pax.on Board
	6:40		1	B			
	6:55		2	B			
	7:10		3	A			
	7:20		4	B			
	7:30		5	A			
	7:40		6	B			
	7:50		12	B			
	8:00		7	A			
	8:10		8	A			
	8:20		9	B			
	8:30		10	A			
	8:40		11	B			
	8:50		1	A			
	9:00		2	B			
	9:15		3	A			
	9:30		4	B			
	9:45		12	B			
	10:00		5	A			
	10:15		6	B			
	10:30		7	A			
	10:45		8	A			
	11:00		1	A			
	11:15		2	B			
	11:30		3	A			
	11:45		4	B			
	12:00		5	A			
	12:15		6	B			
	12:30		7	A			
	12:45		8	A			
	13:00		10	A			
	13:15		11	B			
	13:30		12	B			
	13:45		1	A			
	14:00		2	B			
	14:15		3	A			
	14:30		4	B			
	14:45		13	A			
	15:00		14	B			
	15:15		6	B			
	15:30		12	B			
	15:45		7	A			
	16:00		9	B			
	16:15		3	A			
	16:30		1	A			
	16:45		2	B			
	17:00		10	A			
	17:10		4	B			
	17:20		5	A			
	17:30		11	B			
	17:40		6	B			
	17:50		13	A			
	18:00		14	B			
	18:10		7	A			
	18:20		8	A			
	18:30		9	B			
	18:40		3	A			
	18:50		10	A			
	19:00		4	B			
	19:10		12	B			
	19:20		5	A			
	19:30		11	B			
	19:40		6	B			
	19:50		13	A			
	20:00		7	A			
	20:15		14	B			
	20:30		8	A			
	20:45		9	B			
	21:00		10	A			
	21:15		11	B			
	21:35		13	A			
	21:55		14	B			

Date

Bus Terminal Nyanza

Arrival						
✓	Planned Time	Actual Time	Job No	Operator	Vehicle Number	Driver
	7:15		1	A		
	7:30		2	B		
	7:50		3	A		
	8:00		4	B		
	8:10		5	A		
	8:20		6	B		
	8:30		12	B		
	8:45		7	A		
	8:55		8	A		
	9:05		9	B		
	9:15		10	A		
	9:25		11	B		
	9:35		1	A		
	9:45		2	B		
	10:00		3	A		
	10:15		4	B		
	10:30		12	B		
	10:45		5	A		
	11:00		6	B		
	11:15		7	A		
	11:30		8	A		
	11:45		1	A		
	12:00		2	B		
	12:15		3	A		
	12:30		4	B		
	12:45		5	A		
	13:00		6	B		
	13:15		7	A		
	13:30		8	A		
	13:45		10	A		
	14:00		11	B		
	14:15		12	B		
	14:30		1	A		
	14:45		2	B		
	15:00		3	A		
	15:15		4	B		
	15:30		13	A		
	15:45		14	B		
	16:00		6	B		
	16:15		12	B		
	16:30		7	A		
	16:50		9	B		
	17:05		3	A		
	17:20		1	A		
	17:35		2	B		
	17:55		10	A		
	18:05		4	B		
	18:15		5	A		
	18:25		11	B		
	18:35		6	B		
	18:45		13	A		
	18:55		14	B		
	19:05		7	A		
	19:15		8	A		
	19:25		9	B		
	19:35		3	A		
	19:45		4	B		
	19:45		10	A		
	19:55		12	B		
	20:05		5	A		
	20:15		11	B		
	20:25		6	B		
	20:35		13	A		
	20:40		7	A		
	20:55		14	B		
	21:10		8	A		
	21:25		9	B		
	21:40		10	A		
	21:55		11	B		
	22:15		13	A		
	22:35		14	B		

Date

Bus Terminal Nyanza

Departure							
✓	Planned Time	Actual Time	Job No	Operator	Vehicle Number	Driver	No of Pax. on Board
	5:50		1	A			
	6:05		2	B			
	6:20		3	A			
	6:30		4	B			
	6:40		5	A			
	6:50		6	B			
	7:00		7	A			
	7:10		8	A			
	7:20		9	B			
	7:30		10	A			
	7:40		11	B			
	7:50		1	A			
	8:00		2	B			
	8:10		3	A			
	8:20		4	B			
	8:30		5	A			
	8:45		12	B			
	9:00		6	B			
	9:15		7	A			
	9:30		8	A			
	9:45		9	B			
	10:00		1	A			
	10:15		2	B			
	10:30		3	A			
	10:45		4	B			
	11:00		5	A			
	11:15		6	B			
	11:30		7	A			
	11:45		8	A			
	12:00		10	A			
	12:15		11	B			
	12:30		12	B			
	12:45		1	A			
	13:00		2	B			
	13:15		3	A			
	13:30		4	B			
	13:45		13	A			
	14:00		14	B			
	14:15		6	B			
	14:30		12	B			
	14:45		7	A			
	15:00		11	B			
	15:15		3	A			
	15:30		1	A			
	15:45		2	B			
	16:00		4	B			
	16:15		6	B			
	16:30		13	A			
	16:45		14	B			
	17:00		7	A			
	17:10		8	A			
	17:20		9	B			
	17:30		3	A			
	17:40		1	A			
	17:50		2	B			
	18:00		10	A			
	18:10		4	B			
	18:20		12	B			
	18:30		5	A			
	18:40		11	B			
	18:50		6	B			
	19:00		13	A			
	19:10		7	A			
	19:20		14	B			
	19:30		8	A			
	19:45		9	B			
	20:00		10	A			
	20:15		12	B			
	20:30		11	B			
	20:45		13	A			
	21:00		14	B			