Optimizing Public Bus Network Scheduling

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Abstract

This report explores the optimization of urban bus scheduling systems using operations analytics techniques, based on the model proposed by Berhan et al. (2014). The original linear programming (LP) model aimed to minimize the total number of bus trips while meeting passenger demand, constrained by fleet size, route-specific trip limits, and minimum service levels. Upon reimplementation, the original model proved infeasible when applied to a daily demand of 640,000 passengers across 93 routes and four shifts, revealing critical issues in resource allocation and inflexible planning assumptions.

To address this, an extended version of the model was developed using Google OR-Tools in Python. The extended model introduced a buffer-based constraint adjustment mechanism, allowing limited flexibility in route-level trip assignments. A synthetic dataset was generated to complete missing inputs from the original paper, ensuring a full representation of the urban network.

The extended model successfully identified an optimal solution when a minimal buffer was applied, restoring feasibility while preserving the theoretical integrity of the original approach. Results show that slight flexibility in fleet allocation can significantly improve system efficiency, better align with real-world demand variability, and avoid over-constraining the solution space. The findings highlight the importance of adaptable resource planning in public transit and provide a foundation for future studies incorporating dynamic or real-time data.

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Chapter 1: Introduction

1.1 Problem Description

Bus scheduling in public transportation is the process of assigning a fleet of buses to routes and time slots to meet passenger demand efficiently. This operational planning task must balance service availability against cost constraints. Transit agencies must deploy enough buses to avoid crowding and long waits, but not so many that buses run mostly empty and waste resources. The scheduling decision is thus a trade-off: using too many buses increases operating costs, while too few harms service quality and reliability (Berhan et al., 2014).

In the context of Addis Ababa's Anbessa City Bus Service Enterprise (ACBSE)—the city's sole public bus provider—this problem is especially pronounced. ACBSE operates over 110 urban routes using a fixed daily timetable, meaning the same number of buses is assigned to each route regardless of time-of-day demand. This fixed bus assignment approach has led to operational and financial inefficiencies (Berhan et al., 2014).

1.2 Objectives of the Study

The primary objective of this study is to analyze and optimize urban bus scheduling through the application of Operations Analytics techniques. By examining the current scheduling practices used by Anbessa City Bus Service Enterprise (ACBSE) in Addis Ababa, this project aims to enhance decision-making in public transportation by minimizing operational inefficiencies and improving service reliability.

Building upon the linear programming model proposed by Berhan et al. (2014), this project seeks not only to replicate the original model but also to extend it through a Python-based implementation using OR-Tools. This computational approach enables the integration of route-level passenger demand, heterogeneous bus types, and real-time shift constraints. Furthermore, the extended model allows for future inclusion of additional business considerations, such as minimizing fuel costs, reducing idle time, or optimizing for service quality during peak congestion periods.

1.3 Scope of the Study

The primary objective of this study is to analyze and optimize urban bus scheduling using Operations Analytics techniques. By examining the current scheduling practices employed by Anbessa City Bus Service Enterprise (ACBSE) in Addis Ababa, the study seeks to address inefficiencies in fleet utilization and service delivery by minimizing unnecessary trips and better aligning bus assignments with actual passenger demand.

This project builds upon the linear programming (LP) model proposed by Berhan et al. (2014), which was originally developed to optimize bus deployment across 93 selected routes over four daily shifts. The current study not only replicates this model but also extends it through a practical implementation using Python and Google OR-Tools. This computational approach allows for a flexible and scalable optimization framework that incorporates route-level demand data, shift-specific trip factors, bus capacity constraints, and minimum service levels.

Chapter 2: Literature Review and Model Implementation

2.1 Review of the Selected Article

The article by Berhan, Mengistu, Beshah, and Kitaw (2014) addresses inefficiencies in public bus scheduling within Addis Ababa’s Anbessa City Bus Service Enterprise (ACBSE). The fixed schedule system caused overcrowded and underutilized buses at different times. The authors proposed a linear programming (LP) model to optimize bus deployment across 93 routes and four shifts. The LP model aimed to minimize the total number of trips while satisfying passenger demand, fleet capacity, and service requirements.

2.2 Mathematical Model

The LP model includes two types of buses, each with different capacities. The objective is to minimize total trips:

Minimize $Z = \sum\sum (x_{ij} + y_{ij})$

Subject to constraints on demand satisfaction, fleet size, trip limits per route, and non-negativity. Decision variables x_{ij} and y_{ij} represent trips by each bus type. Parameters include demand D_{ij}, trip factors T_{ij}, proportions P_i, and shift requirements w_j.

2.3 Implementation of the Model Using Google OR-Tools

A prototype model using a subset of 8 routes was first implemented to validate functionality using OR-Tools. All constraints were applied, and the solver returned optimal results for this small dataset. For the full model, synthetic data was generated due to missing route-level details. Despite correct constraint implementation, the model was infeasible under original assumptions. This highlighted the rigid nature of the original model.

2.4 Discussion of Results

The original LP model failed to find a feasible solution when scaled to all 93 routes with full demand. This suggests over-constraining in fleet allocation and demand fulfillment assumptions. Data limitations have likely contributed. Our analysis supports extending the model to introduce flexibility in trip assignment, which is further developed in the next chapter.

Chapter 3: Extension of the Mathematical Model

3.1 Extended Model Proposal and Justification

The original linear programming (LP) model proposed by Berhan et al. (2014) aimed to optimize urban bus scheduling in Addis Ababa using fixed constraints, fixed route demand proportions (P_1 to P_{93}), and rigid fleet allocations. However, when re-implementing the model with a total daily demand of 640,000 passengers, the model proved infeasible. This outcome revealed structural limitations in the formulation and inspired the development of an extended version of the model to regain feasibility while preserving its theoretical integrity.

- Part 1: Interpretation of the Original Model's Infeasibility

The infeasibility of the original model under current input parameters is not a flaw in formulation, but a diagnostic insight into the operational limitations of the transit system. Specifically:

- Rigid Demand Fulfillment: The model required 100% of the estimated demand (640k passengers) to be satisfied.

- Strict Fleet Allocation: Each route was capped to a fixed percentage of the total bus trips.
- Inflexible Frequency Constraints: A minimum number of trips per shift was enforced for all routes.

- Part 2: Minimal Adjustment Strategy – Extended Model

To restore feasibility without discarding the core structure of the original model, we introduced a minimal and justified modification: a 'buffer' margin in the trip allocation per route, allowing controlled flexibility. This buffer slightly relaxes constraints on per-route trip limits, maintaining the model's integrity while providing operational realism.

- Part 3: Academic Justification

This extension preserves the original structure but introduces realistic operational flexibility. It mimics robust scheduling techniques used in transportation research, maintains linearity and solvability, and gives planners insight into system stress by determining the minimal buffer size necessary for feasibility.

3.2 Implementation of the Extended Model

To overcome the infeasibility of the original LP model proposed by Berhan et al. (2014), we implemented an extended version using Google OR-Tools in Python, applying integer programming techniques. This implementation introduced a flexible buffer to the trip constraints, allowing more realistic bus allocations under high-demand conditions.

Given the lack of complete empirical data, we generated a synthetic dataset that included:
- Passenger demand proportions (P_i)
- Demand per shift (D_{ij})
- Trip factors (T_{ij})

This approach allowed us to simulate realistic operational data aligned with the original study's assumptions.

A buffer loop strategy was implemented in Python, incrementally relaxing constraints until an optimal solution was found. The first optimal result occurred at buffer size 28. The model minimized total trips across all routes and shifts while meeting demand and operational constraints.

3.3 Discussion of Extended Model Results

The extended version of the model provided significant improvements in feasibility and flexibility. The buffer parameter allowed for minor constraint relaxation, achieving an optimal solution for the full dataset.

Key outcomes included:
- Feasibility achieved at buffer size 28.
- A total of 7,624 trips required to serve 640,000 passengers.
- Better system adaptability to high-demand scenarios.

This approach preserved all original constraints while introducing controlled slack, making it highly suitable for real-world applications where demand and conditions vary.

Chapter 4: Conclusion and Recommendations

4.1 Summary of Findings

This study explored the modeling and optimization of urban bus scheduling using both the original linear programming model proposed by Berhan et al. (2014) and an extended version developed to address infeasibility and practical limitations.

Key Findings from the Original Model:
- The original model aimed to minimize the total number of bus trips while satisfying strict constraints on demand coverage, trip limits based on fleet availability, and minimum service frequency per shift.
- When re-implemented with a total demand of 640,000 passengers and complete data for 93 routes, the model proved infeasible under its original constraints.
- This infeasibility revealed that the combination of fixed route allocations (based on historical proportions), rigid fleet caps, and uniform frequency standards made the model too restrictive to handle peak demand scenarios.
- The result served as an analytical signal that the system, as modeled, could not realistically support the projected demand without some operational flexibility.

Key Findings from the Extended Model:
- To address infeasibility, an extended version of the model was developed by introducing a small buffer in the trip assignment constraints. This allowed the model to allocate slightly more trips to high-demand routes when needed.
- A looped buffer strategy was used to identify the smallest level of constraint relaxation necessary to restore feasibility. A feasible and optimal solution was found when the trip caps were increased by approximately 28%.
- The extended model preserved all original objectives and most constraints, minimizing the total number of trips while ensuring demand coverage and maintaining shift-level service frequency.
- This model also proved more adaptable to real-world operational challenges, such as demand variability and route-specific peaks, without requiring a complete overhaul of the mathematical formulation.

Overall Improvements in Bus Scheduling Optimization:
- The extended model successfully provided an optimal solution that the original model could not, demonstrating better flexibility and robustness.
- It maintained theoretical rigor while introducing practical adaptability, making it a more useful decision-support tool for transit agencies.
- Through the buffer approach, transit planners can better understand how small policy adjustments (e.g., relaxing strict proportional trip limits) can significantly improve system performance and feasibility.

4.2 Recommendations

Based on the analysis and results of both the original and extended models, several recommendations can be made for transit agencies aiming to optimize urban bus scheduling:

Recommendations for Transit Agencies:
- Introduce Controlled Flexibility in Resource Allocation:
  Instead of assigning bus trips strictly according to historical demand proportions, agencies should consider allowing control adjustments based on real-time or forecasted passenger load. This flexibility can improve service quality on high-demand routes without compromising overall efficiency.
- Use Optimization Tools with Adaptive Parameters:
  Tools like Google OR-Tools can be integrated into planning systems to run simulations under varying constraints. By using adjustable parameters such as buffers or slack variables, planners can evaluate multiple scenarios and choose the one that balances cost and coverage best.
- Monitor System Stress Points:
  The use of a buffer in our extended model highlighted the minimum level of flexibility required to restore feasibility. Transit planners can use similar techniques to identify which constraints (e.g., route caps, fleet size, or service frequency) are most limiting during peak periods.
- Adopt Data-Driven Scheduling Policies:
  Instead of static schedules, consider demand-driven planning where trip assignments are updated regularly based on passenger trends. This requires access to reliable data but can lead to better fleet utilization and passenger satisfaction.

Suggestions for Future Research:
- Incorporating Dynamic Passenger Demand:
  Future models could benefit from integrating time-of-day fluctuations, seasonal variations, or special events to reflect more realistic demand patterns.
- Integration of Real-Time Data:
  Real-time GPS and passenger count data can be used to update schedules dynamically.

This would allow for responsive adjustments, especially during service disruptions or sudden demand spikes.
- Modeling Environmental Objectives:
  Expanding the model to include fuel consumption, emissions reduction, or electric fleet constraints can align transit optimization with broader sustainability goals.
- Considering Multiple Depots and Bus Types:
  Adding complexities such as different garage locations and more diverse bus categories can provide a more granular and practical scheduling approach.

By leveraging these recommendations and continuing to refine optimization models, transit agencies can move toward more efficient, equitable, and sustainable public transport systems.

References

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Appendices

Appendix A: Python Scripts – Original Model

- A.1 – Prototype Script with Limited Sample Data
  This script contains a simplified version of the original linear programming (LP) model, implemented using Google OR-Tools in Python. It uses a limited dataset—covering only a few routes and demand values—to verify the correctness of the model's mathematical structure and constraint logic.

- A.2 – Full Script with Complete Dataset for Original Model
  This script presents the complete implementation of the original LP model, applied to all 93 routes and four shifts. It uses a synthetic dataset to represent missing inputs and includes all constraints proposed in the original study by Berhan et al. (2014).

- A.3 – Python Script for the Enhanced Model
  This enhanced model extends the original LP formulation by introducing a buffer-based flexibility mechanism. The buffer allows a limited number of additional trips beyond the strict trip caps assigned to each route, restoring feasibility under high-demand scenarios. Implemented using Google OR-Tools' CP-SAT solver, the script includes a loop to automatically identify the smallest buffer size needed to achieve an optimal solution.

The python scripts will be uploaded via cascade but is also available in the repo https://github.com/prumucena1979/DAMO-610-6

Appendix B: Individual Contribution & AI Usage Declaration (uploaded on cascade)

This section documents the individual contributions of each team member to the project and describes how AI tools were used responsibly throughout the development process. AI support was limited to permissible tasks, such as idea generation, grammar refinement, code review assistance, and formatting suggestions, in alignment with the institution's academic integrity guidelines.