Minimizing Number of Buses for MBTA Routes

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1 Introduction

The integration of optimization within the Massachusetts Bay Transportation Authority (MBTA) represents a transformative step towards enhancing the efficiency and effectiveness of one of the most extensive bus networks in the United States. Serving millions of passengers daily, the MBTA's commitment to leveraging advanced analytical techniques is a testament to its dedication to innovation and continuous improvement in urban public transportation.

This report encapsulates the essence of this integration, illustrating how optimization can be harnessed to address the complex challenges faced by the MBTA. The emergence of big data and advanced analytics has opened new avenues for optimizing public transportation systems, enabling transit authorities to make more informed, strategic decisions. By analyzing vast datasets encompassing ridership patterns, route efficiencies, and operational constraints, the MBTA can uncover insights that drive more effective resource allocation and service delivery.

Our study revolves around the application of these methodologies to the MBTA's bus network. It demonstrates the power of data-driven decision-making in optimizing route schedules, balancing bus fleets, and enhancing passenger experiences. The focus is not merely on the models developed but on the process of transforming raw data into actionable intelligence. This transformation is crucial in an era where transit authorities must navigate a myriad of operational challenges, including fluctuating demand, budget constraints, and evolving passenger expectations.

In doing so, this research contributes to a broader understanding of how optimization can be pivotal in reshaping public transportation. The insights gleaned from the MBTA's data not only have immediate practical applications but also hold the potential to influence policy decisions and strategic planning. By sharing these findings, we aim to inspire and inform similar initiatives in other transit systems, underscoring the critical role of optimization in the future of urban mobility.

2 Dataset Overview

For our study we used two datasets: Bus Stops and Fall Ridership.
All data was gathered from mbta-massdot.opendata.arcgis.com MBTA's Blue Book Open Data Portal.

Bus Stops Dataset: The Bus Stops dataset is a granular collection of data points detailing the attributes of each bus stop within the MBTA network. Each record in the dataset is identified by a unique *stop_id* and includes a *stop_code*, which is another identifier for the stop. Descriptive attributes such as *stop_name* and *stop_desc* provide the name and a description of the stop, while *platform_code* and *platform_name* offer details about the specific platform at the stop.

Geolocation information is captured in *stop_lat* (latitude) and *stop_lon* (longitude), ensuring that each stop can be precisely located. The *zone_id* pertains to the fare zone, and *stop_address* provides the street address. Additional information on the locality of each stop is given by *municipality*, *on_street*, *at_street*, *neighborhood*, and *vehicle_type*.

Fall Ridership Dataset: The Fall Ridership dataset captures the patterns and volumes of passenger traffic across different routes during the fall season. It includes *mode*, indicating the type of service, and *season*, specifying the time of year the data was recorded. Each entry is associated with a *route_id*, *route_name*, and *route_variant*, which describe the specific bus route and its variations.

The sequence of stops on a route is indicated by *stop_sequence*, and the direction of travel is identified by *direction_id*, 0 or 1. Temporal data is categorized by *day_type_id* and *day_type_name*, which differentiate between weekdays, weekends, and holidays, as well as *time_period_id* and *time_period_name*, which segment the day into time intervals such as rush hours and off-peak times. Each *time_period_id* corresponds to a specific segment of the day, which is crucial for understanding travel patterns and optimizing bus schedules accordingly. The very start of the weekday is marked by Time Period 1. The early morning hours on weekdays are captured by Time Period 2. Morning rush hours are denoted with *AM_PEAK* as Time Period 3. Time Period 4 describes the middle of the day during weekdays and Time Period 5 denotes midday hours on school days. Evening rush hours are denoted with *PM_PEAK* as Time Period 6. Time Period 7 represents evening hours on weekdays. Time Period 8 is designated for late evening hours on weekdays. Night hours are denoted by Time Period 9. Off-peak times during the weekend are indicated by Time Period 10 for Saturday and Time Period 11 for Sunday.

Each stop's name is provided in *stop_name*, linked to the *stop_id*. Passenger flow at each stop is measured by *average_ons* (boardings), *average_offs* (alightings), and *average_load* (the average number of passengers on the vehicle after the stop). The *num_trips* field indicates the total number of trips that occur at each stop within the specified time frame.

Both datasets are instrumental in analyzing and optimizing the bus network. The Bus Stops dataset offers a detailed physical and geographical portrayal of each stop, while the Fall Ridership dataset provides dynamic ridership information, essential for understanding passenger flow and demand across the network. Together, these datasets form the backbone of the optimization models developed in this study.

3 Methodology

To conduct analyses on the number of buses required by the MBTA's bus system, a comprehensive dataset is needed in terms of routes, bus stops, passenger demand at each bus stop, and the geolocation coordinates of the bus stops. Therefore, joining the Bus Stops and Fall Ridership datasets was necessary. Subsequently, the imperative value of passenger demand for each route was calculated to ensure that there are enough buses to cover the demand. Finally, the three following optimization models were created:

1. Minimizing the total number of buses per route in every time period. How many buses does the MBTA need to cover passenger demand?
2. Maximizing the number of passengers transported in each time period given a smaller bus fleet. What happens if the MBTA cannot use all of its buses, how many passengers can be transported, and which routes should be chosen?
3. Minimizing the total number of buses per route in each time period for the highest passenger demand (worst case). How many buses does the MBTA need to cover the all-time highest passenger demand?

4 Data Cleaning and Preprocessing

4.1 Scoping

This analysis focused on fall ridership data of Fall 2022. This season was chosen as it is one of the latest available and representative for current and future fall ridership. The working assumptions is that after COVID-19 especially the bus ridership will slightly increase again over time. Hence, the Fall Ridership dataset was first filtered to only include data from Fall 2022.

4.2 Joining Datasets

In the process of consolidating two distinct datasets for an analysis of bus ridership, several challenges were encountered. Firstly, there was a discrepancy in the number of bus stops listed: the Fall Ridership dataset contained $7,845$ bus stops, whereas the Bus Stops dataset had only $6,879$, posing a significant issue for data integration.

For the Fall Ridership dataset, there was an additional complication due to the presence of similar bus stops in both direction 0 and direction 1. To address this, the data for each direction was processed separately to prevent overlapping issues. This involved creating two distinct datasets, one for each direction. In these datasets, data was grouped by *route_id*, *stop_sequence*, *stop_id*, and *time_period_id*. The mean values of the *average_load* and *num_trips* were then calculated to be used for models (1) and (2), and the maximum values of the *average_load* and *num_trips* were calculated for model (3). The distinction between the two directions was important as the *average_load* for the same stop in both directions should not be calculated together. The datasets for each direction were then merged back together.

Regarding the Bus Stops dataset, some routes included stops without coordinates. These stops were removed, and the stop sequences were updated accordingly. Subsequently, the coordinates were joined based on the *stop_id*.

A crucial step in the data processing was the calculation of the load column, which was determined by multiplying the *average_load* by *num_trips*. The final compiled dataset featured several key columns: *route_id*, *stop_sequence*, *stop_id*, *time_period_id*, *time_period_name*, *direction_id*, *load*, *stop_latitude*, and *stop_longitude*. In total, this rigorous process resulted in a comprehensive dataset comprising $88,215$ different rows, offering a solid foundation for further analysis of bus ridership patterns.

4.3 Passenger Demand/Bus Load Matrices Creation

A notable anomaly was observed with Route ID 171, which did not appear in both directions. This was a critical observation, given our underlying assumption that a bus traveling from the first stop A to the last stop Z would then return from Z to A. This assumption suggests that a single bus could serve a route in both directions (0 and 1). To accommodate this, we developed load matrices for each direction for every time period, resulting in a total of 22 matrices (2 for each of the 11 time periods). These matrices were structured with unique routes as rows, unique stops as columns, and the load at each route-stop intersection as values.https://www.overleaf.com/project/6564aec76971daa8912e6176

Since Route ID 171 was absent in direction 1, the 11 load matrices for direction 1 were changed to accommodate that missing route. For each of the 11 matrices, a row was added at the corresponding index of Route ID 171 filled with 0, as that route does not exist in direction 1.

To have the total load for each time period, the respective matrices for direction 0 and 1 were added for each time period to create 11 total load matrices. This was done because buses covering one route in a time period have to be able to handle both the passenger demand in direction 0 and direction 1.

Finally, these 11 matrices were transformed into one maximum load matrix with the unique routes as rows, time periods as columns and maximum load for each route and time period as values. If route X requires has the highest passenger demand at stop Y, the whole route needs enough buses to ensure that the demand at stop Y is met; the demand of the remaining stops will automatically be met since stop Y has the highest passenger demand. Note that when joining the datasets, the aggregation for the load column was done using the mean to be used for models (1) and (2), and using the maximum to be used for model (3). Hence, we were left with the matrices L_{rt}^{mean} and L_{rt}^{max}. The notation might be misleading since both matrices contain the maximum load for each route at each time period. The difference is how the load was aggregated during the processing step for the final dataset creation.

5 Notation

5.1 Data

- $R \dots$ number of unique routes ($R = 146$)
- $T \dots$ number of time periods ($T = 11$)
- $L_{rt}^{mean} \dots$ Maximum passenger load at route $r = 1, \dots, R$ at time $t = 1, \dots, T$ (average case)
- $L_{rt}^{max} \dots$ Maximum passenger load at route $r = 1, \dots, R$ at time $t = 1, \dots, T$ (worst case)

5.2 Parameters

- $C \dots$ passenger capacity of bus ($C = 50$)
- $B \dots$ maximum number of buses ($B = 1,100$)[1]
- $B' \dots$ maximum number of buses in worst case scenario ($B' = 800$)

5.3 Decision Variables

- $x_{rt} \dots$ number of buses allocated to route $r = 1, \dots, R$ at time $t = 1, \dots, T$
- $y_{rt} = 1$ if route $r = 1, \dots, R$ at time $t = 1, \dots, T$ is chosen, 0 otherwise
- $b \dots$ maximum number of buses to be used in worst case

6 Modeling

6.1 Model (1): Minimizing the Total Number of Buses per Route

$$
\begin{aligned}
\min \quad & \sum_{r=1}^{R} \sum_{t=1}^{T} x_{rt} & \\
\text{s.t.} \quad & C \cdot x_{rt} \geq L_{rt}^{mean} & \forall r = 1, \dots, R,\ \forall t = 1, \dots, T \\
& \sum_{r=1}^{R} x_{rt} \leq B & \forall t = 1, \dots, T \\
& x_{rt} \geq 0,\ \text{integer} & \forall r = 1, \dots, R,\ \forall t = 1, \dots, T
\end{aligned}
\tag{1}
$$

This model minimizes the total number of buses required across all routes and time periods. The first constraint requires that there are enough buses for each route in each time period. This is to cover the maximum passenger load for each route in each time period thereby covering the load for all routes for every time period. Furthermore, not more than the maximum number of buses can be allocated in every time period. Note that L_{rt}^{mean} imposes a lower bound on x_{rt}. If the maximum load is greater than 0, then there will be at least one bus allocated.

[1] https://www.mbta.com/projects/bus-facility-modernization

6.2 Model (2): Maximizing Number of Passengers Transported given Smaller Bus Fleet

$$
\begin{aligned}
\max \quad & \sum_{r=1}^{R}\sum_{t=1}^{T} L_{rt}^{mean} \cdot y_{rt} & & \\
\text{s.t.} \quad & C \cdot x_{rt} \geq L_{rt}^{mean} \cdot y_{rt} & & \forall r = 1, \ldots, R, \ \forall t = 1, \ldots, T \\
& \sum_{r=1}^{R} x_{rt} \leq B' & & \forall t = 1, \ldots, T \\
& x_{rt} \geq 0, \ \text{integer} & & \forall r = 1, \ldots, R, \ \forall t = 1, \ldots, T \\
& y_{rt} \in \{0, 1\} & & \forall r = 1, \ldots, R, \ \forall t = 1, \ldots, T
\end{aligned}
\tag{2}
$$

This model has a similar setup as model (1). However, since not all of the demand can be covered using only 800 buses, not all routes can be chosen. That is why the objective function now maximizes the number of passengers transported. The first constraint links the bus allocation x_{rt} to the route's activation status y_{rt}. Note that since the number of buses is limited due to the second constraint, when a route is not chosen ($y_{rt} = 0$), then no buses will be allocated to that route ($x_{rt} = 0$). This is because buses can be allocated elsewhere to improve the objective function.

6.3 Model (3): Minimizing the Total Number of Buses per Route for the Highest Passenger Demand

$$
\begin{aligned}
\min \quad & \sum_{r=1}^{R}\sum_{t=1}^{T} x_{rt} & & \\
\text{s.t.} \quad & C \cdot x_{rt} \geq L_{rt}^{max} & & \forall r = 1, \ldots, R, \ \forall t = 1, \ldots, T \\
& \sum_{r=1}^{R} x_{rt} \leq b & & \forall t = 1, \ldots, T \\
& x_{rt} \geq 0, \ \text{integer} & & \forall r = 1, \ldots, R, \ \forall t = 1, \ldots, T \\
& b \geq 0, \ \text{integer} & &
\end{aligned}
\tag{3}
$$

This model is also similar to model (1). The differences here are that L_{rt}^{max} is used instead L_{rt}^{mean} to consider the worst-case. Furthermore, the maximum number of buses is now an integer variable, b, to be determined by the model as well.

7 Key Findings

Even though the dataset contained 88,125 rows, Gurobi is able to solve the models in 0.1 seconds. This is because the formulation were made to be simple through extensive preprocessing, load matrices creation, and smart and tight formulating that can reduce the computations needed by the solver.

7.1 Model (1)

The optimal number of buses needed across the eleven time periods is the following:

$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$	$t = 8$	$t = 9$	$t = 10$	$t = 11$
172	243	449	456	385	505	331	152	81	1,054	762

The total buses needed when considering all time periods is 1,054, which is under the maximum capacity of 1,100 buses. However, note that time periods 10 and 11 require an exceptionally high number of buses, and if these periods were excluded, the required number of buses would be much lower, at only 505. The unusually high figures for time periods 10 and 11 could potentially be attributed to factors such as longer bus routes, night service schedules, or errors in data collection of the bus loads.

7.2 Model (2)

Under Model (2), we contemplate a scenario where the MBTA faces the constraint of having only 800 buses available, potentially due to budget cuts or just trying to reduce overall costs. With this reduced fleet, it is not feasible to satisfy the full passenger load. However, the model still achieves an overall satisfaction rate of 92.31% across all time periods.

The fraction of passenger load that can be satisfied in each time period is consistently high, with a value of 100% for every time period except 10, indicating full satisfaction of passenger load despite the limited number of buses. However, there is a notable drop in time period 10, Saturdays, where only 72.4% of the passenger load can be accommodated. All routes are serviced in all time periods except time period 10. In time period 10, 55/119 are serviced, which is less than half; nevertheless about three quarters of the passenger demand is covered.

This result emphasizes the impact of fleet size on service levels, particularly during off-peak periods, which may see a reduced number of buses but still have significant demand. For a detailed understanding of how the reduced fleet affects service levels across all time periods, a graphical representation of the results can be found in the appendix, providing a visual illustration of the selected routes under the constraints of a limited bus fleet for each time period.

7.3 Model (3)

The optimal number of buses need in each time period to account for the worst-case demand is illustrated in the following table:

$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$	$t = 8$	$t = 9$	$t = 10$	$t = 11$
181	283	473	465	463	516	339	153	81	1,136	807

The model delivers a feasible solution, calculating an optimal number of 1,136 buses to adequately cover the worst-case scenario of passenger demand. This represents an increase of 36 buses over the current MBTA fleet size, highlighting the need for additional resources to accommodate peak demand periods. However, if the demand on the weekends were not considered, the requirement would be substantially lower, with only 516 buses needed to satisfy the passenger load during the weekdays.

This analysis points to the importance of dynamic fleet management that can adapt to fluctuating demand, ensuring that the MBTA can provide reliable service even during the busiest times while optimizing the use of its fleet during off-peak periods.

8 Impact

Implementing the optimization models discussed in this report could profoundly impact the Massachusetts Bay Transportation Authority's operational efficiency and service quality. By harnessing these models, the MBTA has the potential to significantly reduce the size of its bus fleet while still maintaining high levels of service coverage. The models indicate that it is possible to reduce the fleet size by approximately 30% and still achieve 92% coverage, with particular attention needed to address service gaps on Saturdays when ridership is high.

The ramifications of optimizing the bus network are multifaceted. We anticipate substantial improvements in bus performance, particularly in on-time arrivals and departures, leading to reduced travel times. As the hardest time period to satisfy are weekends, specifically Saturdays, it is important that the MBTA puts a larger focus on improving other modes of transportation then to alleviate the passenger demand on buses. Such a shift might result in fewer people using buses, further allowing for fleet optimization.

In terms of operational costs, a smaller fleet inherently means less fuel consumption. With optimized routes, buses are likely to travel fewer unnecessary miles, which not only leads to fuel savings but also minimizes the environmental impact of the transit system. This reduction in fuel consumption directly translates to decreased emissions, aligning with broader environmental sustainability goals and contributing to cleaner air quality in the region. Cost savings emerge as another significant benefit. Reduced fuel consumption, lower maintenance costs due to a smaller fleet, and increased operational efficiency all contribute to the financial sustainability of the MBTA. These savings can be redirected towards further improvements in the transit system or the city of Boston.

From a service quality perspective, passengers are the ultimate beneficiaries. An optimized bus network means that riders can expect a more reliable and timely service, which is a crucial factor in rider satisfaction. Higher satisfaction levels could lead to increased ridership, creating a virtuous cycle of growth and improvement for the MBTA.

In conclusion, the deployment of these optimization models presents a compelling case for MBTA to embrace a data-driven approach to route and fleet management. The expected outcomes include not only financial and operational benefits for the transit authority but also environmental benefits for the community and enhanced service quality for passengers. Such an initiative could set a precedent for other transit systems, demonstrating the value of leveraging advanced analytics and optimization in public transportation.

Appendix

Figures

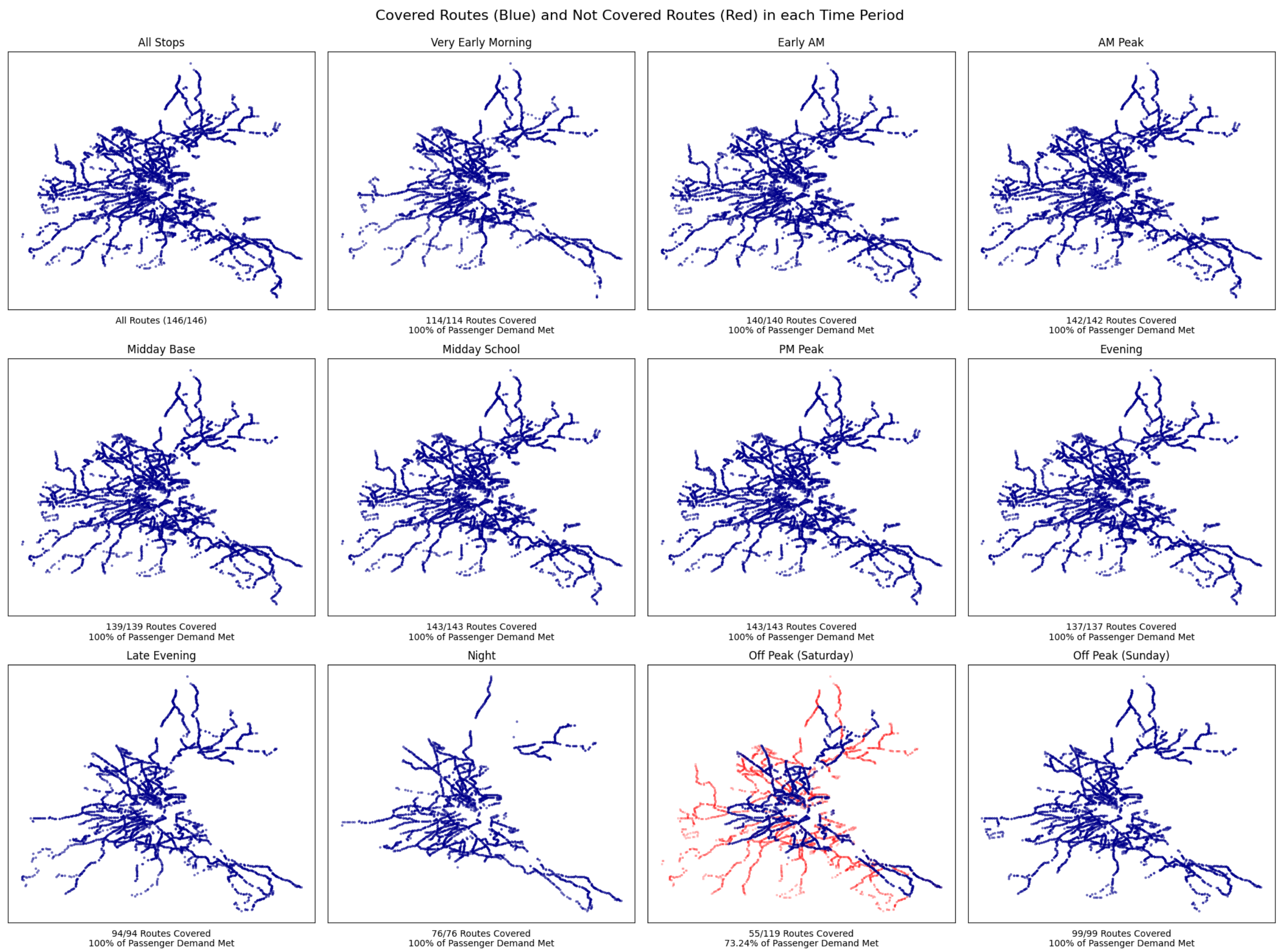

Figure 1: Covered routes for each time period

Preliminary Models

To test the modeling approach before creating model (1), two preliminary models were created. Note that $L_{rt}^{0,mean}$ signifies the maximum load using mean aggregation in direction 0 for route r and time period t. The first one was minimizing the total number of buses per route in time period 1 in direction 0 and the formulation looks as follows:

$$
\begin{aligned}
\min \quad & \sum_{r=1}^{R} x_{r1} \\
\text{s.t.} \quad & C \cdot x_{rt} \geq L_{r1}^{0,mean} \qquad \forall r = 1, \dots, R \\
& \sum_{r=1}^{R} x_{r1} \leq B \\
& x_{r1} \geq 0, \ \text{integer} \qquad \forall r = 1, \dots, R
\end{aligned}
\tag{4}
$$

The second preliminary model was minimizing the total number of buses per route across all time periods in direction 0 and the formulation looks as follows:

$$\begin{aligned}
\min \quad & \sum_{r=1}^{R}\sum_{t=1}^{T} x_{rt} \\
\text{s.t.} \quad & C \cdot x_{rt} \geq L_{rt}^{0,mean} && \forall r = 1,\dots,R,\ \forall t = 1,\dots,T \\
& \sum_{r=1}^{R} x_{rt} \leq B && \forall t = 1,\dots,T \\
& x_{rt} \geq 0,\ \text{integer} && \forall r = 1,\dots,R,\ \forall t = 1,\dots,T
\end{aligned} \tag{5}$$