Equitable Bus Route Electrification Based on a Mixed Integer Linear Programming Approach

by

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Submitted to the Department of Electrical Engineering and Computer Science
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ABSTRACT

While public transportation has seen improvement over time with advancements in vehicle technology and urban planning, low-income populations do not see the full benefit of these advancements. The common approach to transportation planning is to distribute benefits in the most cost-efficient manner, meaning neighborhoods with the best existing infrastructure are likely to receive more timely benefits than low-income areas that require more costly updates. This disparity can be thought of as a lack of equity in transportation planning, where equity means that the population that needs a public service the most should benefit the most from improvement of that service.

This work focuses on improving equity within the proposed electrification of the Massachusetts Bay Transportation Authority (MBTA) bus network in Boston. We are interested in which routes should receive updates first to maximize equity, while understanding that focusing on equity poses an inherent cost trade-off. To solve this problem, an optimal subset of routes must be selected for electrification using an objective function that prioritizes routes with the lowest income riders and the highest levels of pollution from diesel buses.

Assuming an optimal cost structure for the full transition to battery-electric buses, and also assuming that not all depots and routes will be electrified on the same time scale, we use Mixed Integer Linear Programming (MILP) methods and a quantification of transportation equity in various objective functions to decide which bus routes originating from the Cabot depot should be prioritized for electrification benefits from an equity standpoint. We then analyze the sensitivity of our results to changes in the cost constraint and conclude the degree to which equity factors correspond to higher energy transition costs. The results show that high-pollution routes are less attractive from a cost standpoint than low-income ridership routes. It is also shown that a given percentage of total electrification costs can electrify a subset of routes with even larger percentages of total pollution and low-income ridership, meaning that the benefits of including equity factors are high for given cost levels in our problem scope.

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Chapter 1

Introduction

1.1 Background and Motivation

The climate crisis demands a large-scale reduction in greenhouse gas (GHG) emissions to maintain the health of the planet. The transportation sector is a major contributor to emissions, accounting for around 25% of the EU's GHG emissions and 30% of US emissions in 2022 [1]. Specifically, transportation was responsible for 37% of Massachusetts emissions as of 2020 [2]. To satisfy the tightening transportation emission regulations imposed by the Environmental Protection Agency (EPA), it is essential to shift from fossil fuels to clean energy. In past decades, the decreasing prices and increasing efficiencies of large batteries have made electric vehicles a more efficient, sustainable, and competitive option for transportation. The large-scale electrification of transportation has therefore become a more feasible goal, where the term electrification refers to the transition from fossil fuels to electric power.

This work does not address the logistics of replacing personal vehicles with electric vehicles and instead focuses on the electrification of public transportation. Specifically, this work addresses the electrification of bus networks. In response to lower battery prices, higher efficiencies, and the ever-present need for emission reduction, urban planners must determine how to incorporate electric bus fleets into public transportation at the lowest possible cost.

However, minimizing costs can lead to choosing areas for electrification that don't serve critical populations. While electrification costs are still an important part of transportation planning, the primary interest of this work is the less-explored dimension of promoting equitable public transportation in the electrification process.

Equity refers to the idea that the demographic that needs a public service the most should be the demographic that benefits most from the improvement of that service [3]. To promote equity within the bus electrification process, we must ensure that the demographics most in need of bus service and most exposed to bus-related pollution also benefit most from the electrification process.

Public buses are primarily relied upon by the low-income demographic, as those with less disposable income are less likely to own personal vehicles. Additionally, the current bus system imposes a high pollution burden on those who live near the most frequently traveled routes. Therefore, we aim to prioritize the electrification of bus routes that are associated with lower-income riders and higher pollution levels due to high trip frequencies. This approach will promote both equitable improvements to bus transportation and equitable reductions in bus-related pollution.

The scope of the project is the electrification of the Massachusetts Bay Transportation Authority (MBTA) bus routes. The MBTA is a good candidate for the problem because it must by law replace all diesel-powered buses with battery-electric buses by 2040. It is in the process of replacing its current diesel fleets with battery-electric buses and diesel-electric hybrids. After 2027, diesel-electric hybrids will be phased out and the MBTA will purchase only battery-electric buses [4]. With these replacements comes the need to update existing facilities with charging and maintenance infrastructure. The MBTA has laid out a rough timeline for the purchase and integration of battery-electric buses and diesel-electric hybrids through 2040 [5].

1.2 Related Work

The proposed work is a multi-dimensional approach to the prioritization of bus routes for electrification, where the main dimensions are low-income service, pollution reduction, and cost minimization. Related work includes work from the MBTA exploring the equity dimension of transportation and work exploring the minimization of transportation electrification costs. It is important to consider cost minimization along with equity because costs are the main barrier to focusing on preferred demographics when making important updates to infrastructure. Any plan to prioritize low-income individuals and high-pollution areas must also balance the cost component to obtain a workable solution for equitable electrification.

The MBTA has recently demonstrated interest in equitable transportation planning through a report on environmental justice and air quality [6]. This report indicates that low-income communities bear a disproportionate share of pollution, which supports the idea that routes with low-income ridership should be prioritized for electrification. The EPA Report on Greater Boston Priority Climate Action [7] shows that prioritizing bus routes in low-income areas can significantly reduce pollution and improve public health, aligning with broader climate goals.

Although the above work considers the need to prioritize equity within bus electrification, there is still a lack of research incorporating the impacts of equity objectives on electrification costs. There is a largely separate body of work that focuses on cost minimization for electrification planning. Any minimization of vehicle investment and operation costs subject to both vehicle range and transportation demand constraints is known as a Vehicle Routing Problem (VRP). The majority of existing studies on the electric VRP focus on choosing routes and trip frequencies for a new network rather than choosing charger locations for an existing network [8] [9], which is what our problem requires for electrification. Studies that do incorporate charging locations focus on passenger vehicles rather than public transportation fleets [10], or they focus on choosing a network along with charging locations [11]. The literature around the VRP therefore does not address our specific context of selecting charger locations and electric vehicles for existing networks while keeping costs low. However, the literature provides a useful framework where decisions and constraints can be manipulated to address equity considerations within electrification.

There is ongoing work within the MIT LIDS Energy Analytics group that tackles the minimization of electric bus investment and operation costs for the MBTA, with the assumption that buses only charge overnight in depots. This existing work does not consider the use of en-route chargers, where vehicles can charge for short intervals at various stop locations during the day. Incorporating the installation and operation of en-route chargers may allow the optimization to be solved at a lower cost since fewer buses and smaller batteries may be needed when there are options to charge during trips. This work provides valuable context to our problem because we must understand the costs associated with electrification as a constraint when optimizing for equity. The goal of this project is to combine comprehensive cost estimates and equity objectives to make more informed and fair decisions about bus route electrification.

1.3 Project Summary

This problem can be formulated as a Mixed Integer Linear Programming (MILP) optimization where the objective is to maximize the number of low-income riders served by electrified bus routes and to maximize the amount of pollution reduced through electrification. The problem is constrained by the cost of electrification for each selected route.

The first stage of the project was to acquire MBTA bus schedule, emission, ridership, and inventory data, along with census tract data regarding income levels around the MBTA bus routes. We also acquired cost data from the ongoing MIT LIDS project mentioned above to formulate a cost constraint for the equity maximization problem.

After data processing, we devised multiple possible equity maximization models in Python and solved each model using the Gurobi MILP solver. The proposed models have multiple hyper-parameters, including the fraction of total pollution that must be reduced through electrification and the fraction of total electrification costs available in the budget constraint. These correspond to different budget scenarios and different levels of importance for pollution reduction. After solving each proposed model, a sensitivity analysis was performed to determine how the model output varied with the budget constraint. Based on the percentages that selected routes composed of the total low-income ridership and total pollution for various model formulations and budget constraints, we concluded that equity maximization is an appropriate tool for determining which routes to prioritize for electrification from an equity standpoint. Specifically, routes associated with low-income ridership are found to be more attractive from a cost standpoint than routes with high pollution levels. Also, focusing on low-income ridership and pollution is found to be worth the cost trade-off because each percentage of total electrification costs in the budget electrified routes with even larger percentages of total low-income ridership and pollution.

Chapter 2 walks through various model formulations and how they address the problem we want to solve. Chapter 3 describes the data processing that was necessary to run the model. Chapter 4 includes model results and a sensitivity analysis. Finally, Chapter 5 contains a discussion of the results and appropriate continuations for the research.

Chapter 2

Model Formulations

2.1 Problem Statement

In broad terms, the goal of this project is to maximize equity within the MBTA bus electrification process, subject to cost constraints that may prevent the MBTA from electrifying the entire network simultaneously. This problem lends itself to MILP optimization because there is an objective to maximize and constraints to consider. Electrification costs are easy to quantify, but to properly form the problem we must have a way to quantify equity. From Chapter 1, equity is the idea that the demographic that needs a public service the most should benefit most from the improvement of that service. Because public buses are used most by low-income individuals and this same demographic is likely to live near areas with high road pollution, the two equity factors considered in the models outlined below are low-income ridership and the pollution levels associated with bus trips on each route. The following sections will describe models that focus on each equity factor to different degrees in the objective function while making sure the objective is properly balanced with constraints.

2.2 Low-Income Ridership Focused Model

This model maximizes the percentage of low-income riders served by electrified routes originating from the Cabot depot. There is a lower bound on the percentage of pollution reduced through electrification and an upper bound on electrification costs. It is helpful to have one equity factor in the objective and another in the constraint so we can isolate the factor in the objective function or see how various levels of the constraint impact the solution.

2.2.1 Objective Function

We take R to be the set of all Cabot routes, so all variables are indexed with $r \in R$. Our objective is captured by the function:

$$Obj.: \max\left(\sum_{r} \omega_r \cdot x_r\right) \tag{2.1}$$

Where:

- ω_r is the low-income ridership percentage associated with route r
- x_r is the binary variable indicating whether route r is electrified.

2.2.2 Budget Constraint

We take S to be a proper subset of the stops on Cabot depot routes. The stops in this set are determined exogenously for the cost minimization model outlined in the related work. S contains only the most frequently crossed stops as possible charger candidates because if all stops were considered then the problem size of choosing charger stops to minimize electrification costs for the whole depot would be too large.

The cost of electrifying each route includes the cost of the electric buses needed to cover all trips on the route and the cost of installing chargers at charging stops. This information also comes from the cost minimization model. The number of buses for each route and the stops that receive chargers are chosen by this model to minimize the cost of electrifying all Cabot depot routes. We can assume that electric buses are used exclusively for trips on their assigned route, meaning it makes sense to assign the cost of buses to a route. However, many stops that receive chargers are shared between routes, meaning that if the cost of chargers is counted for each route in a naive way then we will double count the cost of many chargers. To remedy this problem, additional logical constraints must be introduced to the model to ensure the cost of each charger is only assigned to one route. To do this, new decision variables must be introduced, where variables are indexed by $r \in R$ and $s \in S$:

- $y_{r,s} = 1$ if stop s is associated with route r, else 0.
- $c_{r,s} = 1$ if route r is selected and stop s is unique to route r, else 0.
- $d_{r,s} = 1$ if route r is selected and stop s is not unique to route r, else 0

And some new exogenous indicators must be introduced:

- $z_{r,s} = 1$ if stop s is on route r, else 0
- $v_{r,s} = 1$ if stop s is only on route r, else 0.

And finally an exogenous set:

- w_s is the set of routes on which stop s is included.

Given $c_{r,s}$ and $d_{r,s}$ in words above, we can now define these variables mathematically as:

$$c_{r,s} = x_r \cdot v_{r,s} \tag{2.2}$$

$$d_{r,s} = x_r \cdot z_{r,s} \cdot (1 - v_{r,s}) \tag{2.3}$$

Where c and d are still linear in x_i due to v and z being exogenous. To make sure the charger costs for each stop are counted exactly once, we must make sure each stop is assigned to at most one route, and we must also make sure each stop is assigned to at least one route. The auxiliary constraints to form the budget constraint are as follows.

A stop can only be assigned to a route if it is on that route. This constraint must ensure $y_{r,s}$ can only be 1 if stop s is on route r. However, since we only want $y_{r,s} = 1$ when we choose to assign stop s to route r as opposed to a shared route, we want the option of $y_{r,s} = 0$ even when stop s is on route r. The constraint is therefore:

$$y_{r,s} \leq z_{r,s}, \quad \forall\ (r, s) \tag{2.4}$$

Then, each stop is assigned to at most one route:

$$\sum_r y_{r,s} \leq 1, \quad \forall s \tag{2.5}$$

Then, the number of stops associated with route r is 0 if route r is not selected, and cannot exceed the total number of stops on route r if route r is selected:

$$\sum_s y_{r,s} \leq x_r \cdot \sum_s z_{r,s} \quad \forall r \tag{2.6}$$

Then, stop s must be associated with route r if route r is selected and stop s is unique to route r:

$$c_{r,s} = 1 \implies y_{r,s} = 1 \tag{2.7}$$

Then, if route r is electrified and stop s is not unique to r, then stop s must be associated with some electrified route:

$$d_{r,s} = 1 \implies \sum_{k \in w_s} y_{k,s} = 1 \tag{2.8}$$

We can now write the budget constraint below specifically in terms of route costs:

$$\sum_{r,s} c_s \cdot y_{r,s} + \sum_{r} c_{r,bus} \cdot x_r \leq MaxCostFrac \cdot B_{total} \tag{2.9}$$

Where:

- $y_{r,s} = 1$ if stop s is counted on route r, 0 else (charger costs for stops shared across routes should only be counted once).
- c_s is the cost of installing a charger at stop s
- $c_{r,bus}$ is the cost of buses for route r
- B_{total} is the cost of electrifying all Cabot depot routes.
- $MaxCostFrac$ is the fraction of B_{total} available in the budget.

2.2.3 Pollution Constraint

For a generalized local pollutant, the amount of pollution reduced through electrifying the chosen routes must exceed a minimum target fraction of the total current pollution. This is represented by the formula:

$$\sum_{r} \phi_r \cdot x_r \geq MinPollFrac \cdot \phi_{total} \tag{2.10}$$

Where:

- ϕ_r is the pollution level for route r before electrification
- $MinPollFrac$ is the minimum fraction of total pollution in the network that must be reduced through electrifying the selected routes
- ϕ_{total} is the total pollution associated Cabot routes before electrification

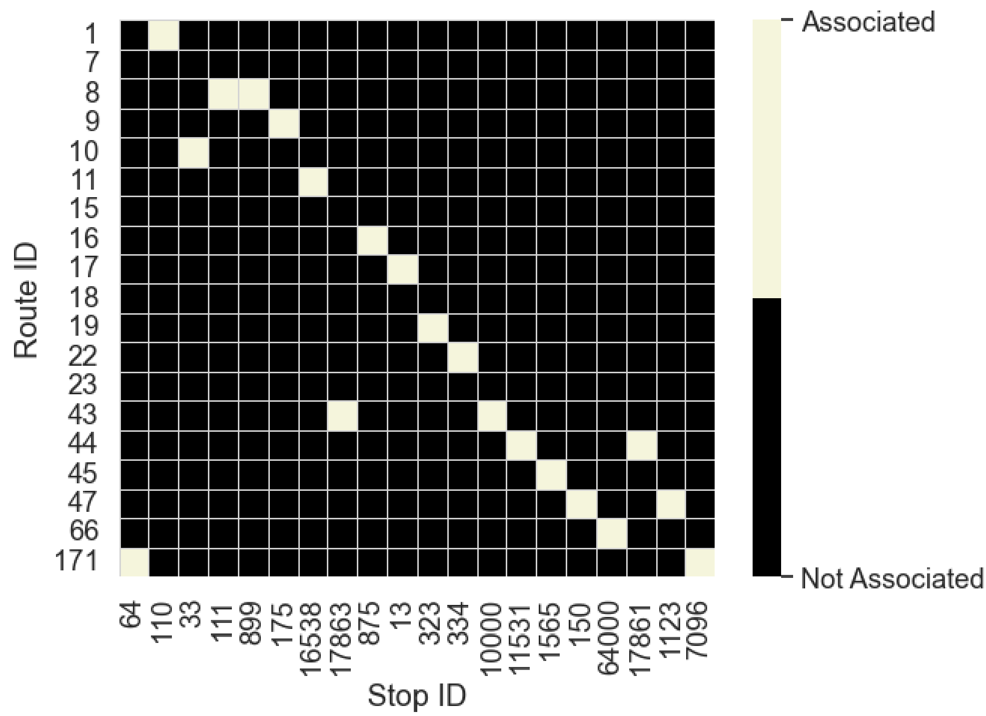

Figure 2.1: Assignment of stops to routes in budget constraint calculation

One test to ensure the model runs as expected is to make sure each stop is assigned to only one route. In Figure 2.1, we see that when the budget is non-binding and all charger stops must be counted in the solution, each stop is assigned to exactly one route. In summary, a model has been created that selects which Cabot depot routes are most important to electrify based on low-income ridership when we have a cost constraint and a minimum percentage of bus pollution that must be reduced through electrification.

2.3 Pollution Focused Model

The formulation above allows us to vary the pollution reduction and cost constraints to see how changing the thresholds impacts the choice of routes to electrify. However, with the above model, we are not trying to maximize pollution reduction. Instead, we are forcing a minimum target level of pollution reduction while maximizing the ratio of low-income routes selected for electrification. The next formulation includes pollutions in the objective function and minimum low-income ridership served by electrified routes as a constraint, which is the opposite of what is above. The reason for doing this is to be able to determine how focusing on pollutions rather than low income in the objective function impacts the model results. When considering pollutions and low income separately in the objective function, there must be a constraint to force a certain level of the other equity factor since it is not focused on in the objective. Note that electrification cost always stays in the constraint because we want the focus of the model to be maximizing equity factors rather than minimizing cost, but we must include cost as a constraint to make sure the model makes a feasible choice.

To focus on maximizing pollution reduction, we can move relative pollutions to the objective function. Our formulation becomes:

$$Obj. : \max \left(\sum_r \phi_r \cdot x_r \right) \tag{2.11}$$

We keep the same logic for the budget constraint and replace the pollution constraint with a low-income proportion constraint as follows:

$$\sum_r \omega_r \cdot x_r \geq MinIncFrac \tag{2.12}$$

Where:

- ω_r is the fraction of Cabot depot low-income riders associated with route r
- $MinIncFrac$ is the minimum percentage of total low-income levels that must be served by electrified routes in the solution.

2.4 Combined Objective Model

The final formulation is to include pollution and low-income ridership in the objective function. The reason for doing this is to observe model results for scenarios between a complete focus on low-income ridership and a complete focus on pollution. A useful check is to make sure that the levels of low-income and pollution reduction in the model solutions for the combined objective lie somewhere between the solutions for separate objective function focuses. When both equity factors are included in the objective function, there is no longer any need to force a certain level of any factor in the constraints.

The objective function is:

$$Obj.: max\left(\sum_r (IncWeight \cdot \omega_r + PollWeight \cdot \phi_r) \cdot x_r\right) \tag{2.13}$$

Where $IncWeight$ and $PollWeight$ are the weights we want to put on low-income ridership and pollution reduction respectively in the objective function. These can be varied to determine how sensitive the solutions are to each equity factor. We keep the cost constraint as the previous models. To summarize, in this chapter three models are devised to maximize equity within electrification subject to electrification costs.

Chapter 3

Data Acquisition and Processing

This chapter describes the data acquisition and processing for the models outlined in Chapter 2. The first section of this chapter lists all the types of data used in the optimization. The following sections go into detail about where each data type was found and how the data were processed into usable forms for the optimization problem. The primary types of data are trip distance and frequency data, ridership data, pollution data, income data, and cost data. The ridership data consist of adjusted Cabot bus route ridership levels aggregated over one week in September 2023. The Cabot bus trip distance and frequency data obtained from the MBTA were used to determine the total distances traveled over each route over one day. These distances were then used to calculate the total pollution per day for each route. The pollution data consist of the numbers of each bus type at the Cabot depot along with emission factors in grams per mile associated with each bus types. The income data consist of percentages of Boston census tract populations that are below the poverty line, along with census tract population-weighted centroid coordinates to facilitate the association of each route with its closest census tract. The electrification cost data are the number of electric vehicles needed for each route, the allocation of chargers to stops on each route, and finally the vehicle and charger installation costs. The final section of this chapter discusses how all of these measures were visualized for each route and the context that these measures provided for the optimization problem.

3.1 Available Data

Ridership and Income Data:

- Boston census tract low-income population percentages, which are shown in Table 3.1 [12]
- Boston census tract population-weighted centroids, which are shown in Table 3.2 [13]
- Ridership Population for each route (p_r): An estimate of how many people use or rely on each bus route. MBTA ridership demand data shown in Table 3.3 can be used to calibrate this estimate.[14]

Bus Network Information From MBTA:

- Route Identifier: A unique ID for each bus route. [15]
- Trip Identifier: A unique ID indicating times that a bus serves each stop, which can vary by season. [15]
- Stop Identifier: A unique ID for each stop and its associated latitude and longitude. [15]
- Frequency of Trips on Each bus stop is shown in Figure 3.1 [15].

Environmental Data:

- Table 3.5 shows the emission factors in g/mile specific to the current engine types at the Cabot depot [16]
- The amounts of each bus type currently operating from the Cabot depot are presented in Table 3.6 [17].

Table 3.1: Low-Income Population Percentages and Deviation by Census Tract (30 out of 255 entries)

GEOID	% Below Poverty Line	Deviation
25025000101	10.4	5.9
25025000102	19.3	6.6
25025000201	14.7	11.3
25025000202	19.7	7.7
25025000301	6.3	3.1
25025000302	4.7	3.7
25025000401	21.5	5.2
25025000402	15.5	5.8
25025000502	23	6.1
25025000503	15.5	5.3
25025000505	26.7	9.4
25025000506	19.3	6
25025000601	11	3.4
25025000603	56.3	17.4
25025000604	34.2	12.2
25025000701	18.3	6.6
25025000703	42.5	8.7
25025000704	22.6	5.8
25025000804	9.8	4.9
25025000805	38.6	8.5
25025000806	31.7	8.9
25025000807	59.2	56.4
25025010103	30.5	9.2
25025010104	32.8	6.8
25025010204	34.1	8.7
25025010205	30.5	9.1
25025010206	32.4	13.9
25025010300	29.1	9.6
25025010403	44.9	11.9

Table 3.2: Census Tract Centroid Latitude and Longitude (30 out of 255 Entries)

Tract GEOID	Population	Centroid Latitude	Centroid Longitude
25025000101	1876	42.360836	-71.132897
25025000102	3714	42.3598	-71.142189
25025000201	3953	42.353099	-71.161791
25025000202	4148	42.352686	-71.154135
25025000301	3136	42.353327	-71.169432
25025000302	3072	42.346918	-71.167641
25025000401	5853	42.343495	-71.148796
25025000402	3644	42.343918	-71.157303
25025000502	6986	42.337992	-71.159931
25025000503	2418	42.339371	-71.150285
25025000505	2196	42.343097	-71.141381
25025000506	2895	42.340021	-71.14585
25025000601	3758	42.352068	-71.14773
25025000603	1757	42.346646	-71.143655
25025000604	2591	42.351059	-71.139316
25025000701	4517	42.347047	-71.137777
25025000703	2442	42.351216	-71.127471
25025000704	5312	42.349589	-71.133471
25025000804	3813	42.357635	-71.132021
25025000805	4616	42.353659	-71.127301
25025000806	1972	42.365658	-71.123235
25025000807	2282	42.353085	-71.118205
25025010103	4697	42.349686	-71.10199
25025010104	5063	42.349646	-71.093064
25025010204	3443	42.346945	-71.104611
25025010205	4906	42.343101	-71.099572
25025010206	2154	42.345879	-71.094076
25025010300	5186	42.33972	-71.101594
25025010403	3179	42.344963	-71.088123
25025010404	5747	42.341866	-71.088997

Table 3.3: Cabot Route Ridership From 2023

Route Name	Week Start Day	Adjusted Riders
1	9/4/2023	8880.47636
7	9/4/2023	2557.70819
8	9/4/2023	2983.271658
9	9/4/2023	4762.298028
10	9/4/2023	2110.942954
11	9/4/2023	2101.622948
15	9/4/2023	4724.467298
16	9/4/2023	5889.361039
17	9/4/2023	2258.080216
18	9/4/2023	224.3803551
19	9/4/2023	2290.967944
22	9/4/2023	6611.496494
23	9/4/2023	10213.71888
43	9/4/2023	422.4312042
44	9/4/2023	2095.125225
45	9/4/2023	1634.802776
47	9/4/2023	4670.398824
66	9/4/2023	10544.15469
171	9/4/2023	15.03302884

Table 3.4: Electric Vehicle (EV) Type Information

Vehicle Type	Energy Capacity	Range	Capital Cost	Maintenance Cost	Full Charge Time	Life Time	# of Buses
Proterra ZX5 BEV (Short-range)	225 kWh	106 miles	$800,000	$0.64/km	0.45 - 4.5 hours	12 years	0
Proterra ZX5+ BEV (Long-range)	450 kWh	197 miles	$821,944	$0.64/km	0.45 - 4.5 hours	12 years	0
BYD K9 Electric Bus (Mid-range)	352 kWh	155 miles	$592,600	$0.64/km	0.45 - 4.5 hours	12 years	139
CapMetro (Mid-range)	385kWh	160 miles	$660,000	$0.64/km	0.45 - 4.5 hours	12 years	0

Cost Data:

- Charger installation costs (Table 3.7) [18]
- Cost of each electric bus type being used (Table 3.6) [19]
- Exogenous possible charging station locations (Table 3.8)
- Number of electric buses required to electrify each route (Table 3.9)

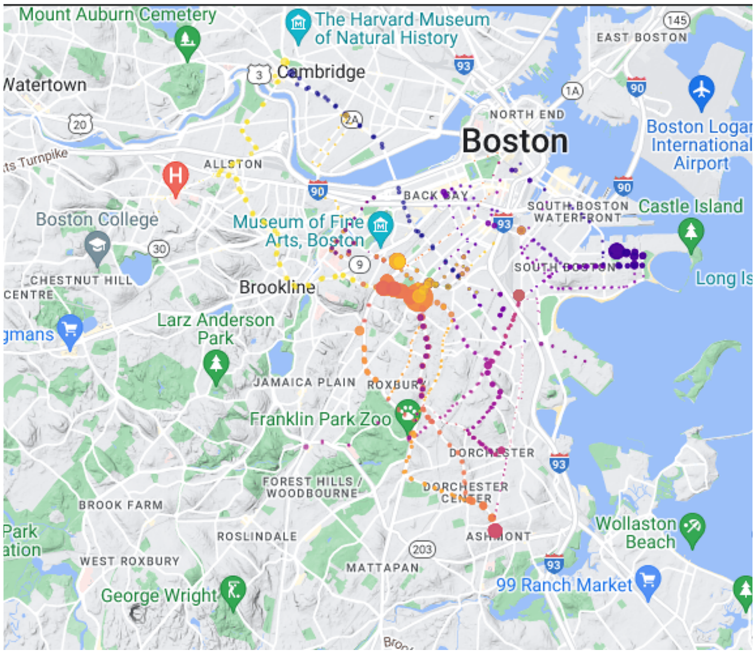

Figure 3.1: Route map with stop circle sizes proportional to trip frequency through the stop

Table 3.5: Current Cabot Bus Emission Factors

Vehicle ID	CO2 (g/mile)	CO (g/mile)	NOx (g/mile)	PM (g/mile)
1600-1774	2815	23.8	0.6	0
1775-1924	1690	0.25	2.63	0.002
Wtd avg	1991.83	6.57	2.09	0.001

3.2 Ridership Data

The ridership data used for this analysis consist of aggregated adjusted ridership over the week of September 4, 2023 as shown in Table 3.3. The ridership for each route is adjusted to account for missing or misleading data resulting from unexpected changes to the schedule within the week, which is why the ridership numbers in the table are not integers. Measuring ridership over one week is useful because it is not long enough to incur seasonal or holiday effects on ridership, but also not short enough to be very sensitive to certain days with outliers. However, for future analyses, it would be better to take a few different weeks and average them to get a better idea of general ridership, or to use historical ridership over many years to control for seasonal and holiday effects. For this analysis, we took the one-week ridership for each route to be a example representation of bus ridership.

We have no way of directly measuring the income levels of each bus rider, so we must instead measure ridership levels and income levels of those living close to each route as separate quantities. We assume that the fraction of low-income riders for each route is similar to the low-income levels associated with the route's location. This assumption allows us to multiply ridership and the low-income percentage associated with each route to obtain a low-income ridership measure. Figure 3.2 shows side-by-side measures of ridership population and low-income populations associated with each route, where the process for obtaining the low-income population percentage for each route is described in Section 3.3. The measures are normalized across routes, meaning both measures can be read as percentages of the total ridership or total low-income population associated with each route. Figure 3.3 shows normalized low-income ridership, which is calculated by multiplying route ridership by low-income percentage and then normalizing the results.

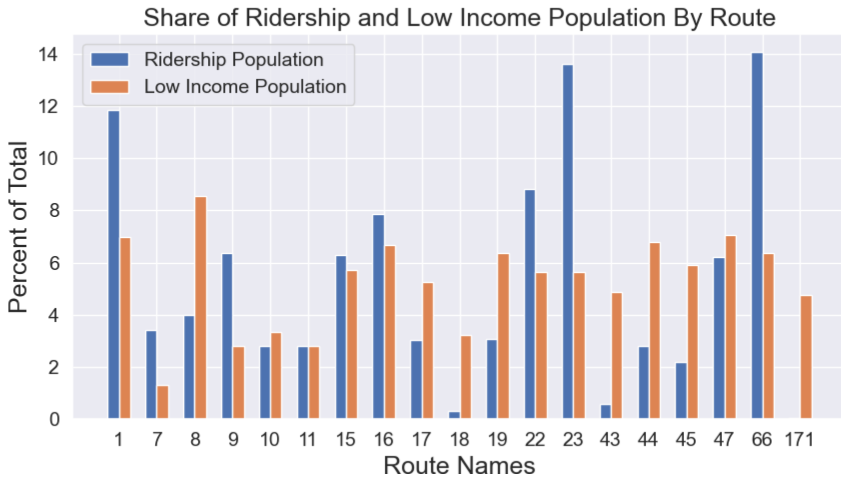

Figure 3.2: Normalized Ridership and Income Levels for Each Route

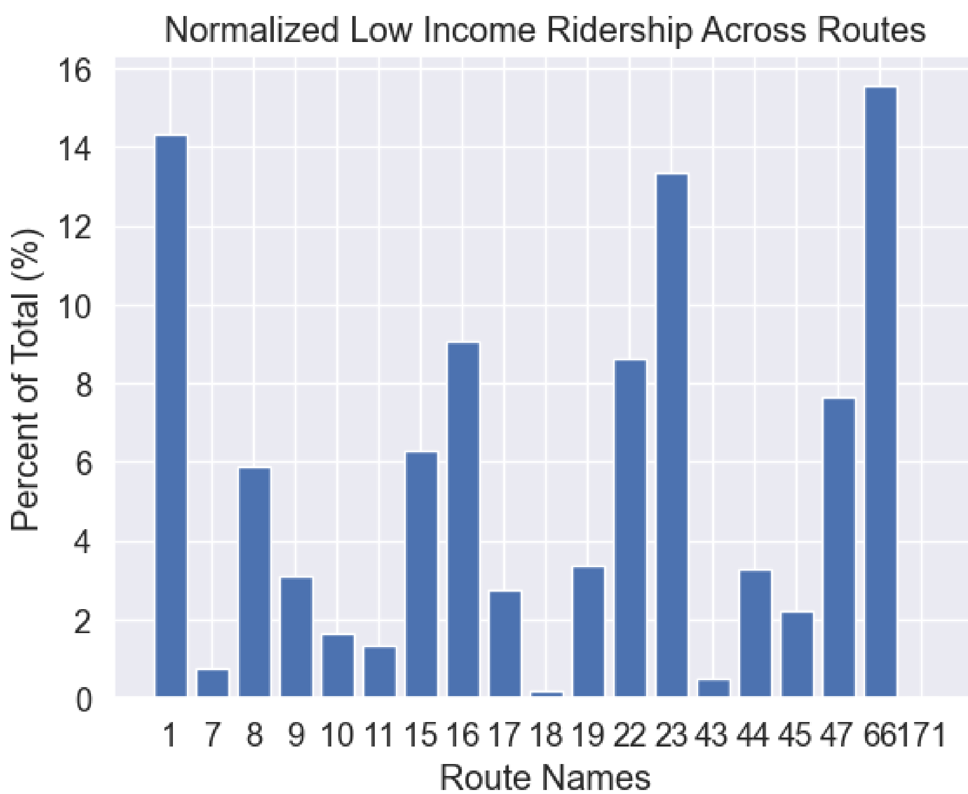

Figure 3.3: Normalized Low-Income Ridership for Each Route

3.3 Income Data

Income data for this project comes in the form of population percentages below the poverty line measured at the Boston census tract level shown in Table 3.1, where the deviation column represents the statistical error bounds in the measurement. This poverty data was acquired from American Census Survey (ACS) poverty status data tables, which are available online through an ACS poverty viewer [12]. Once the income data are acquired, we need to correlate the census tract income levels with each bus route. Each Boston census tract covers between 3,000 and 4,000 residents and spans on the order of 0.25 square miles. This means we can expect each route to span on the order of 10 census tracts. The goal is to identify the census tracts closest to each route in order to assign a combination of the corresponding income levels to that route. A natural way to find the closest census tracts to each route is to measure how each stop on a route is from a central point of each tract and associate each stop with the closest tract. The Census Bureau provides population-weighted centroids of each census tract in the form of coordinates of the point that is determined to be the center of the tract population, as shown in Table 3.2. We can therefore determine the closest census tracts to each route by measuring the distance from each stop to the population-weighted centroid of each census tract and associating each stop with the closest centroid. We can then find the average low-income percentage along the route and compare these levels across routes. More concretely, the process for acquiring route income levels is:

- Calculate the distance between each of 250 census tract population-weighted centroids and 779 stops across all Cabot routes
- Determine the closest centroid to each stop and assign the corresponding low-income population percentage to that stop
- Calculate an aggregated low-income level associated with each route by summing low-income percentage points across all route stops and then dividing by the number of

stops

- Normalize the averaged percentage points across routes to acquire relative income levels for each route, where the normalized measures across routes sum to one. Each route's income level therefore represents a percentage of the total low-income percentage points across all routes

Note that it is important to take the average low-income percentage associated with each route before comparing across routes because the routes have different numbers of stops, and we don't want to associate greater low-income levels with certain routes just because there are more stops. This method of calculating low-income measures for each route also leads to some overlap between routes due to some routes sharing stops. Routes that share stops will each count that same low-income percentage in their average measure. It is also possible that routes with stops that are close enough together will count some of the same tracts in their low-income measure. Therefore when we look at normalized income levels we cannot read these as adding up to the total low-income population served by the Cabot route since some areas will be double-counted. This approach is suitable for our analysis, provided that the aggregate measure for each route includes a sufficient variety of income levels to ensure that the impact of each route on low-income service is distinct, which we assume to be the case.

3.4 Trip Frequency Data

Given the coordinates for each stop associated with the Cabot depot, we aim to calculate the road distances between stops to determine the total distance traveled by buses on each route. This will allow us to estimate the bus pollution incurred based on these distances. We cannot determine road lengths between stops given stop coordinates because calculating the coordinate distance would give the direct distance between stops rather than the road distance. One way to solve this problem is to use MBTA shape files which give specific road shapes to obtain the correct distances. Another way to calculate distances is to plug coordinates into Google maps to find the road distances between stops. To obtain information from Google maps, we used the Google maps Python API to output the travel distances between stops by bus.

The main interest is calculating the total distance traveled on a route across all trips in one day. Not all trips cover the whole route, but it is the case that all trips are contained within a route. This means we can count the number of times we see each stop occur after another one in an ordered sequence (or trip) associated with a route. Then we multiply by the distance from the prior stop to that stop. We do this process for each pair of adjacent stops and take the sum to acquire the total distance traveled along the route within a day. Figure 3.1 visualizes the trip frequencies across stops by highlighting each stop with a circle, where the circle size indicates the frequency of trips through the stop.

3.5 Pollution Data

To calculate total pollution per day for each route, we acquired emission factors for each Cabot depot bus type in grams per mile [16], and then multiplied the emission factor for each route's bus type by the total distance traveled per day over each route as calculated in Section 3.4.

We found that the Cabot depot deploys two main bus types, 2016/2017 New Flyer CNG and 2016/2017 New Flyer Hybrid, in a ratio of 55 to 150. Table 3.6 gives information about these bus types, as well as their bus IDs. The table includes the IDs of all MBTA buses of this type, but we only count the buses allocated to Cabot in our ratio. The number of buses assigned to Cabot can be found in the online MBTA bus inventory [17]. Each bus type has a different emission factor associated with its engine for the pollutants CO2, CO, THC, NOX, and PM, as detailed in Table 3.5. [16] While we have access to the bus ID numbers currently allocated to the Cabot depot, we do not have enough data to know which vehicles or how many of the two engine types are assigned to each route within Cabot. We therefore assume that buses are allocated randomly, meaning each route has the same emission factor for each pollutant. This factor is taken as the weighted average of the factor for each bus type, as shown in Table 3.5. This is a significant simplification of pollution measures for each route, but upon acquiring more specific data for which buses are used on each trip, it will be easy to adjust pollution levels across routes accordingly.

Because emission factors are assumed to be uniform across routes, local pollution for each route scales directly with the road distance traveled on the route. We can still derive significant results with this simplifying assumption because distance traveled is directly related to trip frequencies on a route, which will scale with where public transit demand is highest. By designing the model to choose routes with higher trip frequencies, we are ensuring that routes providing the most service to those in need are the first to see the benefits of cleaner air and improved bus technology. Another implication of this assumption is that there is not much need to differentiate between pollutant types because the relative levels across routes will be the same for all types. We can therefore plot normalized pollution across routes before electrification as in Figure 3.4 without having to discern between pollutant types, and use these percentages as the measure for each route in the optimization model.

Table 3.6: Current Cabot Bus Types

Vehicle ID	Engine Type	Fuel type	Built
1600-1774	Cummins ISLG (CNG)	Natural Gas	2016/2017
1775-1924	Cummins ISB diesel/BAE Hybrid	Diesel/Electric Hybrid	2016/2017

3.6 Cost Data

The final type of data required for the desired optimization is the monetary cost related to electrifying each route. Note that in this analysis we only consider the up-front cost of electrification rather than a full cost-benefit analysis of electrification over time. As a result, the cost appears quite high when in reality the electrification process will pay for itself in

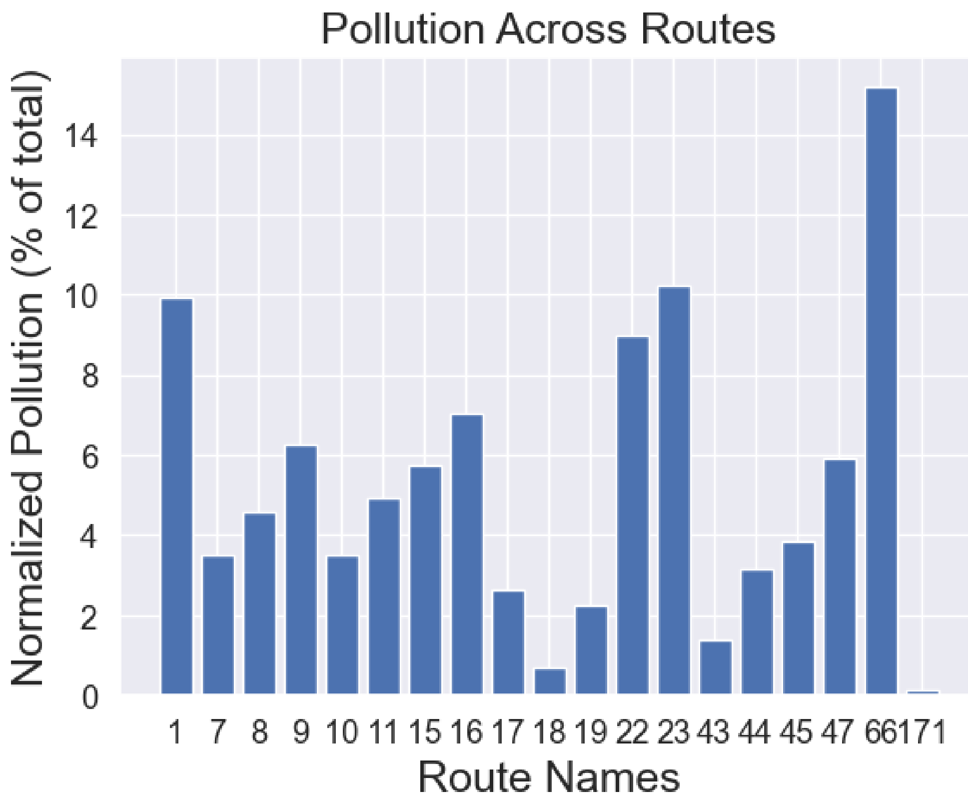

Figure 3.4: Normalized Pollution Levels Before Electrification

fuel and maintenance savings. We were able to acquire price estimates for electric bus types that the MBTA plans to use in its transition to electric power as shown in Table 3.6, along with the installation costs of various bus charger types as shown in Table 3.7. Given this initial information along with the constraint that all trips on the current MBTA schedule must be able to run after the switch to electrification, a minimization of electrification costs is run to determine the necessary number of electric vehicles for each route, as shown in Table 3.9 and Figure 3.5, along with which stops receive chargers, as shown in Table 3.8. To reduce the problem size, a set of possible charging stops is exogenously selected based on which stops are crossed most frequently. Figure 3.1 highlights all Cabot depot stops on a map and color codes the stops by route. The sizes of the stop circles are proportional to how frequently that stop is crossed with a trip. The stops with the largest circles in this figure would therefore be chosen as possible stops. This smaller set of chosen stops still allows the optimization to be solved, which means the problem size is reduced successfully. The cost minimization model therefore chooses which stops should receive chargers from only within this set.

Note that this minimization determines the cost of electrifying the entire network, while the problem at hand is to choose a subset of important routes given a budget constraint. A natural way to form this budget constraint is to set it as a fraction of the total electrification cost found with the aforementioned minimization. However, we are also interested in the cost breakdown for each route. The required output from the minimization is therefore the number of buses allocated to each route and which stops have chargers. The cost for each route can then be calculated by multiplying the number of electric vehicles and chargers on each route by the unit cost information obtained from the MBTA. As mentioned in the model formulation from Chapter 2, we must account for the fact that there are some stops shared by multiple routes when we calculate total route costs. We therefore first run the model to determine which stops to associate with each route when the model electrifies the whole network (i.e., when 100% of the network electrification costs are available in the budget).

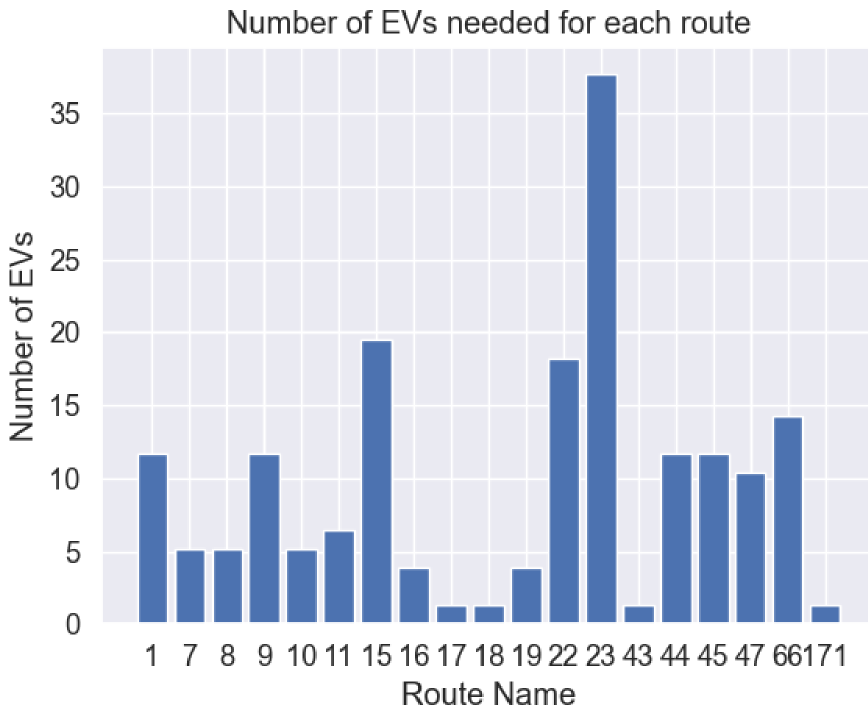

Figure 3.5: Number of EVs needed per route

We then output the route costs determined by the model in this scenario. The resulting cost breakdown per route is shown in Figure 3.6.

Table 3.7: Charger Cost Information

Charger Type	Power Rating	Capital Cost	Installation Cost	Life Time	# of Chargers
Level 2 AC Charger	22 kW	11100	4000	28 years	0
Level 3 DC Fast Charger	50 kW	37000	22626	28 years	0
Level 4 DC Fast Charger	150 kW	45000	22626	28 years	39
Level 5 DC Fast Charger	500 kW	349000	250000	28 years	0

Table 3.8: Charger Allocations (40 out of 87 entries)

Route ID	Stop ID	Chargers
1	64	1
1	110	1
7	33	2
7	16535	0
7	16538	0
8	111	1
8	899	1
8	17861	0
9	33	1
9	175	1
9	11780	0
10	13	0
10	33	2
10	175	0
10	178	0
10	13321	0
11	33	1
11	16538	1
15	117	0
15	185	0
15	323	0
15	334	0
15	1259	0
15	1475	0
15	15100	0
15	17863	1
15	64000	0
16	13	0
16	111	0
16	875	2
16	1565	0
16	35201	0
17	13	1
17	323	1
18	13	2
18	334	2
19	322	0
19	323	2
19	407	0
19	899	0
19	11323	0

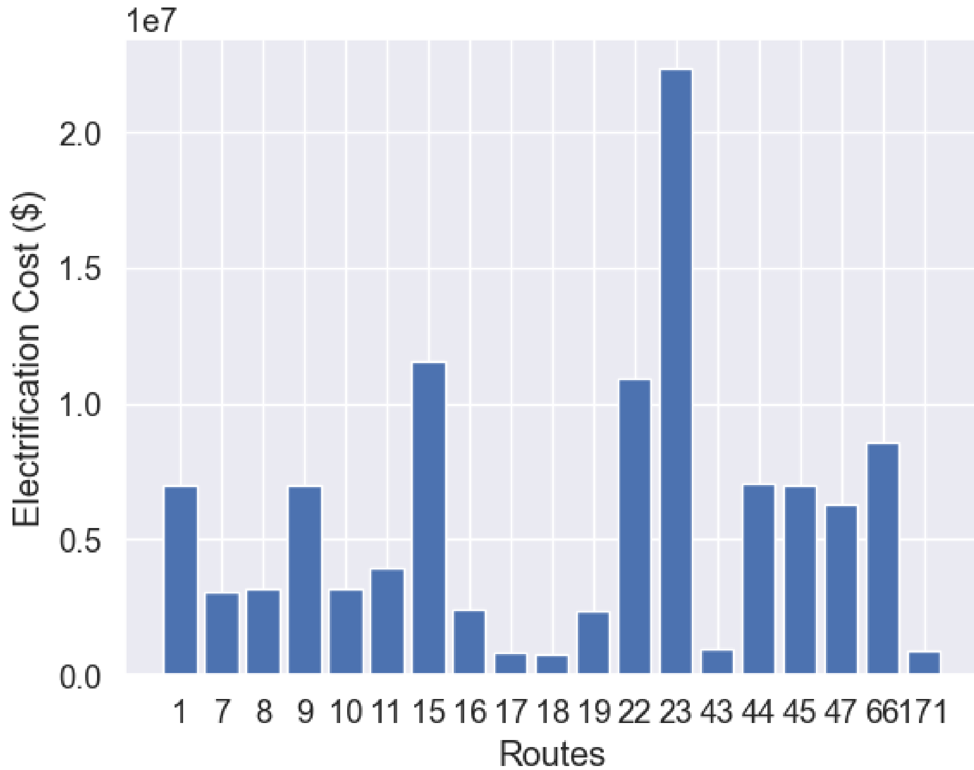

Figure 3.6: Route Electrification Capital Costs

3.7 Visualizing Metrics Within Routes

Once we have obtained and cleaned all necessary data, we can plot the key measures of low-income ridership, pollution levels, and route costs to compare these measures across routes. The processing described above puts each measure into a normalized form so that relative levels can be compared for each route. We can visualize each route's normalized levels for these measures, as demonstrated for some example routes in Figures 3.7, 3.8, and 3.9. These routes were chosen to display because they are each very high in at least one of the normalized measures. Route 23 has high costs, route 66 has high pollution, and route 1 has high low-income ridership. The radar plots let us compare each measure within one route rather than comparing measures across routes in the bar graphs. By visualizing these relative levels for each route, we can gain a sense of which routes should be favored when the model is set to favor various measures.

Table 3.9: EV Allocation

Route ID	Max Cumulative Distance (miles)	EVs Allocated
8	246.035495	4
43	33.074632	1
19	168.288544	3
17	76.906328	1
22	841.987638	14
9	556.389269	9
15	904.465796	15
16	210.084587	3
44	555.590275	9
10	245.488842	4
11	326.645894	5
45	553.037459	9
171	12.682628	1
1	554.345607	9
66	660.318338	11
23	1835.898087	29
7	258.784073	4
47	482.326846	8
18	24.788102	1

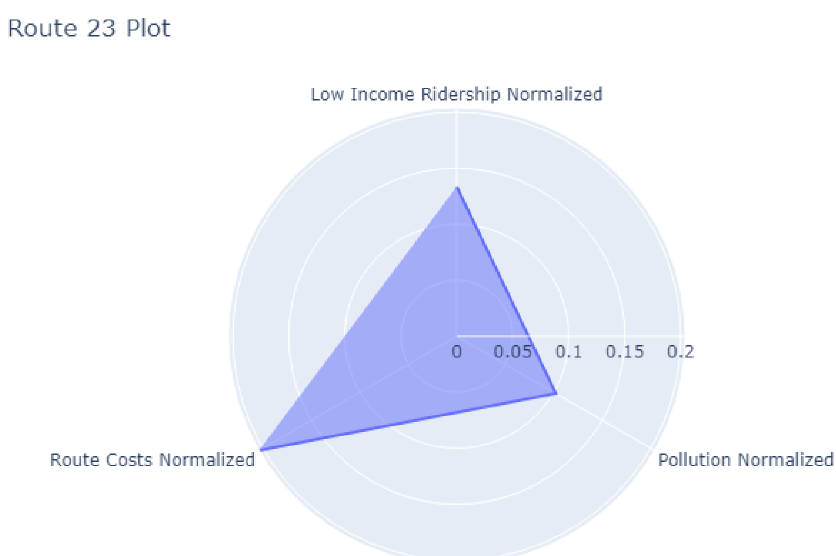

Figure 3.7: Route 23 Normalized Measures Plot

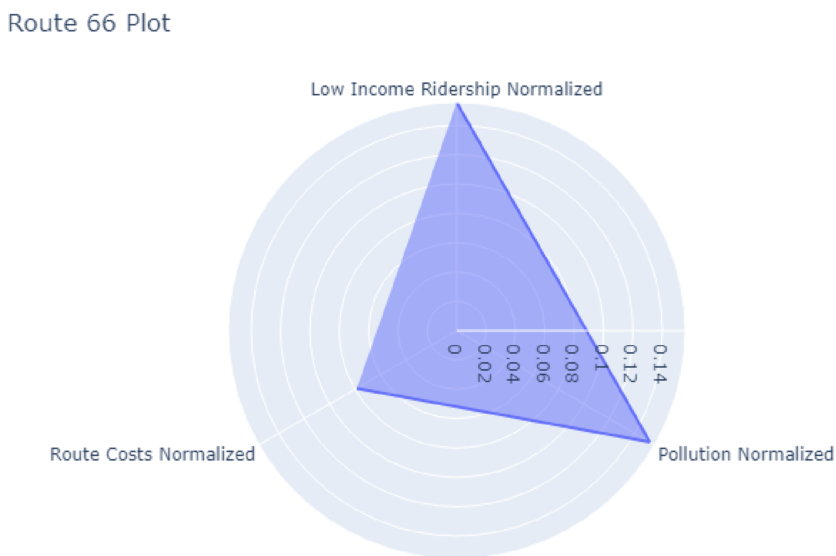

Figure 3.8: Route 66 Normalized Measures Plot

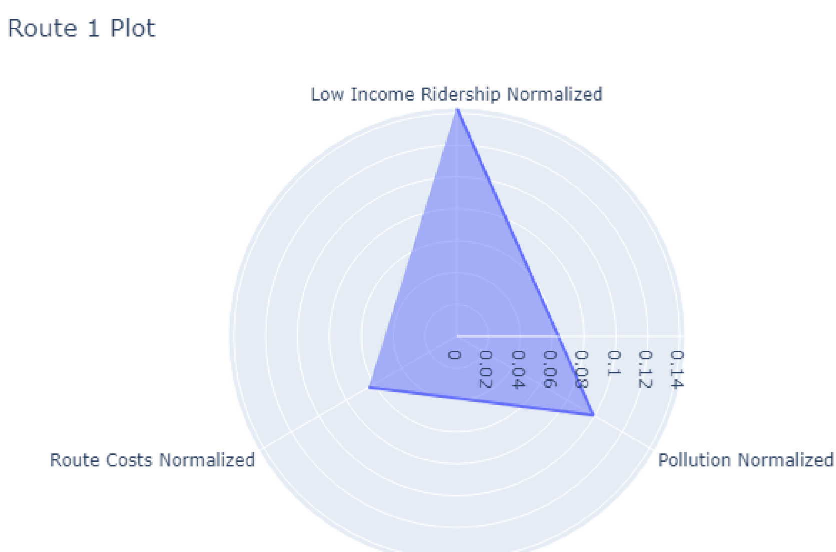

Figure 3.9: Route 1 Normalized Measures Plot

Chapter 4

Results and Analysis

After setting up each variation of the model as described in Chapter 2, we want to see which routes are selected for electrification in various scenarios, along with the values for cost, low-income population, ridership population, and pollution reduction associated with electrifying the routes in these solutions. The model has many parameters that can be set exogenously, such as:

- $MaxCostFrac$, which is the fraction of the full depot electrification cost available the budget constraint, as specified in the constraint from Equation 2.9
- $MinPollFrac$, which is the fraction of total pollution to be reduced through electrification of the selected routes, as specified in the constraint from Equation 2.10
- $MinIncFrac$, which is the fraction of the total low-income ridership that must be contained in selected routes, as specified in the constraint from Equation 2.12
- $IncWeight$ and $PollWeight$, which are the weights to dedicate to route pollution and low-income levels in the objective function from Equation 2.13

In the model analysis, the goal is to vary the $MaxCostFrac$ parameter for each model formulation described in Chapter 2 and comment on any patterns in how the routes in the solutions change. The most important relationship to examine is how the percentage of total low-income ridership contained in solution routes varies with the budget constraint, and how this compares to the way the percentage of total pollution contained in solution routes varies with the budget constraint. The working theory is that routes with more low-income riders tend to be less favored for updates due to requiring more costly updates. If we see that solutions tend to be less income-focused as a function of the budget, this supports the idea that route income levels should be focused on more explicitly in models for electrification planning. If we see that solutions tend to contain lower pollution reduction as a function of the budget, then pollution should be the more explicit focus in electrification models.

The first section of this chapter displays and discusses the model solutions when solving under the income-focused objective function from Equation 2.1. The right-hand side of the pollution constraint from Equation 2.10 is set to zero so that the model chooses routes based only on low-income ridership and cost, and we observe the levels of low-income ridership and pollution associated with each solution when the cost constraint is varied.

The second section of this chapter displays and discusses the model solutions when solving under the second objective function described in Chapter 2, which only contains pollution as an equity factor in the objective function. Similarly to the above description, the right-hand side of the income constraint in Equation 2.12 is set to zero so that the model chooses routes based only on pollution and cost, and we again observe the pollution and low-income ridership levels associated with each solution when the cost constraint is varied. It is expected that the solutions will now be more focused on pollution. However, we want to determine how drastic the change in the focus is. For example, if the level of one equity factor remains higher than the other even when the other factor is now in the objective function, this means that the higher equity factor is naturally more favorable from a cost perspective.

The final section of this chapter displays and discusses the model solutions when solving under the objective function in Equation 2.13, which contains both pollution and low-income ridership as equity factors in the objective function weighted for importance by the fractions $PollWeight$ and $IncWeight$. We again observe the low-income ridership and pollution levels associated with each solution when the cost constraint is varied. It is expected that the low-income ridership and pollution levels in the solutions will lie somewhere between the levels from the previous two parts. If the solution level of one factor remains higher than the other when they receive equal focus, this is a good indicator that the lower factor needs to be explicitly accounted for in cost-based transportation planning models. It also means that the higher factor is easier to focus on from a cost perspective.

4.1 Income Objective Model Solutions

The results show that when we focus on income in the objective function, the solution routes contain a larger percentage of total low-income ridership than total bus pollution. This can be seen in Figure 4.1, which displays the sum of the normalized measures for cost, pollution, and low-income ridership over all the routes in the solution when the budget is set to 50% of the total electrification costs. A good intuition check is that the normalized cost corner lands at 0.5, which is what we expect if the budget constraint is binding because the budget is set to 50% of total electrification costs available. The figure shows that the solution routes contain over 70% of total low-income ridership but just over 60% of total bus pollution. This means that when the budget reaches 50% of total cost, the routes chosen for electrification are more focused on low-income ridership than bus pollution, which is what we expect for the objective function being focused on low-income ridership.

Figure 4.2 can effectively be read as a graph of Figure 4.1 across each budget level rather than just 50%. The percentage of low-income ridership contained in the solution routes is always greater than the percentage of bus pollution, meaning that when low-income ridership is the only equity factor in the objective function the model is forced to prioritize this measure over bus pollution. Both low-income ridership and bus pollution levels are always above the percentage of total cost, which means that it is possible to prioritize low-income ridership and reduction of bus pollution at relatively low costs. This is important to know for electrification planning because it can assure planners that they can focus on disadvantaged populations while still keeping costs low. Note that the budget constraint is always binding, which must be true because it is the only active constraint in this analysis. By plotting the pollution amounts associated with each solution, we see the levels for which the pollution constraint would become binding if it were to be active.

Figure 4.3 shows the breakdown of routes in the solution for different percentages of the total electrification cost in the budget. As the budget increases the same or a larger amount of routes are always selected, which is as expected because more funds means more possible electrification. It makes sense that the number of routes selected could stay the same if the model chooses to switch to more expensive routes. As the available budget increases to 20%, we choose routes 1, 16, 17, 19, and 66. Routes 1, 16, and 66 have very high low-income ridership while routes 17 and 19 have very low costs, as can be seen in Figures 3.3 and 3.6. The model must select low-cost routes when only 20% of electrification costs are available in the budget. Note that routes 8 and 23 are always chosen when the budget is above 20% and 30% respectively, likely because these routes have high low-income ridership. Another important point is that route 23, which has high low-income ridership but also extremely high electrification costs, is chosen for 60% of the available budget onward. To summarize, the trend of the model solutions is exactly as expected, which is that more routes are chosen as the budget increases and that each evolution of route choices reflects a focus on low-income routes while mitigating costs.

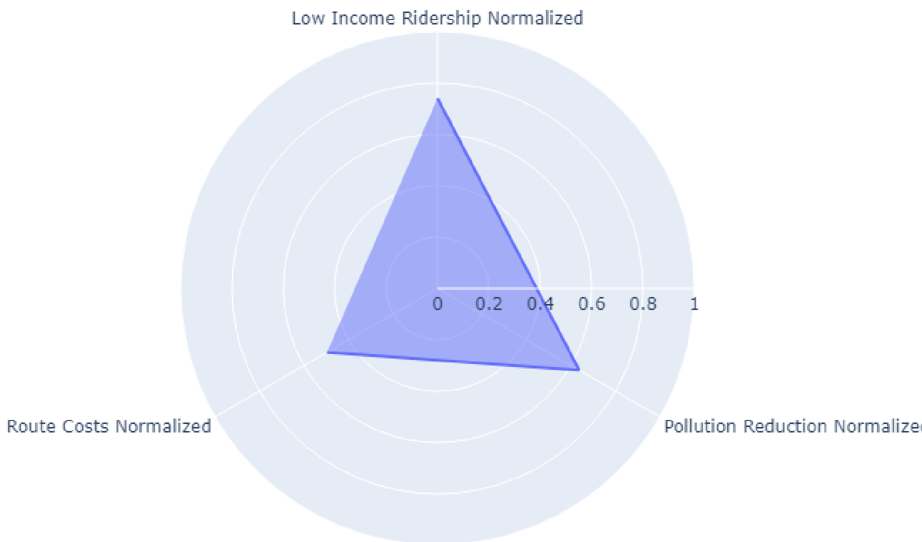

Figure 4.1: Income Objective Aggregated Solution Values: Budget = 50% of Total Costs

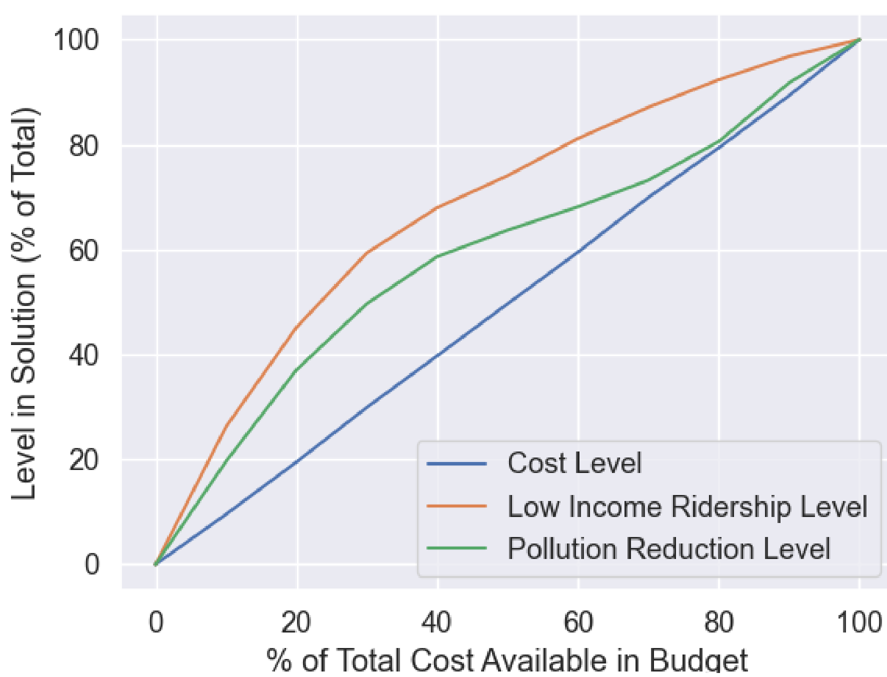

Figure 4.2: Income Objective: Aggregated Solution Values vs. Budget

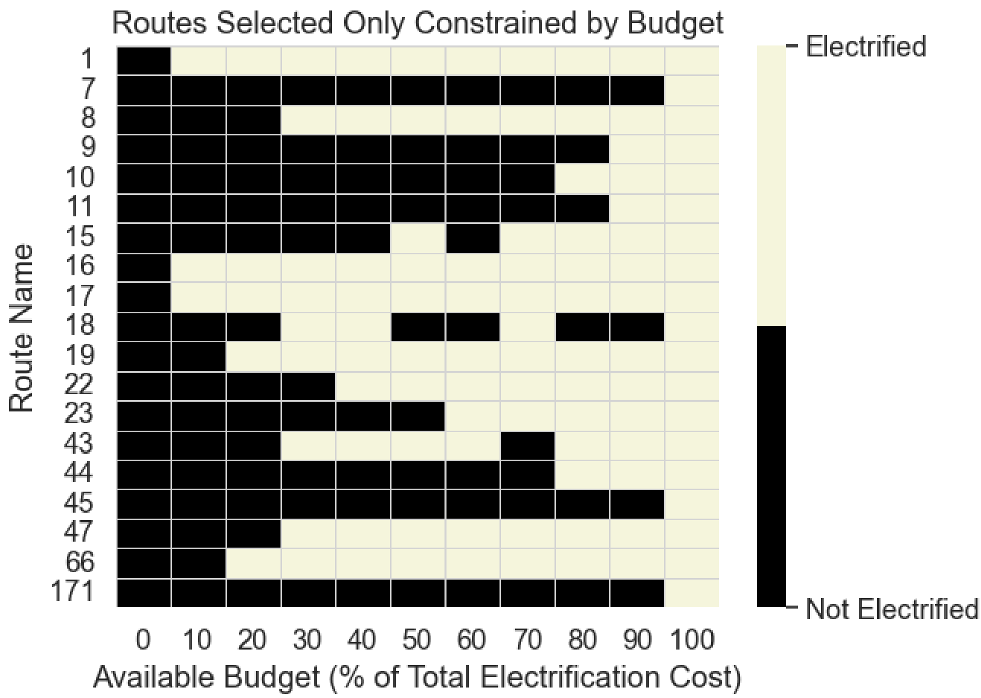

Figure 4.3: Income Objective: Route selection as a function of Budget Constraint

4.2 Pollution Objective Model Solutions

The next step is to do the same variation of the budget constraint on the pollution-centered objective and observe differences in which routes are selected for each level of the budget constraint. We also want to compare these solutions to those from the income-centered objective. Figure 4.4 is analogous to Figure 4.1, but for the pollution-centered objective. The low-income ridership level of the solution routes is almost the same as the pollution level, with the low-income ridership level being slightly below the pollution level. The relationship between the levels is the correct direction for the 50% budget level, but we saw a more noticeable difference in the low-income ridership and pollution levels when low-income ridership was in the objective. This suggests that when the optimization is constrained by costs, routes with higher pollution are less attractive than routes with higher low-income ridership. In other words, routes with higher costs tend to be higher in pollution than they are in low-income ridership. This makes sense because route pollution levels as they are modeled here have a clear relationship to route costs. Higher pollution means more frequent trips on the route, and therefore more buses and chargers that need to be purchased to electrify the route. The relationship between low-income ridership and route costs is less clear, but based on the results we can assume it is less strong than the relationship between pollution and costs. This is important for an electrification planner to know because it suggests that low-income routes are easier to focus on than pollution from a cost standpoint.

Figure 4.5 shows that the pollution level of the selected routes dips below the low-income ridership level, which violates our expectation based on having pollution in the objective function. This is only possible if high pollution routes are highly punished by the cost constraint as explained above, so this figure provides further support for the idea that high pollution routes also tend to be higher cost. The pollution levels in the solutions for each budget level are above those from 4.2, which is expected because having pollution in the objective function should force the model to prioritize high pollution routes for electrification more so than if there is no incentive. The low-income ridership solution levels are also lower with the pollution objective than with the low-income ridership objective, which is expected due to the model shifting cost resources toward routes with high pollution.

In Figure 4.6 we can see that routes 7 and 9 are chosen for much lower budgets than in 4.3, which makes sense because these routes have higher normalized pollution than normalized low-income ridership. We also see that route 23 is only selected when 90% of the budget is available rather than 60% with the low-income ridership objective, which makes sense because route 23 has lower normalized pollution than normalized low-income ridership. The general trend is that this model chooses routes that are more pollution-heavy than choices in the previous model, which is what we expect. To summarize, the comparison between a low-income ridership objective function and a pollution objective function reveals that low-income ridership is easier to focus on from a cost perspective, and that the model choices show appropriate sensitivity to the equity factor in the objective function.

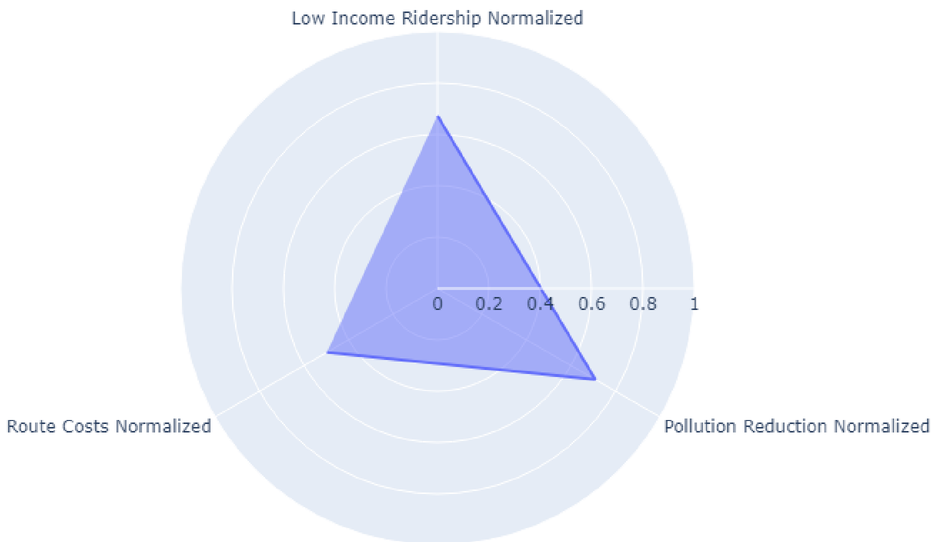

Figure 4.4: Pollution Objective Aggregate Solution Values: Budget = 50%

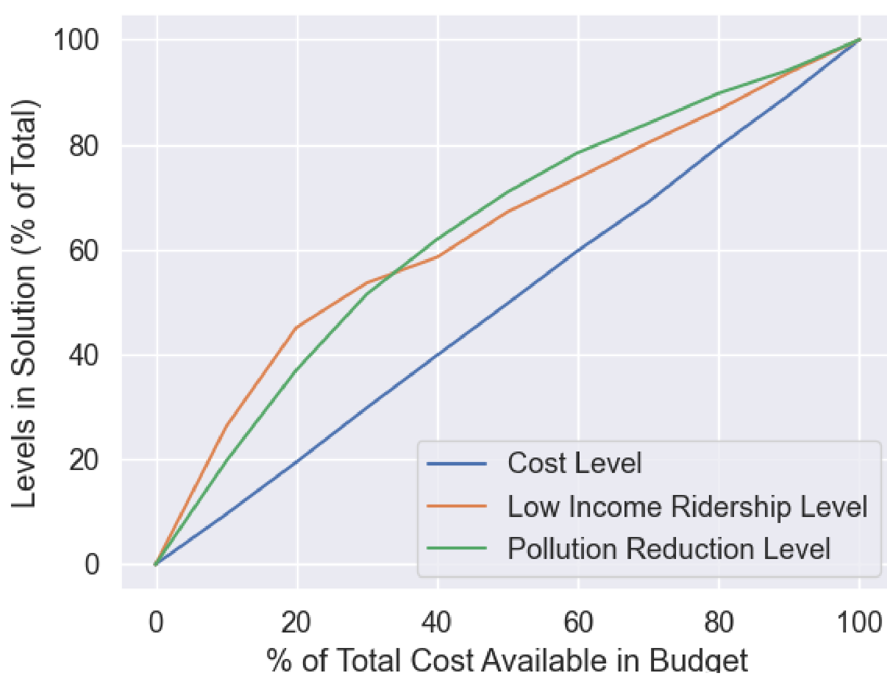

Figure 4.5: Pollution Objective: Aggregated Solution Values vs. Budget

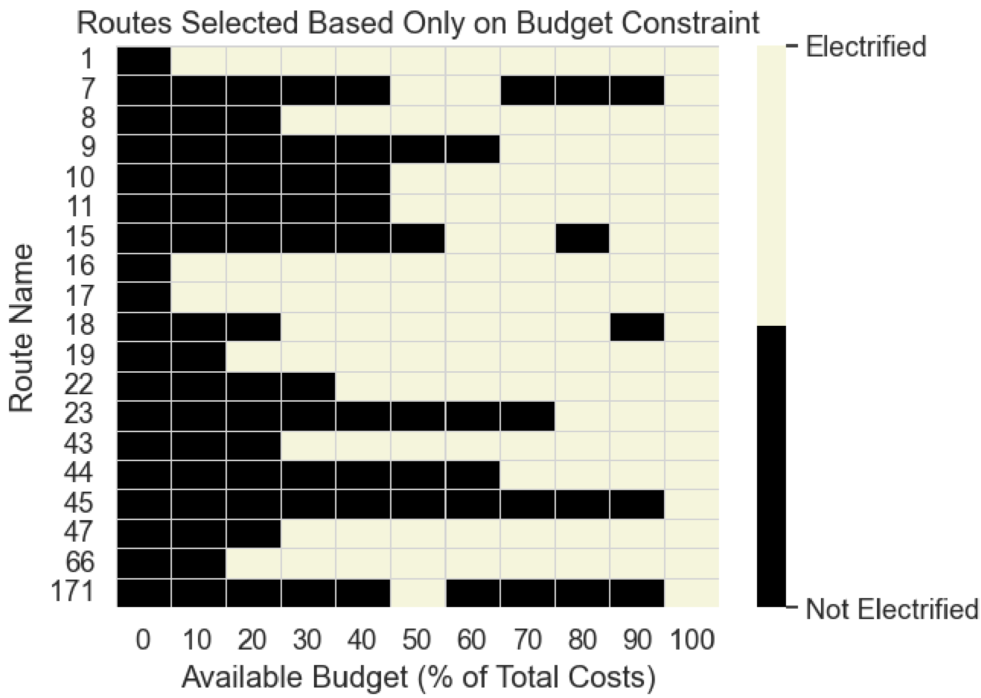

Figure 4.6: Pollution Objective: Route selection as a function of Budget Constraint

4.3 Combined Objective Model Solutions

The final step is to do the same variation of the budget constraint with the objective function that combines pollution and low income. We have discussed the two extremes of focusing on either income or pollution in the objective function, and would now like to see what happens when both are focused on equally. To do this, we set the objective function weights $EmFrac$ and $IncFrac$ each to 0.5 and observe the model outputs when varying the budget constraint. Figure 4.7 shows that the low-income ridership and pollution levels in the selected routes are almost the same at around 65% when the budget is set to 50% of total Cabot electrification costs.

Figure 4.8 shows that the low-income and pollution reduction percentages are a mixture of what we saw in the previous two parts. Specifically, the low-income ridership percentages of the selected routes stay above the pollution levels, but not as high as with the low-income ridership objective. The pollution percentages are also higher for higher available costs than

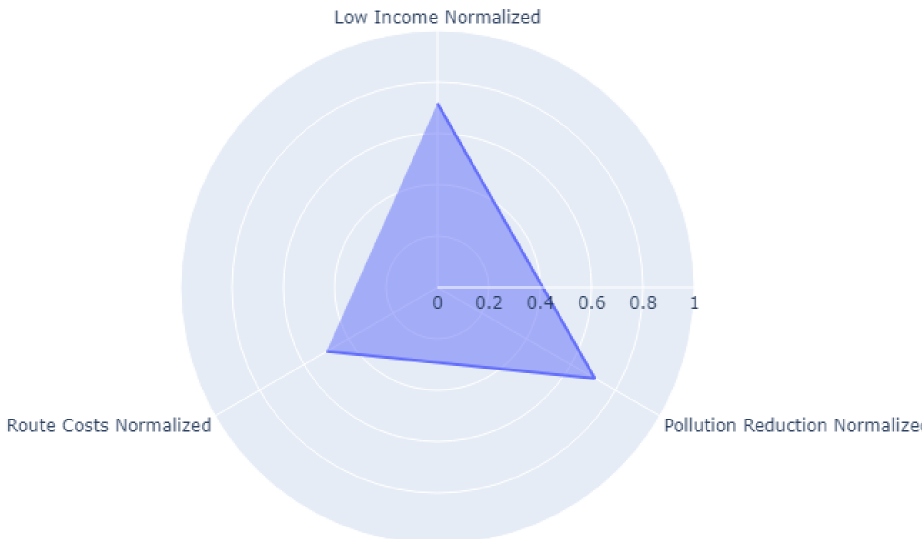

Figure 4.7: Combined Objective Aggregate Solution Values: Budget = 50%

what we see with the low-income ridership objective, but not as high as with the pollution objective. Combining low-income ridership and pollution in the objective function supports the idea that low-income ridership routes are easier to focus on from a cost perspective than high-pollution routes because even with an equal focus on both equity factors, the percentage of total low-income ridership in the electrified routes is always greater than the percentage of pollution reduced by electrifying the selected routes.

Figure 4.9 supports the idea that including both equity factors in the objective leads to a mixture of the solutions from when one or the other is included. Route 23 is now selected at 80% of total electrification costs available, rather than 60% or 90% from the previous formulations. Route 7 is selected with more frequency than with the low-income ridership objective but less than with the pollution objective. Route 9 is also selected sooner than with the low-income ridership objective but later than with the pollution objective.

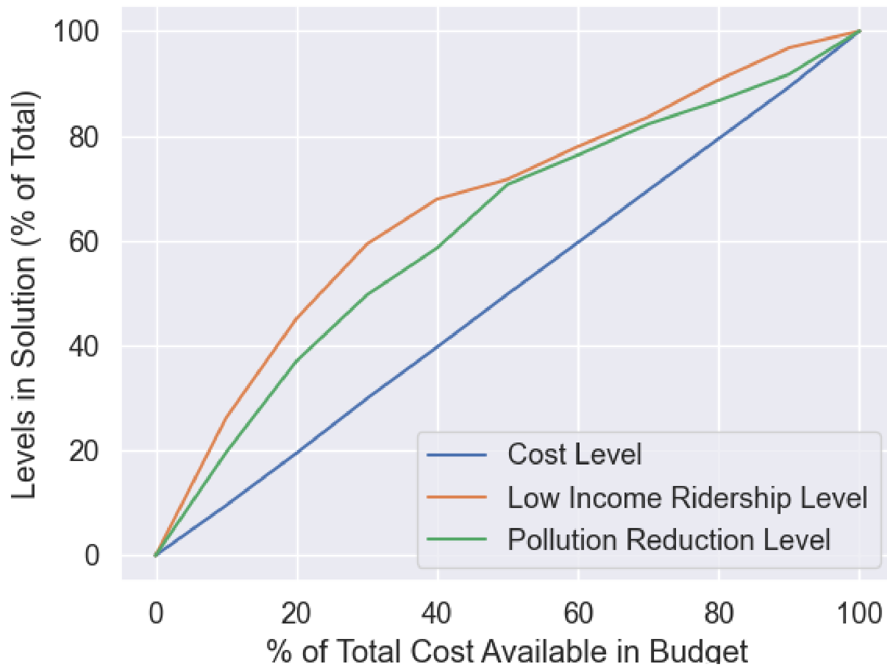

Figure 4.8: Combined Objective: Aggregated Solution Values vs. Budget

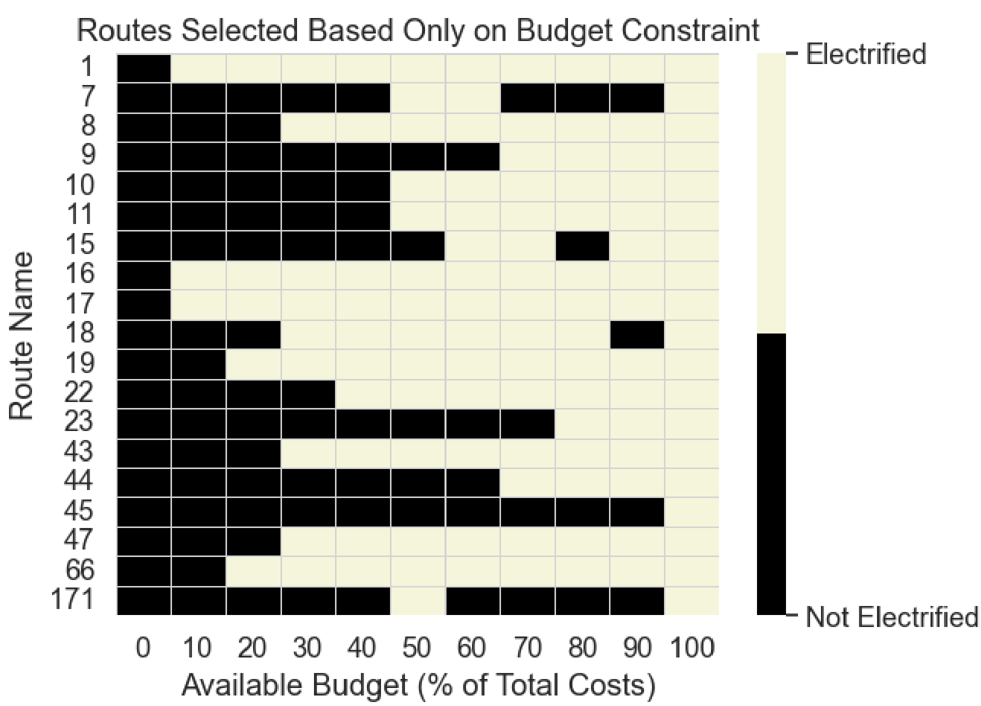

Figure 4.9: Combined Objective: Route selection based on Budget

Chapter 5

Discussion

5.1 Summary of Results

The results indicate that low-income ridership is easier to focus on from a cost perspective than pollution because the levels of low-income ridership in the model solutions for various cost constraints are generally higher than those for pollution even for an equal focus in the objective function. Even when only pollution is in the objective, the low-income ridership level of selected routes is above the pollution level for lower budget constraints before the pollution level recovers at about 30% of total costs available in the budget. We would expect any sensitivity to cost to be more prevalent for lower budgets because the model is less likely to allocate funds to a costly route when there are lower funds. This means that the low-income ridership level exceeding the pollution level at lower budget levels with the pollution objective supports the idea that low-income ridership routes tend to be less costly than routes with high pollution.

Another important implication of the results is that the low-income ridership and pollution levels for selected routes are always above the budget level. This means that for each percentage of the budget that gets used, a larger percentage of low-income ridership and pollution gets covered by electrified routes. This finding is a good incentive for electrification planners to include equity factors in their decisions rather than just relying on costs, because even at lower costs the equity benefit of considering equity factors is larger than the cost. Overall, this work has shown that focusing on low-income ridership as an equity factor for the Cabot depot is less costly than focusing on pollution reduction, and in general that considering equity factors in electrification planning can be well worth the cost trade-off.

5.2 Future Work

One direction to expand this work is to explore the minimal electrification costs subject to minimum levels of pollution reduction and low-income riders served by electric routes. In other words, the trade-offs between costs and equity factors could be explored through cost minimization rather than equity maximization. Another important direction is determining a partial electrification plan for each budget level without equity maximization so that the results can be compared to a plan based solely on cost efficiency rather than comparing across model formulations. This is important to give more credit to the claim that considering equity factors is worth the cost trade-off. A large drawback of this project was the inability to collect granular data about ridership income levels and bus IDs associated with each trip, which led to multiple simplifying assumptions that made the results less powerful. Future projects related to equity considerations in transportation will require close partnerships with transportation agencies to ensure that sufficient data can be acquired.

Finally, more work needs to be done to solve this problem on a larger scale. This analysis is only for one bus depot out of a city-wide bus network, whereas this problem realistically needs to be solved for multiple cities and regions. This can be done with a deeper focus on heuristics for reducing problem sizes and dedication to transportation data collection and processing.

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