A Bi-Objective Model for Battery Electric Bus Deployment Considering Budget Efficiency and Environmental Equity in Disadvantaged Communities

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ABSTRACT

This paper presents a bi-objective optimization model for battery electric bus (BEB) deployment that balances budget efficiency and environmental equity, particularly in disadvantaged communities. By integrating cost-benefit analysis with air quality impact assessments, the model aims to provide insights into equitable and sustainable transit electrification strategies.

1. Introduction

The transportation sector has undergone significant advancements in recent years, particularly with the increasing accessibility of battery technology and electric vehicles (EVs) [1]. Battery-electric buses (BEBs) are emerging as a viable option for transit agencies as battery range improves and costs decline. However, despite decreasing prices, BEBs remain more expensive than conventional internal combustion engine (ICE) buses and require substantial public investment in charging infrastructure and electrical system upgrades [2]. The combined costs of BEB procurement and the need for depot and on-route charging infrastructure introduce an optimization challenge [3], necessitating strategies to minimize construction costs, maximize operational efficiency, and ensure a high return on investment for transit systems.

Our study addresses these challenges by developing a Bi-Objective Model for Battery-Electric Bus Deployment (BOBEBD) to optimize both cost and environmental impact. While previous research has extensively examined technical challenges such as battery degradation and charging strategies, we emphasize maximizing the return on investment in BEB deployment by improving air quality in local communities. Disadvantaged and low-income populations disproportionately experience poor air quality [4], making environmental equity a critical consideration in electrification strategies. Our model integrates seamlessly with existing transit schedules, minimizes charger construction costs, and prioritizes local air quality improvements to enhance public health benefits.

Much of the existing literature on BEBs focuses on the technical and economic challenges of deployment, including battery performance, operational efficiency, and cost-effectiveness. Studies have explored strategies to optimize charging schedules and route planning to improve grid efficiency and reduce energy costs [5, 6], as well as methods to mitigate battery degradation and account for weather-related performance variability [7, 8]. While these factors are essential for long-term BEB adoption, our study shifts the focus from system-wide operational challenges to the feasibility of individual BEB deployments and their environmental impact. By evaluating real-world emissions reductions and air quality improvements, we aim to provide insights into the broader benefits of large-scale BEB integration beyond operational optimization.

The environmental and economic advantages of BEBs are well established, particularly their role in reducing transportation-related emissions. Research consistently demonstrates that replacing diesel and compressed natural gas (CNG) buses with BEBs lowers greenhouse gas (GHG) emissions and reduces air pollution damage [9, 10, 11]. For instance, Holland et al. estimated that BEBs generate air pollution damage of 11 cents per mile, compared to 12 cents for CNG buses and 15 cents for diesel buses [9]. Similarly, Kapatsila et al. and Valenti et al. reported significant reductions in lifetime CO_2 emissions when diesel buses are replaced with BEBs [11, 10]. While the environmental benefits of BEBs are well documented, economic considerations remain central to transit electrification. Lee et al. developed a bi-objective model balancing cost and GHG emissions in BEB deployment, emphasizing the importance

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of incorporating fuel costs and long-term financial sustainability [12]. The broader consensus is clear: electrification of transit fleets improves air quality and mitigates climate impacts. According to the U.S. Environmental Protection Agency (EPA), the transportation sector accounts for approximately 28% of U.S. GHG emissions, underscoring the critical role of BEBs in emission reduction strategies [13].

When evaluating the environmental impact of BEB deployment, it is important to distinguish between climate change mitigation and local air quality improvements. While reducing GHG emissions mitigates global climate change, reducing fine particulate matter ($PM_{2.5}$) emissions has immediate regional health benefits [14]. In 2010 alone, $PM_{2.5}$ from on-road transportation was linked to approximately 3,605 premature deaths in the United States, with a total of 50,223 premature deaths attributed to $PM_{2.5}$ exposure from 2003 to 2016 [15]. Several studies have examined the transportation sector's contribution to local air quality, particularly through $PM_{2.5}$ reduction. McDuffie et al. identified transportation as the largest source of $PM_{2.5}$ emissions, although regional variations exist [16]. While BEBs still emit $PM_{2.5}$ through brake and tire wear [17], they produce no tailpipe emissions. Skipper et al. found that EV adoption in California could significantly reduce both $PM_{2.5}$ and ozone (O_3) concentrations, particularly in high-density urban areas [18]. Ramirez-Ibarra et al. further demonstrated that replacing diesel heavy-duty vehicles with low-emission alternatives could prevent premature deaths and asthma attacks, particularly in disadvantaged communities [19]. However, Mousavinezhad et al. cautioned that the air quality benefits of EV adoption may be influenced by regional atmospheric conditions, emphasizing the need for localized electrification strategies [20].

While prior research has largely focused on aggregate benefits at the fleet or regional level, our study aims to quantify the specific environmental impact of each individual BEB. By assessing emissions reductions on a per-bus basis, we provide more precise insights into the feasibility and effectiveness of each bus in a fleet while developing a BEB deployment strategy. Moreover, as Zhu et al. emphasize, the public health co-benefits of emissions reductions must be equitably distributed to ensure all communities benefit from cleaner air [21]. Understanding the localized impact of each BEB is crucial for maximizing both environmental and public health benefits. This builds upon previous work by Zhou et al., which aimed to balance $PM_{2.5}$ reductions with infrastructure investments while ensuring equitable distribution of environmental benefits across communities [22].

We leveraged several environmental data tools to conduct a precise analysis of BEB impact. First, we used the EPA's Motor Vehicle Emissions Simulator (MOVES)[23] to generate an emissions inventory—detailing the type and quantity of emissions—for each operating bus under both BEB and diesel fuel scenarios. Next, we input these emissions inventories into the Intervention Model for Air Pollution (InMAP)[24] to simulate $PM_{2.5}$ formation and dispersion. (The advantage of using InMAP over more comprehensive models like Weather Research and Forecasting Model with Chemistry (WRF-Chem)[25], Goddard Earth Observing System with Chemistry (GEOS-Chem)[26], or Community Multiscale Air Quality Model (CMAQ)[27] is its ability to provide accurate particulate pollution dispersion estimates with significantly lower computational requirements. Given that our analysis involves hundreds of simulations to cover an entire transit fleet, this efficiency ensures that the model remains both accessible and scalable.) Finally, we quantify the difference in $PM_{2.5}$ concentrations produced by diesel buses and BEBs within the community.

We used the Climate and Economic Justice Screening Tool (CEJST)[28, 29] for our population analysis to ensure that our study effectively accounts for environmental justice considerations. Developed by the Biden White House Council on Environmental Quality, CEJST identifies communities that are disadvantaged based on factors such as pollution burden, socioeconomic indicators, and health disparities. By integrating CEJST data, we can assess whether the air quality benefits of BEB deployment are equitably distributed and whether historically overburdened communities experience meaningful improvements in pollution exposure.

Once the environmental impact of replacing diesel buses with BEBs on $PM_{2.5}$ concentrations is assessed, we use an optimization model to balance maximizing emissions reductions with practical constraints such as budget, bus feasibility, and charger infrastructure. The primary objective is to maximize the environmental impact by replacing diesel buses with BEBs, while minimizing costs associated with purchasing BEBs and building charging infrastructure. Budget constraints limit the total costs, while operational constraints ensure that each bus has sufficient energy, charges at the appropriate locations, and has the necessary charging infrastructure. Constraints are created to approximate battery percentages throughout operations, track partial charging, and ensure there are enough chargers at a terminal to accommodate all BEBs that require charging.

In Utah, where the case study of this project is based, the Utah Division of Air Quality (DAQ) has identified transportation as the source of 26% of nitrogen oxide (NO_x) emissions, a key contributor to $PM_{2.5}$ formation [30]. Utah's geography, characterized by large, bowl-shaped valleys, exacerbates air quality issues, particularly during atmospheric inversions. Our study evaluates how BEB deployment can mitigate these challenges in the Wasatch Front region and provides insights into how electrification strategies can be tailored for regions with similar environmental and operational constraints.

This study aims to provide valuable insights into the potential environmental and public health benefits of BEB deployment while considering the associated fiscal and infrastructure challenges. By integrating emissions modeling, environmental justice considerations, and optimization techniques, we develop a framework that prioritizes both air quality improvements and cost-efficiency in transit electrification. The focus on localized impacts and equitable distribution of benefits is essential for ensuring that disadvantaged communities, often disproportionately affected by air pollution, experience meaningful improvements in their environment. This research not only contributes to the ongoing discourse on transit electrification but also offers actionable strategies for policymakers and transit agencies seeking to maximize the environmental and public health benefits of BEBs while minimizing the associated costs and infrastructure demands.

2. Methodology

Unlike previous studies, which primarily focus on electrifying entire transportation networks or evaluating the costs of electric vehicle deployment, this study uniquely examines the feasibility and local air quality impacts of deploying BEBs within an existing fleet at the level of individual bus operations. The Bi-Objective Model for Battery-Electric Bus Deployment (BOBEBD) provides targeted policy guidance for transit agencies by identifying specific bus schedule blocks—each representing a bus's daily operations, including the terminals visited, departure and arrival times, and assigned routes—that would yield the greatest environmental benefits when assigned a BEB, while minimizing the costs associated with purchasing BEBs and constructing on-route charging infrastructure.

In this study, the bus schedule block serves as the fundamental unit of analysis, with both BEB assignments and the optimization of charging infrastructure driven by the characteristics of these individual schedule blocks. Environmental analysis will be conducted on each schedule block to assess air quality impacts, ensuring that BEB deployment maximizes environmental benefits at the most strategic points in the fleet's operations.

BOBEBD has two primary objectives: (1) maximizing environmental benefits by replacing diesel buses with BEBs, and (2) minimizing costs related to BEB procurement and charging station installation. These objectives are balanced using operational constraints that track and regulate each BEB's range, energy levels, charging intervals, locations, and energy usage, ensuring feasibility and efficiency in BEB deployment.

In subsequent sections, we outline how these components come together to form a comprehensive and practical model. First, we describe the methods used to quantify environmental benefits, focusing on reductions in $PM_{2.5}$ emissions in vulnerable communities. Next, we detail how cost minimization is achieved through strategic BEB assignments and optimal charging infrastructure placement. Finally, we explain how BOBEBD integrates these objectives and constraints into a unified framework, providing a powerful tool for guiding BEB deployment decisions. Together, these methods form a model that supports the transition to cleaner public transportation while ensuring that resources are allocated effectively to maximize both environmental and economic benefits. A visualization of the methodology is provided in Figure 1.

2.1. Quantifying Environmental Impact

To maximize the environmental benefits of a BEB deployment program, it is essential to define a quantifiable metric that captures the advantage of assigning a BEB to a schedule block over a diesel bus. This analysis should prioritize communities most vulnerable to air pollution, as lower-income groups tend to experience higher exposure while also having fewer healthcare resources. [31] [4] Among air pollutants, particulate matter with a diameter of 2.5 μm or smaller—$PM_{2.5}$—is closely monitored by public health agencies due to its significant health impacts, especially respiratory and cardiovascular diseases. [32] [33] Therefore, to have the greatest impact on health outcomes, we will evaluate the $PM_{2.5}$ concentrations generated by buses in each schedule block. By comparing the emissions from a generic diesel bus assigned to a block with those of a BEB assigned to the same block, we can prioritize BEB deployment in areas where reductions in $PM_{2.5}$ would deliver the greatest health benefits, particularly for vulnerable populations.

Both electric and diesel buses generate primary $PM_{2.5}$ emissions through brake and tire wear, however diesel buses also emit precursor pollutants, such as nitrogen oxides (NO_x), sulfur oxides (SO_x), ammonia (NH_3), and volatile organic compounds (VOC). These precursors react with atmospheric gases to form secondary $PM_{2.5}$, compounding the overall $PM_{2.5}$ burden. Accurately comparing emissions between bus types therefore requires modeling the formation of secondary $PM_{2.5}$ and the dispersion of all $PM_{2.5}$.

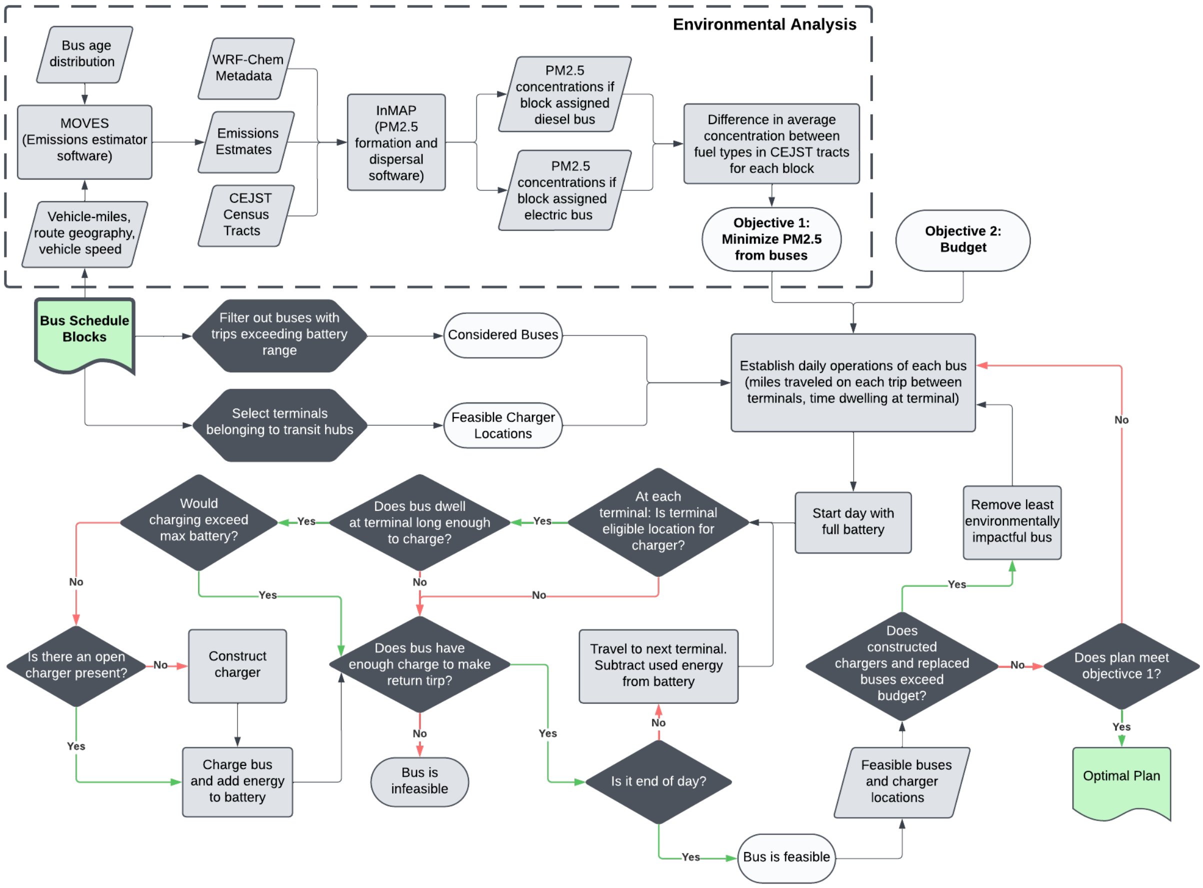

Figure 1: BOBEBD Methodology Flowchart

To model $PM_{2.5}$ formation and dispersion, we utilize InMAP[24]. InMAP integrates background atmospheric data, vehicle emissions inventories, and population data to generate high-resolution maps of $PM_{2.5}$ concentrations in a more computationally efficient way. The model accounts for atmospheric transport processes, chemical transformations, and deposition dynamics to estimate how primary and precursor emissions contribute to $PM_{2.5}$ levels throughout a study area.

InMAP is provided with three key inputs: baseline chemical transport model (CTM) (information describing atmospheric chemistry in the study area), emissions estimates from the United States Environmental Protection Agency's (EPA's) MOtor Vehicle Emissions Simulator (MOVES4.0) (a model that quantifies pollution generated by vehicles), and population data from the White House Council on Environmental Quality's (CEQ) Climate and Economic Justice Screening Tool (CEJST) which includes census tract-level demographic and boundary geospatial information. These inputs enable InMAP to estimate $PM_{2.5}$ concentrations with higher resolution in the studied populated areas, helping to identify which communities are most likely to benefit from emissions reductions. Additionally, the model allows us to quantify differences in $PM_{2.5}$ production and dispersion between diesel and electric buses, offering critical insights for prioritizing BEB deployment in areas most in need of air quality improvements.

2.1.1. MOVES4.0

MOVES4.0 is a comprehensive emissions modeling tool developed by the EPA to estimate pollutant emissions from on-road vehicles[23]. The model accounts for factors such as vehicle class, fuel type, age, driving patterns, and geographic location to simulate emissions under real-world operating conditions. MOVES provides estimates for a wide range of pollutants, including primary $PM_{2.5}$ emissions from brake wear, tire wear, and tailpipe exhaust, as well as precursor $PM_{2.5}$ emissions, including nitrous oxides (NO_x), sulfur oxides (SO_x), ammonia (NH_3), and volatile organic compounds (VOCs).

To generate emissions inventories, MOVES requires detailed input data on vehicle activity and characteristics. Key inputs include vehicle miles traveled (VMT), vehicle type, fuel type, and age distribution. The model assumes vehicle weight and efficiency characteristics based on age; older battery-electric buses (BEBs) are typically heavier due to less efficient batteries, increasing brake and tire wear, while older diesel buses may lack modern emission control systems. MOVES does not differentiate between specific makes or models, treating all vehicles within a given category as generic representations.

The model produces emissions estimates in terms of grams per mile, which can be aggregated into emissions inventories representing total emissions over a given period. These outputs can then be converted into annual emissions estimates for use in air quality models such as InMAP. For our study, emissions inventories are linked to geospatial data to associate emissions with specific locations.

2.1.2. Identifying Disadvantaged Communities with the CEJST

InMAP leverages census data to assess the effects of pollution concentrations on populations within a specific area. Since pollution impacts communities differently, identifying those most likely to benefit from emissions reductions is critical. The CEJST is based on census tracts—geographic areas containing approximately 4,000 people—as defined by the 2010 U.S. Census. It identifies communities disproportionately affected by challenges across categories such as climate change, energy, health, housing, legacy pollution, transportation, water and wastewater, and workforce development[29][28]. A community is flagged as disadvantaged if it meets two conditions: (1) it is at or above the threshold for one or more burdens in categories such as environmental, climate, or health, and (2) it meets the threshold for an associated socioeconomic burden, such as low income. Burdens include:

- **Climate Change:** Communities at or above the 90th percentile for factors like expected agriculture, building loss, population loss, flood risk, or wildfire risk, and at or above the 65th percentile for low income.
- **Energy:** Communities at or above the 90th percentile for energy cost or air pollution ($PM_{2.5}$), and at or above the 65th percentile for low income.
- **Health:** Communities at or above the 90th percentile for conditions like asthma, diabetes, heart disease, or low life expectancy, and at or above the 65th percentile for low income.
- **Housing:** Communities facing historic underinvestment, high housing costs, or lack of basic amenities, with more than 65% of the population at or above the low-income threshold.
- **Legacy Pollution:** Communities with hazardous sites like abandoned mines, Superfund sites, or hazardous waste facilities, and at or above the 65th percentile for low income.
- **Transportation:** Communities with high exposure to diesel particulate matter, transportation barriers, or heavy traffic, and at or above the 65th percentile for low income.
- **Water and Wastewater:** Communities with high levels of underground storage tanks or wastewater discharge, and at or above the 65th percentile for low income.
- **Workforce Development:** Communities with high levels of linguistic isolation, low median income, or high unemployment, and where over 10% of adults have less than a high school diploma.
- **Tribes:** Federally Recognized Tribes and Alaska Native Villages are automatically considered disadvantaged communities.

This tool enables the identification of census tracts within the study area that are economically disadvantaged, exposed to high pollution levels, or otherwise at elevated risk of health issues from $PM_{2.5}$. The CEJST provides a downloadable shapefile with data from the tracts identified as disadvantaged. This shapefile containing census population data, census tract geospatial data, and other metadata. An example of tracts being identified as disadvantaged is found in Figure 2.

[H]

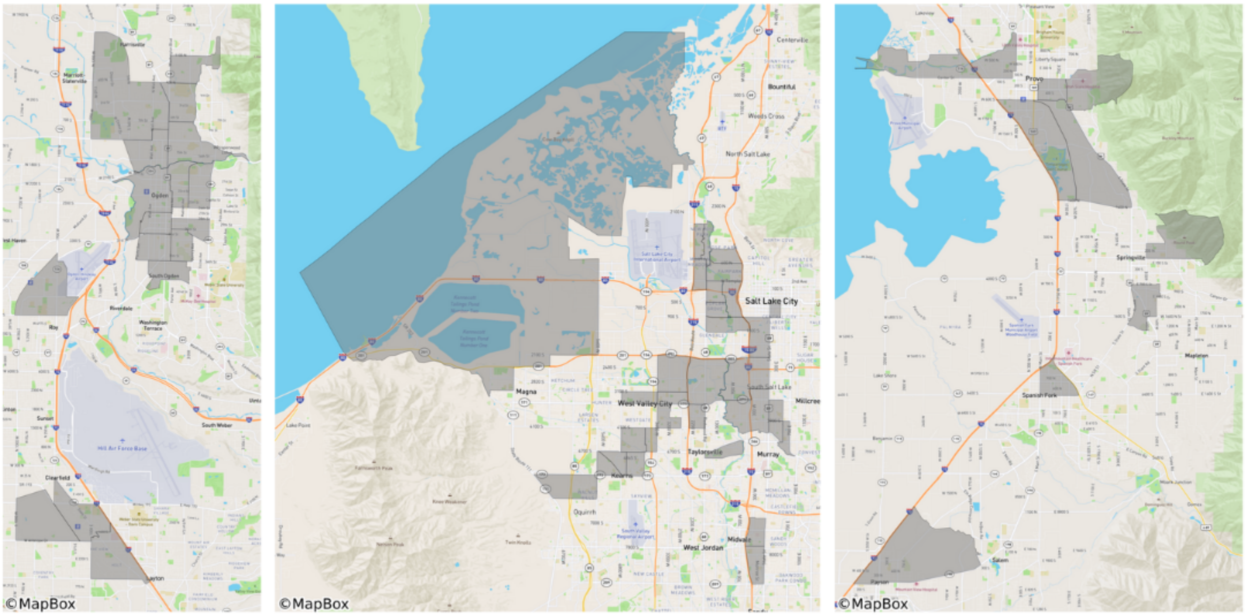

Figure 2: Wasatch Front Area CEJST Tracts

Left: Weber and Davis Counties; Middle: Salt Lake County; Right: Utah County

2.1.3. InMAP

InMAP is a reduced-complexity air modeling tool designed to analyze $PM_{2.5}$ formation and dispersion from given sources and assess its impact on preventable deaths and hospitalizations due to $PM_{2.5}$ exposure. InMAP uses CTM metadata from comprehensive models like GEOS-Chem or WRF-Chem and generates high-resolution outputs for $PM_{2.5}$ dispersion and concentration. CTM data inputs include atmospheric variables such as temperature, existing chemical concentrations, convection height, and ozone levels, which help InMAP determine the formation of secondary particulates and their dispersion patterns.

In atmospheric chemistry analysis, the study area is divided into a grid, with each grid cell accounting for the emissions released within the cell, the pollutants generated or removed through chemical reactions, pollutants removed through deposition, and the transport of pollutants in and out of the cell due to wind. InMAP uses CTM metadata to estimate the dispersion and transformation of pollutants across the grid. It integrates data such as atmospheric conditions (temperature, wind speed, and convection height), existing chemical concentrations, and emissions from various sources. By simulating these factors, InMAP calculates the concentration of pollutants like $PM_{2.5}$ in each grid cell over time. The model also accounts for secondary pollutant formation, such as particulate matter generated through atmospheric chemical reactions, and pollutant removal through processes like dry and wet deposition. This results in high-resolution pollutant concentration grids, which can be used to assess air quality and its associated health impacts in specific regions.

InMAP processes each schedule block's geospatial geometry—defined by the bus's route on a coordinate grid—as if emissions from the assigned bus are released uniformly along the entire route simultaneously. Rather than modeling emissions as originating from a single point or moving source, InMAP distributes pollution continuously across the full extent of the schedule block's path. This approach enables the model to estimate pollutant dispersion and its impact on air quality throughout the study area, though it may simplify the real-world spatial distribution of emissions. Based on this input, InMAP generates an emissions plume, representing the spread of pollutants from the modeled schedule block and their transport through the atmosphere.

A key advantage of InMAP is its ability to start with a broad-resolution grid (e.g., 12 km) and refine the resolution in populated areas with each iteration. This approach allows for the generation of detailed concentration grids around CEJST-identified census tracts while maintaining a lower resolution in less populated regions, optimizing both computation time and storage needs.

2.1.4. Formulating The Environmental Objective

Each schedule block is assigned a single bus. For each block, we model two scenarios: one where the block is assigned a diesel bus and another where it is assigned a BEB. Emissions inventory estimates for each scenario are generated using the MOVES model. These estimates are linked to the shapefile geometry of the bus block, which represents the route's path and geographic coordinates.

To assess the impact of BEB deployment on air quality, InMAP is used to calculate the $PM_{2.5}$ concentrations generated by each bus block under both scenarios. InMAP receives input files containing emissions data, spatial geometries, and atmospheric metadata. The model processes this information and produces a spatial grid of $PM_{2.5}$ concentrations. These concentration grids are then overlaid with CEJST-identified census tracts to evaluate the exposure of disadvantaged communities to bus-generated $PM_{2.5}$.

To quantify environmental benefits, we compute the population-weighted mean$PM_{2.5}$ concentration within CEJST census tracts for each bus block. The reduction in exposure due to BEB deployment is defined as the difference in these weighted means between the diesel and BEB scenarios. This reduction is denoted as V_i for a given bus block i, which serves as the key input to Objective 1 in the optimization model. By prioritizing bus blocks that yield the greatest reductions in $PM_{2.5}$ exposure within disadvantaged communities, the model ensures that BEB deployment maximizes local air quality benefits.

2.2. Bi-Objective Model Formulation

The BOBEBD is a mixed-integer non-linear optimization model designed to identify which schedule blocks should be assigned a battery-electric bus (BEB) to maximize local air quality benefits and determine optimal charging station construction. It accomplishes this by optimizing two key objectives: (1) maximize the environmental benefits of replacing diesel buses with BEBs and (2) minimize the costs associated with bus procurement and charging infrastructure.

The model incorporates constraints that ensure operational feasibility. Each bus starts with a full charge and maintains sufficient energy levels throughout its scheduled operations, and adequate charging infrastructure is provided at depots and terminals. Unlike simpler models that might assume full charging between trips, BOBEBD enables a more realistic assessment of bus replacement feasibility by incorporating partial charging and continuously tracking each bus's energy levels within the existing fleet schedule. The electric bus's range is dynamically linked to its energy consumption and remaining battery level, ensuring a more accurate representation of real-world operational constraints.

The model uses the following notation:

2.3. Indices:

i = index of buses (complete set I)
j = index of on-route charging stations (complete set J)
g = index of in-depot charging stations (complete set G)
k = index of bus terminal sequence

2.4. Parameters:

V_i = Primary quantified environmental goal reached by replacing bus i
C^G = cost of building in-depot charger
C_j^O = cost of building first on-route charging station at j
C_j^S = cost of building each subsequent charging station at j
C^B = cost of purchasing one BEB
C_x = project budget
n^O = number of BEBs that can be charged simultaneously at each on-route charger
n^G = number of BEBs that can be charged simultaneously at each in-depot charger
$d_{i,k-1,k}$ = route distance between terminals at sequences $k-1$ and k for bus i
R = driving range for a BEB with a full battery
T_i = total driving distance for bus i in one day
α_m = set of bus terminal sequences at
$E_{i,k}$ = energy level of bus i at sequence k
M_x^e = maximum battery energy
m_n^e = minimum battery energy allowed

f_b = BEB efficiency (KWh/mile)
P_O = overhead charger power (KW)
$t_{i,k}$ length of time bus i dwells at terminal k
γ_g = bus depot g
L = large number

2.5. Decision Variables:

$$Z_i^B = \begin{cases} 1 & \text{if bus } i \text{ replaced} \\ 0 & \text{otherwise} \end{cases}$$

$$Z_j^O = \begin{cases} 1 & \text{if charger built at terminal } j \\ 0 & \text{otherwise} \end{cases}$$

Y_j^O = number of on-route chargers built at terminal j
Y_g^G = number of in-depot charging stations built at garage g

$$X_{i,k} = \begin{cases} 1 & \text{if bus } i \text{ charged at sequence } k \\ 0 & \text{otherwise} \end{cases}$$

2.6. Objectives:

$$max \sum_i V_i Z_i^B \tag{1}$$

$$min(\sum_g C^G Y_g^G + \sum_j (C_j^O Z_j^O + Z_j^O C_j^S (Y_j^O - 1)) + \sum_i C^B Z_i^B) \tag{2}$$

2.7. Constraints

$$E_{i,0} = M_x^e \quad \forall i \tag{3}$$

$$m_n^e \leq E_{i,k} \leq M_x^e \tag{4}$$

$$X_{i,k} \leq Z_j^O \quad \forall i, j, k \tag{5}$$

$$X_{i,k} \leq Z_i^B \quad \forall i, k \tag{6}$$

$$\sum_{i,k} X_{i,k} \leq n^O Y_j^O \quad \forall i, j, k \tag{7}$$

$$\sum_{i \in \gamma_g} Z_i^B \leq n^G Y_g^G \quad \forall g \tag{8}$$

$$E_{i,k} \geq ((d_{i,k,k+1} + d_{i,k+1,k+2}) f_b) - ((1 - Z_i^B) L) \quad \forall i, k \tag{9}$$

$$E_{i,k} = E_{i,k-1} + X_{i,k} t_{i,k} P_O - Z_i^B d_{i,k-1,k} f_b \tag{10}$$

2.7.1. Model Notes

On a typical weekday, bus i will run through a sequence of terminals. Each terminal has a unique identifier j. For example, a hypothetical bus 1 starts at terminal a on sequence 0, travels 5 miles to terminal b on sequence 1, waits there for 10 minutes, returns to terminal a at sequence 2, waits there for 8 minutes, then ends its day on terminal c at sequence 3.

The first charger built at a location may cost more than subsequent chargers constructed at the same station, as it may require installing electrical grid upgrades and transformers or other upfront investments. Subsequent chargers can then use the existing upgraded grid infrastructure, thereby requiring only the cost of the purchase and installation of the charger.

The energy levels and driving range of each BEB are governed by several factors, including the initial state of charge, energy consumption during operation, and recharging at terminals or depots. The energy level of bus i at sequence k, denoted $E_{i,k}$, is initialized to the maximum battery energy M_x^e at the start of the day. During operation, the energy level decreases proportionally to the route distance traveled, $d_{i,k-1,k}$, and the BEB efficiency, f_b, which represents energy consumption in kWh per mile. The range of the bus is constrained by m_n^e, the minimum allowable energy level, and M_x^e, ensuring the bus remains operational.

Recharging occurs at designated terminals or depots, where the energy replenished is calculated as a function of the charging time $t_{i,k}$, the power of the overhead charger P_O, and the binary decision variable $X_{i,k}$, which indicates whether bus i is charged at sequence k. The energy level at any sequence is expressed as a balance of the energy carried over from the previous sequence, the energy consumed during transit, and the energy gained during recharging. This dynamic ensures that the driving range and energy constraints of BEBs are accurately modeled within the optimization framework.

2.8. Equation Explanation

Objective [1]: Maximize the impact of replacing diesel buses with BEBs.
Objective [2]: Minimize costs associated with purchasing BEBs and building on-route and depot chargers. As increasing the budget means more buses can be replaced to meet objective [1], objective [2] is treated as the constraint

$$min(\sum_g C^G Y_g^G + \sum_j (C_j^O Z_j^O + Z_j^O C_j^S (Y_j^O - 1)) + \sum_i C^B Z_i^B) \leq C_x \tag{11}$$

Transitioning this objective to a constraint turns the problem into a single-objective problem that can be solved using computer software.
Constraint [3]: Ensure each bus starts the day with a fully charged battery.
Constraint [4]: Maintain each bus's energy level within an established minimum and maximum range.
Constraint [5]: Ensure that a bus charges only if an on-route charger is present at the terminal.
Constraint [6]: Limit charging to BEBs.
Constraint [7]: Ensure sufficient on-route chargers are available at the terminal for all buses charging simultaneously.
Constraint [8]: Ensure an adequate number of depot chargers are available.
Constraint [9]: Require that a bus has enough energy to cover the entire return trip upon departure.
Constraint [10]: Define the transition rule for the bus battery energy level between route steps.

These objectives and constraints collectively ensure that only feasible buses are replaced with BEBs, without disrupting existing routes and schedules.

3. Application

We applied the BOBEBD to the Utah Transit Authority (UTA) transit network as a case study to guide the deployment of BEBs. This deployment, funded by grants from the Federal Transit Agency, aims to integrate BEBs into UTA's existing operations. UTA provides public transit services throughout the Wasatch Front—Utah's primary metropolitan area—which includes major cities such as Salt Lake City, Ogden, and Provo. The extent of UTA's routes is shown in Figure 3. The model operates within UTA's established bus routing and scheduling framework, using UTA bus schedule blocks—each containing information about the terminals visited, routes traveled, and terminal arrival and departure times—as the fundamental input.

Potential on-route charging locations were manually identified using terminal coordinates and street maps, focusing on terminals located at transit hubs. This ensures that only sites where UTA owns the land and can feasibly construct the necessary on-route charging infrastructure are considered.

Data engineering was performed using the Python packages Pandas and Geopandas, while optimization tasks were carried out using Gurobi and its Python API, Gurobipy.

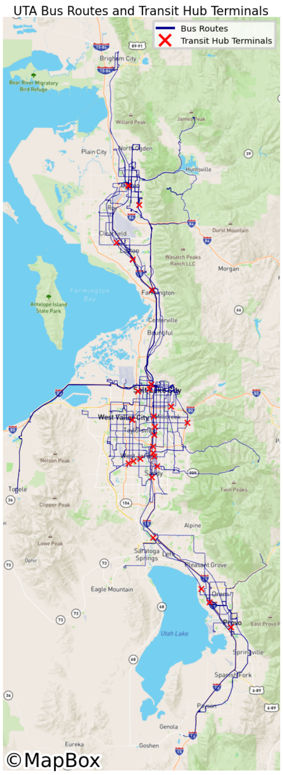

Figure 3: UTA Routes and Eligible Terminals

3.1. Application Parameters

The BEB considered by the UTA is the NewFlyer XE-40, which costs $970,000, has a total battery capacity of 388 kWh, and an observed efficiency of 3 kWh per mile. The model allows for a maximum charge of 80% capacity and a minimum charge of 20%, providing approximately 77 miles of range on a full charge. Charging efficiency decreases as the battery approaches full capacity; therefore, UTA guidelines recommend charging buses to around 80% while on-route. To ensure sufficient charge for returning to the bus depot or addressing emergencies, the battery is kept above 20% under normal operations.

The first overhead charger, along with the necessary transformers and infrastructure, costs $700,000, while subsequent chargers at the same terminal cost $400,000. (The reduced cost of additional chargers encourages the model to prioritize installing multiple chargers at fewer locations.) Each overhead charger has an output of 300 kW, enabling a full charge of 288 kWh from 20% to 80% capacity in approximately 45 minutes under ideal charging conditions. Charging occurs during operator breaks, so only terminals where buses dwell for more than 10 minutes are considered for on-route charging. In-depot chargers, which cost $300,000, can charge up to three buses simultaneously.

The UTA bus runcut file (the spreadsheet containing the bus schedule blocking) contains 345 weekday schedule blocks, 337 of which do not have a terminal-to-terminal trip exceeding the 77-mile range of a fully charged BEB.

3.2. Environmental Analysis

As described in the methodology, we use InMAP to model the creation and dispersion of pollution from each diesel bus and BEB, which requires obtaining emissions inventories from MOVES, population data from the CEJST, and CTM metadata.

3.2.1. Creating Bus Emissions Inventories Using MOVES

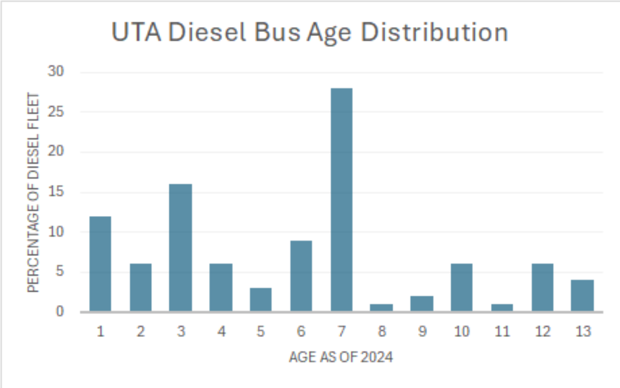

Figure 4: Age Distribution of UTA Diesel Buses

We begin by gathering the inputs for MOVES to prepare vehicle emissions inventories. We used weekday bus schedule block data to generate vehicle-miles data. Each schedule block (see Appendix A: Table 3) was entered as a separate "link" in MOVES, with a single bus assigned to each link. In MOVES, a "link" refers to a segment of roadway or a specific route that a vehicle travels, and it is used as the basic unit for calculating emissions. The length of each link was specified based on the schedule block's daily mileage (see Appendix A: Table 4). Diesel bus ages were extracted from the UTA change day roster report (see Figure 4). MOVES was then run twice: once with all vehicles designated as diesel buses and again with all vehicles designated as BEBs. This provided emissions estimates in kg/mile, which were subsequently converted to kg/year for use as inputs in InMAP (see Appendix A: Table 5 for a sample of the diesel bus inventory and Appendix A: Table 6 for a sample of the BEB inventory). Note that the BEBs still generate primary $PM_{2.5}$ emissions due to brake and tire wear but do not emit any precursor $PM_{2.5}$ gases on-route. Each schedule block's emissions inventory was stored in a separate shapefile, along with the geospatial data for the block's serviced routes. MOVES was operated via its desktop application with a user interface running on a Java Virtual Machine. HeidiSQL was used to convert MOVES output SQL databases into CSV files for streamlined processing.

3.2.2. CEJST Census Data

The CEJST provides a shapefile containing data for each 2010 census tract in the United States that is identified as disadvantaged, which can be downloaded from the CEJST website [CITE]. This shapefile contains comprehensive population data including attributes such as demographics, chronic disease rates, economic conditions, access to healthcare, whether the tract has an unusually high exposure to pollutants, and so forth. For this study, we focus exclusively on demographic and population data, as our primary objective is to analyze pollutant concentrations generated by buses within the study area. We selected the 60 disadvantaged census tracts within Davis, Salt Lake, Utah, and Weber counties—the Wasatch Front counties serviced by the UTA—and retained only the population, demographic, and geospatial data for InMAP.

3.2.3. CTM Metadata

CTM data was obtained from a 12-km resolution global atmospheric chemistry simulation conducted on 2005 conditions using WRF-Chem, the Weather Research and Forecasting (WRF) model coupled with Chemistry[34]. This dataset was provided by the creators of InMAP and serves as the foundation for modeling atmospheric pollutant transport and transformation. These data are included in the InMAP downloadable in a NCF binary file.

3.2.4. Executing InMAP

Our analysis involved 337 unique schedule blocks, requiring a total of 674 individual InMAP simulations. To expedite the processing of emissions concentration data, the computation was moved to the university's high-performance computing (HPC) cluster, enabling parallel execution of multiple simulations, which significantly reduced overall processing time.

For each fuel scenario and schedule block combination, a TOML configuration file was generated, specifying file paths for the emissions inventory, census tract shapefiles, and the CTM metadata NCF binary file. It also included metadata to define the relevant columns for emissions and population data, along with the geographic extent of the study area.

The 674 simulations were parallelized using two SLURM scripts—one for the 337 diesel bus simulations and another for the 337 BEB simulations. Each simulation was assigned to a separate task, with tasks distributed across multiple nodes in the HPC cluster. This approach allows multiple simulations to run simultaneously, dramatically reducing the overall computation time.

3.2.5. Understanding Impact of Diesel Buses

To better understand the emissions impact of the entire network, an additional simulation was conducted, incorporating all schedule blocks simultaneously. The visualization of the pollution dispersion can be seen in figures 5, 6, and 7.

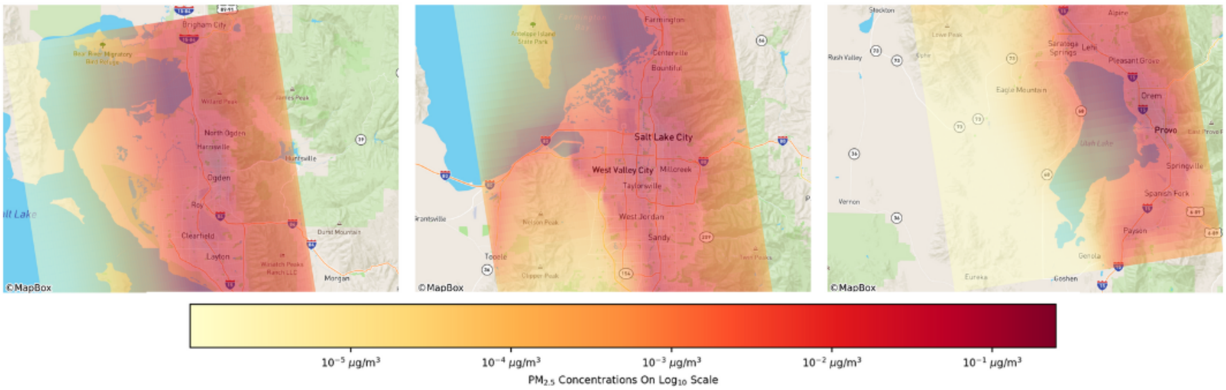

Figure 5: Pollution from all blocks assigned diesel buses

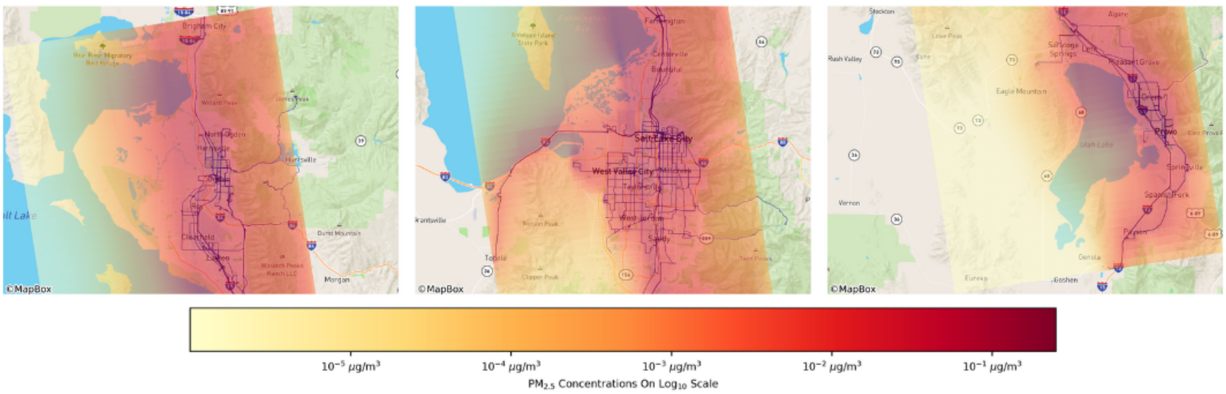

Figure 6: Pollution dispersion with bus routes

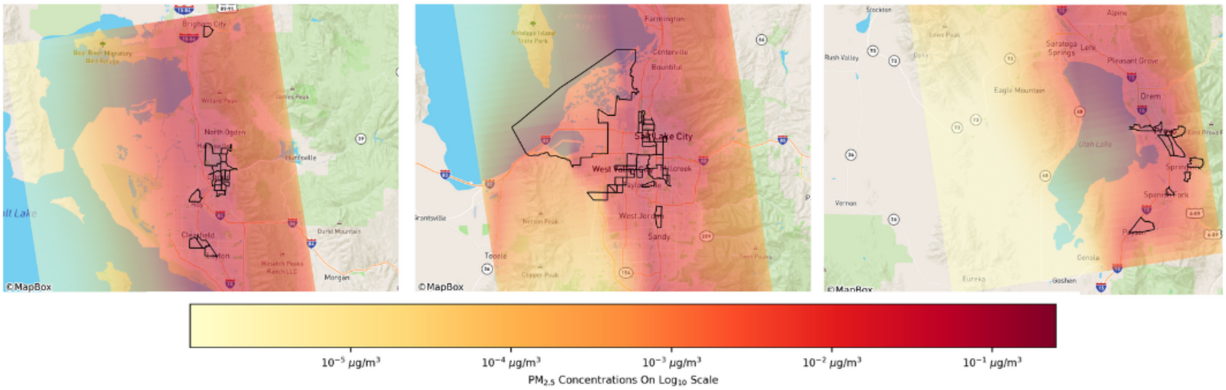

Figure 7: pollution dispersion with CEJST tracts

As seen in Figure 8, within CEJST-identified census tracts the mean $PM_{2.5}$ concentration when all blocks are assigned diesel buses is 0.037, with a median of 0.028 (or -1.739 and -1.547 on a log scale, respectively). When all blocks are assigned BEBs, the mean and median concentrations decrease to 0.012 and 0.009 (or -2.277 and -2.028 on a log scale, respectively). These results indicate a measurable reduction in pollution exposure within populated areas when transitioning from diesel to electric buses.

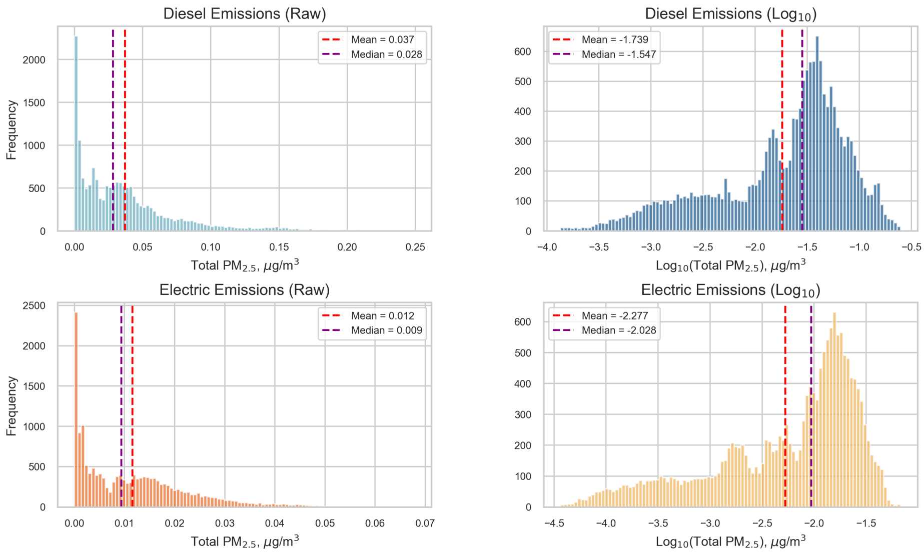

Figure 8: Emissions Distribution Across CEJST Tracts

Grid Cells Have ≈71m X 217m dimensions

3.3. Environmental Analysis Output

InMAP generates a grid across the study area, with higher-resolution grids overlaid on CEJST-identified census tracts, as shown in Figure 9. Areas outside these tracts have grid dimensions of approximately 567 meters by 1734 meters, while areas within them have finer grid dimensions of approximately 71 meters by 217 meters. Each grid cell in the InMAP output shapefile contains the average annual $PM_{2.5}$ concentrations attributable to the analyzed source. To quantify the environmental impact of each schedule block, we compute an environmental objective score by calculating the difference in population-weighted average $PM_{2.5}$ concentrations for the block between fuel types. Since each block, whether assigned a diesel bus or BEB, generates a particulate matter plume with relatively low $PM_{2.5}$ concentrations

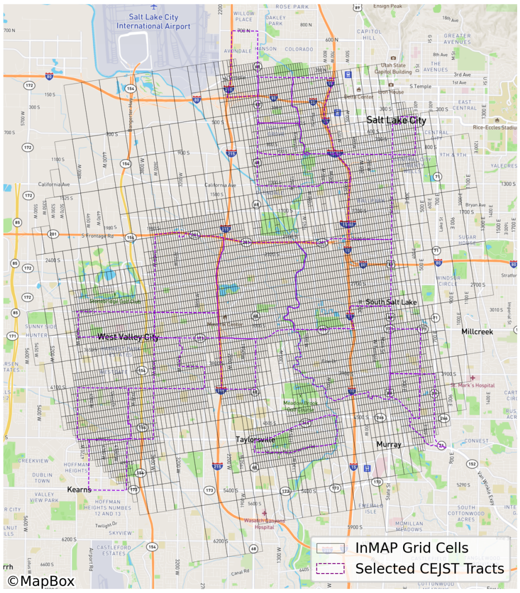

Figure 9: InMAP grid cells have higher resolution around Census tracts

Test	**Statistic**	**p-value**
Paired t-test	$t = 18.653$	$p < 0.00001$
Cohen's d (Effect Size)	$d = 1.140$	-
95% CI for Mean Difference	$(9.40 \times 10^{-5}, 1.16 \times 10^{-4})$	-
Wilcoxon Signed-Rank Test	$W = 0.000$	$p < 0.00001$
Kolmogorov-Smirnov (KS) Test	$KS = 0.540$	$p < 0.00001$

Table 1
Statistical Analysis Results

when analyzed individually, applying population-weighted averaging helps distribute emissions more effectively and highlights areas that benefit most from reduced pollution.

To ensure that the observed differences in $PM_{2.5}$ concentrations between fuel types are statistically significant, we conducted a series of statistical tests (Table 1). The paired t-test yielded a highly significant result ($t = 18.653$, $p < 0.00001$), indicating that the difference in pollution exposure between diesel and BEB scenarios is unlikely to be due to random variation. Cohen's d ($d = 1.140$) suggests a large effect size, reinforcing the practical significance of this difference. Additionally, the Wilcoxon Signed-Rank Test ($W = 0.000$, $p < 0.00001$), a non-parametric alternative to the t-test, confirms this result without assuming normality. The Kolmogorov-Smirnov (KS) test ($KS = 0.540$, $p < 0.00001$) further highlights significant differences in the distributions of $PM_{2.5}$ concentrations between the two fuel types.

These findings validate the environmental objective score as a meaningful metric for comparing schedule blocks. While the absolute differences in pollution concentrations may appear small, their statistical significance suggests that the shift from diesel to BEB has a measurable impact on air quality.

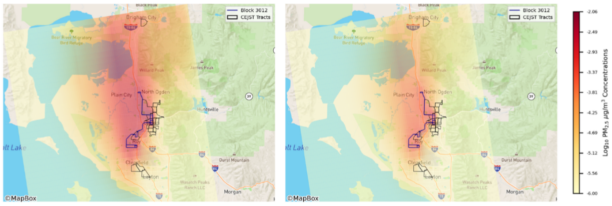

Figure 10: Block 3012 and its emissions plumes

Left: Diesel Bus, Right: Electric Bus

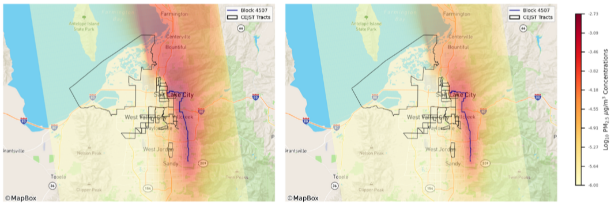

Figure 11: Block 4507 and its emissions plumes

Left: Diesel Bus, Right: Electric Bus

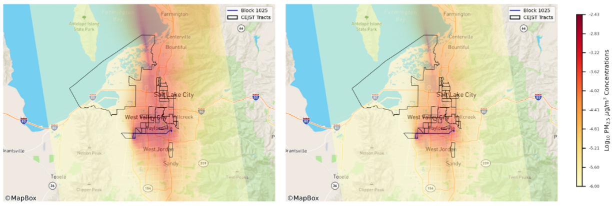

Figure 12: Block 1025 and its emissions plumes

Left: Diesel Bus, Right: Electric Bus

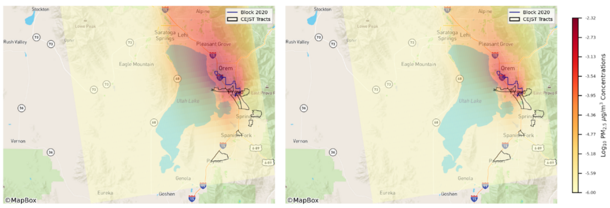

Figure 13: Block 2020 and its emissions plumes: South

Left: Diesel Bus, Right: Electric Bus

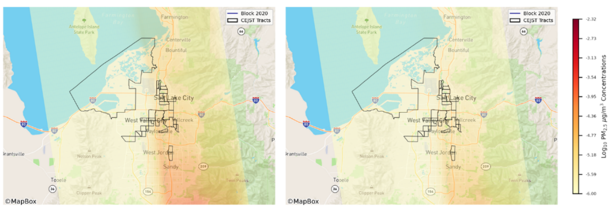

Figure 14: Block 2020 and its emissions plume: Central

Left: Diesel Bus, Right: Electric Bus

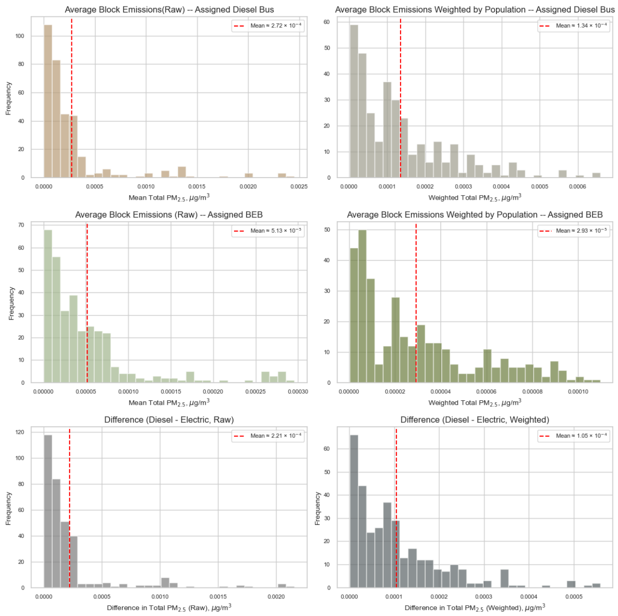

Figure 15: $PM_{2.5}$ Concentrations Across All Analyzed Bus Schedule Blocks

3.4. Implementing BOBEBD

3.4.1. *Varying Budget Constraint*

Different budget levels yield varying results from the model. After accounting for range and charging constraints, 244 weekday schedule blocks are identified as eligible for BEB assignment. This corresponds to a maximum budget of approximately \$283 million, beyond which no additional buses can be feasibly electrified. At this threshold, further increasing the budget has no impact on the model outcomes. Table 7 details the location and count of on-route chargers by budget level, and Table 8 specifies which bus routes receive BEBs at each budget level.

3.4.2. *Model Instability and Flexibility*

The BOBEBD problem is a mixed-integer, non-linear, and non-trivial optimization problem, inherently exhibiting some degree of instability. Unlike linear or convex problems that guarantee an optimal solution, the outcomes of BOBEBD may vary slightly depending on the initial conditions. As shown in Table 2, the maximum number of feasible buses remains constant, whereas the number of chargers fluctuates slightly. Figures 16 and 17 illustrate that charging times vary depending on the chosen random seed. This suggests that the model allows for flexibility in assigning charging schedules. For instance, if a bus arrives at a terminal and all chargers are occupied, the model may opt to wait rather than construct an additional charger. Ultimately, the most critical insights from the model are which bus blocks are electrified and which terminals require charging infrastructure.

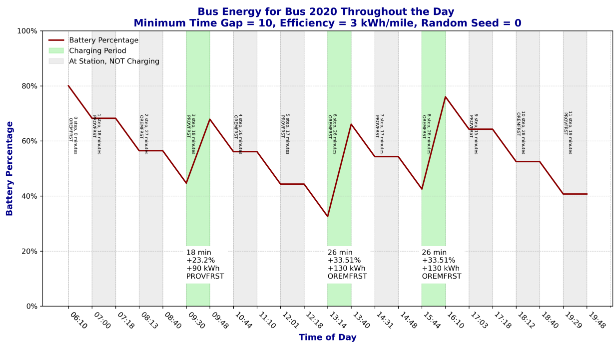

Figure 16: Bus Energy Levels for Bus 2020 and Random Seed 0

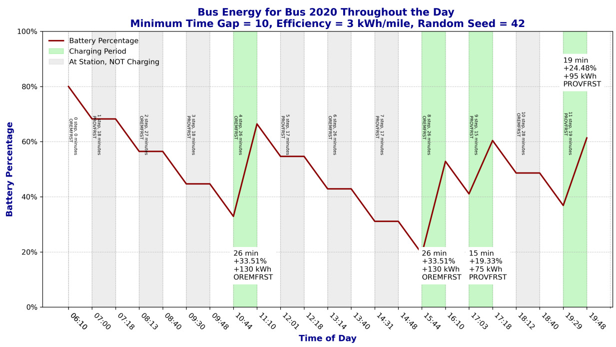

Figure 17: Bus Energy Levels for Bus 2020 and Random Seed 42

4. Discussion

This study provides valuable insights into the environmental, economic, and operational dimensions of transitioning from diesel buses to battery electric buses (BEBs) within the Wasatch Front region. Our environmental analysis demonstrates measurable reductions in $PM_{2.5}$ concentrations when replacing diesel buses with BEBs in CEJST-identified

Random Number Seed	Max Budget	Number of BEBs Replaced	Number of Chargers Required
0	282.8M	244	36
42	281.8M	244	34
43	282.2M	244	35
100	282.2M	244	35
999	281.8M	244	34

Table 2
Optimization Results From Varying Starting Conditions

census tracts. Although these reductions are statistically significant, the absolute changes in $PM_{2.5}$ concentrations remain relatively small. This highlights the importance of contextualizing transit electrification efforts within broader air quality improvement strategies that address other major sources of pollution, such as upstream power generation and fossil fuel refinement. For example, Panta et al. [35] found that 30% of upstream energy should come from clean sources to offset the GHG impact of internal combustion engine (ICE) buses, suggesting that further research could focus on quantifying the $PM_{2.5}$ impact of upstream power generation.

The budget constraint analysis reveals diminishing returns in electrification efforts, with substantial investment enabling the replacement of up to 283 diesel schedule blocks. However, surpassing this budget does not yield additional electrification due to range limitations and charging infrastructure requirements. This finding emphasizes the need for strategic prioritization—targeting bus routes with the highest pollution exposure and most significant population impact to optimize environmental benefits within available financial resources.

The spatial distribution of emissions also warrants attention. The InMAP model used in this study assumes that emissions are dispersed uniformly along each schedule block, which simplifies real-world conditions. Pollution dispersion is influenced by meteorology, traffic congestion, and localized emission sources, and future work could refine this analysis by incorporating dynamic emission modeling to capture these nuances more accurately.

While our results indicate that BEB adoption can reduce local pollutant concentrations, its impact on overall air quality levels depends on the broader regional context, including background pollution and secondary particulate formation. Further research should explore the cumulative effects of transit electrification in combination with policies targeting industrial emissions, vehicular restrictions, and land-use planning to fully assess its contribution to regional air quality improvement.

Additionally, the integration of operational feasibility constraints—such as battery range limitations and charging station placement—provides a more realistic assessment of the potential for bus electrification. While this study focused on weekday service, future research could expand the analysis to include weekend operations, seasonal variations, and evolving battery technologies that may enhance feasibility over time. Future research could also incorporate realtime energy pricing to ensure charging is prioritized when it it most cost effective as proposed by Zhang et al. [36].

In conclusion, this study contributes to the growing body of evidence supporting the environmental benefits of BEB adoption, particularly in areas heavily impacted by air pollution. While the absolute reductions in $PM_{2.5}$ are relatively small, the transition to BEBs presents a significant opportunity to reduce both local air pollution and greenhouse gas emissions. Strategic planning, prioritization, and further research into upstream emissions and regional policies will be key to maximizing the environmental and health benefits of transit electrification, contributing to a more sustainable transportation future.

5. Appendix A

block	LineAbbr	from_stop	FromTime	to_stop	ToTime
1000	35	35S84WWB	3:54:00	MILLCREK	4:45:00
1000	33	MILLCREK	4:49:00	39-SWASB	5:11:00
1000	33	39-SWASB	5:38:00	MILLCREK	6:00:00
1000	35	MILLCREK	6:04:00	35S84WWB	6:45:00
1000	35	35S84WWB	7:11:00	MILLCREK	8:15:00
1000	33	MILLCREK	8:19:00	39-SWASB	8:43:00
1000	33	39-SWASB	9:07:00	MILLCREK	9:30:00
1000	35	MILLCREK	9:34:00	35S84WWB	10:18:00
1000	35	35S84WWB	10:45:00	MILLCREK	11:45:00
1000	33	MILLCREK	11:49:00	39-SWASB	12:14:00
1000	33	39-SWASB	12:36:00	MILLCREK	13:00:00

Table 3
Bus block schedule excerpt

linkID	countyID	roadTypeID	linkLength	linkVolume	linkAvgSpeed	linkDescription	linkAvgGrade
9999	49035	1	0.000	337	0.00	off-network	0
1000	49035	5	232.22	1	19.51	Bus block	0
1001	49035	5	234.71	1	15.16	Bus block	0
1002	49035	5	239.47	1	19.34	Bus block	0
1003	49035	5	239.83	1	15.59	Bus block	0
1004	49035	5	239.83	1	15.59	Bus block	0

Table 4
Adapted road link data excerpt

block	NOx	VOC	SOx	NH3	$PM_{2.5}$
1000	7978.164	192.689	9.003	0.001406	96.295
1001	7542.531	183.684	7.876	0.001051	94.971
1002	8205.655	198.244	9.233	0.001391	99.246
1003	7759.754	188.809	8.171	0.001084	97.174
1004	7759.754	188.809	8.171	0.001084	97.174

Table 5
Annual diesel emissions data by bus schedule block, kg

block	NOx	VOC	SOx	NH3	$PM_{2.5}$
1000	0	0	0	0	48.825
1001	0	0	0	0	51.580
1002	0	0	0	0	50.483
1003	0	0	0	0	52.375
1004	0	0	0	0	52.375

Table 6
Annual BEB emissions data by bus schedule block, kg

6. Appendix B

Terminal Name	Budget Levels						
	\$50M	**\$100M**	**\$150M**	**\$200M**	**\$250M**	**\$275M**	**\$283M**
Central Pointe	-	-	-	1	1	1	1
Clearfield FrontRunner	-	-	-	1	1	1	1
Farmington Station	-	-	-	1	1	1	1
Fashion Place Trax	-	-	-	1	1	1	1
Jordan Valley Trax	-	-	-	-	1	1	1
Lehi FrontRunner	-	-	1	1	1	1	1
Layton Station	-	1	1	1	1	1	1
Midvale Central	-	-	-	1	1	1	1
Midvale Ft. Union	-	-	-	-	1	1	1
Murray Central	1	1	2	1	1	1	2
Murray North	-	-	1	1	1	1	1
N. Temple Station	-	-	-	1	1	1	1
Ogden Central	1	2	2	2	2	2	3
Orange Street Transit	-	2	3	3	3	3	3
Orem FrontRunner	-	3	3	3	3	3	4
Provo FrontRunner	-	2	2	2	2	3	2
SLC Station	1	1	1	1	2	2	3
South Jordan FrontRunner	-	1	1	1	1	1	1
Wasatch Blvd P+R	1	1	2	2	2	2	2
Vineyard FrontRunner	-	1	1	1	1	1	1
West Jordan City Center	3	3	3	3	3	3	3
West Valley Central Trax	2	2	2	2	2	2	2
Total Chargers Constructed	**9**	**18**	**25**	**28**	**31**	**33**	**37**
Electrified Blocks	**41**	**83**	**126**	**171**	**216**	**238**	**244**

Table 7
Terminal Charger Counts by Budget Level

Budget	Number of Electrified Schedule Blocks	Electrified Lines	Electrified Lines Count
$50M	41	39, 45, 47, 54, 217, 227, 240, 248, 509, 603X	10
$100M	83	1, 4, 9, 33, 35, 39, 45, 47, 54, 200, 201, 205, 217, 218, 227, 240, 248, 509, 513, 551, 601, 603X, 604, 613, 830X, 831	26
$150M	126	1, 2, 4, 9, 33, 35, 39, 45, 47, 54, 200, 201, 205, 217, 218, 227, 240, 248, 470, 509, 513, 551, 601, 603X, 604, 613, 626, 627, 628, 640, 830X, 831, 833, 834, 850, 871	36
$200M	171	1, 2, 4, 9, 17, 21, 33, 35, 39, 45, 47, 54, 200, 201, 205, 209, 217, 218, 227, 240, 248, 470, 473, 509, 513, 551, 601, 603X, 604, 613, 626, 627, 628, 640, 805, 822, 830X, 831, 833, 834, 850, 871	40
$250M	216	1, 2, 4, 9, 17, 21, 33, 35, 39, 45, 47, 54, 200, 201, 205, 209, 213, 217, 218, 220, 227, 240, 248, 451, 470, 473, 509, 513, 551, 601, 603X, 604, 606, 613, 626, 627, 628, 630, 640, 805, 822, 830X, 831, 833, 834, 850, 871	46
$275M / $283M	238 / 244	1, 2, 4, 9, 17, 21, 33, 35, 39, 45, 47, 54, 72, 200, 201, 205, 209, 213, 217, 218, 220, 223, 227, 240, 248, 451, 470, 473, 509, 513, 551, 601, 603X, 604, 606, 613, 626, 627, 628, 630, 640, 667, 805, 806, 807, 822, 830X, 831, 833, 834, 850, 862, 871	52

Table 8
Electrified Lines and BEB Counts by Budget Level

Figure 18: $50M Budget, 9 Chargers at 6 Terminals

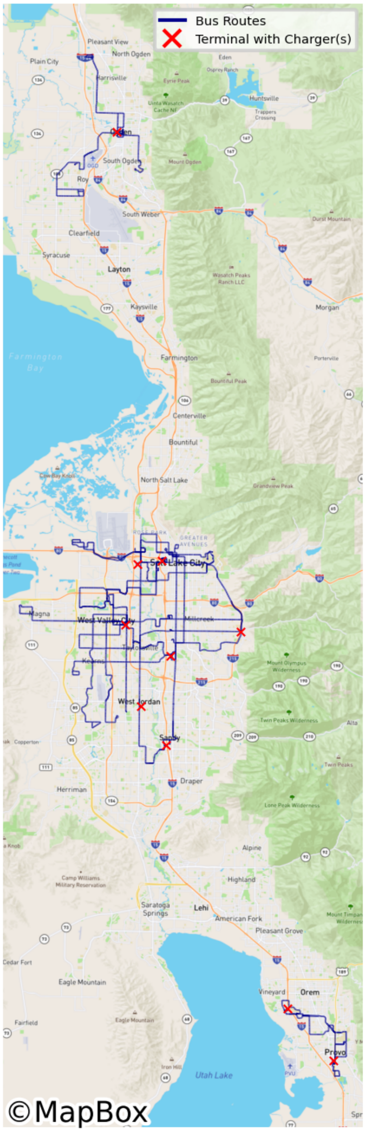

Figure 19: $100M Budget, 18 Chargers at 10 Terminals

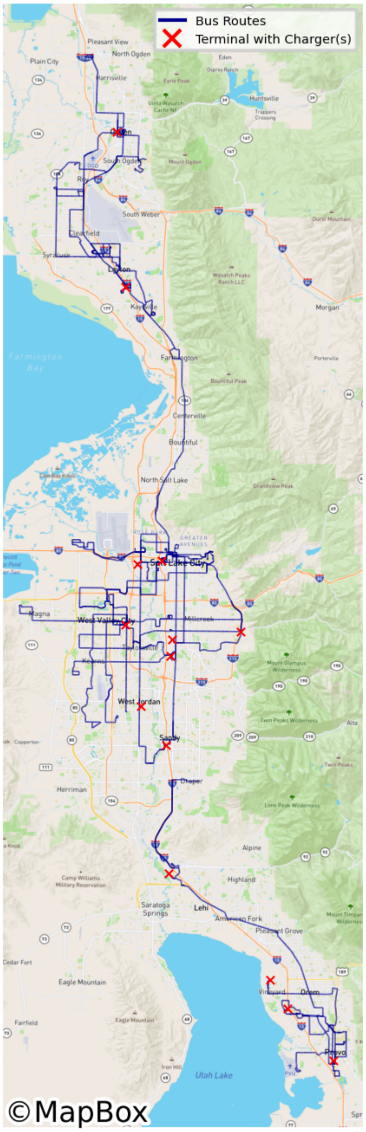

Figure 20: $150M Budget, 25 Chargers at 14 Terminals

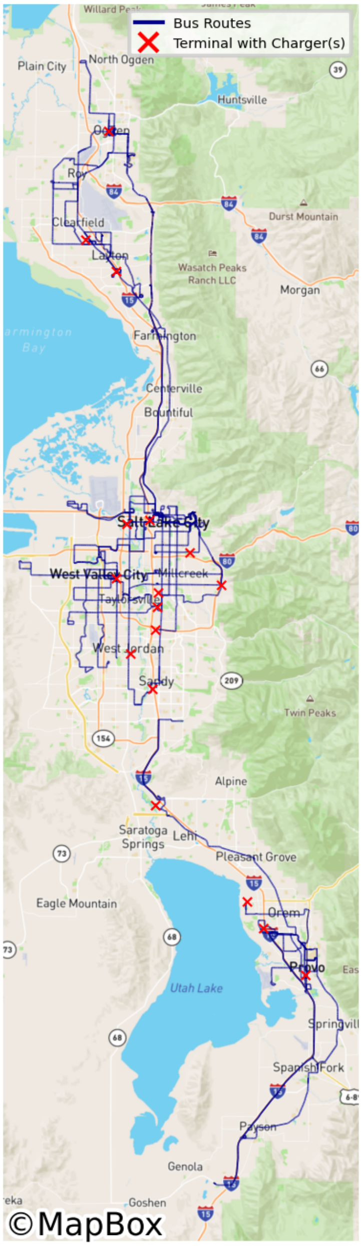

Figure 21: $200M Budget, 28 Chargers at 17 Terminals

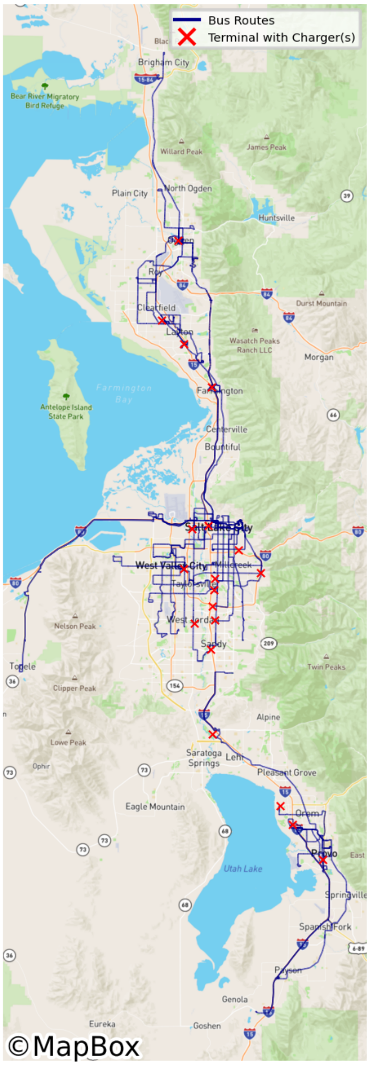

Figure 22: $250M Budget, 31 Chargers at 19 Terminals

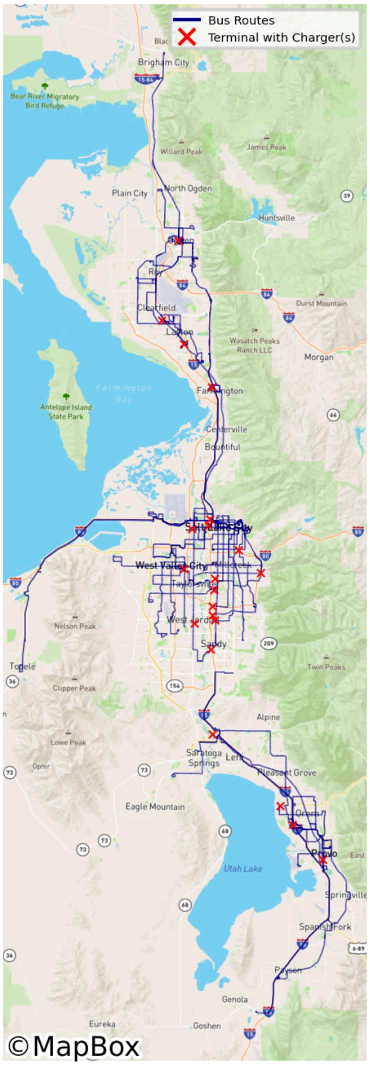

Figure 23: $275M Budget, 33 Chargers at 21 Terminals

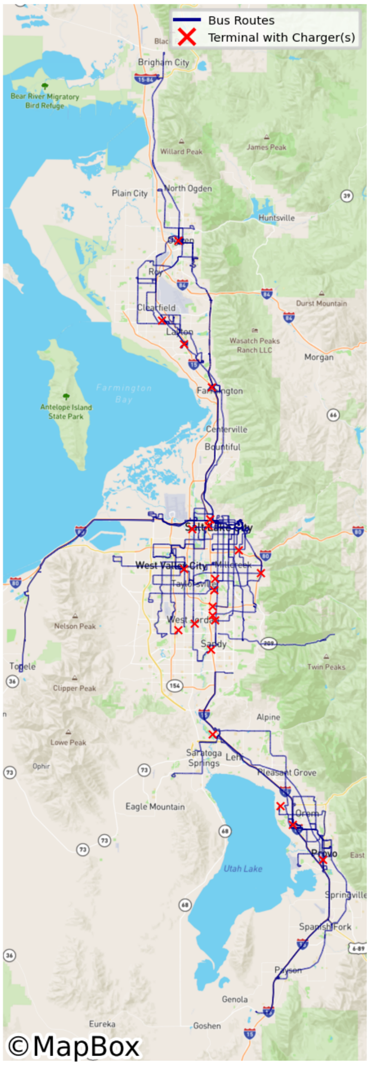

Figure 24: $283M Budget, 37 Chargers at 22 Terminals

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