

**A BI-OBJECTIVE MODEL FOR BATTERY ELECTRIC BUS
DEPLOYMENT CONSIDERING BUDGET EFFICIENCY
AND ENVIRONMENTAL EQUITY IN DISADVANTAGED
COMMUNITIES**

by
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ABSTRACT

This thesis develops and applies a bi-objective optimization model for the deployment of battery-electric buses (BEBs) that explicitly balances environmental benefits with cost effectiveness at the level of individual schedule blocks. The study is situated in the Wasatch Front region of Utah, an area where poor winter air quality and population growth make public transit electrification an urgent planning priority. While much of the existing literature evaluates BEB adoption at fleet-wide or depot scales, this work introduces a finer-grained analysis that operates at the block level, enabling a more precise accounting of trade-offs in operational feasibility, infrastructure requirements, and equity outcomes.

Environmental impacts are quantified through integration of multiple modeling frameworks. Emissions reductions are estimated using MOVES4.0, while regional dispersion patterns of fine particulate matter ($PM_{2.5}$) are simulated with InMAP. To incorporate equity considerations, demographic and vulnerability data from the Climate and Economic Justice Screening Tool (CEJST) are overlaid, allowing the model to prioritize deployment in disadvantaged communities disproportionately affected by transportation emissions. Results demonstrate that replacing diesel buses with BEBs produces statistically significant, though modest, localized reductions in ambient $PM_{2.5}$ concentrations. These findings highlight both the potential and the limitations of vehicle electrification when pursued in isolation, underscoring the need to situate BEB adoption within broader air quality and decarbonization strategies that also address upstream electricity generation and non-mobile pollution sources.

The cost dimension of the analysis reveals nonlinear investment dynamics. While early BEB deployments yield strong environmental and social returns, benefits taper beyond a certain threshold due to limitations in vehicle range, charging infrastructure, and operational flexibility. This emphasizes the value of targeted deployment strategies, where investments are prioritized to maximize both equity and efficiency.

Overall, the thesis contributes a novel methodological framework that integrates optimization, atmospheric science, and equity analysis. Beyond its application in Utah, the model offers a template for transit agencies and policymakers seeking to design electrification strategies that are environmentally meaningful, socially just, and financially prudent.

For my parents, Will and Kristy.
Thanks for instilling in me a love of learning.

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CHAPTER 1

INTRODUCTION

1.1 Transportation, Air Quality, and Public Health

The transportation sector is a major contributor to ambient air pollution, particularly fine particulate matter (PM_{2.5}), which poses severe risks to human health and urban air quality. Globally, traffic sources account for roughly a quarter of urban PM_{2.5} concentrations [1], and sector-specific analyses have shown that transportation-related emissions contribute significantly to premature mortality burdens worldwide [2]. Because tailpipe emissions from on-road vehicles are a dominant source of localized exposure in densely populated regions, electrification of the transportation sector offers a direct and actionable pathway to reduce these impacts. Replacing internal combustion engine vehicles with battery-electric alternatives has the potential to eliminate exhaust-related PM_{2.5} emissions, thereby improving air quality in vulnerable communities and supporting broader decarbonization and public health goals.

When evaluating the impacts of transportation electrification, it is important to distinguish between greenhouse gas (GHG) emissions and local air quality pollutants. GHGs such as carbon dioxide (CO₂) and methane (CH₄) are long-lived pollutants that accumulate in the atmosphere and drive global climate change. In contrast, local air quality is shaped primarily by short-lived pollutants such as nitrogen oxides (NO_x), volatile organic compounds (VOCs), and fine particulate matter (PM_{2.5}), which directly affect human health and visibility in the regions where they are emitted. While reducing GHG emissions is essential for addressing long-term climate goals, prioritizing air quality improvements can yield more immediate and tangible health benefits, particularly for urban populations and vulnerable communities [3]. Alarmingly, PM_{2.5} from on-road transportation alone has been linked to an estimated 3,605 premature deaths in the United States in 2010, with

more than 50,000 such deaths occurring between 2003 and 2016 [4]. Multiple studies identify transportation as a dominant source of $\text{PM}_{2.5}$ emissions, though regional variations exist depending on geography and vehicle mix [5]. Although BEBs still produce some $\text{PM}_{2.5}$ through brake and tire wear [6], the absence of tailpipe emissions remains a crucial advantage. Research demonstrates that electric vehicle adoption can significantly reduce $\text{PM}_{2.5}$ and ozone (O_3) levels in dense urban areas, with measurable reductions in asthma attacks and premature deaths, particularly in historically overburdened neighborhoods [7][8]. At the same time, scholars caution that atmospheric and meteorological variability may influence these benefits, underscoring the need for regionally tailored electrification strategies [9].

$\text{PM}_{2.5}$ refers to microscopic airborne particles less than $2.5\ \mu\text{m}$ in diameter. For context, a human hair is approximately $50\text{--}70\ \mu\text{m}$ wide, meaning it would take $20\text{--}30\ \text{PM}_{2.5}$ particles placed side by side to span its width. Their small size allows them to bypass the body's natural respiratory defenses; whereas larger particles are typically trapped in the nasal passages or upper airways, $\text{PM}_{2.5}$ can penetrate deep into the alveolar regions of the lungs and, in some cases, enter the bloodstream [10]. Epidemiological studies consistently link exposure to elevated $\text{PM}_{2.5}$ concentrations with increased incidence of cardiovascular disease, respiratory illness, lung cancer, and premature mortality [11][12][13]. Given these well-established health risks, reducing $\text{PM}_{2.5}$ exposure remains a critical objective of both environmental health research and transportation planning.

1.2 Historical and Technological Background of EVs

Although electric vehicles (EVs) are often associated with recent technological advances, their history dates back to the late nineteenth and early twentieth centuries. Early EVs competed with steam and gasoline-powered cars, particularly in urban markets where their quiet operation and lack of exhaust made them attractive. However, by the 1920s, improvements in internal combustion engines, the availability of cheap petroleum, and the development of mass production techniques such as Ford's assembly line largely displaced electric models from the consumer market [14]. For much of the twentieth century, EV research remained limited to niche applications, such as forklifts or demonstration projects, until renewed interest emerged in the 1990s in response to tightening air quality

standards and oil price volatility. The twenty-first century brought a decisive shift, driven by advances in lithium-ion battery technology, the rise of companies such as Tesla, and growing public and regulatory pressure to decarbonize transportation. Today, EVs are no longer an experimental technology but a rapidly scaling component of the global automotive industry.

Recent decades have seen enormous strides in increasing the accessibility of battery technology and electric vehicles (EVs) [14]. Early EV development was constrained by antiquated batteries that were large, heavy, and costly, leaving less room in the vehicle for passengers and cargo while also reducing efficiency. This created a frustrating feedback loop in which heavier batteries required more energy to move, in turn necessitating even larger batteries. Limited capacity also meant that vehicles required frequent and lengthy charging, and the high cost of large batteries posed a major hurdle to widespread adoption.

Ongoing research and development has steadily broken this cycle. Advances in chemistry, materials science, and manufacturing processes have produced lighter, more energy-dense, and increasingly affordable batteries [15][16][17]. These breakthroughs are enabling the scaling of battery-electric buses (BEBs) as a viable option for public transit agencies, particularly in regions where reducing tailpipe emissions is a priority. Nevertheless, despite decreasing unit costs, BEBs remain more expensive than conventional internal combustion engine (ICE) buses and require substantial investments in charging infrastructure and electrical system upgrades [18]. The combined costs of vehicle procurement and depot or on-route charging facilities introduce a complex optimization challenge [19], necessitating strategies that minimize infrastructure expenditures, maximize operational efficiency, and ensure that electrification delivers a high return on investment for transit systems.

1.3 Battery-Electric Buses: Promise and Challenges

Within the broader category of EVs, battery-electric buses (BEBs) represent a particularly promising but technically challenging application. Unlike passenger cars, transit buses operate on long duty cycles, carry heavy passenger loads, and require consistent reliability across daily service schedules. These operational demands result in higher energy consumption per mile, faster battery degradation, and greater sensitivity to charging logistics compared to light-duty EVs [18]. At the same time, buses are uniquely well-suited

for electrification because they operate on fixed routes and schedules, return regularly to depots, and are often owned and managed by public agencies capable of coordinating infrastructure investment. Global case studies demonstrate this potential: the city of Shenzhen, China, achieved full electrification of its bus fleet by 2017, operating more than 16,000 BEBs, while large-scale deployments are also underway in North America and Europe [14]. These examples illustrate both the opportunities and the challenges of scaling BEB adoption, highlighting the importance of optimization strategies that balance infrastructure costs, operational feasibility, and environmental benefits.

Although BEBs now achieve greater ranges than ever before, the energy demands of moving a heavy bus over long distances will eventually exhaust even the most efficient battery. When this occurs, vehicles must either recharge at route terminals or return to the depot. Transit agencies seek to minimize unscheduled returns to the garage, as doing so reduces vehicle availability, requires substitution with a spare bus, and ultimately increases operating costs. To maintain service reliability, agencies therefore rely on strategically placed rapid chargers within their service area, allowing BEBs to recharge during layovers without leaving their routes. However, on-route chargers are themselves expensive and often necessitate substantial upgrades to the local electrical grid. This creates a critical planning challenge: minimizing the total number of on-route chargers while maximizing their utility by building them at strategic locations and terminals where multiple BEBs can share the infrastructure.

To prevent disruptions to bus schedules and ensure service reliability, BEB deployment must be planned within the constraints of existing schedules. Transit agencies assign vehicles to fixed blocks that specify routes, locations, and times in order to guarantee consistent service. When a BEB schedule includes dwell time at a terminal (for example, to provide operator breaks or to await a route's departure) this layover can present an opportunity to recharge and extend the vehicle's range. Conversely, if a bus has little or no terminal dwell time, it must have sufficient charge to reach the next available charging point along its route. If the vehicle cannot reach that charger, it would be forced to return to the depot, requiring substitution with a spare bus and causing service inefficiencies. These operational realities must therefore be explicitly considered when assigning BEBs to schedules, both to preserve service quality and to minimize costly returns to the garage.

1.4 Atmospheric Chemistry of PM_{2.5} Formation

In addition to direct emissions from combustion, a substantial portion of ambient PM_{2.5} is formed secondarily through chemical reactions in the atmosphere. Diesel engines emit precursor gases such as nitrogen oxides (NO_x), sulfur oxides (SO_x), ammonia (NH₃), and volatile organic compounds (VOCs), each of which plays a role in secondary aerosol formation. For example, NO_x can react with ammonia and atmospheric oxidants to form ammonium nitrate, while SO_x can be oxidized to produce ammonium sulfate. Similarly, VOCs undergo photochemical reactions that generate secondary organic aerosols. These reactions are influenced by temperature, solar radiation, and atmospheric mixing, meaning the extent and composition of secondary PM_{2.5} vary by season and geography.

Because secondary particles can travel far beyond their point of origin, they contribute to regional haze and pollution episodes that affect populations well outside the immediate source area. This characteristic is especially relevant in Utah, where wintertime atmospheric inversions trap precursor emissions in valley basins and amplify the conversion of gaseous pollutants into fine particulates. Consequently, reducing diesel bus emissions not only decreases direct tailpipe pollution but also curtails the formation of secondary PM_{2.5}, yielding broader public health benefits. Highlighting this chemical pathway underscores why a focus on PM_{2.5} reduction is central to evaluating the environmental impact of bus electrification and situates this study within the broader atmospheric context of air quality management.

1.5 Policy Context: Regulation and State-Level Goals

The regulation of PM_{2.5} in the United States is overseen by the EPA through the National Ambient Air Quality Standards (NAAQS), which establish permissible concentrations of key pollutants under the Clean Air Act. For PM_{2.5}, the current standards limit annual average concentrations to 12 µg/m³ and 24-hr average concentrations to 35 µg/m³ [10]. Regions that exceed these thresholds are designated as “nonattainment areas,” requiring state and local governments to develop implementation plans to achieve compliance. The Wasatch Front in Utah has repeatedly failed to meet NAAQS for PM_{2.5}, particularly during winter inversion events that trap pollutants near the surface. As a result, Utah has adopted its own aggressive air quality targets, including commitments

in the Utah Division of Air Quality's State Implementation Plans (SIPs) to reduce PM_{2.5} through controls on transportation, industry, and residential sources. These plans explicitly recognize the transportation sector as a major source of PM_{2.5} precursors and call for electrification, improved fleet efficiency, and reductions in mobile-source emissions as part of a comprehensive strategy to bring the state into compliance. By aligning the optimization framework developed in this study with both federal regulatory standards and state-level goals, the analysis directly addresses pressing policy needs for Utah's most polluted metropolitan regions.

In Utah, where this study is based, the Division of Air Quality (DAQ) attributes 26% of nitrogen oxide (NO_x) emissions—a key precursor to PM_{2.5} formation—to transportation sources [20]. Compounding this challenge is Utah's unique topography, marked by deep, bowl-shaped valleys that trap pollution during atmospheric inversions and create periods of dangerously poor air quality. These geographic constraints exacerbate the public health risks of transportation emissions and heighten the value of targeted electrification. By evaluating BEB deployment through this localized lens, this study contributes insights that are both environmentally and operationally relevant for regions facing similar topographic and meteorological challenges.

Utah's commitment to controlling PM_{2.5} is further formalized through its State Implementation Plans (SIPs), prepared under the authority of the Clean Air Act. The Utah Division of Air Quality is actively developing "Serious Area" SIPs for nonattainment regions such as Salt Lake City, Provo, and Logan to strengthen emissions control strategies across point, area, and mobile sources [21]. These plans employ Best Available Control Measures (BACM) to enforce stricter emissions standards and require updated inventories, modeling, and rule revisions [21]. Recent SIP revisions submitted by Utah and approved by EPA include updates to the Utah Administrative Code (UAC), such as enhancements to vehicle inspection and maintenance programs (R307-110-32, R307-110-35) and the inclusion of mobile source control rules [22]. These state-level responsibilities and actions reinforce the policy relevance of optimizing BEB deployment to directly contribute to Utah's regulatory trajectory.

At the national level, recent policy developments have accelerated momentum for bus electrification by providing unprecedented levels of funding support. The Federal Transit

Administration’s Low or No Emission Vehicle Program (Low-No) has distributed billions of dollars to transit agencies to offset the higher capital costs of zero-emission buses and associated infrastructure [23]. Similarly, the Bipartisan Infrastructure Law of 2021 [24] and the Inflation Reduction Act of 2022 [25] established long-term funding streams, tax credits, and grant opportunities aimed at decarbonizing the transportation sector and reducing air pollution in disadvantaged communities. These federal initiatives complement state-level policies by reducing financial barriers to electrification and creating a stable policy environment for long-term planning. For Utah agencies operating within federally designated nonattainment areas, such funding mechanisms are particularly relevant, as they not only align with State Implementation Plan (SIP) requirements but also provide the resources needed to meet them. By situating this study within both federal and state policy contexts, the analysis highlights how optimized BEB deployment can advance regulatory compliance while leveraging national investment in sustainable transit infrastructure.

1.6 Equity and Environmental Justice Considerations

Air pollution disproportionately affects children, the elderly, and immunocompromised individuals due to inherent biological vulnerabilities. It also places heavier burdens on low-income populations, who are more likely to reside in neighborhoods with elevated ambient pollution levels and limited access to healthcare resources [26][27]. Several studies have therefore emphasized the importance of incorporating environmental justice considerations into transit electrification strategies, advocating for metrics that explicitly account for the spatial distribution of vulnerable populations when evaluating BEB deployment. These disparities underscore the need to incorporate equity considerations into environmental policy and infrastructure planning, ensuring that public health interventions deliver direct benefits to those most at risk while also advancing social equity by addressing systemic environmental injustices.

For this reason, the second objective of this study is to maximize air quality improvements specifically within disadvantaged communities, as identified by the Climate and Economic Justice Screening Tool (CEJST) [28]. By directing electrification benefits toward populations historically overexposed to pollution and least equipped to bear its costs, the optimization framework ensures that improvements are not distributed uniformly, but

rather weighted toward those with the greatest need. This approach aligns with federal and local environmental justice goals while also maximizing the impact per dollar spent, both in terms of emissions reductions and community health outcomes.

1.7 Research Contribution

Much of the existing literature on BEBs centers on the technical and economic barriers to widespread deployment, particularly in areas such as battery performance, operational logistics, and lifecycle cost-effectiveness. Researchers have investigated a variety of strategies to optimize charging schedules and route planning with the goal of improving grid efficiency and minimizing energy costs [29][30]. Additional studies have explored methods to reduce battery degradation and account for performance variability due to temperature and weather conditions [31][32]. While these factors are critical to ensuring the long-term viability of BEBs, this research diverges by shifting the focus toward the practical feasibility of individual BEB deployments and their real-world environmental impact. Rather than solely concentrating on system-wide optimization, we aim to highlight how targeted BEB investments can generate measurable improvements in air quality and public health.

While the existing literature provides a strong foundation on the technical, economic, and environmental implications of BEB deployment, gaps remain in understanding the localized, per-vehicle impact of BEBs on air quality, especially in disadvantaged communities. Prior studies emphasize aggregate benefits and broad strategies, but few offer tools to quantify how individual deployments contribute to environmental justice goals in specific geographic contexts. By building on these works, this study seeks to bridge this gap with a model that evaluates BEB deployment at the route and vehicle level, integrates emissions modeling, and aligns environmental gains with equity-focused decision-making. This approach enables transit agencies to make informed, location-sensitive investments that deliver both climate and public health benefits where they are needed most.

This study introduces the Bi-Objective Battery-Electric Bus Deployment Model (BOBEED), designed to optimize both infrastructure costs and environmental impact. While previous research has primarily focused on technical aspects of BEB operations such as battery degradation and charge scheduling, this approach integrates operational feasibility with spatially sensitive environmental benefits. The BOBEED model aligns with existing transit

schedules, minimizes charger installation costs, and prioritizes pollution reduction in communities facing the highest environmental burdens. By doing so, it supports both fiscally responsible planning and equitable public health improvements in transit electrification.

1.8 Thesis Roadmap

The remainder of this thesis is organized as follows. Chapter 2 details the methodology, beginning with the schedule block as the fundamental unit of analysis and proceeding to define objectives, indices, parameters, and decision variables. This chapter also presents the formulation of the bi-objective optimization model and explains the constraints and equations that govern it.

Chapter 3 applies the model to case study conditions along Utah's Wasatch Front. It outlines application-specific parameters, conducts an environmental analysis of both diesel and battery-electric bus operations, and presents the resulting outputs. This chapter also demonstrates the implementation of the Bi-Objective Battery-Electric Bus Deployment Model (BOBEBD), highlighting its ability to balance infrastructure costs with environmental benefits.

Chapter 4 concludes with a discussion of findings, including their implications for transit planning, environmental policy, and equity objectives. The discussion also considers the limitations of the study and identifies opportunities for future research to improve modeling approaches and strengthen the integration of air quality and public health priorities into transit electrification strategies.

CHAPTER 2

METHODOLOGY

Unlike previous studies that primarily focus on electrifying entire transit networks or evaluating the system-wide costs of electric vehicle deployment, this study takes a more granular approach. It assesses the feasibility and localized air quality impacts of integrating battery-electric buses (BEBs) into an existing fleet at the level of individual vehicle operations. To achieve this, we introduce the Bi-Objective Model for Battery-Electric Bus Deployment (BOBEBD)—a planning framework that offers targeted, block-level guidance to transit agencies. Rather than treating the fleet as a monolith, BOBEBD identifies specific schedule blocks—each representing a complete daily assignment for a single bus, including its route, stop sequence, terminal layovers, and operating times—that yield the greatest environmental benefit when electrified, while also minimizing the associated capital and infrastructure costs.

2.1 Analysis Unit: Schedule Block

In this framework, the schedule block serves as the fundamental unit of analysis. A schedule block is a predefined sequence of transit operations assigned to a single vehicle over the course of a day. It includes all scheduled trips, layovers, and terminal returns for that vehicle, starting when the bus leaves the depot and ending when it returns. Each block reflects a real-world pattern of vehicle usage, encompassing multiple routes, time windows, and stop locations. Transit agencies use schedule blocks to structure their daily operations and ensure consistent, reliable service delivery. Because each block has known time and distance characteristics, along with designated layover periods and terminal visits, it provides a natural framework for evaluating whether an electric bus can feasibly complete the block without exceeding its battery range or missing charging opportunities. By aligning BEB deployment with the characteristics of individual blocks, BOBEBD supports fine-grained, data-driven decisions about which blocks are best suited

for electrification given route lengths, charging windows, and geographic coverage. This block-level granularity also enables environmental analysis at a micro-operational scale, allowing us to estimate emissions reductions and health benefits with greater spatial precision—particularly in areas with high pollution exposure or vulnerable populations.

2.2 Objectives

BOBEED balances two core objectives:

1. Maximizing environmental benefits, especially reductions in $\text{PM}_{2.5}$ emissions in disadvantaged communities, by replacing diesel buses with BEBs; and
2. Minimizing deployment costs, including the capital cost of BEBs and the installation of on-route charging infrastructure.

These objectives are evaluated under a set of operational constraints that track each BEB's energy consumption, state-of-charge, required charging time, terminal dwell times, and maximum range. This ensures that every recommended assignment is not only environmentally beneficial and cost-efficient, but also operationally feasible within the agency's existing service structure.

The following sections outline the full model architecture. We begin by describing the methodology used to estimate environmental benefits, focusing on spatially-resolved reductions in $\text{PM}_{2.5}$ exposure. We then describe how deployment costs are minimized through optimized vehicle-to-block assignments and charging infrastructure placement. Finally, we present the full formulation of the BOBEED optimization model, integrating both objectives and operational constraints into a unified framework. A visual overview of the methodology is provided in Figure 2.1.

2.3 Quantifying Environmental Impact

While both BEBs and diesel buses generate primary $\text{PM}_{2.5}$ emissions through non-exhaust sources such as brake and tire wear, diesel buses emit a broader range of pollutants that contribute more substantially to overall air quality degradation. In particular, diesel combustion releases precursor gases, including nitrogen oxides (NO_x), sulfur oxides (SO_x), ammonia (NH_3), and volatile organic compounds (VOCs). These pollutants react in the atmosphere to form "secondary $\text{PM}_{2.5}$ ". These secondary particles can travel long dis-

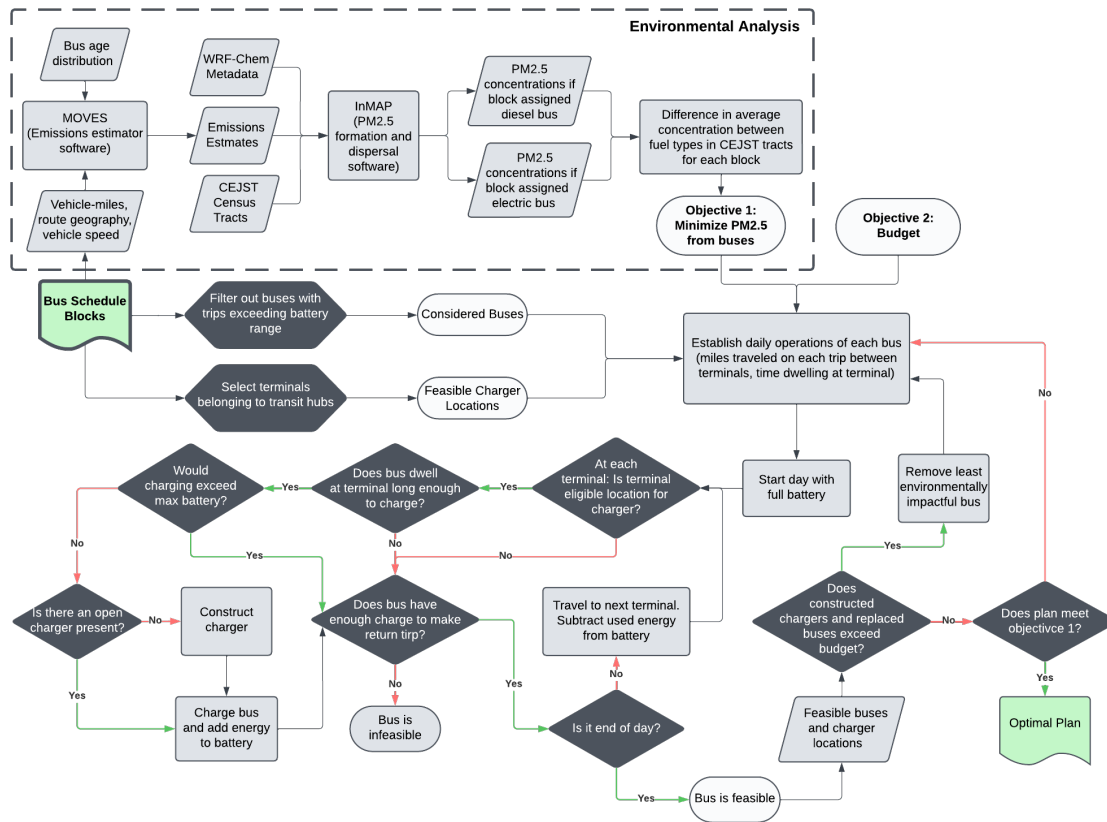


Figure 2.1. BOBEBD Methodology Flowchart

tances, compound regional pollution burdens, and pose serious health risks, especially for vulnerable populations. To accurately assess the environmental benefits of electrifying a bus fleet, it is therefore essential to consider not only direct emissions but also the chemical formation and dispersion of secondary $\text{PM}_{2.5}$.

To conduct this analysis, we employed a combination of established environmental modeling tools that allow for detailed, scalable, and location-sensitive emissions comparisons. First, we used the U.S. Environmental Protection Agency’s Motor Vehicle Emissions Simulator (MOVES4.0) [33] to generate comprehensive emissions inventories for each bus in the study fleet under both diesel and electric operation scenarios. These inventories quantify the specific types and quantities of pollutants emitted under real-world conditions, forming the foundation for downstream air quality modeling.

Next, we fed the MOVES outputs into the Intervention Model for Air Pollution (In-

MAP) [34], a reduced-complexity air quality model designed to estimate annual-average $\text{PM}_{2.5}$ concentrations across large spatial domains with high population resolution. While more complex chemical transport models such as WRF-Chem [35], GEOS-Chem [36], or CMAQ [37] provide greater atmospheric detail, their computational demands are prohibitive for studies requiring large-scale scenario testing. In contrast, InMAP offers a practical tradeoff—retaining sufficient chemical and spatial resolution to inform policy decisions while enabling hundreds of simulations to be conducted efficiently across an entire bus network. This makes it well-suited for modeling the community-level impacts of BEB deployment.

InMAP relies on three key inputs: (1) a baseline chemical transport model that characterizes the atmospheric conditions in the study region, (2) the pollutant-specific emissions inventories generated by MOVES4.0, and (3) high-resolution population data. For the latter, we used the Climate and Economic Justice Screening Tool (CEJST) developed by the White House Council on Environmental Quality [28, ?]. This tool provides geospatial demographic data at the census tract level and identifies communities considered disadvantaged based on criteria such as socioeconomic status, health disparities, pollution burden, and access to public services. By overlaying InMAP output with CEJST community boundaries, we are able to determine not only where $\text{PM}_{2.5}$ concentrations are reduced, but also whether those reductions occur in communities most in need of environmental relief.

The result is a comprehensive environmental impact metric that reflects both the magnitude and the equity of air quality improvements. By comparing the $\text{PM}_{2.5}$ concentrations generated by diesel buses and BEBs at the schedule-block level, we can prioritize electrification strategies that deliver the greatest health benefits per dollar spent—particularly in historically marginalized or pollution-burdened areas. This approach ensures that BEB deployment is not only environmentally effective but also aligned with environmental justice goals, supporting cleaner air for all communities, especially those most impacted by the legacy of transportation-related pollution.

2.3.1 MOVES4.0

MOVES4.0 (MOtor Vehicle Emissions Simulator) is a comprehensive emissions modeling platform developed by the EPA to estimate air pollutant emissions from on-road vehicles [33]. The model is designed to simulate real-world vehicle activity by accounting for key factors such as vehicle class, fuel type, vehicle age, driving patterns, meteorological conditions, and geographic location. It provides detailed estimates for a wide spectrum of pollutants, including both direct (primary) PM_{2.5} emissions—originating from brake wear, tire wear, and tailpipe exhaust—and precursor emissions that contribute to the formation of secondary PM_{2.5}, such as nitrogen oxides (NO_x), sulfur oxides (SO_x), ammonia (NH₃), and volatile organic compounds (VOCs).

To generate accurate emissions inventories, MOVES requires input data on vehicle activity and fleet characteristics. Key inputs include vehicle miles traveled (VMT), vehicle type and classification, fuel type, and the age distribution of the fleet. The model incorporates assumptions about vehicle mass and efficiency that vary by age; for example, older battery-electric buses (BEBs) are modeled as heavier due to the lower energy density of early-generation batteries, resulting in greater non-tailpipe emissions from brake and tire wear. Conversely, older diesel buses may lack advanced emissions control technologies, contributing to higher exhaust emissions. While MOVES does not distinguish between specific vehicle makes or models, it represents all vehicles within a given category as statistical averages, making it suitable for system-level assessments.

MOVES outputs emissions estimates in terms of grams per mile traveled for each pollutant. These per-mile values are then aggregated into emissions inventories, representing the total emissions over a defined operational period. For this study, we used these inventories to generate annual emissions estimates for each vehicle schedule block. The resulting data were spatially linked to the geographic locations of each route, enabling high-resolution environmental impact modeling using tools such as InMAP.

2.3.2 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[38][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 2.2.

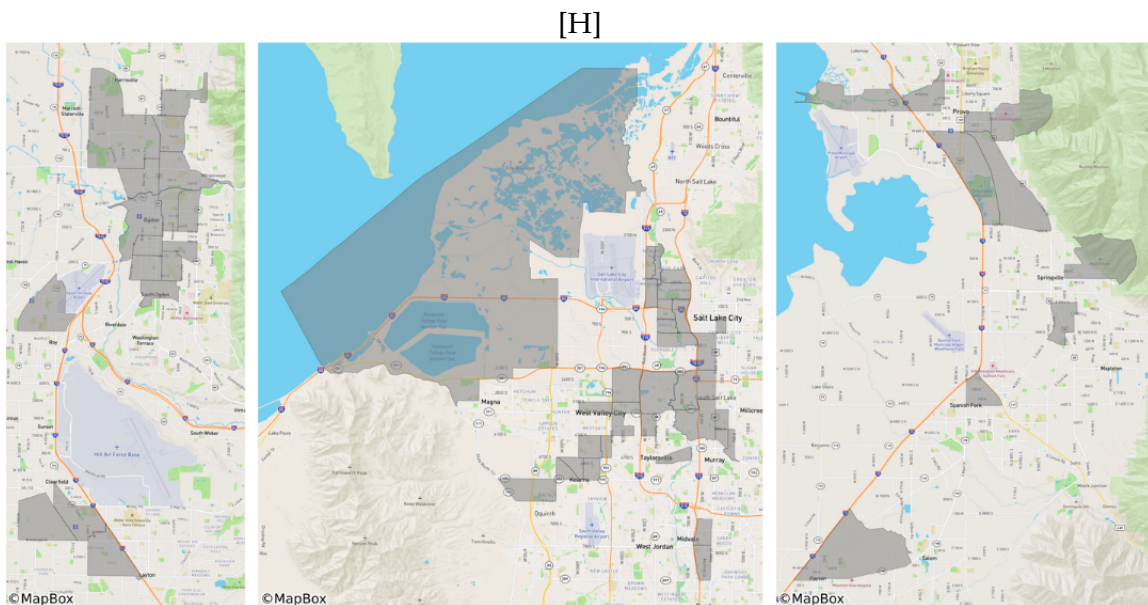


Figure 2.2. Wasatch Front Area CEJST Tracts
Left: Weber and Davis Counties; Middle: Salt Lake County; Right: Utah County

2.3.3 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.

2.3.4 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.

2.4 Bi-Objective Model Formulation

The BOBED 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 opera-

tions, and adequate charging infrastructure is provided at depots and terminals. Unlike simpler models that might assume full charging between trips, BOBEED 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:

2.5 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

2.6 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

2.7 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

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

2.8 Objectives:

$$\max \sum_i V_i Z_i^B \quad (2.1)$$

$$\min \left(\sum_g C^G Y_g^G + \sum_j (C_j^O Z_j^O + Z_j^O C_j^S (Y_j^O - 1)) + \sum_i C^B Z_i^B \right) \quad (2.2)$$

2.9 Constraints

$$E_{i,0} = M_x^e \quad \forall i \quad (2.3)$$

$$m_n^e \leq E_{i,k} \leq M_x^e \quad (2.4)$$

$$X_{i,k} \leq Z_j^O \quad \forall i, j, k \quad (2.5)$$

$$X_{i,k} \leq Z_i^B \quad \forall i, k \quad (2.6)$$

$$\sum_{i,k} X_{i,k} \leq n^O Y_j^O \quad \forall i, j, k \quad (2.7)$$

$$\sum_{i \in \gamma_g} Z_i^B \leq n^G Y_g^G \quad \forall g \quad (2.8)$$

$$E_{i,k} \geq ((d_{i,k,k+1} + d_{i,k+1,k+2})f_b) - ((1 - Z_i^B)L) \quad \forall i, k \quad (2.9)$$

$$E_{i,k} = E_{i,k-1} + X_{i,k} t_{i,k} P_O - Z_i^B d_{i,k-1,k} f_b \quad (2.10)$$

2.9.1 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.

2.10 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

$$\min(\sum_g C^G Y_g^G + \sum_j (C_j^O Z_j^O + Z_j^O C_j^S (Y_j^O - 1)) + \sum_i C^B Z_i^B) \leq C_x \quad (2.11)$$

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.

CHAPTER 3

APPLICATION

This study applies the BOBEED 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 3.1. 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.

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,

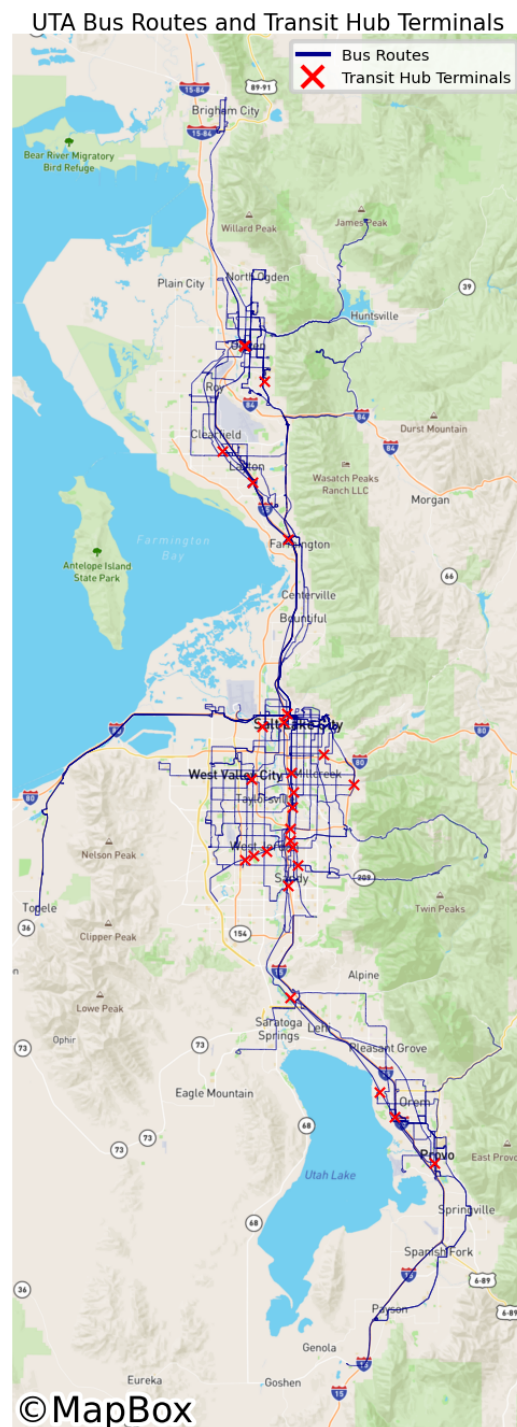


Figure 3.1. UTA Routes and Eligible Terminals

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

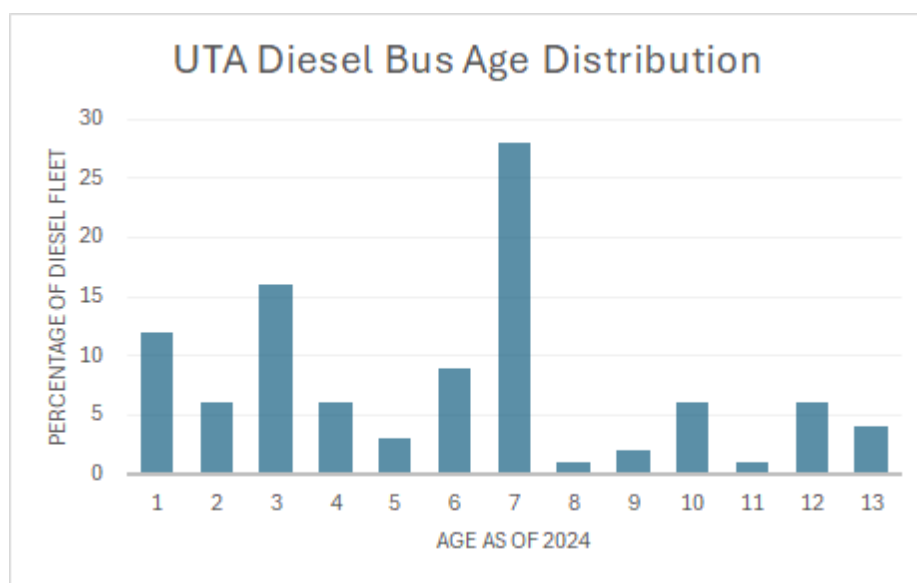


Figure 3.2. Age Distribution of UTA Diesel Buses

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 A.1) 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 A.2). Diesel bus ages were extracted from the UTA change day roster report (see Figure 3.2). 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 A.3 for a sample of the diesel bus inventory and Appendix A: Table A.4 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[39]. 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 3.3, 3.4, and 3.5.

As seen in Figure 3.6, 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.

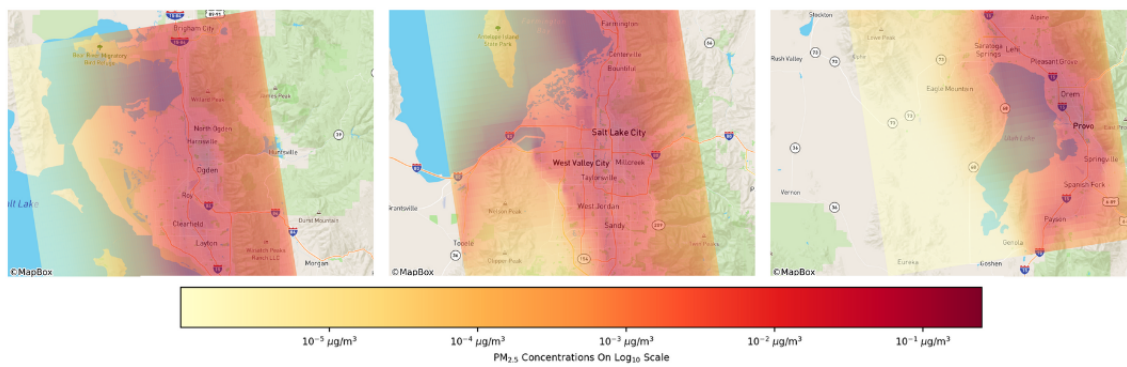


Figure 3.3. Pollution from all blocks assigned diesel buses

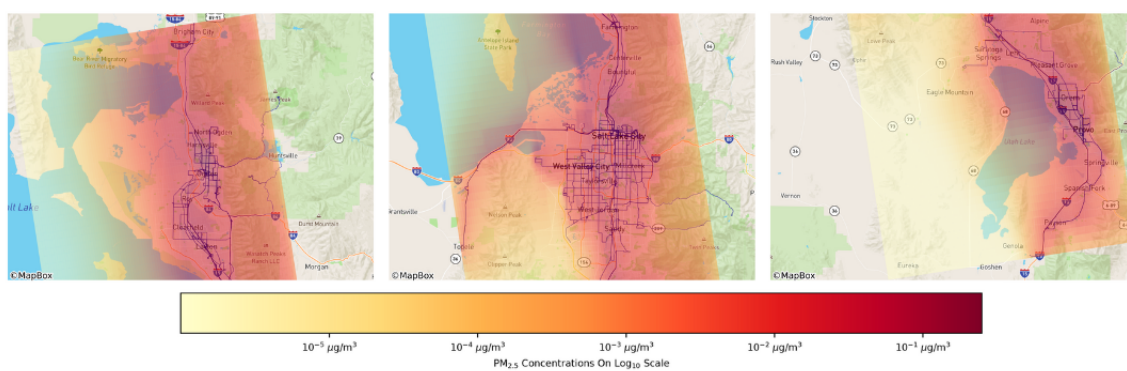


Figure 3.4. Pollution dispersion with bus routes

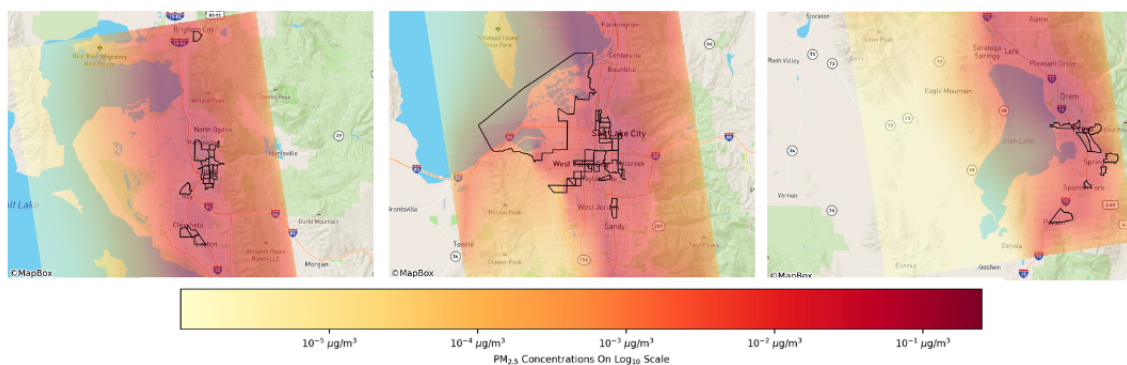


Figure 3.5. pollution dispersion with CEJST tracts

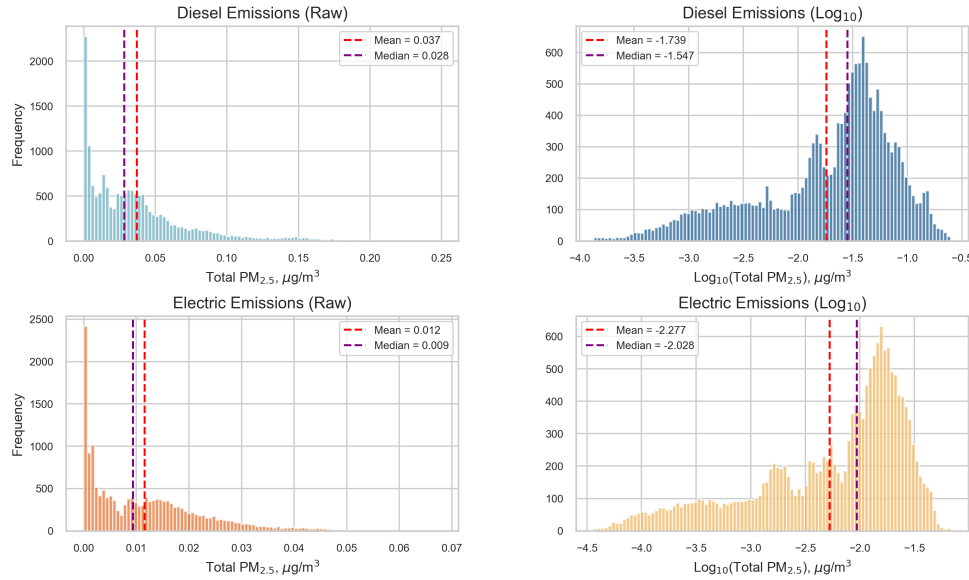


Figure 3.6. Emissions Distribution Across CEJST Tracts
Grid Cells Have $\approx 71\text{m} \times 217\text{m}$ dimensions

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 3.7. 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 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 3.1). 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

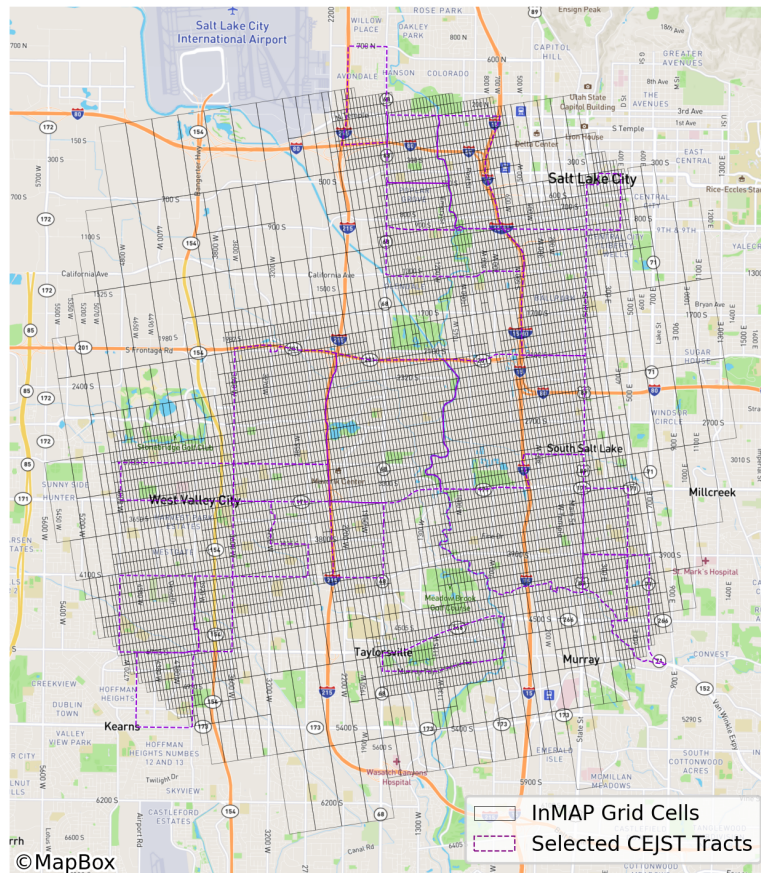


Figure 3.7. InMAP grid cells have higher resolution around Census tracts

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.

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 3.1. Statistical Analysis Results

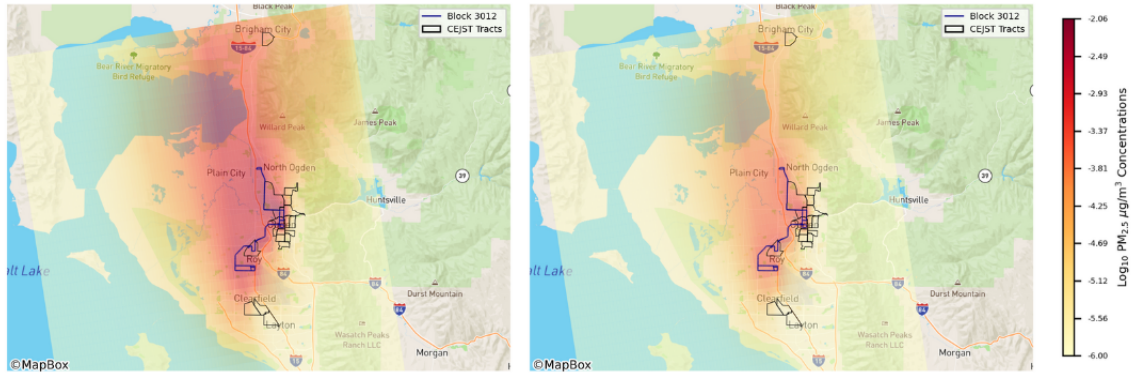


Figure 3.8. Block 3012 and its emissions plumes Left: Diesel Bus, Right: Electric Bus

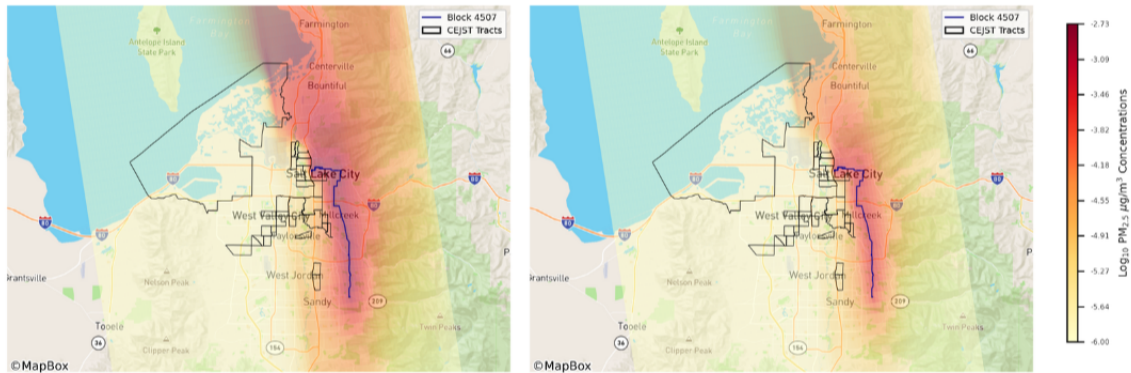


Figure 3.9. Block 4507 and its emissions plumes Left: Diesel Bus, Right: Electric Bus

3.4 Implementing BOBEDD

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

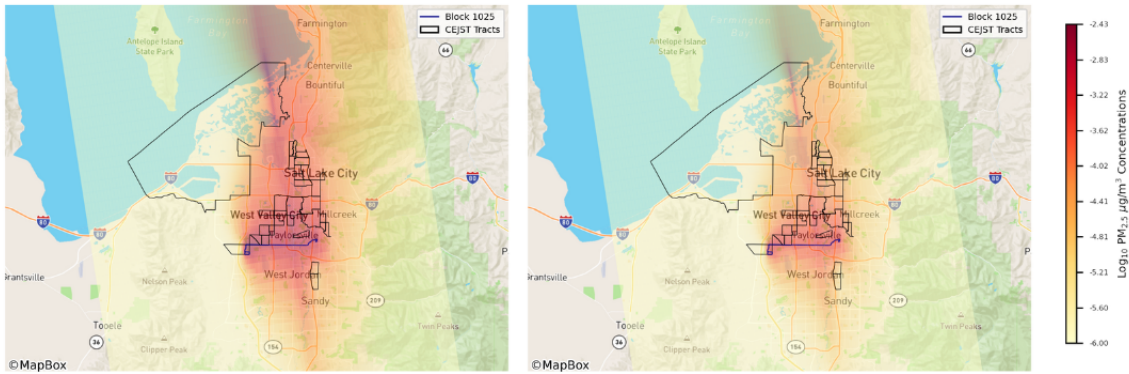


Figure 3.10. Block 1025 and its emissions plumes Left: Diesel Bus, Right: Electric Bus

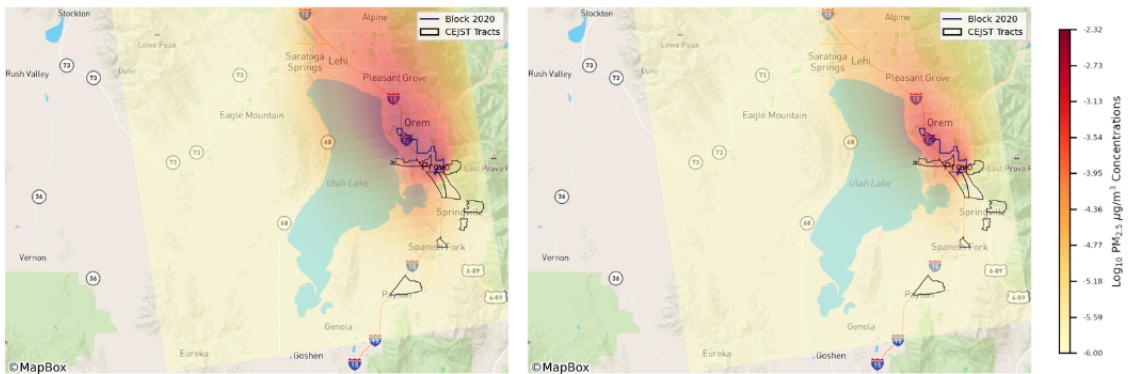


Figure 3.11. Block 2020 and its emissions plumes: South Left: Diesel Bus, Right: Electric Bus

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 B.1 details the location and count of on-route chargers by budget level, and Table B.2 specifies which bus routes receive BEBs at each budget level.

3.4.2 Model Instability and Flexibility

The BOBEED 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 BOBEED may vary slightly depending

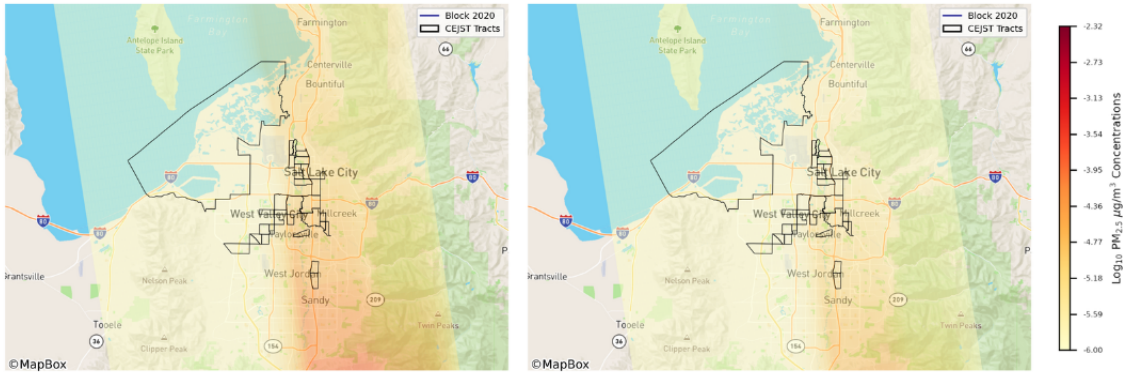


Figure 3.12. Block 2020 and its emissions plume: Central
Left: Diesel Bus, Right: Electric Bus

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 3.2. Optimization Results From Varying Starting Conditions

on the initial conditions. As shown in Table 3.2, the maximum number of feasible buses remains constant, whereas the number of chargers fluctuates slightly. Figures 3.14 and 3.15 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.

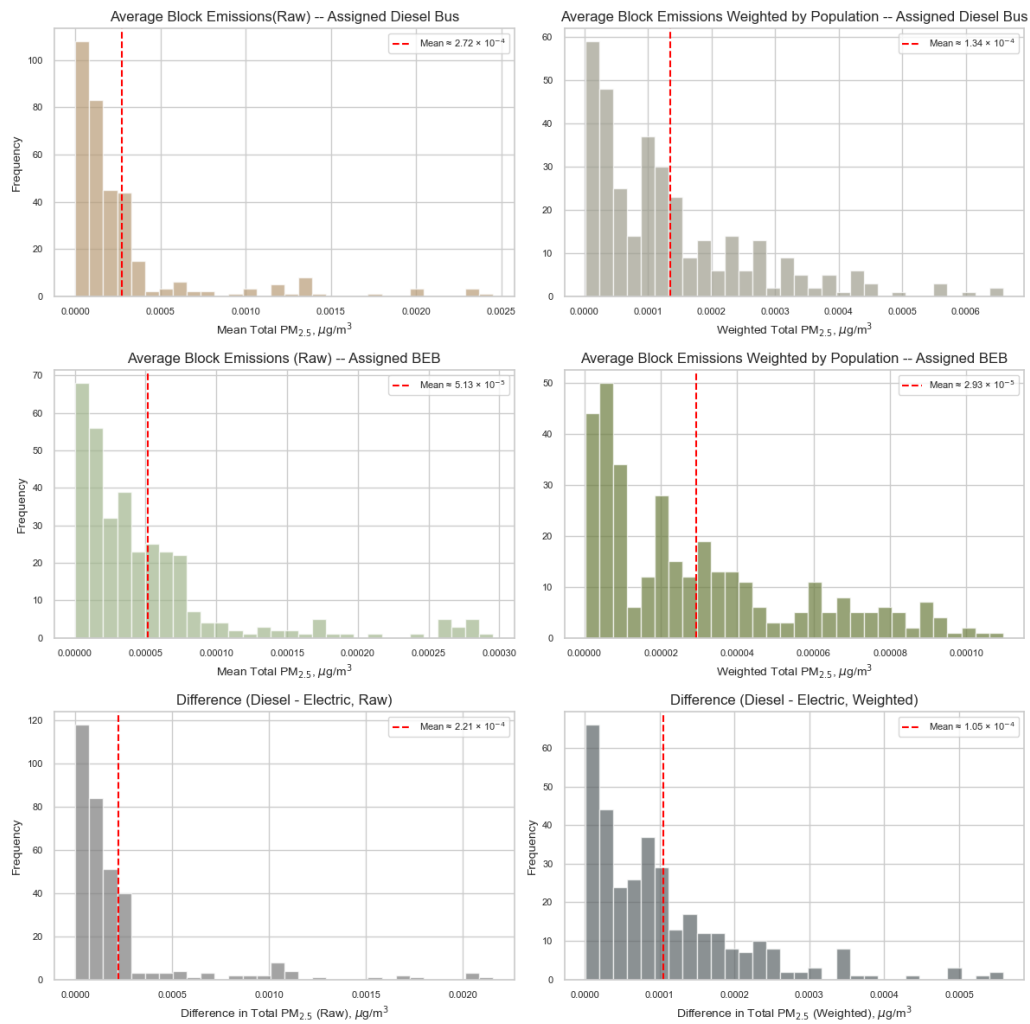


Figure 3.13. $PM_{2.5}$ Concentrations Across All Analyzed Bus Schedule Blocks

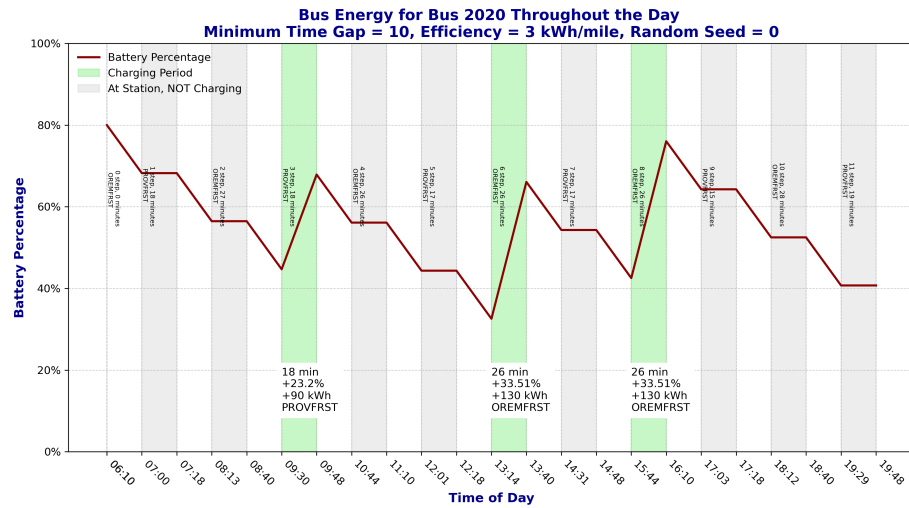


Figure 3.14. Bus Energy Levels for Bus 2020 and Random Seed 0

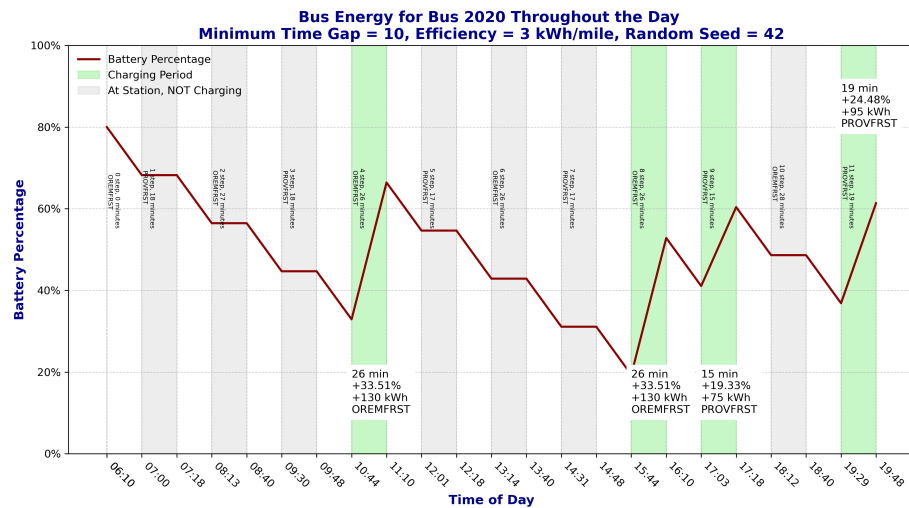


Figure 3.15. Bus Energy Levels for Bus 2020 and Random Seed 42

CHAPTER 4

DISCUSSION

This study provides valuable insights into the environmental, economic, and operational implications of transitioning from diesel to battery-electric buses (BEBs) within Utah’s Wasatch Front region. By combining emissions modeling, air quality simulation, and spatially explicit optimization, the analysis evaluates both the feasibility and real-world environmental benefits of targeted BEB deployment at a granular, schedule-block scale.

The environmental assessment demonstrates measurable reductions in PM_{2.5} concentrations when diesel buses are replaced with BEBs, particularly within disadvantaged census tracts identified using the Climate and Economic Justice Screening Tool (CEJST). Although these reductions are modest in absolute magnitude, they are statistically significant and spatially concentrated in communities with high baseline exposure. This nuance is critical: it underscores that while BEB deployment can meaningfully reduce localized exposure to harmful pollutants, electrification alone cannot dramatically improve regional air quality. Instead, it should be viewed as one component of a broader air quality strategy encompassing industrial emissions, energy production, and urban land-use patterns. As Panta et al.[40] observe, at least 30% of upstream electricity must originate from renewable sources for BEBs to achieve full life-cycle greenhouse gas (GHG) benefits relative to internal combustion engine (ICE) buses. Future work could extend this framework by quantifying upstream PM_{2.5} emissions from electricity generation and integrating those estimates into BEB life-cycle impact assessments.

The budget-constrained optimization results reveal a clear pattern of diminishing marginal returns. Initial investments yield substantial progress in fleet electrification—up to 283 diesel schedule blocks replaced under modeled budget scenarios—yet additional spending beyond this threshold produces limited incremental gains. This plateau effect is largely

driven by operational constraints such as battery range limits and the availability of charging infrastructure at key terminals. These findings emphasize the importance of strategic prioritization: rather than pursuing uniform fleet-wide electrification, agencies should focus resources on routes that deliver the greatest environmental benefit per dollar, especially those serving high-pollution or vulnerable neighborhoods. This targeted approach aligns both with cost-effectiveness principles and with environmental justice mandates embedded in state and federal policy.

The spatial resolution of modeled emissions warrants further reflection. While InMAP provides an efficient and policy-relevant means of estimating regional PM_{2.5} impacts, its assumption of uniform emissions along each bus block simplifies real-world conditions. In practice, traffic congestion, stop frequency, roadway geometry, and meteorological factors strongly influence pollutant concentration and dispersion patterns. Incorporating higher-resolution or dynamic emissions models—potentially supported by mobile air-quality monitoring or vehicle telemetry—could refine these spatial and temporal estimates. Future research might also integrate atmospheric inversion data specific to the Wasatch Front, where wintertime trapping of pollutants remains a defining feature of local air quality dynamics.

The broader context of cumulative pollution exposure is equally important. Diesel transit emissions represent only one element of the region's complex air quality challenge. Significant additional improvements will depend on complementary interventions addressing industrial and residential emissions, fuel production, and urban transportation demand. Integrating BEB deployment with policies such as congestion pricing, low-emission zones, and transit-oriented development could create synergistic effects that amplify both environmental and public health outcomes. A systems-level approach—linking electrification to land use, energy generation, and health planning—offers the clearest path toward sustained air quality gains.

Operational feasibility remains central to achieving these goals. The BOBEED framework explicitly integrates real-world operational constraints—such as route length, layover duration, and charger access—that are often overlooked in theoretical models. These constraints help explain why some schedule blocks remain infeasible for electrification even under generous funding scenarios. Extending this model to include weekend service,

extreme-weather conditions, and alternative battery chemistries would further illuminate the operational frontiers of BEB deployment. Additionally, incorporating stochastic factors such as equipment downtime or power outages could improve resilience analysis and contingency planning for electrified fleets.

Future model iterations could also integrate time-of-day or real-time energy pricing, optimizing where and how much BEBs charge. Such refinements would enable agencies to minimize operational costs, reduce strain on the electrical grid, and align with dynamic-pricing frameworks proposed by Zhang et al.[41], who recommend temporal optimization as a critical element of large-scale electric fleet management.

In sum, this study contributes to the growing body of evidence supporting the environmental and equity benefits of transit electrification. While the absolute reductions in $PM_{2.5}$ concentrations are relatively modest, they represent a meaningful and achievable step toward cleaner air and more sustainable public transit. Crucially, these benefits are not evenly distributed: prioritizing BEB deployment in disadvantaged communities yields disproportionate health and equity gains, translating limited resources into maximum public value. Maximizing the long-term impact of BEB adoption will therefore require sustained investment, adaptive operational strategies, and integration with broader environmental and energy policy frameworks. Through such coordinated efforts, transit electrification can serve not merely as a technological upgrade but as a cornerstone of a healthier, more equitable, and resilient urban future.

APPENDIX A

MODEL INPUT EXCERPTS

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 A.1. 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 A.2. 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 A.3. Annual diesel emissions data by bus schedule block, kg

block	NO_x	VOC	SO_x	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 A.4. Annual BEB emissions data by bus schedule block, kg

APPENDIX B

RESULTS BY FUNDING LEVEL

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 B.1. 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 B.2. Electrified Lines and BEB Counts by Budget Level

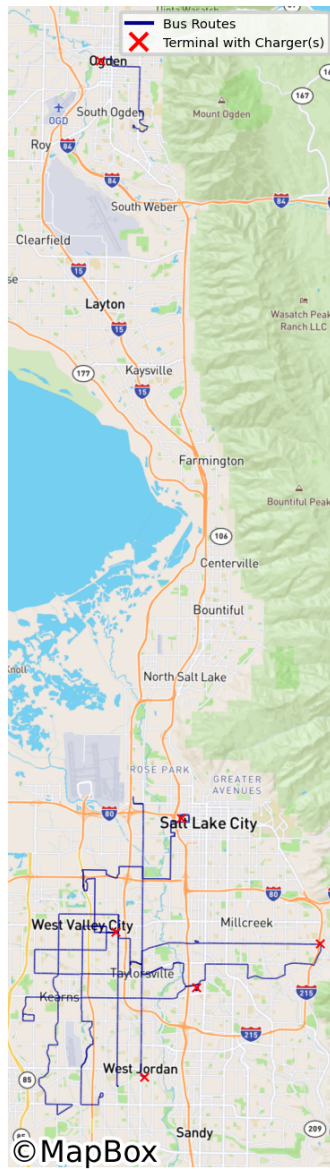


Figure B.1. \$50M Budget, 9 Chargers at 6 Terminals

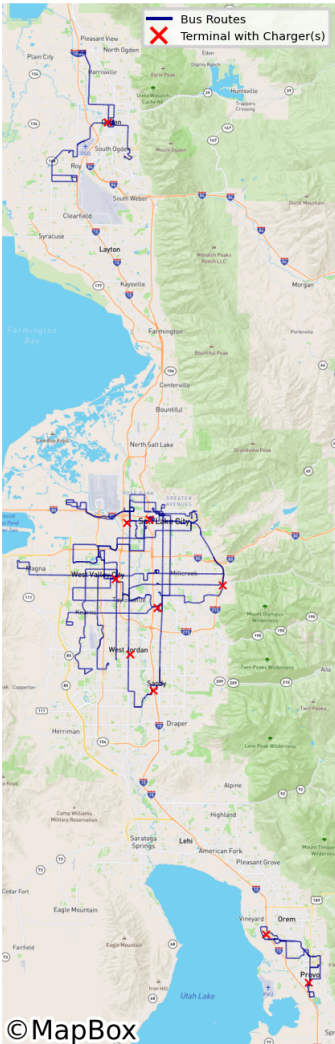


Figure B.2. \$100M Budget, 18 Chargers at 10 Terminals

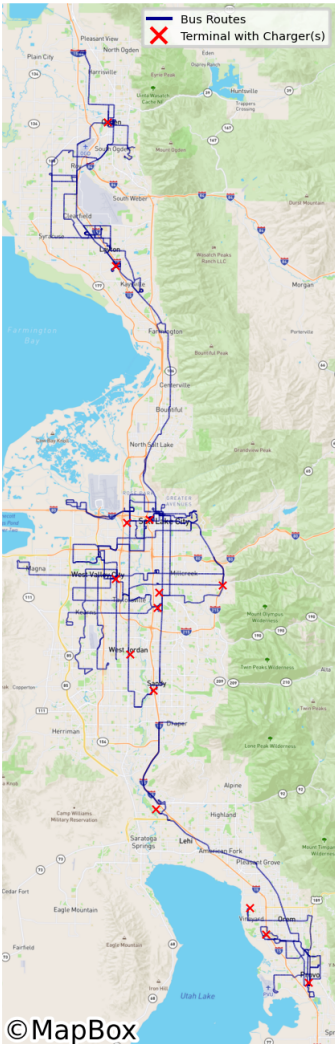


Figure B.3. \$150M Budget, 25 Chargers at 14 Terminals

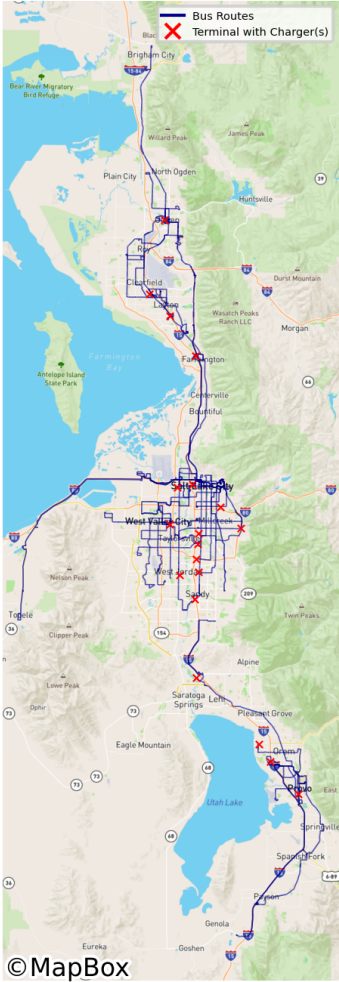


Figure B.5. \$250M Budget, 31 Chargers at 19 Terminals

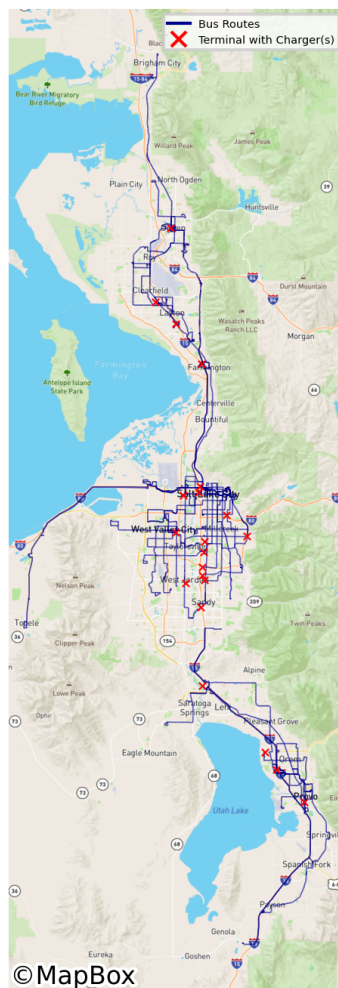


Figure B.6. \$275M Budget, 33 Chargers at 21 Terminals

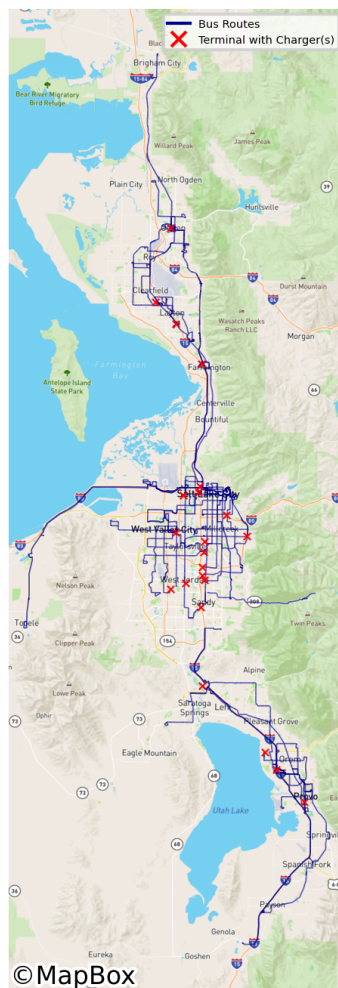


Figure B.7. \$283M Budget, 37 Chargers at 22 Terminals

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