A BI-OBJECTIVE OPTIMIZATION MODEL FOR COST-EFFICIENT AND ENVIRONMENTALLY EQUITABLE BATTERY ELECTRIC BUS DEPLOYMENT

by

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ABSTRACT

Existing battery-electric bus (BEB) optimization studies typically evaluate adoption at the fleet-wide or depot scale, limiting their ability to capture operational feasibility and distributional impacts that vary across daily vehicle assignments. This thesis develops and applies a bi-objective optimization model for BEB deployment that balances environmental benefits and cost-effectiveness at the level of individual schedule blocks. The study focuses on Utah's Wasatch Front, where winter air quality challenges and rapid population growth make targeted transit electrification a pressing planning priority. Environmental impacts are quantified through integration of multiple modeling frameworks. Emissions reductions are estimated using MOVES4.0, and regional dispersion of fine particulate matter ($PM_{2.5}$) is simulated using InMAP. Equity considerations are incorporated by overlaying demographic and vulnerability indicators from the Climate and Economic Justice Screening Tool (CEJST), enabling prioritization of communities with historically elevated transportation-related exposure. Model results indicate statistically significant reductions in ambient $PM_{2.5}$ concentrations, with benefits disproportionately concentrated in disadvantaged communities. The cost analysis reveals nonlinear investment dynamics: early BEB deployments produce relatively large environmental and equity gains, while marginal benefits

diminish beyond a threshold due to vehicle range, charging infrastructure, and operational constraints. These findings highlight the value of precision targeting under constrained budgets. Overall, this thesis contributes a novel block-level methodological framework integrating optimization, atmospheric modeling, and equity analysis. Beyond its application in Utah, the approach provides a transferable template for transit agencies seeking electrification strategies that are environmentally meaningful, socially equitable, and financially efficient.

For my parents, Will and Kristy.

Thank you for instilling in me a love of learning.

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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 [13], and sector-specific analyses have shown that transportation-related emissions contribute significantly to premature mortality burdens worldwide [19]. 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 (CO_2) and methane (CH_4) 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 (NOx), 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 [2]. Prior work estimates that $PM_{2.5}$ 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 [15]. Multiple studies identify transportation as a dominant source of $PM_{2.5}$ emissions, though regional variations exist depending on geography and vehicle mix [18]. Although BEBs still produce some $PM_{2.5}$ through brake and tire wear [12], the absence of tailpipe emissions remains a crucial advantage. Research demonstrates that electric vehicle adoption can significantly reduce $PM_{2.5}$ and ozone (O_3) levels in dense urban areas, with measurable reductions in asthma attacks and premature deaths, particularly in historically overburdened neighborhoods [27][25]. At the same time, scholars caution that atmospheric and meteorological variability may influence these benefits, underscoring the need for regionally tailored electrification strategies [21].

$PM_{2.5}$ refers to microscopic airborne particles less than 2.5 μm in diameter. For context, a human hair is approximately 50–70 μm wide, meaning it would take 20–30 $PM_{2.5}$ 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, $PM_{2.5}$ can penetrate deep into the alveolar regions of the lungs and, in some cases, enter the bloodstream [32]. Epidemiological studies consistently link exposure to elevated $PM_{2.5}$ concentrations with increased incidence of cardiovascular disease, respiratory illness, lung cancer, and premature mortality [24][35][17]. Given these well-established health risks, reducing $PM_{2.5}$ exposure remains a critical objective of both environmental health research and transportation planning.

1.2 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 [3]. 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 [4]. 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 the 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. Buses are dispatched in fixed daily work assignments (blocks), so BEB feasibility depends on the energy and time structure of each block rather than route geometry alone. 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.

1.3 Atmospheric Chemistry of PM2.5 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 (NOx), sulfur oxides (SOx), ammonia (NH_3), and volatile organic compounds (VOCs), each of which plays a role in secondary aerosol formation. For example, NOx can react with ammonia and atmospheric oxidants to form ammonium nitrate, while SOx 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. In this study, these processes are reflected through reduced-form air quality modeling rather than explicit photochemical simulation.

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.

1.4 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 $\mu g/m^3$ and 24-hour average concentrations to 35 $\mu g/m^3$ [32]. 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 [6]. 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 [33]. These plans employ Best Available Control Measures (BACM) to enforce stricter emissions standards and require updated inventories, modeling, and rule revisions [33]. 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 [1]. 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 substantial 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 [8]. Similarly, the Bipartisan Infrastructure Law of 2021 [30] and the Inflation Reduction Act of 2022 [31] 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 because they align with State Implementation Plan (SIP) requirements and provide resources needed to support compliance. In practice, Utah Transit Authority staff have identified improving air quality outcomes in disadvantaged communities as an important consideration in fleet electrification planning. This study operationalizes that consideration by explicitly incorporating communities with legacy exposure to pollutants into the optimization framework. 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.

1.5 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 [10][26]. 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) [7]. By directing electrification benefits toward populations historically overexposed to pollution and least equipped to bear its costs, the optimization framework ensures that benefits are not assumed spatially uniform, but are instead explicitly weighted toward high-burden areas. 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.

1.6 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 [9][34]. Additional studies have explored methods to reduce battery degradation and account for performance variability due to temperature and weather conditions [36][16]. 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.

Despite extensive research on BEB operations and lifecycle impacts, comparatively few studies integrate block-level operational feasibility with spatially explicit environmental equity objectives. Prior work often evaluates electrification at the route or network level, which can obscure feasibility constraints and exposure benefits that vary across daily vehicle assignments. This study addresses that gap with a schedule-block-level optimization framework that links charging feasibility, infrastructure cost, and air quality benefits in disadvantaged communities.

To address this gap, this study introduces the Bi-Objective Battery-Electric Bus Deployment Model (BOBEBD), 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 BOBEBD 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.

1.7 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.

2 METHODOLOGY

Unlike previous studies that primarily focus on electrifying entire transit networks or evaluating the fleet-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

BOBEBD balances two core objectives:

1. Maximizing environmental benefits, especially reductions in $PM_{2.5}$ 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. In implementation, the cost objective is enforced as a budget constraint, yielding a single-objective formulation that maximizes environmental benefit subject to fiscal and operational limits

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 $PM_{2.5}$ 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 BOBEBD 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 $PM_{2.5}$ 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 $PM_{2.5}$". These secondary particles can travel long distances, 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 $PM_{2.5}$.

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) [14] 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 (InMAP) [29], a reduced-complexity air quality model designed to estimate annual-average $PM_{2.5}$ concentrations across large spatial domains with high population resolution. While more complex chemical transport models such as WRF-Chem [23], GEOS-Chem [11], or CMAQ [5] 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 [7], [20]. 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 $PM_{2.5}$ 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 $PM_{2.5}$ 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 [14]. 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 (NH_3), 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[20] [7]. 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 contains census population data, census tract geospatial data, and other metadata. An example of tracts being identified as disadvantaged is found in Figure 2.2.

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 assumption necessarily abstracts away localized emission hotspots and temporal variation; however, the objective of this study is to evaluate long-term health and environmental impacts at the corridor and neighborhood scale, which aligns with the design intent of InMAP. Accordingly, the analysis focuses on annual-average $PM_{2.5}$ exposure rather than short-term peak concentrations.

Additionally, the analysis evaluates hundreds of individual schedule blocks, each requiring a separate emissions simulation. Modeling fine-grained spatiotemporal emission dynamics for each block would impose substantial computational costs without materially improving the policy-relevant comparisons central to this study. As a result, the uniform-distribution assumption represents a deliberate trade-off between spatial granularity and computational tractability, enabling consistent fleet-wide evaluation while preserving the relative differences in exposure and benefit across scenarios. Because this assumption is applied consistently across all schedule blocks and scenarios, it preserves relative differences in exposure and benefit, which are central to the comparative optimization performed here. Based on this input, InMAP generates an emissions plume representing the atmospheric transport and dispersion of pollutants associated with each modeled schedule block.

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, two scenarios are modeled: one in which the block is assigned a diesel bus and another in which it is assigned a battery-electric bus (BEB). Emissions inventory estimates for each scenario are generated using the MOVES model and linked to the shapefile geometry of the corresponding schedule 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 schedule block under both scenarios. InMAP receives input files containing emissions data, spatial geometries, and atmospheric metadata, and produces a spatial grid of $PM_{2.5}$ concentrations. These concentration grids are overlaid with CEJST-identified census tracts to evaluate exposure within disadvantaged communities.

Environmental benefits are quantified by computing the population-weighted mean $PM_{2.5}$ concentration within CEJST census tracts for each schedule block, where weights are based on tract population. The reduction in exposure attributable to BEB deployment is defined as the difference between the population-weighted mean $PM_{2.5}$ concentrations under the diesel and BEB scenarios. This reduction is denoted as V_i for schedule block i and serves as the key input to Objective 1 in the optimization model. By prioritizing schedule blocks that yield the greatest reductions in $PM_{2.5}$ exposure within disadvantaged communities, the model directs BEB deployment toward locations with the highest potential for local air quality improvement.

2.4 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) while determining the optimal placement of charging infrastructure. The model optimizes two objectives: (1) maximizing the environmental benefits of replacing diesel buses with BEBs and (2) minimizing the costs associated with bus procurement and charging infrastructure.

The model incorporates constraints that ensure operational feasibility. Each bus begins with a full charge and must maintain sufficient energy levels throughout its scheduled operations, while adequate charging infrastructure is provided at depots and terminals. Unlike models that assume full charging between trips, BOBEBD allows for partial charging and continuously tracks each bus's energy state across the existing fleet schedule, yielding a more realistic representation of operational constraints.

The model assumes a fixed energy efficiency parameter (kWh/mile) provided by the operating agency and does not explicitly model temperature-dependent battery performance or charging losses. While ambient temperature, auxiliary loads, and charging inefficiencies can meaningfully affect real-world range—particularly in cold-weather operations—these effects are highly fleet-, climate-, and depot-specific and are therefore treated as exogenous to the optimization framework presented here.

The proposed schedule-block-based model is agnostic to the specific efficiency value assumed. Energy efficiency enters the formulation as a tunable parameter, allowing practitioners to readily adapt the model to local operating conditions or revised fleet performance estimates without altering the underlying optimization logic. Under degraded efficiency assumptions, the feasible operating region contracts, but the model's relative prioritization of high-impact schedule blocks remains governed by the same optimization structure.

The model uses the following notation.

2.5 Indices

$i \in I$ index of schedule block corresponding to a single bus's daily assignment

$j \in J$ index of on-route charging stations

$g \in G$ index of in-depot charging stations

k index of bus terminal sequence

2.6 Parameters

V_i quantified environmental benefit obtained by replacing the diesel bus on schedule block i

C^G cost of building an in-depot charger

C_j^O cost of building the first on-route charging station at terminal j

C_j^S cost of building each additional charging station at terminal j

C^B cost of purchasing one BEB

C_x project budget

n^O number of BEBs that can charge simultaneously at each on-route charger

n^G number of BEBs that can charge 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

$E_{i,k}$ energy level of bus i at sequence k

M_x^e maximum battery energy

m_n^e minimum allowable battery energy

f_b BEB energy efficiency (kWh/mile)

P_O overhead charger power (kW)

$t_{i,k}$ length of time bus i dwells at terminal k

γ_g set of buses assigned to depot g

L sufficiently large constant

2.7 Decision Variables

$$Z_i^B \begin{cases} 1 & \text{if schedule block } i \text{ is assigned a BEB} \\ 0 & \text{otherwise} \end{cases}$$

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

Y_j^O number of on-route chargers built at terminal j

Y_g^G number of in-depot charging stations built at depot g

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

2.8 Objectives

$$max \sum_i V_i Z_i^B \tag{2.1}$$

$$min(\sum_g C^G Y_g^G + \sum_j (C_j^O Z_j^O + Z_j^O C_j^S (Y_j^O - 1)) + \sum_i C^B Z_i^B) \tag{2.2}$$

2.9 Constraints

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

$$m_n^e \leq E_{i,k} \leq M_x^e \tag{2.4}$$

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

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

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

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

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

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

2.10 Equation Explanation

- **Objective (1):** Maximize the environmental impact of replacing diesel buses with BEBs.
- **Objective (2):** Minimize costs associated with purchasing BEBs and installing on-route and depot charging infrastructure. Because increasing the budget allows more buses to be replaced to satisfy Objective (1), Objective (2) is treated as a budget constraint:

$$\sum_g C^G Y_g^G + \sum_j \left(C_j^O Z_j^O + C_j^S (Y_j^O - 1) Z_j^O \right) + \sum_i C^B Z_i^B \leq C_x \tag{2.11}$$

This reformulation converts the problem into a single-objective optimization model that can be solved using standard mixed-integer programming solvers while preserving the trade-off structure of the original bi-objective formulation.

- **Constraint (3):** Ensure each bus starts the day with a fully charged battery.
- **Constraint (4):** Maintain each bus's energy level within the allowable minimum and maximum limits.
- **Constraint (5):** Ensure that a bus can charge only if an on-route charger exists at the terminal.
- **Constraint (6):** Restrict charging to BEBs.
- **Constraint (7):** Ensure sufficient on-route chargers are available at a terminal for all buses charging simultaneously.
- **Constraint (8):** Ensure that a sufficient number of depot chargers are available.
- **Constraint (9):** Require that a bus has enough energy to complete the return trip upon departure.
- **Constraint (10):** Define the energy balance governing the battery level between route segments.

2.10.1 Model Notes

2.10.1.1 Schedule Block Terminal Sequencing

On a typical weekday, schedule block i runs through an ordered sequence of terminals. Each terminal has a unique identifier j. For example, a hypothetical schedule block begins at terminal a at sequence $k = 0$, travels 5 miles to terminal b at sequence $k = 1$, dwells for 10 minutes, returns to terminal a at sequence $k = 2$, dwells for 8 minutes, and then ends the day at terminal c at sequence $k = 3$.

2.10.1.2 Charging Infrastructure Costs

The first charger installed at a location may cost more than subsequent chargers constructed at the same site because it can require electrical service upgrades (e.g., transformers, switchgear, and related civil work). Once these fixed upgrades are in place, additional chargers can be deployed using the upgraded interconnection, reducing marginal installation costs.

2.10.1.3 Battery energy accounting and charging assumptions.

The energy state and operating range of each battery-electric bus (BEB) are governed by the initial state of charge, energy consumption during operation, and recharging at terminals or depots. The energy level of schedule block i at sequence k, denoted $E_{i,k}$, is initialized to the maximum battery energy M_x^e at the start of the operating day. During operation, $E_{i,k}$ decreases proportionally to the route distance traveled, $d_{i,k-1,k}$, and the BEB energy-use parameter f_b, expressed in kWh/mile.

The model assumes f_b is constant and representative of average operating efficiency across the service day. This parameter is treated as exogenous to the optimization and can be calibrated to reflect agency-specific fleet performance. Feasible operation is enforced by bounding energy levels between a minimum allowable threshold m_n^e and the maximum battery capacity M_x^e.

Recharging occurs at designated terminals or depots, where the energy replenished is modeled as a function of the dwell time $t_{i,k}$, the rated charger power

P_O, and the binary decision variable $X_{i,k}$, which indicates whether schedule block i charges at sequence k. The energy transition is represented through an energy balance: energy carried over from the previous sequence plus charging energy (if any) minus traction energy consumed during the terminal-to-terminal movement.

Charging power P_O is assumed to be constant, and charging losses are not modeled explicitly. Under this assumption, all delivered charging energy is treated as usable battery energy (i.e., 100% charging efficiency). In practice, charging efficiency and effective range vary with ambient temperature, auxiliary loads, battery thermal management, and charger performance; these effects are incorporated implicitly through the choice of the average efficiency parameter f_b and are discussed as a limitation in Chapter 4.

2.10.1.4 Large-constant formulation

The constant L is a large positive number used to relax the minimum-energy feasibility requirement when a schedule block is not electrified. Specifically, in Constraint [9], the term $(1 - Z_i^B)L$ ensures that if $Z_i^B = 0$ (i.e., the block is assigned a diesel bus), the constraint becomes non-binding, and the model does not attempt to enforce BEB energy feasibility for that block. Conversely, when $Z_i^B = 1$, the relaxation term vanishes and the constraint enforces the required energy condition for BEB operation.

2.10.1.5 Charging Redundancy and Scope of Optimization

The BOBEBD formulation intentionally identifies the *minimum* charging infrastructure required to support a given set of electrified schedule blocks under the stated budget and operational constraints. Redundant or backup charging capacity is not explicitly modeled. Because the objective prioritizes environmental benefit subject to a fixed capital budget, the inclusion of redundant chargers—while operationally desirable—would necessarily reduce the number of blocks that can be feasibly electrified without increasing the modeled objective value.

Accordingly, the model should be interpreted as a planning and prioritization tool rather than a final engineering design. Its outputs identify which schedule blocks are optimal candidates for electrification and which terminal locations constitute binding charging requirements under a given budget. Decisions regarding redundancy, resiliency, and contingency planning are intentionally left to subsequent design and operational phases.

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

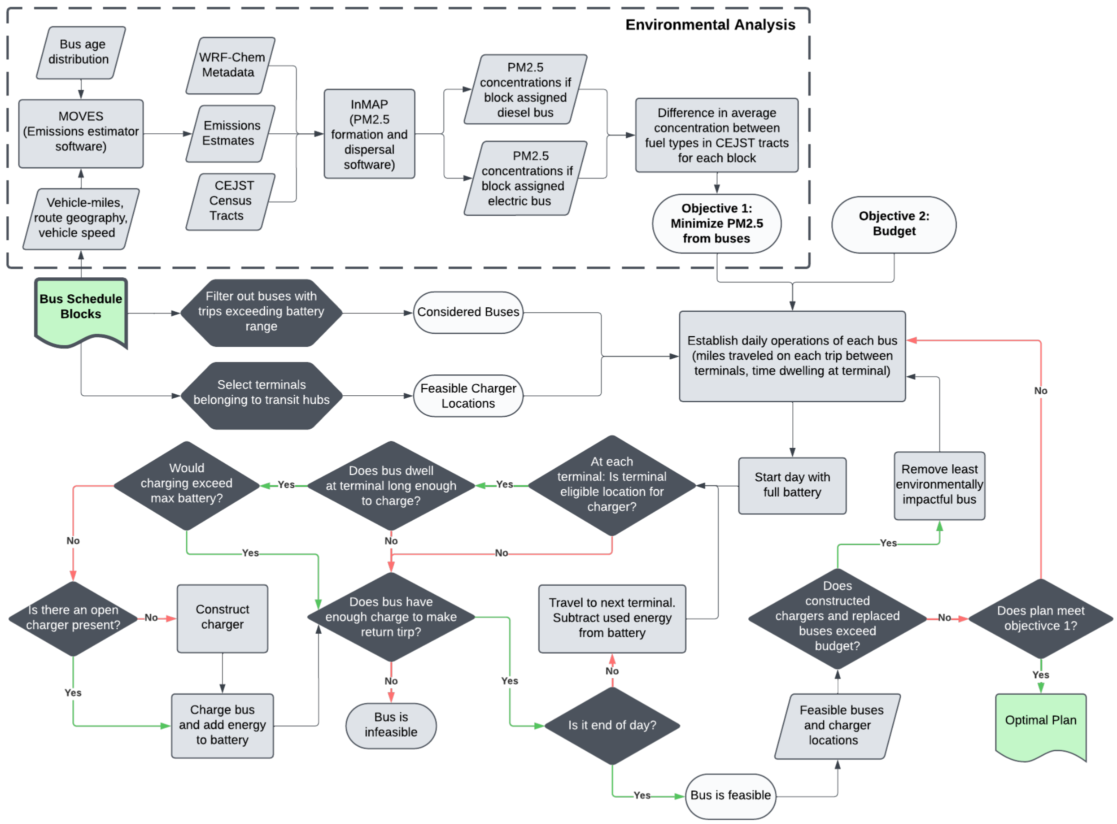

Figure 2.1. BOBEBD Methodology Flowchart.

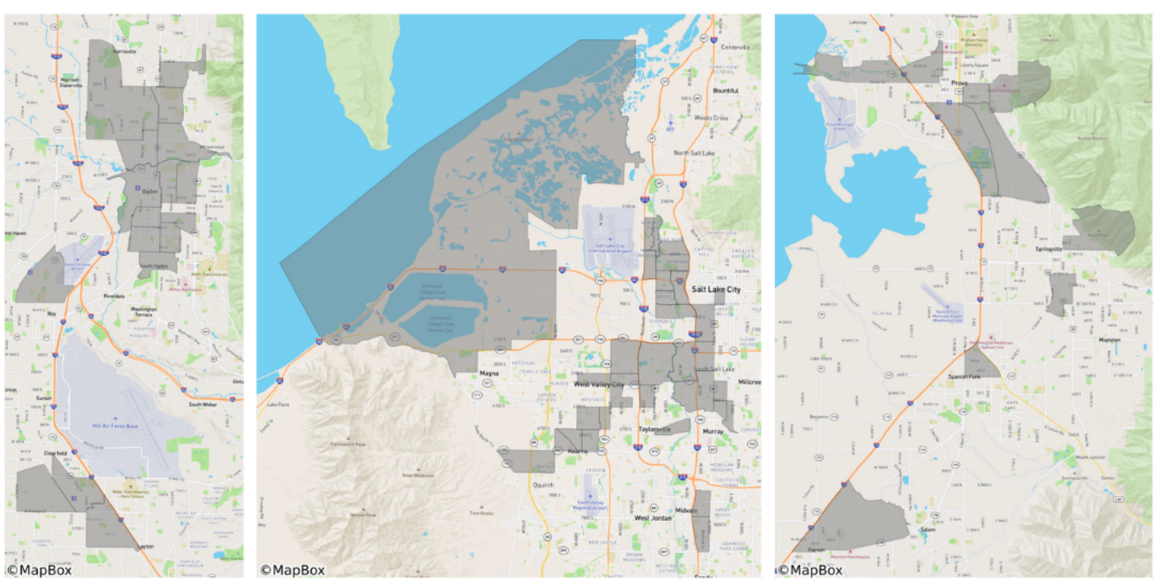

Figure 2.2. Wasatch Front Area CEJST Tracts. Left: Weber and Davis Counties; Middle: Salt Lake County; Right: Utah County

3 APPLICATION

This study applies 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 Administration, 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.

3.1 Data Sources and Preprocessing

The primary operational input to BOBEBD is UTA's weekday runcut file, which defines schedule blocks as ordered sequences of terminal arrivals/departures and associated route assignments. Each schedule block was joined to geospatial route alignments to construct a block-level polyline geometry representing the union of route segments served over the day. Terminal locations were represented as point features derived from UTA terminal coordinates and were linked to schedule-block sequences using terminal identifiers in the runcut. Potential on-route charging locations were manually identified using street maps, selecting only 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.

All preprocessing was performed in Python using `pandas` for tabular operations and `geopandas` for spatial joins and geometry handling. The resulting outputs included (i) a block-level geometry shapefile for emissions modeling and (ii) block-by-terminal sequence tables containing dwell times, terminal identifiers, and inter-terminal distances required by the optimization model.

3.2 Application Parameters

The BEB considered by the UTA is the New Flyer XE-40, which costs $970,000, has a total battery capacity of 388 kWh, and an observed average 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.

3.3 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.

3.3.1 Creating Bus Emissions Inventories Using MOVES

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 Table A.1 in Appendix A) 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 Table A.2 in Appendix A). 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 that were converted to kilograms per year for use as inputs in InMAP. (see Table A.3 in Appendix A for a sample of the diesel bus inventory and Table A.4 in Appendix A 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.

3.3.2 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 [7]. 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.

3.3.3 CTM Metadata

CTM data were obtained from a 12-km resolution global atmospheric chemistry simulation representative of 2005 baseline conditions using WRF-Chem, the Weather Research and Forecasting (WRF) model coupled with Chemistry[28]. 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 NetCDF (.nc) file.

3.3.4 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 NetCDF 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.

3.3.5 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 shown in Figure 3.6, within CEJST-identified census tracts the mean incremental annual-average $PM_{2.5}$ concentration attributable to bus operations is 0.037 $\mu g/m^3$ when all schedule blocks are assigned diesel buses, with a median of 0.028 $\mu g/m^3$ (or −1.739 and −1.547 on a $\log_{10}$ scale, respectively). When all blocks are assigned BEBs, the mean and median decrease to 0.012 $\mu g/m^3$ and 0.009 $\mu g/m^3$ (or −2.277 and −2.028 on a $\log_{10}$ scale, respectively).

These concentrations should be interpreted as *incremental contributions from bus activity alone*, not as the region's total ambient $PM_{2.5}$ burden. Although incremental values are necessarily smaller than ambient concentrations dominated by multiple source sectors, they represent exposure that is both policy-relevant and operationally actionable: electrification eliminates tailpipe emissions along high-ridership corridors and concentrates reductions in populated areas, including CEJST-designated disadvantaged communities. Accordingly, the primary value of the analysis is not the regional mean change, but the ability to *target* limited BEB and charging investments toward schedule blocks that deliver disproportionate exposure reductions where baseline vulnerability is greatest.

3.4 Environmental Analysis Output

InMAP generates a spatial grid over the study area, with higher-resolution cells overlaid on census tracts identified by the Climate and Economic Justice Screening Tool (CEJST), as illustrated in Figure 3.7. Grid cells outside CEJST tracts have approximate dimensions of 567 m by 1,734 m, while cells within CEJST tracts are more finely resolved at approximately 71 m by 217 m. Each grid cell in the InMAP output shapefile reports the modeled average annual $PM_{2.5}$ concentration attributable to the analyzed emissions source.

Because InMAP constructs grids dynamically based on the spatial distribution of emissions and population weighting, the resulting grid geometries differ slightly between pollution scenarios. As a result, direct cell-by-cell comparisons across scenarios are not feasible. Instead, comparisons are conducted using aggregated, area-level metrics (e.g., census tract averages), which preserve internal consistency while enabling robust cross-scenario evaluation. An example of area-level impact for a sample of bus blocks is visualized in Figures fig:block3012, fig:block4507, fig:block1025, fig:block2020, and fig:block2020central.

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 weight emissions by exposure, emphasizing locations where population impacts are greatest. Comparisons of block-level emissions distributions can be found in Figure 3.13.

To evaluate whether the modeled differences in $PM_{2.5}$ concentrations between diesel and battery-electric bus (BEB) operations are statistically meaningful, we conducted a series of paired statistical tests comparing annual-average $PM_{2.5}$ concentrations within CEJST-identified census tracts for each schedule block under the two fuel scenarios (Table 3.1). Because each block is evaluated under both diesel and BEB conditions, paired tests are appropriate.

The paired t-test indicates a highly statistically significant reduction in $PM_{2.5}$ exposure when diesel buses are replaced with BEBs ($t = 18.653$, $p < 10^{-5}$), suggesting that the observed differences are unlikely to arise from random variation. The associated effect size, measured by Cohen's d ($d = 1.140$), corresponds to a large standardized difference, indicating that the shift from diesel to BEB operation produces a substantively meaningful change in exposure distributions despite the small absolute magnitude of concentrations.

To confirm robustness to distributional assumptions, we additionally applied the Wilcoxon signed-rank test, which does not assume normality. This test likewise rejects the null hypothesis of no difference between fuel types ($W = 0.000$, $p < 10^{-5}$). Finally, the Kolmogorov–Smirnov (KS) test ($KS = 0.540$, $p < 10^{-5}$) demonstrates a statistically significant divergence between the full distributions of $PM_{2.5}$ concentrations under diesel and BEB scenarios, indicating that electrification alters not only mean exposure levels but also the spatial distribution of pollution impacts across disadvantaged communities.

These findings support 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.

3.5 Implementing BOBEBD

3.5.1 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 3.2 details the location and count of on-route chargers by budget level, and Table 3.3 specifies which bus routes receive BEBs at each budget level.

It is important to note that the charging infrastructure identified by BOBEBD represents the minimum set required to ensure operational feasibility for the selected schedule blocks under the stated budget constraint. The model does not include additional chargers for redundancy or fault tolerance. As a result, the reported charger counts and locations should be interpreted as *necessary* infrastructure rather than a complete implementation plan.

In practice, transit agencies may choose to install additional chargers at high-utilization terminals to improve resiliency, accommodate unexpected delays, or support future service growth. Such considerations are beyond the scope of the optimization presented here and are more appropriately addressed during detailed engineering design and capital planning.

3.5.2 Efficiency Sensitivity and Robustness

To evaluate the robustness of the optimization results to uncertainty in battery performance, a sensitivity analysis was conducted across a range of assumed BEB energy efficiencies. Table 3.4 summarizes how changes in efficiency affect both the size of the feasible operating region and the optimal deployment decisions under a fixed capital budget. Noe that efficiency is the assumed average energy consumption (kWh/mi). Usable range is computed as the difference between maximum and minimum allowable battery energy divided by Efficiency. "Feasible blocks" are those that satisfy all range and charging constraints under the assumed Efficiency. "Benefit captured" is defined as the fraction of total modeled environmental benefit captured over the *scored* block universe (blocks with computed environmental scores), i.e., $\sum_{i \in \mathscr{S}} V_i Z_i^B / \sum_{i \in \mathscr{S}} V_i$.

As expected, reductions in energy efficiency compress the feasible solution space. As usable range declines from approximately 116 to 67 miles, the number of schedule blocks that satisfy range feasibility decreases modestly, from 343 to 331. The number of blocks selected for electrification declines more sharply, from 248 to 209, reflecting the combined effects of range constraints and increased charging requirements for remaining high-value blocks.

Importantly, moderate deviations from the baseline efficiency assumption (e.g., 2.5 versus 3.0 kWh/mile) result in relatively small changes in the number of electrified blocks and the fraction of environmental benefit captured. This indicates that the optimization is not overly sensitive to modest uncertainty in average operating efficiency and remains stable across plausible real-world conditions.

At lower effective ranges, the model reallocates capital away from bus procurement toward charging infrastructure in order to preserve feasibility for the highest-benefit schedule blocks. This manifests as a nonlinear increase in the number of required on-route chargers at higher energy consumption assumptions. Because the objective function maximizes environmental benefit subject to a fixed budget, this behavior reflects a rational trade-off: electrifying fewer buses while investing in additional charging capacity can yield greater total benefit when range constraints tighten.

Taken together, these results suggest that energy efficiency primarily governs the size of the feasible operating region rather than the relative prioritization of schedule blocks. Under degraded efficiency assumptions, longer and more operationally constrained blocks become infeasible first, while shorter, high-exposure urban blocks remain preferred candidates for electrification. As a result, the model's core policy insight—that targeted deployment of BEBs can deliver disproportionate environmental and equity benefits—remains robust across a wide range of plausible efficiency conditions.

3.5.3 Alternative Optima and Operational 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 3.5, 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.

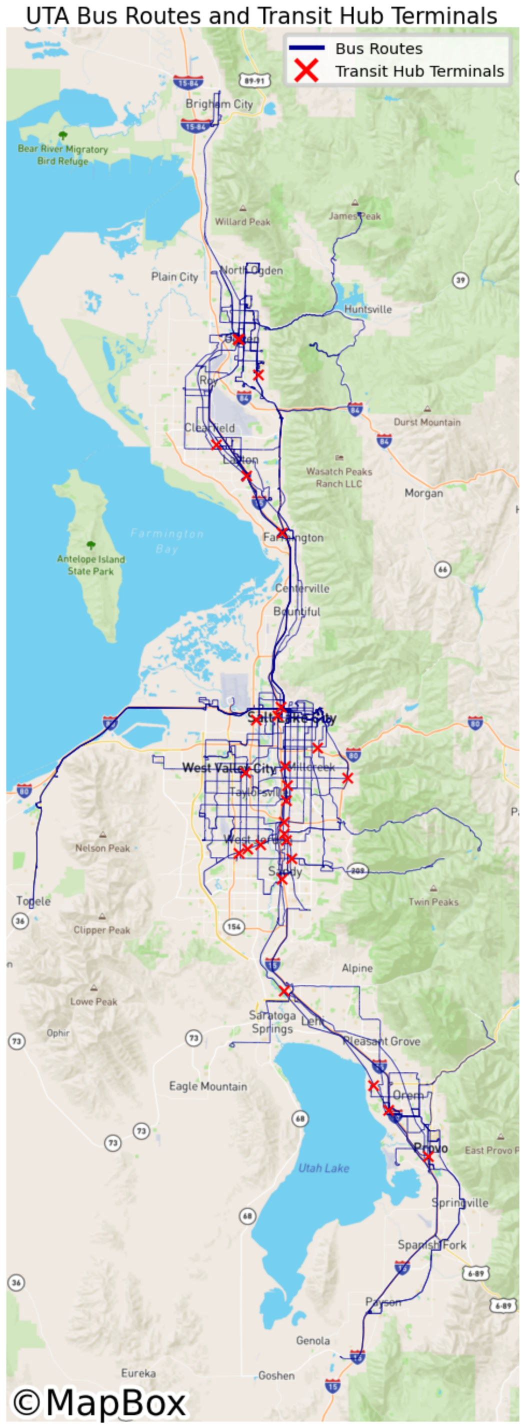

Figure 3.1. UTA Routes and Eligible Terminals.

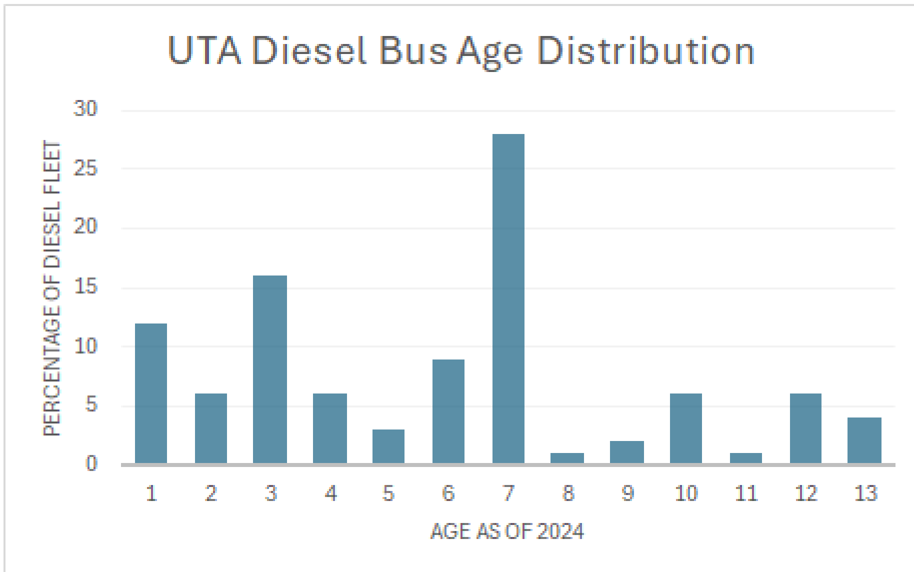

Figure 3.2. Age Distribution of UTA Diesel Buses.

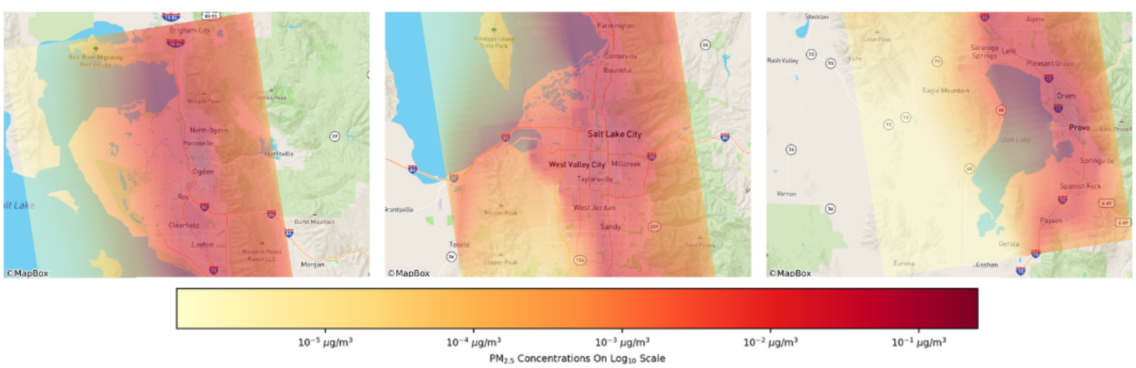

Figure 3.3. Pollution from all blocks assigned diesel buses.

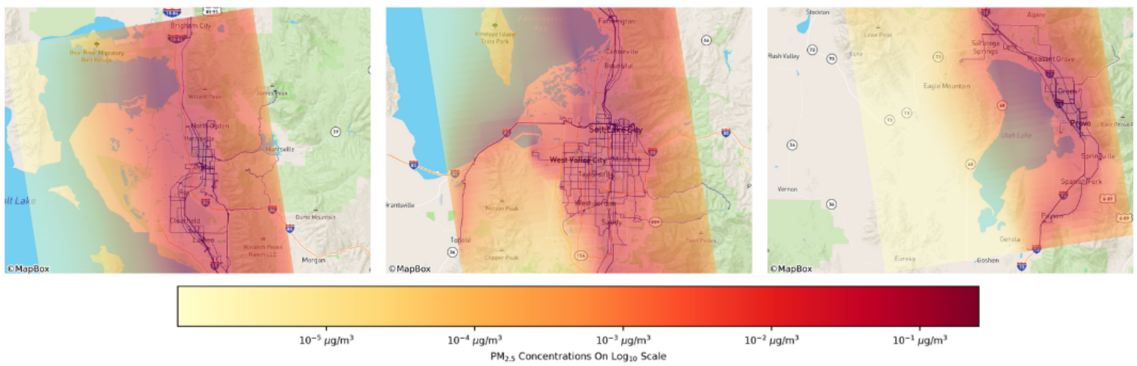

Figure 3.4. Pollution dispersion with bus routes.

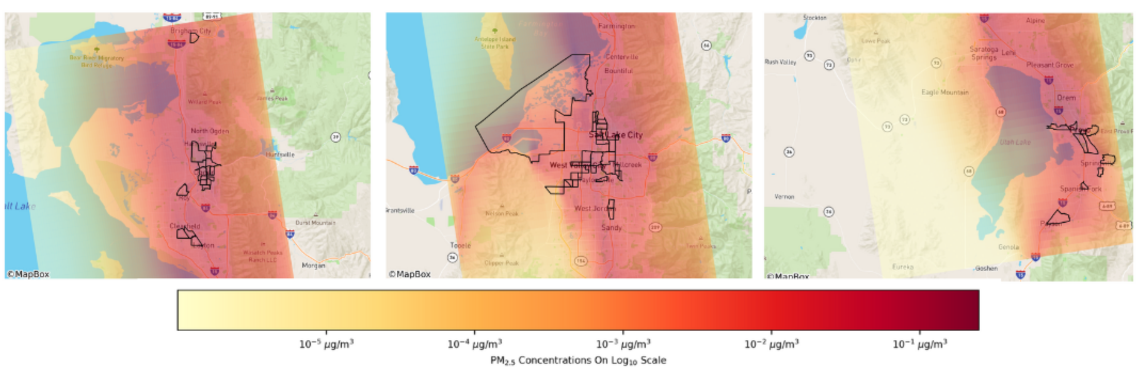

Figure 3.5. Pollution dispersion with CEJST tracts.

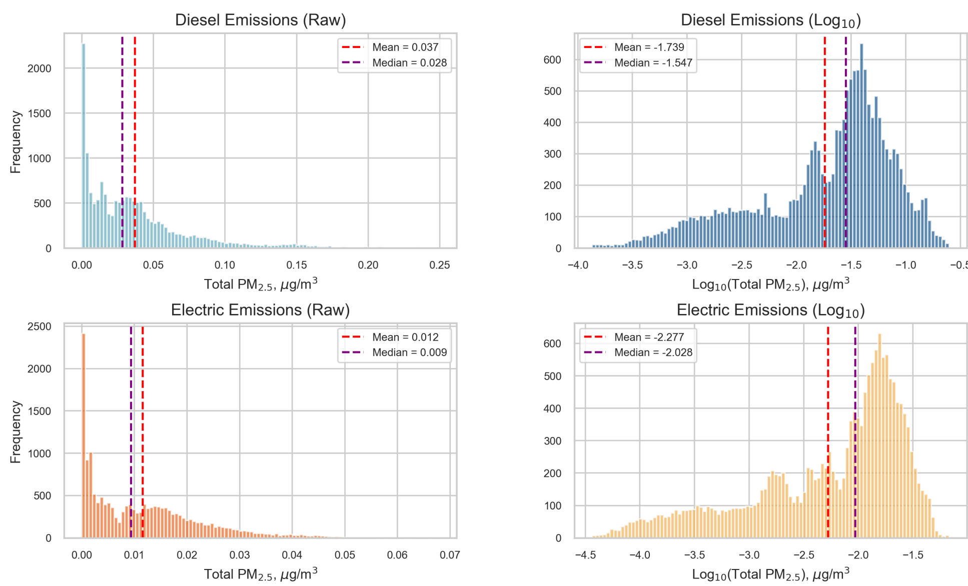

Figure 3.6. Emissions distribution across CEJST tracts. Grid cells are approximately 71 m × 217 m.

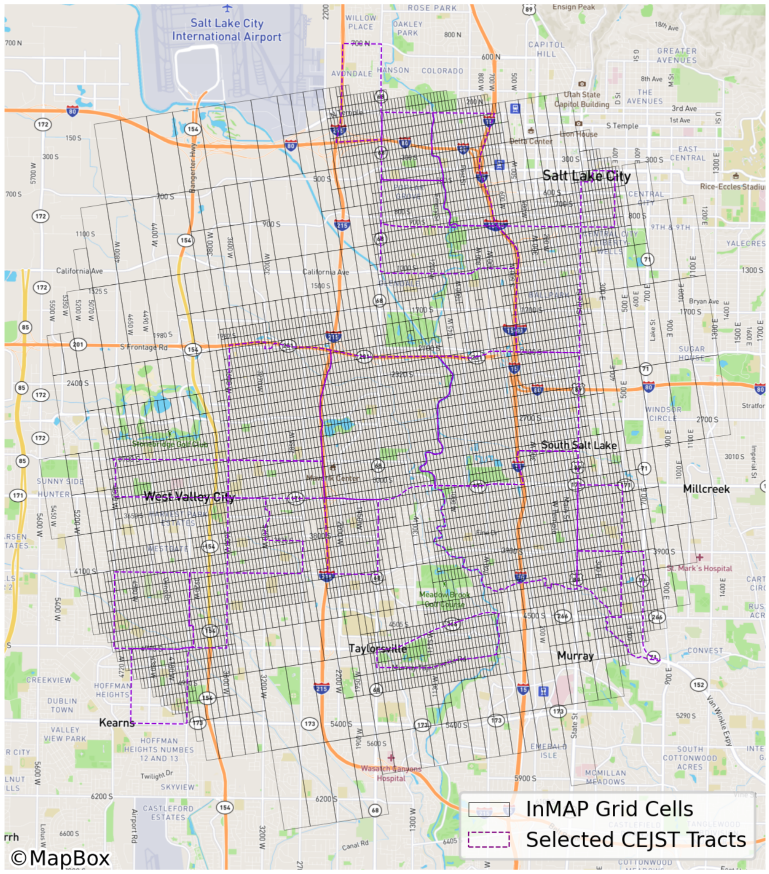

Figure 3.7. InMAP grid cells have higher resolution around census tracts.

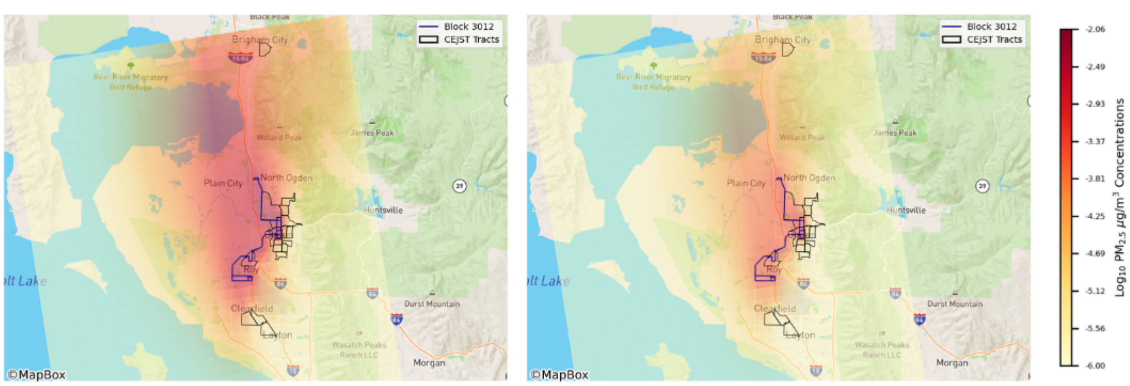

Figure 3.8. Block 3012 and its emissions plumes. Left: Diesel bus; Right: Electric bus.

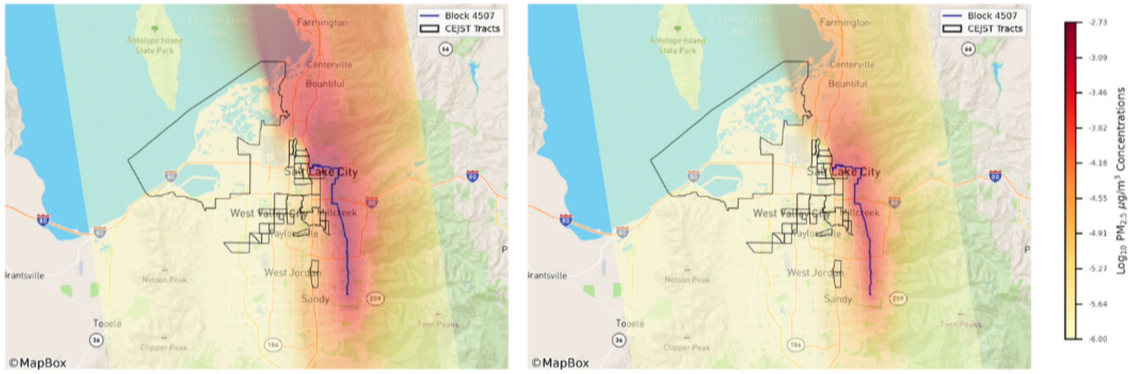

Figure 3.9. Block 4507 and its emissions plumes. Left: Diesel bus; Right: Electric bus.

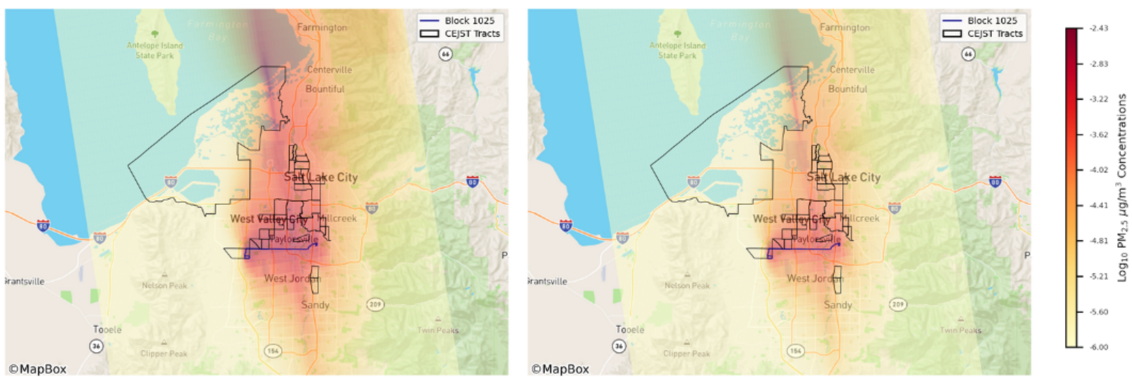

Figure 3.10. Block 1025 and its emissions plumes. Left: Diesel bus; Right: Electric bus.

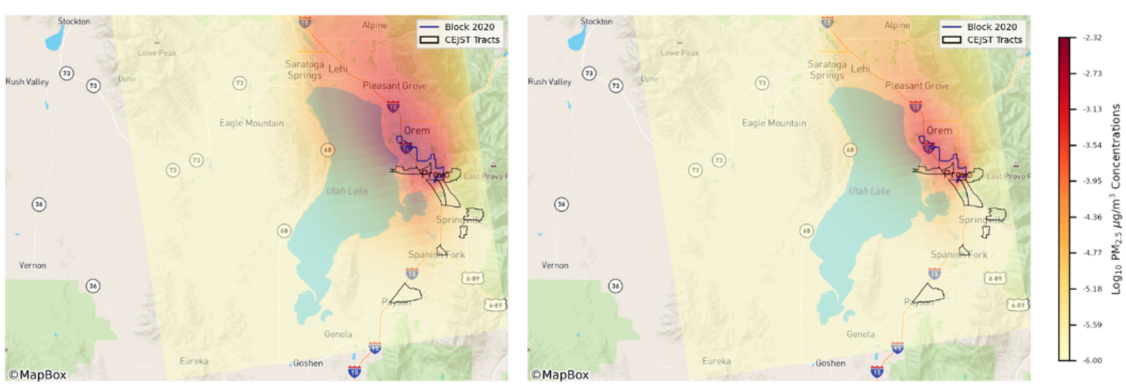

Figure 3.11. Block 2020 emissions plume (South). Left: Diesel bus; Right: Electric bus.

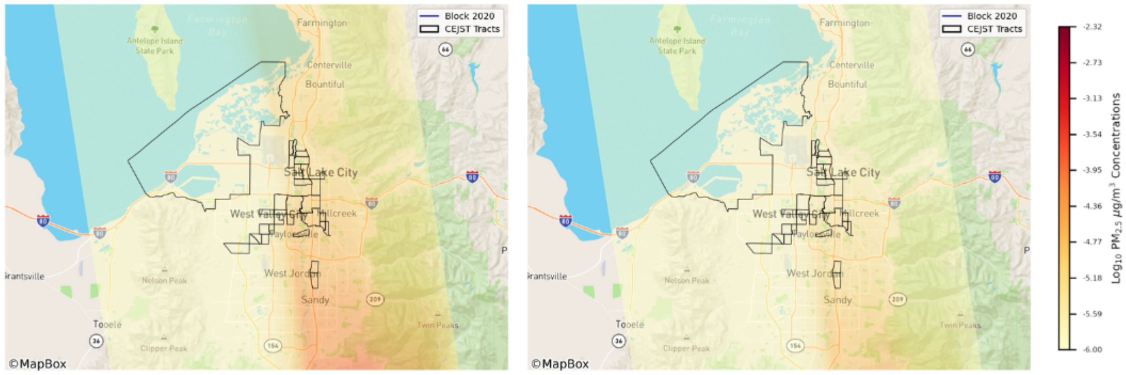

Figure 3.12. Block 2020 emissions plume (Central). Left: Diesel bus; Right: Electric bus.

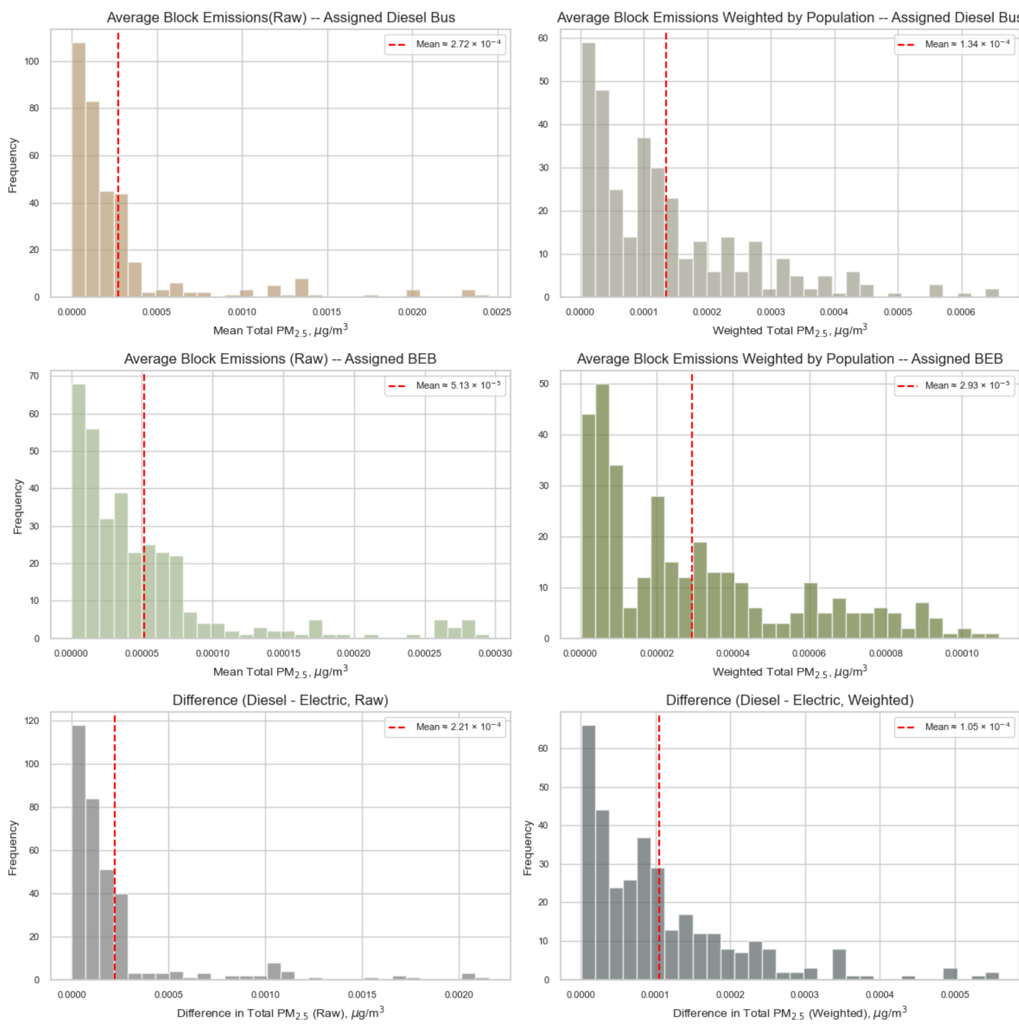

Figure 3.13. PM concentrations across all analyzed bus schedule blocks.

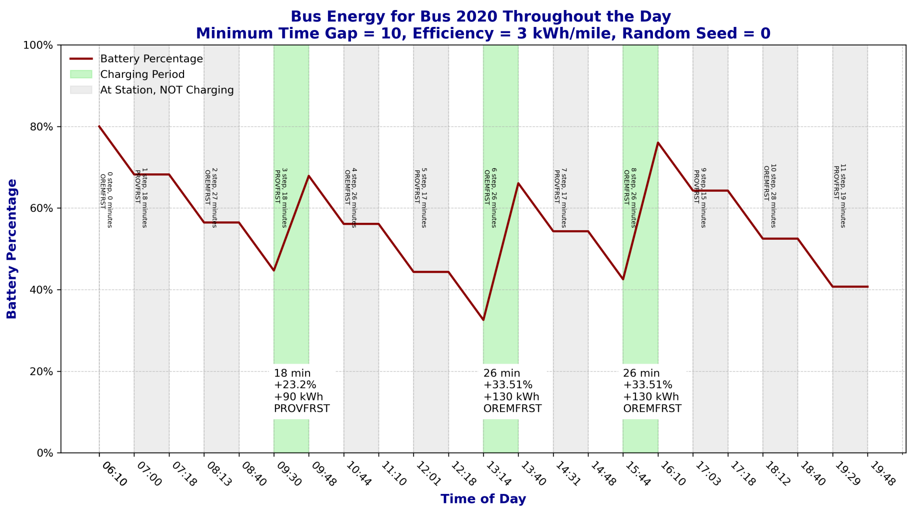

Figure 3.14. Bus energy levels for Bus 2020 and random seed 0.

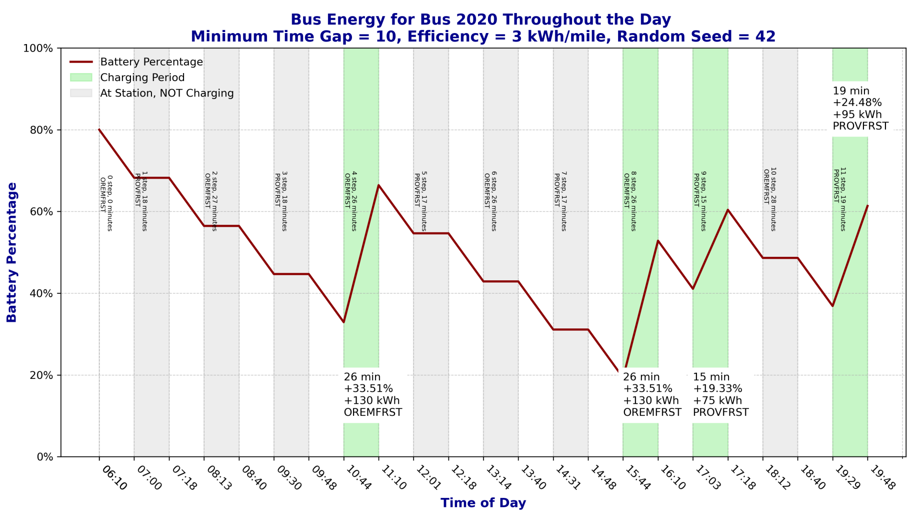

Figure 3.15. Bus energy levels for Bus 2020 and random seed 42.

Table 3.1. Statistical Analysis Results.

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 3.2. Terminal Charger Counts by Budget Level.

Terminal Name	**$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 3.3. Electrified Lines and BEB Counts by Budget Level.

Budget	Electrified Blocks	Electrified Lines	Line 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 3.4. Sensitivity of BOBEBD outcomes to assumed BEB energy efficiency (budget held constant).

Efficiency (kWh/mi)	Usable Range (mi)	Feasible Blocks	Electrified Blocks	Chargers Total	Benefit Captured
2.50	93.12	343	247	30	0.682
2.75	84.65	337	245	33	0.593
3.00	77.60	337	244	37	0.561
3.25	71.63	331	221	98	0.527
3.50	66.51	331	209	94	0.493

Table 3.5. Optimization results from varying starting conditions.

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

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.

4.1 Measurable Reductions in Ambient Pollution

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.[22] 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.

4.2 Diminishing Marginal Returns

The budget-constrained optimization results reveal a pattern of diminishing marginal returns. Initial investments yield substantial progress in fleet electrification—up to 244 of the 337 feasible diesel schedule blocks replaced under modeled budget scenarios—yet additional spending beyond this threshold produces limited incremental gains. This plateau effect visualized in Figure 4.1 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.

4.3 Spatial Resolution

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.

4.4 Pollution Complexity

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.

4.5 Upstream Emissions and Grid Decarbonization

A common critique of battery-electric bus deployment is that emissions are not eliminated but displaced upstream to electricity generation. In regions where the electrical grid remains partially fossil-fuel dependent, this raises concerns about whether electrification yields meaningful net environmental benefits. While this critique is valid in a narrow life-cycle accounting sense, it overlooks two structural advantages of electrified transit systems.

First, electrification shifts emissions from numerous mobile sources operating within densely populated neighborhoods to a smaller number of stationary sources that are subject to centralized regulation, emissions controls, and long-term decarbonization pathways. Unlike diesel buses, which emit pollutants directly into street-level environments where exposure is highest, power plants can be regulated through emissions standards, retrofits, fuel switching, or retirement. This transition fundamentally alters the controllability of emissions, even when the current grid mix is imperfect. This distinction is particularly relevant for environmental justice, as it reduces direct exposure in communities historically burdened by transportation-related pollution.

Second, transit electrification represents a forward-compatible investment that aligns with ongoing and anticipated grid decarbonization. Electrical grids tend to decarbonize over time through renewable portfolio standards, federal incentives, and declining renewable generation costs, whereas internal combustion vehicles are locked into fossil fuel use for their entire service life. As a result, the environmental performance of BEBs improves automatically as the grid becomes cleaner, without requiring changes to vehicle hardware or operations. From a planning perspective, this makes BEB deployment a strategic enabling investment rather than a static emissions-control measure.

Accordingly, while this study focuses on on-route $PM_{2.5}$ exposure and does not explicitly model upstream emissions, the results should be interpreted as conservative with respect to long-term air quality and climate benefits. Incorporating grid evolution scenarios into future model extensions would allow for a more comprehensive life-cycle assessment, but does not alter the near-term public health advantages of eliminating tailpipe emissions in high-exposure communities.

4.6 Operational Feasibility

Operational feasibility remains central to achieving these goals. The BOBEBD 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. Because bus energy efficiency is treated as a fixed, tunable parameter in the model, all feasibility and optimization results should be interpreted as conditional on the assumed kWh/mile value; changes in efficiency primarily affect the size of the feasible operating region rather than the relative prioritization of schedule blocks.

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.[37], who recommend temporal optimization as a critical element of large-scale electric fleet management.

The BOBEBD framework identifies the minimum charging infrastructure required to support a given set of electrified schedule blocks under deterministic operating assumptions. It does not explicitly model redundant chargers or spare charging capacity beyond feasibility requirements. Accordingly, the results should be interpreted as identifying where charging infrastructure is necessary to enable optimal block assignments under a stated budget, rather than prescribing a fully failure-resilient charging network. Incorporating redundancy constraints would increase system robustness but substantially expand the solution space and is therefore left for future work.

4.7 Climate Sensitivity and Operational Robustness

The analysis assumes a fixed average energy efficiency parameter, which abstracts away temperature-dependent effects such as cold-weather battery degradation, auxiliary heating loads, and reduced charging efficiency. In cold climates such as the Wasatch Front, winter conditions can reduce effective BEB range by 20–30% under worst-case scenarios. Conceptually, such degradation compresses the feasible operating region by increasing the effective energy consumption parameter without altering the structure of the optimization problem.

Under reduced efficiency assumptions, fewer schedule blocks satisfy range and charging constraints; however, the relative prioritization of high-impact blocks remains largely unchanged. Blocks that combine long deadhead distances, limited terminal dwell time, or sparse charging access become infeasible first, while shorter, high-exposure urban blocks remain strong candidates for electrification. As a result, the model's primary policy insight—that targeted electrification of a subset of high-impact blocks delivers disproportionate environmental and equity benefits—remains robust under degraded operating conditions.

Future extensions could explicitly incorporate temperature-dependent efficiency parameters or seasonal operating profiles to quantify this compression effect more precisely.

4.8 Conclusion

From a policy perspective, the results indicate that comprehensive fleet-wide electrification is not required to achieve substantial equity-weighted air quality benefits, particularly in budget-constrained contexts. The optimization results demonstrate pronounced diminishing marginal returns: early investments in electrifying schedule blocks located in high-exposure corridors yield substantially larger environmental gains per dollar than later deployments constrained by range, dwell time, and infrastructure availability.

These findings suggest that a targeted deployment strategy—prioritizing the subset of schedule blocks with the highest pollution exposure and population sensitivity—can capture a disproportionate share of the total achievable benefit without incurring the escalating costs associated with marginal electrification. While the precise inflection point depends on local operating conditions and cost assumptions, the general tradeoff observed in this study supports focusing initial investments on a limited fraction of high-impact blocks rather than pursuing uniform or complete electrification.

For transit agencies facing fiscal, infrastructural, or operational constraints, this approach offers a pragmatic pathway to maximize public health and equity outcomes while preserving flexibility to expand electrification as technology performance improves and grid conditions evolve.

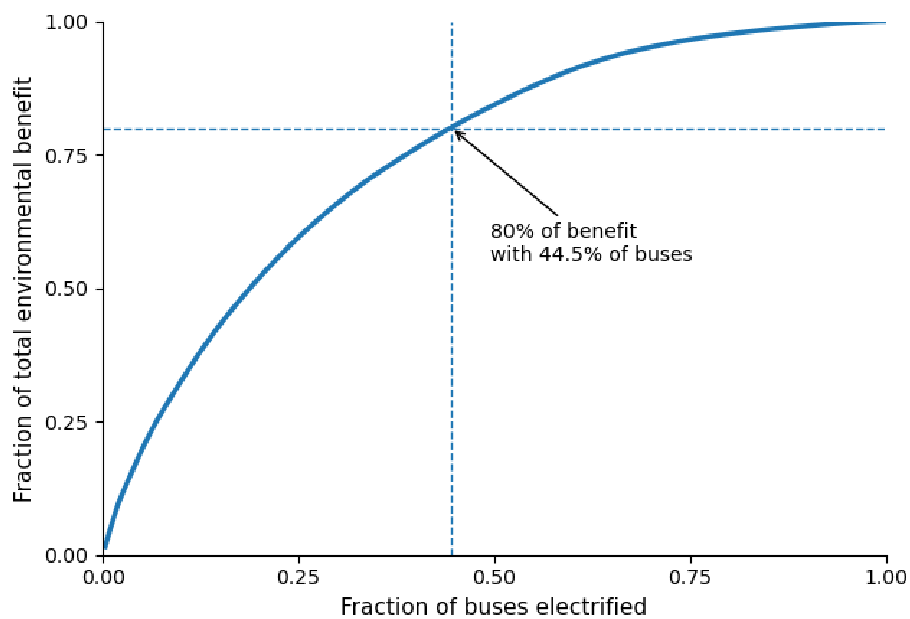

Figure 4.1. Diminishing Returns. Of the 337 schedule blocks feasible for electrification, approximately 150 (44.5%) capture 80% of the modeled environmental benefit.

APPENDIX A

MODEL INPUT EXCERPTS

Table A.1. Bus block schedule excerpt.

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.2. Adapted road link data excerpt.

link ID	cou nty ID	road TypeID	link Length	link Vol ume	link Avg Speed	link Desc ription	link Avg Grade
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.3. Annual diesel emissions data by bus schedule block, kg.

block	NOx	VOC	SOx	NH3	PM2.5
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.4. Annual BEB emissions data by bus schedule block, kg.

block	NOx	VOC	SOx	NH3	PM2.5
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

APPENDIX B

RESULTS BY FUNDING LEVEL

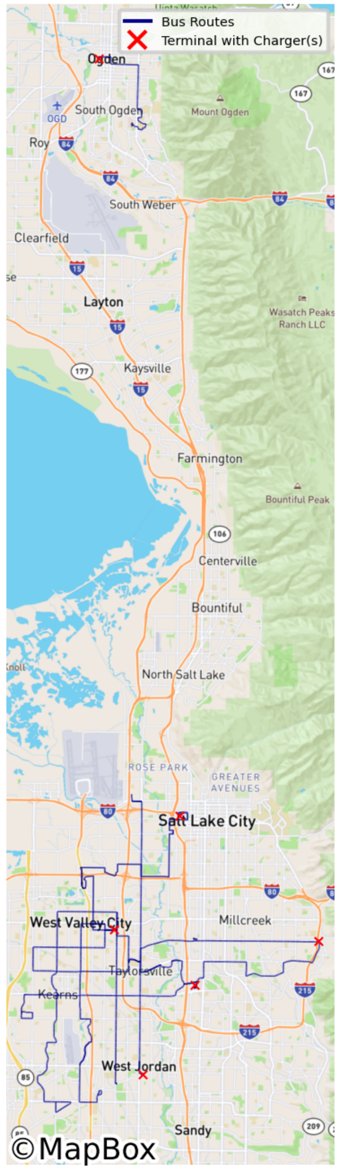

Figure B.1. $50M budget: 9 chargers at 6 terminals

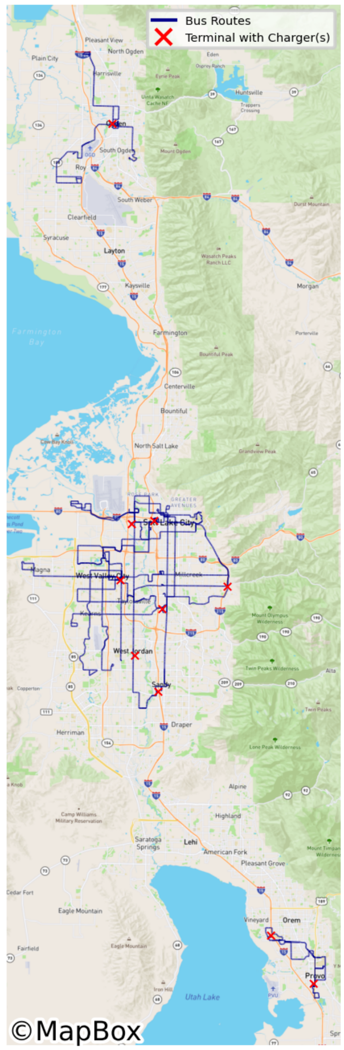

Figure B.2. $100M budget: 18 chargers at 10 terminals

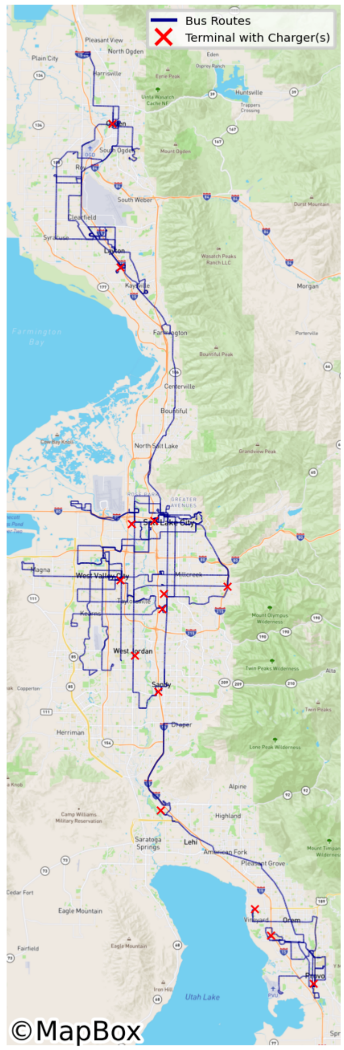

Figure B.3. \$150M budget: 25 chargers at 14 terminals

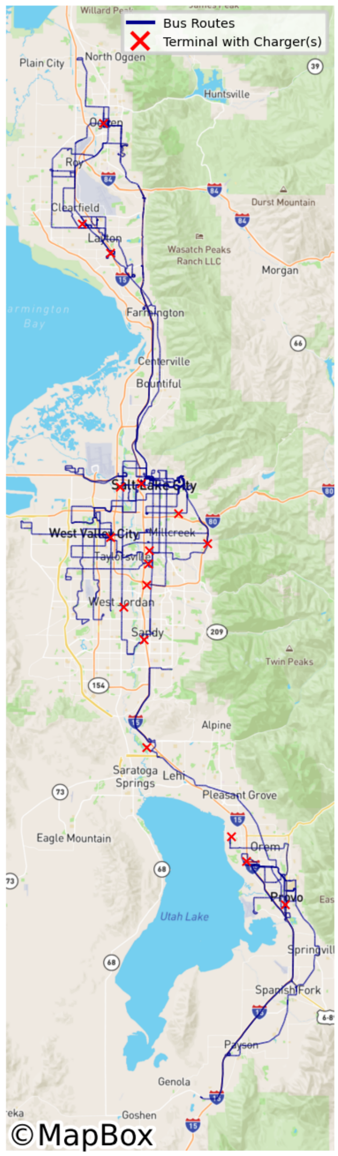

Figure B.4. $200M budget: 28 chargers at 17 terminals

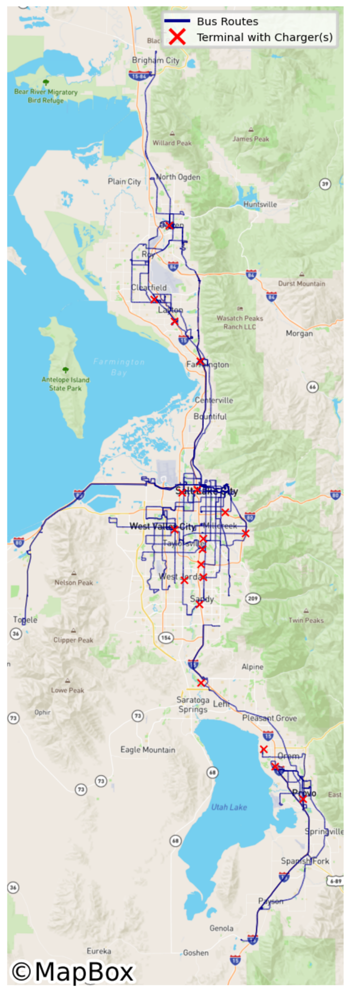

Figure B.5. $250M budget: 31 chargers at 19 terminals

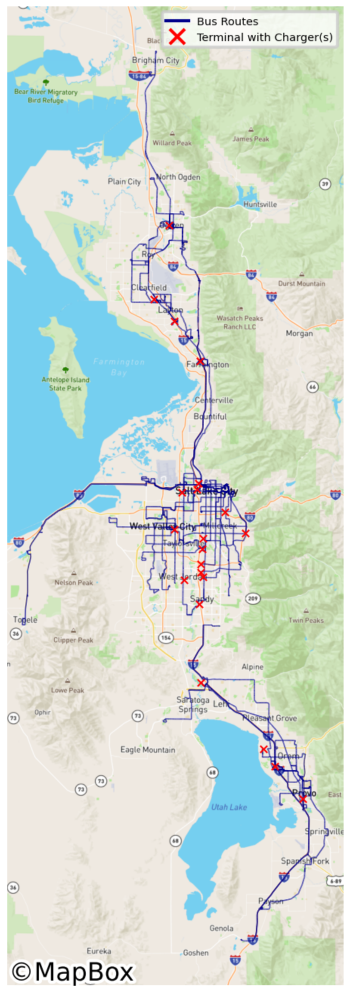

Figure B.6. $275M budget: 33 chargers at 21 terminals

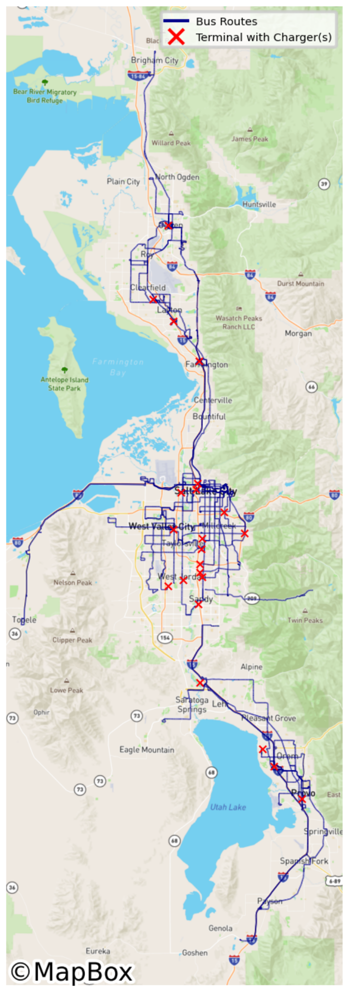

Figure B.7. $283M budget: 37 chargers at 22 terminals

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