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Modeling the Transition to Zero-Emission Transit Buses

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Abstract

The impact of transportation on the environment is a well-documented challenge facing several transportation industries today. To address this concern, several countries and states have created legislation or targets to transition various parts of their transportation fleets to zero-emission vehicles. One of these sectors undergoing an active transition is the public transit bus fleets, as zero-emission buses (ZEBs) are becoming more widespread in the US and around the world. However, transitioning from a traditional fleet to a ZEB fleet is a complicated and expensive process, with many decisions to make along the way. This research aims to model and optimize transit networks of ZEBs by using a mixed-integer linear program (MILP) model and optimizing based on total 12-year cost.

Chapter 2 of this dissertation focuses on developing a method that is used to model transit networks. The MILP is developed and tested on a case-study network, with an energy uncertainty analysis performed to understand how vehicle energy use accuracy affects the model. The model reliably produced results consistent with forecasted implementations of ZEBs within the case study network, and that vehicle energy use had a substantial effect on the estimated best network architecture.

Chapter 3 extends the model, making use of publicly available transit data to optimize 78 transit networks in the United States. For this version of the model, a focus was placed on the relationship between battery pack size and ideal supporting infrastructure at different infrastructure costs. Opportunity charging was found to be too expensive to be an economic solution, and that significant cost reductions would be required for make use of this strategy. What's more, several networks required battery packs of sizes significantly larger than are available on the market today.

Chapter 4 adds fuel-cell electric buses to the model, comparing the two technologies and considering the benefits of a mixed-technology approach to transitioning fleets to ZEBs. We found that

such an approach has several benefits, being able to serve networks that an all-or-nothing approach to batteries and hydrogen otherwise couldn't, while also costing less in terms of vehicles, infrastructure, and fuel. Although operational complications are not accounted for, this new paradigm of mixed-technology networks shows great promise in being a solution to the ZEB transition problem and should be explored further in future research.

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1 Introduction and Motivation

1.1 Policy Environment

Climate change is one of the largest and most urgent challenges facing humanity today. As people around the world continue to face the challenge of climate change, the reduction of greenhouse gas (GHG) emissions remains one of the most important and effective tools available to humanity to mitigate its effects. In 2020, the US Environmental Protection Agency (EPA) estimated that the transportation sector caused 27.3% of the United States's GHG emissions [1]. To address this challenge, many sectors of transportation are moving towards electrification. For example, electric personal use vehicle sales in California have increased from approximately 0.4% of new car sales in 2011 to approximately 12.41% of new vehicle sales in 2021 [2]. What is more, several states have enacted regulations or commitments to increase the number of zero-emission vehicles (ZEVs) in all sectors in the next few decades.

California in particular has created several regulations that require certain sectors to transition to ZEVs over time. One of these regulations is the Innovative Clean Transit (ICT) regulation, a part of a larger strategy on heavy-duty vehicles and their transition to zero-emission alternatives. ICT requires that transit agencies ensure that a certain percentage of their new bus purchases be zero-emission buses (ZEBs) beginning in 2023, increasing with time, until all new bus purchases must be ZEBs by 2028 [3]. With this regulation, the California Air Resources Board (CARB) expects that the entire state's transit bus fleet will be transitioned to ZEB alternatives by the early 2040s.

1.2 ZEB Technologies

At present, there are two types of ZEB technology available to transit agencies. The first of these is battery electric buses (BEBs). These buses carry an on-board battery pack that is used as the primary energy storage on the bus. These packs are far larger than those found on cars, with pack sizes ranging from approximately 150 kWh to as large as nearly 700 kWh. These buses may recharge overnight in a bus depot or may charge during a service day at opportunity charging stations located strategically along a bus's route. Recharging overnight using a depot charger is typically done at power levels between 40-100 kW, with 65 kW being a typical value. This process takes approximately 3-6 hours depending on the size of the battery pack of the bus and the speed of the charger. Opportunity charging works differently; these chargers operate at higher power levels (300-600 kW or more) and typical charging sessions take between 10-15 minutes. In that time, a bus isn't expected to fully recharge; instead, the charging takes place in such a way that the bus can complete its assigned duty cycle with a smaller battery pack than it would otherwise require. This not only lowers the purchase price of the bus, but it also improves the energy efficiency of the vehicle due to the weight savings of the battery pack.

Fuel cell electric buses (FCEBs) are a less mature technology than BEBs, with far fewer FCEBs being utilized by transit agencies today. FCEBs carry a tank of hydrogen that is used to generate electricity in a fuel cell. This electricity is used to charge a small on-board battery pack, which in turn is used to power an electric motor. There are several aspects of FCEBs that make them an attractive option for transit agencies. Primarily, FCEB refueling takes a very short amount of time. Refilling an FCEB is comparable to refueling a fossil-fuel powered bus, requiring very little change in operations after a transition is made. This is a significant advantage compared to BEBs, which can take several hours to recharge. However, there are several obstacles that make FCEBs a difficult proposition. Hydrogen fuel is not produced at a scale to support a large number of FCEBs entering service in the next decade, nor is distribution available at a scale to meet the new demand. Both of these factors and more contribute to the relatively high cost of hydrogen fuel, making transitioning to FCEBs a costly proposition.

1.3 State of the Art

The transition to BEBs is a process that has been in motion for over a decade. Shenzhen in China boasts one of the world's largest all-electric BEB fleet, at over 17,000 buses. The process for electrifying Shenzhen's bus fleet began in 2011 and completed in 2017. The buses were deployed in stages, beginning with a demonstration phase in 2009, small-scale deployments from 2011 to 2015, and finally full electrification by 2017. The majority of these buses are Build Your Dreams (BYD) vehicles, and all are served by depot chargers around the city. Countries in Central and South America have also proven to be early adopters of BEBs. For example. Chile, Costa Rica, and Ecuador all have BEBs active in their cities, with more countries committing to follow their examples. India also placed an order for 1000 BEBs in 2019, representing the second largest such order at the time. The European Union has also adopted policies on transitioning transit buses to ZEBs, especially the Zero-Emission Urban Electric Bus System (ZeEUS). The Netherlands, France, and Sweden have emerged as early leaders in Europe, though many other nations are running demonstration-level deployments with scaling plans for the next decade.

In the United States, CALSTART estimates that in September of 2021, there were approximately 1287 ZEBs currently deployed with a total of 3533 funded or planned vehicles (including the currently deployed vehicles). Of these planned vehicles, CALSTART estimates that 3364 are BEBs, with only 169 FCEBs planned [4]. Despite this small number, there is growing interest in FCEBs due to certain operational advantages that the technology provides, if the obstacles of high cost and fuel availability can be overcome. Several transit agencies are planning or have begun pilot projects to determine the best ZEB type to suit their network and operations. These projects have been an invaluable source of data and information on ZEB operations and understanding the challenges of ZEB deployments.

In response to this availability of data, many studies have been performed on transit networks, modeling them to discover their fitness for different kinds of ZEBs. These studies have each focused on their particular network of interest and have generally relied on data specific to that network to generate their model and results. However, the number of studies that examine the trends of fitness for ZEBs across several networks is still relatively small. Methodologies may be transferable, but the trends of ZEB fitness across different networks have the potential to be enlightening for policymakers and transit agencies alike. These trends may give insight into what makes FCEBs better fit than BEBs (or vice versa) in certain situations, and what kinds of transit agencies may have gaps where neither technology may be the appropriate solution as they exist today. This work sought to begin uncovering these trends. By developing a model that is widely applicable across any kind of transit network and relying only on standardized, publicly available data, we were able to find an optimal economic solution for ZEB deployments in many networks around the United States. The research showed that these trends can meaningfully impact the way ZEB deployments are approached by both transit agencies and policymakers by providing insight into the economically optimized solutions across different networks, expanding our ability to ease the transition to 100% ZEBs in the transit bus sector.

1.4 Structure

This dissertation is structured in five chapters, each with its own specific purpose. Chapter 1 covers background information and motivation behind the research. Chapters 2 through 4 are independent research papers presented in full, each of which represents a stage in the model's development. Chapter 2 focuses on the development of the modeling method and examining some of the sources of uncertainty present when modeling transit bus networks. This foundational method is expanded upon in Chapter 3, where the model is generalized and run on 78 transit networks in the United States. The results from Chapter 3 showed that the current strategies for electrification of transit networks using 100% BEBs are not suitable for all networks and that a more nuanced approach to network electrification may be required in certain cases. To examine one form of alternate strategy, Chapter 4 models a mixed-technology approach to transit networks, considering the economic advantages of mixing FCEBs with BEBs in a ZEB network. Finally, Chapter 5 summarizes the general findings of the research and discusses some limitations and potential future directions for investigation.

2 Examining Energy Uncertainty in Battery Bus Deployments for Transit Agencies in California

2.1 Introduction

In 2018, the US Environmental Protection Agency (EPA) estimated that in the United States of America (USA), the transportation sector accounts for almost 28.2% of greenhouse gas (GHG) emissions [5], the highest among all major energy sectors. In California, on-road fossil-fuel buses estimated to have contributed 1.36 million tons of GHG emissions to California's annual total [6]. Studies have found that transitioning from conventionally fueled vehicles to electrically- or hydrogen-powered vehicles is an effective means of curbing this GHG contribution [7]. In December 2018, the California Air Resources Board (CARB) adopted a regulation require that transit fleets begin the shift to zero-emission buses known as Innovative Clean Transit (ICT) to lower these emissions. ICT affects the purchase of new buses, beginning in 2023 [3]. CARB estimates that the transit bus fleet will complete the transition to 100% zero-emission buses (ZEBs) by the 2040s.

In the wake of this regulation, a transition to ZEBs has already begun in California. Some transit agencies have begun early pilot projects in preparation for a full transition or are planning an earlier-than-required transition to ZEBs to establish themselves as leaders in the field. A survey of transit agencies in the state found 551 battery-electric buses (BEBs) and 38 fuel cell electric buses (FCEBs) that have been deployed in California and an additional 531 BEBs and 8 FCEBs being planned for deployment in the next 5 years. One agency has already completely transitioned its 85-bus fleet to BEBs, and many others that have firm plans to complete their transition ahead of what the ICT timeline. Although these 1,094 buses are currently a relatively small portion of California's 12,500 transit bus fleet, CARB estimates that adoption will accelerate during the middle or end of this decade (Figure 2.1).

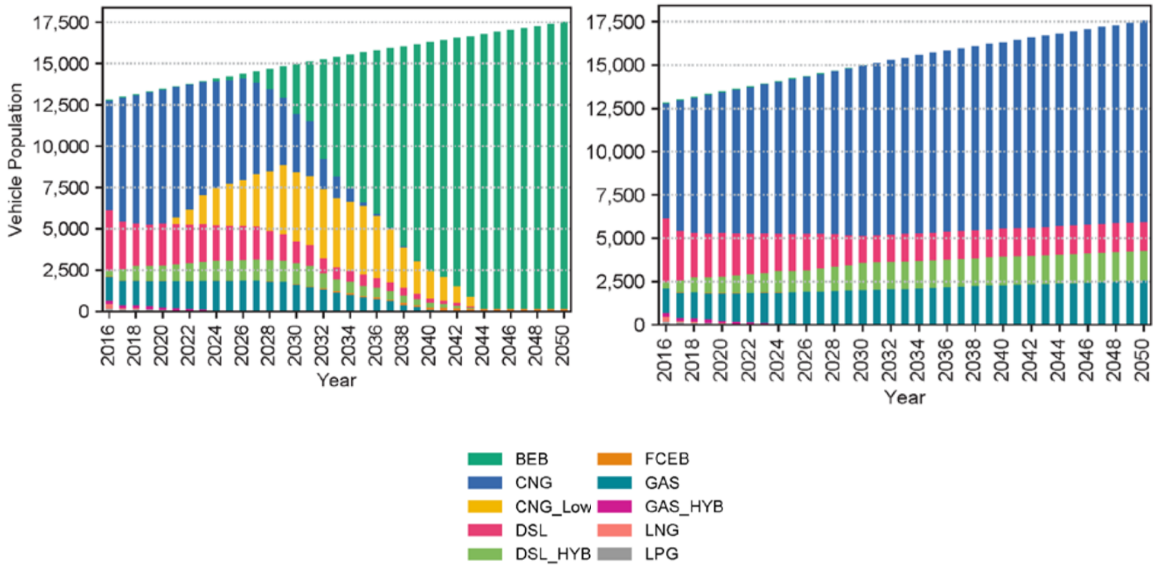


Figure 2.1: CARB projections of the California transit bus fleet population (left) under the ICT regulations adopted in December 2018 and (right) under the previous Business as Usual (BAU) scenario [8][1]

The high costs of ZEB fleet transitions have been examined as parts of demonstration-scale deployments [9], [10], and have been used as inputs in other studies focusing on total cost of ownership [11], [12]. Although the vehicle represents the largest upfront cost, the infrastructure to support these buses is usually one of the first decisions an agency must make when planning a ZEB transition and also represents a significant upfront capital investment. In discussions with transit agencies, it was found that this high cost combined with an overall lack of a knowledge base to draw information from represents a significant obstacle to a willingness to invest heavily in BEB technologies. Agencies currently lack many of the tools to make optimal choices of bus type and infrastructure plan, and rely on expensive, bespoke analyses from third parties to develop a deployment plan. Additionally, there are many sources of uncertainty when estimating the energy use of battery electric buses in real-world

[1] Abbreviations: BEB – Battery Electric Bus; CNG – Compressed Natural Gas; CNG_Low – Low-NOx CNG; DSL – Diesel; DSL_HYB – Diesel Hybrid; FCEB – Fuel Cell Electric Bus; GAS – Gasoline; GAS_HYB – Gasoline Hybrid; LNG – Liquified Natural Gas; LPG – Liquified Petroleum Gas (primarily propane and butane)

conditions. Accounting for these sources of energy uncertainty can drastically affect the decisions surrounding the architecture of ZEB networks, especially when it comes to infrastructure.

This study presents a novel tool for examining the interacting effects of different characteristics of BEB networks on the required vehicles and infrastructure of the system. After a review of other methods that have been used to optimize bus infrastructure, this chapter presents the model as an optimization that aims at supporting the choices a transit agency makes when deploying BEBs. In Addition, an analysis of the effects of uncertainty in energy use by BEBs due to changes in ambient temperature, passenger load, and drive cycle aggressiveness on a network's architecture is presented. From this analysis, conclusions are drawn about the importance of considering these sources of uncertainty when planning a deployment strategy for a BEB network.

2.1.1 Electric Bus Deployment Decisions

Interviews with transit agencies revealed that the decisions that are important from a planning perspective are not necessarily simply about the parts that cost the most. Although several studies have found that infrastructure costs represent a relatively small part of the overall cost of transitioning to a ZEB fleet [13], [14], the selection of infrastructure and charging strategy (or strategies) is one of the first decisions that gets made after planning to perform a full BEB fleet transition. This infrastructure decision drives the rest of the transition process for transit agencies, and these decisions can carry significant implications on the makeup of the transit agency for years or decades to follow. Electric bus charging is currently split between two strategies: opportunity charging and depot charging. Different physical technologies and technical standards have emerged for each, and each has their benefits and drawbacks.

Depot charging is a strategy that employs charging at a bus depot which is owned and operated by the transit agency and uses relatively lower-powered chargers to recharge buses. These chargers are capable of charging at a power of up to approximately 125 kW in most current installations, though future installations of between 200-300 kW are planned [15], [16]. In general, these buses take between 2-6 hours to fully recharge, depending on the specifications of the battery pack and the charger [15], and must carry large battery packs to have adequate range for their shift [17].

Opportunity charging is an alternate method to the depot charging. Rather than charging all buses while they are off shift in a depot, high-power chargers are placed at strategic points along one (or more) routes for buses to recharge briefly at those locations. These chargers tend to have power levels of 300-500 kW or higher, though the specifics change depending on the technology used in the implementation [15], [18], [19]. As a bus travels along its route, it will 'top off' or recharge its battery pack at these locations, taking between 5-15 minutes to recharge to get the range it needs to travel the route. Buses operating under an opportunity charging system can have smaller battery packs as a result, lowering the overall per-vehicle cost relative to depot charging buses [17]. These buses can also be charged in a depot, resulting in increased operational flexibility.

In general, the relative cost performance of these strategies depends on the utilization of these chargers. The more a charger can be used during any given length of time, the better its cost performance will be. Often, depot chargers are set up in a one-charger-per-bus configuration. During normal service hours, many of these chargers are left idle, which decreases their relative cost performance. Conversely, opportunity chargers are used frequently by many buses, increasing their cost performance. This better uptime can overcome the increased upfront cost of opportunity chargers in certain situations.

2.1.2 Literature Review

There are many different ways to approach optimizing infrastructure for BEB deployment, with a variety of previous work to match. Early studies tended to focus on studying complex interactions in isolation of the large bus system by focusing on a single line or vehicle. An example of such a study by Chen focused on the interaction between charging infrastructure, vehicle battery sizing, and on-site energy storage, optimizing choices for a single transit line with a goal of minimizing total lifetime cost [20]. The other main focus of early studies was to focus on a single aspect of a larger transit system, exemplified by Paul and Yamada, who focused on adjusting schedules to maximize the amount of distance travelled by BEBs in a transit network [21]. Most of these early studies used infrastructure or charging speed and behavior as a constraint, rather than as a focus of study. By restricting infrastructure decisions in this manner, these studies build the network by selecting vehicles around the infrastructure. This contrasts with the way transit agencies deploy BEBs, in which infrastructure is typically purchased after vehicles have been deployed (or planned for deployment).

Another common form of study is examining the feasibility or cost of transitioning entire networks to ZEBs as the technology became a more popular choice for lowering urban emissions (**Error! Reference source not found.**). These studies are a mixture of full ZEB transitions, and partial transitions where an optimal mix of vehicle types was found.

Table 2.1: Sample List of Location Specific BEB Studies

Study	Location	Number of Buses in Agency	Methods	Primary Findings
[22]	Park City, Utah, United States	45	Scenario Simulation	Uncoordinated use of BEB chargers may result in exceeding the voltage limit of the system, as well as abrupt current variation and high active energy loss. Introducing coordinated scheduling significantly reduces these losses.
[23]	Connecticut, United States	>400	Mixed-Integer Program	Optimal cost solution occurs at 79% fleet electrification. GHG can

				be reduced further with further electrification.
[24]	Shenzhen, China	16,359	Mixed-Integer Second-Order Cone Program with “No R” Algorithm	A set of locations to build ‘mega-depots’ around the city of Shenzhen was found.
[11]	Aachen, Germany and Roskilde/Copenhagen, Denmark	Varies (number of buses for 2 lines were optimized)	Grouping Genetic Algorithm with Mixed-Integer Non-Linear Program Formulation	Two scenarios (A and B) were developed. Scenario A found that BEBs could replace diesel buses 1-for-1 if they were large enough. In scenario B, this replacement was not possible. The optimal electrification is a heterogenous mix of the two vehicle types, with further savings possible through charger optimization.
[25]	Bangkok, Thailand	Varies	Drive cycle modeling in high-traffic environments, with and without opportunity charging	Including opportunity charging produced energy savings. Charging times and battery pack sizes were found to be more important than total range. Auxiliary loads have a significant impact on energy use.
[26]	Turkey	Varies (entire country is studied)	Mixed-Integer Program	130 of the 136 potential locations were selected to receive a charging station. Driving range of the buses had the largest impact on the overall cost of the system in a sensitivity analysis. The capacity of the charging system was dictated by the number of intercity routes converging on a certain node, not the population of the node itself.

[27]	Stockholm, Sweden	Varies (143 routes were studied)	Mixed-Integer Linear Program	Optimizing for costs results in 42 electrified routes and 101 biodiesel routes, with no cost increase relative to the 'business as usual' scenario. Energy use optimization results in 94 electrified routes, generally closer to the city center.
[28]	Greater Salt Lake City Area, Utah, United States	Varies (system operates 467 buses, different numbers were selected for electrification)	Bi-Objective Optimization Model	Tradeoff between cost and environmental equity works on a logarithmic scale. Bi-objective model formulation is flexible with many applications in a system like public transit with many different pressures

These studies typically did not focus on infrastructure deployment in particular; it was taken as a small part of the larger system. They are suited for policy recommendations and outcome measurement, but other transit agencies cannot derive useful ways to make decisions about how to transition to ZEBs from such studies.

More recently, studies have taken a deeper dive into some particular parts of BEB deployment, developing methodologies to optimize some of the smaller problems associated with deployment. Topics of interest have varied from scheduling and queue resolution in scheduling [29], [30] to larger scale life cycle analysis (LCA) or well-to-wheel (WTW) approaches [12], [31], [32]. The outcomes of these studies are very helpful for research work, as these specific models have informed many of the decisions made in modern ZEB transition optimization studies. Most of these studies have focused on optimizing system costs based on a specific transit system or systems of interest. An example of such a study is that carried out by El-Taweel and others on three small networks in Canada [33]. This study focused on making very specific decisions about charging infrastructure; that is, what type and how many chargers were appropriate for that particular network. A study by Kunith and others represents a very complete study on optimization of infrastructure deployment for BEBs in Berlin [34]. Kunith's study included factors such as battery sizing, infrastructure location, and route-based energy demand simulation in this study. This study relies on a bespoke recording of the tractive force and drive cycle for the studied transit network, limiting its generalizability to other transit networks.

Recently, there has been a move to generalize infrastructure models to allow them to be applied to networks other than the one they were built for without substantial changes and adjustments to the model. Li, Lo, and Xiao presented a thorough model based on an integer linear program. The model was successfully applied to both a theoretical small network, and a simplified version was applied to Hong Kong's bus system [35]. Although the model was successfully used to examine several policies related to BEBs, it was reported that issues arose when applying the model to networks with a large number of origin-destination pairs. Pelletier and others developed an integer linear programming model that examines the transition problem for BEB fleets in a variety of forecasted values for energy prices [13]. The model generated useful results but did not provide many insights in the moment-to-moment operation that the studied network would experience. Lotfi and others developed a model that attempted to capture as many aspects of a BEB network as possible to generate a mixed-integer linear program with the goal of minimizing total ownership [36]. However, this model wasn't applied to an existing network; the authors intentionally applied the model to arbitrary networks, which negated the possibility of benchmarking the model's performance against any kind of an existing case. The model presented in this chapter seeks to add to the range of new models being produced by focusing on the types of data available to transit agencies (timetables, route data that is already collected, etc.) and the decisions that these agencies must make when planning a transition of their full fleet to BEBs to develop a model that focuses on the right mixture of bus types and infrastructure types, and where to install infrastructure that will be used for opportunity charging from among a list of candidate locations.

The impact of various factors on the energy use of buses has been studied, although the impacts on BEBs in particular are still a new area of inquiry. Three main factors have emerged as primary contributors to energy uncertainty in BEBs: passenger load, climate control, and driver behavior (also referred to as drive cycle variation or kinetic intensity). Passenger loading is well known to be an impacting factor on bus energy use in general, and has been studied in that context several times (Liu et al., 2019; Yu et al., 2016 for example). Studies have found that BEBs are resistant to a large increase in energy use from large payloads because of regenerative braking. The effectiveness of regenerative braking depends on the overall aggressiveness of the drive cycle, as 'aggressive' driving cycles tend to have instances of high speed or of stop-and-go driving patterns, both of which are regions where regenerative braking's performance is limited due to system and vehicle dynamics [39], [40]. Studies have found values for energy consumption of a full BEB increasing between 11% [41] to 20% [37] when at high payloads (compared with an empty bus).

The effects of the air conditioning system on a battery electric vehicle have been examined in many studies. Vepsäläinen and others found that the effect of ambient temperature on a BEB can be classified as an "Extensive Noise Factor"; that is, dynamically unpredictable, but with knowable shape and variance that can be used to characterize its effect on the energy use of the vehicle [42]. Zhou and others measured the effect of air conditioning under nearly-worst-case scenarios (Summer in Macau with the system set to maximum) and found that it contributed to an increase in energy use of approximately 10-25% depending on the loading, traffic, and ambient conditions [41]. A detailed background on the overall effect of ambient temperature on this study is available in Appendix A.

Understanding the precise effects of the driver behavior on a BEB route is complicated by several realities of study. In general, it has been found that effect of the kinetic intensity or 'aggressiveness' of the drive cycle (characterized by high-acceleration events, fast stops, high speeds, and irregular speed and acceleration) can have the highest impact on energy use under certain circumstances [43] and that those effects can exacerbate the impact of other factors, especially in load factor and heavy traffic conditions [37], [44]. However, very few studies examine the prevalence of aggressive driving, especially in BEBs. In addition to driver behavior, the KI of the drive cycle can also be affected by external factors, including traffic conditions, geography of the route, number of stops the bus has to make, etc. Although some of these factors are knowable or predictable (such as traffic and elevation change), many are not (such as road conditions, passenger load balance, and the distribution of power between battery cells, as examples) [42].

2.2 Methods and Data

The primary goal of this study was to support the decisions a transit operator would have to make when designing a BEB deployment. Interviews conducted with transit agencies revealed that usually, agencies prefer to focus on meeting their current timetable, with as little disruption to existing service as possible. Agencies are additionally constrained by the configurations of BEBs that are available; there are limitations on the flexibility offered to transit agencies by BEB manufacturers. These limitations were the guiding principle for the formation of this optimization model.

2.2.1 Optimization

The optimization problem formulated for this model is a mixed-integer linear programming (MILP) problem. This formulation has been used many times for similar problems of infrastructure optimization [11], [20], [23], [45], [46]. In general, the nomenclature used in this project uses x to connote a variable, with other letters connoting parameters or sets. Superscripts are used to name the parameter or variable, and subscripts are used to show dependencies. The nomenclature used to define this optimization (Table 2.2) is as follows:

Table 2.2: Optimization Nomenclature

Symbol	Meaning	Units
Sets		
$r; R$	A route in the system; a set of all r	None
$b; B$	A bus "type"; a set of all bus types (a bus type constitutes a vehicle with a specific battery capacity, energy use, and vehicle cost associated with it)	None
$l; L$	A candidate location to install infrastructure; a set of all candidate locations	None
$t; T$	A time during a period of operation; a set of all times tracked	seconds
Parameters		
C_{buses}	Cost of bus purchase and operation	$USD
$c_b^{bus.cost}$	Cost of bus type b	$USD
$c_b^{bus.capacity}$	Energy capacity of the battery pack of bus type b	kWh
$c^{energy.cost}$	Energy cost	$USD
$c_{b,r}^{energy.use}$	Energy used by bus type b on route r	kWh
$c^{service.time}$	Total time a bus is in service	seconds
$c^{depot.cost}$	Cost of a depot charger	$USD
$c^{opp.cost}$	Cost of an opportunity charger	$USD
$c^{opp.rate}$	Rate of charging available at an opportunity charger	kW
$c_r^{route.demand}$	Total number of times route r is to be served	None
$c_r^{route.time}$	Total time (travel time plus idle time) for a bus to travel on route r	seconds
$c_r^{route.headway}$	Headway of route r	seconds
$c^{opp.ratio}$	Number of depot chargers effectively replaced by each opportunity charger	None
$c_b^{can.opp}$	A binary parameter describing whether a bus of type b is able to opportunity charge	None
$c_{r,l}^{route.loc}$	A binary parameter describing whether a bus serving route r can charge at location l	None
$c_{r,l,t}^{bus.status}$	A binary parameter describing whether a bus serving route r is at location l at time t (1 if the bus is in the location, 0 if it is not). Note that only buses that can opportunity charge are tracked in this parameter.	None
Variables		
C_{system}	Total system cost	$USD
$x_{b,r}^{bus.number}$	Number of buses of type b assigned to route r	None
$x^{depot.number}$	Number of depot chargers	None
$x_{b,r}^{bus.assign}$	Number of times a bus of type b is assigned to route r	None
$x_{r,l,t}^{charge.bus}$	A binary variable describing whether to charge a bus serving route r at location l and at time t	None

$x_{l,t}^{charge.avail}$	Number of chargers available at location l and at time t	None
$x_{l}^{opp.number}$	Number of opportunity chargers at candidate location l	None
$x_{l}^{served.bus}$	The number of buses that are served by opportunity chargers at location l	None

The overall goal of the optimization is to minimize system cost. This cost can be broken into three main parts: the upfront cost of purchasing buses, the upfront cost of purchasing infrastructure, and the energy cost associated with operating the buses over their lifetime. This cost minimization is described by Equation 2.1, with Equation 2.2 separately describing the costs of purchasing and operating buses to more clearly illustrate how this is calculated:

$$\min\,(C_{system}) = C_{buses} + x^{depot.number} * c^{depot.cost} + \sum_{l=1}^{L} x_{l}^{opp.number} * c^{opp.cost} \tag{2.1}$$

$$C_{buses} = \sum_{b=1}^{B}\sum_{r=1}^{R}\left(x_{b,r}^{bus.number} * c_{b}^{bus.cost} + c^{energy.cost} * c_{b,r}^{energy.use} * c^{service.time}\right) \tag{2.2}$$

The constraints of the optimization are described in Equations 2.3-2.12. Equations 2.3 and 2.4 require that buses serve the timetable:

$$\sum_{b=1}^{B} x_{b,r}^{bus.assign} \geq c_{r}^{route.demand} \quad \forall\, r \in R \tag{2.3}$$

$$\sum_{b=1}^{B} x_{b,r}^{bus.number} \geq \frac{c_{r}^{route.time}}{c_{r}^{route.headway}} \quad \forall\, r \in R \tag{2.4}$$

Equations 2.5 and 2.6 ensure that an appropriate number of buses are purchased:

$$x_{b,r}^{bus.number} \geq \frac{x_{b,r}^{bus.assign}}{c_{r}^{route.demand}} \quad \forall\, b \in B,\ \forall\, r \in R \tag{2.5}$$

$$x_{b,r}^{bus.number} \leq x_{b,r}^{bus.assign} \quad \forall\, b \in B,\ \forall\, r \in R \tag{2.6}$$

Equation 2.7 requires that the purchased buses have enough total energy capacity to serve the total energy demanded by the system's timetable:

$$x_{b,r}^{bus.number} * c_{b}^{bus.energy} \geq c_{b,r}^{energy.use} * x_{b,r}^{bus.assign} - \sum_{l=1}^{L}\sum_{t=1}^{T}\left(x_{l,t}^{charge.avail} * c^{opp.rate}\right)$$

$$\forall b \in B,\ \ \forall r \in R \tag{2.7}$$

Equation 2.8 requires that the number of charging buses be less than the total number of chargers at any location and time:

$$\sum_{r=1}^{R} x_{r,l,t}^{charge.bus} \leq x_l^{opp.number} \quad \forall\, l \in L,\ \ \forall\, t \in T \tag{2.8}$$

Equation 2.9 requires that a bus be in a candidate location to charge:

$$c_{r,l,t}^{bus.status} \geq x_{r,l,t}^{charge.bus} \quad \forall\, r \in R,\ \ \forall\, l \in L,\ \ \forall\, t \in T \tag{2.9}$$

Equations 2.10 and 2.11 calculate the number of buses served by opportunity chargers:

$$x_l^{served.bus} \leq c^{opp.ratio} * x_l^{opp.number} \quad \forall\, l \in L \tag{2.10}$$

$$x_l^{served.bus} \leq \sum_{b=1}^{B} \sum_{r=1}^{R} \left(c_b^{can.opp} * x_{b,r}^{bus.number} * c_{r,l}^{route.loc} \right) \quad \forall\, l \in L \tag{2.11}$$

Equation 2.12 calculates the number of required depot chargers to serve the remaining buses:

$$x^{depot.number} \geq \sum_{b=1}^{B} \sum_{r=1}^{R} x_{b,r}^{bus.number} - \sum_{l=1}^{L} x_l^{served.bus} \tag{2.12}$$

To minimize the cost, bus types are assigned to routes enough times to meet the pre-existing timetable demands of the transit system. The model can assign each bus type any number of times, but the total assignments must meet the demand of the schedule. After assigning the bus types, the model purchases enough buses of each type to satisfy the total energy demand of each bus type on each route. After buses are purchased and assigned, infrastructure is purchased and assigned based on the number(s) of each type of bus purchased and based on whether it is more cost effective (or even possible) to serve buses through opportunity charging or depot charging. No extra equipment is purchased. The total cost of the system is then calculated by adding the upfront capital cost of purchasing the equipment with the energy cost of running the routes for the period of study, assuming a constant energy cost per kilowatt-hour. The model does not modify the schedule or timetable of the transit agency in any way.

2.2.2 Case Study Data Sources

2.2.2.1 Vehicle Data

Vehicle data used in this model is relatively simplistic: the model requires the vehicle's total cost and the capacity of the vehicle's battery pack. In the case study, these parameters are taken from existing BEBs available in California: the Proterra Catalyst 35-foot XR, the Proterra Catalyst 40-foot E2, the Build Your Dreams (BYD) 45-foot double-decker bus. All of these buses can be used for depot charging, but some are also able to fast charge. The data for the buses used in the case study (Table 2.3) were taken from the manufacturers' websites or, where the manufacturer's website doesn't have the relevant information, from interviews with transit agencies and manufacturers. The available vehicles and their attributes are used as input parameters to this model.

Table 2.3: Bus data for case study (all data taken from 2020 model-year information)

Bus	**Price (US$)**	**Battery Capacity (kWh)**	**Type of Charging**	**Reported Average DC Energy Use (kWh/mile)***
Proterra Catalyst XR, 35-Foot	$650,000	220	Depot	1.73 [47]
Proterra Catalyst E2, 40-Foot	$750,000	440	Both	1.87 [48]
BYD 45-Foot Double-Decker	$800,000	446	Depot	1.93 [49]

*Note that this value does not reflect the energy use of the buses that was used in this study.

2.2.2.2 Route Data

The route data for this case study is based on the Unitrans system, the public transit bus system of the city of Davis, California. The transit system is made up of 19 routes denoted by letter, each operating from one of two hubs (with exceptions for two special routes and weekend service). The agency operates between 30 and 40 vehicles on these routes depending on daily ridership demand.

Most of these vehicles are 40-foot compressed natural gas (CNG) buses. The routes service the town itself (Figure 2.2), with routes ranging in length from 2.5 miles to 13.5 miles. Route timings, including headways and expected travel time, were taken from the Unitrans normal weekday service timetable from Autumn of 2019. The T and O routes were omitted, as these are non-regular routes that run only at specific times.

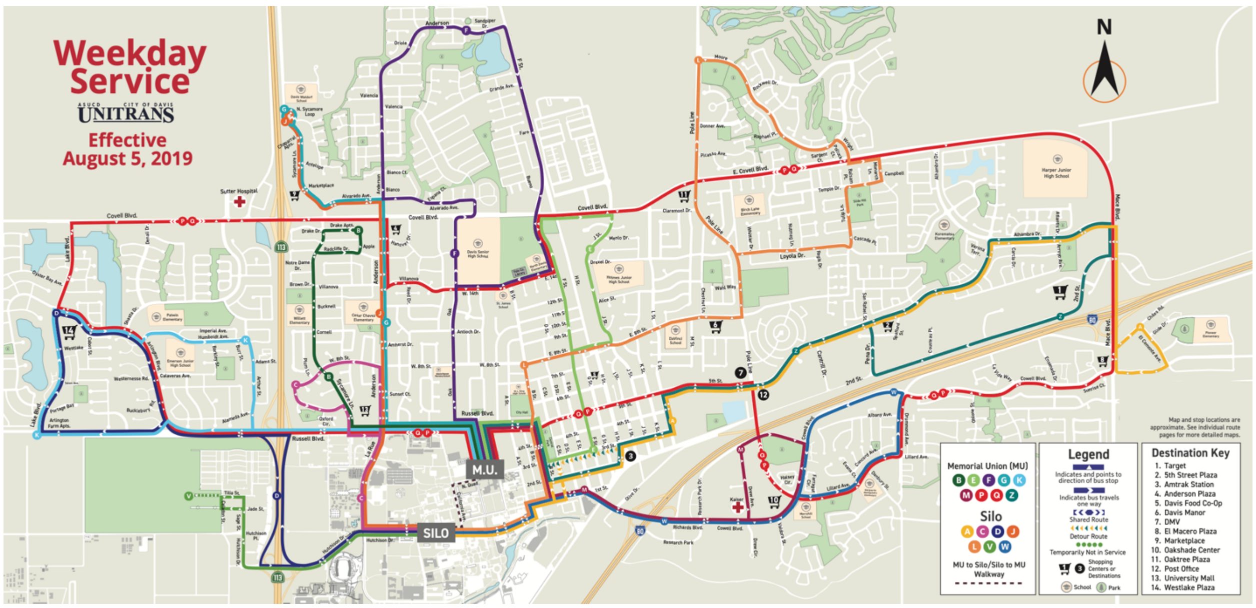


Figure 2.2 A map of weekday service for the case study transit system (source: Unitrans)

2.2.2.3 Energy Use Data

For this model, energy requirements are generated on a bus-route-pair basis from a model developed by Ambrose and others [50]. Ambrose's model uses data from the FleetDNA dataset developed by the National Renewable Energy Laboratory (NREL) [51] to develop energy demands for a particular bus-route combination using a transit agency's General Transit Feed Specification (GTFS) data. GTFS is a standard that transit agencies can use to make their data available for use in third-party applications. GTFS specifies the set of files that must be included in a feed, which are used in this calculation.

2.2.2.4 Other Data Sources

There are several other data that were used as inputs to the model (Table 2.4).

Table 2.4: Data inputs for the case study and their sources

Parameter Name	**Parameter Value**	**Source**
Candidate Locations	Memorial Union (Location 1), Silo (Location 2)	Interviews with Unitrans
Energy Cost	$0.1408 per kWh	Commercial average for electricity in region
Bus Service Time	12 years	Federal requirements, Interviews with transit agencies
Depot Charger Cost	$100,000	[14], [16], Interviews with transit agencies
Opportunity Charger Cost	$600,000	[10], [14], Interviews with transit agencies
Opportunity Recharge Rate	350 kW	Bus specifications
Opportunity Ratio	7 buses per charger	Interviews with transit agencies (see Appendix B)

Candidate locations were selected based on interviews with Unitrans. In those interviews, Unitrans stated that they are limiting the locations where they will consider placing opportunity chargers. Although many stops within the system serve multiple lines, Unitrans is only interested in installing infrastructure in two key locations (the two major hubs of the system) due to cost, permitting, and land use concerns. Charging time is not explicitly constrained; the amount of time a bus is able to charge is an emergent quality of the model. Buses are given an energy credit for charging and are thus encouraged to charge as much as possible but must serve routes when they come up in the timetable before charging. The opportunity ratio (the number of depot chargers an opportunity chargers can effectively replace) was also selected based on interviews with transit agencies operating BEB fleets. This value can vary significantly between agencies and even within an agency day-to-day based on external conditions, such as traffic, weather, or other similar factors. In a small sensitivity study, it was determined that the overall impact of this value on the model is relatively small within a nominal range of values (see Appendix B), and an average value found from discussions with transit agencies was used.

2.2.3 Energy Uncertainty

To understand the effect of energy uncertainty on the overall system design of a BEB transit network, an uncertainty analysis was run on the initial optimization results. The particular type of uncertainty analysis performed on the model was one-way sensitivity analysis, sometimes referred to as 'nominal-range sensitivity analysis'[52]. This analysis is used to understand the impact of changing singular model inputs across a range of values while holding other inputs at their base-case values [52]–[55] and is commonly used to understand the impacts of uncertainty of that particular input on the model as a whole [55]–[57]. This uncertainty analysis took the form of a Monte Carlo analysis focusing on the effects of uncertainty in the energy use of the vehicles based on known distributions of contributions to BEB energy use. For each run of the model, variation in driver energy use was the first factor to be calculated. The distribution of BEB energy use within a population of BEB drivers was based on a study by Kontou and Miles, who studied the results of a BEB pilot program in Milton Keynes in England [9]. The values for driver energy use took the form of a right-skewed normal distribution (Table 2.5). This value is meant to capture the effects of the aggressiveness of the drive cycle, including primarily driver behavior, but also sudden stop-and-go traffic conditions, number of stops to be serviced, and other reasons that a drive cycle might be more or less 'aggressive'. The behavior of individual drivers varies in an unpredictable way from network to network, but it is expected that this sample from the Milton Keynes project can serve as a representative example of how a variety of people drive BEBs in an urban/suburban environment.

Passenger loading was simulated by developing another right-skewed normal distribution from Unitrans's observed ridership (Table 2.5). This function is specific to Unitrans and would need to be redeveloped from ridership data if applied to another transit network. Ridership of Unitrans tends to follow a few predictable trends as laid out in the general manager's report [58]. Buses are considered 'overcrowded' if they carry 60 passengers or more (if an average weight of 150lbs or 68 kg is assumed, this is a mass increase of 9000 pounds or 4082 kg), which occurs 3.5% of the time on Unitrans. Once a ridership value is selected, a penalty of between 0% (empty bus) and 25% (fully crowded bus) is selected based off of the assessment of several studies that find a linear relationship between ridership and energy use [37], [38], [41]. One of the benefits of BEBs operating in crowded conditions is that extra energy can be retrieved through the regenerative braking system. The ability of a driver to retrieve energy from the system depends on how they treat the braking system; in aggressive drive cycles where the brakes are used more 'roughly' are able to retrieve less energy than drivers who are more careful and have training in how to operate regenerative braking systems [39], [44]. To account for this difference, the 'mitigation' of the loading penalty due to regenerative braking is dependent on the driver aggressiveness selected. For values of 1.0 or below, it is assumed that a driver will be able to mitigate the effects of loading by 80% (studies by Liu and others have found that the energy savings can be as high as 90% in theoretical best operation, though it is unlikely that humans can operate the bus to that degree of precision) [37]. For values of 1.6 and above, it is assumed that the driver is still able to mitigate loading effects by 20%. Values in between are assigned a mitigation value on a linear relation basis.

Penalty due to ambient temperature is assigned based on historical weather data for the city of Davis. A temperature profile is selected at random from among the days of the year, and the penalty value is assessed as a comparison to the 'worst case' over the course of the year. Studies under these worst case scenarios have found that the air conditioning can add as much as 25% to the energy consumption on most types of routes [41] (for a more detailed overview of how ambient temperature affects the studied system, see Appendix A). The energy penalty of the value is assigned based on how much and how long the temperature is above the cabin setting compared with the worst day of the year. Additionally, for situations where passenger crowding is high (60 passengers or higher), the temperatures are increased by 3 degrees to account for the added heat and humidity produced by the passengers in the enclosed space.

Finally, an additional factor is included in the total penalty to account for small, random effects on the bus in aggregate as discussed in section 1.2 (Table 2.5). These effects are generally uncontrollable and unpredictable. Factors like the road conditions, particular maintenance condition of the buses (tire inflation, etc.), battery cell charge imbalance, and others have small individual contributions to the energy efficiency of buses, but can have a significant effect when taken altogether [42]. Because these effects are small, unpredictable, and uncontrollable, they are modeled as random noise impacting the overall energy use of the buses.

Table 2.5: Key parameters for Monte Carlo variable distributions

Variable	Distribution Type	Mean	Standard Deviation	Shape Parameter
Driver Energy Effect	Right-Skewed Normal	1.0	0.3	3.0
Passenger Load	Right-Skewed Normal*	5.0	18.7	5.0
Other Small, Random Contributors	Normal	1.0	0.05	n.a

*Note that values less than 0 were redrawn until a value greater than or equal to 0 was selected for each.

2.2.4 Factors Not Modelled

Public transit systems have many different pressures that affect their decisions, and not all of them are able to be included in this model. Though important, externalities such as public health and access, overall local traffic pressures, and city planning constraints are not explicitly included in the model. There are also additional costs that are not modelled, such as driver labor and training, permitting for construction, and charger maintenance that are not included in this model. The variance that exists for these factors is too high to be included in a generalized model beyond limiting the placement of opportunity chargers to a predetermined set of locations. Although not modeled, the implications of these external factors will be discussed along with the model results. Another factor that isn't included is the passenger capacity of the system. Within Unitrans, buses rarely experience overcrowding to the point that extra vehicles are needed, aside from special events. In conversations with Unitrans, it was indicated that the ability to meet the timetable was a much larger concern to them at this time, and therefore passenger capacity is not used as an indicator of service level. Another major factor not modeled is the changes of scheduling and routing of the buses. In interviews with transit agencies, it was reported that there are currently no plans to institute any changes of this kind. Because this study seeks to model the decisions that transit agencies make when deploying BEBs, the ability to modify routes and timetables was omitted from the possibility space.

2.3 Results

2.3.1 Base Case

The optimization formulated as a MILP problem was solved using a CPLEX solver. The uncertainty analysis was carried out by running the optimization 1000 times with a different energy penalty parameter each time. The results of the base case study (**Table 6**) show the optimized result for Unitrans network with 100% BEBs.

Table 2.6: Base case key results

Variable	**Result**
Purchased Proterra Catalyst XR, 35-Foot	14
Purchased Proterra Catalyst E2, 40-Foot	20
Total Buses	34
Opportunity Chargers – Location 1	2
Opportunity Chargers – Location 2	1
Depot Chargers	14
Total Chargers	17
Total System Cost	$34,653,160
Infrastructure and Bus Cost	$28,300,000

The Agency Forecast scenario's total of 34 buses indicates that Unitrans could theoretically replace their fleet with a similar number of BEBs, as the difference between this total and the Unitrans's current fleet of approximately 40 can be accounted for by the fact that the model does not consider special routes, weekend service, or buses held in reserve. The distribution of the buses along the routes allows for all Proterra Catalyst E2 40-foot buses to be served by opportunity chargers, with the 14 depot chargers being used primarily to charge the Proterra Catalyst XR 35-foot buses (it is assumed that Catalyst E2 buses returning to the depot could be 'topped off' with a spare depot charger). The total cost to build the system is also in line with estimations that Unitrans has received for the cost of a total fleet transition. An interesting aspect of the vehicles selected by the model in the base case is the fact that the model preferred two types of buses in nearly equal amounts. The Proterra Catalyst XR is the overall cheapest and most energy efficient bus the model was able to select from, but the Proterra Catalyst E2 is the least expensive bus on a $/kWh basis. This distribution of buses indicates that the selection of the 'best' type of bus is not a straightforward selection that can be decided by a single metric. Agencies that transition to a BEB fleet need to be sure that all aspects and performance tradeoffs of the various options they have are considered.

2.3.2 Sources of Uncertainty in BEB Network Planning

The uncertainty analysis was carried out using a multiplicative energy penalty that was applied over the entire fleet. This penalty value was constructed from a random selection of values for the effects of ambient temperature, passenger loading, and drive cycle aggressiveness. 1000 simulations were run, and a unique energy penalty was generated for each simulation from a unique combination of the three main contributors to energy uncertainty in buses. A histogram of the randomly generated energy penalties is shown below (Figure 2.3)

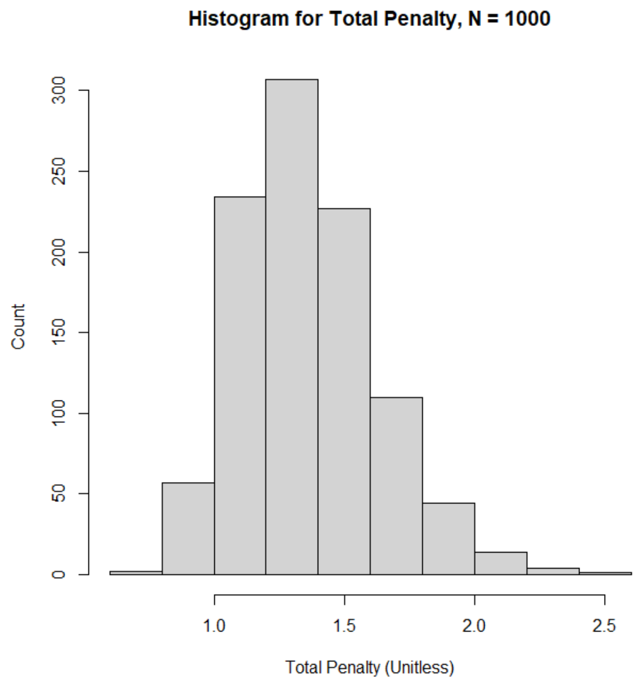


Figure 2.3: Histogram of randomly selected energy penalties resulting from effects due to drive cycle aggression, ambient temperature, and passenger load for uncertainty analysis.

These penalty values have a slight right-skew, with most values falling between 1 and 1.5, and high values in excess of 2.0. This distribution reflects the reality of transit agencies that, even though most operational circumstances place an expected demand on the vehicles of the system, the correct set of circumstances can increase the demand on the buses by 50%-100%. If these situations are not designed for, significant effects on level of service can result. This energy penalty has a significant effect on the expected cost and number of buses in the system (Figure 2.4).

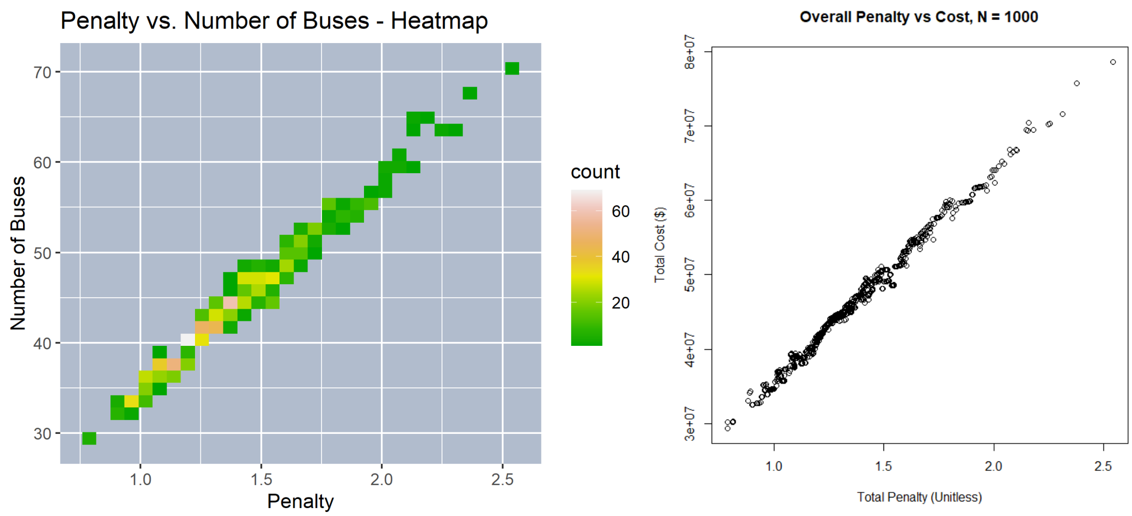


Figure 2.4: Energy penalty vs number of buses heatmap (left) and energy penalty vs total system cost (right). Note that the 'count' variable in the heatmap refers to the number of overlapping points in the region.

These figures show some interesting implications for system design of a BEB transit network. All of the scenarios that were simulated are scenarios that transit agencies may face in their networks in 'worst-case' scenarios – very full buses on a hot day with lots of aggressive starting and stopping. With traditional fossil fuel buses, the impact on most networks as a result of these effects can be mitigated by the flexibility offered by fast refueling turnarounds. However, with BEBs, once a bus is fully discharged and returns to the depot, it often takes several hours before a bus can be fully recharged and re-enter the network. Additionally, the extra energy that is available to the fleet via opportunity charging is insufficient to overcome the increased energy demands on the system, even as the number of opportunity chargers increases with energy penalty (Figure 2.5, left). Therefore, more buses must be made available to the network to ensure that the service offered by the transit agency doesn't collapse under these heavy conditions. This simulation shows that Unitrans may require as many as 70 buses to fulfill the needs of their network under extremely energy-intensive conditions with all BEBs, more than twice as many as the base case of 34 simulated BEBs to service the network under baseline conditions. The cost doubles from approximately $34.6 million under baseline conditions to approximately $68 million-$72 million under worst-case conditions. The infrastructure makeup of the baseline also differs from the infrastructure of the worst-case scenario (Figure 2.5).

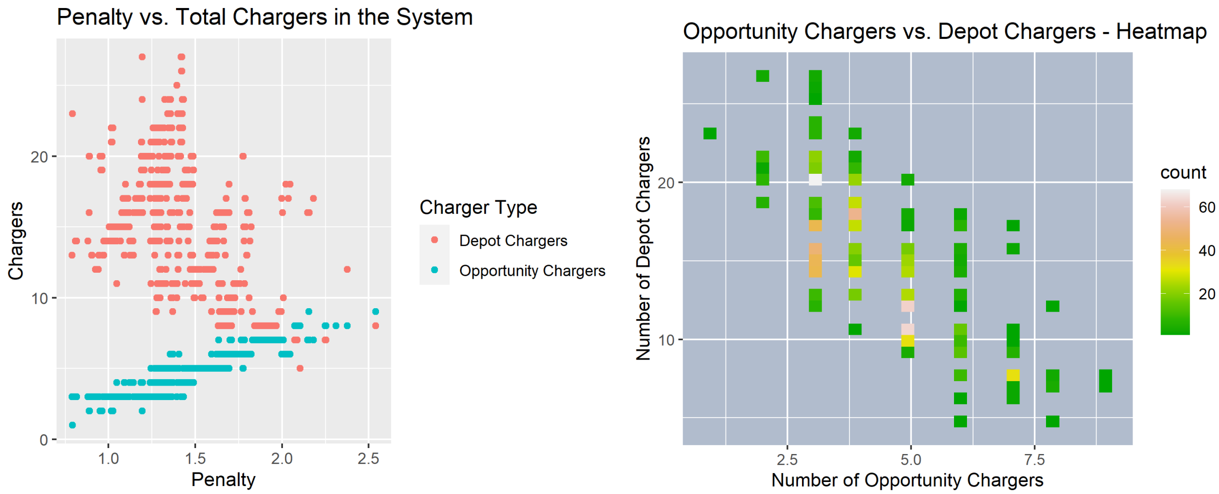


Figure 2.5: A plot of energy penalty vs numbers of both types of chargers in the system (left) and a heatmap of the relationship between the numbers of charge types (right).

The model shows that it is more effective to service as many buses as possible with opportunity charging, as higher levels of depot charging are selected at lower energy penalty levels. This is due to the cost-effectiveness of replacing depot chargers with opportunity chargers when possible. However, this strategy also changes the effectiveness of the composition of fleet vehicles (Figure 2.6).

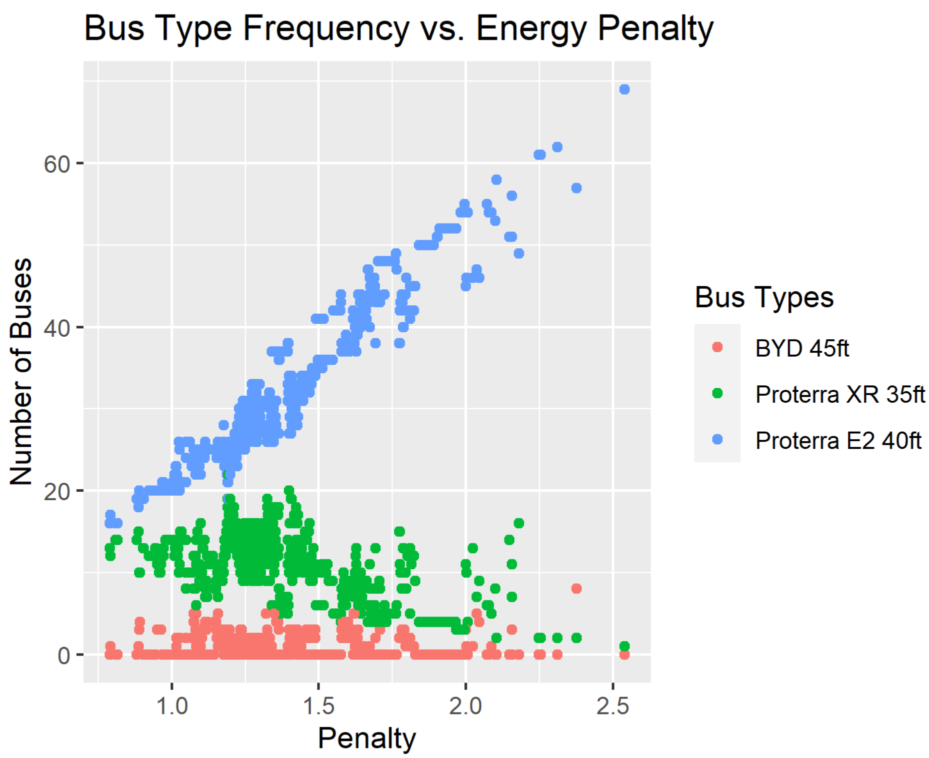


Figure 2.6: A plot of the numbers of different bus types that were selected by the model at different energy penalties.

As the energy use of each bus increases, the model prefers using the Proterra E2 40-foot bus to be a higher percentage of the fleet, with the number of Proterra XR 35-foot buses remaining at much lower quantity for most energy penalty levels, and other buses being selected only occasionally. As discussed in section 2.2.1, the Proterra E2 40-foot bus is the cheapest bus on a $/kWh basis, a metric that becomes more important as more of a bus's energy is expected to be used during normal operation. There is one other key difference between the two Proterra buses: the E2 is able to use opportunity charging, while the XR is not. As the model shifts towards opportunity charging as a way to make up the extra energy that is being used by the vehicles, the selected bus type must be compatible with the charging infrastructure.

2.4 Discussion and Insights

2.4.1 Network Design

The results provide many insights into the design of a network of a 100% BEB system. Fundamentally, the decision of charging strategy has a large impact on the design of the rest of the network. When considering overall network cost based primarily on energy use and equipment cost, it is clear that the effectiveness of using a mixed-network architecture is the optimal outcome for Unitrans, even as energy use of the vehicles changed. However, this effectiveness is based on a variety of assumptions about cost and operation of opportunity chargers as discussed in section 1.1.2. There are tradeoffs between the two strategies that this model does not consider. One of the primary tradeoffs is flexibility in the system. Although not presented here, the overall assigned schedule of each bus was tracked in the model. Examining this schedule showed that buses were moving on and off opportunity chargers at intervals that were extremely short on occasion. This is likely not a replicable process in a real-world situation. Additionally, these schedules are very precise and often make the difference in whether a bus is able to successfully complete its assigned route. Agencies operating BEBs reported in interviews that delays or missed charging events can be expected (though they were described as a 'relatively uncommon' occurrence once drivers had time to learn how to use the system). These delays and missed events can create knock-on effects that can further reduce the overall effectiveness of the transit network. When designing a transit network, it is recommended that agencies consider what margin of error in their scheduling is considered 'acceptable', and design around that decision.

Another tradeoff is energy use timing. Opportunity charging occurs throughout the day on an inflexible schedule and may create energy demand high enough to trigger demand charges from their utility company. In contrast, depot charging occurs in the off-hours of the network, which is usually overnight, a time when energy tends to be cheaper. The power demand of depot charging is also more constant and predictable. This model used a simple, constant cost per kWh to calculate the cost of energy, but agencies need to be aware of the various costs that can accompany a higher-powered, inflexible charging system, as these costs can drastically change the system architecture.

2.4.2 Effects of Energy Uncertainty on the System

The energy uncertainty analysis produced a surprising result. Although it is expected that more energy use would lead to higher costs and more buses, the doubling of these figures was a cost and fleet size increase that was higher than expected. Traditional fossil-fuel buses have a distinct advantage in flexibility of use and refueling schedule as a full refueling event takes approximately 10-15 minutes under most circumstances, allowing them to be rotated in and out of service multiple times during normal operation and to quickly be used to respond to surging demand. BEBs can require multiple hours to recover the same amount of energy in depot charging conditions, and buses that are pulled from the network due to lack of energy often cannot be used again for the rest of the shift. As a result, each bus that runs out of energy during its shift must be replaced by a new vehicle, rather than a vehicle that is rotated through a refueling or re-energizing process as is done with traditional buses. In some cases, it may have been expected that opportunity charging would have been able to help bridge the gap by allowing for rapid re-energization; even the fastest of chargers available today replenish batteries at a rate in the hundreds of kilowatts. Pumping liquid fuel has an effective energy replenishment rate in the tens of megawatts (based on a flow rate of 10 gallons per minute and an energy content of gasoline of 33.1 kWh per gallon). This means that to serve very intensive times, a BEB transit network must be significantly overbuilt for the majority of its operational conditions. In discussions with transit agencies, they reported that their top priority is to ensure that level of service is not impacted at any point during the day for any reason. This implies that most agencies would need to build for the worst-case scenario rather than the base case, buying as many as twice the number of vehicles of the base case. Aside from the increase of expense, this overbuying would also increase the physical space most agencies would require to serve their buses, an issue agencies stated is already a limiting factor. If the number of buses an agency operates doubles within the next 20 years, many agencies will have significant costs in purchasing new facilities to house and service those buses that most forecasts do not consider.

As a result, efforts to improve the energy efficiency of vehicles in a BEB network have much higher payoff than those in a traditional bus network. In fossil-fuel bus networks, the cost of energy inefficiency is measured as the cost of fuel; buses operating below their optimal miles per gallon does not usually result in changes to the timetable or overall system architecture. However, this is not the case with BEB networks. Agencies that plan to ensure that all situations are covered, even the most energy-intensive, may find that too many vehicles are required, which has knock-on effects in terms of the required space to store the vehicles, the EVSE to service those vehicles, and the complexity of scheduling those vehicles. These effects stem beyond what this model captured, including costs of driver labor and training, vehicle and EVSE maintenance, possibly increasing the size of the bus depot, among many others. It is expected that an agency's efforts to improve the operating energy efficiency of their BEBs would have a much larger effect on the design of the overall network and would result in a much larger return on that effort and investment. To illustrate this effect, the energy uncertainty analysis was carried out a second time, this time with the 'aggression' random parameter fixed at 1 to see the effect this change has on the vehicle makeup and the infrastructure required to service those vehicles (Figure 2.7, Figure 2.8).

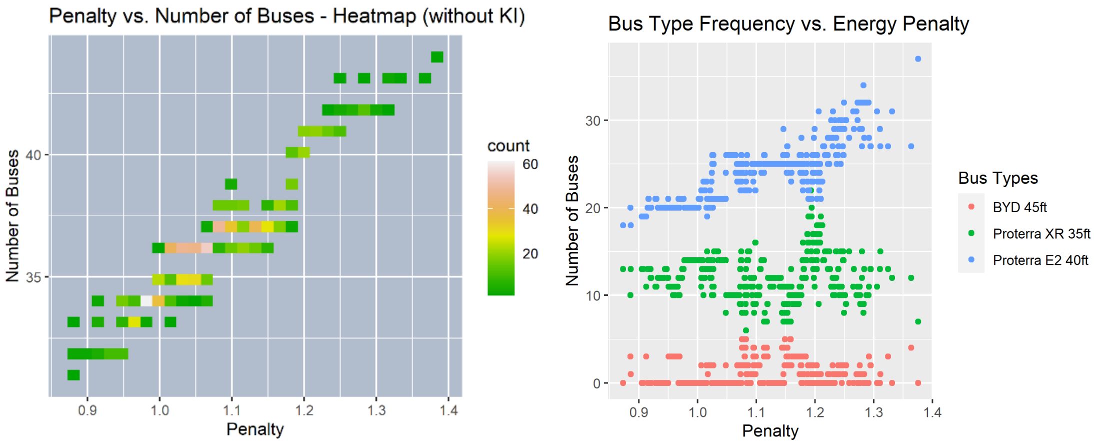


Figure 2.7: Plot of bus heatmap (left) and bus type distribution (right) for second energy analysis of the system (cycle aggression fixed at 1)

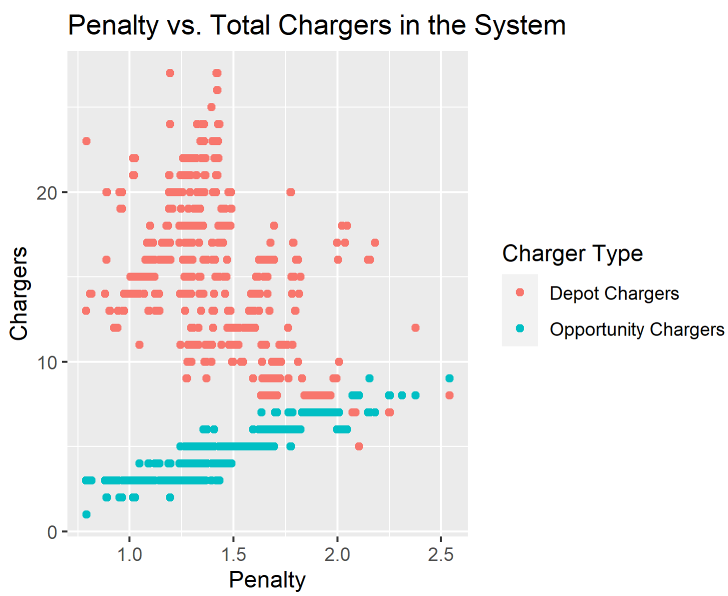


Figure 2.8 Numbers of types of chargers for second energy analysis of the system (cycle aggression fixed at 1)

This analysis shows the impact of eliminating one of the main sources of energy uncertainty decreases both the average and extreme requirements of BEB transit networks (Table 2.7).

Table 2.7: Key differences between the 'with aggression' and 'without aggression' energy analyses

Parameter	**With Aggression**	**Without Aggression**	**% Change**
Maximum Cost	$78.6 million	$46.1 million	41.7%
Median Cost	$45.0 million	$37.4 million	16.8%
Cost Interquartile Range (IQR)	$10.7 million	$3.25 million	69.7%

Maximum Number of Buses	73	45	38%
Median Number of Buses	44	36	18%
IQR of Number of Buses	10	2	80%

In 1000 runs, even the most extreme simulated conditions required only 45 buses to meet the needs of the transit network, which is closer to the total number of buses that Unitrans currently maintains, in contrast to the extreme requirement of up to 73 buses when cycle aggression is not held at 1. The infrastructure requirements are similarly less intense when energy uncertainty can be more controlled, as the number of opportunity chargers required in the system remains below 5, even under the most extreme simulated conditions (as opposed to 10 opportunity chargers that would be required in the extreme case of the initial analysis). The total system cost similarly decreased by a significant amount, with the extreme upper value changing from over $78 million to just over $46 million. The more significant result of this analysis is the decrease of spread of values in the results. The interquartile range (IQR) of the cost dropped by almost 70% when the cycle aggression was removed, and that the IQR of the number of buses decreased by 80%. This decrease in spread represents an improvement in the predictability of the system as the extremes of the system do not vary from the 'base case' by nearly as much as when cycle aggression is in the system. This result confirms that efforts to improve the energy efficiency of a BEB fleet have significant returns on the stability of the network, as better predictability and less variability in the requirements of the network allows for a transit operator to adapt more easily to surges in demand or sudden changes in overall energy use in the system.

2.4.3 Model Limitations

This model has many simplifications and room for improvements. The largest simplification is in the energy cost. For this model, the energy was assumed to have a single cost per kWh, with no additional charges. This does not reflect the reality of operating BEBs, as energy costs typically vary depending on the time of day and many BEB operators must plan for additional demand charges from their utility provider. A future version of this model may seek to incorporate these different energy costs into the optimization, which could change the fleet makeup depending on what times charging may be available (especially to opportunity charging buses).

Although the data that can be gathered in the GTFS format contains a great deal of information that can be used to model energy demand in a transit bus system, there are still aspects of bus operation on a route that are not being captured. The largest of these unaccounted aspects is that of elevation change, which GTFS do not contain any information about. This elevation change can have a significant impact on energy used by a vehicle on the route, especially if the effects of regenerative braking are lessened or removed. The elevation data could be added to the GTFS data before it is used as an input for Ambrose's model, resulting in an even more accurate estimation of energy demands for each route.

The uncertainty analysis performed on this model also has room for improvement in the data used to estimate the size of the effect of energy use uncertainty. Although datasets from published studies were used where available, these datasets tend to be coarse, especially for kinetic intensity resulting from individual driver behaviors. With more data collection, estimates for the size of this effect could be improved, and a better function could be developed. The ambient temperature considerations also focused on hot weather conditions, as these are the conditions are most commonly encountered in the case study network. However, cold weather conditions face a different set of challenges and impacts due to ambient temperatures, and the findings of this study may be less applicable to transit agencies in such climates.

Another major factor that is left out of this model is the ability to change the sizes of the batteries in the buses. Many studies have focused on proper battery sizing to minimize the cost of deploying BEBs, as the battery packs are the most expensive single aspect of a BEB deployment system.

It is possible that transit agencies with the knowledge of the ideal battery size that manufacturers could change the sizes of the packs available in their buses (or make the packs more modular) to better match the ideal pack sizes for different transit agencies. However, this influence and modularity do not currently exist in the relationship between transit agencies and vehicle manufacturers, at least not to the extent that this strategy could be used by transit agencies to select buses. Currently, buses must be selected from a predetermined set of configurations on the market. This reality is reflected in the way that the model has been built. As modularity increases and costs decrease, it is possible that more bespoke battery packs could be ordered on a per-agency basis to lower costs even further.

2.5 Conclusions

This chapter presented a new tool to allow transit agencies to make more informed decisions about deploying ZEBs in a cost-optimized manner. By incorporating individualized route energy use estimates and focusing on the decisions that transit agencies make when planning a ZEB deployment, this model was able to assess a case study agency and produce a result that aligns with the reality of how Unitrans operates. Through an uncertainty analysis, it was shown that a BEB transit network's architecture is highly sensitive to the energy use of the buses, and that differences can produce a network that requires nearly twice as many vehicles, chargers, and monetary investment if it is to be designed for the worst-case scenario. It was also shown that investment in improvements in the energy use of the vehicles can yield very high returns in terms of number of vehicles required and overall system cost. There are a few ways policies or transit agencies can accomplish these changes.

One option agencies have to improve energy efficiency and flexibility in their networks is through finding ways to manipulate the drive cycles of their buses and routes to improve energy efficiency. Although beyond the scope of this model, this could be done by manipulating the timetables and specifics of the routes to attempt to avoid more unnecessary stops and traffic. This could be done by optimizing routes to avoid stoplights, highly trafficked roads, and other sources of stop-and-go events in the cycle. Drivers can also be trained to improve their skill in driving a BEB with the goal of decreasing their energy use while driving by getting more effectiveness from regenerative braking systems, driving less aggressively, and other similar skills. These solutions are obviously not possible for all networks, and agencies should conduct their own analysis to identify opportunities for energy savings.

Another option that can be used to mitigate the effect of energy uncertainty in a BEB system is to allow for other types of buses to be used in these busy conditions. At the moment, the ICT regulation requires all vehicles that are run regularly to be ZEBs. However, if the regulation were modified to allow for buses with a more traditional fuel system to be used when extremely high demand is placed on the system, the flexibility of those traditional buses would allow for existing solutions to be applied to the problem of high demand. This change could allow BEBs to account for the vast majority of the miles that a transit network serves, while eliminating the need to overbuild for the few times when demand surges to very high levels.

This model was developed to try and replicate the decisions transit agencies make when planning a BEB network deployment. In interviews with transit agencies, it was found that it was a very high priority that these networks be able to maintain their current level of service and timetable. This model can replicate that for most cases, but doesn't allow for special routes, irregular timing, or deviation from the timetable in response to surging demand. Similarly, the need for reserve buses or non-service vehicles is not considered at all. Reasons for buying a bus that aren't related to range and energy use are also not considered. These reasons may include passenger capacity, height or width restrictions, and other similar considerations that transit agencies keep in mind during procurement. Although these reasons for purchasing a particular kind of bus were not considered, it is expected that the overall message of our results would remain consistent. These buses are often bought to satisfy particular needs of size or availability, two aspects that can increase the importance of available energy in a vehicle.

Although there are several ways the model can be improved, these initial results are very encouraging in terms of the ability to help transit agencies make informed decisions about how to deploy ZEBs. Future work involving this model will focus on improving the energy use predictions of BEBs and forecasting energy costs of transit agencies. More agency data can also be used as an input to the model. A strength of the presented model is its generalizability. As long as GTFS data, timetable information, and the other necessary inputs are available, the model should function for any transit network (though larger networks may require more computing time). This model can serve as the basis for several interesting investigations into the energy use and infrastructure requirements for BEB transitions and ensure that these transitions can occur in an informed and cost-efficient manner. The model is generalizable; although only one case study is presented here, the approach and equations can be adapted for any agency. Some data preparation is required, but future work on the model will seek to allow raw GTFS data to be used as an input, easing the process of data preparation immensely. Once completed, this generalized model could be used to analyze many different types of agencies, examining the effects of different circumstances on ideal deployment decisions.

3 Range and Infrastructure: The Relationship between Investments in Electrified Transit Bus Networks

3.1 Introduction

There is a concerted effort in the transit bus industry to transition buses from traditional fossil-fuel vehicles to zero-emission buses (ZEBs), a category that includes both fuel cell electric buses (FCEBs) and battery electric buses (BEBs). Studies have found that transitioning from conventionally fueled vehicles to electrically- or hydrogen-powered vehicles is an effective means of curbing greenhouse gas emissions contribution [7], [59], [60], There have been several high-profile deployments of ZEBs in China and Europe, as well as the United States. According to a survey performed by CALSTART, there are currently 3,533 ZEBs either deployed or on order across the United States [4]. Approximately a third of these vehicles are in the state of California. In December 2018, the California Air Resources Board (CARB) adopted a regulation require that transit fleets begin the shift to zero-emission buses known as Innovative Clean Transit (ICT), which affects the purchase of new buses beginning in 2023 [3]. CARB estimates that the California transit bus fleet will complete the transition to 100% ZEBs by the 2040s.

Although California has the most well-developed ZEB policy, New York also has a program for the replacement of diesel commercial vehicles, including transit buses. Additionally, several states have signed onto the Multi-State Medium- and Heavy-Duty Zero Emission Vehicle Memorandum of Understanding (MSMOU), a statement of cooperation between the signees that include 15 states and the District of Columbia. Although it is not legally binding, the MSMOU represents a statement of fostering “a self-sustaining market for zero emission medium- and heavy-duty vehicles through the existing Multi-State ZEV Task Force, which will serve as a forum for state coordination, collaboration and information sharing on market enabling actions, research, and technology developments.” [61]. The action plan laid out in the MSMOU primarily consists of committing to funding and other incentives to encourage the development of a market for ZEBs in their respective states. On a federal level, new funding for ZEBs has recently been introduced in the Infrastructure Investment and Jobs Act. Signed into law in 2021, this act will provide a total of $18.4 billion into federal programs to promote low- and no-emission vehicles, a pool of funding that can be used for ZEBs (among other uses).

As a result of these policies, several transit agencies in the United States have begun developing plans for full-scale transitions to ZEBs, and a few of these agencies have already completed the transition. These transitions have come with a fair share of challenges, from costs of transitioning to the specific strategy or strategies and infrastructure that should be used in a ZEB fleet, to issues of knowledge and operation of the fleets. This study presents a look into the structural solutions that may be used by fleets across the USA to transition transit bus fleets to BEBs.

3.1.1 Costs of Transitioning a Fleet

The high costs of ZEB fleet transitions have been examined as parts of demonstration-scale deployments [9], [10], and have been used as inputs in other studies focusing on total cost of ownership [11], [12]. Most transitions have focused on the vehicles, as these represent the highest upfront cost of the transition and are central to the success of the network. However, vehicles cannot operate without their accompanying infrastructure, and the entire system must be considered when planning a transition. Interviews with transit agencies revealed that planning perspective decisions are not necessarily about the parts that cost the most. Although several studies have found that infrastructure costs represent a relatively small part of the overall cost of transitioning to a ZEB fleet [13], [14], the selection of infrastructure and charging strategy (or strategies) is one of the first decisions that gets made after planning a full BEB fleet transition. This infrastructure decision drives the rest of the transition process for transit agencies, and these decisions can carry significant implications on the makeup of the transit agency for years or decades to follow.

The cost of lithium-ion (Li-ion) batteries is a frequently researched topic, especially as the costs of Li-ion batteries has come down in the decades since the technology was first made commercially viable [62]–[64]. These falling costs have been identified as a key factor in the commercialization of transit buses and other heavy-duty vehicles [65], [66]. The cost of batteries has to be weighed against the cost of opportunity charging infrastructure, which can reduce the required battery pack size of the vehicles in the system under certain conditions [25], [34]. However, these conditions are often applicable to the networks being studied; there have been few to no systematic studies examining large numbers of networks to understand what trends may exist between different networks when considering this tradeoff.

3.1.2 Network Case Studies

There have been many different studies on the costs and methods of transitioning individual networks. The issues surrounding such a transition are numerous and complex. Optimization studies have been performed focusing on everything from vehicle scheduling [21], [22], [67] to optimizing a fleet transition over time [11], [23], [27] to examining the different types and locations of charging infrastructure [24], [26], [68]. These studies have reached a variety of conclusions based on the nature of the network that was the focus of their study, however, the authors are unaware of any larger-scale studies of many different real networks with the intention of examining how a transition to ZEBs may differ between them. By widening the analysis, this study presents a novel set of data that can be used to understand some of the larger-scale patterns and relationships of transitioning to BEB networks, especially where infrastructure and charging strategy is concerned.

3.2 Methods and Data

The model presented in this work is a mixed-integer linear program (MILP) optimization model that is generally applicable to transit agencies with a static general transit feed specification (GTFS) feed.

This model builds on previous work completed by Benoliel, Jenn, and Tal [69]. The improved model focuses on tracking individual buses as they move through the system and understanding the effects of different route characteristics on the overall system. To support these goals, the model presented in the previous work has been substantially updated to track the necessary information.

3.2.1 Optimization Model

3.2.1.1 Model Structure and Assumptions

As in the previous work, this model is a mixed-integer linear program (MILP), a common formulation for solving transit network optimization problems [23], [24], [26], [27]. This model is based on several assumptions about the vehicles and the system in which they operate:

- All buses are identical apart from the sizes of their battery packs. This includes the cost, energy use on a given route, passenger capacity, and other factors that may come into play during vehicle operation.
- The network operates in a deterministic fashion according to its timetable. The effects of traffic and other delays are ignored, as are issues with the charging schedule and other sources of uncertainty that could have a significant impact on the effectiveness of the transit network as these are not the focus of this study.
- The transit agency being modeled possesses enough depot chargers to recharge all service vehicles to full overnight, and that the marginal cost of continuing to use those chargers during the day is negligible. As a result, it is assumed that daytime depot charging is available at no cost.
- All costs that are present in the network regardless of the sizes of the battery packs and type(s) of charger(s) installed are not factored into the optimized cost of the model. Most notably, this means that costs of vehicles (aside from their batteries) and energy

purchase are ignored, as well as costs related to operation, training, construction and installation, and other miscellaneous costs associated with running a transit network.

3.2.1.2 Nomenclature and Equations

The nomenclature to define this problem (Table 3.1) uses *x* to notate variables, *c* to notate parameters that depend on sets, and other letters to notate the sets of the problem:

Table 3.1 Optimization Nomenclature

Symbol	**Meaning**	**Units**
Sets		
$r; R$	A route in the system; a set of all r	None
$b; B$	A bus; a set of all buses	None
$l; L$	A candidate location to install infrastructure; a set of all candidate locations	None
$t; T$	A time during a period of operation; a set of all times tracked	time blocks
Parameters		
$c^{pack.cost}$	Cost of a battery pack per kWh	$USD/kWh
$c_r^{energy.use}$	Energy used by a bus on route r per time step	kWh
$c^{opp.cost}$	Cost of an opportunity charger	$USD
$c^{opp.rate}$	Maximum rate of charging available at an opportunity charger	kW
$c_r^{route.time}$	Total time (travel time plus idle time) for a bus to travel on route r	time blocks
$c^{depot.time}$	Total time that must be spent if a bus is going to daytime depot charge	time blocks
$c_{r,t}^{buses.on.route}$	The count of buses on route r at time t	buses
$c_{r,t}^{trip.start}$	A binary parameter signifying the start of a trip on route r at time t	None
$c_{r,l,t}^{can.charge}$	A binary parameter describing whether a bus serving route r can charge at location l at a time t	None
$c_{r,b}^{bus.assigned}$	A binary parameter describing if a bus b is assigned to route r	None
Variables		
$C_{capital}$	Capital costs of interest of the system	$USD
$x_{b,t}^{energy.status}$	The amount of energy stored by bus b at time t	kWh
$x^{depot.chargers}$	Number of day-use depot chargers. Must be an integer.	None
$x_l^{opp.chargers}$	Number of opportunity chargers at location l. Must be an integer.	None
$x_{b,t}^{opp.amount}$	Amount of energy gained via opportunity charging by bus b at time t	kWh
$x_b^{pack.size}$	The pack size of bus b	kWh
$x_{r,b,t}^{on.route}$	A binary variable describing if bus b is on route r at time t	None
$x_{b,t}^{charging.depot}$	A binary variable describing if bus b is depot charging at time t	None

$x_{b,l,t}^{charging.opp}$	A binary variable describing if bus b is opportunity charging at time t and location l	None

The model's behavior is defined by the following set of equations. Equation 3.1 defines the objective function of the model of minimizing the costs of interest.

$$\text{Min}\ (C_{capital}) = \sum_{l=1}^{L}\left(x_l^{opp.chargers}\right) * c^{opp.cost} + \sum_{b=1}^{B}\left(x_b^{pack.size}\right) * c^{pack.cost} \tag{3.1}$$

$$w.r.t.\ x_b^{pack.size}, x_l^{opp.chargers}, x_{r,b,t}^{on.route}, x_{b,l,t}^{charging.opp}, x^{depot.chargers}, x_{b,t}^{charging.depot}$$

Equations 3.2 and 3.3 define the movement of energy into and out of buses in the system. Equation 3.2 in particular defines how energy changes as a result of buses either servicing routes or opportunity charging. Equation 3.3 restricts the energy levels of the buses from exceeding their respective battery pack sizes.

$$x_{b,t}^{energy.status} = x_{b,t-1}^{energy.status} - \sum_{r=1}^{R}\left(c_{r,b}^{bus.assigned} * c_r^{energy.use} * x_{r,b,t}^{on.route}\right) + x_{b,t}^{charging.depot} * c^{depot.rate} + x_{b,t}^{opp.amount}, \qquad \forall b \in B, \forall t \in T \tag{3.2}$$

$$x_{b,t}^{energy.status} \leq x_b^{pack.size},\ \forall b \in B, \forall t \in T \tag{3.3}$$

Equations 3.4-3.6 define how buses service routes. Equation 3.4 ensures that buses cannot service more than one route at a time and cannot serve routes while charging at the depot (or vice versa). Equation 3.5 forces buses to complete routes that they start, while ignoring any new trips that begin while they are still servicing a route. Equation 3.6 ensures that, at any given time, there are the correct number of buses servicing each route.

$$\textstyle\sum_{r=1}^{R}\left(c_{r,b}^{bus.assigned} * x_{r,b,t}^{on.route}\right) + x_{b,t}^{charging.depot} \leq 1,\ \forall b \in B, \forall t \in T \tag{3.4}$$

$$\sum_{t}^{t+c_r^{route.time}} \left(x_{r,b,t}^{on.route}\right) \geq c_{r,t}^{trip.start} * \left(x_{r,b,t}^{on.route} - x_{r,b,t-t}^{on.route}\right) * c_r^{route.time}, \ \forall r \in R, \forall b \in B, \forall t \in T \quad (3.5)$$

$$\sum_{b=1}^{B} \left(c_{r,b}^{bus.assigned} * x_{r,b,t}^{on.route}\right) = c_{r,t}^{buses.on.route}, \ \forall r \in R, \forall t \in T \quad (3.6)$$

Equations 3.7 and 3.8 describe the way depot charging works in the model. Equation 7 ensures that daytime chargers are counted as buses use them, while equation 8 requires that charging take place over a specified minimum time.

$$\sum_{b=1}^{B} x_{b,t}^{charging.depot} \leq x^{depot.chargers}, \ \forall t \in T \quad (3.7)$$

$$\sum_{t}^{t+c^{depot.time}} \left(x_{b,t}^{charging.depot}\right) \geq c^{depot.time} * \left(x_{b,t}^{charging.depot} - x_{b,t-1}^{charging.depot}\right), \ \forall t \in T \quad (3.8)$$

Equations 3.9-3.12 describe the way opportunity charging takes place in the model. Equation 3.9 ensures that enough chargers are present for every bus that is charging (or put another way, that there can't be more buses charging than there are chargers at the location). Equation 3.10 ensures that buses are only taking up once charger at a time and can only charge at chargers on their designated routes. Equation 3.11 dictates that buses can only charge when they are at a stop where their route allows for opportunity charging. Finally, equation 3.12 allows for a bus to receive less than the full rate of opportunity charging in a timestep but restricts it from receiving more.

$$\sum_{r=1}^{R} \sum_{b=1}^{B} \left(c_{r,b}^{bus.assigned} * x_{r,b,l,t}^{charging.opp}\right) \leq x_l^{opp.chargers}, \ \forall l \in L, \forall t \in T \quad (3.9)$$

$$\sum_{r=1}^{R} \sum_{l=1}^{L} \left(c_{r,b}^{bus.assigned} * x_{r,b,l,t}^{charging.opp}\right) \leq 1, \ \forall b \in B, \forall t \in T \quad (3.10)$$

$$x_{r,b,l,t}^{charging.opp} \leq \sum_{r=1}^{R} \left(c_{r,b}^{bus.assigned} * c_{r,l,t}^{can.charge} * x_{r,b,t}^{on.route}\right), \ \forall r \in R, \forall b \in B, \forall l \in L, \forall t \in T \quad (3.11)$$

$$x_{b,t}^{opp.amount} \leq c^{opp.rate} * \sum_{r=1}^{R} \sum_{l=1}^{L} x_{r,b,l,t}^{charging.opp}, \ \forall b \in B, \forall t \in T \quad (3.12)$$

Equations 3.13-3.17 restrict certain variables to the positive domain. Although it is not specified in these equations, the variables $x^{depot.chargers}$ and $x_l^{opp.chargers}$ are also restricted to being integers.

$$x_{b,t}^{energy.status} \geq 0,\ \forall b \in B, \forall t \in T \tag{3.13}$$

$$x_b^{pack.size} \geq 0,\ \forall b \in B \tag{3.14}$$

$$x_{b,t}^{opp.amount} \geq 0,\ \forall b \in B, \forall t \in T \tag{3.15}$$

$$x^{depot.chargers} \geq 0 \tag{3.16}$$

$$x_l^{opp.chargers} \geq 0,\ \forall l \in L \tag{3.17}$$

Together, equations 3.2-3.17 specify a set of constraints that, combined with the objective function in equation 3.1, define a system that can effectively model a transit bus network that has transitioned to 100% BEBs.

3.2.2 Model Data

3.2.2.1 General Transit Feed Specification (GTFS)

The inputs for this model are primarily taken from each network's GTFS data feed. These data feeds are maintained by transit networks for use in external applications and are traditionally available through from either transit agencies or third parties. Most frequently, developers use these feeds to create applications that keep track of the times and locations of buses within the networks using "dynamic feeds" that allows customers to avoid wait times and better plan their trips on the network. These feeds also contain a "static feed" containing information about the routes and trips within a network, including trip times, stop locations, and location information about both. This model uses these feeds to construct a set of tables that are used to represent the timetable, stops, and candidate charging locations in the model, as well as to find the energy use of the buses on each route.

3.2.2.2 Energy Data and Energy Use Modeling

For this model, energy requirements are generated on a bus-route-pair basis from a model developed by Ambrose and others [50]. Ambrose's model uses data from the FleetDNA dataset developed by the National Renewable Energy Laboratory (NREL) [51] to develop energy demands for a particular bus-route combination using a transit agency's GTFS data feed. By using information present in the GTFS data and employing regression on the FleetDNA dataset and using characteristic velocity, acceleration, and network size as the most significant indicators of energy use, Ambrose's model can develop an estimation for energy use on any transit route that is present in a transit network's GTFS data feed.

3.2.2.3 Charger Candidate Locations

Candidate locations for opportunity charger installation for each network were determined using the following algorithm:

1. Sort all stops by number of times a bus stops at that location.
2. Select the first stop as the initial candidate location.
3. Note all routes that stop through the candidate location.
4. For the second location, select the highest-ranked stop that serves at least one route which is not already being served by the previous candidate location(s) selected.
5. Repeat until every route is served by at least one candidate location.

This algorithm allows for each route to have at least one location at which opportunity charging would be theoretically available, enabling the strategy to be employed network-wide if it was optimal to do so.

3.2.2.4 Depot Chargers

To account for the number of depot chargers that the network would need to refill the buses at night, the depot chargers were calculated after optimization based on the needs of the buses at that point. This calculation was made using the assumption that an agency had 6 hours to recharge buses, and that each charger supplied 65 kW of power. Using these assumptions and the knowledge of the energy deficit at the end of the day, the required number of depot chargers for each network was calculated.

3.2.2.5 Other Inputs

There are several other inputs to the model that haven't been discussed. They are briefly mentioned below (**Error! Reference source not found.**)

Table 3.2: Other values used as inputs to the model

Value Name	Value	Source
Pack Cost ($c^{pack.cost}$)	\$170 per kWh	[62]
Opportunity Charging Rate ($c^{opp.rate}$)	300 kW	Discussions with Agencies, [15]
Depot Charging Time ($c^{depot.time}$)	180 minutes	Discussions with Agencies
Depot Charger Cost	\$30,000 per	Discussions with Agencies, [70]

3.2.3 Transit Networks Modeled

This project makes use of the GTFS feeds of many transit networks in the United States. These feeds were accessed using OpenMobilityData (previously TransitFeeds) [71], an open-source repository and API to access the feeds of different transit agencies around the world. Of the over 800 feeds within the repository, 78 networks were identified as having feeds suitable for use in the optimization model. These networks were each optimized as described above. Table 3.3 contains a set of summary statistics for the set of modeled networks.

Table 3.3: Summary Statistics for Modeled Networks

Statistic	Units	Average	Standard Deviation	Minimum	Maximum
Number of routes	Routes	12.9	12.3	1	60
Average route time	Minutes	47.6	47.5	13.7	298.7
Average route length	Miles	25.1	37.6	3.6	201.1
Average of route velocity	Mph	24.9	8.9	9.9	53.0
Average energy use	kWh/mile	2.49	0.37	1.94	3.86

The states with at least one network included in the model are mapped below (Figure 3.1).

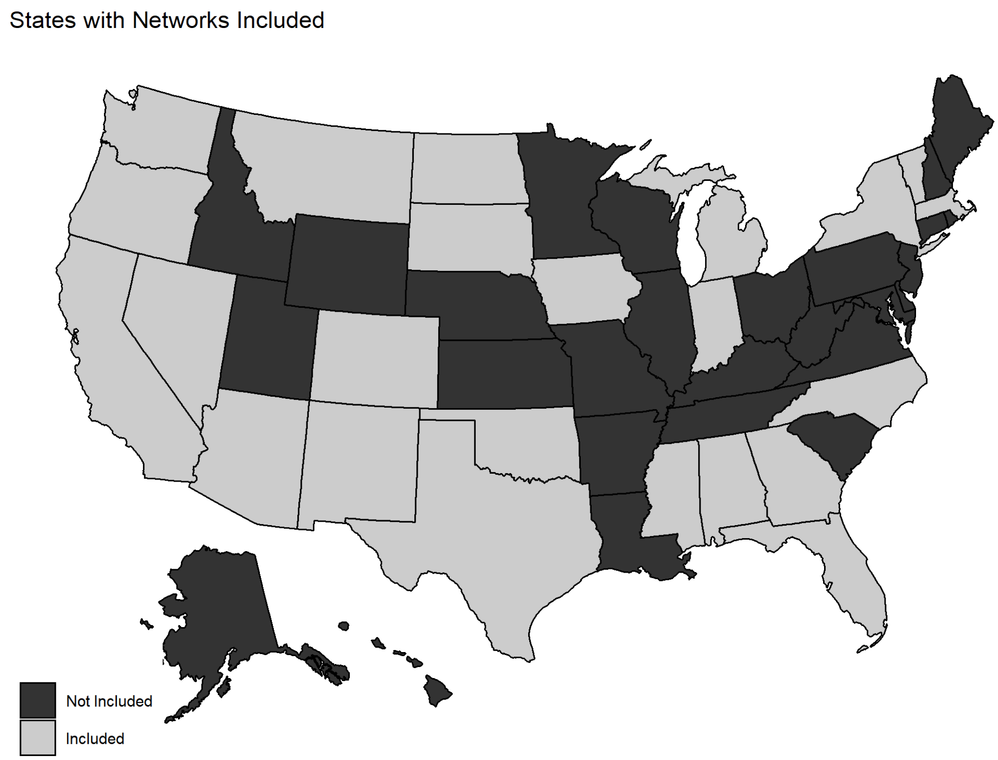


Figure 3.1: A map indicating the states with networks included in the study. Light states were included; dark states had no networks suitable for this model (for detailed selection criteria, see Appendix C).

3.2.4 Scenario Analysis

3.2.4.1 Vehicle Scenarios

The model requires that a number of buses be designated for each network before optimization. Each vehicle scenario was formed on the basis of a 'minimum' number of vehicles that each network could require. This minimum number is equal to the number of buses in the network if each bus had an infinitely large battery pack, a number that is determined by both the number of routes in a network and the frequency of those routes. For the base case scenario, the number of vehicles was increased by 30% over this minimum. In addition to the base case, two additional scenarios for the number of vehicles were developed: a 'few vehicles' and a 'many vehicles' scenario. For the few vehicles scenario, an increase over the minimum required vehicles of 10% was used; for the many vehicles scenario, this increase was 50%. These vehicles were each assigned to a specific route in the system based on where they were needed. These limits serve to establish a theoretical minimum and maximum number of vehicles a transit agency might use in a transitioned BEB system.

3.2.4.2 Opportunity Charger Cost Scenarios

For each of the vehicle scenarios, four levels of opportunity charger cost were developed. Opportunity charging costs are highly volatile and not very well reported in situations where they have been installed, and their cost varies based on the particular technology used in the implementation of opportunity charging [70], so a wide range of prices were used as scenarios. The four levels of opportunity charger cost were $300,000, $200,000, $150,000, and $50,000. These scenarios will be referred to as the "pessimistic", "grounded", "optimistic", and "pushed" scenarios respectively. Each of these cost levels was run for each vehicle scenario to explore the impacts of both the pricing and various other route characteristics on the outputs of the model.

3.3 Results and Discussion

The model was run on the 78 networks described above. This section will present several key data outputs from the model and discuss some key insights of the results.

3.3.1 Case Study Examples of Model Findings

It is impractical to examine the findings of all 78 networks analyzed in detail. To analyze trends within analyzed networks, three illustrative case studies will be discussed in detail. In particular, the MuscaBus, Huntsville Shuttle, and Riverside Transit agencies are discussed. These agencies were selected for two reasons: First, they are typical examples of a small, medium, and large network, respectively. Second, these networks illustrate trends in network-level charging that are present in the broader findings of the analysis.

3.3.1.1 Networks Overview

3.3.1.1.1 MuscaBus

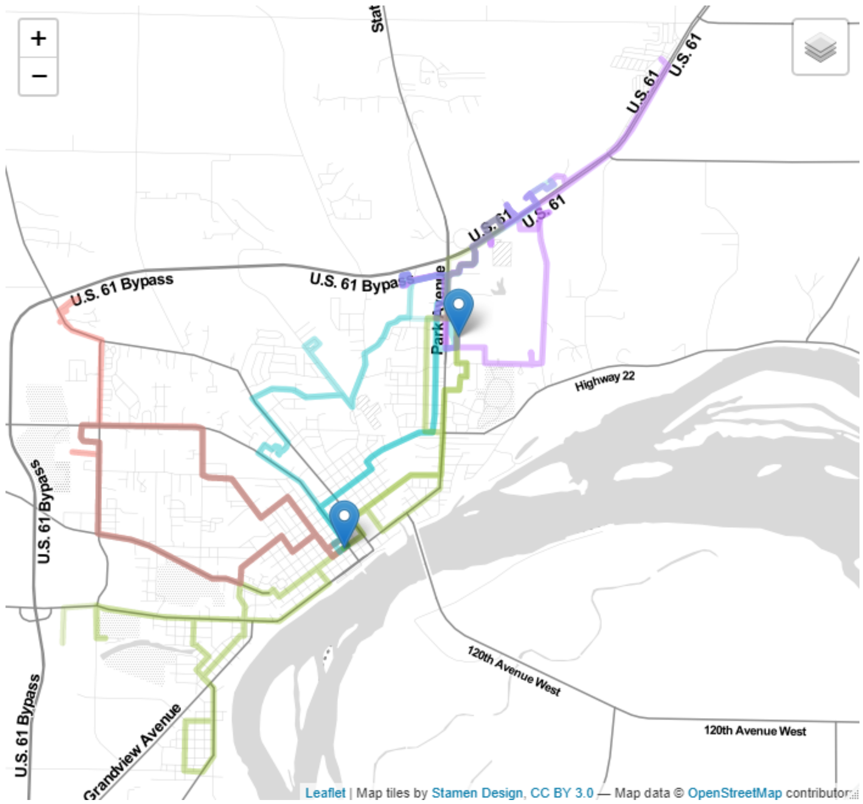
The MuscaBus transit network is based in Muscatine, Iowa in the United States, a small-to-medium-sized town with a population of approximately 23,800 people. The network is made up of 4 routes serviced by small vehicles with trips approximately every half hour. Because this model only considers 40-ft buses, the base number of vehicles considered for this network was set to 4, as 1 bus per route would be theoretically sufficient to service the network. These buses could be adequately served by two candidate locations, if it was determined that opportunity charging was economically viable. A map of the routes and candidate locations for MuscaBus is shown in Figure 3.2(A).

3.3.1.1.2 Huntsville Shuttle

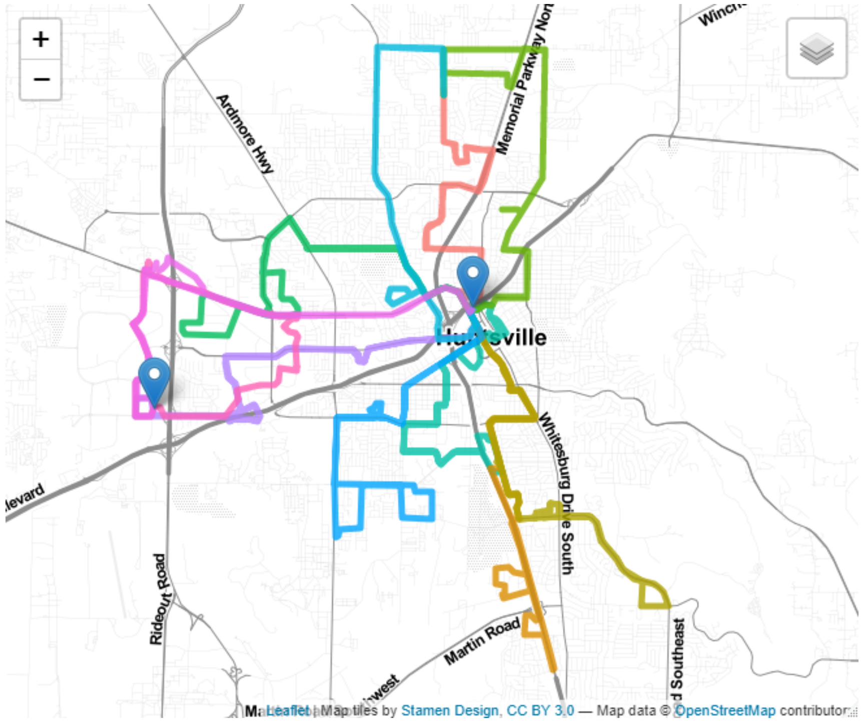
The Huntsville shuttle, also known as Orbit, is a service for Huntsville, Alabama in the United States, a major city in the area with a population of almost 220,000 in the city and almost 500,000 in the greater metropolitan area. The Huntsville shuttle consists of 11 routes serviced by 15 buses. Trips on these routes also leave approximately every half hour for most of the day, with slight reduction in service frequency during early morning and late-night hours. Like MuscaBus, two candidate locations are suitable to service all of the routes in the network. A map of the Huntsville Shuttle is shown in Figure 3.2 (B).

3.3.1.1.3 Riverside Transit Agency

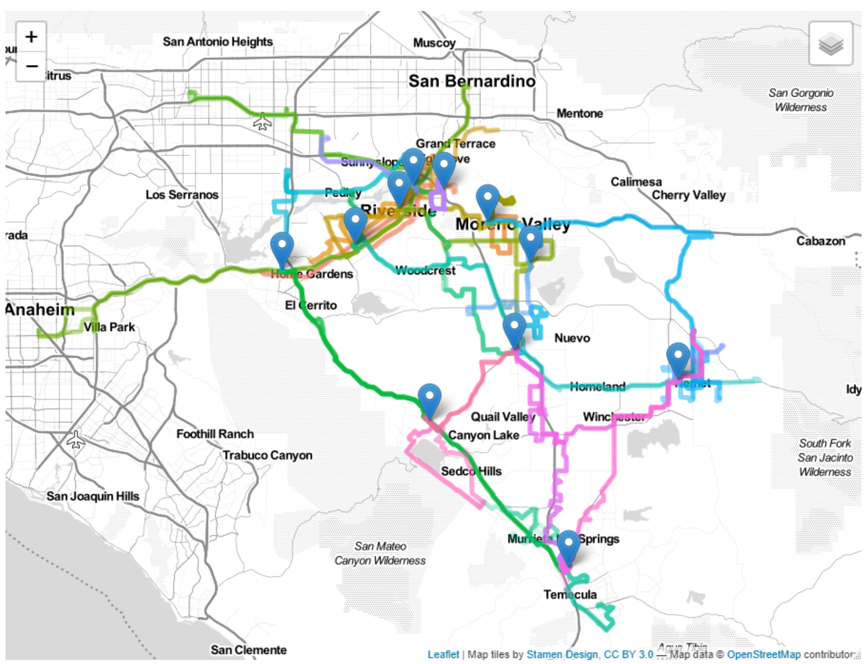
The Riverside Transit Agency (RTA) services the city of Riverside, California in the United States, a major city with a population of approximately 315,000 within the city and a population of over 4.5 million people in its greater metropolitan area. The RTA network consists of 41 routes served by a fleet of 339 buses. This network not only has routes within the city of Riverside, but also the neighboring cities of Ontario, Temecula, Anaheim, and Hemet, among others. To service these routes, 11 candidate locations for opportunity charging were identified. A map of these locations and the service area of RTA is shown in Figure 3.2 (C).



A



B



C

Figure 3.2: Route maps for Muscabus (A), Huntsville Shuttle (B), and Riverside Transit Agency (C). For all networks, the blue pins represent potential locations for charger installation.

3.3.1.2 Energy within Networks

Understanding how buses are charged within the networks provides key insight into how the networks are constructed. For this section, two scenarios are considered: the low opportunity charger cost scenario and the high opportunity charger cost scenario. In this section, two scenarios are considered: the "low cost" scenario in which the cost of opportunity chargers was set to its lowest value, and the "high cost" scenario, in which the cost of opportunity chargers was set to its highest value. Between these scenarios, there are significant differences in how energy flows into the system from the grid (Figure 3.3).

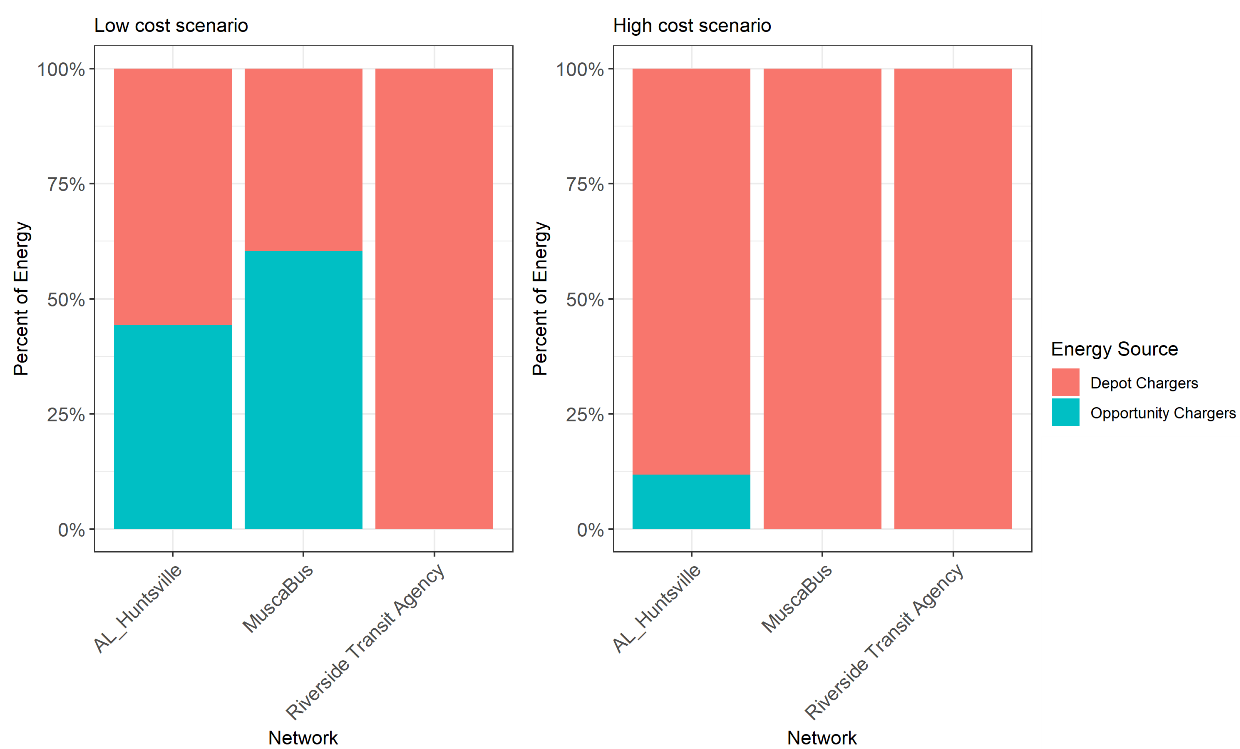


Figure 3.3 The relative amount of energy input to the system under both the low-cost scenario (left) and the high-cost scenario (right) for the case study networks.

The figure shows that cost of opportunity charging has a substantial effect on the source of energy for both networks that make use of opportunity charging. These differences in amount of opportunity charging also have a significant impact on the overall state of charge (SOC) of the buses within the network. The average and range of bus SOCs for the three networks are shown below (Figure 3.4, Figure 3.5, Figure 3.6).

RTA's results for both scenarios are the same, as the network engages in no opportunity charging in either scenario. However, both MuscaBus and Huntsville Shuttle are significantly changed from one scenario to the other. MuscaBus sees the biggest change, as the network changes from having more than half of its energy delivered by opportunity charging to none of it (Figure 3.5), and its SOC pattern changes wildly as a result. In the low-cost scenario, MuscaBus gets most of its energy via opportunity charging. The SOC pattern reflects this, with average SOC in the system remaining around 50% for the majority of the day, dipping down lower at the end, with high variance within the four vehicles as they use the chargers at different times. In contrast, there is no opportunity charging at all in MuscaBus in the high-cost scenario, and the SOC in the network shows a much less variable, consistent movement from full to empty as the day goes on. This change from highly variant to more consistent also appears in the Huntsville Shuttle, though to a lesser extent (as the Huntsville Shuttle still employs some opportunity charging even in the high-cost scenario). This higher variance is also an indication of the smaller battery packs present in the buses when opportunity charging is available. Because the packs are smaller overall, small changes to the energy level have a larger impact on overall SOC.

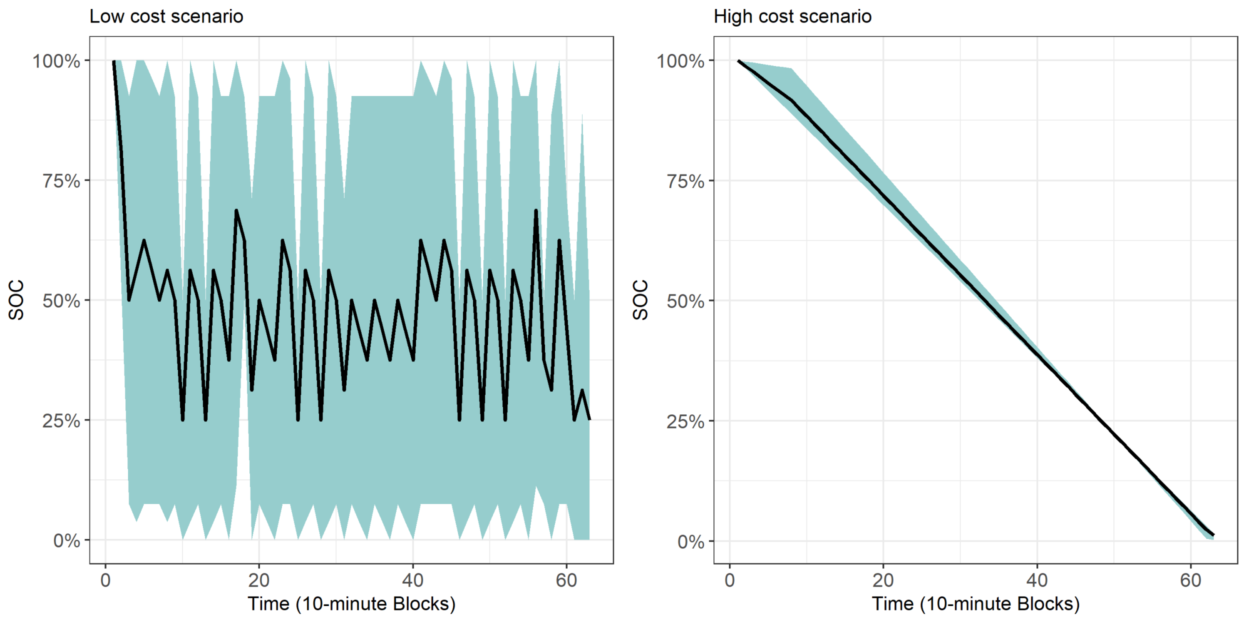


Figure 3.4: The average (black) and range (green) of bus SOCs in the MuscaBus network in the low opportunity charger cost scenario (left) and the high opportunity charger cost scenario (right)

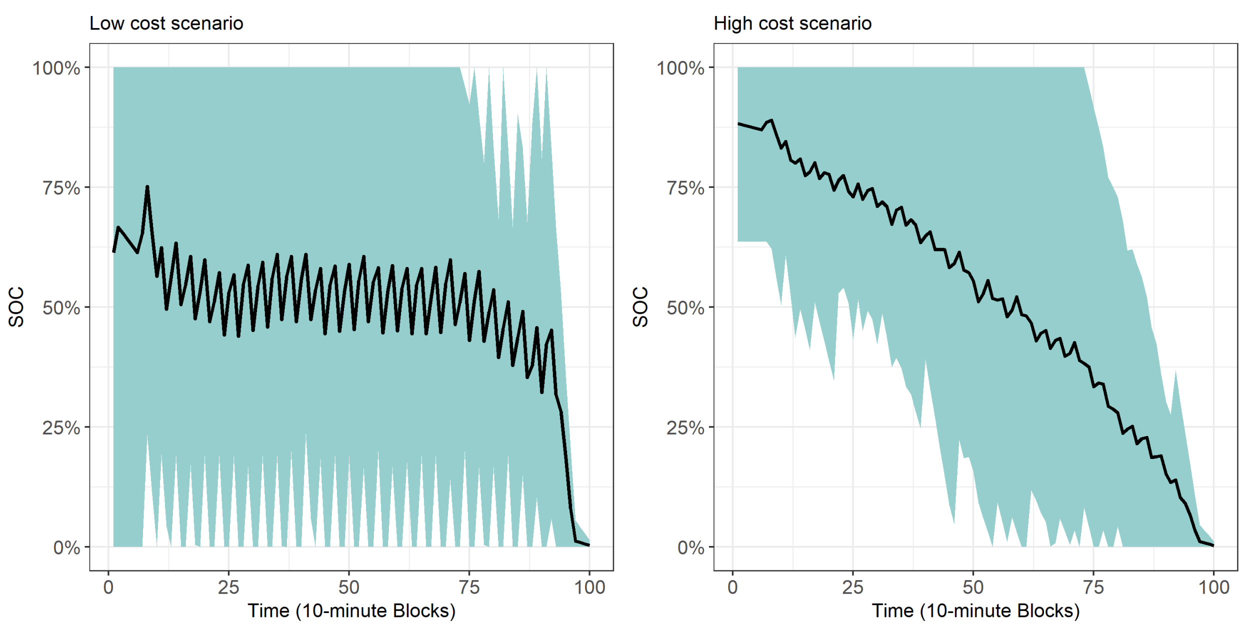


Figure 3.5: The average (black) and range (green) of bus SOCs in the Huntsville Shuttle network in the low opportunity charger cost scenario (left) and the high opportunity charger cost scenario (right)

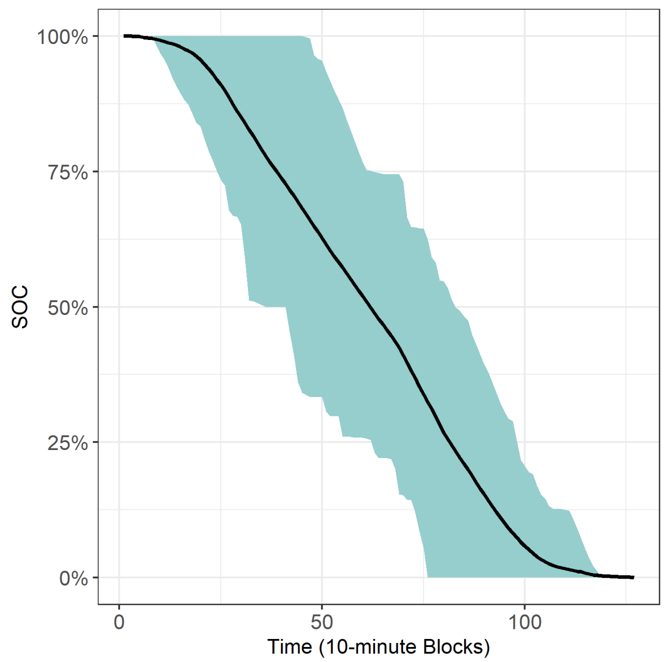


Figure 3.6: The average (black) and range (green) of bus SOCs in the RTA network in both the low and high opportunity charger cost scenarios.

If opportunity charging is not used (as in the high-cost scenarios), most networks will exhibit a much narrower envelope of SOCs in which the network can continue to operate. Both RTA and Muscabus have significant times of the day where the envelopes of the SOCs of vehicles on the route are very narrow. This narrow range of acceptable SOCs indicates a lack of operational flexibility, as less margin for error exists. If the issue is bad enough, it could require the activation of a 'backup' bus or lowering the overall level of service of the route for a time. This effect is particularly striking in MuscaBus and other small transit networks, where the margins for acceptable SOCs of the buses are extremely narrow. In contrast, if opportunity charging is used (as in the low-cost scenarios for MuscaBus and Huntsville Shuttle), the envelope of SOCs for buses in the optimized system is much wider. This may allow for some degree of operational flexibility, assigning buses that have lower-than-expected SOCs to routes or charging time slots that allow for a recharge ahead of what was otherwise scheduled while maintaining the network level of service.

3.3.1.3 Effects on Network Costs

The relative costs of the networks are broadly split into four categories: The cost of the vehicles is based off the theoretical contribution of the parts of the vehicle that don't include the batteries and drivetrain (motor, regenerative braking system, etc.) to the total vehicle purchase cost. For this project, this was estimated to be $150,000 per vehicle. The cost of infrastructure is broken up into two parts; costs of opportunity chargers are based off the scenario that was being examined, while the cost of the depot chargers was assumed to be $30,000 per unit (**Error! Reference source not found.**). Finally, the total cost of the battery packs is determined from the model output based on a unit price of $170 per kWh (Table 3.2). The breakdowns of the different costs across scenarios are shown below (Figure 3.7).

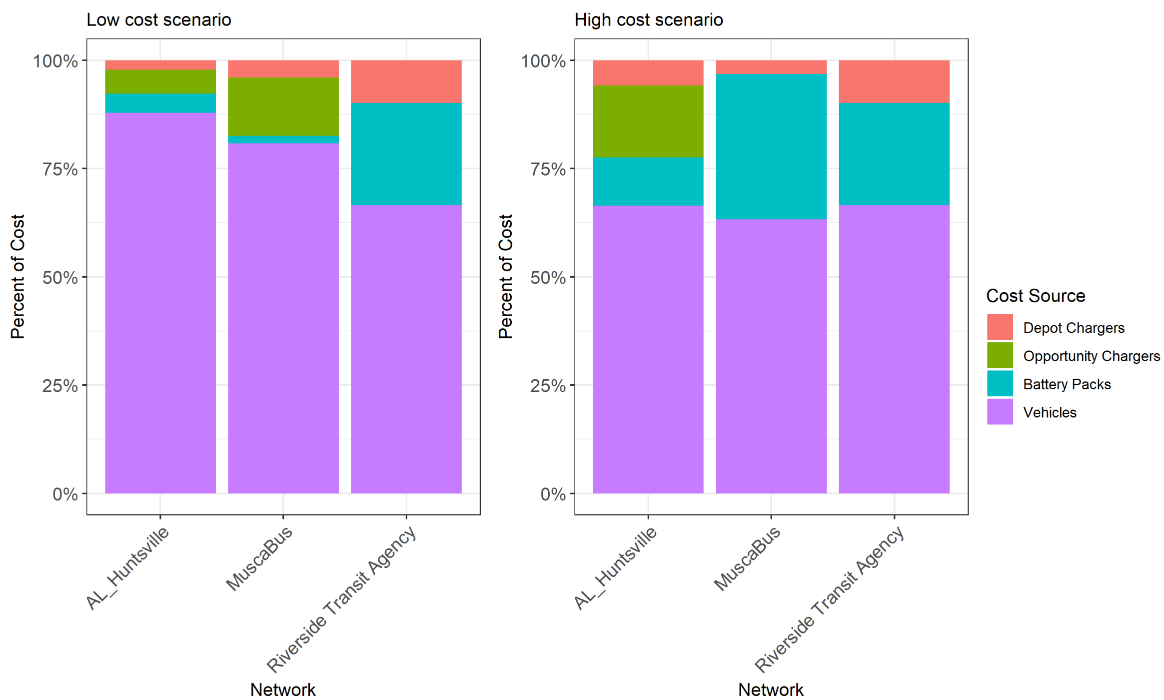


Figure 3.7: Costs of the network as a percentage of total cost for each network for the low-cost scenario (left) and the high-cost scenario (right).

The cost breakdown for RTA doesn't change, as opportunity charger costs are the only difference between these two scenarios. However, there are some interesting observations to make about the breakdowns for all networks. First, the cost of the vehicles makes up the largest share of the overall network cost in all scenarios and for all networks. These breakdowns are in the 'least vehicles' scenario, showing that the biggest driver of network transition costs is the cost of the vehicles. If the total cost of vehicles and drivetrains can be decreased, it will have the largest impact on overall transition costs for networks. When examining the differences in costs between scenarios for the networks that employ opportunity charging, there are more interesting observations to be made. In both cases, the cost of the battery packs and depot charging increase significantly as the overall number of opportunity chargers decreases, as networks have to purchase additional units of both to offset the loss of energy input that the opportunity chargers provide. This is more obvious when considering the values between networks for a single network (Figure 3.8).

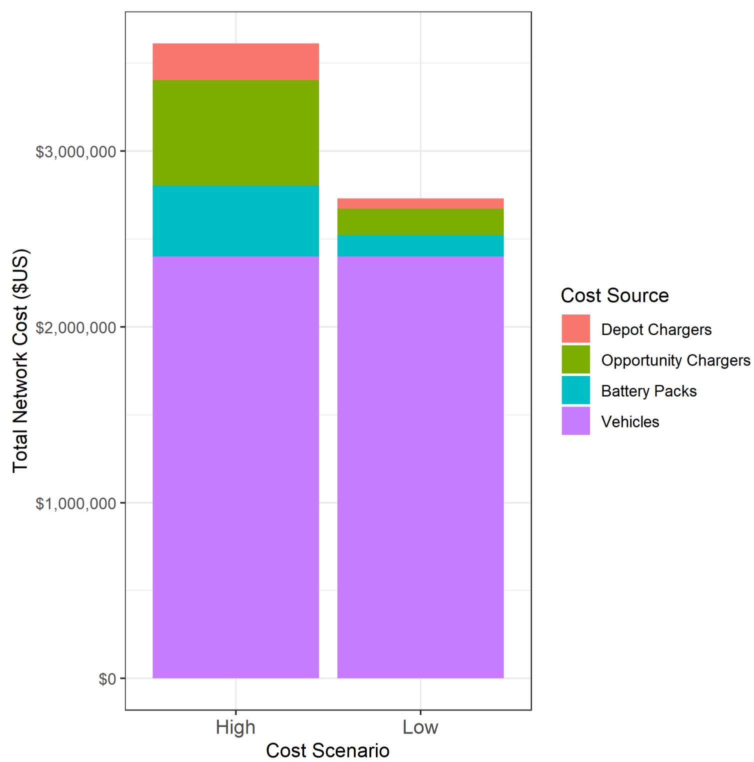


Figure 3.8: Total cost and breakdown for the Huntsville Shuttle for both cost scenarios.

For the Huntsville Shuttle, the low opportunity charger cost scenario resulted in three chargers being installed, while the high opportunity charger cost scenario resulting in the installation of only two chargers installed. However, despite the other costs in the network not changing, the costs of the depot chargers and especially the battery packs increased significantly to offset the loss of this infrastructure. This shows that, despite being a small part of the overall cost of a network, the decisions of how much infrastructure to install (and where to install it) can have a significant impact on the overall costs and potential savings in designing a BEB network. This further illustrates the potential savings opportunity charging infrastructure can provide if they can be obtained and installed economically.

3.3.2 Comparing Vehicle and Infrastructure Choice among Networks

Although increasing the cost of opportunity charging (and therefore, decreasing the number of opportunity chargers purchased within a network) increased the cost of both depot charging and battery packs, implying an increase in the total size of the battery packs within a system (Figure 3.7, Figure 3.8), the same does not hold true when networks are compared against one-another (Figure 3.9).

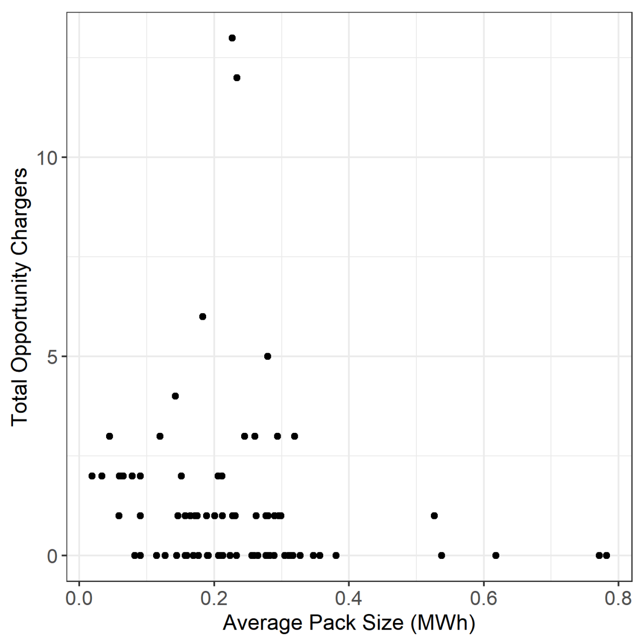


Figure 3.9: The relationship between battery pack size and number of opportunity chargers in a network. This graph shows the few buses and cheapest opportunity chargers scenario.

It appears that, on a network scale, there is no strong relationship between the average size of the battery packs in the vehicles and the ideal number of opportunity chargers in that network.

Therefore, the size of the battery packs in a transit network's vehicles should not be used as a predictor for the ideal infrastructure type to service those vehicles.

The relationship between the longest route in a network and the largest battery pack required by a vehicle in that network is shown in Figure 3.10.

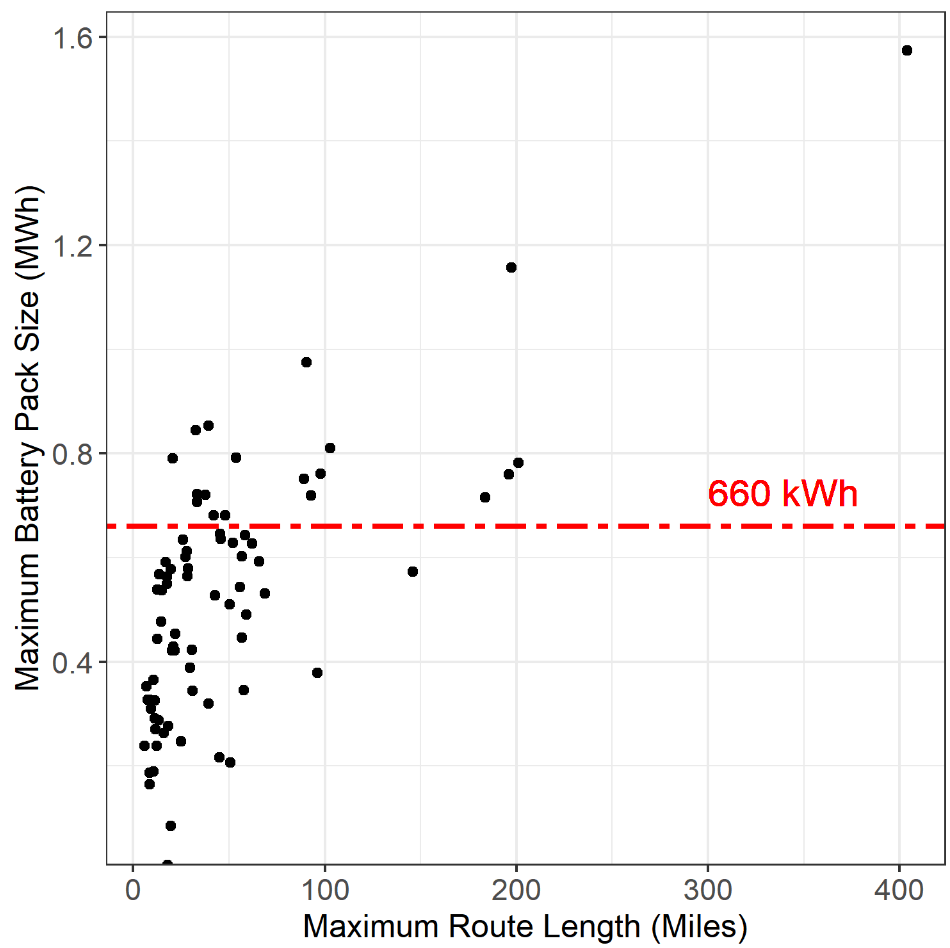


Figure 3.10: Maximum pack size in a network plotted against the length of the longest route within the network. The red line connotes a representative value for the largest battery pack sizes available today.

This figure reveals two aspects of BEB transitions. First, it appears that maximum route length is a reasonable predictor of the largest battery pack that would be required to meet the needs of the entire network, giving network operators a sense of what kind of buses they should consider for their networks. Second, the red dashed line indicates the size of battery packs in the largest buses available on the market today [72], with a pack size of 660 kWh (shown as 0.660 MWh on the figure). 22.4% of the networks required at least one vehicle with a larger battery pack, with 2 networks requiring at least one vehicle with a pack larger than 1 MWh. This indicates that, while BEBs are a solution for most routes in most networks, they are not yet able to serve all current needs of transit networks, especially the smaller and more rural networks which may have longer routes. This is backed up by other studies examining the BEB transition problem allowing for partial transitions, which often find that cost-optimal transitions use BEBs for a significant portion of the routes, with liquid fuels supplementing the routes with more intense energy requirements [11], [23], [27].

3.3.3 Effective Use of Opportunity Chargers

When deciding whether to build opportunity charging into a transit network, the network operator has two strategic decisions to make: how many chargers to install, and where to install them. Data on both of these decisions was gathered from the model.

3.3.3.1 Charger Locations

In general, locations central to a network are preferred for opportunity charging, and chargers at the periphery of the networks are the first to get dropped from networks as the cost of chargers increases. This relationship is shown in Figure 3.11**.**

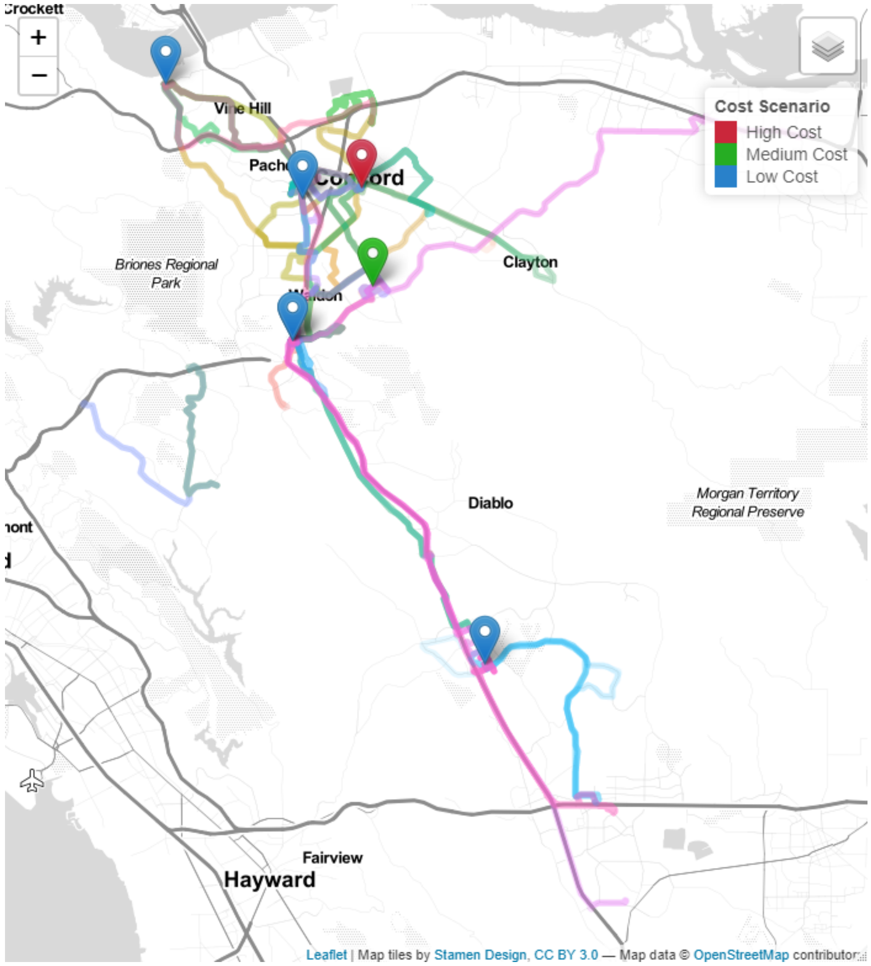


Figure 3.11: A map of the County Connection network with the locations of installed chargers in different scenarios. Note that each of the scenarios installed locations include the locations at higher costs (for example, the low-cost scenario has chargers at all six locations).

County Connection utilizes one charger in the high-cost scenario, two chargers in the medium-cost scenario, and six chargers in the low-cost scenario. As Figure 3.11 shows, the chargers exclusive to the low-cost scenario are located on the periphery of the network and are placed at hubs where two to four routes intersect, allowing buses on these routes to utilize the chargers to lower the need for batteries. In the medium- and high-cost scenarios, these peripheral chargers are no longer economically viable, and only the chargers in the central location of the network where the most routes intersect remain as an economical choice.

3.3.3.2 Opportunity Charger Operations

Figure 3.12 shows the average duty cycle of all opportunity chargers within a network plotted against the total number of opportunity chargers within that network across all charger cost scenarios.

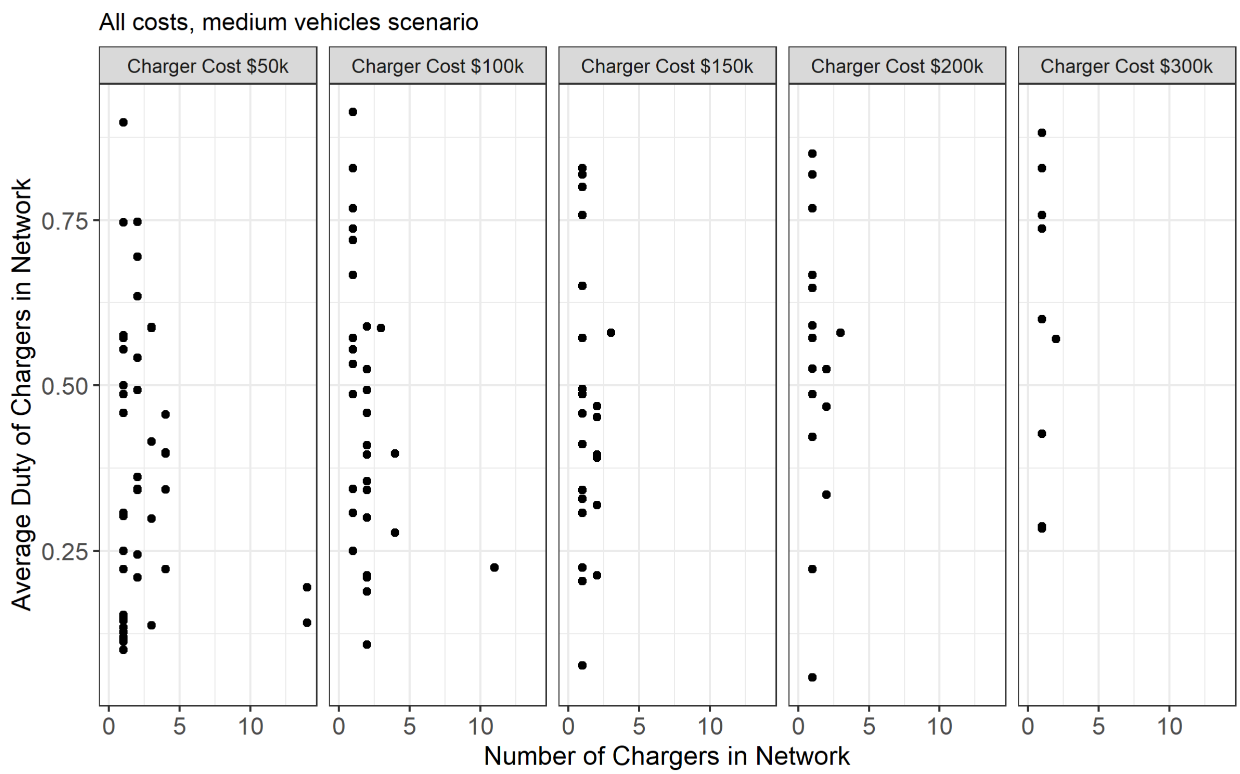


Figure 3.12: Number of opportunity chargers in a network vs average duty cycle of all chargers within the network.

The figure shows that the expected duty of a charger can be a strong indicator of whether a charger is worth the cost of purchase and installation. As chargers get more expensive, higher duties are required to be cost effective, as is shown in the progression of the charts from left to right. Although there are some networks that, even at higher charger costs, can use opportunity charging in specific locations that can still be cost effective, even though the overall duty is low. However, when charger costs are very high, only duties greater than 50% are sufficient to make it worthwhile to install these chargers. Examining how these chargers are used throughout the day, only the networks that can make use of chargers continuously (and thus, have higher duty cycles) maintain an economic advantage by using opportunity chargers even in higher-cost situations. In contrast, if the cost of the infrastructure is low enough, then even lower overall duty cycles can be economically viable (Figure 3.13).

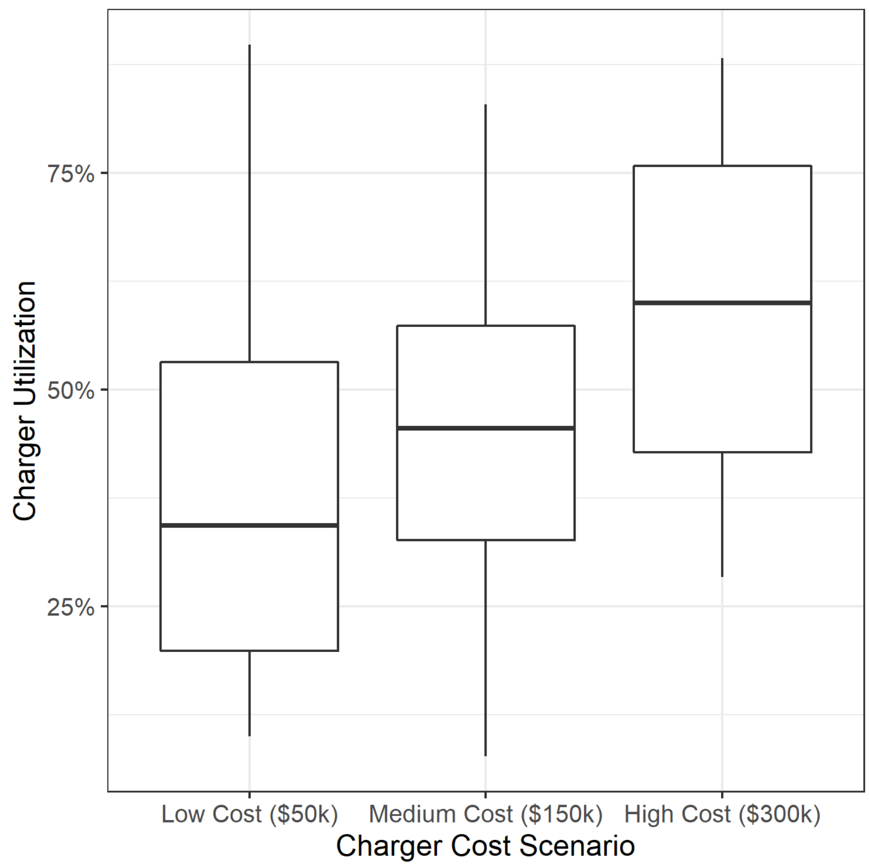


Figure 3.13: A box plot showing the range and average of charger utilization in the networks across the low-, medium-, and high-cost scenarios.

Although it is difficult to identify single characteristics as the cause of high charger utilization, the biggest predictors in the data appeared to be the overall regularity of the routes, as well as networks with a schedule that didn't have too many buses in the key locations at the same time, allowing buses to 'cycle' through the opportunity chargers. Additionally, other studies have shown that characteristics of individual routes within a network can be used to estimate which of those routes is well suited for BEBs and opportunity charging [11], [23], [27]. If the cost of opportunity chargers is brough low enough, it has the potential to offset a huge amount of overall battery pack size in the networks that are able to economically install them.

3.3.4 Depot Charging vs Opportunity Charging

The results of this study have a lot of implications on the direct relationship between the use of depot charging and opportunity charging. Although the depot chargers calculated for the networks were made available during the service day, no network made use of this daytime depot charging. Instead, the depot chargers were used only overnight to refill the batteries of the buses. This indicates that the cost of pulling a bus out of service for a significant amount of time is not worth the extra energy that can be saved elsewhere by recharging in this manner. Although only one time for depot charging was tested (3 hours), results from other studies using this model have also indicated that daytime depot charging is not an optimal strategy unless a very high rate of flexibility is maintained [69]. Additionally, it was found that there were few strong correlations between the tested network characteristics and the optimal strategy across different networks. In most cases, the number of depot chargers required is less than the number of buses in the network (Figure 3.14).

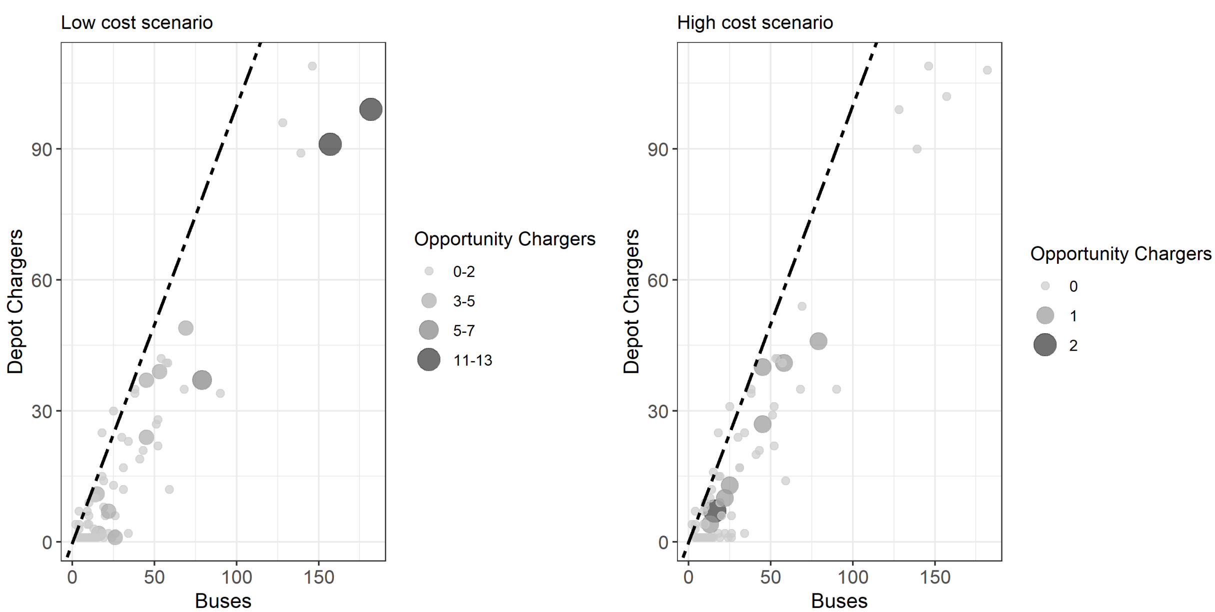


Figure 3.14: The number of buses in a network vs the number of depot chargers required for the network to recharge overnight, with a line of equality for the low opportunity charger cost scenario (left) and high-cost scenario (right)

This finding shows that many networks that are currently deploying BEBs may be overbuying depot chargers. Currently, a depot charger purchase strategy of assigning each bus an individual charger is dominant. However, most networks do not need this many depot chargers to meet the overnight charging needs of the network. This is especially true in larger networks, and the largest number of depot chargers required by a network is just over 100 (despite the corresponding network using over 200 buses). This shows the potential of smartly scheduling depot charging overnight, potentially saving the purchase of tens of chargers, each of which currently costs over $10,000.

3.4 Conclusions and Policy Implications

This chapter presented a unique study examining the trends of BEB transition at network level by modeling the optimal battery packs and charging strategies of more than 75 networks in the United States. As transit networks begin transitioning from traditional fossil fuels to zero-emission technologies, the question of what infrastructure is needed and where to install it will become more important. Currently, the dominant strategy to recharging buses is to purchase a depot charger for each BEB and recharge all buses overnight. This strategy results in a requirement for larger battery packs among vehicles. The results of this study indicate that opportunity charging has several roles to play in the transition of transit networks to BEBs. First, especially if the chargers can be acquired cheaply, they can serve as a way to replace several large battery packs. If the network is particularly compatible with opportunity charging due to overall regularity of routes that are neither too long nor run too frequently, they can even overtake traditional depot charging as the primary energy delivery method in a network (though this is very rare).

Lessons from this study have been discussed throughout the results section. To summarize, there are several challenges that must be tackled on a network-by-network basis when considering BEB infrastructure decisions, limiting the effectiveness of sweeping standards for transition. Individual networks should consider their charging strategy as a full part of the network architecture, not a secondary supporting technology that can be considered after the network has been planned. This is because, in many networks, the selection of one charging strategy versus another can have a significant impact on the optimal arrangement of buses, batteries, chargers, and charging schedules, drastically affecting how a network is operated. Another lesson is understanding that BEBs may not be suited to all networks and all route types. This study identified several networks with routes that are too long to be supported by BEBs available on the market today. These routes are more common in smaller, rural networks, as the lower population density of these locations requires longer journeys to service the population. Finally, as the vehicles and battery packs represent the largest overall investment into the capital cost of BEB transitions, network architecture decisions must be made in service of utilizing these assets as much as possible. This is easier with smaller battery packs, as opportunity charging enables buses with smaller packs to use the same amount of energy for less upfront capital cost in certain circumstances, effectively transferring some of the burden of storage to the grid.

4 The Benefits of Diversification: Examining the Economic Case for a Mixed-Technology Approach in Zero-Emission Bus Networks

4.1 Introduction

There is a concerted effort in the transit bus industry to transition buses from traditional fossil-fuel vehicles to zero-emission buses (ZEBs), a category that includes both fuel cell electric buses (FCEBs) and battery electric buses (BEBs). Transitioning from fossil-fueled transit buses to ZEBs has been found to be an effective method of curbing greenhouse gas emissions from the transit sector [59], [60], [73]. Transit agencies around the world have begun transitioning their fleets to ZEBs as part of an effort to meet climate change goals. According to a study performed by CALSTART, there are currently 3,533 ZEBs either deployed or on order across the United States, approximately one third of which are in the state of California [4]. In December 2018, the California Air Resources Board (CARB) adopted a regulation require that transit fleets begin the shift to zero-emission buses known as Innovative Clean Transit (ICT), which affects the purchase of new buses beginning in 2023 [3]. CARB estimates that the California transit bus fleet will complete the transition to 100% ZEBs by the 2040s.

Although California has the most well-developed ZEB policy, New York also has a program for the replacement of diesel commercial vehicles, including transit buses. Additionally, several states have signed onto the Multi-State Medium- and Heavy-Duty Zero Emission Vehicle Memorandum of Understanding (MSMOU), a statement of cooperation between the signees that include 15 states and the District of Columbia. Although it is not legally binding, the MSMOU represents a statement of fostering "a self-sustaining market for zero emission medium- and heavy-duty vehicles through the existing Multi-State ZEV Task Force, which will serve as a forum for state coordination, collaboration and information sharing on market enabling actions, research, and technology developments." [61]. The action plan laid out in the MSMOU primarily consists of committing to funding and other incentives to encourage the development of a market for ZEBs in their respective states. On a federal level, new funding for ZEBs has recently been introduced in the Infrastructure Investment and Jobs Act. Signed into law in 2021, this act will provide a total of $18.4 billion into federal programs to promote low- and no-emission vehicles, a pool of funding that can be used for ZEBs (among other uses).

As a result of these policies, several transit agencies in the United States have begun developing plans for full-scale transitions to ZEBs, and a few of these agencies have already completed the transition. These transitions have come with a fair share of challenges, from costs of transitioning to the specific strategy or strategies and infrastructure that should be used in a ZEB fleet, to issues of knowledge and operation of the fleets. A primary concern for transit agencies transitioning to ZEBs is a decision of which technology to use: FCEBs or BEBs. This study presents an examination of the factors that can impact that decision for small networks in the United States and considers the "hybrid-network" solution of mixing BEBs and FCEBs to create a more economical transition that allows agencies to enjoy the benefits of both technologies.

4.1.1 ZEB Technologies

When transitioning to ZEBs, there are generally two technologies available to power the buses: BEBs and FCEBs. Each of these vehicles has advantages and disadvantages relative to each other, and relative to traditional fossil fuels. BEBs tend to be less expensive to purchase than FCEBs, with some companies offering buy-lease plans where agencies are not burdened with the purchase and ownership of the battery pack [74]. The range on these buses is variable, from smaller lighter vehicles with shorter ranges to vehicles with large battery packs that rival the range of FCEBs (though neither can currently compete with the range offered by fossil-fueled buses). Deploying small-scale pilot projects is also relatively easy with BEBs, as the supporting infrastructure for BEBs is scalable with the size of the deployment of buses. However, moving from pilot studies to full-scale BEB deployments has proven difficult for transit agencies, due to poor cost scaling of infrastructure and issues with electrical grid connections [75]. FCEBs, in contrast, are much less restrictive in terms of route assignment when compared with BEBs, as their operation is much more similar to a traditional fossil-fueled bus than BEBs especially in terms of refueling. Hydrogen can be produced either on-site or off-site, and buses most often need only be refueled once per day for approximately 10 minutes to meet the needs of route service [76]. This also allows the buses to be refueled quickly in the event that a bus gets called into service at an unplanned time (such as during a local emergency requiring evacuation or in the case of another vehicle breaking down during its service day). However, the prices of FCEBs are much higher than BEBs due to their less mature technology. The ability of hydrogen fuel to be produced and distributed is also not at the level to handle a large influx of FCEBs presently. There is also no large-scale distribution network of hydrogen fuel, presenting challenges for networks deploying FCEBS in the near future, as they must select from a limited pool of expensive solutions. The actual emissions reduction from FCEBs depends heavily on the production method of hydrogen, as a selection between "grey" hydrogen (which is produced with the use of fossil fuels, especially natural gas) and "green" hydrogen (which refers specifically to hydrogen produced through electrolysis using renewable electricity sources) can make the difference between well-to-wheel emissions reductions relative to existing fleets being as high as 50%, or as low as 10% [77]. Due to both issues in production and distribution, the price of hydrogen fuel is also high relative to grid electricity.

4.1.2 Network Case Studies

There have been many different studies on the costs and methods of transitioning individual networks. The issues surrounding such a transition are numerous and complex. Optimization studies have been performed focusing on everything from vehicle scheduling [21], [22], [67] to optimizing a fleet transition over time [11], [23], [27] to examining the different types and locations of charging infrastructure [24], [26], [68]. These studies have reached a variety of conclusions based on the nature of the network that was the focus of their study. FCEB networks and transitions are a field that is increasing in study as it becomes clear that FCEBs will be heavily incorporated into ZEB fleets around the world. Specific network studies tend to focus on concerns of fuel production and refueling scheduling of buses [78] while larger-scale studies are more focused on emissions reductions, especially from a well-to-wheel perspective [32], [79]. Several comparative assessments and reviews of the state of technology also exist [10], [76], [80], and have found that the primary impediment for FCEBs is cost, distribution, and the need to commit to a scaled-up distribution. Some pilot projects have also shown the effectiveness of FCEBs on certain routes [10], [81]–[83], however, it appears that there have been minimal studies on the potential of mixing FCEBs and BEBs within the same network. This study examines the question of the effectiveness of mixing these technologies in an attempt to employ the benefits of both technologies and offsetting the weaknesses each has.

4.2 Methods

To model the networks, a mixed-integer linear program (MILP) optimization model was developed. This type of modeling is well established for solving these types of problems and has been used to solve network configuration problems in several other studies [11], [27], [69]. This model can be generally applied to any transit agency with a static general transit feed specification (GTFS) compliant data feed and focuses on the optimal mix of fuel types for vehicles and infrastructure within the transit network.

4.2.1 Optimization Model

4.2.1.1 Model Structure and Assumptions

This model is based on several key simplifications and assumptions about the vehicles and the system in which they operate:

- All buses of the same type are completely identical to each other. It is also assumed that all buses of all types are identical in terms of passenger capacity, physical size, and in all other ways aside from mass, cost, energy storage and powertrain technology.
- Each network operates in a predictable, deterministic fashion according to its timetable, neglecting the impacts of traffic, road conditions, and other delays on the operation of the network. Although these issues may have a significant impact on the operations of a transit network in real-world conditions, these factors are not the focus of this study.
- The network operates identically each day, with identical costs and energy use, for 365 days and for 12 years. The time-variant aspects of ZEBs and the effects of seasonal weather and other seasonal effects on ZEBs are not the focus of this study.
- Hydrogen stations are limited only by their daily capacity for refueling, and that any minor scheduling conflicts at the time of refueling can be resolved without affecting overall service. It is also assumed that hydrogen distribution to these networks has a solution whose cost is included in the overall cost per kilogram of hydrogen fuel.
- Operation costs, administrative costs, and installation costs beyond the cost of equipment are neglected. Though they can be quite high and may be a driving factor in the decision of certain transit agencies, these costs have a very high variance and are specific to the environment in which a transit agency operates. They are not the focus of this study.

4.2.1.2 Nomenclature and Equations

The nomenclature to define the model uses x to notate variables, c to notate parameters that depend on sets, and other letters to notate the sets of the problem (Table 4.1).

Table 4.1: Model Nomenclature

Symbol	Meaning	Units
Sets		
$r; R$	A route in the system; a set of all r	None
$b; B$	A bus; a set of all buses	None
$l; L$	A candidate location to install infrastructure; a set of all candidate locations	None
$t; T$	A time during a period of operation; a set of all times tracked	time blocks
$y; Y$	A bus type; a set of all possible bus types	None
$s; S$	A hydrogen station type; a set of all possible station types	None
Parameters		
$c_y^{bus.cost}$	The cost of bus type y	$USD
$c_y^{pack.size}$	The battery capacity of bus type y	kWh
$c_y^{hydro.capacity}$	The hydrogen capacity of bus type y	kg
$c_s^{station.capacity}$	The daily hydrogen capacity of station type s	kg
$c_s^{station.cost}$	The cost of station type s	$USD
$c_y^{is.hydrogen}$	A binary parameter signifying if type y is a FCEB	None
$c_{r,y}^{energy.use}$	Energy used by a bus of type y on route r per time step	kWh
$c_r^{route.time}$	Total time (travel time plus idle time) for a bus to travel on route r	time blocks
$c_{r,t}^{buses.on.route}$	The count of buses on route r at time t	buses
$c_{r,t}^{trip.start}$	A binary parameter signifying the start of a trip on route r at time t	None
$c_{r,b}^{bus.assigned}$	A binary parameter describing if a bus b is assigned to route r	None
$c^{charger.cost}$	The cost of each depot charger	$USD
$c^{hydro.cost}$	The cost of hydrogen fuel	$USD/kg
$c^{elec.cost}$	The cost of electricity	$USD/kWh
$c^{hydro.convert}$	A conversion factor to convert kg of hydrogen to kWh	kWh/kgH2
$c^{charge.amount}$	The amount of energy provided by each depot charger overnight	kWh
Variables		
C_{Total}	Total cost (capital plus energy) of the system	$USD
$C_{capital}$	Capital costs of the system	$USD
C_{energy}	12-year energy costs of the system	$USD
$x_{b,y}^{type.assign}$	A binary variable describing whether bus b is assigned type y	None
$x_{b,t}^{energy.status}$	The amount of energy stored by bus b at time t (both electrical and as hydrogen)	kWh
$x_{b,t,y}^{elec.status}$	The amount of electrical energy in bus b of type y at time t	kWh
$x_{b,t,y}^{hydro.status}$	The amount of hydrogen in bus b of type y at time t	kg
$x^{elec.deficit}$	End-of-day deficit of electrical energy in the buses	kWh
$x^{hydro.deficit}$	End-of-day deficit of hydrogen in the buses	kg
$x^{depot.chargers}$	Number of depot chargers. Must be an integer.	None
$x_{r,b,t,y}^{on.route}$	A binary variable describing if bus b of type y is on route r at time t	None

$x_s^{hydro.stations}$	The number of station type s present in the system	None

The model's behavior is governed by the following set of equations. Equation 4.1 serves as the objective function to minimize the total cost of the system.

$$\min C_{total} = C_{captial} + C_{energy} \tag{4.1}$$

The total cost is made of the capital cost component and energy cost component, which are described in Equations 4.2 and 4.3, respectively.

$$C_{captial} = \sum_{b=1}^{B}\sum_{y=1}^{Y}\left(x_{b,y}^{type.assign} * c_y^{bus.cost}\right) + x^{depot.chargers} * c^{charger.cost} + \sum_{s=1}^{S}\left(x_s^{hydro.stations} * c_s^{station.cost}\right) \tag{4.2}$$

$$C_{energy} = 12 * 365 * \left(x^{hydro.deficit} * c^{hydro.cost} + x^{elec.deficit} * c^{elec.cost}\right) \tag{4.3}$$

Equations 4.4 and 4.5 describe the calculation of the end-of-day deficit for both the electricity and hydrogen.

$$x^{elec.deficit} = \sum_{b=1}^{B}\sum_{y=1}^{Y}\left(x_{b,y}^{type.assign} * c_y^{pack.size} - x_{b,t,y}^{elec.status}\right), t = \max(T), b \in B, y \in Y \tag{4.4}$$

$$x^{hydro.deficit} = \sum_{b=1}^{B}\sum_{y=1}^{Y}\left(x_{b,y}^{type.assign} * c_y^{hydro.capacity} - x_{b,t,y}^{hydro.status}\right)$$
$$t = \max(T), b \in B, y \in Y \tag{4.5}$$

As buses travel on their routes for the day, the energy levels in the buses change depending on the energy use of each route. This movement of energy and the physical limitations of the energy storage systems are governed by Equation 4.6-4.9. Equation 4.6 describes energy lost as a bus serves a route. Equations 4.7 and 4.8 constrain the maximum amount of energy each bus has based on the capacity of its assigned type. Equation 4.9 defines the total on-board energy as the sum of the on board electrical and hydrogen power.

$$x_{b,t+1}^{energy.status} = x_{b,t}^{energy.status} - \sum_{y=1}^{Y} \sum_{r=1}^{R} \left(c_{r,y}^{energy.use} * x_{r,b,t}^{on.route} \right) ,t \in T, b \in B \tag{4.6}$$

$$x_{b,t,y}^{elec.status} \leq c_{y}^{pack.size} * x_{b,y}^{type.assign}, t \in T, b \in B, y \in Y \tag{4.7}$$

$$x_{b,t,y}^{hydro.status} \leq c_{y}^{hydro.capacity} * x_{b,y}^{type.assign}, t \in T, b \in B, y \in Y \tag{4.8}$$

$$x_{b,t}^{energy.status} = \sum_{y=1}^{Y} \left(x_{b,t,y}^{elec.status} + x_{b,t,y}^{hydro.status} * c^{hydro.convert} \right), t \in T, b \in B \tag{4.9}$$

Equations 4.10 and 4.11 constrain buses to only being on one route and only being of one type. Additionally, buses can only be on a route if they are assigned a type (implying that the bus exists within the network).

$$\sum_{y=1}^{Y} \left(x_{b,y}^{type.assign} \right) \leq 1, b \in B \tag{4.10}$$

$$\sum_{r=1}^{R} \left(x_{r,b,t,y}^{on.route} \right) \leq x_{b,y}^{type.assign}, t \in T, b \in B, y \in Y \tag{4.11}$$

Equations 4.12 and 4.13 define how buses service routes. Equation 4.12 dictates that buses must be on a route that they start service on for the entire service duration of that route. Equation 4.13 ensures that the correct number of buses are servicing each route at any given time.

$$\sum_{t}^{t+c_r^{route.time}} \left(x_{r,b,t}^{on.route} \right) \geq c_{r,t}^{trip.start} * \left(x_{r,b,t}^{on.route} - x_{r,b,t-t}^{on.route} \right) * c_{r}^{route.time},\ r \in R, b \in B, t \in T \tag{4.12}$$

$$\sum_{b=1}^{B} \left(c_{r,b}^{bus.assigned} * x_{r,b,t}^{on.route} \right) = c_{r,t}^{buses.on.route},\ \forall r \in R, \forall t \in T \tag{4.13}$$

Finally, Equations 4.14 and 4.15 dictate the amount of infrastructure required to service the buses by defining the required amount of hydrogen stations and depot chargers respectively.

$$x^{hydro.deficit} \leq \sum_{s=1}^{S} \left(c_{s}^{station.capacity} * x_{s}^{hydro.stations} \right) \tag{4.14}$$

$$x^{elec.deficit} \leq x^{depot.chargers} * c^{charge.amount} \tag{4.15}$$

Together, Equations 4.2-4.15 specify a set of constraints that, when combined with the objective function in Equation 4.1, define a system that effectively models a transit bus network that has transitioned to 100% ZEBs, through some mixture of BEBs and FCEBs and their respective infrastructure.

4.2.2 Model Data

4.2.2.1 Network Information

Inputs for transit agency timetable information and route operations are taken from each network's GTFS data feed. The data feeds are maintained by transit networks and are commonly used by external applications to gather information about the operation of the network. This model makes use of the "static feed" of each transit network, which contains information about the routes and trips within a network, including trip times, stop locations, and other pertinent information about network operations. This model uses these data feeds to construct a set of tables to represent the timetable, stops, and energy use of buses on each route.

4.2.2.2 Energy Data and Energy Use Modeling

Vehicle energy use values are generated for each bus type on each route using a model developed by Ambrose and others [50]. Ambrose's model uses data from the FleetDNA dataset developed by the National Renewable Energy Laboratory (NREL) [51] to develop energy demands for a particular bus-route combination using the physical characteristics of the bus and a transit agency's GTFS data feed. By using information present in the GTFS feed and employing regression on the FleetDNA dataset using characteristic velocity, acceleration, and network size as the most significant indicators of energy use, Ambrose's model can develop an estimation for each bus-route pair based on the route's GTFS information and the bus's physical characteristics.

4.2.2.3 Infrastructure

To account for the number of depot chargers that a network would need to refill the buses overnight, the calculation for the number of required depot chargers was performed based on the deficit in the battery packs at the end of the day. The calculation was based on the assumptions that the agency had 6 hours to refill the buses and that each charger was capable of supplying 65 kW of power. It was also assumed that scheduling conflicts could be resolved, and that no additional operational costs were incurred to move buses from their parking spots (Table 4.2).

The hydrogen stations used in this model are based on the Heavy-Duty Refueling Station Analysis Model (HDRSAM) developed by Argonne National Laboratory [84]. Using HDRSAM, three hydrogen station were selected for modeling in a simplified manner as supporting infrastructure for networks using FCEBs. Three station models were selected based on daily refueling capacity: a low-, medium-, and high-capacity station were each used. All of these stations were modeled as being refueled by liquid hydrogen truck deliveries, and that the only limitation on a station's ability to service the buses is that station's daily capacity (Table 4.2).

Table 4.2: Infrastructure Input Data

Infrastructure Type	Energy Provided/Capacity	Cost
Depot Charger	65 kW	$16,000
Hydrogen Station (Small)	500 kg per day	$2,915,853
Hydrogen Station (Medium)	750 kg per day	$2,961,509
Hydrogen Station (Large)	1000 kg per day	$3,014,345

4.2.2.4 Vehicles

The vehicles available to select from were based on vehicles available for purchase in today's market. Both BEBs were based on Proterra's ZX5 line of buses, and the FCEB was based on a New Flyer Xcelsior FCEB. To model these vehicles, the battery pack, hydrogen capacity, and vehicle weight and cost were taken from public resources. To allow for enough charge in a realistic scenario for deadheading and battery health preservation, it was assumed that 80% of the battery pack would be used, holding 20% in reserve. The FCEB was modeled as having access to its entire hydrogen reserve, as refueling hydrogen buses is operationally simple compared to recharging BEBs (Table 4.3).

Table 4.3: Vehicle Input Data

Vehicle Type	Energy Source	Usable Energy Capacity	Mass	Cost
Small BEB	Battery Electric	180 kWh	26,649 kg	$700,000
Large BEB	Battery Electric	540 kWh	33,149 kg	$900,000
Hydrogen Bus	Hydrogen Fuel Cell	37.5 kg Hydrogen	44,000 kg	$1,200,000

4.2.3 Transit Networks Modeled

This network was run on 53 networks from around the United States. The GTFS feeds used were accessed using OpenMobilityData, an open-source repository and API to access the feeds of different transit feeds from around the world. The networks modeled for this project were small, with the largest modeled network being allotted 88 buses and the highest number of routes being 21. This decision was based on computation limitations, as larger models were too computationally intensive to solve. To compare routes by their energy intensity, a reference energy value for is used as a point of comparison. This value is equal to the energy use by the smallest BEB modeled (Table 4.4).

Table 4.4: Network Summary Statistics

Statistic	Units	Average	Standard Deviation	Minimum	Maximum
Number of routes	Routes	9.0	5.03	2	21
Number of buses	Vehicles	29.1	18.8	6	88
Route time	Minutes	32.6	23.6	0.48	198.3
Route length	Miles	14.1	16.0	0.08	139.8
Average route velocity	Mph	22.6	8.8	9.1	56.4
Reference energy use	kWh/mile	4.5	1.2	3.3	16.0

4.2.4 Scenario Analysis

To compare the results of different fuel requirements, three different scenarios were modeled. The "base case" scenario allows networks to use a mixture of both FCEBS and BEBs to meet the network needs, should such a "hybrid network" be determined to be the optimal setup. Additionally, each network was modeled for "all BEB" and "all FCEB" cases, where each network was forced to select all one type of fuel source or the other. Finally, as several networks required an allotment of additional buses, the "all BEB" scenario was rerun allotting more buses to the networks relative to the minimum required vehicles within the network. These scenarios allow for a comparison of the different costs associated with different decisions about how to supply the energy needs of a transit network in a ZEB transition scenario.

4.3 Results and Discussion

Throughout these results, networks are classified based on the amount of each powertrain technology that was used. Networks are classified as "All Battery" or "All Hydrogen" if every vehicle in that network is the respective technology. "Mostly Hydrogen" and "Mostly Battery" refers to networks that have a mixture of buses, but more than 80% of the vehicles are of the noted technology. "More Battery" and "More Hydrogen" refers to networks with a mixture of bus types but neither type has greater than an 80% share.

4.3.1 Base Case Results

Overall, networks made use of a mixture of technologies to meet the demands of the network (Figure 4.1: A histogram of networks by the percentage of buses that were FCEBs (rather than BEBs). Colors indicate the technology classification of the network.).

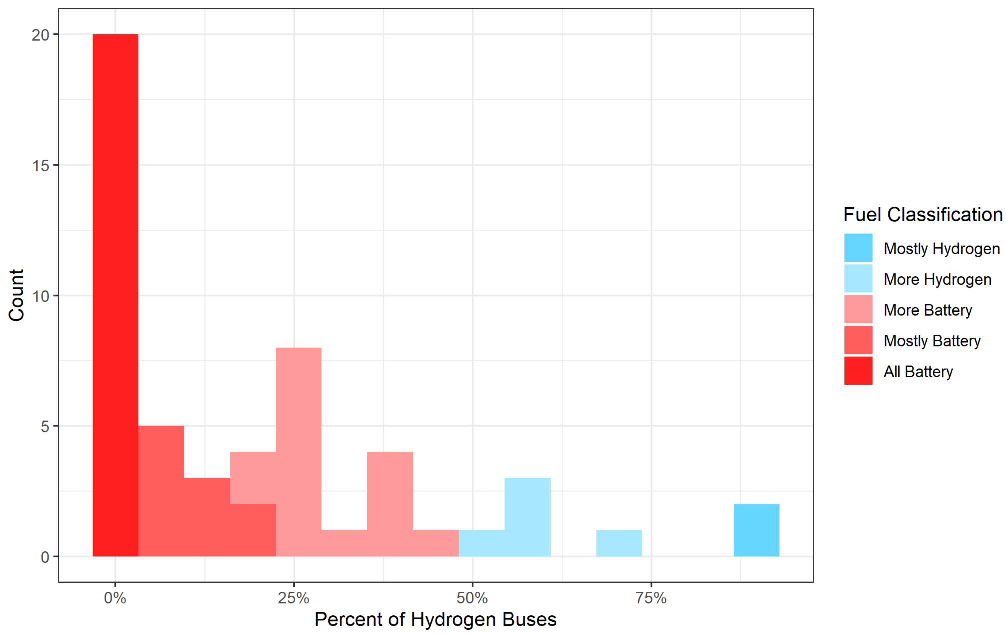


Figure 4.1: A histogram of networks by the percentage of buses that were FCEBs (rather than BEBs). Colors indicate the technology classification of the network.

This is an interesting result, since the common wisdom is that smaller networks are better served by BEBs, due to the issues FCEBs tend to have with smaller-scale deployments. However, if infrastructure can be right-sized, then even relatively small networks can see benefits by switching some amount of their buses to FCEBs (Figure 4.2).

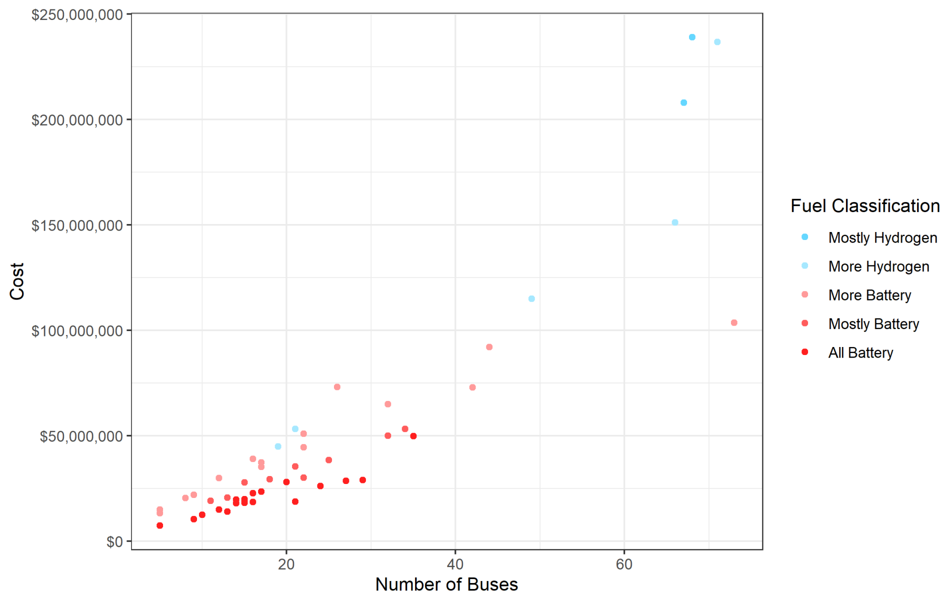


Figure 4.2: A plot of the number of buses versus the total cost of the network, with networks colored to indicate their technology classification.

The addition of FCEBs into a network shifts some of the costs from the upfront capital costs (vehicles and infrastructure) to the 12-year energy cost due to the difference in the cost per kWh of hydrogen fuel versus that of electricity (Figure 4.3).

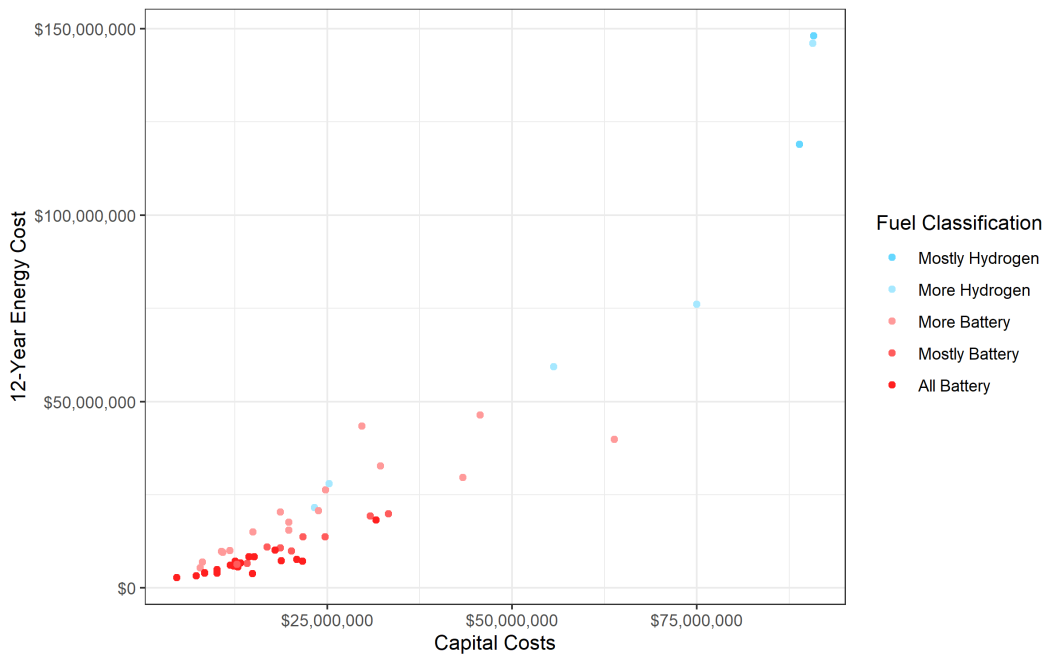


Figure 4.3: A plot of capital costs (horizontal axis) versus 12-year energy cost (vertical axis) for all modeled networks.

Although it appears that FCEBs are only used sparingly, a closer examination of the data shows that approximately a quarter of all vehicles that were selected among the networks were FCEBs. Splitting these buses up by type allows an examination of the trends in which routes are better matches for which technology (Figure 4.4).

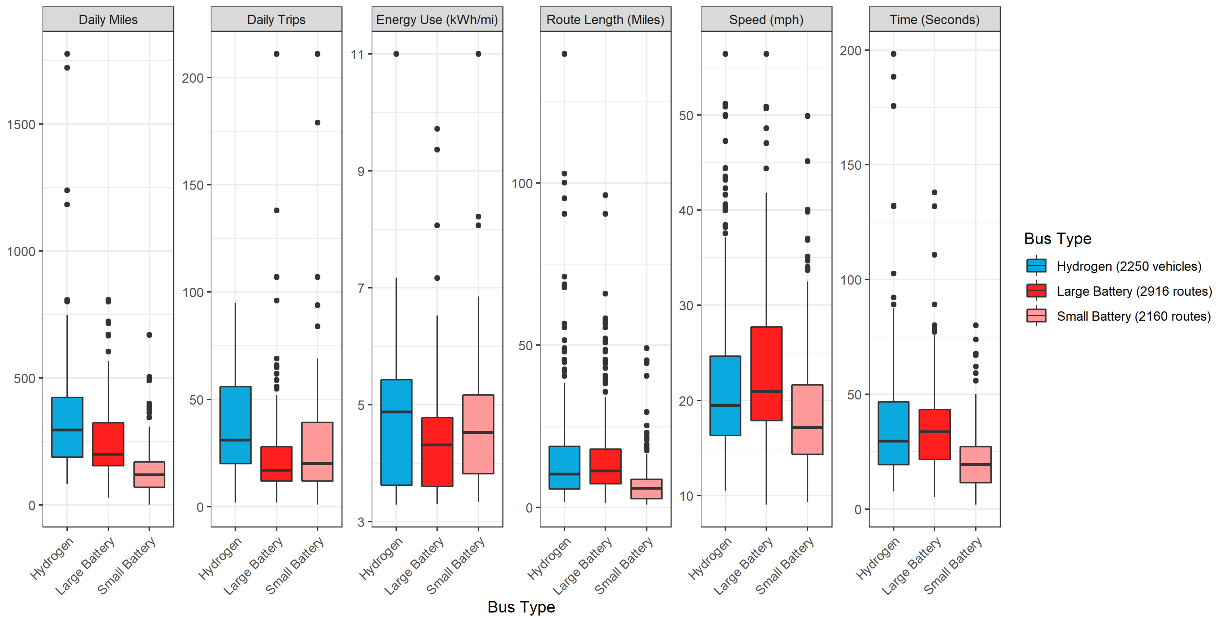


Figure 4.4: A boxplot of the relationship between several route characteristics and the selected bus strategy.

In general, it appears that FCEBs may be better suited for routes that have more daily mileage (far left) than either size of BEB, especially smaller BEBs. It also appears that FCEBs and large BEBs (in this case, with an assumed useable range of 520 kWh) can be used interchangeably in most route situations, indicating that either technology may be suitable for many kinds of routes.

4.3.2 Scenario Analysis

To compare these results to the theoretical all-or-nothing approach that is commonly taken when deploying ZEBs in a network, three alternate scenarios were also modeled. Two of the scenarios were the same as the base case, except that the vehicle selections were limited to only the FCEB and only the two BEBs for the “All Hydrogen” and “All Battery” scenarios respectively. Additionally, initial modeling suggested that the “All Battery” scenario was unable to reach a solution for most of the modeled networks due to a lack of allocated buses. To attempt to mitigate this, a further “All Battery, Extra Buses” scenario was modeled, allocating twice the number of buses than the minimum required to run the network (rather than the 50% more that the other scenarios used). As only 30 networks were able to be modeled in this way, only those networks that were modeled successfully were compared in this way (Figure 4.5).

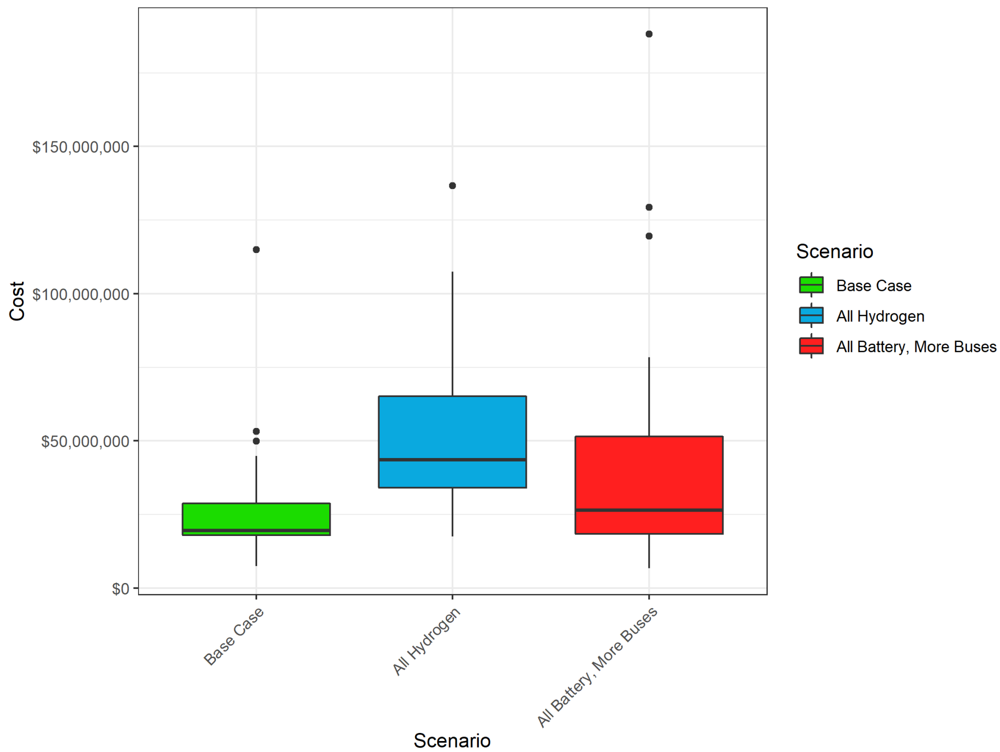


Figure 4.5: A boxplot comparing the total network costs of the thirty modeled networks for the mixed-technology (base case) scenario (left, green), the 100% FCEB scenario (center, blue) and the 100% BEB scenario where extra buses were alotted (right, red).

Comparing the three technologies against the scenarios that were all modeled successfully, it is clear that a mixed-technology approach is the most economical in most cases. Although the "All Battery, More Buses" scenario can be close in many circumstances (as several networks selected 100% BEBs in the mixed-technology case), but when that is no longer the optimal solution, costs start increasing rapidly. Currently, forcing all networks to be 100% FCEBs increases the overall costs significantly, as current costs of both buses and fuel are higher for hydrogen.

An interesting effect of these scenarios is the differences that emerge in required vehicles in these three scenarios (Figure 4.6).

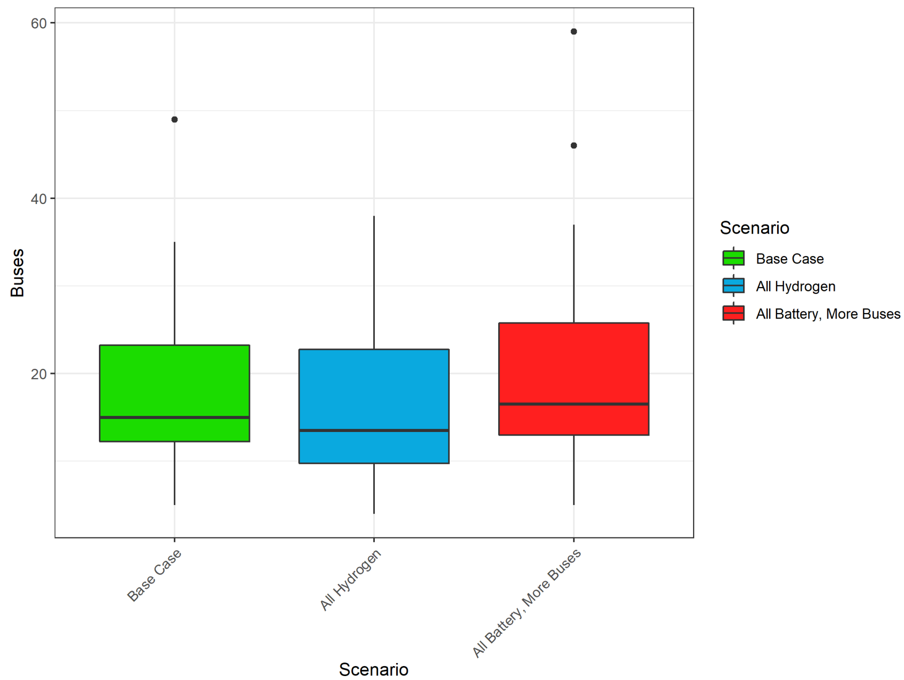


Figure 4.6: A box plot of the number of vehicles required in each modeled scenario for the 30 networks successfully modeled in all scenarios.

Although the differences in bus numbers are subtle, it appears that the “All Hydrogen” scenario may be preferred if the fewest number of vehicles is desired regardless of the cost of implementation. Deploying all FCEBs in the modeled networks removes the high outlying vehicle numbers (noted by the dots on the chart) and decreases the overall average by a few buses. In contrast, that all BEB approach requires extra vehicles in many cases, both increasing the average number of vehicles required on each route and generating an additional outlier in vehicle requirements relative to the base case.

4.4 Conclusion

This chapter examines the effectiveness of mixed-technology solutions on the cost of ZEB deployments. By developing a MILP model that simulates the operation of any transit network based off of its GTFS feed, 53 networks were investigated to examine the effectiveness of a mixed-technology approach. Only via the mixed-technology approach were all 53 networks able to be adequately modeled; FCEBs required extra vehicles to meet the needs of the modeled networks, and the 100% BEB case could only be modeled for 30 out of the 53 networks, even with extra buses allotted. In ZEB deployments, one of the most challenging aspects for most transit agencies to overcome is the overall cost of the transition, as ZEBs are still significantly more expensive to their fossil-fueled counterparts. The results of this study show that significant amounts of money can be saved on both buses and energy by considering the use of a mixed-technology approach. The increased flexibility of the mixed-technology approach may make it seem to be an intuitive solution, this approach is currently not favored by many transit agencies due to a perception of increased costs due to operational complexity and the need to train maintenance staff on multiple types of vehicles. However, the potential for cost savings by maintaining a mixed-technology fleet may be larger than many decision-makers realize, and it should not be dismissed out-of-hand as a solution, even with the increase in complexity. This is especially true in reaction to knowledge of how expensive it may be to procure energy in the form of hydrogen and electricity. Although simplified average values were used in this model, transit agencies and energy companies should consider the impact of finding economic solutions to energy procurement. Energy costs constitute half or more of the costs of most networks and finding a way to lower these costs could open significant opportunities to lower the burden of ZEB deployment.

There are several limitations to the modeling methods that were used in this study. Due to a lack of computing power, the scale of the modeled networks was limited in scope to relatively small networks, with transit networks of large metropolitan areas proving too computationally intensive to model in a timely fashion. Additionally, several simplifications in terms of costs were used. This is especially true of energy costs, where a single value was used for all networks in all circumstances. Energy costs for both electricity and hydrogen are frequently very complex, with different cost structures depending on use factors, delivery methods, and other unpredictable reasons. However, these are very individualized aspects of ZEB deployment; the goal if this project was to develop a generalized model to examine the potential of mixed-technology approaches to ZEB deployment.

Future studies may incorporate these more complex types of cost or may focus on larger networks by developing further optimizations to ZEB network modeling. Overall, multi-technology deployment strategies remain an area of high potential to reduce the cost of ZEB deployments.

5 Conclusions and Future Directions

Transitioning a transit network to 100% ZEBs is a complex problem, with many different factors to consider. Between choices of technology, concerns of operational complexity, and economic costs and benefits, each transit network represents a highly complex system with an equally complex set of possible solutions. This research examined the complexities of just some of the ZEB transition problem, focusing on the economics of the situation. By simplifying certain aspects of transit networks, we were able to model the highly complex system as a set of equations that, altogether, made a MILP optimization problem. This optimization presented several insights into the transition problem.

In Chapter 2, a method for modeling transit networks as a MILP was established, and the method was tested on a case study network. It was established that the proposed model can represent the network as it exists, returning results that are resemble the case study network closely in both scale and proposed cost of a ZEB solution. Using this outcome, a sensitivity analysis allowed further insights to be gained both in how the model reacts to variations in certain inputs, and in how these variations may in turn affect the solution for other networks to be modeled in the future. This project also showed several weaknesses in the construction of the model, allowing it to be refined in future studies.

In Chapter 3, the model was expanded to accept data taken from public GTFS feeds, expanding the number of networks modeled from 1 to 78. By considering a wide range of networks rather than just one, it was possible to examine trends in factors such as battery size and infrastructure placement as they relate to infrastructure costs and network conditions. It was found that opportunity charging infrastructure needed to be significantly less expensive than current prices if it was to become widely spread, and that encouraging opportunity charging could save costs for transit agencies in both depot charging infrastructure and vehicle battery pack size. The study also gave insight into how BEBs as a technology would struggle to meet the needs of certain kinds of networks, encouraging the investigation of alternative technologies to meet network needs.

Chapter 4 incorporated FCEBs, the other type of ZEB, into the modeling framework. Rather than an unconstrained battery pack size for BEBs (as was present in Chapter 3), vehicles modeled in Chapter 4 were based off of vehicles that are available in the US market. Although a full BEB transition was the optimal solution for several networks studied, more than 50% of the networks modeled had an optimal solution that incorporated some mixture of BEBs and FCEBs. In aggregate, the mixed-technology solution also outperformed the single-technology solutions in terms of cost. This suggests that mixed-technology approaches are worth studying, and if concerns of operational complexity and fuel distribution can be overcome, the future ZEB transition may resemble this mixed-technology approach.

The research presented in this dissertation contributes to the wider academic study of ZEB fleet transitions by creating a generalized approach to optimizing ZEB networks. This is in contrast to most literature on ZEB transition studies, which focus on the specific cases or networks that the reader has chosen to focus on. By expanding on this approach in Chapters 3 and 4, a truly novel approach to considering the network transition problem at a large scale was established. Thinking about the problem in this manner opens several novel avenues of study and questioning, both academic and practical. Considering these transitions as parts of a larger whole can inform decisions on policy from a broader perspective, rather than thinking of ZEB networks as isolated, special cases. As more and more fleets move towards ZEBs, the questions surrounding their transition will grow with the scale of deployments, from demonstration and pilot projects up to full-scale deployments and larger all-ZEB networks. By examining this perspective, patterns across networks can begin to emerge that may inform the decisions of other, similar transit networks.

All research constitutes a work in progress, and this project is no exception. There are several aspects of this project that have gone understudied or remain open avenues for future expansion. One of the primary underdeveloped aspects of this project is the way energy costs were handled. This project treated energy costs as constant value, uniform during the day, and unchanging as years pass. None of these assumptions adequately reflect the realities of the energy market. Although incorporating the more complex structures of this market, understanding how the flows of energy cost affect the optimal architecture for a ZEB network is an open question to consider in future research.

Another potential avenue for further research is a refinement of the energy use model that was used throughout this model. Although the regression method used in this model is sound, the data on which the regression method occurs was collected between 2012 and 2015 [51]. Vehicle technology has advanced significantly since these data were collected, and an updated dataset may improve the accuracy of forecasts created with this model. Additionally, the energy model currently doesn't directly consider the impacts of factors such as elevation, climate, traffic conditions, and other route factors. This was discussed in Chapter 2 but wasn't revisited in later iterations of the model. Future projects could seek to improve and refine the method by which vehicle energy is calculated, improving the accuracy of route energy use by ZEBs.

This research also did not compare the model output with existing ZEB networks to consider the differences between modeled results and real-world implementation. There are several 100% ZEB networks in operation around the world, but none of these were modeled in this project. Thus, it is currently unclear how the modeled optimized results compare with how agencies implement a ZEB transition. An obvious avenue of study that arises from this situation is model validation; however, another way this comparison could be examined is in an attempt to examine the value of operational simplicity, or other decisions made for reasons other than visible cost. This peek into the decision-making behavior of transit agencies could provide even more insight into the challenges and considerations of implementing a ZEB network.

Overall, this research provides insight into the challenges of transitioning a transit network to 100% ZEBs. The model developed is highly flexible, allowing insights into this transition to be generated from a variety of angles. In particular, we were able to show the challenges of a 100% BEB approach and make an economic case for a mixed-technology approach to ZEB transitions. Transitioning to ZEBs is an endlessly complex endeavor, with countless avenues of exploration and optimization to be had. This research is a small examination of this task, with a litany of possibilities present for further understanding. In all, we hope that this research can help improve the ability of transit networks to transition to ZEBs and help researchers understand this transition, improving the outlook on sustainable transportation.

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Appendix A: A Discussion on the Effects of Ambient Temperature on Chapter 2 Analysis

As discussed in Chapter 2, the energy use per mile of a BEB can be affected by ambient temperature. For the analysis, the primary effect of concern was the effect of air conditioning (AC) on the energy use per mile of the bus. This effect was selected due to it being the primary concern in the network that was being studied. The effects of the air conditioning system on a battery electric vehicle have been examined in many studies. Vepsäläinen and others found that the effect of ambient temperature on a BEB can be classified as an "Extensive Noise Factor"; that is, dynamically unpredictable, but with knowable shape and variance that can be used to characterize its effect on the energy use of the vehicle [42]. Zhou and others measured the effect of air conditioning under nearly-worst-case scenarios (Summer in Macau with the system set to maximum) and found that it contributed to an increase in energy use of approximately 10-25% depending on the loading, traffic, and ambient conditions [41].

However, AC is not the only way in which ambient temperature can affect bus performance. Cold temperatures can affect BEB performance in several ways. The primary effects of concern are the auxiliary power of a heater to heat the cabin of the bus, and capacity fade of the batteries due to cold temperatures. Capacity fade occurs in batteries once they reach certain high or low temperatures. This fading effect is due to issues in the underlying chemical reactions when they occur at high or low temperatures, causing irreversible damage to the battery cell [85]. These effects can be exacerbated by battery age, or can themselves cause premature aging of the battery pack [86], [87]. However, these effects are not considered in this study as capacity fade (and its effects) are not considered as part of the model and the weather in the studied network generally does not get cold enough for the capacity fade to be significant, especially during the normal operating hours of the network.

Finally, heating of the cabin of a BEB can have a significant impact on the energy use per mile if an electric resistive heater is used. However, alternative options for cabin heating exist. A primary alternative is the fuel-fired heater (FFH), which uses a liquid fuel (typically diesel, though other fuels are sometimes used) to heat a liquid that is used to heat the cabin of a bus. In a survey of this technological solution, Sutton and others found that almost all BEBs available in the market have the option of adding a FFH to the purchased vehicle, and that these additions were generally allowed by ZEB mandates in states with colder climates [88]. California's ICT regulation does not allow for FFHs to be fitted on ZEBs, although mechanisms exist to apply for an exception (as the law does not take affect until 2031, it is unclear whether these exceptions will be granted for cold weather, or how common they may be) [3]. Although values for number of buses fitted with these heaters are not available in the US, a study of buses in Slovakia found that a majority of the country's BEBs are fitted with such heaters [89], and that the use of a FFH results in a BEB's energy consumption per mile remaining fairly constant in cold weather conditions (although the emissions per mile of these FFH-fitted buses is significantly worse than their electric resistive counterparts) [89], [90].

Appendix B: Chapter 2 System's Sensitivity to Opportunity Ratio

To understand the effect of the opportunity ratio on the system architecture, a side study was run examining the effects of changing the opportunity ratio on the system. Overall, the system was mostly unaffected by changing the opportunity ratio apart from the specifics of the infrastructure selected. The effect on the systemwide cost was minimal (Figure A.1, a and b)

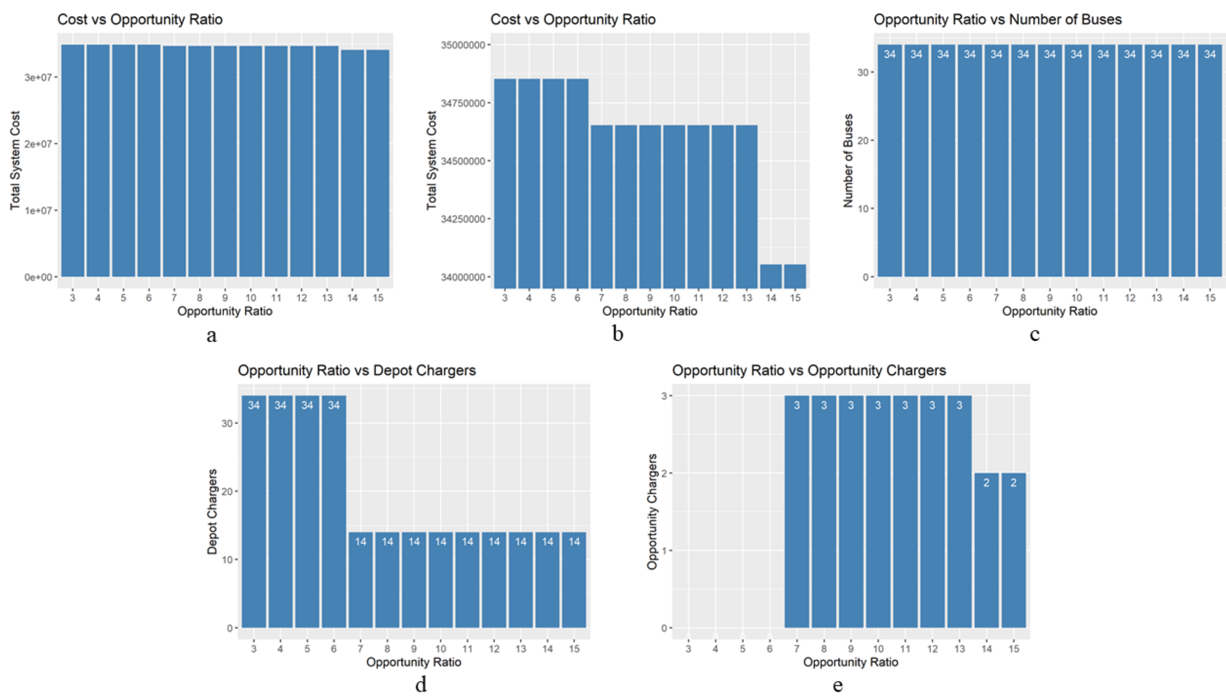

Figure A.1 The effect of changing opportunity ratio on the cost of the system (a) with a detail of the affected region (b), the number of buses (c), the number of depot chargers (d), and the number of opportunity chargers (e).

The overall effect on the cost was a difference of less than $750,000, or less than 2.2% of the overall cost at the extremes. The opportunity ratio didn't change the number of vehicles required to service the system (Figure A.1, c). Investigation into the types of buses selected revealed no changes. The opportunity ratio dictates the mix of infrastructure that is required of the system; the biggest changes occur when the opportunity ratio falls below 6 or rises above 13 (Figure A.1, d and e)

These breakpoints are a result of the relative cost of opportunity chargers to depot chargers, as well as the number of buses at each hub. An opportunity charger is assumed to cost six times as much as a depot charger for this study ($600,000 and $100,000 respectively), so with an opportunity ratio of 6 or below, these chargers are not a cost-efficient option as the energy savings does not overcome the relative costs of the chargers. At higher opportunity ratios, these chargers can service more buses per charger. The 'location 1' hub has 14 buses that can opportunity charge passing through it. Once the opportunity ratio increases above that point, a charger can be removed from that station, decreasing the overall system cost. Overall, it can be concluded that the system is not very sensitive to the opportunity ratio. Although this ratio is not usually fixed and is dictated by the realities of running a timetable with unpredictable perturbations, the effects of changing it on the system are relatively small aside from major, knowable breakpoints. Fixing this ratio can be used as a tool to study networks without drastically impacting the final architecture of that network.

Appendix C: Selection Criteria and Network List for Chapter 3

In Chapter 3, 78 transit networks were modeled. These networks were selected based on the following criteria:

1. Availability of data. Networks were selected based on the feedlist provided via the OpenMobilityData database. Networks were considered if they were present in that database, located in the United States, and provided URL correctly pointed to a GTFS feed.

2. Computational fit to model. Above a certain size, networks became so large as to be impossible to solve within a practical amount of time. This primarily eliminated very large networks, such as the Los Angeles Metro transit network or the New York City transit bus network.

3. GTFS compliance. Networks were eliminated if some part of their GTFS feed didn't comply with the standards as laid out in the GTFS standards website.

This left 78 networks listed below (Table A.1). GTFS static feeds are constantly updating. Data presented in this work was retrieved in January 2022.

Table A.1 List of Networks Analyzed in Chapter 3

ABQ RIDE	Norwalk Transit System
Alabama Huntsville	Palos Verdes Peninsula Transit Authority
Amador Transit	Petaluma Transit
Anaheim Resort Transportation	Plumas Transit
Beaumont Transit	Red Apple Transit
Big Blue Bus	Redding Area Bus Authority
Bustang	Redwood Coast Transit
Calaveras Transit	RiverCities Transit
Centro	Riverside Transit Agency
City of San Luis Obispo Transit	RTC RIDE
Corona Cruiser	Sage Stage
County Connection	San Benito County Express
DC Circulator	San Joaquin Regional Transit District (RTD)
Dodger Area Rapid Transit	Santa Maria Area Transit

Duarte Transit	Simi Valley Transit
El Dorado Transit	Sioux Area Metro
El Monte Transit	Siskiyou Transit and General Express
Emery Go-Round	SolTrans
Escambia County Area Transit	Sonoma County Transit
Fairfield and Suisun Transit	Spirit Bus
Fresno County Rural Transit Agency	Stanford Marguerite Shuttle
Gwinnett County Transit	Stanislaus Regional Transit
JTRAN	Sun Metro
Kern Transit	Sunline Transit Agency
Laguna Beach Transit	Tar River Transit
Lake Transit	Terre Haute Transit
Lassen Rural Bus	The Bus
Livermore Amador Valley Transit Authority	Thousand Oaks Transit
Martha's Vineyard Transit Authority	Trinity Transit
Mendocino Transit Authority	U-Trans
Metropolitan Tulsa Transit Authority	Unitrans (Davis)
Michigan Flyer	University of AZ - Cat Tran - Free Shuttle Service
Modesto Area Express	Vail Transit
Mountain Line	Vermont Translines
Mountain Transit	Victor Valley Transit Authority
MuscaBus	WestCat (Western Contra Costa)
MVgo Mountain View	Wilmington MOOver
ND_Fargo	Yosemite Area Regional Transportation System
Nevada County Gold Country Stage	Yuba-Sutter Transit

Appendix D: List of Networks Analyzed in Chapter 4

Table A.2 List of Networks Analyzed in Chapter 4

Amador Transit	Nevada County Gold Country Stage
Anaheim Resort Transportation	Palos Verdes Peninsula Transit Authority
Beaumont Transit	Petaluma Transit
Calaveras Connect	Plumas Transit
City of San Luis Obispo Transit	Red Apple Transit
Corona Cruiser	Redding Area Bus Authority
Dodger Area Rapid Transit	Redwood Coast Transit
Duarte Transit	RiverCities Transit
El Dorado Transit	San Benito County Express
El Monte Transit	Santa Maria Area Transit
Emery Go-Round	Simi Valley Transit
Escambia County Area Transit	Sioux Area Metro
Fairfield and Suisun Transit	SolTrans
Fresno County Rural Transit Agency	Spirit Bus
JTRAN	Stanford Marguerite Shuttle
Kern Transit	Stanislaus Regional Transit
Laguna Beach Transit	Tar River Transit
Lake Transit	Terre Haute Transit
Lassen Rural Bus	Thousand Oaks Transit
Martha's Vineyard Transit Authority	Trinity Transit
Mendocino Transit Authority	U-Trans
Modesto Area Express	Unitrans
Mountain Line	University of AZ - Cat Tran - Free Shuttle Service
Mountain Transit	Vail Transit
MuscaBus	Wilmington MOOver
MVgo Mountain View	Yuba-Sutter Transit
ND_Fargo	