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Examining energy uncertainty in battery bus deployments for transit agencies in California

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ABSTRACT

Due to the adoption of the Innovative Clean Transit (ICT) regulation, California is transitioning its public transit buses from fossil fuel to zero-emission buses (ZEBs). Due to required high upfront investment for battery electric buses (BEBs), transit agencies must make planning decisions with a system-wide optimization mindset. This study presents a tool to investigate the optimal split between depot charging and opportunity charging for transit networks. A case study was performed on the Unitrans transit system in Davis, California, and it was found that 35 buses would be sufficient to provide the existing level of service over the bus network, which is approximately the same number of buses that Unitrans is currently using to serve those routes. The sensitivity of the relationship between the energy use of BEBs and the deployment decisions was investigated. Decreasing the energy use of the buses by removing the probabilistic effects of drive cycle aggression decreased the maximum required number of buses from 73 to 45 and the interquartile range (IQR) of the number of buses from 10 to 2. The results indicate that a BEB fleet is more sensitive to these changes than a fossil fuel fleet. This relationship needs to be more strongly considered in planning BEB deployments.

1. Introduction

In 2018, the 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 ("Sources of Greenhouse Gas Emissions | Greenhouse Gas (GHG) Emissions | US EPA," n.d.), 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 ("GHG 2019 California Emission Inventory Data," 2019). Studies have found that transitioning from conventionally fueled vehicles to electrically- or hydrogen-powered vehicles is an effective means of curbing this GHG contribution (Logan et al., 2020). 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 (*Article 4.3.* Innovative Clean Transit, 2018). CARB estimates that the transit bus fleet will complete the transition to 100% zero-emission buses (ZEBs) by the 2040 s.

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).

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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 (Fig. 1).

The high costs of ZEB fleet transitions have been examined as parts of demonstration-scale deployments (Eudy et al., 2016; Kontou and Miles, 2015), and have been used as inputs in other studies focusing on total cost of ownership (Rogge et al., 2018; Sheth and Sarkar, 2019). 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 conditions. These sources of uncertainty can compound, and accommodating energy uncertainty can lead to very distinct systems, 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 paper presents the model as an optimization that aims at supporting the choices a transit agency makes when deploying BEBs. Finally, 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.

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 (Nicholas, 2019; Pelletier et al., 2019), 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

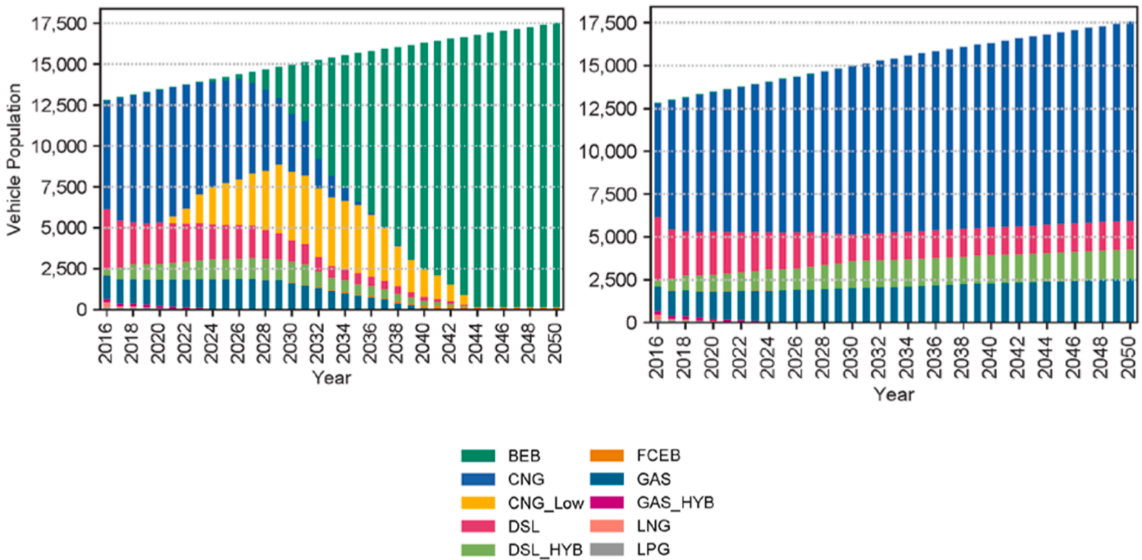


Fig. 1. CARB projections of the California transit bus fleet population (a) under the ICT regulations adopted in December 2018 and (b) under the previous Business as Usual (BAU) scenario (Appendix L: Emissions Inventory Methods and Results for the Proposed Innovative Clean Transit Regulation, 2018).

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 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 and 300 kW are planned (Infrastructure, 2019, "Smart Charging Stations | ChargePoint," 2019). In general, these buses take between 2 and 6 h to fully recharge, depending on the specifications of the battery pack and the charger ("Charging Infrastructure | Proterra," 2019), and must carry large battery packs to have adequate range for their shift (Nicolaides et al., 2019).

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 ("Charging Infrastructure | Proterra," 2019, "eBus charging infrastructure | Electromobility | Siemens," n.d.; Li, 2016). As a bus travels along its route, it will 'top off' or recharge its battery pack at these locations, taking between 5 and 15 min 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 (Nicolaides et al., 2019).

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.

Table 1
Sample List of Location Specific BEB Studies.

Study	Location	Number of Buses in Agency	Methods	Primary Findings
(Bagherinezhad et al., 2020)	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.
(Islam and Lownes, 2019)	Connecticut, United States	>400	Mixed-Integer Program	Optimal cost solution occurs at 79% fleet electrification. GHG can be reduced further with further electrification.
(Lin et al., 2019)	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.
(Rogge et al., 2018)	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.
(Thitacharee and Sripakagorn, 2016)	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.
(Uslu and Kaya, 2021)	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.
(Xylia et al., 2017)	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.
(Zhou et al., 2020)	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

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 of the time, vehicle battery sizing, and on-site energy storage, optimizing choices for a single transit line with a goal of minimizing total lifetime cost (Chen et al., 2013). 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 (Paul and Yamada, 2014). Most of these early studies used infrastructure or charging speed and behavior as a constraint, rather than as a focus of study. This framing of the infrastructure decision does not reflect the reality of how transit agencies must select their charging infrastructure.

Another common form of study is an examination the feasibility or cost of transitioning entire networks to ZEBs as the technology became a more popular choice for lowering urban emissions (Table 1).

These studies typically didn't 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 (De Filippo et al., 2014; Ke et al., 2016) to larger scale life cycle analysis (LCA) or well-to-wheel (WTW) approaches (Correa et al., 2019; Dong et al., 2018; Sheth and Sarkar, 2019). 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 (El-Taweel et al., 2017). 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 (Kunith et al., 2017). 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 (Li et al., 2019). 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 (Pelletier et al., 2019). 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 (Lotfi et al., 2020). 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 paper 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 (Rask et al., 2013; Thomas et al., 2017). Studies have found values for energy consumption of a full BEB increasing between 11% (Zhou et al., 2016) to 20% (Liu et al., 2019) 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 (Vepsäläinen et al., 2018). 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 (Zhou et al., 2016).

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

(Kivekäs et al., 2018) and that those effects can exacerbate the impact of other factors, especially in load factor and heavy traffic conditions (Liu et al., 2019; Perrotta et al., 2014). However, very few studies examine the prevalence of aggressive driving, especially in battery electric buses. 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, the distribution of power between battery cells as examples) (Vepsäläinen et al., 2018).

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.

2.1. Optimization

The optimization problem formulated for this model was made as a mixed-integer linear programming (MILP) problem. This formulation has been used many times for similar problems of infrastructure optimization (Chen et al., 2013; He et al., 2019; Islam and Lownes, 2019; Rogge et al., 2018; Wang et al., 2017). 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) is as follows:

Table 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	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 Eq. (1), with Eq. (2) separately describing the costs of purchasing and operating buses to more clearly illustrate how this is calculated:

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

$$C_{buses} = \sum_{b=1}^{B}\sum_{r=1}^{R}\left(x_{b,r}^{bus.number} * c_b^{bus.cost} + c^{energy.cost} * c_{b,r}^{energy.use} * c^{service.time}\right) \tag{2}$$

The constraints of the optimization are described in Eqs. (3)–(12). Eqs. (3) and (4) require that buses serve the timetable:

$$\sum_{b=1}^{B} x_{b,r}^{bus.assign} \geq c_r^{route.demand} \forall r \in R \tag{3}$$

$$\sum_{b=1}^{B} x_{b,r}^{bus.number} \geq \frac{c_r^{route.time}}{c_r^{route.headway}} \forall r \in R \tag{4}$$

Eqs. (5) and (6) ensure that an appropriate number of buses are purchased:

$$x_{b,r}^{bus.number} \geq \frac{x_{b,r}^{bus.assign}}{c_r^{route.demand}} \forall b \in B, \forall r \in R \tag{5}$$

$$x_{b,r}^{bus.number} \leq x_{b,r}^{bus.assign} \forall b \in B, \forall r \in R \tag{6}$$

Eq. (7) requires that the purchased buses have enough total energy capacity to serve the total energy demanded by the system's timetable:

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

$$\forall b \in B, \forall r \in R \tag{7}$$

Eq. (8) requires that the number of charging buses be less than the total number of chargers at any location and time:

$$\sum_{r=1}^{R} x_{r,l,t}^{charge.bus} \leq x_l^{opp.number} \forall l \in L, \forall t \in T \tag{8}$$

Eq. (9) requires that a bus be in a candidate location to charge:

$$c_{r,l,t}^{bus.status} \geq x_{r,l,t}^{charge.bus} \forall r \in R, \forall l \in L, \forall t \in T \tag{9}$$

Eqs. (10) and (11) calculate the number of buses served by opportunity chargers:

$$x_l^{served.bus} \leq c^{opp.ratio} * x_l^{opp.number} \forall l \in L \tag{10}$$

$$x_l^{served.bus} \leq \sum_{b=1}^{B}\sum_{r=1}^{R}\left(c_b^{can.opp} * x_{b,r}^{bus.number} * c_{r,l}^{route.loc}\right) \forall l \in L \tag{11}$$

Eq. (12) calculates the number of required depot chargers to serve the remaining buses:

$$x^{depot.number} \geq \sum_{b=1}^{B}\sum_{r=1}^{R} x_{b,r}^{bus.number} - \sum_{l=1}^{L} x_l^{served.bus} \tag{12}$$

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. *Case study data sources*

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 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.

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 (Fig. 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.

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 (Ambrose et al., 2017). Ambrose's model uses data from the FleetDNA dataset developed by the National Renewable Energy Laboratory (NREL) ("Fleet DNA Project Data," 2019) 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.

2.2.4. Other data sources

There are several other data that were used as inputs to the model (Table 4).

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 A), and an average value found from discussions with transit agencies was used.

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'(Frey and Patil, 2002). 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 (Borgonovo and Plischke, 2016; Frey and Patil, 2002; Hamby, 1994; Lenhart et al., 2002) and is commonly used to understand the impacts of uncertainty of that particular input on the model as a whole (Borgonovo and Plischke, 2016; Pathmanathan et al., 2019; Saltelli, n.d.). 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 (Kontou and Miles, 2015). The values for driver energy use took the form of a right-skewed normal distribution (Table 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.

Table 3
Bus data for case study.

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 (STURAA TEST 12 YEAR 500,000 MILE BUS from PROTERRA, INC - PTI-BT-R1107, 2012)
Proterra Catalyst E2, 40-Foot	$750,000	440	Both	1.87 (Federal Transit Bus Test for Proterra Catalyst E2 - Report LTI-BT-R1706-P, 2017)
BYD 45-Foot Double-Decker	$800,000	446	Depot	1.93 (45' Double Decker Electric Bus - Technical Specifications [WWW Document], n.d.)

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

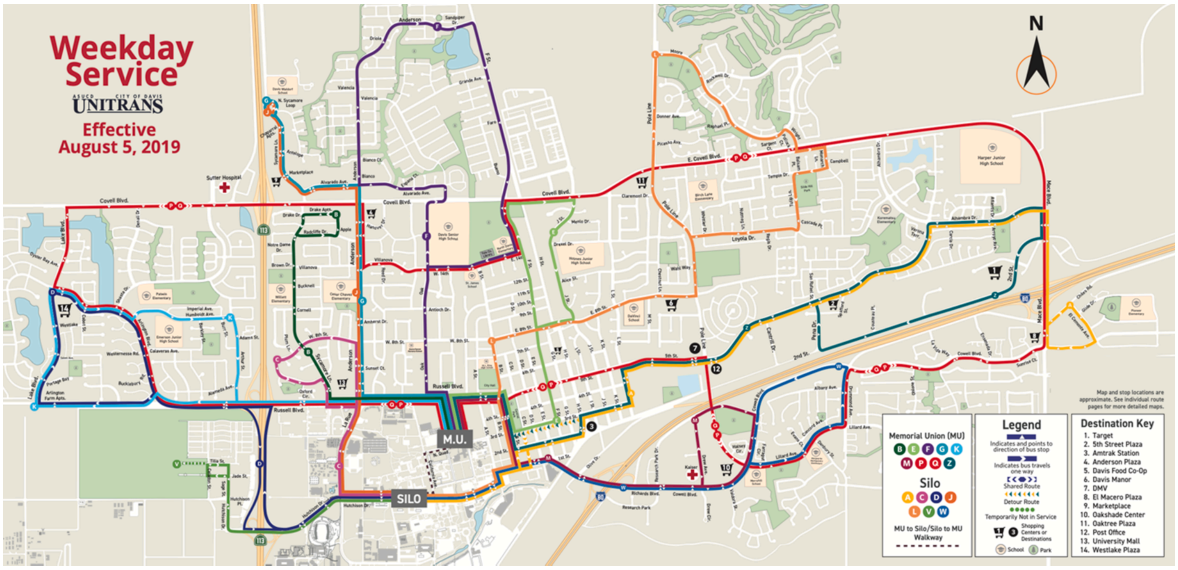


Fig. 2. A map of weekday service for the case study transit system (source: Unitrans).

Table 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	(Nicholas, 2019; "Smart Charging Stations | ChargePoint," 2019), Interviews with transit agencies
Opportunity Charger Cost	\$600,000	(Eudy et al., 2016; Nicholas, 2019), Interviews with transit agencies
Opportunity Recharge Rate	350 kW	Bus specifications
Opportunity Ratio	7 buses per charger	Interviews with transit agencies (see Appendix A)

Table 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.

Passenger loading was simulated by developing another right-skewed normal distribution from Unitrans's observed ridership (Table 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 (Unitrans General Manager's Report: Fiscal Year 2018–2019, 2019). 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 lb 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 (Liu et al., 2019; Yu et al., 2016; Zhou et al., 2016). 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 (Perrotta et al., 2014; Rask et al., 2013). 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) (Liu et al., 2019). 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 (Zhou et al., 2016). 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 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 (Vepsäläinen et al., 2018). Because these effects are small, unpredictable, and uncontrollable, they are modeled as random noise impacting the overall energy use of the buses.

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 as a result of 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.

3. Results

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.

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

Table 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

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.

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 (Fig. 3)

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 (Fig. 4).

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 (Fig. 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 (Fig. 5).

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 (Fig. 6).

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

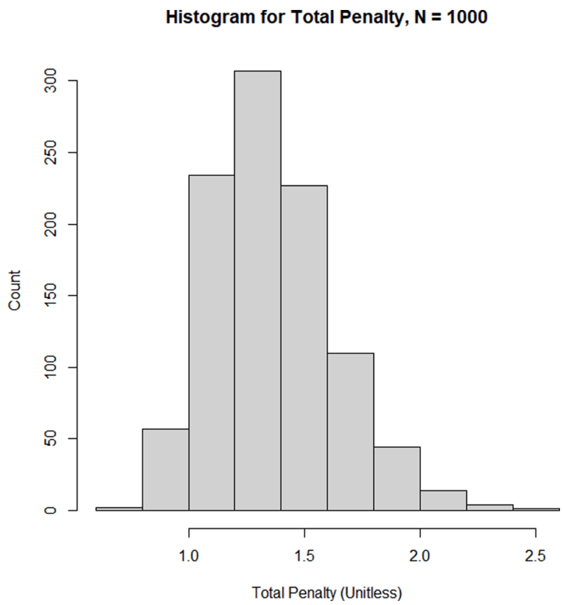
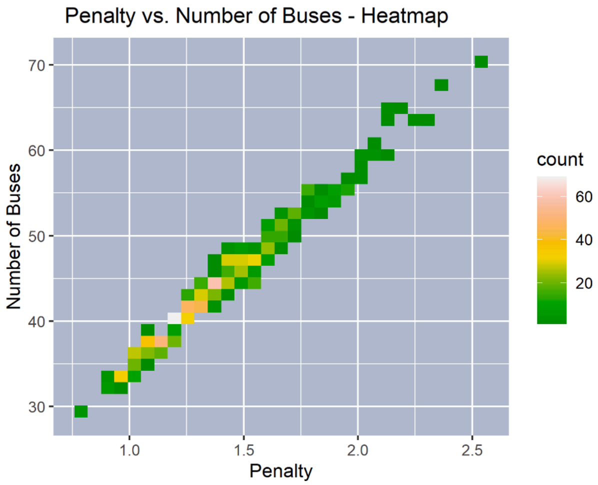


Fig. 3. Histogram of randomly selected energy penalties resulting from effects due to drive cycle aggression, ambient temperature, and passenger load for uncertainty analysis.



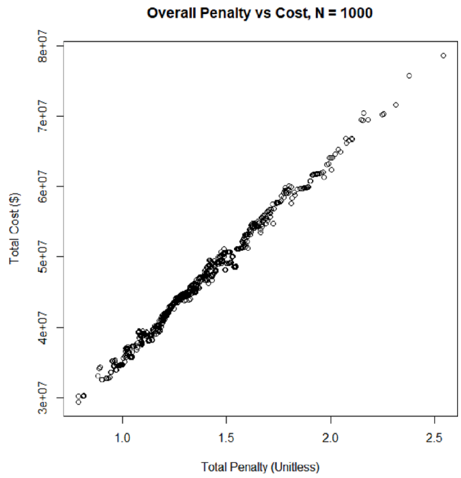
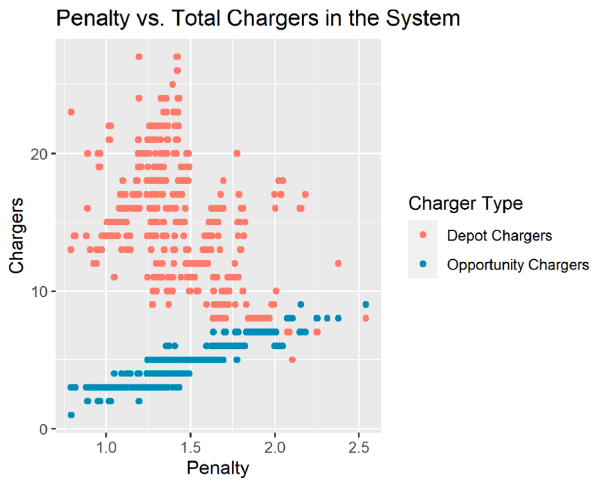


Fig. 4. Energy penalty vs number of buses heatmap (left) and energy penalty vs total system cost (right). Note that the 'count' variable in the heatmap refers to the number of overlapping points in the region.



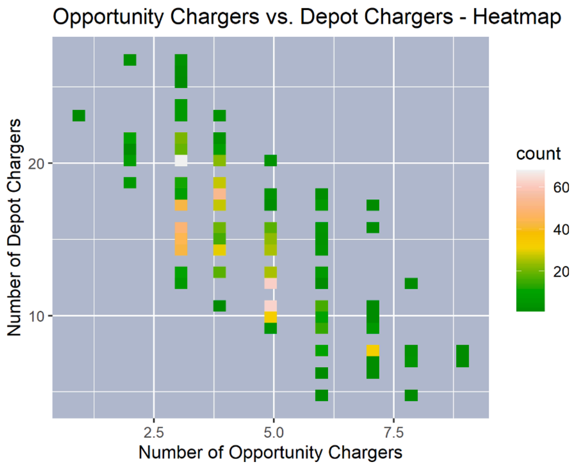


Fig. 5. A plot of energy penalty vs numbers of both types of chargers in the system (left) and a heatmap of the relationship between the numbers of charge types (right).

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.

4. Discussion and insights

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

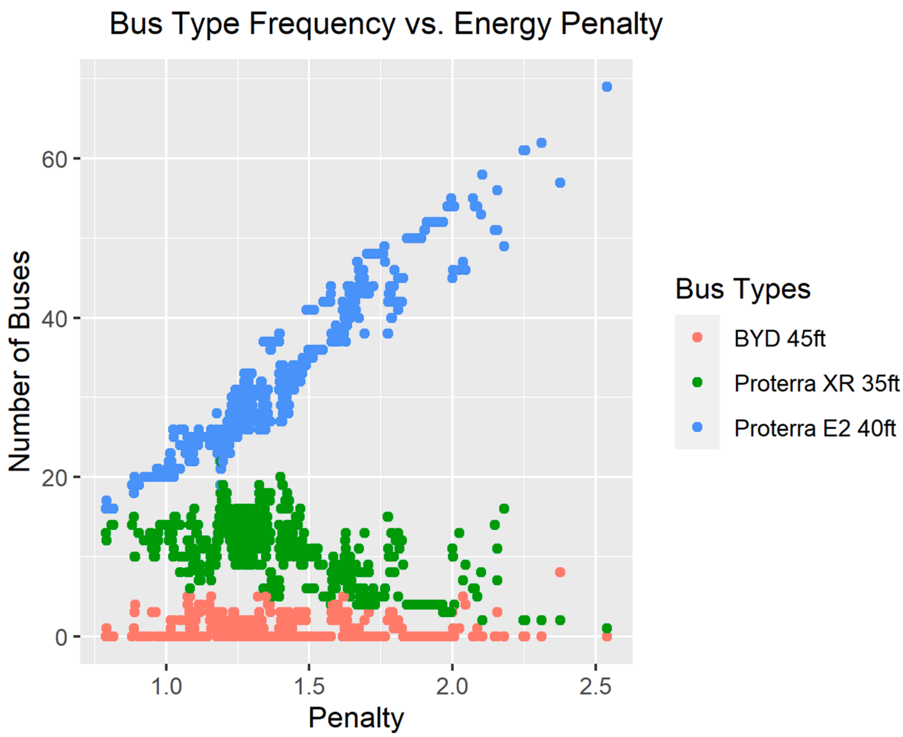


Fig. 6. A plot of the numbers of different bus types that were selected by the model at different energy penalties.

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.

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 min 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 (Figs. 7 and 8)

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 7).

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.

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.

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

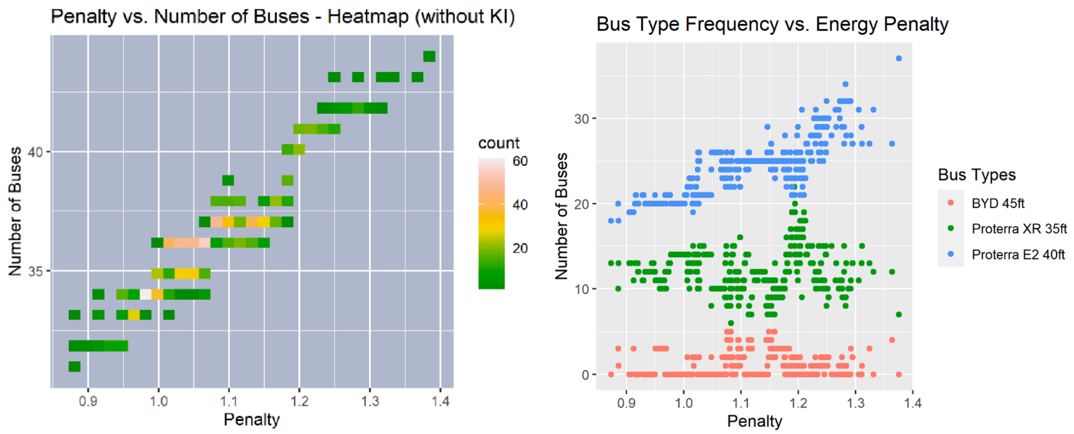


Fig. 7. Plot of bus heatmap (left) and bus type distribution (right) for second energy analysis of the system (cycle aggression fixed at 1).

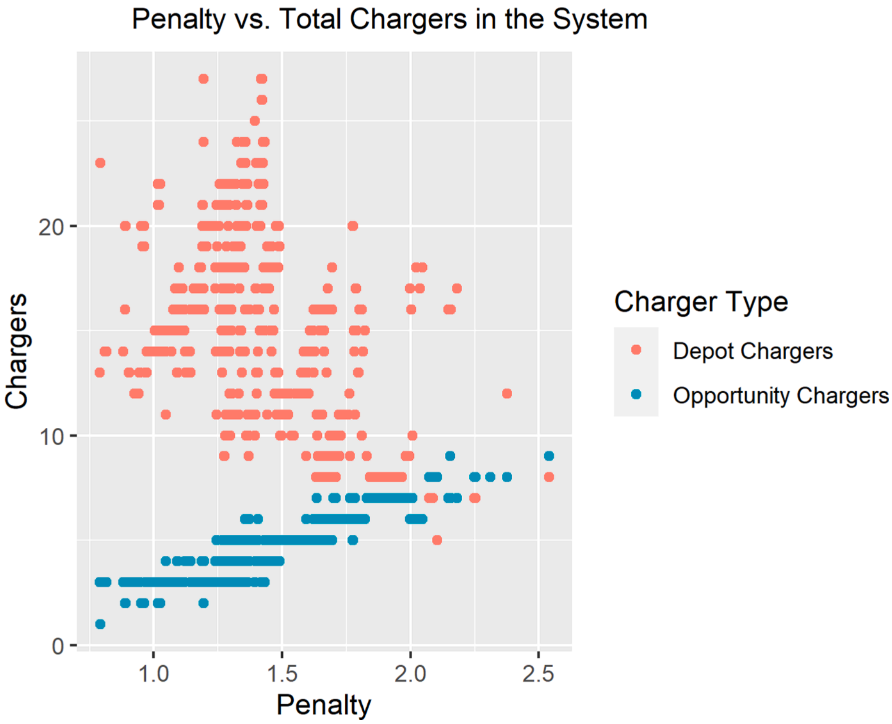


Fig. 8. Numbers of types of chargers for second energy analysis of the system (cycle aggression fixed at 1).

Table 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%

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.

5. Conclusions

This paper 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.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: P. Benoliel, A. Jenn, G. Tal; data collection: P. Benoliel; analysis and interpretation of results: P. Benoliel, A. Jenn, G. Tal; draft manuscript preparation: P. Benoliel, A. Jenn, G. Tal. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2021.102963.

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Appendix L: Emissions Inventory Methods and Results for the Proposed Innovative Clean Transit Regulation, 2018.

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