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Charging Hub for Electrified Mobility

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RESEARCH REPORT

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Charging Hub for Electrified Mobility

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16. Abstract

With the growing concern over global climate change, the pace of transportation electrification has greatly accelerated in recent years to achieve net-zero greenhouse gas (GHG) emissions. However, electricity is not entirely generated from renewable resources at the moment. The overall carbon emission per kWh of electricity fluctuates due to the inconsistent nature of renewables such as solar and wind. How to utilize the low-carbon electricity remains a challenge. On the other hand, current designs and research on charging infrastructure separate electric buses and passenger cars, neglecting the great potential of coordinated charging between different transport modes. How to deploy and operate public charging infrastructure to best serve an electrified multi-modal transportation system while maximizing the benefits of decarbonization remains unclear. This research tries to integrate different transport modes into the strategic planning and design of the shared charging hubs to produce an efficient and low-carbon electrified transportation ecosystem. Shared charging hubs can provide holistic energy management to maximize GHG emission reduction given budget limits while balance peak power demands by integrating real-time electricity carbon intensity (ECI) and vehicle-to-grid (V2G) technology. The model was successfully applied to bus fleets of seven transit agencies and the park-and-ride cars of twelve rail transit stations in Contra Costa County, California. This research will help policy makers and transportation agencies make more informed decisions regarding the planning and design of charging infrastructure.

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Executive Summary

Executive Summary

Transportation electrification holds the potential to establish a truly zero-emission ecosystem when coupled with renewable power generation. However, electricity is not entirely generated from renewable resources at the moment. The carbon emission per kWh of electricity, or electricity carbon intensity (ECI), fluctuates due to the inconsistent nature of renewables such as solar and wind. In solar-rich regions like California, for example, afternoon electricity is notably "greener". To harness this eco-friendly energy while avoiding expensive investment in stationary energy storage systems, one solution is to utilize "mobile batteries" — electric vehicles — to capture this energy. However, most vehicles predominantly charge during the non-working hours, typically from evening to early morning. Coincidentally, the ECI is at its highest during this period. Hence, a scheduling mechanism is desired that allows vehicles to charge green electricity during working hours without disrupting their existing usage patterns. In short, it is promising to establish charging facilities beyond homes and bus depots.

Besides locations, power capacity is another constraint on the charging station's ability to absorb green energy. Increasing a station's power capacity incurs significant short-term capital and potential long-term costs in electricity bills on demand charge. Leveraging the charging time differences between various transport modes can potentially reduce the power capacity requirement. For instance, if a charging station serves both buses and passenger cars, and given buses have relatively short and fixed charging durations during work hours, we can momentarily reduce the charging power for passenger cars when buses begin charging. This ensures the overall charging power does not exceed the designed limit. However, current charging facilities mainly cater to a single type of transport mode, either bus or passenger cars, without the flexibility of coordinated charging scheduling. To be more cost-effective towards decarbonization, it is of great interest to consider multi-modal shared charging hubs in places where buses and cars meet, for example: park-and-ride facilities.

Considering the aforementioned issues, this study proposed to deploy shared charging hubs for buses and cars, and design coordinated charging schedules between these two transportation modes to fully utilize the green electricity. An optimization model is hereby developed to support the planning and scheduling in a regional context. The objective of the optimization model is to minimize GHG emissions within specified budgets by jointly determining which buses to electrify, where to place charging hubs, and the required number of chargers and power capacities at these hubs. Beyond the hardware investment decisions, the optimization model also produces coordinated charging schedules, factoring in time-varying ECI, electricity costs, and battery degradation, while leveraging the capabilities of vehicle-to-grid (V2G) technology.

The effectiveness of the model is demonstrated through a case study in Contra Costa, California, by assuming all twelve BART stations in the county are candidate charging hub locations. We analyzed the phased implementation of the charging hub network under various budget constraints and explained the behind-the-scene reasons why the model makes such decisions for each phase. The results underscored the advantages of shared charging hubs, the significance of incorporating time-varying ECI, and the benefits of enabling V2G

functionality. In support of initial development, we also examined detailed planning outcomes under constrained budgets. The model can be easily customized for other regions by integrating local data, including potential charging hub locations, transit schedules, patterns of passenger car usage, and cost factors.

In sum, this research aims to facilitate the transition to a carbon-neutral transport sector by proposing innovative charging schemes and a model tool that support the associated development. More details can be found in the rest of the report and the following journal article:

Ye, Zuzhao, Nanpeng Yu, Ran Wei, and Xiaoyue Cathy Liu. "Decarbonizing regional multi-model transportation system with shared electric charging hubs." Transportation Research Part C: Emerging Technologies 144 (2022): 103881.

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Introduction

Achieving net-zero global greenhouse gas (GHG) emissions by the middle of this century is essential to reaching the objectives of the Paris Agreement to limit the rise in global temperatures to well-below 2°C (Obergassel et al., 2016). The transport sector produces more than 16 percent of the global GHG emissions and its pace of growth is the fastest among all economic sectors (Ritchie and Roser, 2020). Hence, proper analysis and planning to decarbonize the transport sector will be critical to mitigating climate change. Transportation electrification holds the potential to establish a truly zero-emission ecosystem when coupled with renewable power generation (Lutsey and Sperling, 2009, Pan et al., 2018, Sofia et al., 2020).

However, at present and within a certain period in the future, electricity is not entirely generated from renewable resources. The carbon emission for every kilowatt-hour, quantified as electricity carbon intensity (ECI), fluctuates throughout the day due to the inconsistent nature of renewables such as solar and wind. In solar-rich regions like California, for example, afternoon electricity is notably "greener", as indicated by a reduced ECI. To harness this eco-friendly energy, one strategy is a significant investment in stationary energy storage systems. However, the prevailing costs of these systems hinders their mass deployment. Another solution is to utilize "mobile batteries" — electric vehicles — to capture and use this energy.

Yet, there is a problem: Most vehicles, whether private cars or buses, predominantly charge during the non-working hours, typically from evening to early morning. Coincidentally, the ECI is at its highest during this period. Hence, it would be promising if there were a scheduling mechanism allowing these vehicles to charge green electricity during working hours without disrupting their existing usage patterns or charging costs. Taking it a step further, we could even employ Vehicle-to-Grid (V2G) technology. This would enable electric vehicles to charge when the ECI is low and discharge back to the grid when the ECI is high, further reducing the reliance on fossil fuels. To achieve this goal, we need to establish more charging facilities beyond homes and bus depots, and if feasible, equip them with V2G capabilities.

Besides where a charging station is placed, the power capacity is another major constraint on the charging station's ability to absorb green energy. Increasing a station's power capacity incurs significant short-term and long-term costs. In the short term, raising the power capacity escalates the investment cost of the hardware. In the long run, operating at high power levels leads to increased monthly demand charges for the station. An effective approach to reduce the power capacity and enhance efficiency is by leveraging the charging time differences between various transport modes. For instance, if a charging station serves both bus and passenger car, and given buses have relatively short and fixed charging durations during work hours, we can momentarily reduce the charging power for passenger cars when buses begin charging. This ensures the overall charging power does not exceed the designed limit. However, current charging facilities mainly cater to a single type of transport mode, either bus or passenger cars. This is not the most cost-effective approach towards decarbonization. Thus, it is of great interest to consider multi-modal shared charging hubs.

For private vehicles, the optimal locations of charging hubs will be where cars can be parked for several hours, such as at work, a shopping center, public garage or near public transit stations. Buses would require locations where they can lay over without traveling too far from their scheduled route. As a result, park-and-ride facilities become ideal locations for the shared charging hubs. An underlying advantage of shared charging hubs worth noting is their ability to link different transport modes. For example, electric car, e-bike, and e-scooter users would find it convenient to transfer to public electric buses if there is a shared charging hub where they can park, charge, and then ride.

As a short summary, the effective decarbonization of the transport system in a regional area depends on multiple factors, including 1) Charging infrastructure where buses and cars have access during low-ECI periods, which are mostly working hours, 2) ECI-oriented charging scheduling, 3) V2G technology, and 4) a scheme of shared charging hubs. In this research project, we aim to integrate all these considerations into an optimization model that helps us automatically determine the ideal planning scenarios. As an initial exploration, the multi-modal charging hubs will cater to two transport modes: public buses and private passenger cars.

This report is arranged as follows: We begin by introducing the current background of charging infrastructure planning, ECI, and V2G technology. Subsequently, we present our optimization planning model, which can select suitable locations for shared charging hubs from a list of potential sites given a specific budget. This model also helps determine which public buses should be prioritized for electrification and determine coordinated charging schedules for electric buses and cars. Lastly, we present a case study conducted on Contra Costa County based on this model.

Background

Charging Infrastructure Planning

Transitioning to electric vehicles will require construction of a network of charging infrastructure. In addition to home charging which is usually L1 or L2 charging, DC fast public charging is also needed by many of the passenger cars. Much of the existing research is focused on where charging stations should be located and how many chargers should be installed considering the charging demand approximated via stochastic modeling or derived from traffic data (Frade et al., 2011, Yang et al., 2017, Kontou et al., 2019, Wolbertus et al., 2021).

In contrast to passenger cars, transit buses have exact and rigid operational schedules. In addition, the cost of converting one conventional bus (diesel or CNG) to an electric one is substantial and this cost needs to be considered. Therefore, the deployment of bus charging stations comes along with the decisions on electrification of individual buses in the fleet, and requires spatial-temporal planning to ensure that the individual energy demand is satisfied through charging in the terminals (Kunith et al., 2017, Wei et al., 2018). In addition to terminal charging, battery swapping stations (Moon et al., 2020) and charging lanes (Liu et al., 2017) have also been considered. The cost competitiveness of different types of charging infrastructure is analyzed by (Chen et al., 2018). Other research has looked at electrifying bus fleets in stages in line with changing ridership (Xie et al., 2018, Lin et al., 2019).

In summary, while numerous research efforts have been dedicated to planning charging infrastructure, they have either solely focused on either buses or passenger vehicles, with shared charging hubs for both vehicle types rarely discussed.

Electricity Carbon Intensity and Prices

While vehicle electrification reduces GHG emissions directly from the transport sector, there are still emissions associated with upstream power generation. The rate of GHG emission from power generation is termed electricity carbon intensity (ECI) and measured as grams of equivalent carbon dioxide emissions per kilowatt-hour (gCO_2e/kWh). ECI can vary significantly from time to time, depending on the time of day the electricity is produced. In areas where a high proportion of electricity is produced from solar generation, the ECI is usually low at noon and high after sunset. For example, the ECI of a typical day in California is shown in **Error! Reference source not found.**. The lowest ECI is found around 9 AM-3 PM when solar generation reaches a peak. In the evenings and early mornings, electricity is mainly generated by natural gas power plants, which leads to higher ECI.

Similar to ECI, electricity price varies across a day. Typically, utility companies will specify time-of-use schedules based on the load levels of the electricity market. The price will be higher during on-peak hours and lower during off-peak hours. The electricity prices are also different for commercial and residential users. While charging hubs will pay for a commercial rate, EVs performing home-charging will be billed under a residential rate. Typical commercial rates are higher than residential rates. We adopt the electricity prices from the service provider of Contra Costa (MCE, 2022), as shown in Figure 1.

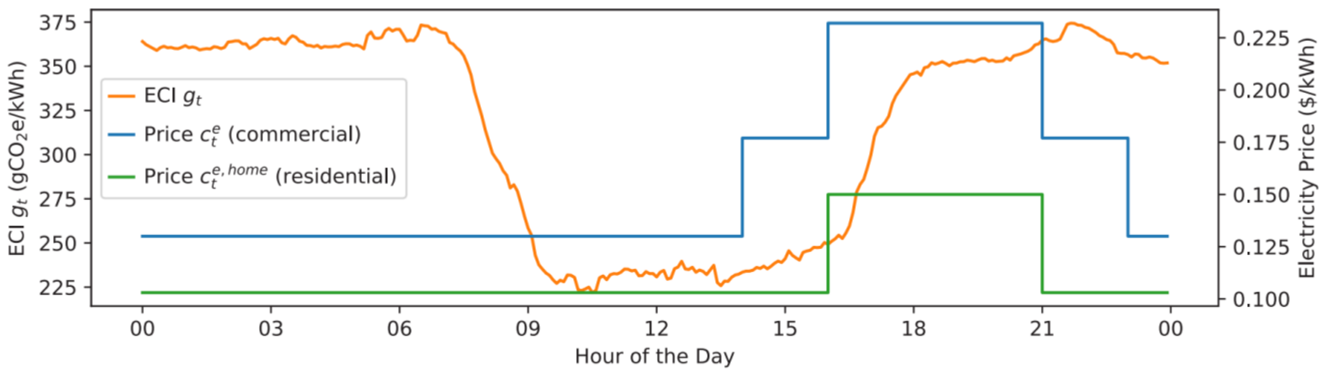

Figure 1. The electricity carbon intensity (ECI) and the electricity prices at different time of the day.

The varying of ECI within the day suggests that there are opportunities to reduce GHG emissions by scheduling vehicle charging at the time when the ECI is low (Hoehne and Chester, 2016, Brinkel et al., 2020, Tu et al., 2020) and incentivizing consumer charging behavior to use less carbon-intense electricity (Santarromana et al., 2020). On the other hand, it is critical to ensure that the cost of charging is not increased under the new charging schedules considering the price variations in the day. This is especially important for private car owners.

Vehicle-to-Grid

To further enhance the effects of charging scheduling, vehicle-to-grid (V2G) is a promising add-on to the current charging technology. By allowing sending electricity back to the grid, it is even more effective to reduce generation requirements when the ECI is high. In the literature, the application of V2G jointly with that of the consideration of varying electricity prices can generate great economic benefits, under which scenario, individual vehicle owners will be trading energy with the grid through various incentives when their vehicle is not in use (Pillai and Bak-Jensen, 2010, López et al., 2015, Sarker et al., 2016). This concept could be extended to reducing GHG emissions by shifting the triggering signal from electricity prices to time-varying ECI.

Model Formulation

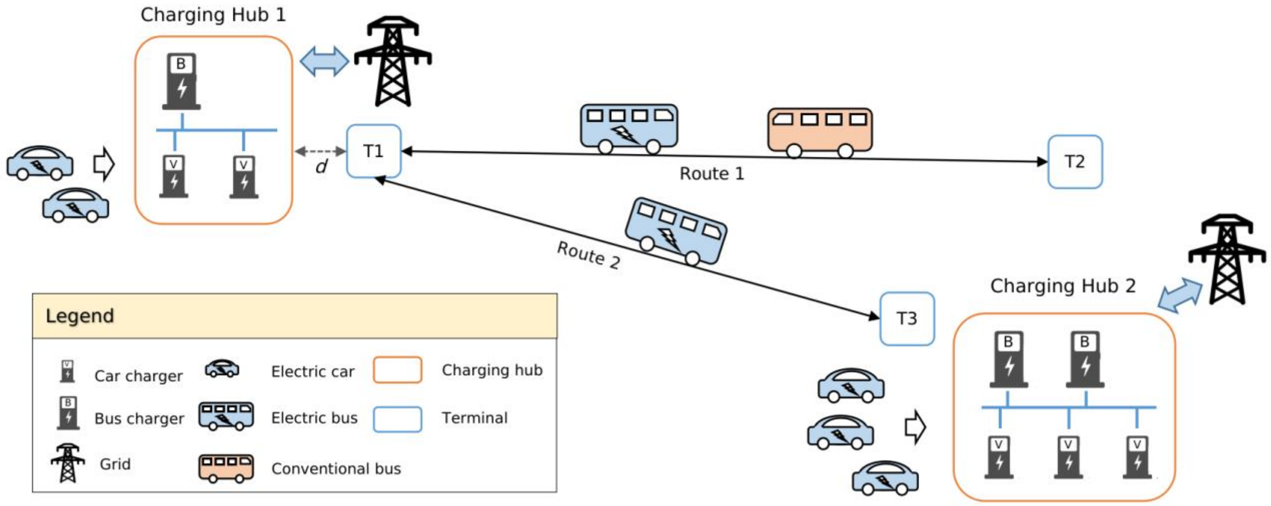

Figure 2. Illustration of the system studied.

As discussed in the Introduction section, to achieve effective decarbonization in a regional area, we propose to deploy shared charging hubs to places where the electric buses and cars are parked when the electricity is in a low-ECI period. We will need a spatial-temporal optimization model to help us automatically determine the following items:

- Where to deploy the charging hubs in a set of candidate locations;
- How many bus and car chargers are needed in each of the charging hub;
- Which conventional buses in the fleet shall be prioritized for the conversion;
- What are the charging schedules for the buses and the cars.

The objective of the optimization model will be minimizing the GHG emissions at a given budget. The illustration of the system being studied is shown in Figure 1. The charging hubs will provide service to electric buses whose terminal is within a certain distance (e.g. $d < 0.5$mile) and electric cars parking in the charging hubs.

The charging infrastructure deployment and the conversion of buses will be supported by public funding. For the car sectors, the cost of conversion is on private individuals and hence not considered in the budget. We will only consider electric cars in this study, so in the rest of this report, we use “car” to solely referring to electric passenger car. The optimization model will have the following major constraints:

- Bus sector: The buses, when converted to electric, shall be able to finish their original daily trips under the same patterns before conversion;
- Car sector: The electric cars shall be able to charge enough energy that covers their daily usage;
- Charging Infrastructure - Chargers: The number of chargers in each of the charging hubs shall be able to support the planned charging schedules;
- Charging Infrastructure - Power system: The combined charging power of buses and cars shall not exceed the planned power capacity in each of the charging hubs;
- Budget: The total cost shall not exceed the budget limit.

The detailed assumptions for different categories of the system are listed in the following table.

Table 1. List of assumptions.

Category	Item	Assumptions
Bus sector	Charging place	Charging hubs and depots.
	Criteria for a bus to use a charging hub	The bus terminal is within 0.5 mile of the charging hub; The bus is dwelling more than 10 minutes in the terminal.
	Schedules	Kept unchanged post-conversion.
	Specifications	Detailed in the Data Description section.
Car sector	Charging place	Charging hubs and home.
	Criteria for a car to use a charging hub	As long as the car is dwelling in the charging hub.
	Schedules	Derived from ridership of public transit.
	Specifications	Detailed in the Data Description section.
Charging infrastructure	Criteria of a candidate charging hub location	Places where the bus terminals and car parking lots are neighboring (e.g. park-and-ride facilities).
	Power system capacity	The total power of a charging hub is the combined power of bus and car chargers.
Budget	Items covered by public budget	Charging hub construction; Bus/car chargers in the charging hubs; Conversion of conventional buses; Bus charging cost.
	Items assumed existed	The bus chargers at depot; Electric passenger cars and their chargers at home.
	Items not covered	Charging cost and battery degradation of cars.

In general, we also assume that the public transit agencies will be leasing charging infrastructure and electric buses from private vendors on an annual basis to reduce the financial risk of high upfront costs and the costs associated with large fleet maintenance, as proposed in Electrification Coalition (2010), Li et al. (2018), Jattin (2019) and practiced by Lunden (2018), Proterra (2022). We also assume that the chargers can be shared among cars through a smart charging scheme such that when one car's charging demand is satisfied, the charger can be moved to other waiting cars, reducing the cost of leasing extra chargers. Such a scheme can be achieved through multiple ways, e.g. valet service or mobile chargers (Doll, 2022).

The model is formulated as a Mixed-Integer Programming (MIP) problem and the details of the equations along with the required inputs parameters and the output decision variables is presented in the Appendix and can be also found in Ye et al., (2022). The sources of the associated inputs parameters are discussed in the Data Description section.

Data Description

Study Area

Contra Costa, California is selected as the study area to illustrate the effectiveness of the proposed model. The public ground transportation in this area is served by one rail agency (Bay Area Rapid Transit or BART) and seven bus agencies. There are twelve BART stations within Contra Costa. Serving as an efficient travel mode between Contra Costa and downtown San Francisco, BART connects with several bus lines and has a large demand of private vehicles to park-and-ride in the vicinity of its stations. Therefore, BART stations are ideal locations for shared charging hubs. There are in a total of twelve BART stations in Contra Costa, and we consider all of them as candidate charging hubs as shown in Figure 3.

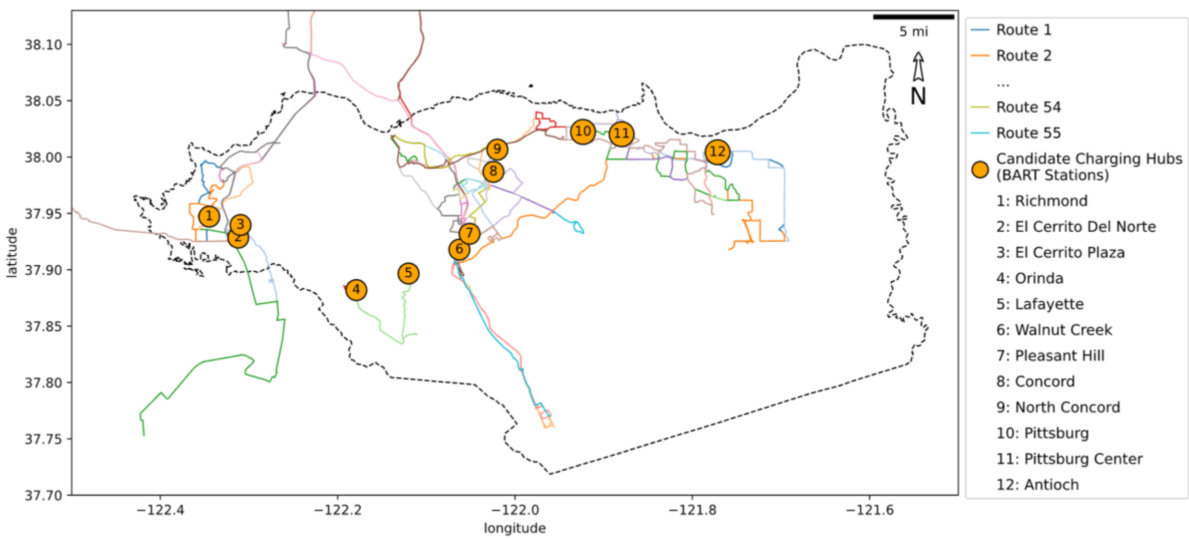

Figure 3. The selected bus routes and candidate charging hubs within the study area: Contra Costa County, California.

Bus Sector

The data of bus sector is obtained from the General Transit Feed Specification (GTFS) of each transit agency (511 Open Data, 2021). GTFS data consists of detailed information on bus routes, schedules, stops, and other necessary information. It is assumed that an EB can be charged in a charging hub if at least one of its terminal stations is within 0.5 miles of the charging hub. In such a scenario, the energy cost and time required to reach a charging hub from a nearby terminal is considered to be negligible. There are 55 identified bus routes, of which at least one terminal station is within 0.5 miles of a candidate charging hub, as shown in Figure 3.

While the schedule of a bus route can be extracted from the GTFS data, the information regarding individual buses that serve a route or their depot locations are unavailable to the public. A first-in-first-out (FIFO) model is adopted to address this problem (Ceder, 2016). The FIFO model takes the schedule of a bus route as input and then outputs the required number of buses and the schedule of each bus on this route, by assuming: (1) no interlining of buses or deadhead trips (i.e. a bus only serves one specific route) and (2) a bus is at its depot during the longest break between services and in this case, the time returning to depot is neglected. Specifically, the FIFO model works as follows in determining the bus schedules for a two-terminal route: (1) A bus will be created at a terminal for the earliest scheduled trip; (2) Then this bus will make the first feasible connection with a departure after it has dwelt for more than 10 min at the other terminal of the route. Such connections will continue until this bus finishes the final applicable trip of the day; (3) Initiate a new bus for the earliest unassigned trip, and repeat steps (1) and (2) until all of the trips in the time table are assigned. After the three steps, we will obtain the number of buses serving this route and the detailed schedule of each bus. A similar process is also applicable to one-terminal routes, or round routes. The only change is in step (2) where the connection will happen in the same terminal. Through the FIFO model, a set I of 234 buses is obtained. It should be noted that the FIFO model could potentially exaggerate the number of buses. Reducing the number of buses through well-designed dispatching strategies is an ongoing research topic (Janovec and Kohání, 2019; Kang et al., 2019; Li et al., 2019). Nevertheless, the existing bus schedule is just an input into the modeling framework. The proposed framework can be equally applied once the actual detailed bus-level data becomes available.

Once the schedule of a bus is obtained, its daily GHG emission can be estimated by assuming the current conventional bus fleet uses diesel as the fuel, and based on the fuel efficiency of diesel buses and the carbon intensity of diesel. Figure 4 shows the histogram of GHG emissions of the buses in the study. Depending on the dispatch frequency and route distance, the daily GHG emissions of buses have wide variations, ranging from less than 50 kgCO_2e/day and up to more than 1,000 kgCO_2e/day.

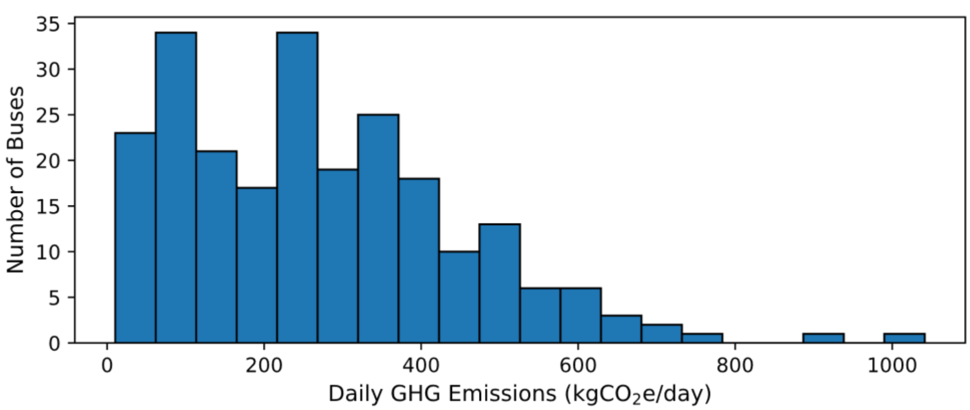

Figure 4. The distribution of daily GHG emissions of the bus fleet.

When a conventional bus is converted to an electric one, its battery capacity is assumed to be $e^{b,max} = 225\text{kWh}$ and $e^{b,min} = 0$. The maximum charging/discharging power is 150kW, i.e. $x^{max} = 150\text{kW}$ and $x^{min} = -150\text{kW}$. The energy efficiency of an electric bus η^b is 0.56 mile/kWh. The energy levels, charging power limits, and energy efficiency are selected based on information from the state-of-the-art bus vendor (Proterra, 2021). The battery cycle efficiency κ is set at 0.95. For the convenience of readers, we summarize the data of the bus sector as shown in Table 2.

Table 2. Bus sector information

Item	Description
Transit schedules	Derived from GTFS data. Kept unchanged w/ or w/o EB(s) in the fleet.
Individual bus schedules	Derived from the transit schedules assuming first-in-first-out and no interlining. The model can be easily updated with real-world individual bus schedules.
Number of routes	55
Number of buses	234
Electric bus battery size	225 kWh
Electric bus max/min charging power	150/-150 kW
Electric bus energy efficiency	0.56 mile/kWh
Conventional bus energy efficiency	3.26 miles/gallon

Electric Car Sector

As the candidate charging hubs are located around the BART stations, most users are expected to electric car owners who park and ride BART. From the annual average hourly entry- and exit-pattern of the BART stations shown in Figure 5 (BART, 2021), riding in the morning and returning in the evening is a clear pattern for BART riders in Contra Costa County. Assuming that park-and-ride car drivers follow similar travel behavior, a stochastic Poisson arrival model for cars can be established, with the hourly arrival rate in BART station k at hour h to be:

$$\boldsymbol{\lambda}(\boldsymbol{k}, \boldsymbol{h}) = \text{Ridership}(\boldsymbol{k}, \boldsymbol{h}) \times \text{EV penetration rate} \times \text{park-and-ride rate}$$

The electric car penetration rate is set at 30% to reflect the growth of electric vehicle population in the near future. The park-and-ride rate is assumed to be 10%. Upon arrival, it is assumed that the parking time for cars follows Gaussian distribution $\mathcal{N}(8, 2^2)$, i.e. the mean parking time is eight hours and the standard deviation is two hours. This is in-line with the exit pattern shown in Fig. 4 (right). In total, 1527 individuals cars are identified for the twelve BART stations.

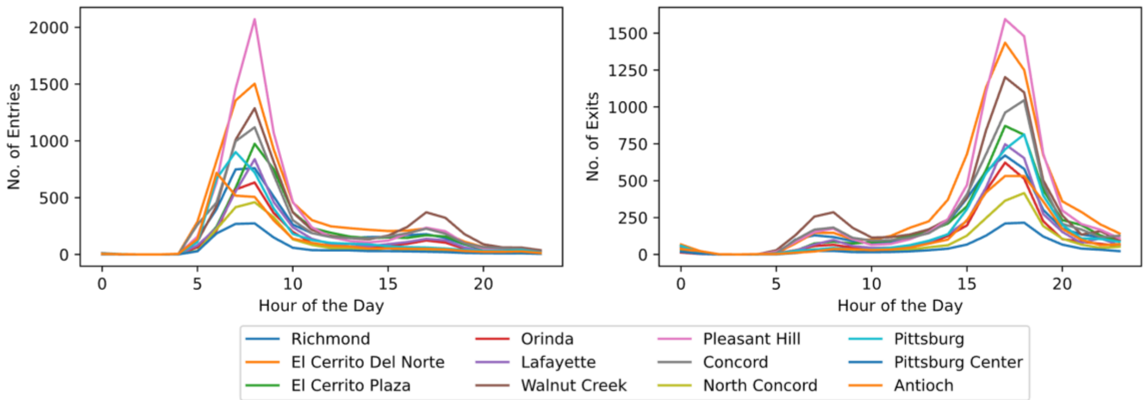

Figure 5. The annual average number of entries (left) and exits (right) of the all twelve BART stations in Contra Costa, California.

The time horizon T is split into three parts for a car $\boldsymbol{j}$: at-home T_j^{home}, in-hub $T_j^{v,hub}$, or on-road for the rest of the time. A car is on-road one hour before it arrives at the charging hub and one hour after it leaves the hub. A car requires an energy supply that covers its daily consumption. The daily travel distance of a car is a stochastic number generated by following the distribution of vehicle daily travel distance in the National Household Travel Survey (Federal Highway Administration, 2017).

Cars have options to be charged either at home with low-power AC chargers or at the charging hubs with DC-fast chargers, both have V2G functions. The maximum charging/discharging power is 50kW in a charging hub and 10kW at home, i.e. $y^{max} = 50\text{kW}$, $y^{min} = -50\text{kW}$, $y^{home,max} = 10\text{kW}$, and $y^{home,min} = -10\text{kW}$. Without losing generality, a car's battery capacity is assumed to be $e^{v,max} = 100\text{kWh}$ and $e^{v,min} = 0$. The battery cycle efficiency of charging car batteries is the same as that of buses. For convenience, we summarize the data of the car sector in Table 3**.**

Table 3. Car sector information

Item	Description
Electric car schedules	Derived from BART ridership patterns.
Number of electric cars	1,527
Electric car battery size	100 kWh
Electric car max/min charging power	50/-50 kW in a charging hub, 10/-10 kW at home
Electric car energy efficiency	3.33 mile/kWh

Electricity Carbon Intensity

Discussed in the Background section.

Cost Coefficients

Property-leasing cost

The leasing costs of charging infrastructure and EBs will be closely related to the lifespan of the properties. The annual leasing price c of a property is determined by that the net present value of leasing over the lifespan shall be no less than the initial investment. The detailed process of calculating the leasing cost based on initial investment, lifespan, and interest rate can be found in Ye et al. (2022).

The public transportation agencies will lease five different types of properties as stated in (25). The initial investment of an EB is taken from Johnson et al. (2020). An EB consists of a frame and a battery, which have different lifespans. While a frame can typically last 12–14 years (Noel and McCormack, 2014; Bi et al., 2017), a battery will need to be replaced every 6 to 8 years (Noel and McCormack, 2014; Franca et al., 2017). A new lithium-ion battery will cost around $140 per kWh (Edelstein, 2021) and as a result, an EB battery with a capacity of 225 kWh will cost $35,000. The initial investment of chargers are determined by multiple factors, including material and labor. Nicholas (2019), Nelder and Rogers (2019) summarized the ranges of unit cost to install DC-Fast chargers. The lifespan of a charger is estimated to be 10 years. The initial investment of power equipment on a per-kW basis is derived from the cost of transformers and other necessary make-ready investments, including wires, conduits, meters, and etc. (Nelder and Rogers, 2019). The lifespan of power equipment is estimated to be 20 years (Biçen et al., 2014). The initial investment of a charging hub can vary from location to location, depending on the local real estate price, complexity of engineering, and other factors. For simplicity, here we assume that it is the same for the twelve candidate charging hubs and use 10 years as an estimated lifespan. Note that the model formulation allows us to use a different initial investment for each location if such information becomes available.

Table 4 lists the initial investments, lifespans, and the resultant annual leasing costs for each property based on an annual interest rate of 10%.

Table 4. List of initial investments, lifespans, and the annual leasing costs.

Property	Initial investment ($)	Lifespan (years)	Leasing cost ($/year)
Bus charger (150kW)	100,000	10	14,795
Car charger (50kW)	30,000	10	4,439
Power equipment	200 (per kW)	20	21 (per kW)
Charging hub	1,000,000	10	147,950
Electric bus, include:	900,000	-	122,715
• Battery	35,000	6	7,306
• Frame	865,000	12	115,409

Electricity cost

Discussed in the Background section.

Battery degradation cost

The degradation of a lithium-ion battery is impacted by multiple factors and despite it is a non-linear process, linearized degradation models could approximate the nonlinear model quite well. We estimated the cost of degradation to be 0.031/kWh. The detailed process of estimation can be found in Ye et al. (2022).

Results and Discussion

This section presents the study results based on the optimization model and the input data introduced in the Data Description section. First of all, a comprehensive cost–benefit analysis is conducted to quantify the reductions of GHG emissions under different annual budget levels and how the budget is allocated to different sectors. Secondly, load profiles of charging hubs are presented and discussed, highlighting the benefit of the shared charging scheme. Thirdly, the impacts of incorporating time-varying ECI and V2G function in the operation are analyzed. Finally, a priority analysis is conducted to address the questions of resource allocations under budget limitations, providing necessary information to local decision-makers.

Cost-Benefit Analysis

A cost-benefit analysis was conducted to understand the potential of decarbonization under different annual budget levels.[1]

The overall results are presented in Figure 6. First, the total reduction of GHG emissions increases as more chargers are added, as shown in Figure 6 (a). The marginal benefits of a adding more chargers gradually decline as the total GHG reduction curve becomes flat.

Under the full annual budget level of $44 million, the total GHG reduction is 62.6 metric tonnes of CO_2e per day (mTCO_2e/day), in which the bus sector yields a reduction of 54.2 mTCO_2e/day or 86.6% of the total, while the car sector has a reduction of 8.4 mTCO_2e/day or 13.4%. The results of other key parameters under different budget levels are presented in Figure 6 (b)-(g). Figure 6 (b) shows the number of charging hubs selected for deployment. Figure 6 (c) shows the number of procured electric buses and the number of cars that get charged in the charging hubs. Figure 6 (d) shows the total number of bus and car chargers deployed. Figure 6 (e) shows the total power capacity required for all charging hubs and the power demands for buses and cars. Figure 6 (f) and (g) presents the allocation of calculated budgets in the form of absolute values and percentages, respectively. All of the results are automatically determined by the model when given a series of budget. Based on the results, we split the overall development into five phases as shown in Figure 6.

[1] The optimization model was solved under a range of annual budgets from $0 to $44 million. The level of decarbonization is measured by R, the reduction of GHG emissions. The value of R under a certain budget B' is calculated by $R(B = B') = U(B = B') - (B = 0)$, i.e., the difference of GHG emissions between budget B' and $0. The latter case serves as a baseline for performance comparison.

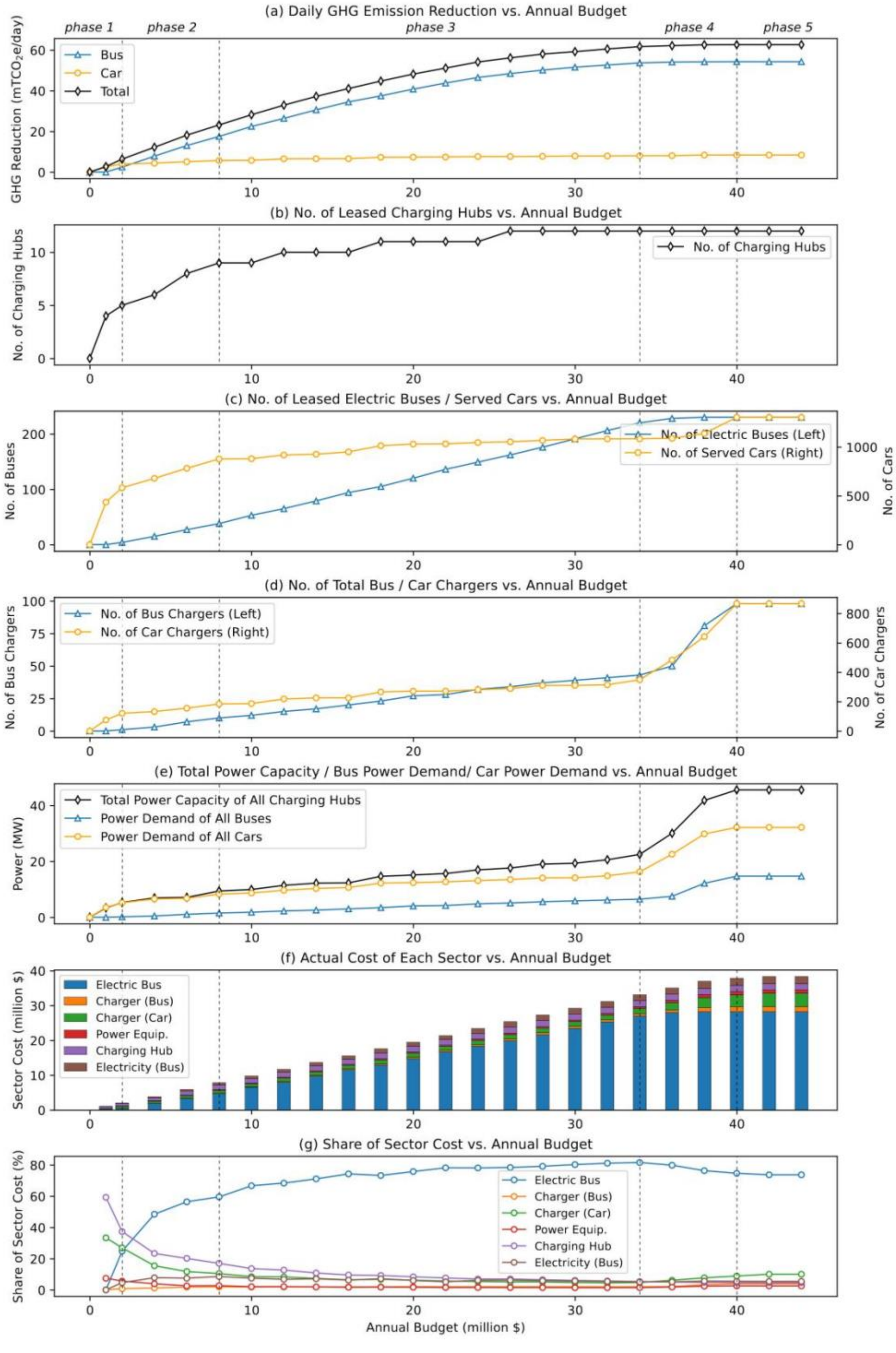

Figure 6. Overview of the planning results under different budget levels.

Phase 1 (Car-dominant): Annual budget $0-$2 million. In this phase, the budget is mainly allocated to serving car charging needs. Specifically, with a budget of $2 million, five charging hubs are deployed as shown in Figure 6 (b) and a significant amount of cars can be charged in the charging hubs as shown in Figure 6 (c). The numbers of electric buses added to the fleet and bus chargers installed in the hubs are very limited, as shown in Figure 6 (c) and (d). In this phase, the majority of the reduction in GHG emissions comes from cars. At low budget levels, it is more efficient to first deploy charging hubs, which are the foundation for the cars and buses to utilize low-ECI electricity. Then the model chooses to prioritize car chargers instead of bus chargers, given the high cost of leasing electric buses.

Phase 2 (Sector-switching): Annual budget $2-$8 million. In this phase up to nine charging hubs are sited as shown in Figure 6 (b). While the car sector is also emphasized, its marginal contribution to the GHG reduction is diminishing as the cars with the most potential to utilize low-ECI electricity are mostly served. Given that there have been five charging hubs sited in Phase 1, the cost of charging hub construction is no longer heavily occupying the budget. Also considering the reduced marginal effects of the car sector, the model decides to add more electric buses to the fleet and correspondingly install more bus chargers.

Phase 3 (Bus-dominant): Budget $8-$34 million. At the end of this phase, all twelve charging hubs are completed. The primary focus in this phase is procuring electric buses and installing bus chargers. The joint effect of converting conventional buses to electric ones and enabling their access to low-ECI electricity contributes to the majority of GHG reduction. Despite the model still adds car chargers given their low cost and to potentially accommodate more cars during the low-ECI period, the car sector is close to saturate, or in other words, the GHG reduction from car sector is nearly plateaued.

Phase 4 (Pre-saturated): Budget $34-$40 million. In this phase, the number of both bus and car chargers and the associated power capacity are soaring to accommodate a few more buses and cars that have limited contribution to the GHG reduction due to their daily operational schedules. In Phases 1-3, when the number of chargers are limited, the model will assign the buses and cars that have relatively lower battery energy for high-power charging during the day time, in order to maximize the absorption of low-ECI electricity. However, with excess budget in this phase, more chargers can be built to charge the buses and cars that have lower potential to absorb electricity and schedule conflicts with the high-potential vehicles. While the budget increased significantly compared with Phase 3, the GHG reduction has very limited improvement in this phase. This marks a significant drop in the marginal benefit of investment.

Phase 5 (Saturated): Budget $40 million and above. When the budget reaches $40 million, both the bus and the car sector are saturated. No more reduction of GHG emissions is observed as budget increases. All eligible conventional buses are converted to electric ones. The constant numbers of chargers and power capacity indicate that the charging demand and the potential of utilizing low-ECI electricity is fully satisfied. There are a few conventional buses that are not electrified, because of extremely long route distance or high frequency of dispatches.

Based on the above cost-benefit analysis, we suggest that investment in building charging hubs should focus on Phases 1 and 2, in which the marginal benefit is substantial. If more funding is available, reaching a certain stage of Phase 3 is also a good choice. However, investing heavily in Phases 4 or 5 is not recommended as the marginal benefit is very low. Actually, after the development in Phases 1-3, the bus fleet will be mainly electric, and while still keeping the overall transit timetable unchanged, it will be more beneficial to reschedule the dispatch timetable of individual buses to create more space for low-ECI electricity usage, both spatially and temporally. This is a promising future work.

The Advantages of Shared Charging Hubs

In the proposed model, the planning of the bus and car sectors are carried out in a collaborative manner through the scheme of shared charging hubs. Here we illustrate how such a scheme improves the overall reduction of GHG emissions. To make this point, a comparison between the shared and the isolated charging schemes is conducted. The proposed model is solved under three different scenarios: 1) Shared charging hubs, 2) Bus charging stations only, and 3) Car charging stations only[2]. For scenario 2, the number of EV chargers is set to be zero in the model. Similarly, for scenario 3, the number of bus chargers is set to be zero$K$. The reductions of GHG emissions of these three scenarios under different budget levels are shown in Figure 7. First of all, it is noticed that under low budget levels, the GHG reductions for scenarios 1, 2 and 3 are very close, indicating that developing either bus or car charging stations is equally as good as developing shared charging hubs. However, in scenario 2 when the budget increases, the marginal benefit of bus charging stations decreases faster than scenario 1. The performance of scenario 3 is even less ideal in the high budget region. Actually, in the high budget region of scenario 3, most of the GHG reduction is contributed by electrifying buses that can be operated without terminal charging (with depot charging only). This can be inferred from Figure 6 (a) where the GHG reduction from the car sector is saturated at low budget levels. On the other hand, though the marginal benefits of scenario 2 is similar to scenario 3 at low budget levels, the growth of GHG reduction in scenario 2 is faster in high budget levels compared to scenario 3, because the establishment of bus charging stations makes it possible for more buses to be converted to buses. Overall, the shared charging hubs of scenario 1 show the best performance under various budget levels among the three scenarios. The reason behind is that with shared charging hubs, the model can implicitly determine the optimal allocation of budget between the bus and car sectors. This contrasts with the isolated charging stations, where the resources are entirely poured into a single transportation mode without the flexibility to achieve collaborative development across different modes.

[2] For scenario 2, the number of car chargers is set to be zero, i.e., $N_k^v = 0, \forall k \in K$ in the model. Similarly, for scenario 3, the number of bus chargers is set to be zero, i.e., $N_k^b = 0, \forall k \in K$ in the model.

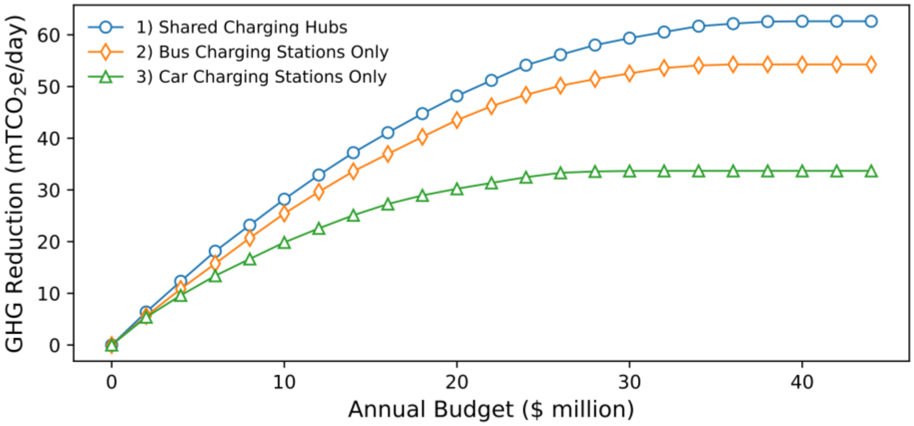

Figure 7. Reduction of GHG emissions under three different planning scenarios: 1) Shared charging hubs for both EBs and EVs, 2) Bus charging stations only, and 3) Car charging stations only.

Reducing peak power through coordinated charging is another potential benefit of the shared charging hubs. To analyze this effect, the charging power of bus and car sectors at different times of the day are presented in Figure 8 for three deployed charging hubs. The results are obtained under an annual budget of $12 million. Based on the observation of Figure 8, the peak charging demands of buses and cars all occur around 9 AM–3 PM when both the ECI and the electricity cost are low due to excess power from solar plants, while discharging usually happens at night to offset GHG emissions when both the ECI and the electricity cost are high. An interesting phenomenon is that neither charging or discharging is preferred in the early morning, as the signals of ECI and electricity price contradict each other. During the period of peak charging demand, clear patterns of coordinated charging can be found in all of the three charging hubs, as indicated by the gray arrows. Taking charging hub El Cerrito Del Norte as an example, there are two outstanding peak stages of car charging power between 9 AM–3 PM, correspondingly, the charging power of buses experience two valleys at the same time as the peaks of cars, such that the peak power of the charging hub is not exceeded. Similar phenomena can be observed in the other two charging hubs. Keeping peak power consumption at a low level has multiple benefits. On one hand, the initial capital required for power equipment is reduced immediately. This effect has been considered in the proposed model. On the other hand, the charging hubs will receive lower electricity bills due to reduced peak demand charges, which implies profound benefit in the long run.

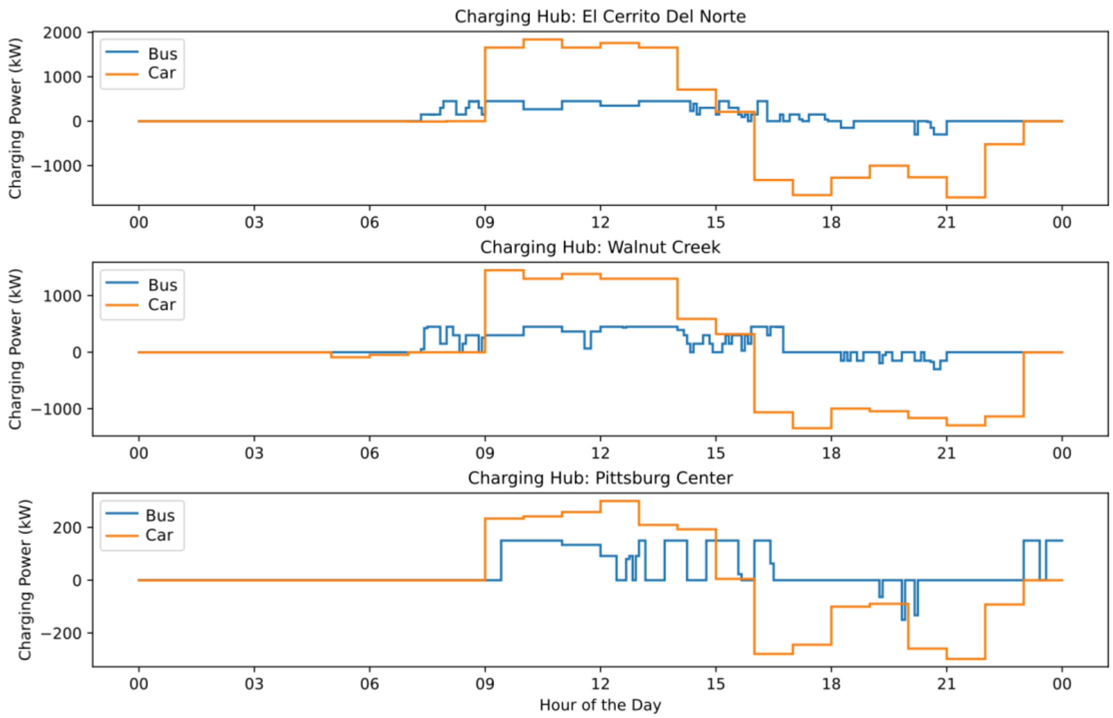

Figure 8. Load profiles of three charging hubs. Gray arrows indicate coordinated charging between buses and cars to limit the increase of total peak power demand.

The Impacts of ECI and V2G

The time-varying ECI and V2G technology are included in the proposed planning model. In this subsection, we quantify their contributions to the decarbonization effort. To do this, the proposed planning problem is solved under three different settings: 1) incorporating time-varying ECI and V2G is enabled (w/ ECI, w/ V2G, this is the default setting of the model), 2) incorporating time-varying ECI, but V2G is disabled (w/ ECI, w/o V2G), and 3) without consideration of time-varying ECI and V2G is disabled (w/o ECI, w/o V2G)[3]. Figure 9 (a) shows the GHG emission reductions of the above three cases under different budget levels. Using case 3 as the baseline, a substantial improvement of GHG reduction is observed when the time-varying ECI is considered in case 2. Further enabling the V2G in case 1 results in an even more significant improvement. Taking the budget of $30

[3] For case 2, the model is solved by setting $x^{min} = 0$, $y^{min} = 0$, and $y^{home,min} = 0$, i.e., not allowing discharging from buses or cars. For case 3, besides the modifications made in case 2, the daily average ECI $\bar{g}$ is adopted to replace g_t, where $\bar{g} = \frac{1}{|T|}\sum_{t\in T} g_t$ is a constant throughout the study time horizon T ($|T|$ measures the number of time steps in T), such that the modified model does not consider ECI, and as a result charging at different times of the day makes no difference to the model's objective function. After obtaining the optimization results for case 3, actual GHG emissions are calculated based on the real-time ECI information. In most of the existing charging infrastructure, there is no ECI-oriented scheduling or V2G function. This situation is represented by case 3.

million as an example, the GHG reductions are 59.4, 50.6, and 47.8 $mTCO_2e$/day, for cases 1, 2, and 3, respectively. The consideration of time-varying ECI increases the GHG reduction by 5.8% from case 3 to case 2. The better performance in case 2 comes from the optimized charging schedule that avoids charging in high ECI periods. Enabling V2G further increases the GHG reduction by 17.3% from case 2 to case 1, and 24.1% from case 3 to case 1. The reason behind such a substantial improvement is that the V2G function allows discharging buses/cars to serve the demand of the grid, such that less electricity is requested from power generation units. This is especially meaningful when the ECI is high. It should be noted that the V2G function is only beneficial when there is consideration of time-varying ECI, which serves as the triggering signal of charging or discharging.

Comparing the planning results under different settings provides additional insights. By checking the total number of bus chargers shown in Figure 9 (b), it is found that more bus chargers are installed in cases 2 and 3 compared with case 1. The reason behind is that when the V2G function is disabled, the car owners will find it uneconomical to use the charging hubs where the electricity price is high (charging hubs use commercial rate), but selling electricity through V2G is not feasible. In this case, the model devotes most of the budget to the bus sector. This can be inferred from Figure 9 (c) where car chargers are not invested in case 2 or 3. The obvious difference in the number of car chargers between case 1 and cases 2/3 also points to the additional benefit provided by cars in the system as energy storage units. When there is no V2G function as in cases 2/3, the contribution to GHG reduction from the car sector is reduced significantly, as there is less incentive for the car user to utilize the low-ECI electricity during their dwelling at park-and-ride facilities.

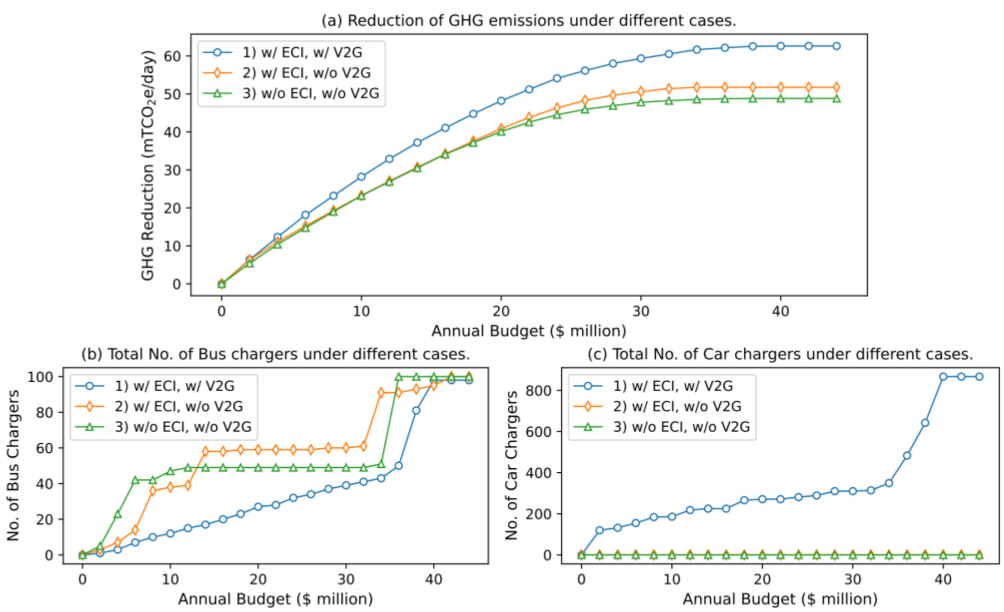

Figure 9. The impacts of ECI and V2G on (a) GHG reductions, (b) required number of bus chargers, and (c) required number of car chargers.

Priority Analysis

The available budget is usually limited for the initial demo deployment of charging hubs. Under such circumstances, in order to make best use of available funds it is important to identify the priorities of investment and development in different sub-sectors. For this purpose, the planning results under four relatively low budget levels ($0.5, 1, 2, and 4 million) are analyzed in this subsection. The planning results are automatically determined by the model when the budget is given. The deployed charging hubs, the number of bus/car chargers in these charging hubs, and the routes in which at least one bus is electrified are presented in Figure 10. At low budget levels, e.g $0.5 and 1 million, all of the budget is allocated to lease charging hubs and car chargers, as indicated in Figure 10 (a) and (b). The first electric bus and bus charger is introduced when the budget is $2 million as shown in Figure 10 (c). Further increasing the budget to $4 million, the model decides to procure more more electric buses, while keeping a low number of bus chargers through optimized charging schedules to save budget. For example, when there are 15 electric buses, only three bus chargers are needed as shown in Figure 10 (d), benefiting from the optimized charging schedules. Table 5 lists the planned number of bus/car chargers in each candidate charging hub. A worth-mentioning phenomenon is that when budget increases, the number of car chargers in a deployed charging hub remains largely unchanged. This is because when the budget increases, the model deploys new charging hubs such that the marginal benefit of adding car chargers to the new charging hubs is greater than that of the existing charging hubs.

In terms of deciding which buses have higher priorities to be electrified, a straightforward idea is to select those that have higher daily GHG emissions. However, there are other factors that can affect this rule. Table 6 lists the top buses ranked by daily GHG emissions. Generally speaking, the order of a bus being electrified when the budget increases follows the order of its daily GHG emissions, but buses 65, 41, and 163 are exceptions as shown in Table 6. By checking each bus in detail, two reasons are found that prevent the electrification of a bus with high daily GHG emissions. One reason is the operation limits of buses, represented by buses 65 and 41. Bus 65 is dispatched nine times a day resulting in a total of more than five hundred miles of travel distance. Bus 41 has a one-way travel distance of more than seventy miles and its dwelling time in BART Walnut Creek is only 14 min. As a result, the currently available battery capacity and charging power fail to satisfy the electricity demand of buses 65 and 41. Another reason is that the corresponding charging hub has not been deployed, represented by bus 163. The applicable charging hub for bus 163 is BART Pittsburg Center, which has not been deployed due to budget limit. This means that electrifying bus 163 requires leasing a charging hub at BART Pittsburg Center at the same time, leading to a higher bundled cost compared to electrifying bus 96 that uses an existing charging hub.

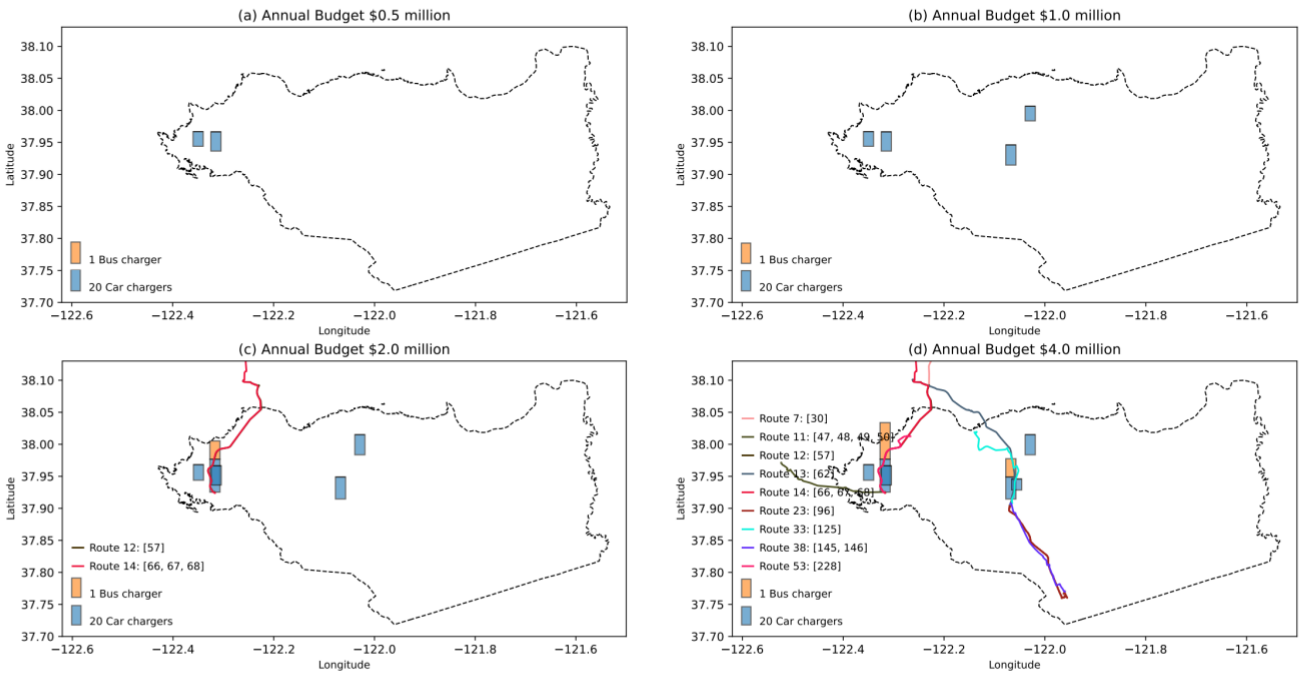

Figure 10. Planning results under four low budget levels: deployed charging hubs, number of bus/car chargers, and bus routes with buses being electrified[4].

Table 5. List of sited charging hubs and number of bus/car chargers.

Candidate Charging Hub ID	Candidate Charging Hub Name	No. of Bus/Car Chargers			
		Annual Budget ($ Million)			
		0.5	1.0	2.0	4.0
1	Richmond	0/16	0/16	0/17	0/17
2	El Cerrito Del Norte	–	–	1/36	2/36
3	El Cerrito Plaza	0/21	0/21	0/21	0/21
4	Orinda	–	–	–	–
5	Lafayette	–	–	–	–
6	Walnut Creek	–	0/22	0/24	1/24
7	Pleasant Hill	–	–	–	0/12
8	Concord	–	0/16	0/22	0/22
9	North Concord	–	–	–	–
10	Pittsburg	–	–	–	–
11	Pittsburg Center	–	–	–	–
12	Antioch	–	–	–	–

[4] Each vertical bar represents a deployed charging hub and the height of the bar indicates the number of bus/car chargers leased in this charging hub. The individual buses being electrified are listed behind its route ID and the format is "Route ID: [Bus ID1, Bus ID2, …]".

Table 6. Rank of buses based on daily GHG emission and analysis of model results.

Bus ID	Route ID	Agency, Route Name Terminal Stations	Emission ($kgCO_2e$/day)	Budget Level When Electrified ($ Million)	Reason Not Electrified
65	14	SolTran,R BART El Cerrito Del Norte - Suisun City	1042		High frequency dispatches.
66	14	SolTran, R BART El Cerrito Del Norte - Suisun City	926	2.0	
57	12	SolTran, R BART El Cerrito Del Norte - Vallejo	736	2.0	
41	9	Fairfield and Suisun, BLUE BART Walnut Creek - Sacramento	708		Long route distance and short dwelling time at terminal.
68	14	SolTran, R BART El Cerrito Del Norte - Suisun City	694	2.0	
62	13	SolTran, Y BART Walnut Creek - Vallejo	644	4.0	
145	38	The County Connection, 21 BART Walnut Creek - San Ramon	635	4.0	
163	41	TriDelta, 391 BART Pittsburg Center - Brentwood Park & Ride	631		Charging hub Pittsburg Center BART has not been sited.
96	23	The County Connection, 96X BART Walnut Creek - Bishop Ranch	615	4.0	

Conclusion

This study focuses on the optimal deployment and operation of the shared charging hubs as well as the electrification of public transits within a regional context. The objective of the optimization model is to minimize GHG emissions within specified budgets by jointly determining which buses to electrify, where to place charging hubs, and the required number of chargers and power capacities at these hubs. Beyond the hardware investment decisions, our optimization model also produces coordinated charging schedules, factoring in time-varying ECI, electricity costs, and battery degradation, while leveraging the capabilities of V2G technology.

We demonstrated the effectiveness of the model through a case study in Contra Costa, California, analyzing the phased implementation of the charging hub network under various budget constraints. The results underscored the advantages of shared charging hubs, the significance of incorporating time-varying ECI, and the benefits of enabling V2G functionality. In support of initial development, we also examined detailed planning outcomes under constrained budgets. The model can be adapted to other regions by incorporating local data such as potential charging hub locations, transit schedules, passenger car activity patterns, and cost considerations.

It is worth mentioning that while predetermined charging schedules are feasible for buses due to fixed operating schedules, the stochastic arrivals and departures of passenger cars necessitate on-line scheduling algorithms for coordinated charging in practice. Our study's use of off-line optimization is designed to offer an initial assessment of the maximum decarbonization potential, but future work should integrate online control algorithms with the proposed model.

Appendix

Model Formulation (Detailed)

In a regional area, suppose there are a set I of public conventional buses and a set J of private EVs. The goal of local public decision-makers is to minimize the GHG emissions from bus and car sectors through the following strategies: (1) converting the conventional buses to electric buses, (2) providing charging services to both buses and cars in a set K of candidate charging hubs, and (3) optimize the charging schedules of buses and cars incorporating the time-varying ECI. Note that converting non-electric private cars to their electric counterparts is relying on the decisions of individuals and it is hence not within the scope of this study. The deployment of these strategies is subject to constraints of operational schedule of buses, energy limits of electric buses and cars, number of installed bus/car chargers, number and power capacities of the deployed charging hubs, and most importantly, the budget. Table 7 lists the notations used in this study. The following assumptions are made in the proposed model:

- The public transit agencies will be leasing charging infrastructure and electric buses from private vendors on an annual basis to reduce the financial risk of high upfront costs and the costs associated with large fleet maintenance, as proposed in Electrification Coalition (2010), Li et al. (2018), Jattin (2019) and practiced by Lunden (2018), Proterra (2022).
- Buses can be charged in a charging hub or its depot and cars can be charged in a charging hub or at home. For the buses/cars to be charged in a charging hub, there need to be sufficient bus/car chargers. On the other hand, it is assumed that the charging facilities in bus depots are ready for use as buses are congregated in depots and charging infrastructure can be established in an economically efficient way by corresponding transit agencies. It is also assumed cars have access to low-power chargers at home, which does not rely on the budget of public transit agencies.
- A bus can be charged in a charging hub if the following two conditions are satisfied: Its terminal station(s) is within a certain threshold distance (e.g. 0.5 mile) of a charging hub and its dwell time in the terminal is longer than a threshold time (e.g. 10 min). Given the first condition, the energy consumption and time to drive the bus to/from the charging hub can be neglected. For example, in Figure 1, a bus dwelling at terminal T1 will have access to Charging Hub 1 if d is less than 0.5 mile and its dwelling time is more than 10 min. Being close to a stop rather than a terminal does not qualify a charging hub to be used by a bus, as it usually has very limited dwell time at a stop. Binary parameters β_{ikt} are used to indicate if bus i at time t is having access to candidate charging hub.
- The schedules of individual buses are kept unchanged post-conversion to electric buses, relieving the potential frictions in transit agencies during the transition phase. The schedules of individual buses are known parameters.

- A car can be charged in a charging hub when it is parked in a charging hub. The chargers can be shared among cars through a smart charging scheme such that when one car's charging demand is satisfied, the charger can be moved to other waiting cars, reducing the cost of leasing extra chargers. Such a scheme can be achieved through multiple ways, e.g. valet service or mobile chargers (Doll, 2022).

The above assumptions are made to greatly enhance the flexibility of charging. It can help obtain an optimistic estimation of decarbonization potential that can serve as a baseline and reference for future policy decisions.

Table 7. Summary of Notation for Sets, Parameters, and Decision Variables.

	Sets
I	Set of buses.
J	Set of cars.
K	Set of candidate charging hubs.
T	Set of time steps of the study time horizon.
$T_i^{departure}$	Set of time steps at which bus i departs from its terminal stations.
T_i^{depot}	Set of time steps at which bus i is parking in its depot.
$T_i^{b,hub}$	Set of time steps at which bus i $i$is having access to a candidate charging hub.
$T_j^{v,hub}$	Set of time steps at which EV j is parking in a charging hub.
T_j^{home}	Set of time steps at which EV j is parking at home.
	Parameters
u_i^b	Daily carbon emission of bus i if it uses diesel as the fuel.
g_t	Electricity carbon intensity of the grid at time t.
$e^{b,min}/e^{b,max}$	Minimal/maximal battery energy of a bus.
$e^{v,min}/e^{v,max}$	Minimal/maximal battery energy of a car.
x^{min}/x^{max}	Minimal/maximal charging powers of a bus charger.
y^{min}/y^{max}	Minimal/maximal charging powers of a car charger.
$y^{home,min}/y^{home,max}$	Minimal/maximal charging powers of a home charger.
s_{it}^b	Power consumption rate of bus i at time t.
s_{jt}^v	Power consumption rate of car j at time t.
η_b	Energy efficiency of electric buses.
η_v	Energy efficiency of electric cars.
κ	Cycle efficiency of charging/discharging batteries.
d_i	One-way distance of the route served by bus i.
β_{ikt}	$\beta_{ikt} = 1$ indicates bus i is parking in charging hub k at time t. Otherwise, $\beta_{ikt} = 0$.
γ_{jkt}	$\gamma_{jkt} = 1$ indicates car j is parking in charging hub k at time t. Otherwise, $\gamma_{jkt} = 0$.
c^b	Cost of one bus charger.
c^v	Cost of one car charger.
c^p	Cost of providing one kW of power capacity at a charging hub.

c^f	Cost of make-ready, including licensing, construction, and etc.
c^{eb}	Cost of one electric bus.
c_t^e	Cost of charging 1 kWh electricity at time in a charging hub (commercial rate).
$c_t^{e,home}$	Cost of charging 1 kWh electricity at time t at home (residential rate).
c^{deg}	Cost of battery degradation by charging/discharging 1 kWh of electricity.
B	Budget.
	Decision Variables
U^b	Daily GHG emission of the bus sector.
U^v	Daily GHG emission of the car sector.
z_i	Binary variable, $z_i = 1$ indicates bus i is electrified. Otherwise, $z_i = 0$.
x_{it}	Charging power on bus i at time t.
y_{jt}	Charging power on car j at time t.
P_k	Power capacity of charging hub k.
P_{kt}^b	Power demand of buses in charging hub k at time t.
P_{kt}^v	Power demand of cars in charging hub k at time t.
N_k^b	Number of bus chargers installed at charging hub k.
N_k^v	Number of car chargers installed at charging hub k.
n_{kt}^b	Number of buses charging in hub k at time t.
n_{kt}^v	Number of cars charging in hub k at time t.
$\widehat{N}_k$	$\widehat{N}_k = 1$ indicates the candidate charging hub k is selected for deployment. Otherwise, $\widehat{N}_k = 0$.

Objective Function

The objective function is the minimization of the sum of GHG emissions from the bus and the EV sectors:

$$\min \boldsymbol{U^b} + \boldsymbol{U^v} \tag{1}$$

where $\boldsymbol{U^b}$ and U^v are the GHG emissions from the bus sector and EV sector respectively, and:

$$\boldsymbol{U^b} = \sum_{i \in I} (\boldsymbol{1} - \boldsymbol{z_i}) \boldsymbol{u_i^b} + \sum_{i \in I} \sum_{t \in T} \boldsymbol{g_t x_{it} \Delta t} \tag{2}$$

$$\boldsymbol{U^v} = \sum_{j \in J} \sum_{t \in T} \boldsymbol{g_t y_{jt} \Delta t} \tag{3}$$

For the bus sector, U^b is jointly determined by conventional buses and EBs. The GHG emission from conventional buses is measured by $\sum_{i \in I} (1 - z_i) u_i^b$ where u_i^b is the daily GHG emission from bus i when it is a conventional bus. $z_i = 1$ indicates that bus i is converted to an EB such that its GHG emission from consuming fossil fuels is removed. On the other hand, despite zero on-road emission, EBs still create GHG emissions on the upstream power generation. The amount of GHG emissions from EBs is measured by $\sum_{i\in I}\sum_{t\in T} g_t x_{it}\Delta t$, where g_t is the ECI at time t and x_{it} is the charging power on bus i at time t. Δt is the length of time corresponding to one time step. For the EV sector, U^v is solely determined by EVs and it is measured by $\sum_{j\in J}\sum_{t\in T} g_t y_{jt}\Delta t$, where y_{jt} is the charging power on EV j at time t.

Constraints

Bus Sector

$$\boldsymbol{e^b_{it'}} = \boldsymbol{e^b_{it}} + \left[\boldsymbol{x_{it}} - \left(\boldsymbol{1} - \sqrt{\boldsymbol{\kappa}}\right)|\boldsymbol{x_{it}}| - \boldsymbol{z_i s^b_{it}}\right]\Delta \boldsymbol{t}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t}, \boldsymbol{t'} \in \boldsymbol{T} \tag{4}$$

$$\boldsymbol{e^b_{it}} \geq \frac{\boldsymbol{d_i}}{\boldsymbol{\eta^b}} - (\boldsymbol{1} - \boldsymbol{z_i})\boldsymbol{G}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T^{departure}} \tag{5}$$

$$\boldsymbol{z_i e^{b,min}} \leq \boldsymbol{e^b_{it}} \leq \boldsymbol{z_i e^{b,max}}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{6}$$

$$\boldsymbol{z_i x^{min}} \leq \boldsymbol{x_{it}} \leq \boldsymbol{z_i x^{max}}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \left\{\boldsymbol{T^{b,hub}_i} \cup \boldsymbol{T^{depot}_i}\right\} \tag{7}$$

$$\boldsymbol{x_{it}} = \boldsymbol{0}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \notin \left\{\boldsymbol{T^{b,hub}_i} \cup \boldsymbol{T^{depot}_i}\right\} \tag{8}$$

$$\boldsymbol{z_i} \in \{\boldsymbol{0}, \boldsymbol{1}\}, \quad \forall \boldsymbol{i} \in \boldsymbol{I} \tag{9}$$

Constraint (4) defines the transition rule of the battery energy level of the bus i from time t to the next time step t'. Note that when t is the final time step in T, t' will be the first time step, such that the energy level of a bus forms a repeated closed-loop, which guarantees sustained inter-day operation. The energy loss due to charging/discharging is considered and measured by $-\left(\boldsymbol{1} - \sqrt{\boldsymbol{\kappa}}\right)|\boldsymbol{x_{it}}|$ (refer to Foggo and Yu (2017)), where $\boldsymbol{\kappa}$ is the battery cycle efficiency. $\boldsymbol{s^b_{it}}$ is the power consumption rate of bus i at time t. Constraint (5) requires that a bus needs to have enough energy to cover an entire trip upon departure, where $\boldsymbol{d_i}$ is the one-way distance of the route served by bus i and $\boldsymbol{\eta^b}$ is the electricity fuel efficiency of EBs. $\boldsymbol{G}$ is a relatively large positive number such that constraint (5) is only binding for EBs but not for conventional buses. Constraint (6) specifies the range of bus energy level, while constraint (7) specifies the range of bus charging power. When $\boldsymbol{x^{min}},$ the EBs are allowed to be discharged and send energy back to the grid. Note that when a bus is not in a charging hub or its depot, its charging power is zero as stated in constraint (8).

The constraints (4) - (9) are simultaneously applicable to conventional buses and EBs. When bus i is a conventional bus, i.e. $z_i = 0$, constraint (4), (5), (6), (7), and (8) are satisfied automatically with $e^b_{it} = 0,\ x_{it} = 0, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T}$. This also means that there is no energy or power constraint for conventional buses, reflecting the fact that conventional buses can easily obtain fuel supply from existing fossil fuel infrastructure.

Electric Car Sector

$$\boldsymbol{e^v_{jt'}} = \boldsymbol{e^v_{jt}} + \left[\boldsymbol{y_{jt}} - (\boldsymbol{1} - \sqrt{\boldsymbol{\kappa}})\left|\boldsymbol{y_{jt}}\right| - \boldsymbol{s^v_{jt}}\right]\Delta\boldsymbol{t}, \quad \forall \boldsymbol{j} \in \boldsymbol{J}, \forall \boldsymbol{t}, \boldsymbol{t'} \in \boldsymbol{T} \tag{10}$$

$$\boldsymbol{e^{v,min}} \leq \boldsymbol{e^v_{jt}} \leq \boldsymbol{e^{v,max}}, \quad \forall \boldsymbol{j} \in \boldsymbol{J}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{11}$$

$$\boldsymbol{y^{min}} \leq \boldsymbol{y_{jt}} \leq \boldsymbol{y^{max}}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T^{v,hub}_j} \tag{12}$$

$$\boldsymbol{y^{home,min}} \leq \boldsymbol{y_{jt}} \leq \boldsymbol{y^{home,max}}, \quad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T^{home}_j} \tag{13}$$

$$\boldsymbol{y_{jt}} = \boldsymbol{0}, \quad \forall \boldsymbol{j} \in \boldsymbol{J}, \forall \boldsymbol{t} \notin \left\{\boldsymbol{T^{b,hub}_j} \cup \boldsymbol{T^{home}_j}\right\} \tag{14}$$

Constraint (10) defines the transition rule of the battery energy level of the EV j from time t to the next time step t'. Similar to EBs, the energy loss due to charging/discharging is measured by $-(\boldsymbol{1} - \sqrt{\boldsymbol{\kappa}})\left|\boldsymbol{y_{jt}}\right|$. $\boldsymbol{s^v_{jt}}$ is the power consumption rate of EV j at time t.

While EBs need to have sufficient energy upon every departure, EVs are more flexible. Hence, it is assumed that the only requirement is the daily amount of electricity charged into an EV is equal to their daily energy consumption, such that they can maintain sustained operation, as implied by (10). Constraint (11) specifies the range of an EV's battery energy level. Constraints (12) and (13) determine the range of EV charging power in a charging hub and at home. Specifying different charging power limits in different places is because home charging is usually under alternating current and lower charging powers. Constraint (14) mandates that when an EV is not in a charging hub or at home, its charging power is zero.

Power Capacity

$$\boldsymbol{P_k} \geq \left|\boldsymbol{P^b_{kt}} + \boldsymbol{P^v_{kt}}\right|, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{15}$$

$$\boldsymbol{P^b_{kt}} = \sum_{\boldsymbol{i}\in\boldsymbol{I}} \boldsymbol{\beta_{ikt}} \boldsymbol{x_{it}}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{16}$$

$$\boldsymbol{P^v_{kt}} = \sum_{\boldsymbol{j}\in\boldsymbol{J}} \boldsymbol{\gamma_{jkt}} \boldsymbol{y_{jt}}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{17}$$

There must be enough power capacity P_k in each charging hub k to fulfill the combined peak charging power of EBs and EVs at any time t, as shown in constraint (15). The charging power of EBs P^b_{kt} or EVs P^v_{kt} at a charging hub k at time t is the sum of the charging power of individual EBs/EVs that are dwelling at the charging hub k at the time, indicated by binary parameters β_{ikt} for EBs, or γ_{jkt} for EVs. The use of the absolute sign in the right-hand side of constraint (15) considers the potential negative charging power (i.e., discharging) under the V2G function. The power capacity in a charging hub is determined by the capacity of sub-station, inverters, converters, wires, and other factors. A higher power capacity usually comes with a higher cost. In a shared charging hub, EBs and EVs can share common power facilities. When their charging schedules are coordinated to reduce the maximum combined charging power, the required power capacity in a charging hub can potentially be reduced, leading to significant cost savings.

Number of Chargers

$$\boldsymbol{N_k^b} \geq \boldsymbol{n_{kt}^b}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{18}$$

$$\boldsymbol{N_k^v} \geq \boldsymbol{n_{kt}^v}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{19}$$

$$\boldsymbol{n_{kt}^b} = \sum_{\boldsymbol{i} \in \boldsymbol{I}} \boldsymbol{\hat{x}_{ikt}}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{20}$$

$$\boldsymbol{n_{kt}^v} = \sum_{\boldsymbol{i} \in \boldsymbol{I}} \boldsymbol{\hat{y}_{jkt}}, \quad \forall \boldsymbol{k} \in \boldsymbol{K}, \forall \boldsymbol{t} \in \boldsymbol{T} \tag{21}$$

$$\boldsymbol{\hat{x}_{ikt}} = \begin{cases} \mathbf{1}, & \text{if } \boldsymbol{\beta_{ikt} x_{it}} \neq 0 \\ \mathbf{0}, & \text{otherwise} \end{cases} \tag{22}$$

$$\boldsymbol{\hat{y}_{jkt}} = \begin{cases} \mathbf{1}, & \text{if } \boldsymbol{\gamma_{jkt} y_{jt}} \neq 0 \\ \mathbf{0}, & \text{otherwise} \end{cases} \tag{23}$$

In addition to power capacity, the number of chargers should also match the charging demands. Constraints (18) and (19) require that the number of installed EB chargers $\boldsymbol{N_k^b}$ and EV chargers $\boldsymbol{N_k^v}$ should be no less than the number of in-use chargers at any time, where $\boldsymbol{n_{kt}^b}$ and $\boldsymbol{n_{kt}^v}$ are the number of EB and EV chargers in-use at time t, respectively. A binary variable $\boldsymbol{\hat{x}_{ikt}}$ is introduced to indicate whether a bus i is connected to a charger in charging hub k at time t. As shown in constraint (20), $\hat{x}_{ikt} = 1$ if the following two conditions are true: a) Bus i is dwelling at charging hub k at time t , i.e. $\beta_{ikt} = 1$**,** b) Bus i has none-zero charging power, either being charged or discharged, i.e. $x_{it} \neq 0$. When $\hat{x}_{ikt} = 1$, bus i must be occupying one EB charger at charging hub k. Then the number of in-use EB chargers at time t is the sum of $\hat{x}_{ikt}$ over the set I of buses, as shown in constraint (22). Similar relationships between $\boldsymbol{n_{kt}^v}$ and $\boldsymbol{\hat{y}_{jkt}}$ can be found in constraints (21) and (23) for EVs.

Investment Decision on Candidate Charging Hubs

$$\boldsymbol{\hat{N}_k} = \begin{cases} \mathbf{1}, & \text{if } \boldsymbol{N_k^b} + \boldsymbol{N_k^v} > 0 \\ \mathbf{0}, & \text{otherwise} \end{cases} \tag{24}$$

When the number of EB chargers or EV chargers is greater than zero, a candidate charging hub is said to be sited or built, indicated by a binary variable $\hat{N}_k$ as shown in constraint (24). In other words, if a charging hub k is not established, i.e., $\hat{N}_k = 0$, then both of N_k^b and N_k^v are zero. As a result, no EBs or EVs can get charged at charging hub k according to constraints (18) - (23). How the siting of a charging hub constrains the charging of EBs and EVs is explained as follows. Taking EB for example, $N_k^b = 0$ indicates that $n_{kt}^b = 0, \forall t \in T$ according to (18), as n_{kt}^b is the sum of non-negative numbers. In this case, $\hat{x}_{ikt}$ must be 0 $\forall i \in I, \forall t \in T$, i.e., $\beta_{ikt} x_{it} = 0, \forall i \in I, \forall t \in T$. This can be broken down into two scenarios. First, if $\beta_{ikt} = 1$, then x_{it} must be zero. Second, if $\beta_{ikt} = 0$, this means that the bus is not dwelling in the charging hub k, so x_{it} must be zero according to constraint (8). Hence, when $\widehat{N}_k = 0$, no EBs can be charged in this unbuilt charging hub. The same effect can be explained in a similar way for EVs.

Budget

$$\sum_{k \in K} \left(\boldsymbol{c^b N_k^b} + \boldsymbol{c^v N_k^v} + \boldsymbol{c^f \widehat{N}_k} + \boldsymbol{c^p P_k} \right) + \sum_{i \in I} \boldsymbol{c^{eb} z_i} + \boldsymbol{D} \sum_{t \in T} \sum_{i \in I} \boldsymbol{c_t^e x_{it} \Delta t} \leq \boldsymbol{B} \quad (25)$$

The overall project is constrained by a budget $\boldsymbol{B}$, and the total cost consists of five parts: cost of the procurement and installation of EB chargers ($\boldsymbol{c^b N_k^b}$) and EV chargers ($\boldsymbol{c^v N_k^v}$), fixed cost of construction of charging hubs ($\boldsymbol{c^f \widehat{N}_k}$) including necessary permitting process, land purchasing, and construction work, cost of installing new or upgrading existing power equipment ($\boldsymbol{c^p P_k}$), and cost of purchasing electric buses ($\boldsymbol{c^{eb} z_i}$).

The public transit agencies will lease electric buses and charging infrastructure from private vendors on an annual basis. The overall project is constrained by an annual budget $\boldsymbol{B}B$, and the total annual cost consists of two categories: (1) Property-leasing cost, which includes cost of leasing bus chargers $cbNkb$ ($\boldsymbol{c^b N_k^b}$) and car chargers ($\boldsymbol{c^v N_k^v}$)kv , cost of leasing charging hubs $cf\ N$($\boldsymbol{c^f \widehat{N}_k}$) k and paying for enough power capacity $cpPkcap$($\boldsymbol{c^p P_k}$), and cost of leasing electric buses ceb($\boldsymbol{c^{eb} z_i}$). (2) Operational cost, or electricity cost $ctexitD \sum_{\boldsymbol{t \in T}} \sum_{\boldsymbol{i \in I}} c_t^e \boldsymbol{x_{it}} \Delta \boldsymbol{t}$, where DD is the number of days in a year and $c_t^e cte$ is the electricity price at time tt.

Electricity Cost of Cars

$$\boldsymbol{D} \left(\sum_{t \in T_j^{v,hub}} \boldsymbol{c_t^e y_{jt}} + \sum_{t \in T_j^{home}} \boldsymbol{c_t^{e,home} y_{jt}} + \sum_{t \in T} \boldsymbol{c^{deg}} \left| \boldsymbol{y_{jt}} \right| \right) \Delta \boldsymbol{t} \leq \boldsymbol{C_j^{car,home}}, \forall \boldsymbol{j} \in \boldsymbol{J} \quad (26)$$

While car chargers are covered by public budget, the car owners are still supposed to pay for their own electricity usage. On the other hand, we also want to ensure that cars are incentivized to participate in reducing GHG emissions. For this purpose, we require that the charging scheduling results will not lead to a cost higher than the minimal cost of home charging. This requirement is applicable to each individual car, as shown in constraint (25), where $c_t^{e,home}{}_{ome}$is the electricity price of home charging, which can be different (usually lower) than that in the charging hub (c_t^e). For private cars, battery degradation needs to be considered as a cost. This is in contrast with buses, in which their batteries are leased and the degradation cost is reflected in the leasing price. In (25), $cdeg\ c^{deg}$ is the battery degradation cost for charging/discharging 1 kWh of electricity. $CjEVC_j^{car,home} min$ is the annual minimal electricity cost of cars j and it can be obtained by slightly modifying and solving (10)–(14) with home charging only and with the objective of minimizing electricity cost. The process of obtaining $C_j^{car,home}min$ can be found in Ye et al. (2022).

Summary of the Model

As a summary of the model formulation in this section, the model is solved under objective function (1) and subject to constraints (2) - (25). Specifically, (22), (23), and (24) will be reformulated using standard techniques such that the optimization problem is transformed to a mixed-integer linear program problem (MILP), which can be handled by commercial solvers. Here we choose to use Gurobi solver on AWS cloud server with AMD CPUs. To balance the operational time accuracy requirement and the solver time, the control time intervals were set to be 5 minutes for the bus sector and 60 minutes for the EV sector. The study time horizon was one day. Also, to demonstrate that the optimization problem (1) - (25) is successfully implemented without violating any constraints, we include an analysis below regarding the daily activities of a selected bus.

Daily Bus Activity

Here we show the daily activities of a selected bus to demonstrate that the optimization problem (1) - (25) is successfully implemented without violating any constraints. As shown in Figure 11, the following time-series parameters are presented (in 5-minute intervals):

- Location indicators: Indicating whether the bus is in a charging hub, its depot, or its terminal. If their values are all zero, the bus is running.
- State of charge and charging power: The state of charge is ranging from 0-100% while the charging power is ranging from -150-150 kW. The negative charging power value means the battery is discharging through V2G functionality.
- ECI of the day: We include the ECI of the day for reference.

First, we notice that the charging power can only be zero if the bus is not dwelling in a charging hub (i.e. the in-hub indicator = 0) or not in its depot (i.e. the in-depot indicator = 0). This result shows that the optimization framework works successfully in terms of enforcing the spatial and temporal constraints.

Second, by checking the state of charge and charging power, we find that the bus is only charged during the valley of ECI (around 08:00 – 17:00, i.e., 8AM – 5 PM), while it is discharged at one of the peaks of the ECI (around 21:00, i.e., 9 PM). This result demonstrates that the proposed framework is able to optimize the charging schedules of the bus to minimize the GHG emissions.

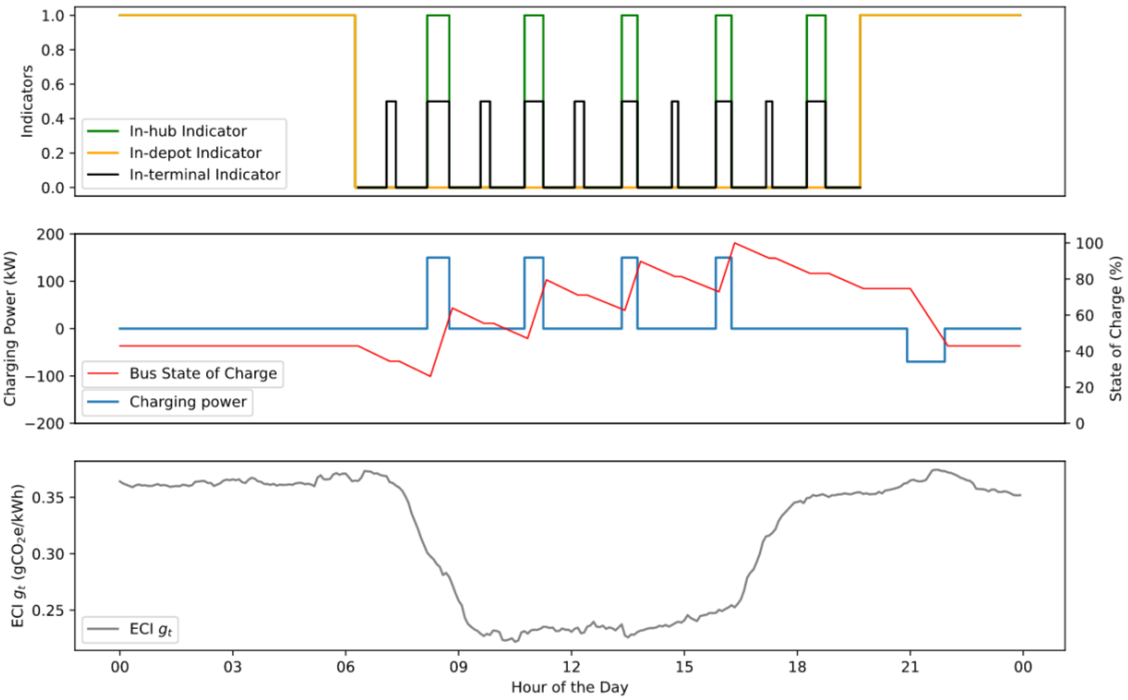

Figure 11. Daily activities of a bus, including 1) Location indicators of the bus (Top); 2) State of charge and charging power of the bus (Middle); and 3) ECI as a reference (Bottom).

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