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SMART CHARGING FOR ELECTRIC RIDE-HAILING VEHICLES USING RENEWABLES: A SAN FRANCISCO CASE STUDY

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ABSTRACT

Charging large fleets of electric ride-hailing vehicles (ERVs) is a complex matter that could serve different objectives: lower carbon dioxide emissions, lower monetary expenditures, or maximize solar photovoltaics (PV) energy consumption. Currently, it is unclear how each of those objectives could impact the business and performance of a ride-hailing fleet. In order to fill this gap, this article employs a dynamic transportation model: a smart charging simulation that combines agent-based, discrete-event, and system dynamic modelling by comparing the above-mentioned objectives in separate scenarios. The results show that each scenario successfully manages to shift between 34% and 87% of all load to hours of the day when the objectives of those scenarios are met. Therefore, in comparison to the baseline, smart charging can save between 5% and 26% of monthly emissions and between 4% and 57% of monthly expenditures. The solar PV scenario, however, results in the highest savings, while ensuring profitable economics via net metering in the short- as well as long term. Finally, the sensitivity analysis points to important trade-offs between several fleet performance metrics. The article concludes by giving business and policy recommendations for maximising the economic, energy and environmental efficiency of large ERV fleets.

Contribution/Originality: The contribution of this article is that it defines several EV smart charging optimization objectives and quantifies their impact on the energy, emission, and economic bottom lines of a fleet of electric ride-sharing vehicles. It also gives relevant stakeholders recommendations on how to integrate these technologies into future transportation networks.

1. INTRODUCTION

1.1. Opportunities with Electric Ride-Hailing Vehicles

The transportation sector is undergoing several major transformations including electrification and on-demand services. The main benefits of electrification are economic and environmental since electric vehicles (EVs) have lower operation and maintenance costs than internal combustion engine (ICE) cars (Loeb, Kockelman, & Liu, 2018). Furthermore, EVs have zero downstream (tailpipe) emissions, however, their upstream emissions depend on the local grid mix. That is why charging EVs with renewable energy can reduce their carbon emissions even more (Lee, Iyengar, Irwin, & Shenoy, 2016; Onat, Kucukvar, & Tatari, 2015; Robinson, Brase, Griswold, Jackson, & Erickson, 2014; Tian, Jiang, Shahidehpour, & Krishnamurthy, 2014). The second transformation includes on-demand transportation services, such as carsharing (e.g. Car2Go) and ride-hailing (e.g. Uber). Research shows that these services are associated with many household and social benefits: such as reduction in household transportation costs, emissions, traffic, and private vehicle usage (Cohen & Kietzmann, 2014; Martin & Shaheen, 2011; Martin, Shaheen, & Lidicker, 2010). For example, it is estimated that carsharing reduces individual carbon footprint by 51% (Chen & Kockelman, 2016a). Another benefit is the fact that sharing increases the utilisation of any given vehicle substantially, as it does not spend 95% of the time parked (Boldrini, Bruno, & Laarabi, 2017). Finally, these services use algorithm-based software that dynamically allocates vehicles to passengers and re-routes vehicles in order to save time. Therefore, they are not tied to predetermined routes like public buses. Combining electrification with on-demand services could amplify the benefits of energy savings, emissions, time, public space, and resources. While the combination of both shared and electric vehicles is not yet widely commercially available, it has been studied scientifically under different forms: shared electric vehicles, shared electric and autonomous vehicles, etc (Chen & Kockelman, 2016b; Loeb et al., 2018). The rest of this article will focus specifically on electric ride-hailing vehicles (ERV) and the challenges associated with their energy operations. Analysing this problem is especially important today considering private company trends, such as Lyft's announcement in 2020 that they will convert their fleet to 100% electric by 2030 (Lyft, 2020).

1.2. Energy Problems Related to ERV's: The Grid, Charging Infrastructure, and Renewable Energy

There are several barriers to high penetration levels of ERVs: for example, making sure the electricity system (e.g., the grid, transformers, transmission lines) can support large EV loads (Abdalrahman & Zhuang, 2017; Figueiredo, Nunes, & Brito, 2017; Ma & Mohammed, 2014; Schuller, Dietz, Flath, & Weinhardt, 2014). In perspective, each EV adds on average a load equal to that of one household. These issues would only escalate over time as EV adoption rises and ride-hailing companies utilise EVs (which drive longer hours each day and therefore use more electricity) (Abdalrahman & Zhuang, 2017; Flath, Ilg, Gottwalt, Schmeck, & Weinhardt, 2014). The higher daily utilisation of ERVs also implies a higher demand for charging stations. Charging infrastructure, however, is usually insufficient. There is a large body of literature dedicated to the so-called "range anxiety" problem: the driver's fear that they would not have enough charge to reach their destination (Abdalrahman & Zhuang, 2017; Goldin, Erickson, Natarajan, Brase, & Pahwa, 2014). The time an EV takes to charge is determined by the EV charging level of the station: it can vary between 20 minutes- 1.2 hours (Level 3), 3-7 hours (Level 2) and 7-17 hours (Level 1) (Abdalrahman & Zhuang, 2017; Loeb et al., 2018; Longo et al., 2016). In an ERV fleet, some drivers would need time to charge and therefore be unavailable to pick up passengers (Loeb et al., 2018). This complexity needs to be studied to determine an optimal fleet of vehicles to meet passenger demand. The third and final energy problem related to ERVs is the source of electricity. Considering the high carbon footprint of fossil fuels, it is important to increase the renewable energy share of the grid mix, such as solar photovoltaics (PV) and wind energy. However, introducing those technologies into the existing infrastructure presents a complex problem. Considering solar and wind are variable and uncertain, it is essential that vehicles charge when green electricity is available. To do so, storage or smart charging could be utilised (Lee et al., 2016; Mwasilu, Justo, Kim, Do, & Jung, 2014; Saber & Venayagamoorthy, 2011). The latter is a mechanism that determines the most optimal time for the vehicles to charge: based on the source of electricity, such as solar PV. However, smart charging can also be programmed to minimise electricity costs, emissions, and grid peak loads; or to maximise charge events with regard to charging station locations or curtailed grid PV energy (Fattori, Anglani, & Muliere, 2014; Figueiredo et al., 2017; Lee et al., 2016; Ma & Mohammed, 2014; van Der Kam & van Sark, 2015a). In effect, smart charging could address all energy problems associated with ERV's, as described in this section. While there are many smart charging optimization objectives, it is unclear how they compare, to what extent they solve the energy problems associated with ERVs, and whether they can be integrated simultaneously. Therefore, fleet-owners might be faced with the challenge of charging their ERVs without a clear indication of how each charging schedule would impact their triple bottom line— energy consumption, economics, and emissions, or overall fleet performance metrics, such as passenger wait time, empty miles travelled, etc. In order to analyse this problem, the following research questions are asked: *Are the objectives of maximising renewables, minimising costs, and minimising emissions via smart charging mutually exclusive? How do their impacts differ in the context of a fleet of electric ride-hailing vehicles?*

1.3. Literature Review

1.3.1. Charging Individually Owned EVs with Rooftop Solar Energy

While charging ERVs has not been extensively studied, individually owned EVs have been analysed carefully in the literature. A particularly common case study are EVs and residential solar PV panels. Specifically, studies have explored PV self-consumption, battery size, smart charging, and vehicle-to-grid technologies, among other topics. Most of them conclude that PVs can partially meet the electricity demands of EVs. In order to do so completely, however, storage and smart charging are two necessary technologies that would have to be deployed. They could be used to overcome solar energy intermittency and shift charge events to off-peak times (Abdalrahman & Zhuang, 2017; Bhatti et al., 2019; Brenna, Dolara, Foiadelli, Leva, & Longo, 2014; ElNozahy & Salama, 2014; Figueiredo et al., 2017; Goldin et al., 2014; Ma & Mohammed, 2014; Nunes, Farias, & Brito, 2015; van Der Kam & van Sark, 2015a). For example, Brenna et al. (2014) focus on urban-level PV-EV interactions, (Bhatti et al., 2019)- on the solar charger itself; (ElNozahy & Salama, 2014)- on residential technologies, and Goldin et al. (2014)- on solar charging stations. However, it is still unclear how entire ERV fleets could be charged sustainably with PV farms on an urban level- as opposed to private ones on an individual level.

1.3.2. Fleets of Shared and/or Electric Vehicles

Dynamically modelling large fleets of vehicles is a relatively under-studied area. It comprises articles that simulate shared ICE vehicles, shared autonomous vehicles, or electric autonomous vehicles (AVs) (Chen & Kockelman, 2016a, 2016b; Fagnant & Kockelman, 2014). For example, Fagnant and Kockelman (2014) model autonomous car-sharing services in an urban environment in order to quantify the emission implications of the fleet. Kang, Feinberg, and Papalambros (2017) on the other hand, design a framework for shared, autonomous, and electric vehicles that focuses on fleet sizing and schedules among other issues. Henao and Marshall (2019) focus on Vehicle Miles Travelled (VMT). They estimate that 'empty miles' (distances driven to meet a passenger, to reach a charging station, looking for a passenger, etc) account for 40.8% of total VMT. Therefore, a large portion of fleet operations are largely under-utilised and inefficiently managed. Finally, Loeb et al. (2018) studies the trade-offs between fleet size, charge time, range, vehicle response time. While these studies address important issues pertaining to fleet management and operations, many of them model ICE vehicles; those that focus on EVs, on the other hand, do not account for smart charging. Therefore, there is a gap in the literature that could be filled by dynamically simulating a fleet of ERVs.

1.3.3. EV Smart Charging

Smart charging has a great potential for ride-hailing services. While some authors have examined it in the context of renewables, or curtailed wind and solar (Abdalrahman & Zhuang, 2017; Fattori et al., 2014; Figueiredo et al., 2017; Ma & Mohammed, 2014; Mwasilu et al., 2014; van der Kam & van Sark, 2015b) others have evaluated it in combination with the grid (Flath et al., 2014; Mu, Wu, Jenkins, Jia, & Wang, 2014). The main objective of those studies is to use smart charging to shift EV loads to off-peak hours, to reduce renewable energy curtailment, and to optimise PV-EV integration. Indeed, this integration could be mutually beneficial for both technologies: solar panels could be used to provide electricity for the vehicles during peak hours and EVs could be used to minimise the amount of renewable energy curtailed. Most of those studies conclude that smart charging could have significant technological and economic benefits to the individual driver and the system as a whole. Fattori et al. (2014) for instance, find that in an uncoordinated charging system, PVs cannot meet transportation demands; however, vehicle-to-grid could better integrate the two technologies. Furthermore, the results of van der Kam and van Sark (2015b) show that smart charging can increase PV self-consumption from 49% to 62%-87%.

Despite the relevance of these studies, they take a small sample of individually owned vehicles or panels. None of those studies, therefore, takes a fleet of ERVs or contrasts different smart charging objectives: such as an emission-based smart charging mechanism versus an economic scenario. Therefore, it is important to scientifically study how each of those smart charging objectives varies over time and how it compares to the rest of the scenarios.

2. METHODS

2.1. Methods Overview

This article utilises a model, which dynamically simulates transportation energy consumption and renewable energy production. Its goal is to optimise ERV energy consumption in order to maximise solar PV energy use, minimise grid emissions, and minimise electricity rates. The model is built in Java-based AnyLogic, using object-oriented programming (AnyLogic, 2019). AnyLogic is a versatile software that supports agent-based, systems dynamics, and discrete event models. First of all, vehicles, passengers, and stations are agents who interact in a geospatial environment. Secondly, electricity production and consumption is represented as a system dynamics model. Finally, the vehicle routing, driving, and charging logic is modelled as a discrete event model. Routing directions in AnyLogic are sourced from Open Street Maps.

In order to evaluate the impact of smart charging on the triple bottom line, this article examines five scenarios:

(1) Scenario 1: Baseline scenario- ERVs without smart charging:

(2) Scenario 2: Smart charging using solar PV (later referred to as "Solar PV scenario");

(3) Scenario 3: Smart charging that minimises monetary expenditures (later referred to as "Expenditures scenario");

(4) Scenario 4: Smart charging that minimises emissions (later referred to as "Emissions scenario");

(5) Scenario 5: Smart charging with 2020 rate schedules (later referred to as "EV rates 2020 scenario");

The objective is to quantify the impact of smart charging on the triple bottom line as well as to see how it imacts fleet performance: passenger wait time, empty VMT, vehicle and charging station utilisation, etc.

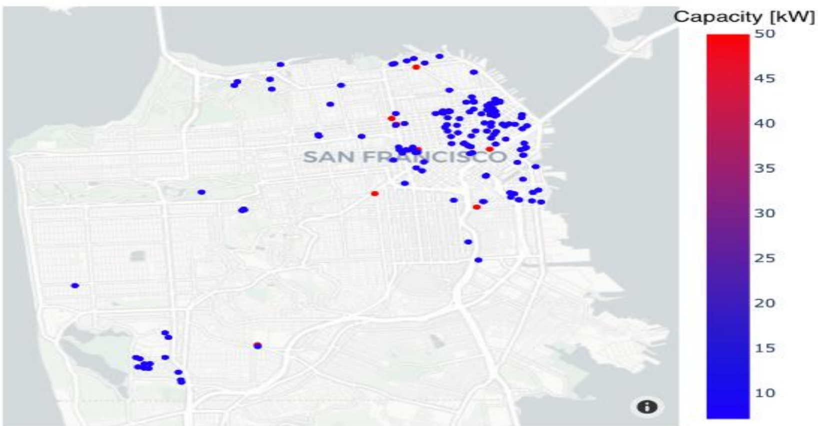
2.2. Simulation Scenarios

2.2.1. Scenario 1: Baseline Scenario

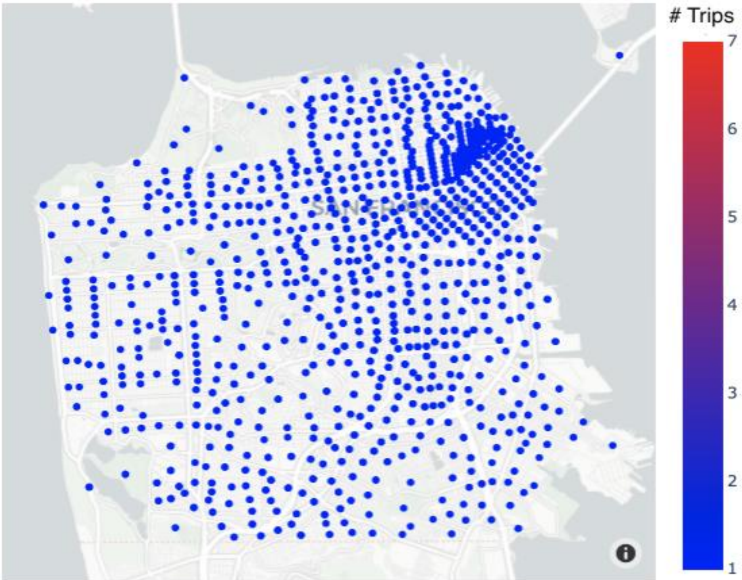
The baseline scenario models ride-hailing trips fulfilled by ERV vehicles without smart charging. The origins, destinations, and departure times are based on 2015 ride-hailing San Francisco data (SFCTA, 2022). The vehicles are passenger cars with 4 seats, and they form a fleet that is centrally operated by an authority that aims to optimise the efficiency of its operations. A subset of the original trip data is used, resulting in 2,874 trips per day (only trips with a probability of occurrence above 50% are selected in order to exclude unlikely trips). Their spatial and temporal distribution are shown in Figures 1b and 1c. Once a passenger requests a pickup from a Traffic Analysis Zone (TAZ) origin, the message enters a central, cumulative list in a chronological order. The vehicle, on the other hand, responds to messages as they are received by passengers— they are programmed to pick up passengers within a distance of 1 km (this parameter is later varied in the sensitivity analysis. The value eventually selected ensures that empty miles do not account for a significant portion of the trip. Current estimates show that these empty miles account for at least 40% of ride-hailing miles (Barboza, 2020; Henao & Marshall, 2019).

Once the vehicle arrives at the passenger origin TAZ, the system checks all requests collected up to that point: if there are more pooling requests, more available seats, enough electricity in the battery of the car, as well as passengers within 1km who are willing to share their trip and are heading in the same direction as the current passenger, the ERV picks up one more passenger. To account for the latter, preferences were randomly assigned to passengers so that about 25% of all trips are shared. This figure is based on other studies as well as historic Lyft and Uber data (Hou et al., 2020; Iqbal, 2022; Lunden, 2016). If all conditions are met, the vehicle drives to the second passenger. The first passenger to be dropped off is selected based on proximity.

After the car arrives at the last passenger destination, it recharges its battery if critically low. A critically low state of charge is considered 20% or less. If this is the case, the vehicle is sent to the nearest available charging station while DC charging stations are prioritised. Charging station locations are based on Department of Energy, DOE data and shown in Figure 1a (DOE, 2019). For the purposes of this model, it is assumed that only vehicles in the ERV fleet are using the stations. Charging station specification data is obtained from ChargePoint (2019) due to their common use in San Francisco and throughout the country. Therefore, charge duration times are based on the specifications of the station itself. The carbon footprint of the energy consumed, on the other hand, is based on grid mix data from California Independent System Operator, CAISO, which provides data for each hour of the year (CAISO, 2019). After the battery is recharged, the car waits for more requests and the logic repeats. The EV charges until only until 80% of the battery is full— the reason is that charging beyond that percent shortens battery life (Xu, Oudalov, Ulbig, Andersson, & Kirschen, 2018). Considering ERVs drive more miles per day than individually owned cars, saving battery life is essential (Jenn, 2019).



(a)



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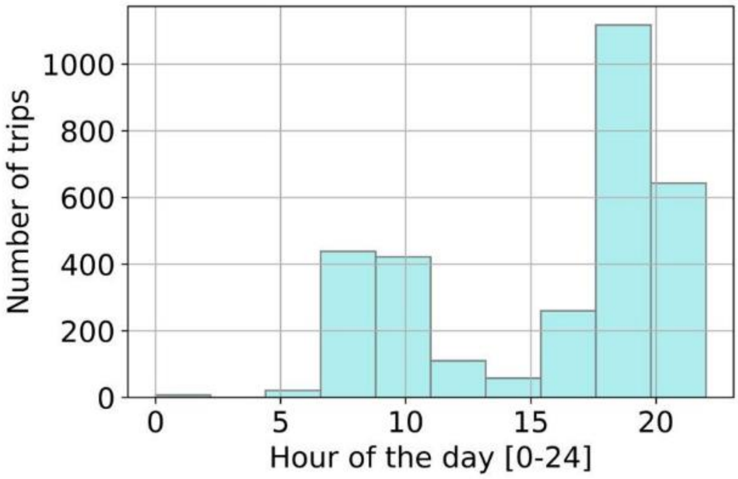


(c)

Figure 1. (a) Spatial distribution of EV charging stations by station capacity in San Francisco; (b) Spatial distribution of ride-hailing trips in San Francisco- one average day, (c) Temporal distribution of daily ride-hailing trips in San Francisco, 2015- one average day.

EV electricity consumption is dynamically calculated as the vehicle drives through town. The formula used is described in Equation 1 (Ben-Chaim, Shmerling, & Kuperman, 2013; Hermans, 2013). It accounts for a list of dynamic variables: technical as well as environmental. Vehicle specifications, for example, vary by make. For simplicity reasons, this study models the vehicles after the Nissan Leaf (Edmundus, 2020). The sensitivity analysis then tests the models with long range vehicles, modelled after the Tesla Model S. Other constants and variables accounted by the equation are road speed, wind speed, vehicle coefficient of rolling resistance, and average human body weight (CDC, 2017; Data, 2019; Engineering Toolbox, 2008; Iowa State University, 2019). These values are also dynamically calculated as the vehicle drives.

$$E_{ij} = \left(\frac{\left[\left(m_{ij} \, . \, g . f\right) + \left(0.5 . \rho \, . \, C_x \, . \, A \, \left(v_{ij}^2 - W\right)\right)\right] . \, d_{ij}}{\eta}\right)/3600 \tag{1}$$

Where:
i= Starting point of the trip.
j= Ending point of the trip.
E_{ij}= Mechanical energy required to drive from i to j [kWh].
m_{ij} = Total vehicle mass [kg].

g= Gravitational acceleration [m/s^2].
f= Vehicle coefficient of rolling resistance [-].
ρ= Air density [kg/m^3].
C_x= Drag coefficient of the vehicle [-].
A= Vehicle cross section area [m^2].
v_{ij}= Vehicle speed between points i and j [m/s].
d_{ij}= Distance driven between points i and j [m].
W= Wind speed [m/s].
η= Engine efficiency [%].

2.2.2. Scenario 2: Smart Charging using Solar PV Energy

The next scenario aims to maximise solar PV energy via smart charging. The main ERV driving logic is similar to that in the baseline scenario except for the source of electricity being solar PV (Figure 2). The next consideration that has to be made is the solar configuration. A fleet owner can charge their vehicles with solar energy in one of several ways: 1) solar PV charging stations; 2) community solar shares; 3) curtailed grid-level solar energy; 4) using a Power Purchase Agreement (PPA) contract; 5) buying Renewable Energy Credits (REC's); or 6) offsetting their consumption with an off-site net-metered PV energy, while charging the ERVs locally with grid energy. This article focuses on option 6 due to the limitations of the other options. Specifically these are their constraints: 1) solar PV stations are still too expensive and charge EVs too slowly to meet the requirements of a ride-hailing fleet (Envision Solar, 2020; Silverstein, 2020) community solar in California is still not offering savings (PGE, 2020a) while there is a lot of curtailed PV energy in CAISO, the fleet owner does not economically benefit from charging at times when that electricity is in excess; however, they would have to pay for an expensive smart charging system (therefore, in that scenario the fleet manager pays but the grid benefits) (California ISO, 2020) PPAs require that the fleet owner actually uses the PV energy, which in this situation would be unfeasible since the charging stations are in multiple locations in San Francisco but the PV farm would be outside of the city or on the roof of an individual building (SEIA, 2020) RECs have a variable price and difficult to predict economically (SRECTrade, 2020) Offsetting meets the criteria of the fleet owner because PV energy production and consumption does not have to take place at the same location. Therefore, a solar farm could be anywhere on the local Pacific Gas and Electric, PGE territory; the owner, on the other hand, would receive credit for every kWh they feed back to the grid at that particular Time-of-Use (ToU) rate. Therefore, the goal of this scenario is to size the system to meet 100% of the fleet load, so that while the cars charge from the grid, their consumption is offset by the PV farm. To do so, they will sign up for a large business net metering program for large businesses (PGE, 2020b).

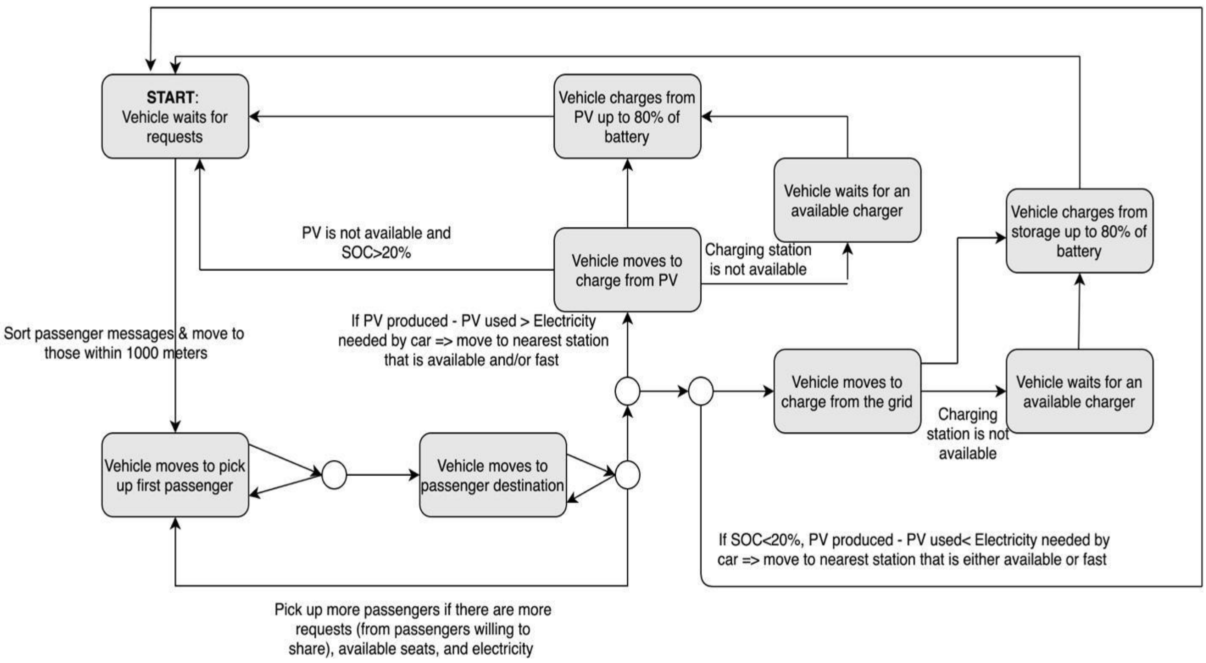


Figure 2. Scenario 2—Workflow diagram for ERV movement in a smart charging scenario that Optimises PV energy.

Solar generation data is simulated using the National Renewable Energy Laboratory, NREL PV Watts tool (NREL, 2019). Specifically, it provides solar irradiation data for San Francisco and estimates PV output, using built-in formulas. The generic panel used for this purpose is a 4kW panel of 20-degree tilt, 14.08% system losses, and 96% inverter efficiency. The number of panels of this kind needed to meet the demand of the entire fleet is then optimized using Equation 2, 3,4 and 5. Optimizations are run in AnyLogic, which uses the OptQuest Engine. The search algorithm includes metaheuristics and is based on tabu search, scatter search, integer programming, and neural networks (OptTek, 2022).

Solar PV energy optimization at each hour is shown in Equation 2, 3,4 and 5:

Maximise:

$$\sum_{i=1}^{n} \quad (P_i^{PV-S} . t_i^{PV-S}) \tag{2}$$

Where:

P_i^{PV-S}= power used to charge an EV i at the time when PV energy is produced (consumption is synchronised with production, therefore it is abbreviated as “PV-S”) [kW].

t_i^{PV-S}= time spent charging an EV battery i to 80% at the time when PV energy is produced [hours].

i=vehicle i in the fleet.

The model constraints at each hour are shown in Equations 3- 5. The aim of (3) to ensure that the amount of energy consumed does not exceed actual production. The second constraint Equation 4 is that the total amount of un-synchronized production and consumption does not exceed 40% of total energy production. It should be noted that 100% synchronisation is also possible. However, it would result in too much electricity that exceeds cumulative fleet energy needs since EVs often have to charge early or late during the day when PV energy is not produced. 40%, on the other hand, was chosen because PV energy is generated only half of the hours of the day and therefore any percent below 50%, such as 40%, is considered optimistic. Finally, Equation 5 tests how large the entire system should be— the equation bounds of 160kW and 480kW were obtained after running the model many times to estimate what the demand for electricity is.

$$\sum_{i=0}^{n} \quad G_j . t_j \;\; \geq \sum_{i=1}^{n} \quad (P_i^{PV-S} . t_i^{PV-S}) \tag{3}$$

$$\frac{\sum_{i=1}^{n} \quad (P_i^{PV-NS} . t_i^{PV-NS})}{\sum_{i=0}^{n} \quad G_j . t_j} \leq 40\% \tag{4}$$

$$160 < S^{PV} < 480 \tag{5}$$

Where:

G_j= the amount of solar power produced by panel j [kW].

t_j= time spent producing energy by solar panel j [hours].

P_i^{PV-NS}= power used to charge EV i from PV energy when PV energy is not produced (consumption is not synchronised with production, therefore “PV-NS”) [kW].

t_i^{PV-NS}= time spent charging EV battery i to 80% from the panels when PV energy is not produced [hours];

S^{PV} = the size of a solar power system [kW].

After a trip is completed, the vehicle checks if there is enough PV energy produced. If there is, it charges; if there is not and the state of charge is not below 20%, the event is postponed. If there is not enough PV at the moment, but the battery is below 20%, the vehicle charges from the grid.

2.2.3. Scenario 3: Smart Charging that Minimises Expenditures

The objective of this scenario is to minimise grid electricity expenditures. PGE ToU rates in 2015 had the following levels: off-peak (9:30pm- 8:30am), partial-peak (8:30am-12:00pm), and peak pricing (12:00pm-6:00pm). Electricity rates for the A-10 schedule (large business) had summer values of respectively $0.14642, $0.17087, and $0.17891, as shown in Figure 4 (PGE, 2019). Therefore, the goal is that the car postpones the charge event until the price is as low as possible. The exception is again when its State of Charge (SoC) is less than 20%: in that case, the car charges regardless of the price in order to avoid being stranded without electricity.

2.2.4. Scenario 4: Smart Charging that Minimises Emissions

The fourth scenario aims to minimise grid carbon emissions. Vehicle movement logic once again resembles that of the previous scenarios. The main point of difference is the charging logic. If the grid emission factor is the lowest possible level, the vehicle charges immediately. If it is not, it waits until it is the lowest (unless its SoC is once again critically low).

The average grid emission factors were estimated from CAISO time series data of electricity supply by energy source (CAISO, 2019) and carbon emission factors per electricity source (California Air Resource Board, 2018);

(Sohnen, Fan, Ogden, & Yang, 2015). Figure 3 shows that high renewable energy production during daytime hours lowers the average emission factor for an average day. Therefore, the grid is the cleanest during the day. However, this is when A-10 tariffs are the highest, as shown in Figure 4. Therefore, there is a trade-off between environmental and economic goals. Scenario 5 will try to balance those objectives out.

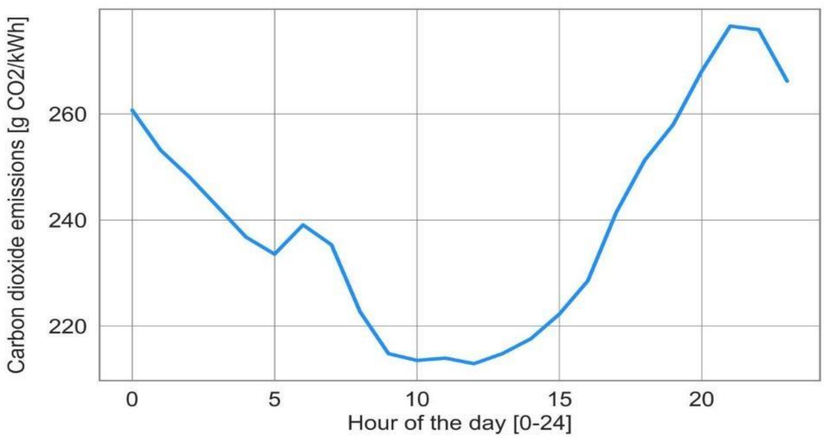


Figure 3. Average hourly carbon emissions of the CAISO grid, 2015.

2.2.5. Scenario 5: Smart Charging with 2020 EV Rate Schedules

As previously mentioned, the objectives of the scenarios above are not always in line with each other. For example, emissions drop the most when electricity is the most expensive; solar energy production also peaks in the middle of the day when rates are again the highest. The only two objectives that are in line are solar production and grid emissions; however, that is not practically useful because the PV smart charging objective reduces emissions significantly more than the grid emission smart charging objective (therefore it overrides it). In order to design a scenario where objectives are in line, one more scenario is proposed where PGE 2020 EV rate schedules are used. The reason is that as Figure 4 shows, those tariffs do not peak around noon like A-10, but later in the evening. Therefore, it is hypothesised that they might not be in conflict with the emission objective as much and therefore allow fleet managers to balance multiple objectives simultaneously.

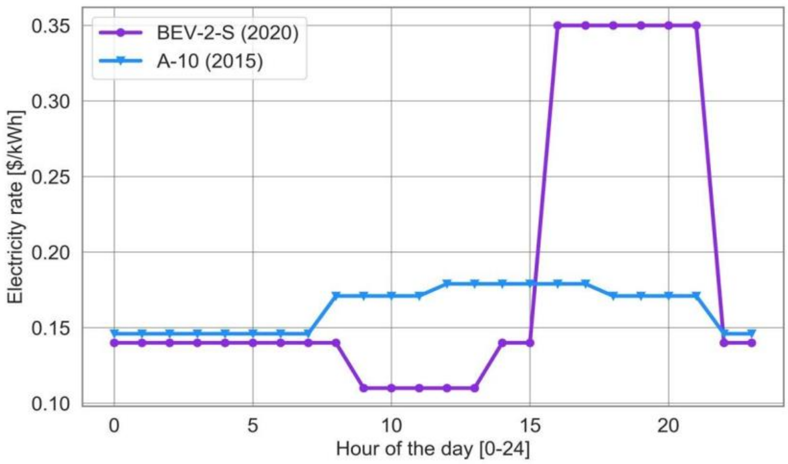


Figure 4. Comparing PGE A-10 rate schedules with 2020 EV rate schedules, BEV-2-S.

2.2.6. Sensitivity Analysis

The last step is the sensitivity analysis: testing the impact of several sets of parameters on various fleet performance metrics as well as the triple bottom line. The first set of scenarios quantifies the impact of vehicle distance to a passenger on empty mile electricity consumption and the percent of trips that are shared. The next sensitivity analysis models the impact of fleet size on fleet performance metrics, such as percent fulfilled requests, idle time, passenger wait time, empty miles, and shared trips. The third set of scenarios calculates the impact of high-capacity vehicles (such as Tesla's) and high-capacity charging stations (such as DC fast charging stations) on fleet performance metrics. The assumption in these models is that there is an inherent trade-off between the parameter tested as well as the output of the sensitivity analysis.

3. RESULTS AND DISCUSSION

The results of the model will be presented as follows: section 3.1. below first summarises the optimization results of the solar PV scenario because of this additional layer of optimization. This layer is important to understand before comparing the solar PV scenario to other ones. Once those outputs are described, all scenario results will be simultaneously described in section 3.2. below.

3.1. Optimization Results for the Solar PV Scenario

As mentioned in the methodology section, the PV scenario is optimised in order to obtain the number of panels needed to meet the electricity demand of the fleet. The PV optimization model shows that a 160kW PV farm can meet between 50% and 100% of the electricity needs of a 450-478 vehicle fleet, while ensuring at least 60% of synchronisation between PV energy generation and EV energy consumption. (As the sections below show, the size of the fleet needed to service about 2,874 passengers per day varies between 450 and 478 cars). The exact synchronisation percentage varies depending on the state of charge of the vehicles at the beginning of the day. If PV-EV synchronisation is 100%, grid expenditures would roughly equal net metering benefits (slight variations would depend on the ratio of ToU rates when electricity is bought to ToU rates when electricity is sold). For example, if 100% of the load is offset by solar, the fleet manager could payback all of their expenses or even be at a profit if they charged at low ToU rates. If PV-EV synchronisation is below 100%, that means that the solar farm has generated less than the EV load and the difference was supplied by the grid. For example, if PV energy meets only 55% of the load, the fleet would offset roughly half of its costs and pay about $780 in the end of the first week. However, this is still lower than the total expenses of $1,413, which the fleet would have incurred without PV net metering.

It should be noted that the solar farm could be sized above 160kW to ensure it always meets all loads or that its production is always aligned with EV consumption. However, that would significantly increase the upfront cost of the project; furthermore, it is unclear whether this added cost would justify the benefits. Nevertheless, the suggested capacity sizing has favourable Return on Investment (ROI), between 2 and 4 years, depending on the financial assumptions (PGE, 2020c). Therefore, the fleet owner would charge their ERVs at no cost beyond the point of ROI, which would improve the business bottom line of any company or organisation.

3.2. Scenario Results

Next, the results of all scenarios are simultaneously shown in Table 1, 2 and 3 and Figure 5. All tables and figures show averaged results on a daily basis. The first table focuses on fleet performance metrics. The size of the fleet varies slightly between 450 and 478 cars because smart charging imposes different constraints on the vehicles and their availability. The dissimilar number of vehicles required by the scenarios and their contrasting charging schedules results in a slightly different percent of shared rides as well: ranging between 26% and 28%.

Table 1. Daily fleet performance metrics by scenario.

Scenario	Utilised vehicles	Passengers per vehicle	Shared trips [%]	Station visits per car	Passenger wait time [min]	Unmet demand [%]	Idle time [%]
Baseline	455	7	26%	0	14	1%	29%
Solar PV	450	7	26%	1	11	0%	29%
Expenditures	458	7	27%	1	13	0%	30%
Emissions	470	6	28%	1	15	0%	28%
EV Rates 2020	478	6	28%	1	15	1%	27%

Fleet size dissimilarities impact average wait time, too: fleets with fewer shared rides arrive slightly quicker (in about 11min and 14min) than those with more shared rides (about 15min) due to the fact that they service the passenger immediately as opposed to after picking someone else up. Figure 5 shows that most of the wait time takes place in the first half of the day. While some passengers wait longer, others are not picked up at all. However, this fraction is negligible—about 0-1% across all scenarios (Table 1). These passengers are not serviced due to the fact that their location and trip preferences do not meet the conditions of any of the cars: such as the allowed distance to passengers, currently set at 1km. Increasing this number would increase the share of empty miles per vehicle beyond 50% and that would undesirable from a fleet operations point of view.

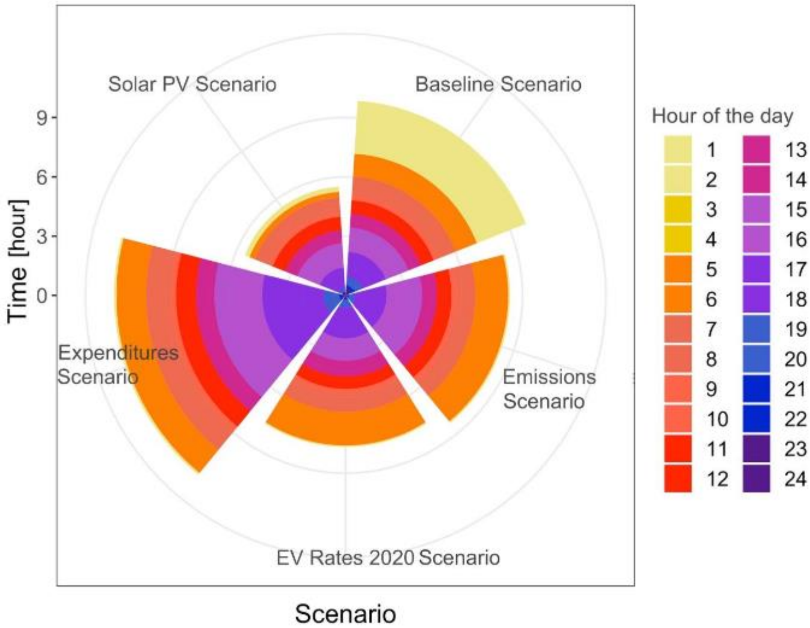


Figure 5. Passenger wait time by scenario- average daily values.

Generally, however, the average car in all scenarios drives about 6-7 passengers per day, charges once per day, and stays idle about 27-30% of the hours of the day. Given that there are almost no trips overnight, this is a good vehicle utilisation. Despite the minor differences shown in Table 1, however, the scenarios output similar results and therefore smart charging does not compromise fleet operations quality.

Table 2 summarises electricity consumption patterns across the scenarios. Namely, the electricity consumed by each car can be categorised as electricity needed to reach the origin of a passenger, the destination of a passenger, or a charging station. As the table below shows, the passenger trip accounts for the largest share: at least 55% of total electricity consumption in all scenarios. Trips to the charging station, on the other hand, constitute the smallest fraction— less than 1% in all cases. Finally, electricity needed to reach a passenger is about 44-45% in most scenarios. These numbers confirm the observations made in Table 1— that smart charging does not negatively impact the performance of the fleet or push the vehicle to spend a disproportionate amount of its energy on either VMT type. The fact that empty miles consistently account for 45% of all energy, however, confirms observations made in the literature. Therefore, the problems inherent in ICE ride-hailing fleets would translate to ERV fleets as well. Solving this problem, however, would require either buying more vehicles (which is expensive) or compromising passenger wait time (which is undesirable). Finally, energy spent on reaching a charging station is not substantial due to the small area of the city of San Francisco and the large number of existing charging stations.

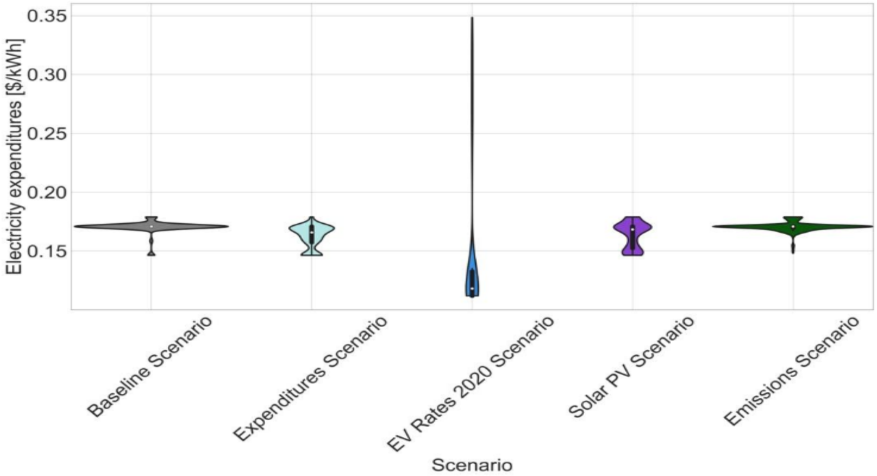
Table 2. Electricity use percent share by type and by scenario.

Scenario	Electricity for passenger trip [%]	Electricity to reach passenger [%]	Electricity to reach a station [%]
Baseline Scenario	55.10	44.90	0.01
Solar PV Scenario	56.27	43.69	0.04
Expenditures Scenario	55.27	44.69	0.04
Emissions Scenario	54.72	45.20	0.06
EV Rates 2020	54.55	45.36	0.08

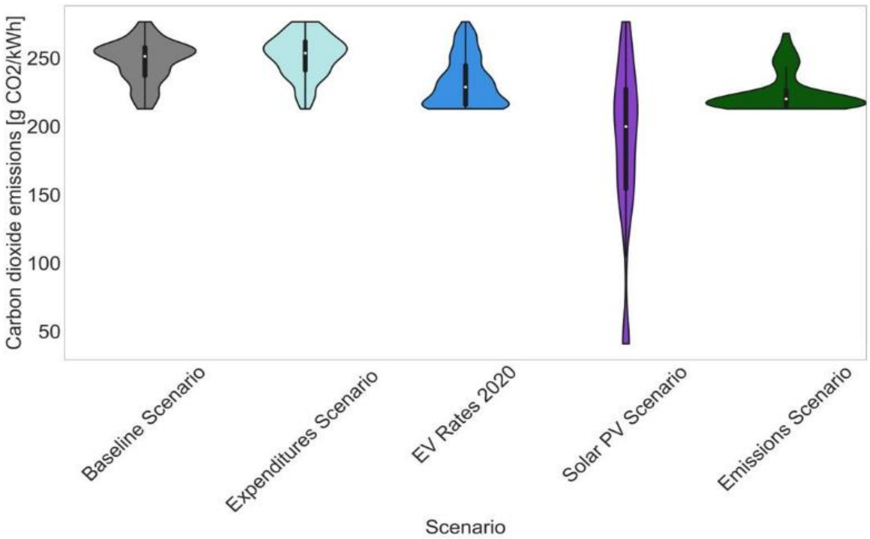
While smart charging does not compromise fleet operations, it does improve the objective it is set to maximise or minimise in each scenario. Table 3 shows the triple bottom line of each scenario, with all values being normalised by 1kWh of electricity consumption. As the first column illustrates, the solar PV scenario has the lowest emissions, followed by the emissions scenario, the EV rates 2020 scenario, the baseline, and finally- the expenditures scenario. The lowest energy expenditures are once again in the PV scenario, followed by the EV rates 2020 scenario, the expenditures scenario, and then the baseline and emissions scenarios are tied. These results are confirmed by Figure 6, which shows violin plots of annual values of electricity emissions and expenditures by scenario.

Table 3. Triple bottom line results by scenario— carbon emissions, expenditures, and energy consumption.

Scenario	Carbon emissions [g CO2/kWh]	Expenditures [cent/kWh]	Load shifting [%]	Monthly emission savings from baseline	Monthly monetary savings from baseline
Baseline Scenario	247.7	17.0	/	/	/
Solar PV Scenario	182.3	7.3	34.0%	-26%	-57%
Expenditures Scenario	252.8	16.3	42.7%	2%	-4%
Emissions Scenario	226.0	17.0	87.4%	-9%	0%
EV Rates 2020	235.1	14.9	86.7%	-5%	-13%



(a)



(b)

Figure 6. Violin plots of average (a) carbon dioxide emissions by scenario and (b) electricity expenditures by scenario.

Based on these results, it can be concluded that the objectives of the scenarios are achieved: the carbon footprint of the emission scenario is lower than that of the baseline, as it lowers it from 247.7g CO_2/kWh to 226g CO_2/kWh; the two expenditure scenarios (2015 and 2020 electricity rates) improve the economics of electricity from ¢17/kWh in the baseline to ¢16.3/kWh and ¢14.9/kWh respectively; and finally—the PV scenario improves both economics and emissions, as it reduces the footprint to 182.3g CO_2/kWh and the expenditures—to ¢7.3/kWh (where the latter are not zero due to the fact that there are days when the farm does not produce enough to cover all needs, as discussed in the sections above).

The last column in Table 3 shows what percent of electricity consumption is shifted towards the objective of a given scenario: e.g. to consume solar instead of grid energy; low price energy as opposed to high price energy, and low-emission energy instead of high-emission energy. Specifically, these shares respectively are 34%, 42.7%, 87.4%, and 86.7%. Therefore, smart charging has succeeded in pushing the vast majority of the load to the desirable advantageous energy types.

Finally, Figure 7 shows how smart charging reshapes the average daily load curve of the ERVs. The solar PV objective, for example, lowers the evening peak from the baseline and offsets it with daytime solar energy. The heatmaps in Figure 8 illustrate this point by showing the distribution of PV charge events during daytime and those of grid charge events early in the morning and late in the evening. The emissions scenario accomplishes a similar but more pronounced outcome: daytime charging exceeds evening charging. These graphs show that smart charging can make a substantial impact on the load curve, which benefits the fleet owner as well as grid operators because those benefits accumulate on a network level. Most importantly, smart charging does so without compromising the quality of the ERV service or customer experience.

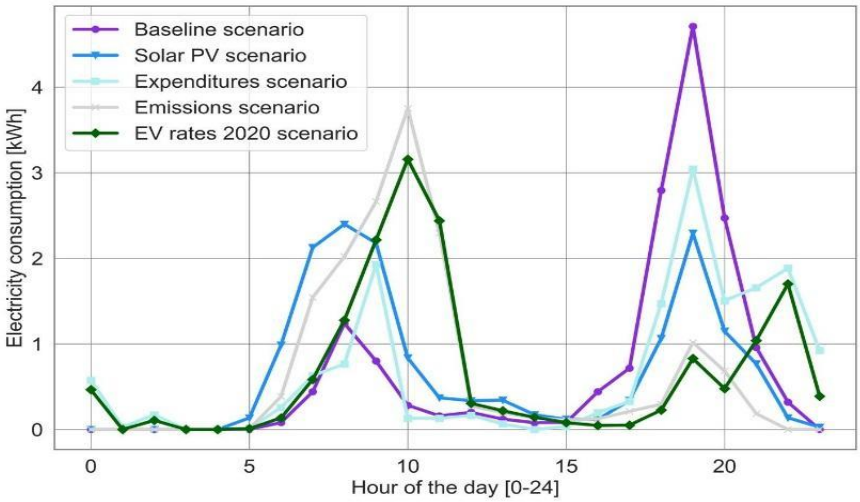
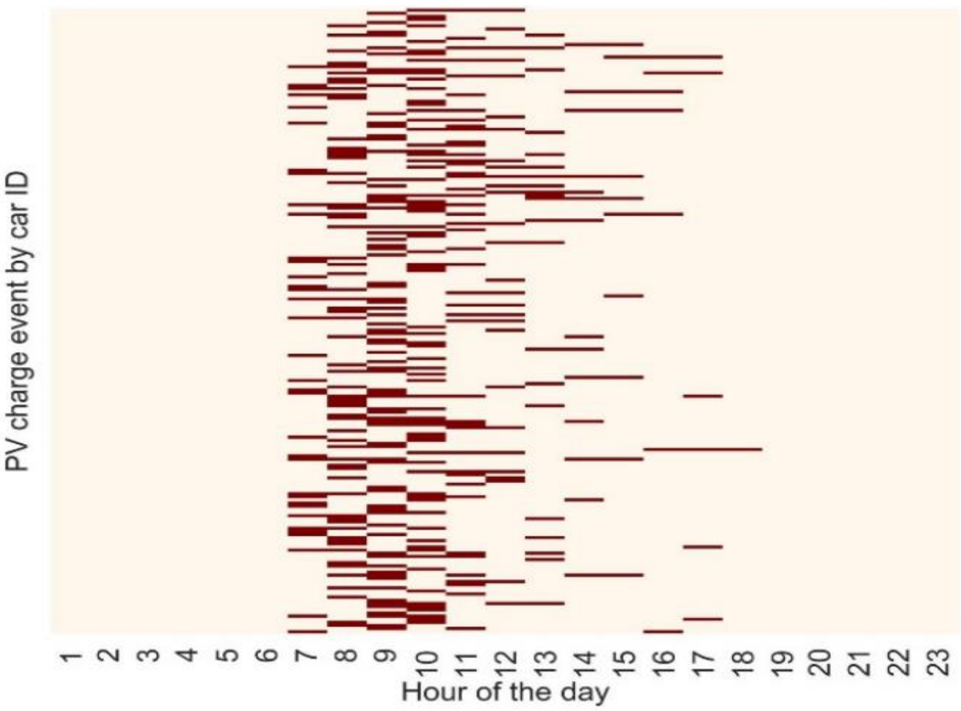


Figure 7. Average hourly EV electricity consumption: Comparison across scenarios.



(a)

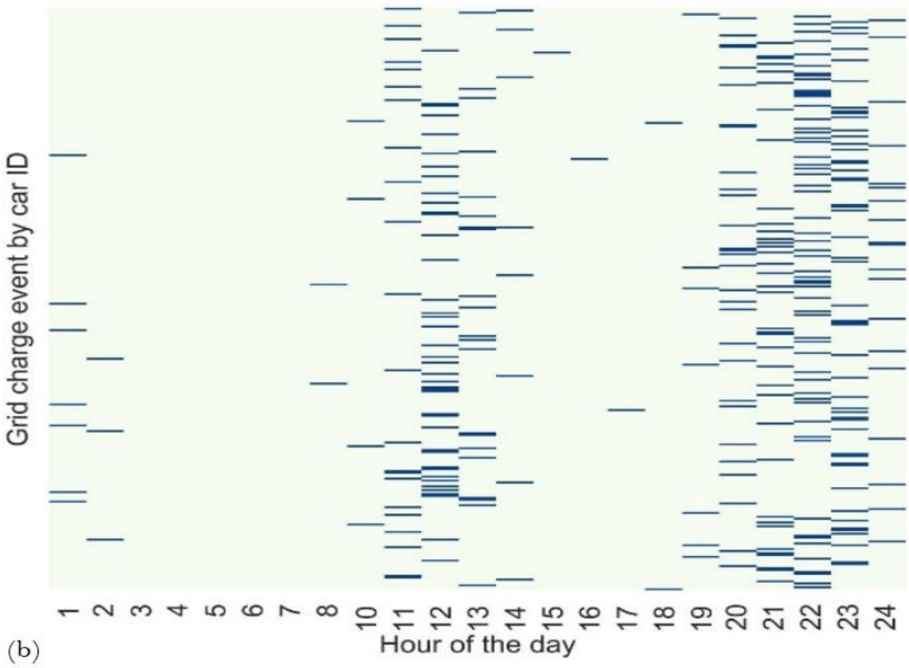


Figure 8. Heatmap of (a) Solar energy consumption and (b) Grid electricity consumption in the Solar PV scenario (dual colour scheme: Darker colours indicate that a charge event is taking place).

3.3. Sensitivity Analysis Results

Figure 9,10,11 and 12 show the results of the sensitivity analysis. As mentioned above, the goal is to quantify the trade-off between a number of variables. The first set of sensitivity scenarios (Figure 9) concerns the impact of the distance to a passenger on the percent of trips that are shared and on empty mile energy consumption. As the figure shows, those two independent variables have an inverse relationship with the dependent variable: the further away a vehicle is from a passenger, the more empty miles it will accrue (and therefore energy as well). However, as it gets further away, the fraction of shared trips declines because the car spends more time driving to reach a passenger than it does fulfilling requests.

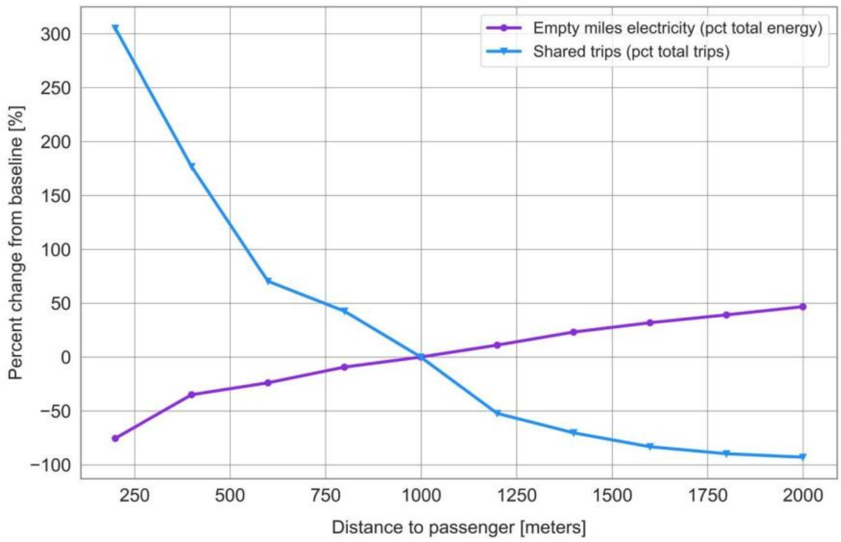


Figure 9. Sensitivity analysis: impact of the distance to a passenger on empty miles and shared trips.

Figure 10 shows the second set of sensitivity scenarios: the impact of fleet size on a number of fleet performance metrics. As the number of cars increases- but demand is held constant- the same number of trips is distributed over more vehicles and therefore sharing decreases. Furthermore, as the number of vehicles grows, they have shorter distances to drive (as there would be more of them scattered throughout town) and the percent of empty miles would decrease as well. Similarly, as the fleet grows, vehicles arrive at the passenger pickup point faster and passenger wait time decreases. However, having more cars also implies that more cars would be queuing at a charging station (since the latter stays fixed)- and therefore the percent met demand could increase as well.

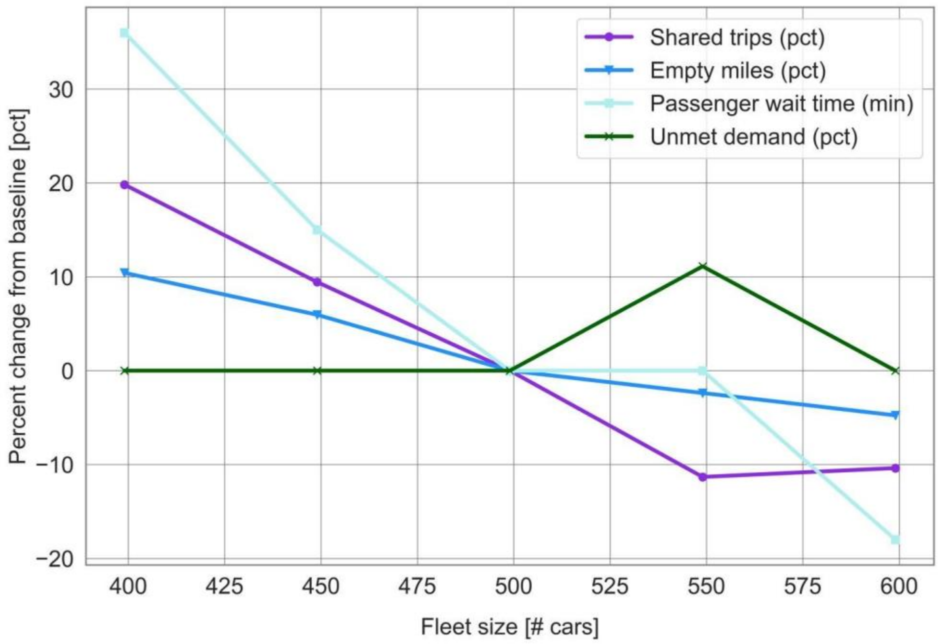


Figure 10. Sensitivity analysis: impact of fleet size on fleet performance metrics (the Baseline has 500 cars).

The next sensitivity analysis measures the impact of fleet share of high capacity vehicles on fleet operations (where large battery vehicles are modelled after the 2015 Tesla Model S and the rest of the cars remain unchanged from the scenarios above, i.e. 2015 Nissan Leaf's) (Figure 11). As Figure 11 shows, most of the metrics do not diverge significantly from the baseline. Generally, however, the more vehicles have large batteries in a fleet, the better the metrics of the fleet are. For example, charge events and idle time would decrease. The reason is that larger batteries allow an EV to drive more miles before charging and therefore its time is also better utilized. The only exception is the fact that Tesla vehicles have larger batteries which therefore take longer to charge. That is why passenger wait time could increase and percent met demand could decrease.

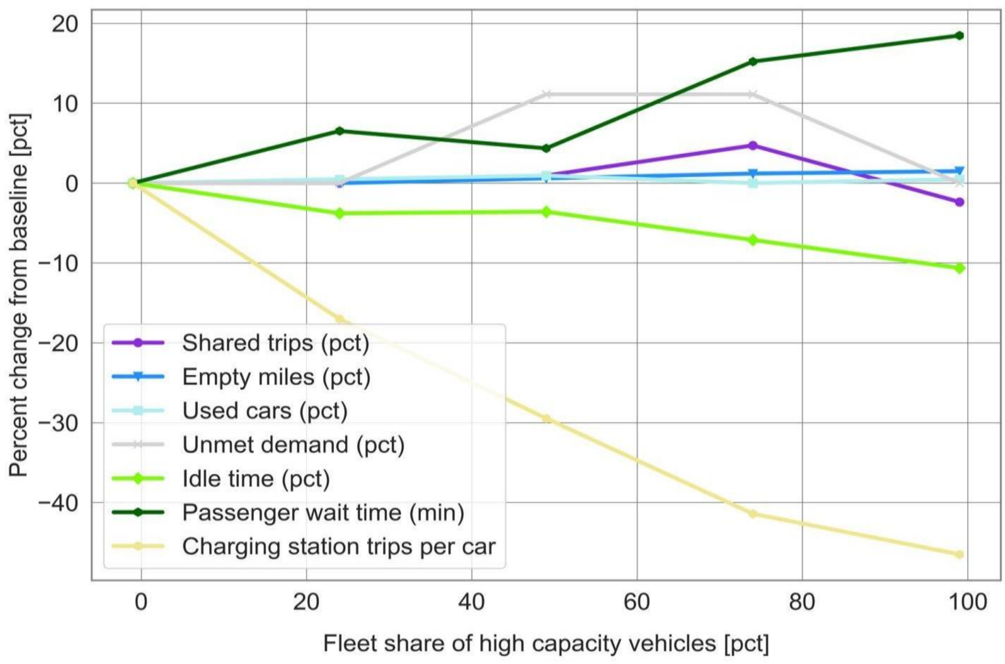


Figure 11. Sensitivity analysis: impact of fleet share of high capacity vehicles on fleet performance metrics.

The last sets of parameters varied in a sensitivity analysis are EV battery and charging station capacity (Figures 12-13). The results generally show a slight trend towards larger capacities saving both more money and more emissions. That was expected because a larger battery vehicle can absorb more electricity at a given charge event and benefit more at the hours when electricity is clean or cheap. Similarly, faster charging stations (Figure 13) can supply more cheap or clean electricity to more cars in a given hour. The steepest decline of expenditures, however, is observed when larger battery vehicles replace smaller ones (Figure 12). Most of the rest of the variations, however, are not substantial.

3.4. Discussion and Recommendations

Preparing for and launching a fleet of ERVs while meeting economic, environmental, and energy objectives is a complex task. First of all, a fleet owner should clearly weigh their costs and benefits as well as their priorities. Given the results in this study, the PV scenario outperforms all other scenarios in the short-run and even provides economic, energy, and emission benefits to fleet owners in the long-run as well. Therefore, this scenario is recommended to those interested in all criteria in the triple bottom line. The second-best scenario is the "2020 EV rates" scenario. Unlike the emissions or the expenditures scenarios (which achieve one objective at a time), this one manages to balance both. This is due to the fact that ToU rates in 2020 peak later during the day and do not create a situation where electricity is cheapest when it is most polluting and vice versa. However, this scenario does not produce economic benefits in the future like the PV scenario beyond the first a couple of years.

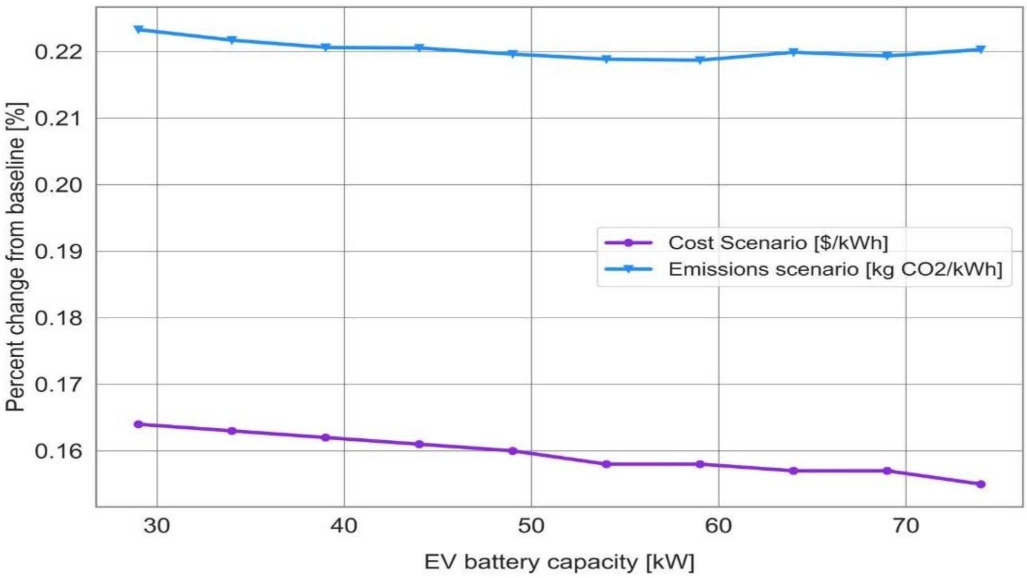


Figure 12. Sensitivity analysis: impact of EV battery capacity on carbon emissions and dollar expenses per kWh.

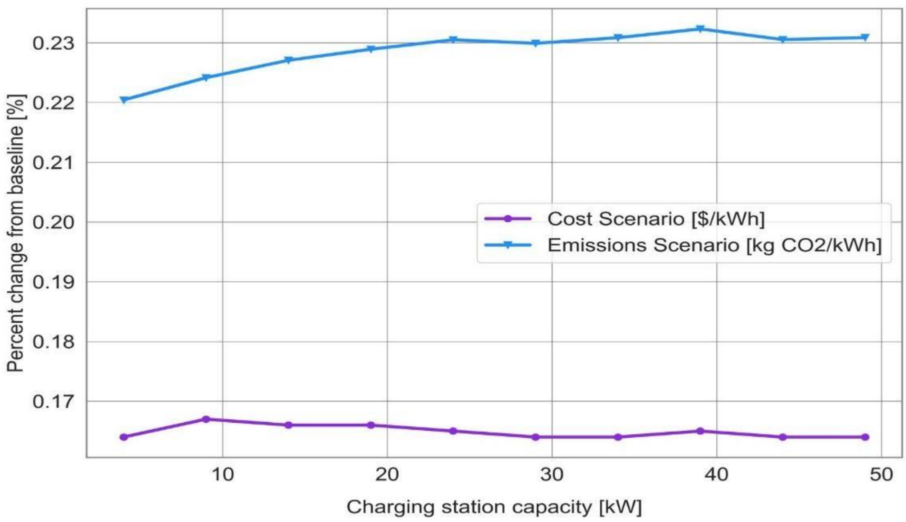


Figure 13. Sensitivity analysis: impact of charging station size on carbon emissions and dollar expenses per kWh.

The scenarios and sensitivity analysis models show that there are many trade-offs within the fleet composition parameters. For example, it is possible to achieve high ridesharing percentages with smaller fleets. However, that results in more empty miles because shared rides imply more trips to reach a passenger, which is essentially an empty mile. Furthermore, the fewer the cars, the longer passengers will wait to be picked up. On a more conceptual level, these interdependencies are between costs, user convenience, and environmental priorities. If a fleet owner invests in a large fleet, it would be expensive, however, users will be satisfied as cars would arrive faster and it would be more likely they will not have to share the ride with strangers. Despite these difficult choices, this study shows that smart charging can result in large savings each month. Therefore, interested parties can learn from these results and make decisions about their priorities and the parameters they are willing to sacrifice and those they would like to maximise.

4. CONCLUSIONS

The problem framed in this paper is charging fleets of ERVs in the most environmental or economic manner. Smart charging technology was suggested as a solution to be tested with its numerous implementation possibilities: charging to optimise solar PV, carbon emissions, or expenditures under 2015 and 2020 rate schedules. The results show that each of the scenarios successfully manages to shift between 34% and 87% of all loads to hours of the day when the objectives of those scenarios are met. Therefore, in comparison to a baseline, the scenarios improve the economic and environmental performance of the fleet between 4%-57% and 5%-26% respectively. While all scenarios achieve savings, the PV scenario significantly outperforms all others and it is recommended to fleet owners who would like to save emissions and costs at the same time. In addition to choosing the energy source, fleet managers would have to make decisions regarding the exact fleet parameters, which are intertwined in a complex web of interdependencies. Nevertheless, an acceptable balance can be reached where a daily demand of 2,874 trips can be met with about 450-478 vehicles, which utilises vehicles on average 30% of the time and leaves passengers waiting for about 10-15min.

The results of the study could be useful for stakeholders beyond fleet owners. For example, utilities can gain insight from the impact rate schedules have on the economics of EV charging. As shown, 2020 ToU schedules are significantly more favourable to EV owners than 2015 rates. The reason is that the former peak at the same time when solar energy is produced and when emissions are the lowest. 2020 rates, on the other hand, arrive at a compromised schedule, which allows that both emissions and costs can be reduced. Therefore, it is recommended that policymakers and utility officials take into account the contrasting objectives of different parties when designing tariffs in the future. Doing so would benefit not only the fleet owner but also the grid operators as well. The reason is that ToU by definition shifts peak loads to off-peak hours. Considering that EV loads will increase considerably in the future, this study could inform states without ToU on the utility and benefits that these tariffs can have on a larger grid basis too. Another important takeaway is the value of net metering, which is what essentially enables the economics and the fast payback of the solar farm. It benefits not only the fleet manager but also the grid, which becomes cleaner. Many states, however, have net billing, as opposed to net metering and therefore selling electricity to the grid is more or less expensive than buying electricity. Therefore, the economics of ERVs in those places might not be as advantageous as they are in California. Finally, net metering was chosen as an option in this study due to the current limitations of the other five options listed in this paper- such as community solar, curtailed PV energy, PV charging stations, etc. While these alternatives are not currently feasible, they could be more effective once they gain economies of scale. PV charging stations, for example, allow EVs to not simply offset electricity but also to directly use the solar energy generated. Therefore, they could eventually have a much greater potential.

The main contribution of this paper is to clearly outline different pathways fleet owners can take (different scenarios) and then quantify and discuss the benefits and downsides associated with a list of technological choices. The lessons learned could be beneficial for city fleet owners, ridesharing companies, campus fleet managers, or policy officials looking for ways to boost the environmental performance of their vehicles. The limitation of this study is the fact that San Francisco is not a typical American city. Due to lack of data, however, many of the other locations with more standard characteristics could not be used.

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