Evaluating the Impact of Clean Miles Standard on the Transportation system: A Microscopic Simulation in San Francisco

April 2024

A Research Report from the Pacific Southwest Region University Transportation Center

Peng Hao

Haishan Liu

Guoyuan Wu

Matthew Barth

Pacific Southwest Region UTC
University Transportation Center

UCR College of Engineering – Center for Environmental Research and Technology

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. PSR-22-17	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Evaluating the Impact of Clean Miles Standard on Transportation system: A Microscopic Simulation in San Francisco		**5. Report Date** April 22, 2024 **6. Performing Organization Code** N/A
7. Author(s) Peng Hao, ORCID 0000-0001-5864-7358 Haishan Liu, ORCID 0000-0002-0817-9928 Guoyuan Wu, ORCID 0000-0001-6707-6366 Matthew Barth, ORCID 0000-0002-4735-5859		**8. Performing Organization Report No.** TBD
9. Performing Organization Name and Address METRANS Transportation Center University of Southern California University Park Campus, RGL 216 Los Angeles, CA 90089-0626		**10. Work Unit No.** N/A **11. Contract or Grant No.** USDOT Grant 69A3551747109
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590		**13. Type of Report and Period Covered** Final report (August 15, 2022 - August 14, 2023) **14. Sponsoring Agency Code** USDOT OST-R
15. Supplementary Notes: https://doi.org/10.25554/a6n5-3086 https://www.metrans.org/research/evaluating-the-impacts-of-clean-miles-standardon-transportation-system		
16. Abstract In California, the transportation sector accounted for about 50% of greenhouse gas (GHG) emissions when accounting for fuel production, and transportation network companies (TNCs) emerge as a growing source of vehicle-miles-traveled (VMT) and GHG emissions. As directed by Senate Bill (SB) 1014, the California Air Resources Board (ARB) developed the Clean Miles Standard Program reduce to GHG emissions from TNC vehicles and increase the use of zero-emission vehicles (ZEV). This research investigates the potential benefits and impacts of the electrified TNC fleet at system level with the enforcement of Clean Miles Standard in California. A microscopic traffic simulator, SUMO, was utilized to develop the TNC mixed electric fleet operation scenarios. Two optimization modules were proposed to support order dispatching and EV charging station assignment tasks. A case study was conducted using TNC demand data from San Francisco with different ratios of EVs in the mixed fleet. The results indicate that higher electrification levels in the TNC fleet lead to a slight increase in rider average waiting time and driver empty distance due to the charging needs of EVs during operating hours, but TNC fleet electrification yields significant reduction in CO_2 and criteria air pollutant emissions.		
17. Key Words Transportation network companies, simulation, Clean Miles Standard, greenhouse gas emission	**18. Distribution Statement** No restrictions.	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 35 — **22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Contents

About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

Peng Hao, Haishan Liu, Guoyuan Wu and Matthew Barth conducted this research titled, "Evaluating the Impact of Clean Miles Standard on Transportation system: A Microscopic Simulation in San Francisco" at the Center for Environmental Research and Technology, College of Engineering, University of California at Riverside. The research took place from August 15, 2022 to August 14, 2023 and was funded by a grant from the U.S. Department of Transportation in the amount of $99,852. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Acknowledgements

This research was supported by a grant from the Pacific Southwest Region 9 University Transportation Center.

Abstract

In California, the transportation sector accounted for about 50% of greenhouse gas (GHG) emissions when accounting for fuel production, and transportation network companies (TNCs) emerge as a growing source of vehicle-miles-traveled (VMT) and GHG emissions. As directed by Senate Bill (SB) 1014, the California Air Resources Board (ARB) developed the Clean Miles Standard Program reduce to GHG emissions from TNC vehicles and increase the use of zero-emission vehicles (ZEV). This research investigates the potential benefits and impacts of the electrified TNC fleet at system level with the enforcement of Clean Miles Standard in California. A microscopic traffic simulator, SUMO, was utilized to develop the TNC mixed electric fleet operation scenarios. Two optimization modules were proposed to support order dispatching and EV charging station assignment tasks. A case study was conducted using TNC demand data from San Francisco with different ratios of EVs in the mixed fleet. The results indicate that higher electrification levels in the TNC fleet lead to a slight increase in rider average waiting time and driver empty distance due to the charging needs of EVs during operating hours, but TNC fleet electrification yields significant reduction in CO_2 and criteria air pollutant emissions.

Evaluating the Impact of Clean Miles Standard on Transportation system: A Microscopic Simulation in San Francisco

Executive Summary

Transportation activity has been consistently contributing to a significant impact on mobility and environment. In California, the transportation sector accounted for about 50% of greenhouse gas (GHG) emissions when accounting for fuel production, and 70% of the transportation-related emissions comes from light-duty vehicles. To collectively decarbonize the transportation sector, Electric vehicles (EVs) are gaining unprecedent popularity recently due to the low greenhouse gas emissions and zero tail-pip pollutants characteristics. On the other hand, due to the high accumulated driving mileage on the ride-hailing services, electrifying a ride-hailing vehicles enables triple emission reduction compared to electrifying a passenger vehicle. As directed by Senate Bill (SB) 1014, the California Air Resources Board (ARB) developed the Clean Miles Standard and Incentive Program, as a first-of-its kind regulation designed to reduce GHG emissions from TNC vehicles and increase the use of zero-emission vehicles (ZEV). The primary requirements of the Clean Miles Standard are to increase the percentage of total miles driven by TNC using ZEVs, and to reduce GHG emissions per passenger miles traveled.

This study is to evaluate the potential mobility and environment impact on TNCs and the entire transportation system with the implementation of Clean Miles Standard. To this end, a comprehensive simulation framework was proposed to simulate the transitioning process with TNC electrifying process by gradually increasing EVs penetration rate in the TNC fleet. A microscopic traffic simulator, SUMO, was used to construct the simulation platform and experiments with different scenario setup. The ride-hailing data from San Francisco was integrated into the simulations to quantitively study the mobility, charging demand, and emission impact changes given the penetration of EVs. Along with the vehicle dispatching policy without considering the vehicle heterogeneity in the fleet, we also tested an eco-friendly ride-hailing dispatching policy where EVs are prioritized to operate during the off-peak hour.

Experimental results showed that the off-peak EV priority policy depends on a larger EV fleet size to sustain the TNC service effectively. The TNC platforms need to balance the trade-off between service efficiency and environmental impact. Secondly, the charging demand steadily increases with a higher EV ratio in the mixed fleet. The off-peak EV priority policy has higher charging loads compared to the baseline policy because the TNC platform utilizes EVs to serve more riders. However, the peak charging hour in the off-peak EV priority policy occurs before 6 pm in the afternoon, which results in less marginal CO_2 emissions during daytime hours and enables the fleet to be adequately prepared for the evening peak in ride-hailing requests.

The evaluation of CMS compliance reveals that the eVMT target is easier to achieve compared with the GHG target. By increasing the utilization of EVs to serve ride requests, the eVMT targets can be achieved. However, the TNC companies should pay more attention to ride

pooling in order to meet the more constrained GHG targets. Thirdly, the off-peak EV priority policy shows superiority in saving an extra 30% of CO_2 compared to the baseline policy when ev_ratio is at 50%. In summary, to comply with CMS, the TNC platforms should encourage more EV participation in the ride-hailing service, and deploy an eco-friendly dispatching policy to increase EV utilization and ride pooling.

According to the sensitivity analysis, the repositioning strategy has less impact on the rider average waiting time. This can be attributed to San Francisco's dense ride-hailing demand pattern, where even without active repositioning, drivers efficiently serve riders due to the concentrated demand in various areas. With higher home charge access, TNC drivers can serve the ride-hailing trips with limited public charging demand. These findings underscore the critical need for stakeholders to consider home charge access when planning and constructing charging infrastructure.

1. Introduction

Transportation sector generates the largest share of greenhouse gas emissions (GHG) in the US, accounting for 28% in 2022 and growing with high momentum [1]. With the increasing travel demand, the passenger light-duty vehicle miles traveled accounted for more than 90% of total annual VMT in 2019 and is projected to grow with annual rate of 0.5% through year 2049 [2].To collectively decarbonize the transportation sector, Electric vehicles (EVs) are gaining unprecedent popularity recently due to the low greenhouse gas emissions and zero tail-pip pollutants characteristics. In the U.S, nearly 4 million plug-in electric vehicles have been sold in total from 2010 to June of 2023 [3]. Despite the strong public support, households still facing multiple challenges when choosing an EV, which slow down the adoption of EVs. The widely discussed factors include high purchase cost, limited travel range, and charging requirement (charger access and charging speed). The level 2 chargers typically require several hours (10-20 mile/hour) to fully charge a longer-range EV. While public DC charging requires less charging time (180-240 mile/hour), relatively few fast charging stations are available leading to longer waiting time and increasing charging cost [4].

The transportation network companies (TNCs) such as Uber and Lyft, providing services to connect self-employed drivers and passengers via online platforms, have the potential to overcome these EV adoption barriers and play an important role in transportation electrification. On average, full-time TNC drivers have a daily 180-190 driving mileage while personal vehicles only drive below 35 miles per day [5]. EVs provide more benefits to TNC drivers than gasoline vehicles (GVs) due to the much less vehicle maintenance fee for operating EV, which can offset the high purchasing cost in the long term. On the other hand, the higher accumulated mileage for TNC vehicles indicates that transitioning a gasoline vehicle driving on TNC platform to an EV can bring significant emission reduction compared to transitioning an personal used vehicle [5].This emission benefit was estimated to be triple, which indicating electrifying a single full time TNC vehicle can have the same emission benefits as three private vehicles [6], and up to 5 times when consider the cleaner grid development [7]. Thanks to the development of the advanced battery technology and increasing accessibility to charging infrastructures, multiple recent studies have confirmed the feasibility of driving an EV in the ride-hailing service with an EV with range around 200 miles [8], [9]. For example, by investigating the RideAustin dataset, Wenzel *et al.* found that 94% of full-time driver's shifts are under 200 miles, and around 35% of full-time drivers never exceeded 200 miles in any shift [10]. Besides, more EVs in the TNC fleet can facilitate higher utilization rate of fast charging station, which is beneficial to stabilizing pricing and expansion of DCFC stations [11]. Another non-trivial benefit is that EVs on the TNC platform can broaden the consumer exposure to EVs and increase the public awareness of EV technology and experiences [11].

The charging infrastructure is a key component to support the vehicle electrification. In the ride-hailing service, some researchers have been focusing on studying the charging infrastructure deployment to specifically meet the charging needs of TNC vehicles. A quantitative analysis was conducted by Nicholas et al. to identify the charging needs of ride-hailing vehicle and the corresponding charging infrastructure requirements to support future fully electric ride-hailing fleet, considering the miles driven per vehicle, home charging access, and exiting charger types [12]. Serval optimization models have been proposed to solve the charging infrastructure placement and sizing problem with the multiple objectives to minimize the drivers charging trips distance and installation cost [13]–[15]. For example, Anastasiadis *et al*. presented an optimization approach to model location planning of TNC-owned charging facilities. The simulation results indicated that nearly 180 new charging stations need to be installed to meet the charging demand of a TNC fleet with 3000 vehicles in Chicago [13]. Zhang et al. instead utilized an agent-simulation model, BEAM, to first identify the charging needs of the EV fleet and then adopted a hybrid algorithm to decide the charging stations spatial distribution and charger numbers [16]. Moreover, a country wide DCFC requirements were estimated to support 384 cities TNC's fleet electrification in the United States. Estimation results indicated that ride-hailing fleet requires 17.5 DCFC chargers per 1000 electric vehicles in the TNC fleet which is three times that of personal electric vehicles [8].

Given the charging infrastructure network, it is crucial for TNC platform to coordinate the three main tasks effectively: vehicle dispatching, repositioning, EV charging. Some pioneering works have been seeking for new ride-hailing fleet management strategies to ensure the TNC service efficiency. The synergies between vehicle repositioning and charging were explored in both [17], [18]. For example, Yi et al proposed the joint repositioning and charging decision making method to guide the idles vehicles to still get charged to be prepared for future trips [17]. Maljkovic et al proposed a pricing mechanism to balancing the charging load over the charging stations and guide the charging station selection [19]. Recently, reinforcement learning was a promising approach to solve the fleet management problem. Shi et al proposed a decentralized learning and centralized decision-making framework to support the EV fleet operating for ride-hailing service, where each EV was formulated as an RL agent with the possible actions to serve rider trips, charging and idle [20]. Yu et al. utilized a asynchronous learning method to solve the vehicle dispatching, relocation, and recharging problem by approximating the optimal value function [21].

From the practical perspective, top transportation network companies (TNC) such as Uber and Lyft, have announced multiple plans to support the transition to a zero-emission platform by 2030 [22], [23]. Uber has partner with EvGo and wallbox to provide fast charging solution and all-in-one home smart EV-charging solution. Drivers with battery electric vehicles are eligible for the incentive for $1 per ride. According to the ESG report, Uber has more than 37700 ZEV active drivers on the road, which represents a 4-fold increase over the same period a year ago [24]. Other leading ride-hailing service providers also offer similar effort to support the fleet electrification, including ZEV ride incentive, competitive charging pricing and charging station support, EV rental, etc. However, given the less transparency of TNC business to the public, it is still unclear about the exact impacts of TNC trips from both system mobility perspective and environmental impact perspective.

To regulate the TNC operation, the California Air Resources Board (CARB) developed the Clean Miles Standard (CMS), a first-of-its kind regulation designed to reduce GHG emissions from TNC vehicles and increase the use of zero-emission vehicles (ZEV). The primary requirements of the Clean Miles Standard are to increase the percentage of total miles driven by TNC using ZEVs, and to reduce GHG emissions per passenger miles traveled. CARB has proposed the gradually increasing requirements for annual ZEV miles, reaching 90% in 2030 and the gradually decreasing greenhouse gas emission per passenger miles travelled, targeting 0 grams per passenger mile in 2030. Starting from 2023, the TNCs with 5 million annual VMT are required to submit the annual compliance report to CARB, which includes vehicle population of the TNC fleet, total VMT, total compliance of GHG target and % eVMT target, etc. Detailed Trip data and driver profiles are required to provide for CARB to ensure the compliance report fidelity [25].

Given the enforcement of CMS, it is necessary for TNCs to encourage more EVs to participate in the ride-hailing service. In this research, we aim to investigate the mobility performance, charging demand and emission impact of the TNC service with a mixed energy fleet (MEF) which consists of gasoline vehicles (GVs) and electric vehicles (EVs). We specifically quantified the fleet electrification requirements and fleet operation strategies for TNCs to comply with the CMS from year 2023 to year 2029. To this end, a simulation platform was constructed in a microscopic traffic simulator, SUMO. Large-scale simulations were conducted in San Francisco with real world city network, charging stations distribution, parking areas, ride-hailing demand and generated TNC fleet. TNC fleet electrification process was simulated by gradually increasing EVs penetration rate in the TNC fleet. An eco-friendly ride-hailing dispatching policy was tested which giving high priorities to use EVs to serve the rides during the off-peak hours. The performance of the off-peak EV priority policy and baseline policy (without EV priority) were analyzed and compared with each other.

2. TNC Mixed Fleet Management

Conventionally, a TNC management system needs to solve two main problems: (1) Rider dispatching: to match the ride-hailing requests in real-time with the current available drivers; (2) Vehicle repositioning: to provide repositioning guidance to idle vehicle in advance to prepare for future ride requests. However, with the participation of EVs in the ride-hailing service, a more complex decision-making process emerges when integrating EVs' battery capacity, charging need, availability of charging infrastructure etc. Furthermore, under the governmental regulation, TNC platforms need to balance the economic profit and the emission impacts when making dispatching decisions. Efficiently utilizing EVs in the mixed energy fleet (MEF) is crucial to leverage the zero-emission utility from EVs while maintaining high service level to the riders. To achieve this goal, TNC platforms should pay attention to two more aspects: (1) Charging station assignment, TNC should monitor the State of Charge (SOC) of EVs. If an EV's SOC is lower than a predetermined threshold, TNC should not dispatch rider to it. Instead, TNC should recommend a charging station for the EV to get charged. (2) Dispatching policy, to efficiently utilize EVs to serve ride demand while maintaining the ride-hailing service level such as minimize the rider waiting time, reduce rider cancellation, etc.

2.1 Overall Framework

To facilitate the TNC to operate in both efficient and eco-friendly manners, we proposed a comprehensive MEF management framework, presented in Figure 1, which has three modules: Charging Station Assignment, Rider Dispatching, and Vehicle Repositioning. The operation environment is defined by the city road network, charging station distribution, and parking area distribution. When a rider submits a riding request consisting of origin, destination, and preferred pick-up time to the online platform, the request enters the dispatching module and waits for a matched driver. On the other hand, with all idle vehicles, the ride-hailing platforms first check each EV's state of charge (SOC) to ensure that the SOC is above a predefined threshold before dispatching an EV. If an EV's SOC is below the threshold, the TNC platform should assign a charging station to the driver. The ride requests are dispatched to the mixed fleet according to the dispatching policy. After dispatching riders to available drivers, if some drivers remain idle, the system will provide repositioning locations for drivers to be prepared for future riders. Thus, there are three key modules in the fleet management framework:

1) **Charging Station Assignment**: to assign charging stations for EVs whose SOC is lower than the predefined charging threshold;

2) **Rider Dispatching**: to dispatch riders to vehicles, after that rider will receive notification about the vehicle information and wait for pick-up;

3) **Vehicle Repositioning**: to dispatch idle vehicles to parking areas in the city in order to prepare for future rider requests.

More eco-friendly dispatching policy can be designed to leverage the EVs emission efficiency, which is the main expectation of electrifying the TNC fleet. With this proposed framework, we conducted extensive experiments to unveil the mobility performance, charging demand and environmental impact of a TNC with the MEF under different dispatching policies. Further, the process of transitioning to fully electrified fleet was modelled by gradually increasing the EV penetration rate in the MEF. Analytical evaluation was provided to quantify these impacts and seek for policy implications. In the following sections, we presented the optimization models for rider dispatching and charging station assignments. Then, a hot zone based greedy algorithm was proposed to solve the vehicle repositioning problem.

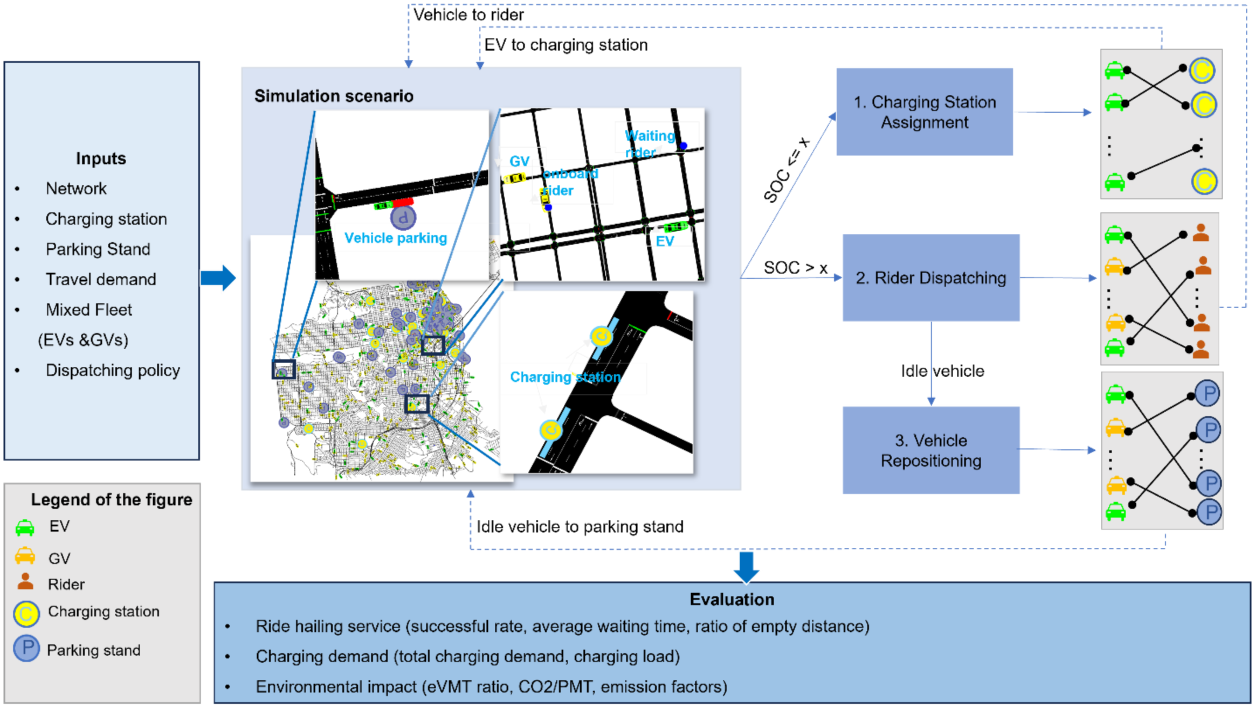

Figure 1. TNC mixed fleet management framework

2.2 Rider Dispatching Module

The mixed energy fleet dispatching problem (MEFDP) is a combination of ride-hailing problem (RHP)[26] and the variant of mixed fleet Electric Vehicle routing problem (MF-EVRP)[27]. To deal with the stochastic nature of the rider demand and driver availability, we created dispatching windows to periodically make the dispatching decisions, as shown in Figure 2. The time window length is controlled by Δt. Note that the dispatching decision depends on the supply (available vehicles) and demand (ride requests) distribution. If demand exceeds supply, i.e., during peak hours, then riders would have to wait longer for a matched driver. A maximum waiting time t_w^{max} can be set to model the request cancellation due to long waiting time. On the other hand, during off-peak hours, some drivers will be idle and waiting for the platform to summon.

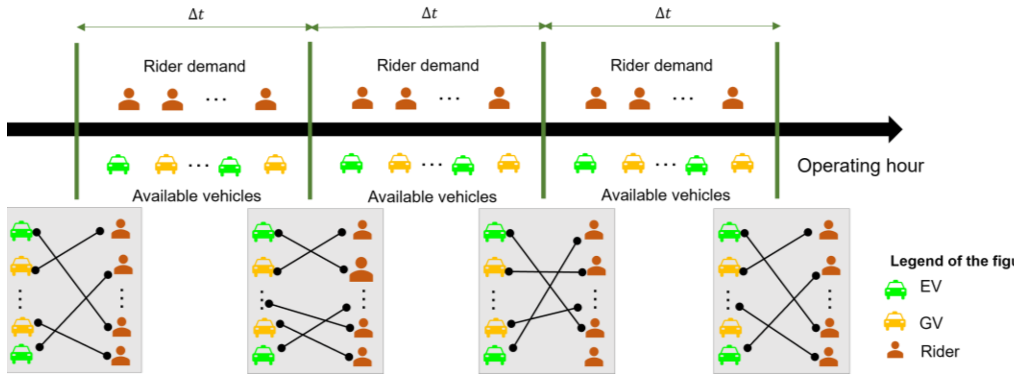

Figure 2. The mixed fleet periodical dispatching process with time window $\Delta \boldsymbol{t}$

At a given time step $T = n\Delta t$, a weighted bi-partite graph is constructed with $|V|$ available drivers and $|R|$ rider requests. The edge weight r_{vr} determines the objective of interests. In this study, we define the weight r_{vr} as a combination of request waiting time and rider pick-up time. In the current time step T, if the request arrival time is t_r, then the request waiting time is $(T - t_r)$. If a rider is waiting at the location r_o, the vehicle current location is v_{pos}, then the customer pick-up time is the travel time from vehicle's current location to rider's waiting location, defined as $f_t(v_{pos}, r_o)$, where f_t is the travel time function considering the network traffic status. We define the decision variable as x_{vr}, which takes value 1 if rider *r* is served by vehicle *v*; otherwise, x_{vr} equals 0. To simplify the model construction, let $\delta_r = \sum_v x_{vr}$ to indicate whether rider *r* is dispatched. If δ_r = 1, then rider r is dispatched. Otherwise, δ_r = 0. We assume in the mixed fleet the number of gasoline vehicles (GVs) and electric vehicles (EVs) is m^G and m^E respectively. The indicator y_v is utilized to indicate the vehicle type. If v is an EV, then $y_v = 0$. Otherwise, $y_v = 1$. Then the MFDP can be formulated as follows:

$$min \sum_{v\in V}\sum_{r\in R}\left((T - t_r) + f_t\left(v_{pos}, r_o\right)\right) x_{vr} - \sum_{r\in R} B\,\delta_r \tag{1}$$

subject to

$$\sum_{r\in R} x_{vr} \le 1 \quad \forall v \in V \tag{2}$$

$$\sum_{v\in V} x_{vr} = \delta_r \quad \forall r \in R \tag{3}$$

$$(1 - y_v)R_v \ge R_c \quad \forall v \in V \tag{4}$$

$$\sum_{v\in V}\sum_{r\in R} x_{vr}(1 - y_v) \le m^E \tag{5}$$

$$\sum_{v\in V}\sum_{r\in R} x_{vr} y_v \le m^G \tag{6}$$

$$x_{vr}, \delta_r, y_v \in \{0, 1\} \quad \forall r \in R, \forall v \in V \tag{7}$$

The objective is to minimize the total request waiting time and rider pick-up time to guarantee the customer equity and system efficiency. If a request has been waiting for dispatching for longer time, then in the next time step, it will have higher opportunity to be matched. In this way, the platform can also avoid rider cancellation. Besides, we add an extremely high penalty B to avoid ignoring long-waiting riders. Each vehicle will serve at most one rider every time, and each rider will be served by at most one vehicle, as defined by constraint (2) and (3) respectively. When matching a rider with an EV, the solution is constrained by the EV's remaining range. As stated in constraint (4), the EV's remaining range should be higher than the charging threshold R_c, Otherwise, the EV will go through the charging station assignment module (described in the following section). The charging threshold R_c can be customized according to the distribution of charging station, vehicle's energy efficiency, drivers' preferences, etc. Constraint (5) and (6) guarantee the number of the dispatched EVs and GVs is aligned with the fleet composition. Constraint (7) defines the decision variables x_{vr} and auxiliary variables δ_r, y_v according to the problem setting.

2.3 Charging Station Assignment Module

The purpose of this module is to match the best charging station for EVs looking for charging opportunities. As a preliminary study, we construct a simpler version of charging station assignment model based on the study of [17]. Assuming that there are $|C|$ available charging stations and $|V|$ EVs needing to charge. A charging station c 's location is c_o. The vehicle v is at its current location v_{pos}. Then the travel time from the vehicle's position to a charging station is $f_t(v_{pos}, c_o)$, where f_t is the travel time function considering the network traffic status. The decision variable is a binary variable x_{vc}, which equals 1 if charging station c is assigned to vehicle v . Otherwise, charging station c is not chosen. e_{vc} is the energy required for vehicle v to travel to charging station c. N_c is the number of available chargers at charging station c. With the variables defined above, the optimization model can be formulated as follows:

$$min \sum_{v \in V} \sum_{c \in C} \left(f_t(v_{pos}, c_o) \right) x_{vc} - \sum_{v \in V} B\, \delta_v \tag{8}$$

subject to

$$\sum_{c \in C} x_{vc} \leq N_c \quad \forall v \in V \tag{9}$$

$$\sum_{v \in V} x_{vc} = \delta_v \quad \forall c \in C \tag{10}$$

$$e_{vc} x_{vc} \leq R_v \quad \forall v \in V, \forall c \in C \tag{11}$$

$$x_{vc} \in \{0, 1\} \quad \forall v \in V, \forall c \in C \tag{12}$$

This model aims to minimize the fleet total travel time to visit the charging stations. This objective function is designed to reduce the driver's range anxiety by assigning closest available charging stations. Besides, in order to avoid ignoring available charging station, a high penalty factor B is enforced. Constraint (9) sets the number of vehicles assigned to a charging station c should be no more than the available chargers N_c to avoid long queue in front of the charging station. Constraint (10) enforces each vehicle can only be assigned to at most one charging station. Constraint (11) guarantee the assignment feasibility by ensuring the vehicle has enough battery to travel to the charging station. Constraint (12) defines the decision variables.

2.4 Idle Vehicle Repositioning Module

Vehicle repositioning has direct impact on the supply side by proactively deploying idle vehicles to a specific area in anticipation of future ride request. Successful repositioning of idle vehicles is beneficial to reduce driver idle time, rider pickup time and increase the overall efficiency of the system. In this module, we implemented a greedy algorithm to search for repositioning area for idle vehicles. It includes two steps:

(1) Hot Zone Identification: The weight of selecting each parking area is calculated according to the zone-level pick-up numbers. This can reduce the overall rider waiting time for pickup.

(2) Reposition Zone Selection: For each idle vehicle, the platform selects a parking area based on the zone weight and direct the vehicle to wait there. It's important to note that even as the driver en-route to the assigned parking area, the platform retains the capability to dispatch new rider requests. In such instances, the driver promptly adjusts course, diverting to the new rider's pick-up location rather than proceeding to the parking stand.

3. Development of TNC Simulation Platform

3.1 Data Preparation Workflow

In this work, the simulation platform was constructed with SUMO, which is an open-source, microscopic and continuous traffic simulation software[28]. The newly added Taxi module, Electric module, and station module inside SUMO make it possible to simulate the TNC mixed fleet operational scenarios. Besides, it provides high resolution microscopic simulation considering the real traffic status including traffic signals, vehicle routes, rider and driver behaviors which can reach to the real-world operation case to the most. Due to the data availability, we only simulated the TNC operation in the City of San Francisco, California.

To construct the simulation, multiple sources of dataset needed to import into SUMO. The dataset preparation workflow is shown in Figure 3, which includes five main data sources: charging station, network, parking area, TNC demand generation and mixed fleet generation. We described each data source processing in the following section.

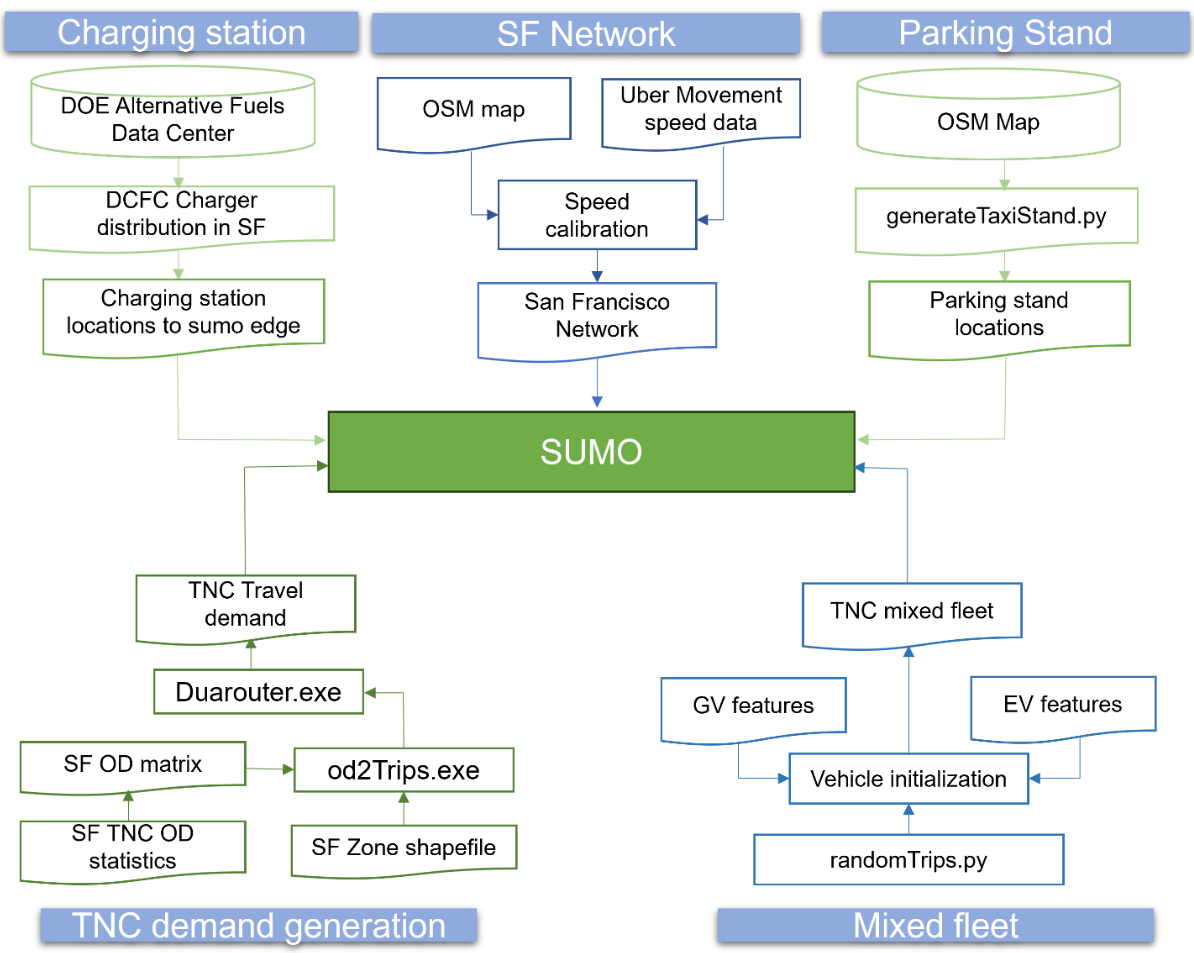

Figure 3. The workflow of dataset preparation for SUMO simulation

3.2 Input Dataset

Network: The San Francisco urban area road network was first obtained from OpenStreetMap. To simulate the real-world traffic status, we further calibrated the OSM link speed according to the Uber movement dataset[29]. Uber has released large scale, aggregated, and anonymized data on average travel speed and travel time statistics for multiple cities. This dataset can provide a convenience and low-cost approach for us to explore and simulate the real-world traffic status, especially for TNCs. We utilized the movement-data-toolkit to obtain the average speed data from Uber dataset in the San Francisco network. On the other hand, the TNC vehicles were reported to cause 15% of average speed reduction. A ratio of 1.15 was added to the Uber speed dataset in order to offset the speed reduction incurred by TNC vehicles so that the network average speed can converge to the real-world Uber speed dataset to the most.

Then we mapped the link with the same origin and destination osmID in the OSM network and modified the speed according to the Uber movement dataset. However, we can only map 53% of speed data from the Uber movement data to the OSM network. This is because the OSM data is open-sourced, and people can constantly contribute to updating the map to improves its accuracy and coverage. This poses a challenge to map the uber movement data to OSM network since the osmID are changed or disappeared as roads are split, combined, newly built, or removed. For those unmatched links, we kept the free flow speed from the OSM network. The merged network speed profile is presented in Figure 4.

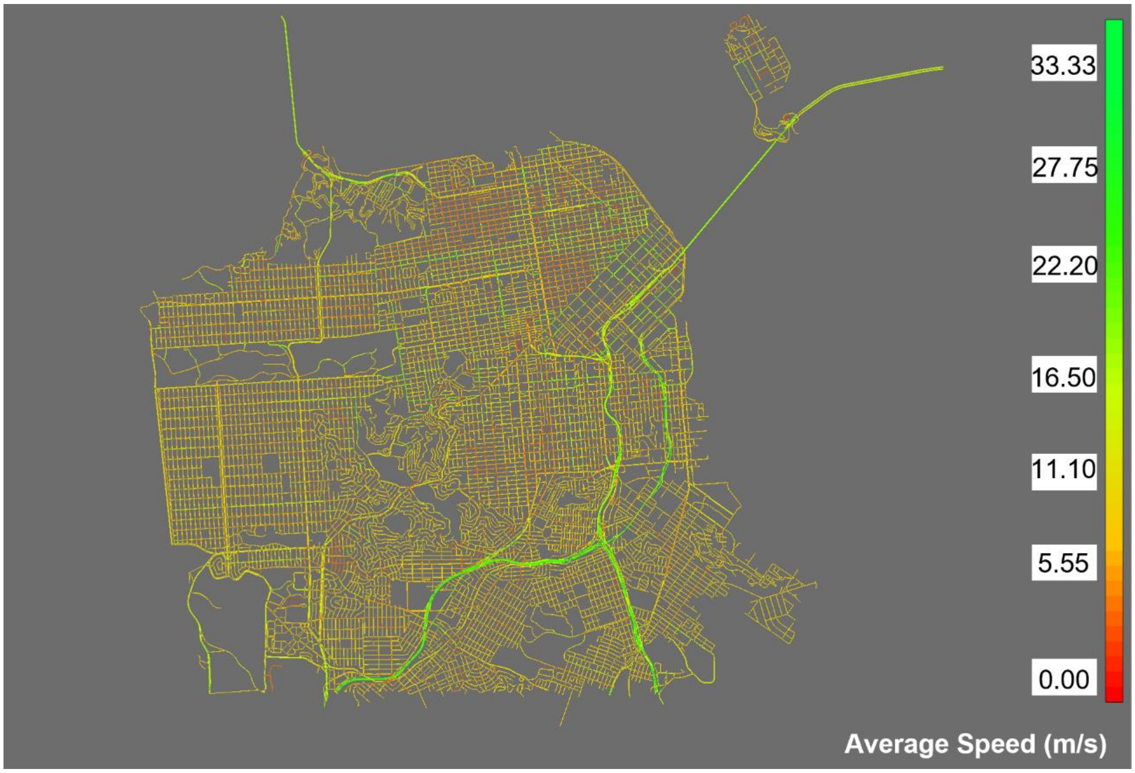

Figure 4. Calibrated San Francisco network average speed

Charging Station: The public charging station data in San Francisco (SF) was obtained from the Alternative Fuels Data Center including location, number of chargers, power level [30]. We only imported DC fast charging stations because the shorter charging time can meet the charging needs of vehicles in the TNC service. There is total 124 DC fast chargers in SF. However, due to our sampling process of the TNC demand and the TNC vehicles (explained in Chapter 4), only 25 charging stations were imported into SUMO across all experiments in this report. The imported charging stations are shown in Figure 5.

Parking Area: The SUMOAcitivityGen tool was used to generate the taxi parking stands inside the city. Total 60 taxi stands were extracted from the OSM file. The taxi parking stands were used as idling places for TNC vehicles in the simulation. The imported parking stands were presented in Figure 5.

Figure 5. Imported DC Fast charging stations (yellow circled with letter C) and parking areas (purple circle with letter P) in San Francisco

Mixed Energy Fleet: In the simulation study, we generated the vehicles' initial location with the randomTrip.py, which is a sumo tool for the trip generation. And then the vehicle type was specified to indicate whether the vehicle is an EV or a GV. As reported in [31], only 29% of drivers dwell in San Francisco and most drivers are coming into the city from other counties in the Bay Area. To simulate this phenomenon, we generated the drivers around the fringe of the city. When the driver trips are generated, vehicles will be loaded to the simulation according to the trip start time and wait for the platform dispatching assignment.

TNC Trips: This study utilized the dataset from 2017 TNC today study which provided a profile of San Francisco TNC activities [31]. We obtained the total 981 TAZ zones and the pick-up and drop-off statistic of each TAZ zone over 24 hours. The raw dataset collected from the Uber and Lyft APIs was not publicized. We instead relied on the hourly pick-up and drop-off statistics to generate the OD matrix and then used the *od2trips* tool in SUMO to generate TNC trips. To further ensure the trips connectivity, we utilized DUARouter (dynamic user assignment router) [28] to validate each trip. As shown in Figure 5, the generated TNC trips preserve the temporal and spatial patterns of the real-world TNC trips distribution. Each trip has the features of origin, destination, depart time (rider request time). Most of the ride request are occurred in the northeast quadrant of SF, which is the most congested area in the city. The total number of generated trips has matched the TNC today trips to 99%, which preserves the peak hour and off-peak hour patterns of the original data.

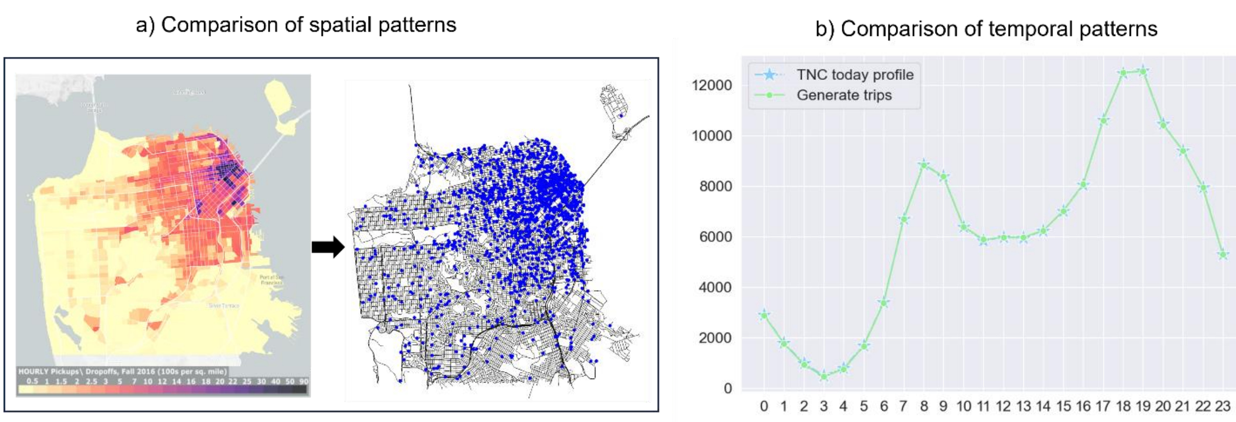

Figure 5. The spatial and temporal patterns between original data and generated data into SUMO

3.3 Key Simulation Tools

TraCI: To interact with SUMO, an application programming interface (API) tool--TraCI (Traffic Control Interface) is utilized to retrieve the current status of simulated objects and to change their behaviors during the simulation. It uses a TCP based cline and server architecture to access SUMO. At each time step, TraCI first retrieves new riders, waiting riders, available vehicles, EVs' SOC, and the charging stations usage. After the mixed fleet dispatching module and charging station assignment module obtain the optimal solution, TraCI sends the dispatching command and charging station selection command back to SUMO to let the vehicles move accordingly. If some vehicles remain idle, TraCI sends idle vehicles to parking areas according to the repositioning strategy.

Gurobi: The commercial solver, Gurobi, is utilized to solve both rider dispatching module and charging station assignment module. If the time interval Δt is controlled, the optimal solution can be obtained with reasonable computational time. During the model construction, we use DUARouter to get the real-time travel time cost between any two locations, such as driver to rider, driver to charging station. This can ensure the optimal solution considers the real time traffic status. Each linear programming model is constructed and solved by Gurobi. After that, the optimal solution is deciphered into TraCI to execute the corresponding vehicle behaviors.

3.4 Simulation Framework and Snapshots

To summarize, a simulation framework is shown in Figure 6. With the input datasets, SUMO loaded the SF network, charging stations and parking areas into sumo to initialize the simulation environment. The charging stations were placed on the lane of the road network, where vehicles can stop for a moment to get charged. At each time step, sumo first deletes the riders that have been waiting up to 5 minutes for a match driver. Then new riders and drivers are loaded. As the simulation snapshot shown in the right part of Figure 6, EVs are presented in green color, GVs are in yellow color. Riders wait at the origin location for driver to pick up.

Next, we checked the EVs' remaining travelling range and compare it with the charging threshold to filter out EVs that need to get charged. Then EVs are split into two modules, one is the mixed fleet dispatching module along with all idle GVs to serve riders, the other to charging station assignment module to visit a charging station in the next time step. Gurobi solver was leveraged to obtain the optimal solution. Finally, idle drivers were assigned with parking areas based on the repositioning strategy. After obtaining decisions (repositioning, dispatching, charging) for each vehicle and rider, TraCI was utilized to interact with the SUMO simulation and send corresponding decision command. The simulation continues until the end of the simulation.

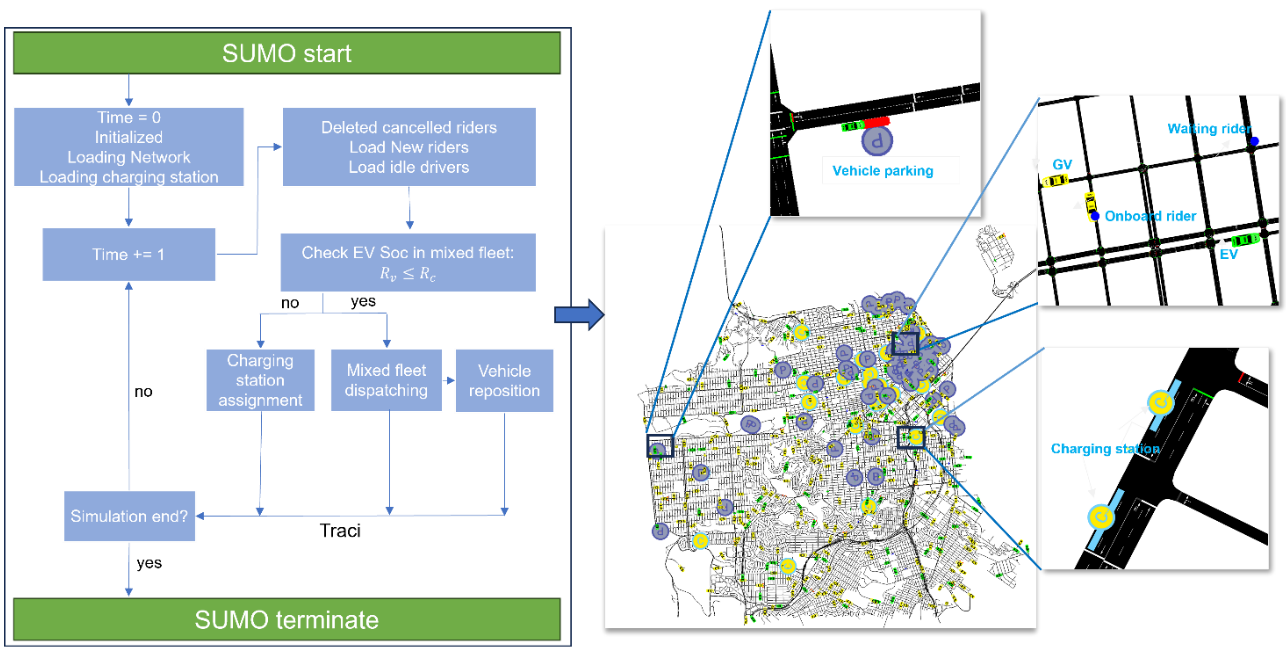

Figure 6. The overall simulation framework for ride-hailing services with a mixed energy fleet

4. Simulation Scenario Design

4.1 Experimental Scenarios Setup

- **Ride-hailing Requests**

The total generated 24 hours TNC trips (as shown in Figure 5) is 149994 trips. To reduce the SUMO simulation time, the simulation time was narrowed to 8am-8pm, where 73% of TNC trips occurred. Next, 20% of TNC trips were sampled out of these operating hours. Total 21754 TNC trips are loaded into SUMO. Each trip has a pick-up location, drop-off location, and request time. In the simulation, we assumed the rider expects prompt response after placing an order on the platform. The scheduled rides are out of the scope this study. The sampled trips were plotted in Figure 7. The hourly TNC demand is between 1194 and 2509 trips, which is handleable by SUMO to calculate the real-time travel time via DUARouter and Gurobi to solve the optimization problem. Besides, this selected operating hours cover the morning peak and evening peak of TNC trips which accounting for the most portion of system performance and impact. During the simulation, the riders maximum waiting time to wait for a matched drivers is set to be 5 minutes. If after 5 minutes, the platform can't response to rider with an assigned driver, then riders will cancel the request and leave the platform. SUMO updates the driver and rider status in every one minute.

- **EV Charging Behavior**

We utilized the calibrated energy consumption results for the Kia Soul EV 2020, as provided by SUMO [21]. The calibrated EV model includes factors such as air drag efficient, propulsion efficiency, radial drag coefficient, etc. The maximum battery capacity is 64 kwh. In simulating the charging scenario, we assume 50% EVs have home charge access which indicates 50% EVs start operating with fully battery capacity. For the rest portion of 50% without home charge, the initial battery capacity was sampled from a normal distribution with a mean value of 32 kwh and a variance of 5kwh. EV's remaining driving range (R_v) was calculated as the average energy consumption rate(km/wh) multiplied by the actual battery capacity(wh). We established the charging threshold R_c to be 50km to ensure the vehicle can reach an assigned charging station. This parameter can be adjusted according to the driver's preference or platform's consideration.

The charging stations were imported with charging power of 50KW for DC fast chargers. The charging duration is estimated with $(SOC_{target} - SOC_{actual})/charging\_power$. Since in real-world, the charging rate will decrease when SOC approaches to 100%. We set the target SOC to 90%. After the EV is charged to 90%, it will be available again and wait for platform's rider assignment. The charging power could be varied with different levels to simulate the impact of charging speed. More details will be discussed in the case study section.

- **TNC Fleet Electrification Process**

According to the TNC today study, the hourly active drivers is around 5000 vehicles with all TNC trips. In this simulation study, we generated 1000 vehicles according to the sample ratio (20%)

in the TNC trips. The TNC fleet electrification process is simulated by setting the EV ratio in the mixed fleet ranging from 10% to 90%, with 10% increasement interval. This setting can let us explore the TNC impacts along with this electrification trend.

- **Dispatching Policies**

Apart from the fleet electrification process, another main objective of this work is to explore a new TNC dispatching policy which aims to utilize EVs to reduce the environmental impact. However, from the TNC platform side, the main goal is to increase benefits by serving more riders. To the best of our knowledge, most TNCs ignore the vehicle heterogeneity and use EVs and GVs without priority during their dispatching process, which is the baseline policy shown in Figure 7(a). Although some TNCs may have proposed to incentives to encourage more EV drivers participating in the services. The EV's zero-emission utility may be under-utilized because of the dispatching policy.

This study aims to strike a balance between minimizing environmental impact and maximizing the benefits of Transportation Network Companies (TNCs). We propose and assess an Off-peak EV Priority Policy, outlined in Figure 7(b), which prioritizes the use of electric vehicles (EVs) to serve riders during off-peak hours. If the rider demand is higher than the EV supply capacity, a portion of gasoline vehicles (GVs) are randomly selected to serve the requests during the off-peak period. Conversely, during peak hours when demand surges, TNCs will utilize a full mixed fleet (comprising both GVs and EVs) to meet the demand effectively.

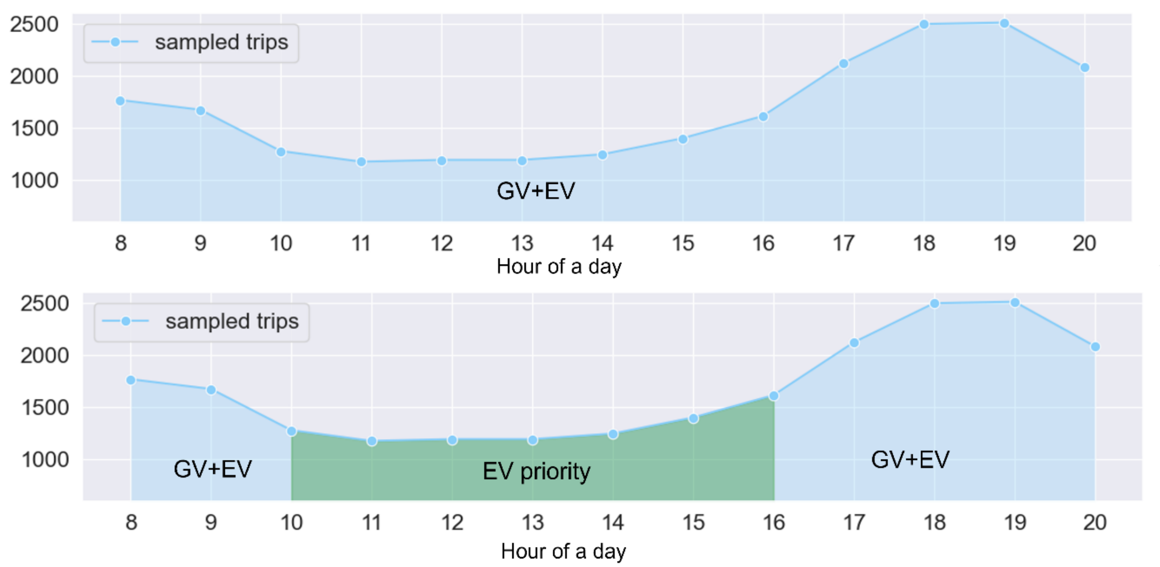

Figure 7. Illustration of baseline policy and off-peak EV Priority policy

The overall simulation runs were summarized in table 1. The main experiments are designed to investigate the impact of EV ratios in the mixed fleet under the different rider dispatching polices. Then a set of sensitivity analysis were conducted to specifically evaluate the impact of vehicle repositioning strategy and ratio of home charging access.

Table 1. Parameters in the simulation

Parameter	Value simulated
EV penetration rate	10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%
Vehicle dispatching strategies	Baseline policy, EV priority policy
Sensitivity Analysis	Value simulated
Repositioning strategy	Hot zone repositioning (baseline), Random repositioning, None repositioning
Home charge access	40%, 50% (baseline), 60%, 70%, 80%

4.2 Evaluation Metrics

To evaluate the operational and environmental performance of the TNC platform under a given scenario, serval factors need to be quantified after the simulation. The main objective of this study is to investigate the operational and environmental impacts of TNC trips under the implementation of Clean Miles Standard. The selected factors to evaluate the system performance include: (1) Average waiting time; (2) Successful rate of ride request; (3) Ratio of deadheading distance; (4) Total charging trips per day; (5) Total charging load; (6) ratio of electric vehicle miles traveled (eVMT); (7) CO2 emission per passenger miles travel (PMT).

These seven factors can be grouped into three categories, as shown in table 2. Average waiting time measures the duration between the riding request placing time and the pick-up time, serving as a metric to evaluate the TNC system efficiency. Besides, riders are inclined to cancel their orders if he/she waits longer than 5 minutes. The successful rate of ride request quantifies the number of successfully served riders over the total number of riding requests. The deadheading distance indicates the driving distance without any riders onboard, encompassing repositioning miles, charging miles, miles en-route to pick up riders. The ratio of deadheading distance is computed by dividing the deadheading distance by the overall driving distance of TNC vehicles in the system. Total charging trips per day quantifies the total number of charging events occurring during the operating hour, while total charging load presents the TNC vehicles charging amount at the charging stations. The ratio of eVMT and the CO2/PMT are metrics to specifically evaluate the environmental benefits of the fleet electrification according to the Clean Miles Standard.

Table2. Description of evaluation metrics

Group	Metric	Description
TNC operational performance	Average waiting time	Rider waiting time for pick up
	Successful rate of ride request	ratio of successfully completed rides
	Ratio of deadheading distance	The portion of distance without a rider onboard.
EV charging	Total charging trips per day	The number of charging events
	Total charging load	The amount of charging power
Environmental impact	ratio of eVMT	distance driven by electric vehicles
	CO2/PMT	CO2 emission

5. Result Analysis

In this section, we first present the simulation results to investigate the mobility performance, charging demand, and environmental impact of the TNC services with a mixed energy fleet. The trend of fleet electrification was studied by varying the EV penetration level in the MEF. The proposed off-peak EV priority policy was evaluated. Then a sensitivity analysis was conducted to determine the impact of vehicle repositioning strategies and home charge access.

5.1 TNC Performance

- **Mobility Performance**

The TNC operational performance was graphically shown in Figure 8. Results generally shows that the overall fleet with 1000 vehicles is sufficient to serve the simulated ride-hailing trips effectively. The successful rate of ride requests exceeds 99% in all simulated scenarios. Discrepancies are observed in deadheading distance and average waiting time concerning the baseline policy and EV priority policy.

First, under the baseline policy (represented by left blue bars in Figure 8), both the ratio of deadheading distance and average waiting time presents a slow increasing trend with higher EV ratios. This trend is attributed to the increasing EV charging events resulting in more empty distance travelling to charging stations and fewer vehicles in the fleet leading to longer pick-up distance. However, since both EVs and GVs are equally dispatched without any constraints, the charging behavior of EV only has marginal impact of the two indicators.

In contrast, with the EV priority policy, the ratio of deadheading distance and rider average waiting time represents an opposite trend with the increasing the EV ratios in the MEF. When EVs are limited in the fleet, the off-peak EV priority policy depletes EV batteries quickly due to the higher utilization rate of each EV, incurring more charging trips per vehicle. Limited EVs also result in a sparse distribution of EVS in the city, increasing the en-route distance to pick up riders. These findings underscore the dependence of the off-peak EV priority policy on a larger EV fleet size to sustain the TNC service effectively.

Another important comparison is the performance difference between the baseline policy and off-peak EV priority policy under every EV ratio. The discrepancy between the two policies, especially in terms of ratio of deadheading distance and average waiting time, diminishes with the increasing EV ratio in the MFE. Consequently, when the EV capacity reaches a substantial level, both policies can deliver an equivalent quality of ride-hailing service.

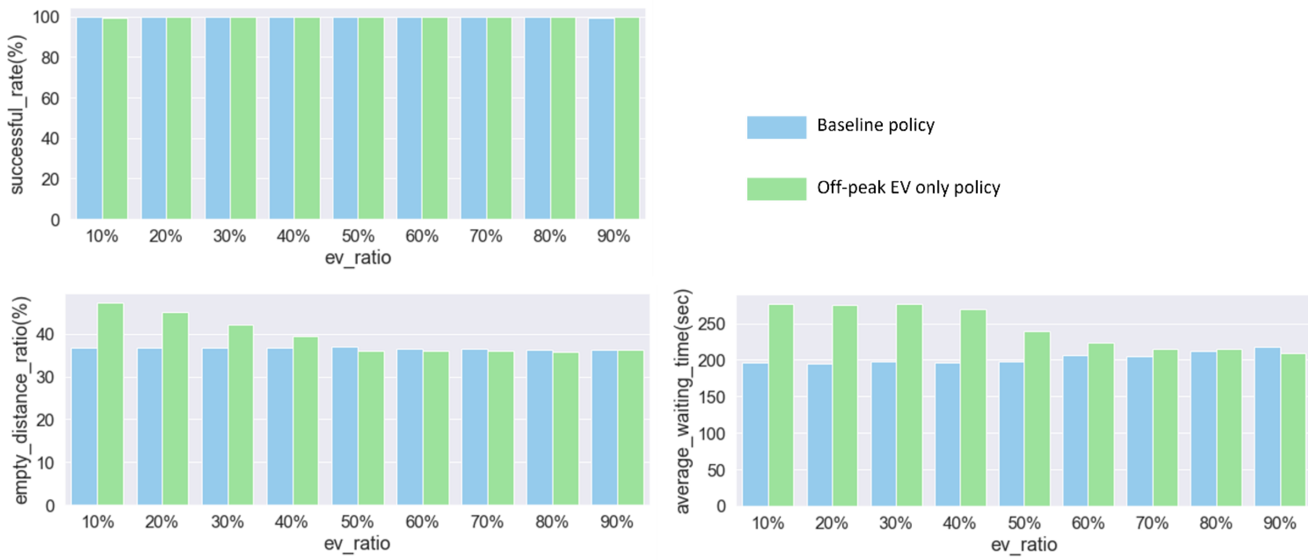

Figure 8. Mobility performance under different EV ratios and different dispatching policies

Additionally, Figure 9 presents the EV's average daily driving distance. The off-peak EV priority policy demonstrates a more intensive utilization of EVs compared to the baseline policy. Under the baseline policy, an EV with a range of 180 km is sufficient to support daily TNC services. However, with the implementation of the EV priority policy and 10% EVs in the mixed fleet, EVs are required to have a driving range of approximately 250 km to fulfill daily TNC trips without charging, assuming a full charge at the beginning of the day. As the number of EVs in the MEF increases, the per-EV driving distance decreases to 188 km due to the higher availability of EVs within the system. The battery requirements for an EV to fulfill the daily travel demand depends on the vehicle utilization rate.

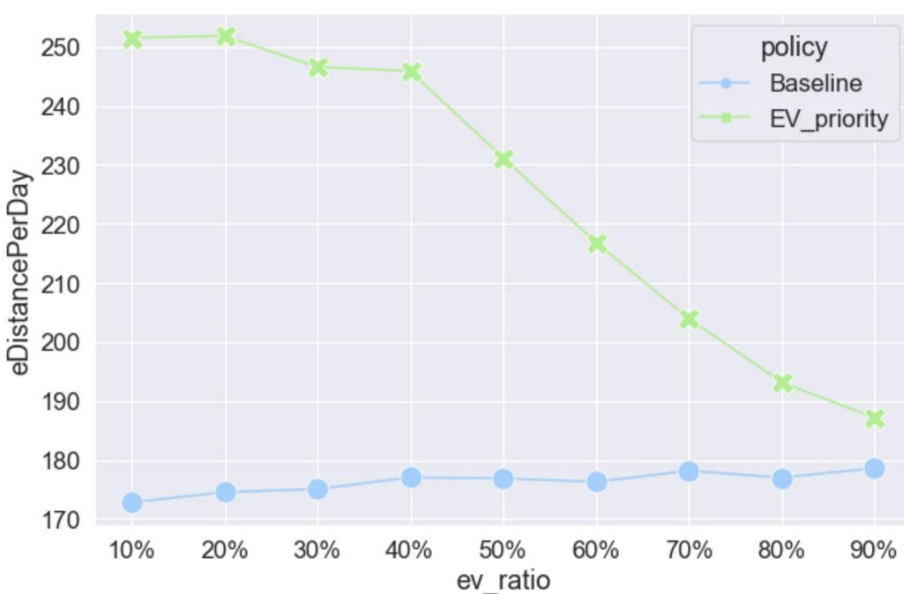

Figure 9. EVs average driving distance(km) per day

- **EV Charging Load Profile**

Figure 10 illustrates the charging load across the charging stations under different cases. The charging load is positively proportional to the ev_ratio (i.e. EV penetration rate) in the MEF. As more EVs are deployed for completing ride-hailing trips, a higher charging load is observed. For instance, when the ev_ratio is 10%, the peak-hour charging load of the simulated fleet is below 300 kw. Conversely, with an ev_ratio of 90%, the peak-hour charging load surges to 1600 kw. These findings emphasize the necessity for charging infrastructure expansion to accommodate the charging requirements of the growing TNC fleet during the electrification process.

Comparing the charging load between the baseline policy and off-peak EV priority policy, in most cases, the peak charging hour in the off-peak EV priority policy occurs before 6 pm in the afternoon. This timing choice results in reduced marginal CO2 emissions during daytime hours. Additionally, pre-charging before 6 pm enables the fleet to be adequately prepared for the evening peak in ride-hailing requests, ensuring efficient service provision.

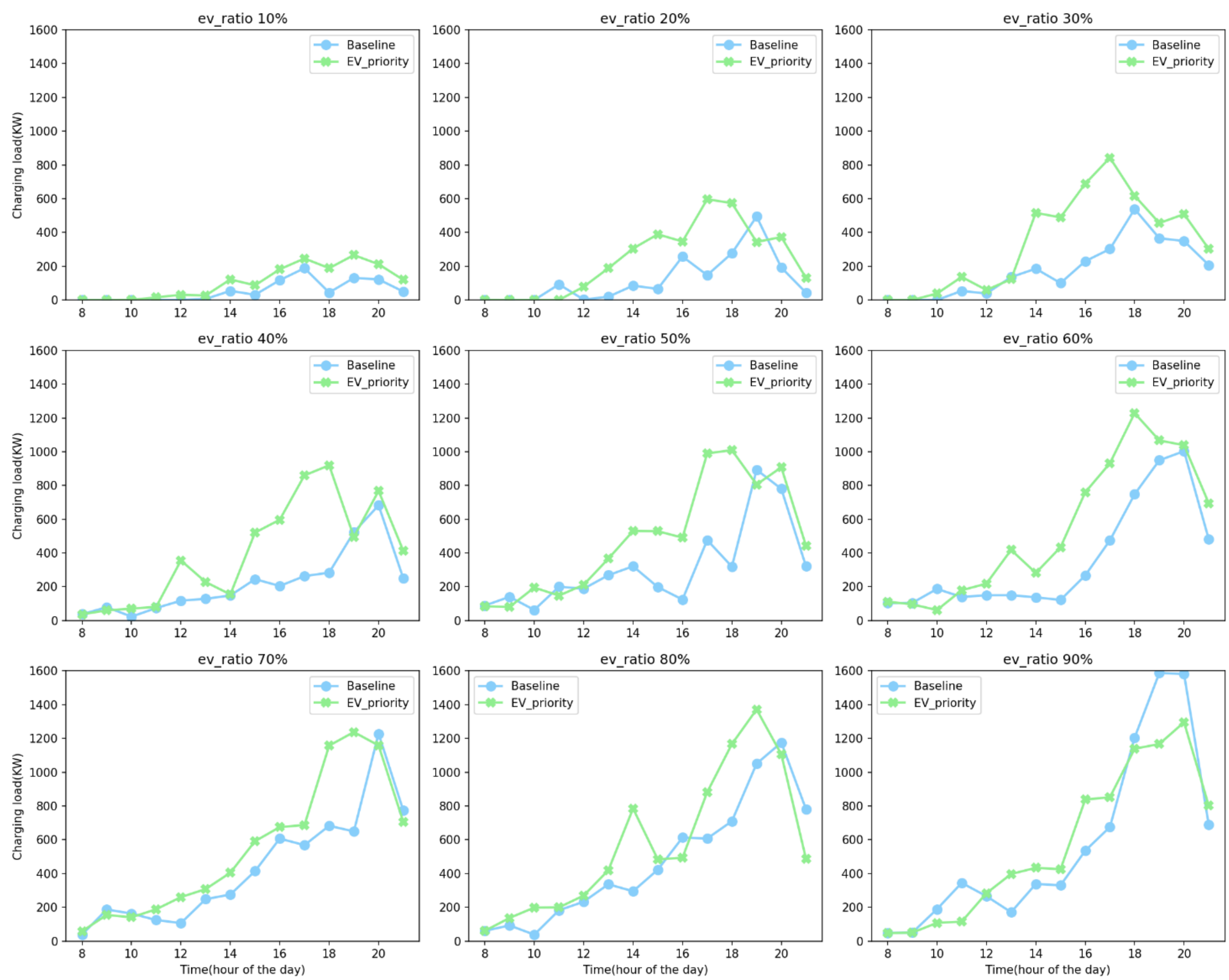

Figure 10. The charging loads of EVs under different EV ratios and different dispatching policies

- **Compliance with Clean Miles Standard**

In this section, we evaluated the greenhouse gas (GHG) factor and eVMT ratio as required by the Clean Miles Standard (CMS). The GHG factor quantifies the gram of CO2 emissions per passenger miles travelled. The eVMT represents the electric miles travelled by a BEV or fuel cell electric vehicle. In this study, we computed the eVMT ratio as the electric miles driven by EVs as a percentage of total VMT. The annual targets were listed in Table 3, where GHG target is gradually decreasing from 252 g/PMT in 2023 to 0 g/PMT in 2030 and the eVMT target is gradually increasing from 2% in year 2023 to 90% in year 2030.

Table 3. Annual Targets from Clean Miles Standard[25]

Calendar Year	GHG Target (grams CO2/PMT)	eVMT Target
2023	252	2%
2024	237	4%
2025	207	13%
2026	161	30%
2027	110	50%
2028	69	65%
2029	30	80%
2030	0	90%

Although SUMO has the emission model HBEFA to quantify the CO2 emission from GVs, the HBEFA model calculates the emissions when vehicle is stopped. This could lead to overestimating of CO2 emissions since the vehicle redundancy in the MEF and all vehicles were loaded in the first simulation hour. To avoid this overestimation, we utilized equation (13) to compute the GHG factor according to the CMS. The CO2 emission rate was set as 232 g/mile, which was obtained by averaging the CO2 rates from vehicle model years ranging from year 2008 to year 2020 provided in CMS. The compliance occupancy was defined as 1.5 for non-pooled rides and as 2.5 for pooled rides in CMS. According to TNC report 2020 in SF, 7% of trips were successfully pooled [32]. We tested three pooled scenarios with 7%, 15% and 30% of pooled rides by setting the compliance occupancy to be 1.57, 1.65 and 1.80 respectively.

$$\frac{gCO_2}{PMT} = \frac{\sum(VMT \ \times \ CO_2 \, emission \, rate \,)}{\sum(VMT_{occupied} \times occupancy)} \qquad (13)$$

Table 4 presents the results of greenhouse gas factor and eVMT ratio under different dispatching policies and ride pooling ratios. The scenarios outputs (GHG factor and eVMT factor) that could comply with the CMS in year 2023, 2026, 2029 were colored in pink, yellow and green. One important finding is that the eVMT ratio target can be complied with lower EV ratios in the mixed energy fleet compared to the compliance with the GHG target. For example, with ev_ratio of 30%, the E_P policy could meet the year 2026 targeted eVMT ratio of 30%. But it requires 40% - 50% of EVs in the mixed fleet to compliance with the greenhouse gas target depending on the ride pooling rate. With the baseline policy, the compliance of 30% eVMT target requires 60% of EVs in the MEF. Besides, the compliance of greenhouse gas target relies on the occupancy factors. With the 7% and 15% ride pooling, the baseline policy is unable to comply with the CMS at year 2029 even with 90% of EVs in the mixed fleet. These results emphasize the importance of encouraging ride pooling to comply with the CMS during the fleet electrifying process. The dispatching policies also influence the TNC's compliance with CMS. When ev_ratio is lower than 10%, due to the random selection of GVs to serve the ride demand, the off-peak EV priority is unable to comply with the CMS in year 2023. However, the off-peak EV priority policy meets the compliance of CMS in year 2026 and 2029 with lower ev_ratio in the MEF due to the efficiently utilization of EVs to serve the rider requests.

Table 4. Scenario requirements for TNCs to comply with CMS in year 2023 (colored in pink), year 2026 (colored in yellow), and year 2029(colored in green)

Policy	B (Baseline Policy)				E_P (off- peak EV Priority)			
EV ratio	7% pooled (g/pmt)	15% pooled (g/pmt)	30% pooled (g/pmt)	eVMT ratio (%)	7% pooled (g/pmt)	15% pooled (g/pmt)	30% pooled (g/pmt)	eVMT ratio (%)
10%	291	277	**254**	**9%**	340	324	297	10%
20%	261	**248**	**227**	18%	284	270	**248**	**22%**
30%	228	217	199	28%	**220**	**210**	192	**36%**
40%	199	190	174	**37%**	168	**160**	**147**	49%
50%	166	**158**	**145**	48%	**115**	109	100	63%
60%	**135**	128	117	57%	90	86	79	71%
70%	95	91	83	70%	61	58	53	**81%**
80%	66	63	58	79%	42	40	36	87%
90%	34	32	**29**	**89%**	**21**	**20**	**18**	93%

Figure 11 presents the CO_2 emission from the TNC mixed fleet during the operating hours. There is substantial reduction in CO2 emissions with higher EV ratio. Take ev_ratio at 10% as the baseline, the TNC service with 90% EVs in the fleet can reduce 89% CO2 emissions with the baseline policy and 92% of CO2 emission with the off-peak EV priority policy. Due to the shortage of EVs when limited number of EVs in the MEF, the CO2 emission with the off-peak EV priority policy is higher than that with the baseline policy. Notably, the off-peak-EV priority policy demonstrated remarkable sustainability when increases the ev_ratio in the MEF, such as it reduces an extra 30% of CO_2 compared to the baseline policy when the ev_ratios is at 50%. This emission gap between the two policies narrows down when ev_ratio is smaller (10%) or larger (90%). The reason behind this phenomenon is that when there are limited EVs in the MEF, the TNC platform is compelled to dispatch riders to Gasoline Vehicles (GVs) even with the EV priority policy. Conversely, when the system boasts a higher number of EVs, the baseline policy can still dispatch more EVs to serve the riders, diminishing the gap in emissions between the two policies.

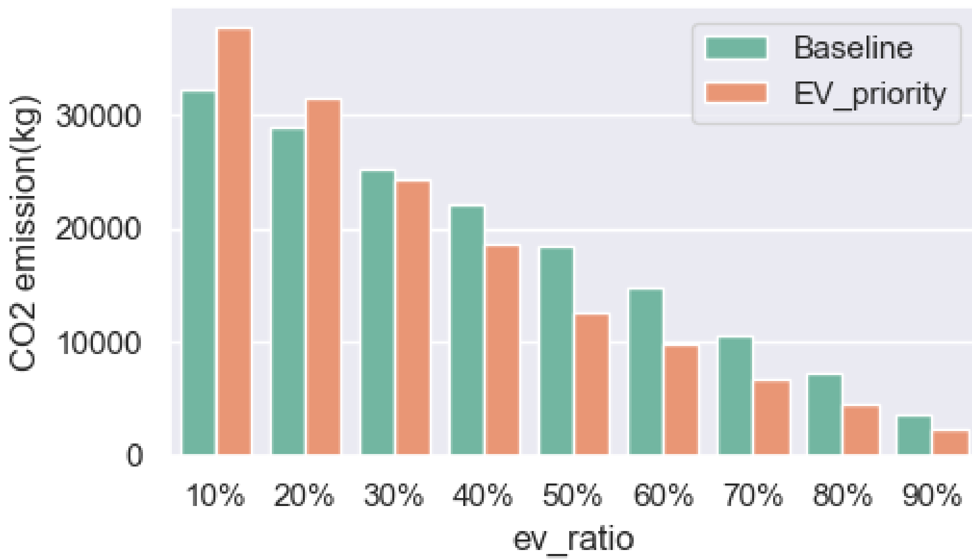

Figure 11. Total CO2 emission of mixed fleet under different policies

5.2 Sensitivity Analysis

In this section, sensitivity analysis was carried out to investigate the impact of vehicle repositioning strategies and home charge access. We select the MEF with 50% of EVs as the study scenario. In each simulation run, we only modify one factor to ensure fair comparison.

- **Vehicle Repositioning Strategy**

Vehicle repositioning plays a crucial role in ensuring the optimal spatial alignment between the Transportation Network Company (TNC) fleet and ride demands. In this section, we explored two distinct repositioning strategies and compared their outcomes with the hot zone repositioning strategy:

Random Repositioning: The TNC platform randomly selects the parking area for idle vehicles without considering the parking area characteristics.

Non-repositioning: In this case, drivers remain stationed at their last drop-off location without any active repositioning efforts.

The evaluation results were summarized in Table 3. Among the three repositioning strategies, the average waiting time remains negligible. This phenomenon occurs due to the concentrated ride demands in the northeastern part of San Francisco (in Figure 5). After the warm-up status of the system, most drivers naturally gravitate toward the densely populated areas for both picking up and dropping off riders. Consequently, the repositioning strategy has a minimal impact on rider waiting times.

However, it is noteworthy that the hot zone repositioning outperforms the random repositioning in terms of CO2 emission, VMT and the deadheading distance. This superiority stems from the hot zone strategy's ability to deploy vehicles to areas with higher ride demands, thereby reducing pickup distances. Another interesting observation is that the None repositioning strategy still fares reasonably well in the simulated scenario. This can be attributed to San Francisco's dense ride demand pattern, where even without active repositioning, drivers efficiently serve riders due to the concentrated demand in various areas.

Table 3. Comparison of different repositioning strategies

Scenario	None	Random	Hot zone
average waiting time (sec)	235.93	232.04	239.58
CO2 Emission (kg)	20829.97	40852.18	38382.97
eDistancePerDay (km)	191.82	234.06	231.22
Total VMT (km)	137387.47	182343.28	176910.31
Ratio of deadheading distance (%)	17.54	37.86	36.00
CO2/PMT (g/PMT)	96.18	188.61	177.35

- **Home Charge Access**

The percentage of home charge access of EV drivers is expected to heavily influence the charging load of the charging network. However, the home charge access depends on various factors, including parking location, house type, charging facilities availability, etc. We employed the estimating home charge access likelihood from the outcomes explored in the residential access survey. The simulated home charge access probabilities are 40%, 50%, 60%, 70% and 80%. The charging load of each scenario is plotted in Figure 13. the charging load significantly diminishes with a higher percentage of home charge access. These findings underscore the critical need for stakeholders to consider home charge access when planning and constructing charging infrastructure.

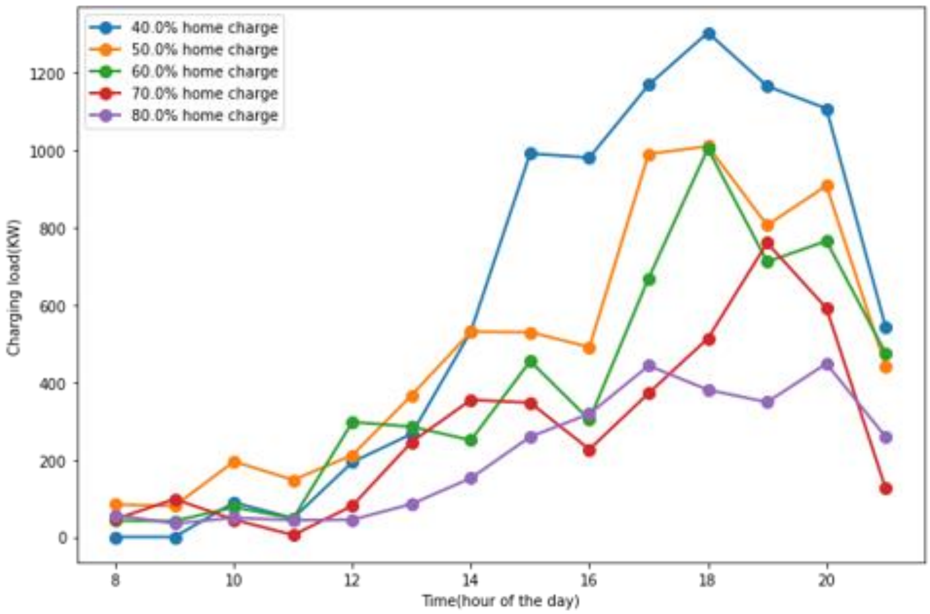

Figure 13. The charging loads of EVs under different home charge access scenarios

6. Conclusion

In this study, we developed a simulation-based platform to model and evaluate performance of transportation network company (TNC) ride-hailing service with a mixed fleet of electric vehicles (EV) and gasoline vehicles (GV). The purpose of this study is to discover the mobility performance, charging demand and emission impact during the TNC fleet electrification process and to specifically quantify the compliance of Clean Miles Standard under different TNC operating scenarios. A case study has been designed in San Francisco with real-world traffic status, trip demand and charging station. Totally 18 scenarios were simulated in SUMO with the combination of 9 EV ratio in the mixed fleet and two driver dispatching policies.

Experiment results showed that the mobility performance in terms of empty distance and rider average waiting time increase slowly with higher EV ratio in the mixed fleet. This is due to the increasing EVs charging demand and charging down time. The off-peak EV priority policy depends on a larger EV fleet size to sustain the TNC service effectively. When EV ratio is lower than 40%, it is undesirable to force the off-peak EV priority policy due-to higher portions of long waiting and deadheading distance. Secondly, the charging demand steadily increases with higher EV ratio in the mixed fleet. The off-peak EV priority policy has higher charging loads compared to the baseline policy, because the TNC platform utilize EVs to serve more riders. However, the peak charging hour in the off-peak EV priority policy occurs before 6 pm in the afternoon, which results in reduced marginal CO2 emissions during daytime hours and enables the fleet to be adequately prepared for the evening peak in ride-hailing requests.

When quantifying the compliance of CMS, we found that the eVMT ratio target is easier to achieve with lower EV ratios in the mixed energy fleet compared to the compliance with the GHG target. By increasing the utilization of EVs to serve ride requests, the eVMT targets can be achieved. However, the TNC companies should pay more attention to ride pooling in order to meet the more constrained GHG targets. With 15% pooled rides, TNC can meet the year 2026 GHG target with 40% of EVs in the MEF with the off-peak EV priority policy. While with 7% pooled rides, the TNC should have 50% of EVs in the MEF in order to meet the GHG targets. Thirdly, the off-peak EV only policy shows superiority in saving extra 30% of CO2 compared to the baseline policy when ev_ratio is at 50%. This emission gap between the two policies narrows down when ev_ratio is smaller (10%) or larger (90%).

According to the sensitivity analysis, the repositioning strategy has less impact on the rider average waiting time. This can be attributed to San Francisco's dense ride demand pattern, where even without active repositioning, drivers efficiently serve riders due to the concentrated demand in various areas. With higher home charge access, TNC drivers can serve the ride-hailing trips with limited public charging demand. These findings underscore the critical need for stakeholders to consider home charge access when planning and constructing charging infrastructure.

Reference

[1] O. Us Epa, “Inventory of U.S. Greenhouse Gas Emissions and Sinks,” Feb. 2017, Accessed: Aug. 01, 2023. [Online]. Available: https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks

[2] “Office of Highway Policy Information - Policy.” https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_model_dev.cfm (accessed Oct. 10, 2023).

[3] “Light Duty Electric Drive Vehicles Monthly Sales Updates.” https://www.anl.gov/esia/light-duty-electric-drive-vehicles-monthly-sales-updates (accessed Jul. 24, 2023).

[4] “Charger Types and Speeds.” https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds (accessed Oct. 10, 2023).

[5] A. Jenn, “Emissions benefits of electric vehicles in Uber and Lyft ride-hailing services,” *NATURE ENERGY*, vol. 5, no. 7, pp. 520–525, Jul. 2020.

[6] “Ride-Hailing’s Climate Risks,” *Union of Concerned Scientists*. https://www.ucsusa.org/resources/ride-hailing-climate-risks (accessed Oct. 11, 2023).

[7] Y. Li, X. Li, and A. Jenn, “Evaluating the emission benefits of shared autonomous electric vehicle fleets: A case study in California,” *Appl. Energy*, vol. 323, Oct. 2022, doi: 10.1016/j.apenergy.2022.119638.

[8] M. Moniot, Y. Ge, and E. Wood, “Estimating Fast Charging Infrastructure Requirements to Fully Electrify Ride-Hailing Fleets Across the United States,” *IEEE TRANSACTIONS ON TRANSPORTATION ELECTRIFICATION*, vol. 8, no. 2, pp. 2177–2190, Jun. 2022.

[9] L. Hu, J. Dong, Z. Lin, and J. Yang, “Analyzing battery electric vehicle feasibility from taxi travel patterns: The case study of New York City, USA,” *Transp. Res. Part C: Emerg. Technol.*, vol. 87, pp. 91–104, Feb. 2018.

[10] T. Wenzel, C. Rames, E. Kontou, and A. Henao, “Travel and energy implications of ridesourcing service in Austin, Texas,” *Transp. Res. Part D: Trans. Environ.*, vol. 70, pp. 18–34, Apr. 2019.

[11] M. S. Hunt J, “Accelerating Ride-Hailing Electrification: Challenges, Benefits, and Options for State Action,” *Northeast States for Coordinated Air Use Management*, 2020.

[12] M. Nicholas, P. Slowik, and N. Lutsey, “Charging infrastructure requirements to support electric ride-hailing in U.S. cities,” unknown, Mar. 2020. doi: 10.13140/RG.2.2.22007.78244.

[13] E. Anastasiadis *et al.*, “On the Selection of Charging Facility Locations for EV-Based Ride-Hailing Services: A Computational Case Study,” *Sustain. Sci. Pract. Policy*, vol. 13, no. 1, Jan. 2021, doi: 10.3390/su13010168.

[14] D. Paudel and T. K. Das, “Infrastructure planning for ride-hailing services using shared autonomous electric vehicles,” *INTERNATIONAL JOURNAL OF SUSTAINABLE TRANSPORTATION*, doi: 10.1080/15568318.2022.2155892.

[15] A. Jenn, “Charging forward: deploying EV infrastructure for Uber and Lyft in California,” *Transportation* , doi: 10.1007/s11116-023-10381-5.

[16] H. Zhang, C. J. R. Sheppard, T. E. Lipman, T. Zeng, and S. J. Moura, “Charging infrastructure demands of shared-use autonomous electric vehicles in urban areas,” *Transp. Res. Part D: Trans. Environ.*, vol. 78, p. 102210, Jan. 2020.

[17] Z. Yi and J. Smart, “A framework for integrated dispatching and charging management of an autonomous electric vehicle ride-hailing fleet,” *TRANSPORTATION RESEARCH PART D-TRANSPORT AND ENVIRONMENT*, vol. 95, Jun. 2021, doi: 10.1016/j.trd.2021.102822.

[18] M. D. Dean, K. M. Gurumurthy, F. de Souza, J. Auld, and K. M. Kockelman, “Synergies between repositioning and charging strategies for shared autonomous electric vehicle fleets,” *Transp. Res. Part D: Trans. Environ.*, vol. 108, p. 103314, Jul. 2022.

[19] M. Maljkovic, G. Nilsson, and N. Geroliminis, “A Pricing Mechanism for Balancing the Charging of Ride-Hailing Electric Vehicle Fleets,” in *2022 EUROPEAN CONTROL CONFERENCE (ECC)*, 2022, pp. 1976–1981.

[20] J. Shi, Y. Gao, W. Wang, N. Yu, and P. A. Ioannou, “Operating Electric Vehicle Fleet for Ride-Hailing Services With Reinforcement Learning,” *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 11, pp. 4822–4834, Nov. 2020.

[21] G. Yu, A. Liu, J. Zhang, and H. Sun, “Optimal operations planning of electric autonomous vehicles via asynchronous learning in ride-hailing systems,” *OMEGA-INTERNATIONAL JOURNAL OF MANAGEMENT SCIENCE*, vol. 103, Sep. 2021, doi: 10.1016/j.omega.2021.102448.

[22] “Electric Vehicles on the Lyft Platform.” https://www.lyft.com/impact/electric (accessed Jul. 25, 2023).

[23] “Uber sustainability.” https://www.uber.com/us/en/about/reports/sustainability-report/

[24] Uber, “Uber Environmental, Social, and Governance Report,” 2023. [Online]. Available: https://www.uber.com/us/en/community/esg/

[25] “Clean Miles Standard.” https://ww2.arb.ca.gov/our-work/programs/clean-miles-standard/about (accessed Sep. 06, 2022).

[26] Z. (tony) Qin *et al.*, “Ride-Hailing Order Dispatching at DiDi via Reinforcement Learning,” *INFORMS Journal on Applied Analytics*, vol. 50, no. 5, pp. 272–286, Sep. 2020.

[27] D. Goeke and M. Schneider, “Routing a mixed fleet of electric and conventional vehicles,” *Eur. J. Oper. Res.*, vol. 245, no. 1, pp. 81–99, Aug. 2015.

[28] “Documentation - SUMO Documentation.” https://sumo.dlr.de/docs/index.html (accessed Jul. 25, 2023).

[29] “Uber Technologies, Inc. 2019. Data retrieved from Uber Movement, (c) 2019 . https://movement.uber.com.”

[30] “Electric Vehicle Charging Station Locations,” *U.S. Department of Energy*. https://afdc.energy.gov/fuels/electricity_locations.html#/find/nearest?fuel=ELEC (accessed Aug. 01, 2023).

[31] T. San Francisco County Transportation Authority, “Today: A profile of San Francisco transportation network company activity.” San Francisco County Transportation Authority, 2017.

[32] “TNCs 2020: A Profile of Ride-Hailing in California,” *SFCTA*. https://www.sfcta.org/projects/tncs-2020-profile-ride-hailing-california (accessed Nov. 15, 2023).

Data Management Plan

Products of Research

Data collected in this research include ride-hailing trips generated by od2trips tool in SUMO, and vehicle data from simulation for evaluating the operational and environmental impacts of TNC trips under the implementation of Clean Miles Standard.

Data Format and Content

The ride-hailing trips data and vehicle simulation data were saved in txt files. The trips data include pick-up locations, drop-off locations, and request time stamps for all the vehicles generated in simulations. The vehicle simulation data include the location, emission and charging information as the output of SUMO.

Data Access and Sharing

The data are publicly available via the UC Riverside instance of Dryad: https://datadryad.org/, which is in compliance with the USDOT Public Access Plan.

Hao, Peng; Liu, Haishan; Wu, Guoyuan; Barth, Matthew. (2024). Ride-hailing Trip and Vehicle data in Simulation for Evaluating the Impact of Clean Miles Standard on the Transportation system [Dataset]. Dryad. https://doi.org/10.5061/dryad.bg79cnpjq

Reuse and Redistribution

The data are restricted to research use only. If the data are used, our work should be properly cited:

Hao, Peng; Liu, Haishan; Wu, Guoyuan; Barth, Matthew. (2024). Ride-hailing Trip and Vehicle data in Simulation for Evaluating the Impact of Clean Miles Standard on the Transportation system [Dataset]. Dryad. https://doi.org/10.5061/dryad.bg79cnpjq