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Evaluation of Mixed Electric Fleet for Ride-Hailing Services under California's Clean Miles Standard: A Case Study in San Francisco

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Abstract — Electrifying the ride-hailing services has the potential to significantly reduce greenhouse gas emissions in the shared mobility sector. However, these emission reduction benefits depend on the utilization of EVs to serve trip requests, especially during the fleet electrification process. In this paper, we evaluated the performance and emission impacts of ride-hailing service with three dispatching policies and various EV penetration levels in the ride-hailing fleet. A large-scale simulation platform was developed for the city of San Francisco in SUMO to enable the application of ride-hailing, electric vehicle charging, and idle vehicle repositioning. Simulation results indicate that with a 60% EVs in the simulated fleet, the off-peak EV priority policy and off-peak EV only policy can reduce CO_2 emissions by 32% - 40% while preserving the mobility performance in terms of deadheading, total travel distance, and average rider pick-up time. It is important for ride-hailing platforms to increase the zero-emission rides and encourage ride pooling to comply with California's Clean Miles Standard.

I. Introduction

Transportation network companies (TNCs), such as Uber and Lyft, have significantly changed personal travel patterns and reshaped the transportation sector. As of 2023, over 7.6 billion trips were fulfilled by Uber globally with 130 million monthly active users [1]. In San Francisco, Uber and Lyft have served approximately 15% of person trips [2]. The fast-growing TNC business may bring new issues, including urban city congestion, excessive energy consumption and pollutant emissions due to deadheading mileage, substitution of public transit, and induced travel demand. An analysis conducted by the Union of Concerned Scientists estimated that TNC rides produce 69% more greenhouse gas emissions compared to the individual trips that riders might make on their own [3]. An empirical data analysis based on 1.5 million individual rides from Austin found 41% - 90% more energy consumption by TNC ride-hailing trips even under the scenario where TNC has high fleet efficiency and high share of pooled rides [4].

Accelerating vehicle electrification is a key strategy to decarbonize the transportation sector while prioritizing the ride-hailing fleet electrification could bring more environmental and societal benefits due to the high daily driving mileage of ride-hailing vehicles. Based on the 1.4 million ride-hailing trips data provided by TNCs, Jenn et al. found that the emission benefits of electrifying a ride-hailing vehicle are three times higher than those from electrifying a regularly used vehicle in California [5] and up to 5 times when considering the cleaner grid development [6]. Mohan *et al* estimated that electrification of Uber and Lyft can reduce the life cycle GHG emissions per trip by 40% - 45% [7]. Additionally, the lower operating/maintaining cost of EVs is attractive to drivers with high driving mileage. Taiebat *et al* utilized a Total Cost of Ownership method to model the EV cost in a ride-hailing service [8]. Results show that a BEV with an annual 10,000 VMT under a 10,000 subsidy and over a five-year commitment period, costs 29% less than an ICEV. In addition, more EVs in the TNC fleet can boost the utilization rate of fast charging stations, which can stabilize charging prices and improve the expansion of DCFC stations [9]. Another non-trivial benefit is that EVs on the TNC platform broaden consumer exposure to EVs and increase public awareness of EV technology and experiences [9].

Consistent with the trend of vehicle electrification, top transportation network companies (TNCs) such as Uber and Lyft, have announced multiple plans to support the transition to a zero-emission platform by 2030 [10], [11]. Uber has partnered with EvGo and Wallbox to provide the fast-charging solution and all-in-one home smart EV-charging option. Drivers with battery electric vehicles are eligible for $1 incentive per ride. More than 37700 ZEV active drivers on the road as reported by Uber, which represents a 4-fold increase over the same period a year ago [1]. As directed by Senate Bill (SB) 1014, the California Air Resources Board (CARB) developed the Clean Miles Standard and Incentive Program, a first-of-its-kind regulation designed to reduce GHG emissions from TNC vehicles and increase the use of zero-emission vehicles (ZEV) [12]. The primary objectives of the Clean Miles Standard (CMS) are to increase the percentage of total miles driven by TNC using ZEVs, and to reduce GHG emissions per passenger mile traveled. The TNCs with 5 million annual VMT are required to comply with this regulation starting from 2023 [12].

However, with the enforcement of California's CMS, it is still unclear about the potential mobility and environmental impact of different TNC operation strategies (as considered part of Intelligent Transportation Systems) and how TNCs could meet the requirements while maintaining high service quality. To bridge this gap, we developed an optimization-based simulation platform to actively explore feasible and eco-friendly vehicle dispatching policies. The contributions can be briefly summarized as follows. Firstly, a large-scale ride-hailing simulation platform was developed in a microscopic traffic simulator, SUMO, with a high-resolution city network, charging stations, parking areas, ride demand as inputs in the city of San Francisco. Secondly, multiple fleet dispatching policies were tested under the fleet electrification process. Thirdly, we evaluated the performance of TNC services and specifically quantified the greenhouse gas emission and eVMT share targets to discover the TNC operation requirements in order to comply with the CMS.

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II. DATASET

A. San Francisco Network

The San Francisco network was first obtained from OpenStreetMap (OSM). To simulate the real-world traffic status, we further calibrated the OSM link speed according to the Uber movement dataset [13] which provide the link-level daily average speed of Uber driver across the city. According to SFCTA, the TNC vehicles were reported to cause a 15% average speed reduction [14]. We first multiplied a ratio of 1.15 with the Uber speed dataset to offset the speed reduction incurred by TNC vehicles so that the network average speed can converge to the real-world Uber speed in the simulation. SUMO network speed was calibrated by mapping the Uber speed with the same link according to osmID. Only 53% of speed data from the Uber movement data can be mapped to the OSM network because Uber used an older version of OSM. This poses a challenge to map the Uber movement data since some osmID change or disappear as roads are split, combined, newly built, or removed. For those unmatched links, we kept the free flow speed from the OSM network.

B. Charging Stations and Parking Areas

The public charging station data in San Francisco (SF) was obtained from the Alternative Fuels Data Center including location, number of chargers, and power level [15]. Currently, SF has 124 DC fast chargers. However, due to our sampling process of the TNC travel demand and the TNC vehicles (explained in the following sections), 25 charging stations with 50 KW rated power were imported into SUMO.

The *SUMOActivityGen* tool was used to generate the taxi parking stands inside the city [16]. A total of 60 taxi stands were extracted. The taxi parking stands were used as idling places for TNC vehicles in the simulation. As an example, Figure 1 presents a snapshot of the simulation environment.

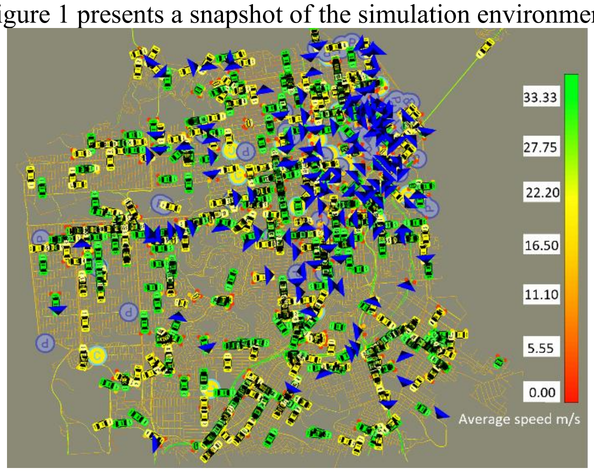

Figure 1. SF network with charging stations (yellow circle with C), parking areas (blue circle with P), TNC vehicles (yellow vehicles are GVs, green vehicles are EVs) and riders (dark blue triangles).

C. TNC Demand

San Francisco County Transportation Authority (SFCTA) released a dataset from the 2017 TNC Today study which provided the hourly pickup and drop-off numbers in 981 traffic analysis zones (TAZ) in San Francisco [2]. 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 origin-destination (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) [17] to validate each trip and deleted the unconnected trips. Tuesday's statistic was selected to generate the travel demand which indicates 150,200 TNC trips over 24 hours. Each trip has the features of origin, destination, trip request time. As shown in Figure 2, the generated TNC trips preserve the spatial patterns from the real-world data. Most of the ride requests are occurred in the northeast quadrant of SF, which is the most congested area in the city. In this study, we simulated the TNC trips from 8 am - 9 pm covering both morning peak and evening peak, with a 20% sample (21754 trips) to reflect a certain level of TNC service and avoid excessive computational time in the microscopic simulation.

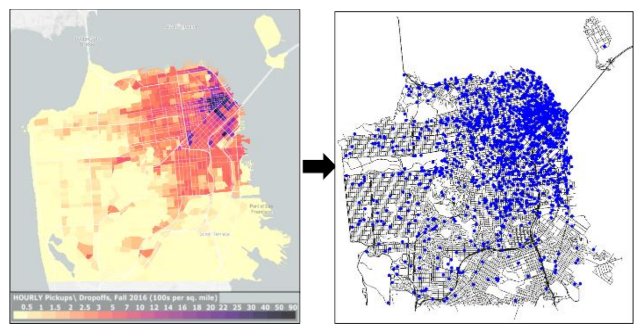

Figure 2. The spatial patterns of TNC today data (left) [2] and generated trips in SUMO (right).

D. Ride-Hailing Fleet

The fleet size is critical to serve the demand through the operating hours. There are around 5000 hourly active drivers in San Francisco with all TNC trips [2]. With the sampled 20% of TNC trips in this simulation study, we set the fleet size to be fixed at 1000. To ensure fair comparisons, all vehicles were loaded into the simulation in the first hour. TNC fleet electrification process was simulated by setting the EV ratio in the mixed fleet ranging from 10% to 90%, with a 10% increment interval.

EVs are assumed to be typical, such as a Kia Soul EV 2020 with calibrated energy consumption parameters provided by SUMO [17], which considers air drag efficiency propulsion efficiency, radial drag coefficient in its energy model. The maximum battery capacity is 64 kwh. We assumed 50% of EVs in the mixed fleet have the home charge option, thus starting the shift with a 100% SOC. While other EVs' initial SOC was generated with a normal distribution with a mean of 32 kwh and variance of 5 kwh. Gasoline Vehicles (GVs) are assumed to have a full tank of fuel.

We set the charging threshold R_c to be 10% of SOC to ensure the vehicle can reach an assigned charging station. This parameter can be tuned according to the driver's preference or the platform's consideration. The charging rate will decrease when SOC approaches to 100%. In the simulation, when an EV reaches 80% SOC at the charging station, it will be available again and wait for new rider assignment.

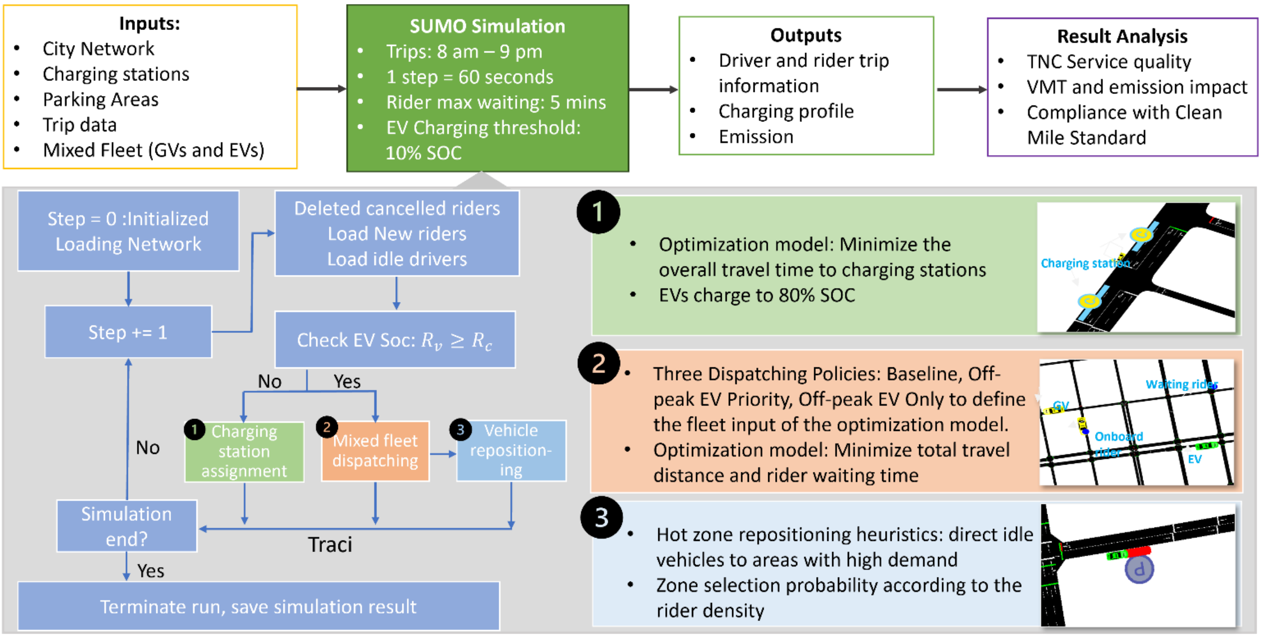

Figure 3. SUMO simulation framework for TNC mixed fleet dispatching, charging station assignment and repositioning

III. METHODOLOGY

In this section, we described the methodology to simulate the TNC ride-hailing service by first presenting the simulation framework. Next, three key modules were explained in detail, including charging station assignment, mixed fleet dispatching, and idle vehicle repositioning.

A. Simulation Framework

The simulation platform was constructed with SUMO, which is an open-source, microscopic and continuous traffic simulation software [17]. The newly added Taxi module, Electric module, and charging station module make it possible to simulate the TNC mixed fleet operational scenarios. The overall simulation framework was presented in Figure 3. SUMO takes the city network, charging stations, and parking areas as inputs to load the TNC operating environment. There are two types of vehicles in the simulation: Electric Vehicles (EVs) and Gasoline Vehicles (GVs). TNC drivers fulfill the customer rides according to the platform dispatching results. Riders enter the system with their origins and destinations, anticipating having a matched driver shortly. SUMO loads ride requests from 8 am to 21 pm and updates the system status every 60 seconds.

In each simulation time step, trip requests that haven't been responded after 5 minutes will be canceled by riders. With the updated trip requests and driver information, the platform first checks the EVs' battery status and enforces EVs to charging stations whose SOC is lower than 10% of battery. Secondly, with a mixed fleet of vehicles, the platform dispatches drivers to serve the travel demand. Finally, idle drivers choose to relocate to the areas with high demand. The behavior of riders and drivers were observed and controlled via *TraCI* (***Tra****ffic* ***C****ontrol* ***I****nterface*). Details about these three steps are provided in the following subsections. At the end of the simulation, high-resolution trip status outputs, charging station utilization, and emission profiles were obtained, based on which we further analyze the performance and impacts of TNC services.

B. Charging Station Assignment

Assuming that there are $|C|$ available charging stations and $|V|$ EVs require charging. A charging station c's location is c_o. The vehicle v's current location is v_{pos}. Then the travel time from the vehicle's position to a charging station is $f_t(v_{pos}, c_o)$. 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 selected. Let $\delta_v = \sum_c x_{vc}$ to indicate whether vehicle c is assigned to a charging station. If $\delta_v = 1$, then vehicle v is dispatched. Otherwise, $\delta_v = 0$. 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. The optimization model can be formulated as follows:

$$min \sum_{v \in V} \sum_{c \in C} \left(f_t(v_{pos}, c_o)\right) x_{vc} - \sum_{v \in V} B\, \delta_v \quad (1)$$

subject to

$$\sum_{v \in V} x_{vc} \leq N_c \quad \forall c \in C \quad (2)$$

$$\sum_{c \in C} x_{vc} = \delta_v \quad \forall v \in V \quad (3)$$

$$e_{vc} x_{vc} \leq R_v \quad \forall v \in V, \forall c \in C \quad (4)$$

$$x_{vc} \in \{0, 1\} \quad \forall v \in V, \forall c \in C \quad (5)$$

This model aims to minimize the total travel time to visit the charging stations. This objective function is designed to allow the EVs to visit a nearby available charging station to alleviate the range anxiety. Besides, to avoid ignoring available charging stations, a high penalty factor B is enforced in the objective function. Constraint (2) sets the number of vehicles assigned to a charging station c should be no more than the available chargers N_c to avoid long queues. Constraint (3) enforces each vehicle can only be assigned to at most one charging station. Constraint (4) guarantees the assignment feasibility by ensuring the vehicle has enough battery to reach the charging station. Constraint (5) defines the decision variables.

C. TNC Mixed Fleet Dispatching

With the updated availability of drivers and ride requests, a weighted bipartite graph can be constructed with $|V|$ available drivers and $|R|$ rider requests. At time step T, if a rider places a request at t_r, then the rider waiting time is $\max(0, T - t_r)$. The travel time from vehicle v*'s* current location v_{pos} to rider's origin location is defined as $f_t(v_{pos}, r_o)$, where f_t is the travel time function considering the network traffic status. The decision variable is a binary variable x_{vr}, which takes value 1 if rider r is served by vehicle v; otherwise, x_{vr} equals 0. To simplify the model construction, we use $\delta_r = \sum_v x_{vr}$ to indicate whether rider r is dispatched. If δ_r = 1, then rider r is dispatched. Otherwise, δ_r = 0. The mixed fleet consists of m^G gasoline vehicles (GV) and m^E electric vehicles (EVs). 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 mixed fleet dispatching model can be formulated as follows:

$$min \sum_{v\in V} \sum_{r\in R} \Big(max(0, T - t_r) + f_t\big(v_{pos}, r_o\big)\Big) x_{vr} - \sum_{r\in R} B\, \delta_r \quad (6)$$

subject to

$$\sum_{r\in R} x_{vr} \leq 1 \quad \forall v \in V \quad (7)$$

$$\sum_{v\in V} x_{vr} = \delta_r \quad \forall r \in R \quad (8)$$

$$(1 - y_v) R_v \geq R_c \quad \forall r \in R \quad (9)$$

$$\sum_{v\in V} \sum_{r\in R} x_{vr}(1 - y_v) \leq m^E \quad (10)$$

$$\sum_{v\in V} \sum_{r\in R} x_{vr} y_v \leq m^G \quad (11)$$

$$x_{vr}, \delta_r, y_v \in \{0, 1\} \quad \forall r \in R, \forall v \in V \quad (12)$$

This model aims to minimize the total request waiting time and rider pick-up time to guarantee both customer equity and system efficiency. If a request has been waiting for a long time, then in the next time step, it will have a higher opportunity to be matched. In this way, the platform can 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 constraints (7) and (8) respectively. When matching a rider with an EV, the solution is constrained by the EV's remaining range. As stated in constraint (9), the EV's remaining range should be higher than the charging threshold R_c which can be customized according to the distribution of charging stations, vehicle's energy efficiency, drivers' preferences, etc. Constraints (10) and (11) guarantee the number of dispatched EVs and GVs complies with the fleet composition. Constraint (12) defines the decision variables x_{vr} and auxiliary variables δ_r according to the problem setting.

To explore the strategies that utilize EVs efficiently to serve the ride requests, we investigated three dispatching policies during the fleet electrification process.

- Baseline policy (**B**): EVs and GVs are dispatched equally in the platform. $|V|$ consists of all available EVs and GVs.
- Off-peak EV Priority policy (**EV Priority**): During the off-peak hours, the platform utilizes EVs with higher priority. If EVs are not sufficient to serve all ride requests, GVs are randomly selected and added to the fleet set $|V|$. During the morning peak and evening peak, the platform employs the baseline policy to dispatch riders.
- Off-peak EV Only Policy (**EV Only**): This policy enforces more constrained requirements, in which only EVs are allowed to serve ride requests during the off-peak hours and the fleet set $|V|$ only contains EVs.

D. Repositioning Strategy

In this module, a greedy algorithm was implemented to search for vehicle repositioning areas. It includes two steps:

(1) Hot Zone Identification: The probability of selecting each parking area is calculated according to the zone-level rider number.

(2) Reposition Zone Selection: The platform selects a parking area for each idle vehicle according to the zone probability. It's important to note that even as the driver is heading to an assigned parking area, the platform retains the capability to dispatch new rider requests to the repositioning vehicles.

E. Model Initialization

During each simulation step, the charging station assignments model was instantiated by finding the current locations of all EVs that need to get the battery charged and the locations of charging stations. We queried the travel time between the combination of all possible charging station and EV pairs by calling the *DUARouter.* Similarly, in the mixed fleet dispatching model, we first obtained all driver locations and rider locations and then queried the travel time of all possible combinations from the drivers' location to the rider's pick-up location. The rider waiting time was calculated with $T - t_r$. The Gurobi solver was employed to solve these two models optimally. Finally, idle drivers are repositioned to high demand areas. Each driver only repositions once to wait for the next trip assignment.

Table 1. Scenario requirement for TNC to compliance with the CMS in year 2023(252 g CO_2/PMT & 2% eVMT, colored in pink), year 2026 (161 g CO_2/PMT & 30% eVMT, colored in yellow), year 2029 (30 g CO_2/PMT & 80% eVMT, colored in green)

Policy	**B (Baseline Policy)**				**E_P (off- peak EV Priority)**				**E_O (off-peak EV Only)**			
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 (%)**	**7% pooled (g/pmt)**	**15% pooled (g/pmt)**	**30% pooled (g/pmt)**	**eVMT ratio (%)**
10%	291	277	**254**	**9%**	340	324	297	10%	256	**243**	**223**	**20%**
20%	261	**248**	**227**	18%	284	270	**248**	**22%**	**200**	190	174	**35%**
30%	228	217	199	28%	**220**	**210**	192	**36%**	**150**	**142**	**131**	51%
40%	199	190	174	**37%**	168	**160**	**147**	49%	118	113	103	61%
50%	166	**158**	**145**	48%	**115**	109	100	63%	94	90	82	69%
60%	**135**	128	117	57%	90	86	79	71%	78	74	68	75%
70%	95	91	83	70%	61	58	53	**81%**	58	55	51	**81%**
80%	66	63	58	79%	42	40	36	87%	39	37	34	88%
90%	34	32	**29**	**89%**	**21**	**20**	**18**	93%	**21**	**20**	**18**	93%

IV. Evaluation and Results

The SUMO simulation was run for each EV ratio (10% - 90%) in the mixed fleet according to three dispatching policies: baseline (B), off-peak EV priority (E_P), and off-peak EV only (E_O). A total of 27 simulation runs were conducted, holding fixed the TNC ride demand, EV charging behaviors and other model assumptions. In this section, we compared the results of our simulation studies and specifically quantified the criteria in Clean Miles Standard to understand the compliance of it. Finally, extra simulation studies were conducted to study the necessary redundancy of the EV fleet during the day and explore the potential to enforce EV only strategy across the overall simulating hours.

A. *Impact Evaluation*

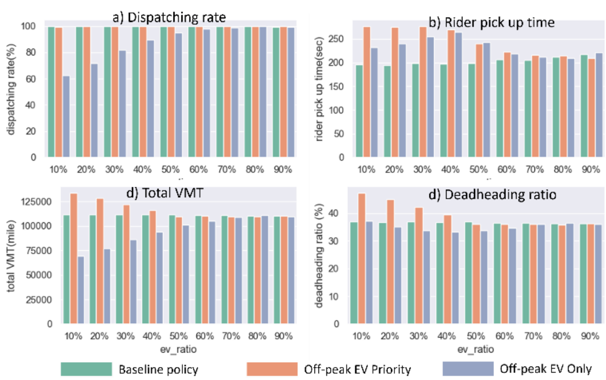

Figure 4. TNC system performance under three fleet dispatching policy

The four subgraphs in Figure 4 illustrate key performance metrics: the dispatching rate (ratio of riders where a driver is assigned to the rider within 5 minutes), rider average pickup time, total VMT (total travel miles), and deadheading ratios (the percentage of driving miles without a rider onboard). Notably, the dispatching rates of B and E_P policies surpass those of the E_O policy when the EV ratio is below 40%. This is because the dispatching rate is heavily influenced by the available vehicles to serve the ride requests. With a limited number of EVs in the mixed fleet, relying solely on EVs to fulfill ride requests during off-peak hours is impractical. The average pickup time under both E_P and E_O policies is initially higher than that of the baseline policy but eventually converges to a similar level. This inefficiency is attributed to the scarcity of EVs in the system, leading to longer distances traveled to pick up riders. On the other hand, the E_P policy exhibits higher VMT and deadheading ratios when the EV ratio is lower owing to the random selection of GVs to serve riders when there are insufficient EVs during off-peak hours. All metrics ultimately converge to similar levels as the EV ratio increases in the system, which underscore the potential of implementing eco-friendly policies to efficiently serve a larger number of riders.

B. *Clean Miles Standard (CMS) Compliance*

In this section, we quantified the greenhouse gas factor (gram CO2 emission per passenger miles travelled) and the eVMT ratio (the number of miles driven by EVs as a percentage of total VMT). 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. We then calculated the greenhouse gas factor with equation (13). 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 [18]. Thus, we tested the pooled scenarios with 7%, 15% and 30% of pooled rides with the compliance occupancy set to be 1.57, 1.65 and 1.80.

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

Table 1 presents the results of greenhouse gas factor and eVMT ratio under different dispatching policies and ride pooling ratios. We marked the results in pink, yellow and green color to represent the scenario which could meet with the CMS target at year 2023, 2026, and 2029. We found that the eVMT ratio is easier to achieve compared to the greenhouse gas 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. 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.

C. EV Redundancy in the Fleet

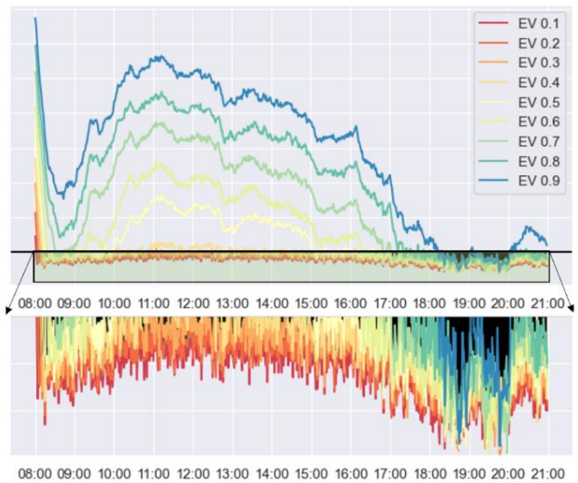

Figure 5. EV redundancy changes with the EV-priority policy

In this section, to further explore the EV requirements to support the TNC operation during the entire simulation hours, we simulated the EV Priority policy for all simulation hours. The EV redundancy is recorded in every simulation step, which is defined as the number of available EVs minus the number of riders at the time step. A positive value indicates EV redundancy while a negative value indicates EV shortage.

The result is plotted in Figure 5. With EVs ratio higher than 50%, it is practical to enforce the off-peak (10 am – 16 pm) EV only policy since the EV redundancy is above zero. When ev_ratio is at 90%, the simulated fleet can cover the morning peak (8 am-10 am) demand. However, it is still not sufficient to cover the evening peak demand within the simulated scenario as there is a negative gap between the available EVs and travel demand. More advanced strategies should be developed to guide the off-peak hour charging in order to prepare the fleet for the peak demand.

V. Conclusions and Future Work

In this paper, a simulation-based platform was developed to model and evaluate the performance of ride-hailing services with a mixed fleet of electric vehicles (EVs) and gasoline vehicles (GVs). A large-scale ride-hailing simulation has been designed in San Francisco with the SUMO simulator, along with the charging station assignment module, mixed fleet dispatching module, and vehicle repositioning module to support realistic TNC operations. We evaluated the ride-hailing service performance and its compliance with Clean Miles Standard under different dispatching policies. Experiment results showed that the performance of the E_P and E_O policies, in terms of dispatching rate and rider pickup time, is dependent on the available number of EVs in the mixed fleet. With a higher penetration rate of EVs, the performance of these two policies reaches the same level as in the baseline policy. The compliance with the eVMT target is much easier than that of the greenhouse gas target. Meeting the latter objective requires a more focused effort on encouraging ride pooling and increasing the zero-emission rides. In the future, more realistic demand setting and charging behavior of ride-hailing drivers will be investigated.

Acknowledgment

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