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RESEARCH ARTICLE

Exploring the Potential of Placing Charging Stations at Relief Stands for EV Fleets in Ride-Hailing and Taxi Services

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ABSTRACT In recent years, there has been a significant surge in the adoption of electric vehicles (EVs) in public transportation services, particularly in sectors like bus and taxi operations. This paper focuses on the management of EV fleets within the specific framework of ride-hailing services. To comprehensively assess various aspects of such a system, a Discrete Event Simulation (DES) model has been developed, with a thorough description provided herein. The DES is used to investigate various charging strategies with different levels of involvement of the dispatcher, evaluating their impact on operational efficiency and financial performance. One notable aspect explored is the potential utilization of taxi relief stands as charging station locations for EV fleets. The proposed system is analysed through a case study for New York City. Our findings underscore the pivotal role of charger quantity within the system and the level of dispatcher engagement. Leveraging real-world data, the case study provides valuable insights into the practical implementation potential of the proposed system, offering actionable guidance for future applications in this domain.

INDEX TERMS Charge scheduling, discrete event simulation, electric vehicle fleet, mathematical modeling, taxi service.

I. INTRODUCTION

In recent times, the adoption of electric vehicles (EVs) has surged worldwide. This increase is significantly supported by various government incentives that aim to achieve net zero carbon emissions [1], [2]. EVs play a critical role in reducing the carbon emissions attributed to motorized personal transportation, which accounts for approximately one-third of the global carbon emissions [3]. Extensive research efforts are underway to enhance the adoption of EVs by developing advanced charging infrastructures and leveraging the adaptability of EV charging [4]. This flexibility in charging is crucial in addressing the challenges associated with the growing integration of renewable energy sources, as explored in the works of [5], [6], and [7]. There has been an extensive effort for the electrification of public transportation through using electric buses and fleets of EVs in taxi or ride-hailing services. An extensive review on the use of electric buses in public transport can be found in [8]. Specific studies include, e.g. [9], where the authors investigated ways to answer the research question about the potential for total energy savings and all-electric operation for a plug-in hybrid-electric bus fleet operated according to selected management strategies with a case study for Curitiba, Brazil. A case study for the City of Graz, Austria, can be found in [10]. The authors use an

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integer linear programming-based optimization model for determining an optimal technology decision for various bus lines, considering the integrated effects on charging and vehicle scheduling as well as infrastructural design.

The transition to EVs in taxi fleets has encountered various challenges, as evidenced by real-world pilot projects and studies. For instance, a London-based pilot project conducted by Uber unveiled substantial hurdles, including limited access to home charging for over 80% of the EV drivers and inadequate public infrastructure hindering their ability to serve rides efficiently, especially compared to Internal Combustion Engine Vehicles (ICEVs) [11]. Reports from transportation network company (TNC) drivers with EVs echoed similar sentiments, citing reduced ride availability due to insufficient charge and revenue losses from prolonged charging times and queuing issues [12]. Moreover, research in regions like South Korea and Beijing pointed out the challenges faced by EV taxis, such as lower cost-effectiveness compared to natural-gas-powered counterparts due to limited charging infrastructure and battery range [13], [14].

Driven by environmental concerns and policy mandates, China has aggressively pursued EV adoption in transportation, particularly within taxi fleets. Notably, Shenzhen has emerged as a leading example, fully transitioning its sizable taxi fleet of over 20,000 vehicles to EVs [15]. However, interviews with drivers and media reports highlight significant time losses during charging, with some drivers spending over three hours daily at charging stations. This extended charging duration leads to revenue losses, compounded by challenges related to queuing at popular charging spots [16]. Efforts to address these challenges include optimizing the placement of charging stations [17], [18]. A second direction has been the analysis [15] and development of effective charging schedules [19], [20] for taxi EV fleets.

When assessing the effectiveness of various strategies, simulations play a crucial role, often employing agent-based modeling due to their ability to accurately depict interactions among system participants. For instance, agent-based models are utilized in optimizing dispatching and charging management for autonomous EV ride-hailing fleets, as evidenced in studies like [21] and [22]. These models also prove useful in evaluating the impact of advanced control systems in ride-hailing services, particularly those incorporating reinforcement learning techniques [23].

Another powerful simulation method for modeling EV fleets is discrete event simulation (DES), known for its effectiveness in capturing EV usage patterns in urban settings [24]. DES, in conjunction with genetic algorithms, has been successfully applied to solve fleet allocation problems in EV sharing systems [25]. Furthermore, DES is instrumental in evaluating optimal EV fleet sizes for ride-sharing services [26] and analyzing operational strategies for electric buses [27] and autonomous EVs [22]. Additionally, DES-based simulations are valuable in assessing ride-hailing services using EVs [21] with a special focus on dispatching and charging management. In [28], DES is integrated with a Stackelberg game model where a central dispatcher offers prices for each charging station to influence and balance the charging demand at each node.

This study focuses on analyzing the charging management of an EV fleet within a ride-hailing or taxi service context. Specifically, we aim to explore the feasibility of utilizing taxi relief stands as potential locations for EV charging points. These stands are commonly used by taxi or ride-hailing service drivers to park their cars for several hours during the day. By installing charging points at these locations, we anticipate providing a significant level of convenience to EV drivers, as these spots are already strategically chosen for driver convenience.

Metropolitan areas typically have numerous taxi relief stands, which often feature a limited number of parking spots but offer the potential for installing charging points. This initiative aims to leverage existing infrastructure efficiently, aligning with the growing EV market's needs and supporting sustainable transportation solutions.

The primary objective of this study is to assess the viability of establishing a system for managing EV charging within a fleet context. To facilitate a comprehensive analysis of this system, a DES model has been developed. This model integrates various components to enable the evaluation of multiple approaches to fleet charging management. Furthermore, the model assesses the impact of different charging system capacities, specifically the total number of available chargers.

This analysis is grounded in real-world data and is conducted through a case study focused on New York City, USA. By utilizing actual data, the study aims to provide practical insights into the effectiveness and feasibility of implementing such a charging management system within a large metropolitan area like New York City.

The paper is structured as follows: The subsequent section offers an in-depth description of the proposed DES model, along with detailed explanations of the strategies proposed for fleet charging management. Section III delves into the used data sources, providing insights into their characteristics and properties. Following this, the ensuing section presents the outcomes of the computational experiments conducted, based on a case study focused on New York City. Finally, the paper concludes with a summary of key findings, concluding remarks, and potential avenues for future research.

II. DISCRETE EVENT SIMULATION

This section introduces the simulation model designed for employing an EV fleet within a ride-hailing service. We begin with an overview of the modeled system, followed by an in-depth exploration of the proposed DES.

The system comprises of a dispatcher, a network of charging stations, and a fleet of EVs. The dispatcher serves as the central hub for distributing information about ride requests from potential passengers. Furthermore, when employing more sophisticated charging strategies, the dispatcher also coordinates the charging sessions for the EVs. In this and subsequent sections, the term *charging session* refers to the period during which a specific EV charges at a particular charging station. Each individual EV is responsible for executing tasks related to both ride requests and movement related to charging sessions. Finally, the charging stations are tasked with managing the queuing processes, monitoring resource utilization times, and overseeing other critical aspects of the EVs' charging-related activities. This integrated approach ensures a realistic representation of the modeled ride-hailing system.

The proposed system is effectively modeled using DES. The foundational setup is structured as follows: the simulation is conducted over a specific time window (or time horizon), ranging from 1 to T, to capture the dynamics of the system under study. It begins with the assumption that all ride requests received by the dispatcher are accompanied by critical details such as the time of request, pick-up and drop-off locations, as well as the estimated length and duration of each ride. These details are essential for scheduling and dispatching the fleet efficiently.

The system employs a fleet of N EVs, each designated to fulfill transportation requests. Each EV is equipped with state variables that continuously update its current location and state of charge. This dynamic tracking helps in optimizing route planning and energy management, ensuring that the vehicle behavior reflects the state of charge (SoC). Furthermore, the charging stations, pivotal components of this network, have specific locations and capacities (the number of charging points they house). In the DES framework, these charging stations are treated as resources. Each station's role is to facilitate the recharging of EVs.

In the simulation model, certain events – for instance, when a ride request is received or when a charging station is ready to be used – start other actions. These actions affect the location of EVs and the operation of the whole system. With the intention of having a simpler implementation some system parameters are considered global and available to all the DES components. These values are the battery capacity of each EV, EV speed, charging power at stations, electricity consumption per kilometer, and hourly electricity prices.

The objective of the model is to make it possible to have a detailed examination of how different strategies affect the efficiency of the EV fleet, such as the number of satisfied requests, costs, charging waiting times and others. It should be noted that in the proposed model things like different driver habits, labour laws and traffic congestion are not considered.

The DES is modeled over the given time window consisting of individual time periods. Events in the simulation are processed at each time period. In the proposed simulation each time period corresponds to a minute in the real world. The processing of events has the following components:

- The dispatcher assigns charging sessions to EVs based on their current state of charge and other factors
- The dispatcher receives and assigns ride requests to EVs.
- EVs resolve the assigned ride requests or they continue the tasks related to previously assigned requests.

In the following subsections, each of these components will be analyzed.

A. ASSIGNING RIDE REQUESTS

We begin by outlining the procedure for assigning ride requests within our system. At each time interval t, the dispatcher receives a collection of ride requests denoted by R. It is crucial to note that each request is associated with a specific time constraint, requiring that an EV arrives at the pick-up location within a predetermined duration.

To optimize the assignment of these requests, the dispatcher evaluates the current locations of all available EVs in the fleet. The assignment is made based on proximity, specifically choosing an EV that can reach the pick-up location the fastest. Here, "closest" (as a substitute for fastest) refers not to geographical distance but to the shortest estimated travel time.

When no EV can reach the pick-up location within the set time limit, the ride request is (unfortunately) dropped. The system ensures that ride requests are handled efficiently, minimizing waiting times for passengers and optimizing the use of fleet resources. An EV follows a specific sequence when addressing a ride request in our proposed DES model. Initially, upon accepting a ride request, the EV is marked as unavailable and then proceeds to the passenger's pick-up location. Note that an EV will not accept a ride if after its competition, the SoC would be bellow a specific threshold. After arriving, it completes the journey by transporting the passenger from the pick-up to the drop-off location.

To address common concerns such as range anxiety among EV drivers, the model incorporates a charging component directly linked to the ride-request process. Range anxiety typically occurs after the SoC decreases significantly, which is a frequent outcome after completing a ride. To manage this, the simulation dictates that if the SoC falls below a predetermined threshold, the driver must consider recharging the vehicle. This decision point is critical: the driver can either opt to charge the EV, thereby temporarily rendering the vehicle unavailable, or decide against charging, in which case the EV can immediately accept new ride requests. The completion of the charging process also marks the EV as ready for further assignments.

This workflow is crucial for managing both the logistical aspects of EV operation and the psychological comfort of drivers concerning vehicle range. A detailed visual representation of this ride-request resolution process, including decision points related to charging, can be seen in Figure 1. This figure helps to illustrate the sequence of events from accepting a ride request to becoming ready for subsequent tasks, providing clarity on the operational dynamics of the EV within the simulation model.

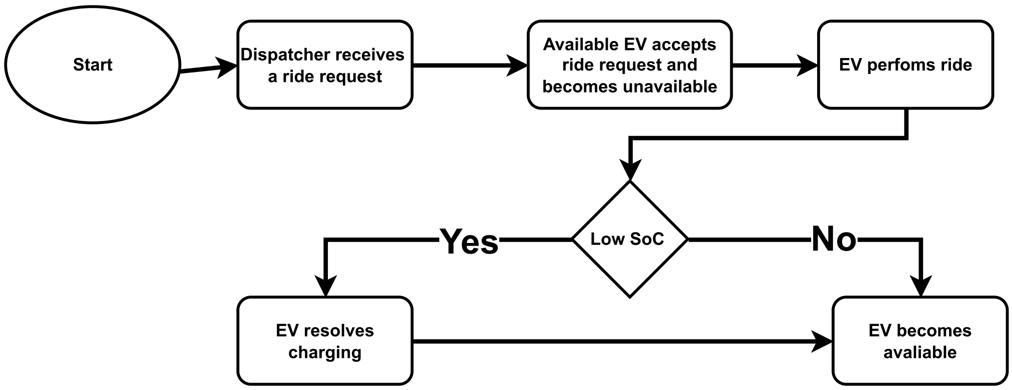


FIGURE 1. Illustration of the process of resolving a ride request in the DES.

B. EV CHARGING PROCEDURE

An EV follows a detailed procedure to resolve charging needs, as illustrated in Figure 2. Initially, the driver either selects or is assigned a charging station and then proceeds to travel to this location. Upon arrival, the driver assesses the suitability of the station, considering factors such as the length of the queue and the state of charge of the EV. If the station does not meet the driver's criteria related to queue length, the driver chooses another station and repeats this evaluation process. Once a suitable station is found, the driver queues for a charger if necessary, charges the vehicle for the required number of time periods to fully recharge the battery, and then departs from the station.

Several assumptions underpin the charging process and the EV's state of charge in our DES model. First, it is assumed that the battery depletes at a constant rate, which correlates directly with the traveled distance. Additionally, the charging speed is considered linear; specifically, the charging time is calculated as the amount of charge needed to reach full capacity divided by the charger's power output. Note that this assumption is exact for charge until 80% of SoC.

Each charging station in the DES is modeled as a standard resource with a specified capacity, which simplifies the management of queue times within the simulation by automatically resolving the waiting periods based on available resources.

C. LOAD MANAGEMENT STRATEGIES

The subsection introduces various charging strategies employed within the DES. These strategies encompass two primary components. The first component outlines how drivers choose or are assigned a charging station and determine its suitability for their needs. The second component delves into the dispatcher's role in assigning charging sessions to drivers.

It is important to note that not all strategies encompass both components mentioned earlier. The focus is on evaluating the differences in driver autonomy and dispatcher involvement across these strategies. Detailed explanations of each strategy follow in the subsequent text.

In the implementation of these strategies, a simple estimation of waiting time at a charging station is approximated using the equation provided below.

$$T_w = \frac{Q_l}{N_s} \frac{0.8 \cdot BatteryCapacity}{ChargerPower} \tag{1}$$

Eq. (1), states that the waiting time T_w is proportional to the queue length (Q_l) divided by the number of chargers at the station (N_s). This value is divided with the expected time needed to charge an EV. It is assumed that the SoC is at 20% and that the charging speed is linear so it is equal to $0.8 \cdot BatteryCapacity$ divided by the $ChargingPower$. Note that more advanced queuing models, such as the M/M/c (Erlang–C model), are not used because other approximations in the DES would negate the additional precision these models provide. Thus, incorporating them would not significantly enhance the overall accuracy of the model.

Within the DES, three distinct charging strategies are explored, each reflecting varying degrees of driver autonomy within a ride-hailing service. These strategies include: completely free driver decision making (CFD), drivers requesting a charging session (DRC) and dispatcher assigning charging sessions to drivers (DAC).

1) COMPLETELY FREE DRIVER DECISION MAKING (CFD)

In this scenario, an EV driver initiates the charging process when the SoC falls below a predetermined threshold. The driver then heads to the nearest available charging station. With the intention of having a more realistic representation of driver behavior, when selecting the nearest station the distance is multiplied with a random value to represent specific preferences. Upon arrival, if the estimated waiting time at the station is shorter than the maximal waiting time the driver is willing to tolerate, the driver joins the charging queue. However, if the expected waiting time exceeds the driver's acceptable limit, the driver searches for the next closest charging station to attempt charging there instead. This iterative process continues until the driver finds a suitable station or determines that relocating to another

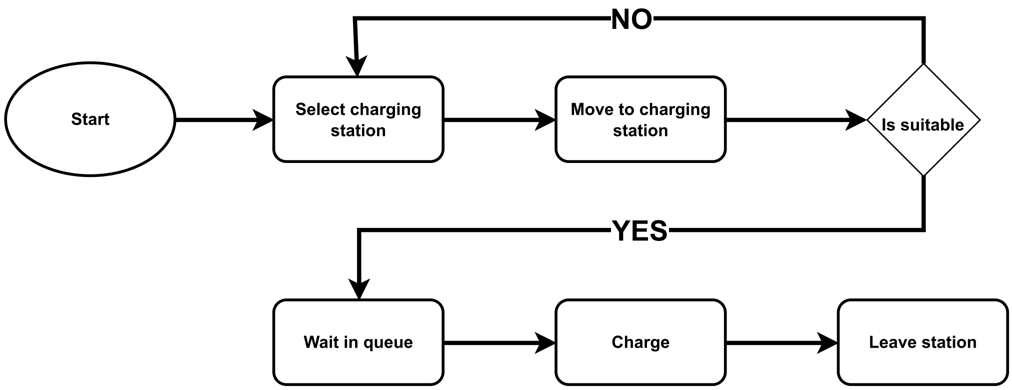


FIGURE 2. **Illustration of the process of resolving a charge request in the DES.**

charging station carries too much risk due to the EV's low SoC.

2) DRIVERS REQUESTING A CHARGING SESSION (DRC)

In this scenario, it is assumed that the dispatcher possesses information regarding the queue length at each charging station and the precise location of the EV requesting a charge. The driver's decision-making process for initiating charging remains the same as in the CFD scenario. However, in this case, instead of autonomously choosing a station, the driver sends a request to the dispatcher specifying the need for a charging session. The dispatcher then evaluates all available charging stations based on the sum of the time required for the driver to reach each station and the expected waiting time at each station's queue. The dispatcher directs the driver to a station where this combined time is minimal. An important distinction from the CFD scenario is that once the dispatcher assigns an optimal station, the driver does not move to another station. This setup allows for a more coordinated approach, where the dispatcher optimizes station assignments based on real-time data, reducing the likelihood of drivers needing to relocate to different stations during the charging process due to long queues.

3) DISPATCHER ASSIGNING CHARGING SESSIONS TO DRIVERS (DAC)

In this setting, the dispatcher exercises a higher level of control over the charging of the EV fleet. It is assumed that the dispatcher is also aware of the SoC of all EVs in the system. The goal is to leverage this additional information to minimize the total cost of charging for the entire fleet. It is important to note that while the dispatcher has significant control over charging, drivers may still request to be charged if their SoC falls below a minimal threshold due to range anxiety.

In the DES model, the process is as follows: at each time period, the dispatcher first assigns charging sessions to available vehicles and then handles ride requests. Once an EV accepts a charging session, it becomes unavailable and begins the charging process. The choice of charging station for each EV follows the DRC approach. After charging is complete, the EV becomes available again.

The main challenge in this strategy is how to optimally assign charging sessions to EVs to minimize costs. Several assumptions are made about the information available to the dispatcher: day-ahead electricity pricing with known hourly rates, an estimate of the number of daily charges per EV (d_c), the total available charges in the system (C) with a recommended occupancy rate, and the average number of time periods required to charge an EV (t_c).

The dispatcher's objective is to determine the best assignment of charging sessions to EVs. This problem is divided into two subproblems: determining the number of EVs to be charged at each time period in advance, and deciding which EVs will be charged at each time period online, based on real-time information.

The first step in solving this problem is specifying the total number of time periods all the EVs need to be charged. This can be modeled using the following equation:

$$T_c = N \cdot d_c \cdot t_c \tag{2}$$

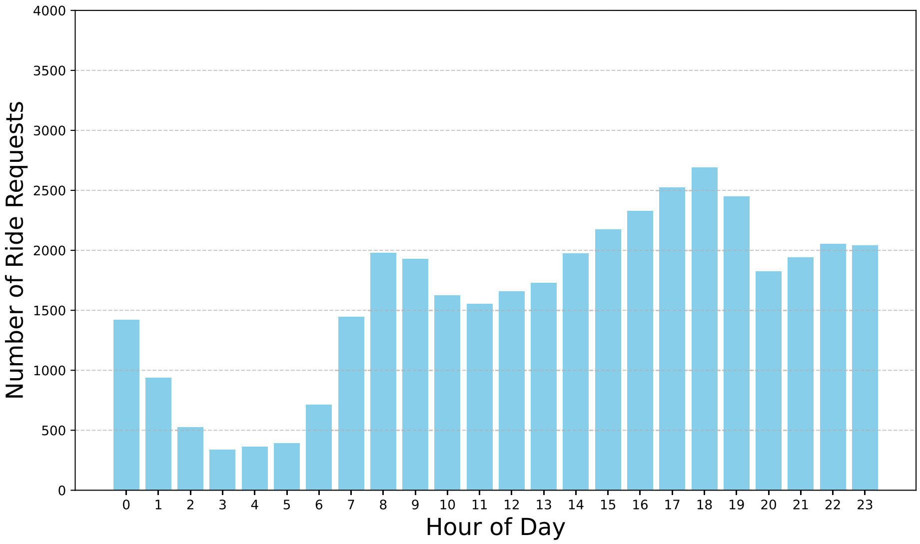
where T_c represents the total number of EV charging time periods needed per day.

The model optimization can be achieved through the following linear programming approach. Given the assumption of constant charging power in the DES, pricing can be designated for each time period per EV undergoing charging. The integer decision variables x_i for $i = 1 \ldots T$ provide information on the number of vehicles to be charged during each time interval. The proposed model has the following form.

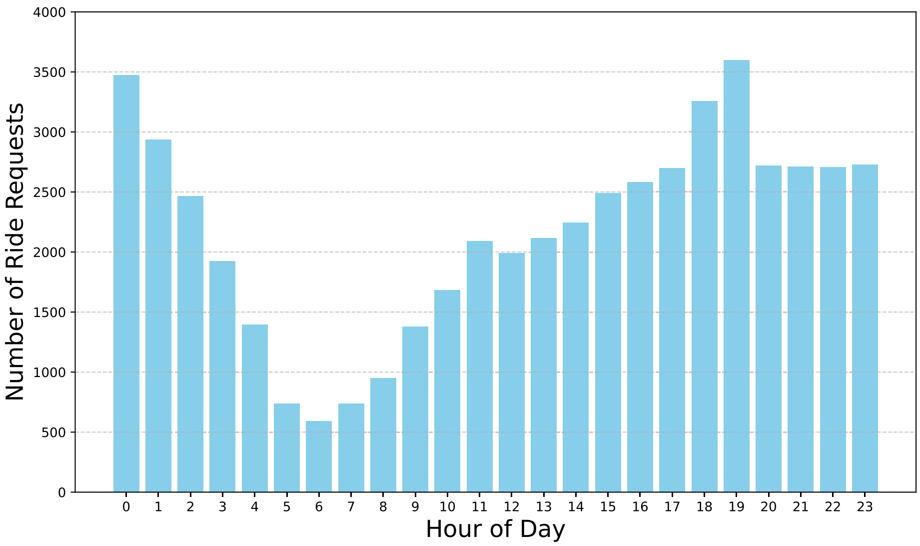
$$\text{minimize} \quad \sum_{i=1}^{T} p_i x_i \tag{3}$$

$$\text{s. t.} \quad \sum_{i=1}^{T} x_i = T_c \tag{4}$$

$$0 \leq x_i \leq C, \ i = 1 \ldots T \tag{5}$$



(a) Work day



(b) Weekend

FIGURE 3. **Ride-request frequency during work days and weekends.**

Equation (3) defines the objective as minimizing the total charging cost across all time periods. This cost for each time period is determined by multiplying the number of EVs being charged by the price per EV charged during that period (p_i indicating the price during period i). Equation (4) ensures that the total charging time for all EVs equals the required charge T_c, while (5) imposes the constraint that the number of EVs charged in any time period cannot exceed the available chargers.

The second part of assigning charging sessions involves determining which EVs are charged at each time period. In the DES model, this is accomplished by comparing the current number of EVs being charged (c_n) with the planned number (x_t) for that period. If c_n is less than x_t, $x_t - c_n$ EVs with the lowest SoC are selected for charging. The charging station that will be used by an EV is acquired as in the DRC approach.

III. DATA

The objective of this study is to utilize the presented DES model for evaluating the feasibility of different charging strategies of an EV fleet in a ride-hailing service. The aim is to achieve a more realistic assessment of the system by incorporating real-world data into the computational experiments. This includes utilizing actual data for ride requests, electricity pricing, and identifying potential locations for charging stations. By integrating real-world data, the simulation can provide insights into the practical implications and viability of deploying an EV fleet within the ride-hailing domain.

The first data set that is used is the trip records collected from the NYC Green Taxi data [29]. The trip records contain information such as pick-up/drop-off dates and times, locations, distances, fares, rate and payment types, and passenger counts as reported by drivers. The datasets were gathered by the technology providers authorized under the Taxicab & Livery Passenger Enhancement Programs (TPEP/LPEP) and provided to the NYC Taxi and Limousine Commission (TLC). An extensive analysis of this data set can be found at [30].

Due to the fact that this data has been collected using taxi meters, which could be affected by various sources of errors the following data cleanup has been used. We excluded records of rides from further analysis if they met the following criteria:

- The trip distance is smaller than 0 km or greater than or equal to 100 km.
- The trip duration is less than 0 minutes or greater than or equal to 100 minutes
- The average speed is less than or equal to 1 km per hour or greater than or equal to 100 km per hour
- The pick-up or drop-off location were outside the bounding box in which New York is located.

One of the most intriguing insights from this data, particularly for the modeled system, is the frequency of ride requests throughout the day, as depicted in Figure 3. One notable observation is that there is roughly a 25% increase in ride requests on weekends compared to weekdays. Another key observation is that during weekdays, the peak frequency of ride requests aligns with morning and evening periods, coinciding with peak electricity usage times.

This observation has implications for the feasibility of using Vehicle-to-Grid (V2G) technology within a fleet of EVs in a ride-hailing service, especially concerning challenges related to the "duck curve" faced by electricity distribution companies. The "duck curve" refers to the graph's shape when plotting electricity demand throughout the day, with a significant dip during midday and a steep rise during evening hours, particularly influenced by solar generation during daylight hours [31], [32].

The issue arises because the highest demand for vehicles to perform rides coincides with the time when they would ideally be used to discharge energy back into the grid. This overlap presents a challenge for effectively leveraging V2G technology to mitigate the impacts of the duck curve on electricity distribution systems. It should be noted that previous research on the use of EV taxi fleets in a V2G setting have shown that only limited financial benefits can be achieved [33], [34].

In the conducted case study, day-ahead electricity prices have been sourced from the online repository of NYISO (New York Independent System Operator) [35]. This specific data source was chosen due to its reliability and accuracy in providing real-time and historical electricity pricing information for the New York region. By leveraging data from NYISO, which is a reputable and authoritative source in the energy industry, we ensure that our simulations are based on actual market conditions and pricing dynamics.

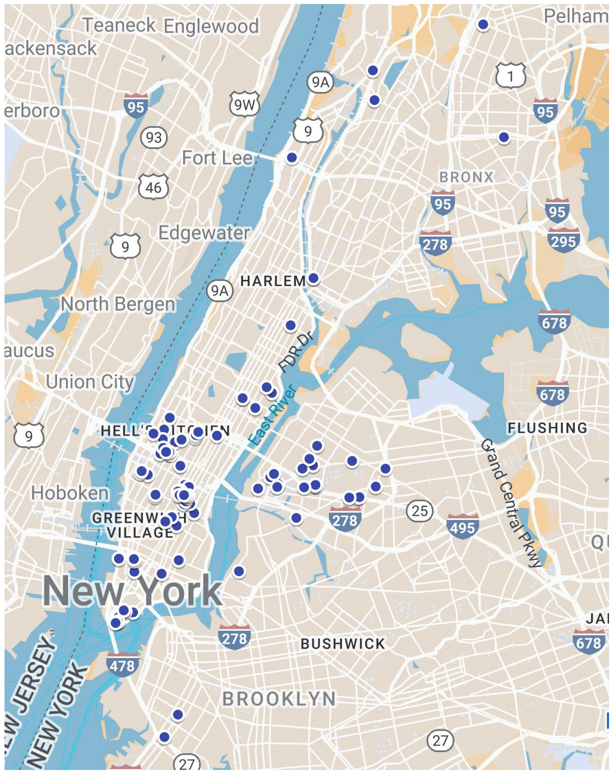
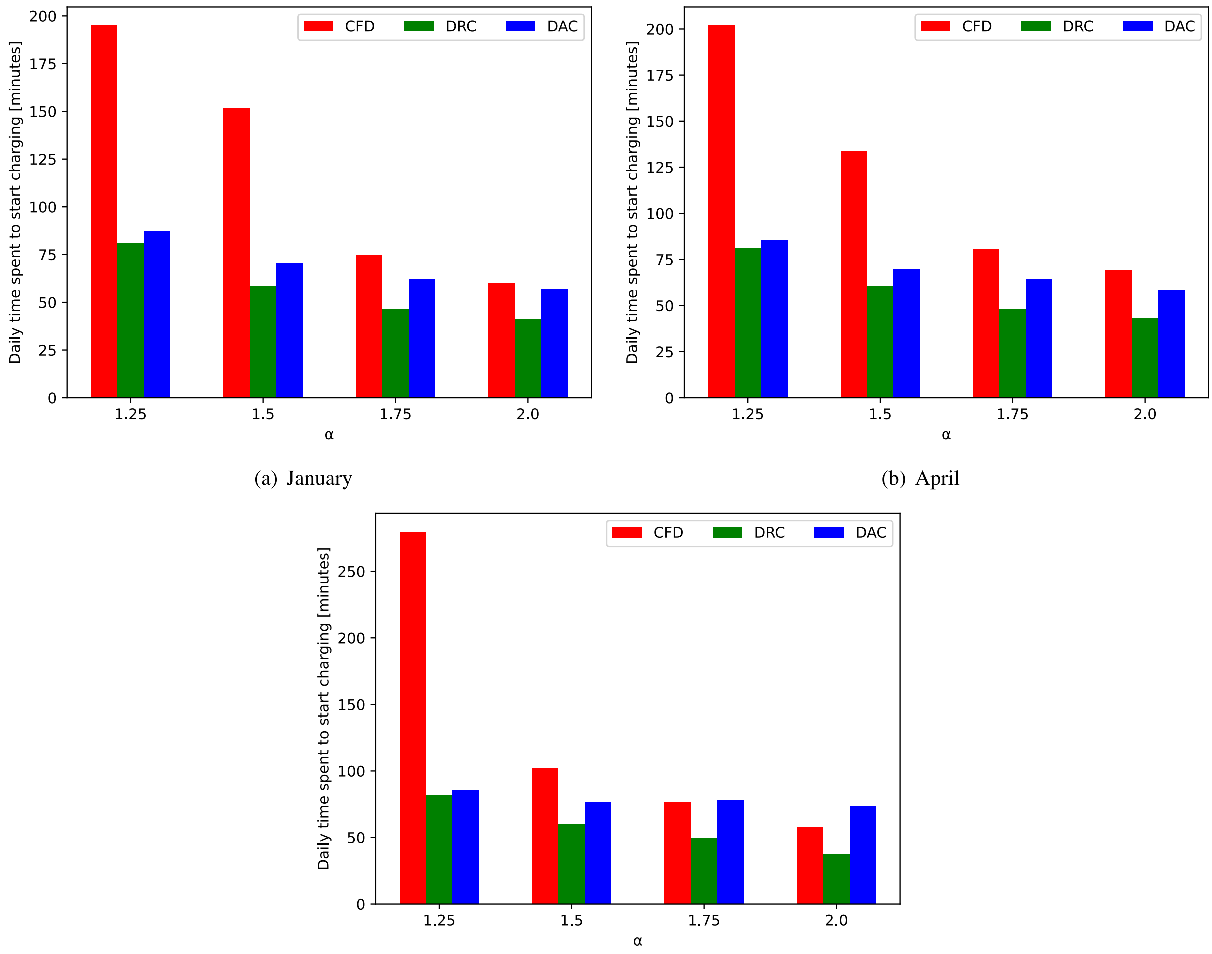


FIGURE 4. Locations of relief stands in New York City.

The last dataset used pertains to the selection of charging station locations. The objective is to choose charging station sites that can be seamlessly integrated into the existing NYC taxi system. A logical option is to consider the current taxi relief stands. This data is sourced from NYC OpenData [36], providing information on the locations of Taxi and For Hire Vehicle (FHV) stands, along with the number of available spaces. Taxi and FHV relief stands are designated for longer-term vehicle parking, making them ideal candidates for potential charging locations due to their extended parking durations. There is a total of 93 taxi relief stands in New York. A graphical illustration of these locations can be seen in Fig. 4.

IV. CASE STUDY OF NEW YORK CITY

This section presents the findings of a case study exploring the utilization of an EV fleet with charging stations located at taxi relief stands in New York City, as simulated using the DES model described earlier. The DES was implemented in Python within the PyCharm integrated development environment, leveraging the Simpy Python



(a) January (b) April

(c) June

FIGURE 5. **Graphical illustration of the time needed for EV drivers to start charging (travel time to station plus queue waiting) during the day. These values are given for different charging strategies and the relative numbers of chargers in the system (α).**

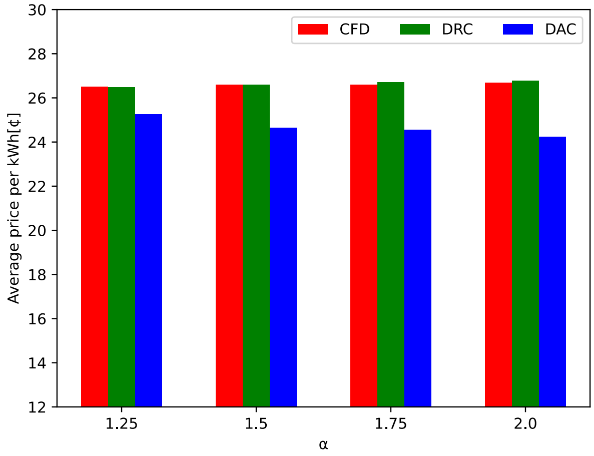
package for simulation capabilities. The MIP model related to charge scheduling has been implemented using CPLEX. Computational experiments were conducted on a personal computer operating on Windows 10, equipped with an Intel(R) Xeon(R) Gold 6244 CPU @ 3.60 GHz and 128 GB of memory.

A. SIMULATION SETTING

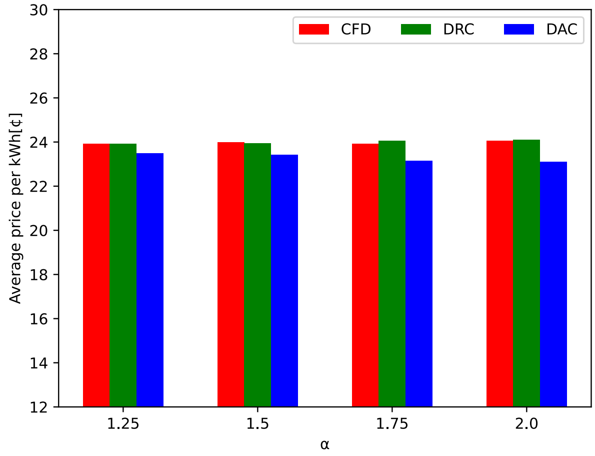
The following general assumptions underlie the modeled system. Firstly, uniformity is assumed within the fleet, with all EVs possessing a standardized battery capacity of 50 kWh. Similarly, all chargers within the system are presumed to operate at a uniform power level of 50 kW. It is assumed that an EV used 0.2 kWh per kilometer. To enhance realism, the duration and distances of the rides are sourced from NYC Green Taxi data [29]. Additionally, for non-ride movements, EVs are assumed to maintain a consistent speed of 30 km/h. The distance covered by an EV is computed using the Haversine formula based on the latitude and longitude of the start and end locations. Note that this can potentially give lower travel times since traffic conditions are not considered.

The case study conducts computational experiments over a full week, from Monday to Sunday, allowing for an extended observation of EV behaviors. This seven-day period is essential to capture the nuances of EV operation over time. The analysis spans three distinct months: January, April, and June, chosen specifically to examine the impact of varying weather conditions—cold, mild, and hot, respectively—on EV performance.

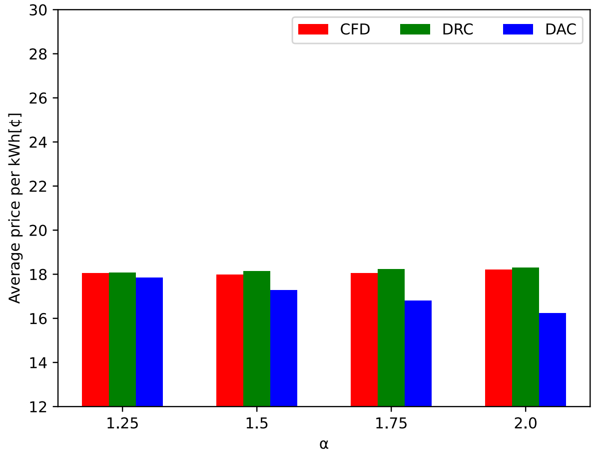
The dataset used for analyzing ride requests is from 2016, as more recent data from the NYC Data repository omits the latitude and longitude of pick-up and drop-off locations for privacy reasons. The inclusion of these geographical details in the 2016 data is crucial for a more accurate assessment of the system's efficiency and operational dynamics. This geographical information helps in understanding how location and travel distances affect EV usage patterns and system performance under different environmental conditions.



(a) January



(b) April



(c) June

FIGURE 6. Graphical illustration of the average price of kWh for charging EVs. These values are given for different charging strategies and relative numbers of chargers in the system (α).

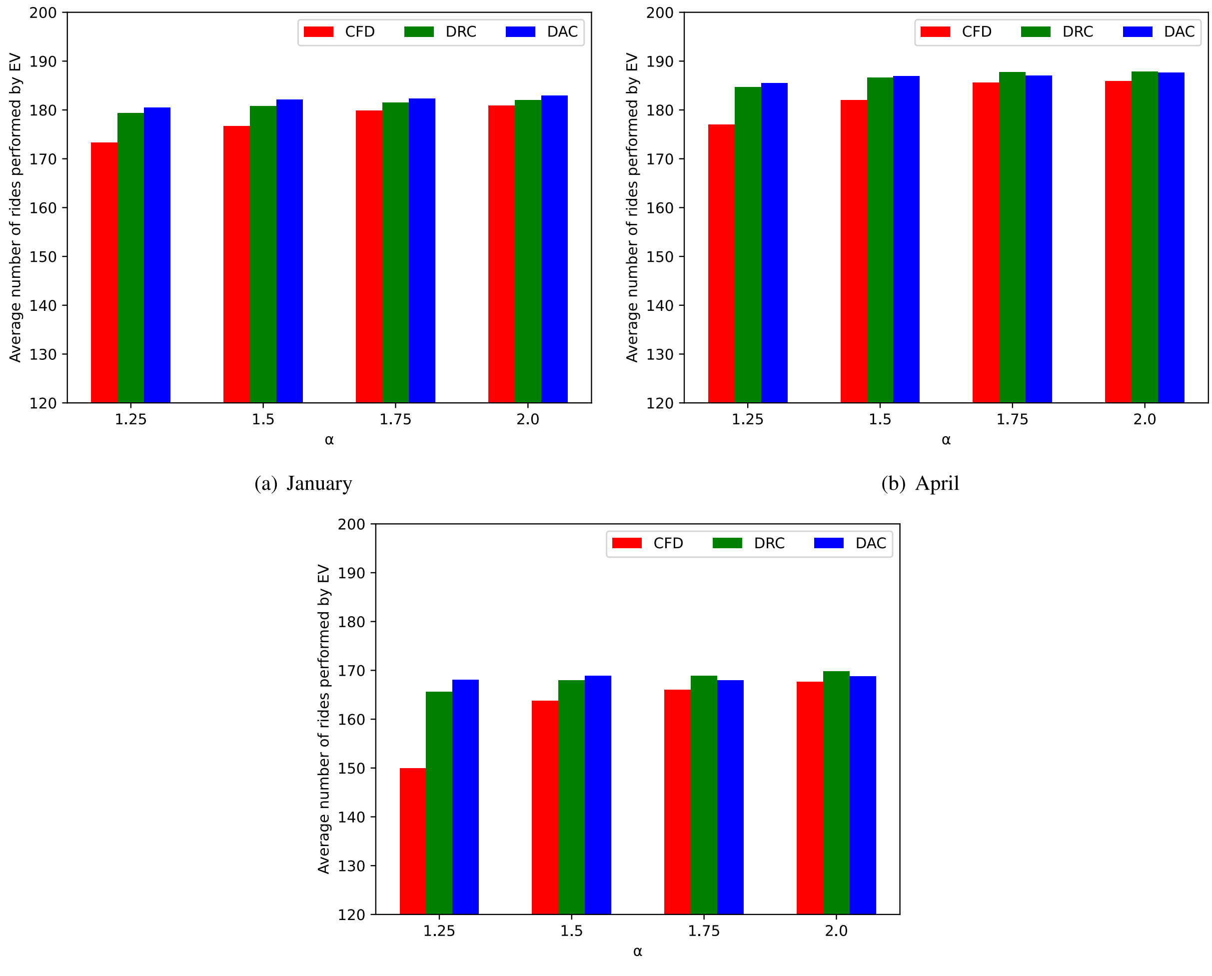
The number of EVs used in the simulation has been selected so that 80% - 85% of the ride requests are satisfied. This resulted in having 1500 EVs in January and April, and 1200 in June. In the model, the time limit for reaching a pick-up location was 10 minutes. The capacity and the number of chargers of the charging stations in the system have been set randomly. To be more precise, K chargers are to be allocated to the system. Firstly a single charger would be allocated to each charging station. The remaining chargers are randomly allocated, using a uniform distribution, to the charging stations in the system. In practice, this resulted in a system having a large number of charging stations with a small number of charging points.

In all the conducted simulations, all the EVs are initially placed at random locations within New York City. The SoC of each EV is randomly selected from 20% to 90% using a uniform distribution. The threshold for an EV to seek charging is that the state of charge is below 25%.

B. ANALYSIS

In this section, the analysis of the potential of using taxi relief stands for locations of charging stations for an EV fleet in a ride-hailing system is provided. The relation between different charging strategies and the number of chargers in the system is evaluated. The evaluation is done for the previously presented charging strategies: CFD, DRC and DAC.

The number of chargers in the system is determined based on the daily charging requirements of the EVs to fulfill all ride requests. It is estimated that each EV will require about two charging sessions per day, depending on the traveled distance. This estimate was confirmed during initial simulations, which operated under the condition of an unlimited number of chargers. For the sake of calculation, let C_{min} represent the minimum number of chargers needed to ensure all EVs can undergo two charging sessions daily, assuming continuous and optimal usage of each charger. This figure serves as a baseline for planning the necessary



(a) January

(b) April

(c) June

FIGURE 7. Graphical illustration of the number of rides performed per week by an EV. These values are given for different charging strategies and relative numbers of chargers in the system (α).

charging infrastructure to meet the operational demands of the EV fleet. In the conducted case studies, the number of chargers in the system was equal to αC_{min}, for $\alpha \in \{1.25, 1.5, 1.75, 2.0\}$, corresponding to increased investment in the charging infrastructure.

In our analysis, the first aspect we focus on is the time required for an EV to begin charging. Specifically, we examine the duration needed for an EV to travel to a suitable charging station and the time spent waiting in line. It is important to note that our analysis excludes the actual charging time, as this is typically fixed—around 100 minutes per day for two sessions—and cannot be substantially reduced through operational improvements. The summarized results for this analysis can be seen in Fig 5 where each sub-figure corresponds to a different period of the year.

From the analysis, it becomes evident that with a limited number of chargers and autonomous driver behavior, as seen in the CFD strategy, the time required for EVs to initiate charging can be excessively long. Specifically, with a charger-to-EV ratio of $\alpha = 1.25$ and $\alpha = 1.5$, vehicles experience waiting times ranging from 200 to 250 minutes and 100 to 150 minutes per day, respectively. This demonstrates that in environments with scarce charging infrastructure, high autonomy among drivers may adversely impact the efficiency of EV-based ride-hailing or taxi services.

Conversely, under the DRC and DAC strategies, where there is more structured control over charging operations, the initiation times for charging are significantly reduced to between 80 and 50 minutes. However, the improvement achieved with the increase in the number of chargers in the system, while notable, averages only about 20 minutes—a modest gain considering the additional investment.

It is also observed that increasing the number of chargers dramatically ($\alpha = 2.0$) improves outcomes for the CFD strategy, aligning the start times for charging closely with those under DRC and DAC scenarios. Moreover, among the dispatcher-controlled strategies, DRC generally results in slightly shorter charging initiation times compared to DAC. A closer examination of the simulation data reveals that vehicles under the DAC strategy tend to undergo a higher number of charging sessions, which may contribute to the marginally longer waiting times.

The subsequent part of our analysis focuses on the economic aspect, particularly examining the average cost of electricity (price per kWh) used to charge the EVs in the fleet. This is depicted in Figure 6. Initially, it is evident that for the CFD and DRC strategies, the average price of electricity remains stable regardless of the number of available chargers. This stability is attributed to the fact that charging sessions under these strategies are distributed relatively evenly throughout the day, closely mirroring the average electricity rates during the analyzed period.

In contrast, the DAC strategy, which allows greater managerial control when EVs are charged, demonstrates clear economic advantages. Generally, adopting the DAC strategy leads to a reduction in the average price per kWh by about 5% to 10%. Notably, the cost savings are lowest during mild weather conditions, such as in April, suggesting that weather-related factors may influence the efficiency of electricity usage.

Additionally, increasing the number of chargers in the system from $\alpha = 1.25$ to $\alpha = 2.0$ is observed to further decrease the average cost per kWh by approximately 5%. This reduction underscores the potential financial benefits of scaling up charging infrastructure within the fleet, particularly under strategies that optimize charger usage times.

Another crucial financial aspect of evaluating an EV fleet's performance is the number of completed rides. The results related to this metric, obtained from the DES across various charging strategies and charger quantities, are illustrated in Figure 7.

Initially, it is evident that under the CFD strategy, having a limited number of chargers (e.g., $\alpha = 1.25$ and $\alpha = 1.5$) significantly hampers the total number of completed rides, with a notable decline ranging from 5% to 10%. Conversely, strategies with increased dispatcher involvement in EV charging sessions show a rise in completed rides as the number of chargers increases, albeit to a lesser extent of only a few percentage points. Notably, the DAC strategy often yields slightly more completed rides than the DRC strategy. This difference is likely due to DAC's ability to align charging times with periods of lower electricity costs, coinciding with lower ride-request volumes, while DRC maintains a relatively even distribution of charging sessions throughout the day.

The conducted case study yields a significant conclusion regarding the viability of using taxi relief stands as charging station locations. It becomes apparent that under the CFD strategy, there exists a critical threshold of chargers below which this approach proves highly ineffective. Conversely, considering driver comfort and potential revenue from completed ride requests, DRC and DAC strategies achieve a near-optimal performance even with a relatively modest number of chargers.

Interestingly, while increasing the number of chargers beyond a certain point does not offer additional benefits for DRC, this is not the case for DAC. Additional chargers under DAC can lead to reduced system running costs by lowering the average cost per kWh paid for electricity. This insight underscores the importance of efficient charging management in optimizing the financial performance of an electric vehicle fleet.

V. CONCLUSION

In this study, we have conducted an investigation into EV fleet management within the realm of ride-hailing services. Central to our analysis is the development and implementation of a DES model, which serves as a powerful tool for exploring various charging strategies and their implications.

Our findings shed light on the critical importance of effective charging management strategies in maximizing both operational efficiency and financial viability within EV fleets. The integration of charging points at taxi relief stands emerges as a promising approach, offering convenience and operational advantages to EV drivers.

One of the key takeaways from our research is the necessity of scaling charging infrastructure. The CFD strategy, with complete driver autonomy, exhibits inefficiencies when faced with a limited number of chargers, underscoring the significance of strategic infrastructure planning. Conversely, the DRC and DAC strategies, with a higher level of involvement of the dispatcher in fleet charging, can provide a significant increase in driver comfort in the sense of decreasing the time needed to start charging sessions during the day for a low number of chargers in the system. It is notable that an increase in the number of chargers in the system can result in substantial reductions (5% to 10%) in electricity costs for DAC.

Our study emphasizes the pivotal role of dispatcher involvement in charging operations, as well as the importance of selecting an adequate number of chargers in the system. These factors collectively contribute to achieving optimal outcomes in EV fleet management within dynamic urban ride-hailing environments.

Moving forward, our research opens avenues for further exploration, including the integration of advanced optimization algorithms for charging strategies that consider the frequency of ride requests during the day. Another direction of research is including other aspects of real-world systems like driver behavior, labour laws, non-linear charging speeds, and disturbances (like traffic congestions) into the model.

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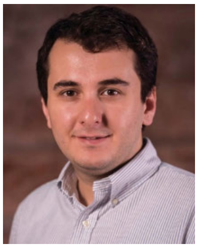

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