POET: Towards Power-System-Aware E-Taxi Coordination under Dynamic Passenger Mobility

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ABSTRACT

Electric vehicle (EV) fleets, e.g., electric taxis, buses, and trucks, have been increasingly implemented in cities. Compared with internal-combustion vehicles, the operation of EV fleets requires resilient charging infrastructures. Notably, the charging of EV fleets can bring significant reliability and efficiency challenges to the operation of the underlying power system. Based on the real data collected from New York City (NYC), our analysis shows that an increased power load ramping can result from various charging behaviors of electric taxis (e-taxis). Additionally, the increase of the peak load can further overload the local power distribution network. To address these problems, we exploit the possibility of utilizing e-taxi fleets' mobility to improve the reliability and reduce the cost of the power system, while maintaining the taxi service quality. Specifically, we design POET, a POwer-system-aware E-Taxi coordination algorithm, and evaluate the solution with comprehensive datasets for taxis and power distribution systems from NYC. These data include (i) more than 13,000 taxis with more than ten million taxi trips per month, (ii) a city local power distribution network with 38 local area substations and nearly 45 GWh overall power consumption per day, and (iii) deployed EV charging stations. The extensive data-driven evaluation demonstrates that, compared with the existing e-taxi charging solution that focuses on optimizations of taxi service quality, our solution decreases the power load ramping of local regions by 22.3% and reduces the daily peak charging load by 44.2% while achieving almost the same taxi revenue.

CCS CONCEPTS

• Hardware → Power and energy; **• Computing methodologies → Modeling and simulation**.

KEYWORDS

Electric taxis, coordination, power systems, passenger mobility

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1 INTRODUCTION

As various sensing, control, and communication technologies are deeply embedded into modern transportation systems, vehicles are becoming increasingly connected and coordinated, enabling new applications and services of Internet of things (IoT), such as smart traffic control [1], coordinated heterogeneous transportation systems [2], and taxi fleet management [3, 4]. Recently, electric vehicle (EV) designs emerge, accelerating a revolution in existing transportation systems [5]. Since EV has several major advantages over traditional gas-powered vehicles – environment friendly, cheaper to maintain, and improved safety [6] – different types of EV fleets, e.g. electric taxis, buses, and trucks, have been increasingly deployed in urban cities. For example, e-taxi fleets have been deployed in metropolitan areas, e.g., Amsterdam [7], Shenzhen [8], and London [9]. Notably, Tesla has become the first all-electric car to be approved for use as an official NYC yellow cab [10].

New challenges arise with such large scale deployment of EV fleets. The range of most electric vehicles is less than that of gas-powered vehicles, e.g., below 200 miles [11], and the operation of EV fleets requires relatively frequent, high-power, and timely charging. Among the many challenges raised by the large-scale deployments of EV fleets, an important one is its impact on power system resilience [12]. The power grids that support all the charging stations have various limitations and constraints that EV charging should consider. Indeed, EV fleet charging patterns can significantly increase the operation cost and compromise the reliability of power grids. For example, a large number of EVs may need to be charged at the same time period at a popular location, creating a surge of power load in a local power distribution network. Moreover, with fast charging technologies requiring high power, a large load increase can occur even for a small number of simultaneous charges.

Let us take a close look at the interaction between power grids and an EV fleet service, e.g. e-taxis. The primary function of an e-taxi fleet service is to provide flexible mobility for passengers and meet dynamic passenger demand. This fleet service relies on a power grid to charge its vehicles at fixed charging stations. This close dependency between a fleet service and the power grid not only limits the quality of service that the fleet can provide to its passengers but also imposes significant pressure on the power grid. Specifically, this paper studies the effects of fleet service on power grids, which are manifested as 1) a large amount of additional power to supply all the e-taxis, 2) an increased city-level and region-level load ramping due to concentrated charging of e-taxis, and 3) an increased peak load due to e-taxi charging. Indeed, large ramping and high peaks typically require more expensive power supplies. Addressing these issues under the constraints in power grids and charging infrastructures is a very challenging problem.

To help the power system improve its resilience and efficiency in the presence of highly variable generation and load, researchers have investigated designs for charging station deployment [13], charging rate control at a charging station [14], and battery technologies [15]. However, none of these designs utilizes the spatial-temporal flexibility of taxi service and charging behaviors to co-optimize the operations of transportation service and power grids. To the best of our knowledge, this paper is the first one to explore and show the potential of utilizing the flexibility of e-taxis' charging activities and the mobility of e-taxis to achieve high-quality taxi service with minimum impact on the power grid.

Existing e-taxi fleets are equipped with wireless radios and various sensors to collect location, occupancy status, battery status, etc. This allows not only passenger demand and charging demand to be analyzed and predicted, but also e-taxis to be dispatched to perform their services collaboratively. On the other hand, the power grid can monitor status of each charging station/point, e.g., charging load, connection status, battery status, etc. These infrastructures provide an opportunity for power systems and e-taxi fleets to be connected and coordinated, enabling novel EV fleet services.

Specifically, we consider the e-taxi fleet that aims to achieve the social optimum of both transportation system and power grid operations. We consider an e-taxi coordination algorithm with two sets of objectives: a) efficiently serving the passengers and b) minimizing its impact on power grid operations. To capture the above, in addition to maximize the profit for the set of all e-taxis, we introduce the following power-system-aware metrics in our objective function: a) the ramping of the total load (i.e., the existing load plus the additional load for charging e-taxis), b) the ramping of the load in each region (i.e., the existing load in a region plus the additional load for e-taxis in the same region), and c) the peak of total load (i.e., the maximum total load during a day). We note that these are critical metrics commonly pursued by power system operators to reduce cost and improve reliability of power supplies. We note that, in practice, an e-taxi fleet may however not be able to coordinate with the power system in such an ideal way. In light of this, we also study the use of Time-Of-Use pricing programs for the power system to impact the charging behaviors of e-taxis. The evaluation results show that applying a real-world TOU program with POET at the peak charging time can effectively reduce the daily peak load of the city by 36.4%, compared with existing taxi dispatch solutions that focus on optimizing the passenger service quality. The POET under the TOU program achieves 85.9% daily peak load reduction of the POET without TOU, which represents the ideal taxi coordination algorithm with the power system.

The **contributions** of this paper are as follows:

- To the best of our knowledge, it is the first work to design a coordination algorithm for e-taxi fleets to explore the potential of co-optimizing the quality of taxi service and the cost in the power grids due to charging.
- This work provides an analysis of the cost in the power grids given different charging strategies with real-world datasets of passenger mobility and power grids from NYC. The results show that various charging behaviors of e-taxis can significantly increase the cost of power supply (e.g., due to increased overall load and ramping) and challenge the reliability of power distribution systems (e.g., due to increased ramping and peak loads).

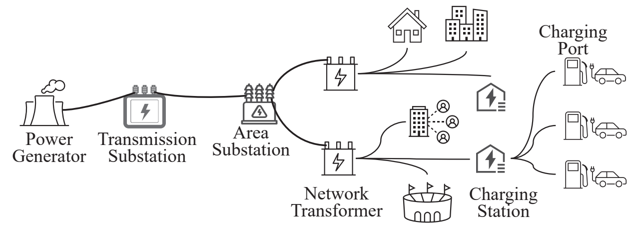


Figure 1: Demonstration of a power grid

- We formulate the e-taxi coordination problem of charging and serving passengers as a multi-objective mixed-integer linear programming problem. Different from previous e-taxi charging research that only focuses on reducing charging cost or matching taxi supply with passenger demand, our problem considers matching both passenger demand and power load to improve taxi service quality and decrease the cost of power grids.
- Our study is based on very comprehensive datasets from NYC that consist of (i) over 13,000 taxis with over ten million taxi trips per month, (ii) a local power distribution network with 38 area substations and nearly 45 GWh overall daily power consumption, and (iii) deployed electric vehicle charging stations with 750 charging ports. The extensive data-driven evaluation shows that our solution significantly decreases the power load ramping of local regions by 22.3% and reduces the daily peak charging load by 44.2% with only a 1.4% decrease in the taxi revenue compared with the existing solution only optimizing taxi service quality.

2 MOTIVATION

2.1 Data Description

In this part, we describe the data collected from Manhattan, including the data for power distribution network, EV charging stations, and taxi trip records. Table 1 shows the examples of the three datasets.

Table 1: Attributes of the datasets

Power distribution network
Network vertices, hosting capacity (MW), predicted power load & corresponding datetime
Electric vehicle charging station
Station name and address, GPS location, # of outlets
Taxi trip record
Pickup datetime and GPS location, dropoff datetime & GPS location, trip distance (mile), fare amount ($)

City power distribution network: Figure 1 depicts the main components of a power grid. In this work, we focus on the city power distribution network, including the area substations, local power distribution networks, and end users. The electric service in NYC is provided by Con Edison [16]. The company partitions the entire area of Manhattan into multiple local regions.The end users in a local region are supplied by the local distribution network from the same area substation. A local region is described as a polygon bounded by the GPS coordinates of multiple geographical locations. As shown in Table 1, the hosting capacity platform [17] shows the area substation hosting capacity and the forecasted hourly power load from end users in the same region for three years.

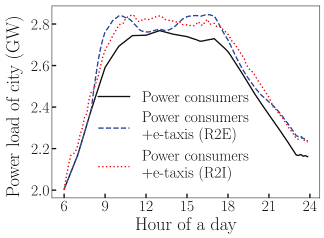


Figure 2: The city's load

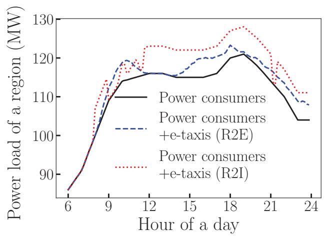


Figure 3: A region's load

Electric vehicle charging stations: With the growth in the electric vehicle (EV) market, commercial EV charging stations have already been deployed across the world. We retrieve the information of the current nearly 290 EV charging stations in Manhattan from [18]. It includes station name, address, GPS coordinates, the number of charging ports, and charging power for each charging station.

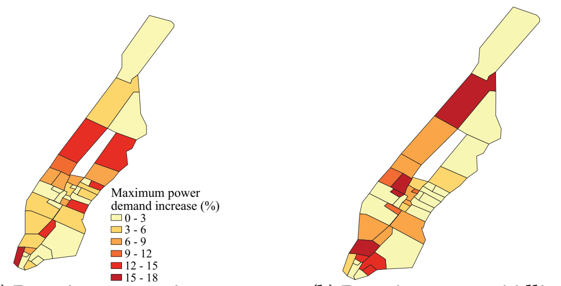
Taxi trip record data: Multiple types of sensors, e.g., GPS devices, and communication modules, have already been deployed in the taxis to upload the real-time trip record data for monitoring and improving the service quality. The New York City Taxi and Limousine Commission (TLC) has already collected and published the taxi trip records data from 2009 to 2019 in [19], which includes pick-up and drop-off dates/times, pick-up and drop-off GPS locations, trip distances, and itemized fares. There are over 10 million taxi pickup records per month in Manhattan of around 13,000 yellow taxis.

2.2 Data-Driven Analysis

In this part, we conduct the data-driven analysis to study how the future e-taxi fleets influence the city power distribution network. The analysis results show that the charging behaviors of e-taxis can result in negative effects on the power grid, e.g., total city-level load ramping, regional/local-level load ramping, and the increase of the peaks of local load.

2.2.1 Setup. Since e-taxi fleets have not been deployed in Manhattan, we make several assumptions about future e-taxi systems and charging infrastructure based on the datasets from the existing systems. First, we assume that the regular taxis in the taxi dataset are upgraded to e-taxis. Second, based on the implementation of e-taxis in London [9] and Shenzhen [20], we set up the specifications of e-taxis as: 40 kWh battery capacity; 50 kW maximum charging rate; 174 miles maximum distance. Third, the current EV charging stations are expanded (at the same locations) so that there is a charging port for every three e-taxis [21]. Since e-taxis need to recharge their battery quickly to serve passengers during daily operations [22], we assume that the charging points are DC fast chargers (50 kW). The predicted load from users provided by ConEd is employed as the actual load. A time slot is set as 10 minutes.

Two basic charging strategies are employed in this analysis to determine the charging behaviors of e-taxis. The first strategy is called *reactive charging to the e-taxi's remaining energy (R2E)* [23]. An e-taxi starts to charge the battery only when its remaining energy is below a threshold, i.e., 15%. The charging station with the minimum sum of driving time and waiting time is selected by an e-taxi for charging. The charging process terminates when the battery is fully charged. The second strategy is called *reactive charging to the e-taxi's idling time (R2I)*. At the beginning of a time slot, a centralized controller first dispatches e-taxis over the regions for matching the passenger demand. After dispatching, if the e-taxi supply is more than the passenger demand in a region, some e-taxis are idling and are scheduled to the nearest station with at least an open charging port for charging the battery during the current time slot. Such a process repeats at the beginning of every time slot. It is noted that a part of passenger demand is not satisfied in the case of R2E because some of the vehicles have to stop to charge. It is also shown in Figure 10 that R2E introduces less profit than R2I does.



(a) Reactive to e-taxi energy **(b) Reactive to e-taxi idling**

Figure 4: Increase of local peak load due to e-taxis

The results demonstrate three types of power load. The first one is the power load from the end users. The second type is from the end users and the e-taxis by the strategy R2E. The last type is from the end users and the e-taxis by the strategy R2I.

2.2.2 Results. Figure 2 shows the total load of the city during a day. Due to the charging behaviors of the e-taxis, the load of the city during a time slot increases by 3.0% and 2.5% on average when using the two charging strategies. In detail, the daily peak power load increases from 2.76 GW to 2.83 GW and the daily total power consumption increases from 45.59 GWh to 46.95 GWh by R2I. This suggests that transmission and generator capacities need to increase significantly as more and more EVs are adopted. Notably, the cost of such upgrades would however be very high [24]. We also observe that the total load by the strategy that is reactive to e-taxi energy ramps up and down from 9 am to 6 pm. To match the power demand with high ramping, the power system operators need to rely on fast-ramping generators or energy storage which can be very expensive [25]. The exact cost will depend on the day-to-day operation cost of the power system. We leave accurate long-term cost modeling of power load profiles (and their changes with better managed e-taxi coordination) for future work.

In Figure 3, we plot the local power load by the different charging strategies, where a representative region is selected. The main observation is that there exists a power load ramping for both strategies. For example, the load of a time slot decreases from 119 MW to 115 MW, and increases back to 123 MW from 10 am to 6 pm by the strategy that is reactive to e-taxi energy. Meanwhile, the curve of the strategy that is reactive to e-taxi idling fluctuates from 8 am to 12 pm and from 7 pm to 10 pm. The fast ramping of local loads can cause voltage rise and fall outside the normal region.

We obtain the (daily) peak load in each region of three types of power loads. We then show the increase of peak loads due to the e-taxis by two strategies. The value is equal to (the daily max power load in a region by a strategy - the daily max power load in the same region without e-taxis)/the daily max power load in the same region without e-taxis. The results are shown in Figure 4. We observe that there are 7 and 11 regions where the increase of peak load due to the e-taxis is above 9% by the two strategies. Such an increase could

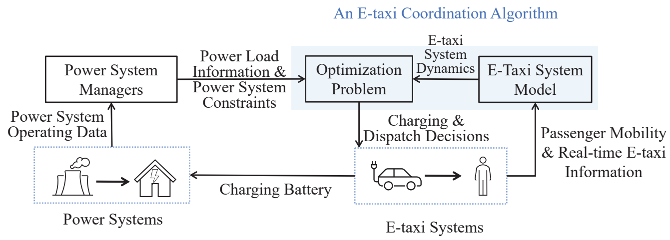


Figure 5: Framework of POET

result in the overloading of power distribution networks due to the constraints of a large number of system components, e.g., the capacities of local transformers and lines.

In summary, our data-driven analysis results show that the e-taxis' charging activities require a large amount of additional power to support e-taxis, and could increase the city-level and region-level power load ramping and the daily peak power load.

3 POET OVERVIEW

To address the negative impact of e-taxi charging on the power grid, we design a POwer-system-aware E-Taxi coordination algorithm, called POET. Specifically, POET coordinates the e-taxis' behaviors of charging batteries and searching for next passengers, aiming to maximize the utility of serving passengers and minimize the impact on the city distribution network. Figure 5 shows the framework of POET. It is designed based on the existing taxi system, where multiple devices, i.e., GPS modules, fare meters, and communication modules, are installed in the taxis. These devices are used to report real-time locations and occupancy status, and receive scheduling commands for improving the taxi service quality [26, 27].

As shown in Figure 5, the algorithm periodically makes the coordination decisions, i.e., how many e-taxis are scheduled for charging in spatial-temporal dimensions (charging decisions), and how many e-taxis are dispatched in spatial-temporal dimensions for serving passengers (dispatching decisions). This coordination algorithm consists of two components: an e-taxi system model and an optimization problem. The e-taxi system model describes how the states of an e-taxi fleet transit over the discrete temporal domain given the decisions. It is fed by the real-time e-taxi information and the historical passenger trip data. During the daily operation, the power system managers always send the power load information and the hard power system constraints to the optimization problem component, which determines the charging and dispatch decisions.

There are two control loops in this system. One loop is in the e-taxi systems for dispatch decisions. The coordination algorithm determines the dispatch decisions of e-taxis based on the predicted passenger demand, and then dispatches e-taxis to serve passengers. Another loop is in the power systems for charging decisions. E-taxis are scheduled to charge their batteries at the charging stations, and the charging decisions are obtained based on information shared from power systems, e.g., current loads and charging load constraints. These two loops affect each other. For example, the charging decisions influence the current and future e-taxi supply for serving passengers. The dispatch decisions affect the distribution of e-taxis, which is considered when making the charging decisions. Therefore, the charging and dispatch decisions correlate with each other and must be considered jointly.

4 LOCAL POWER DISTRIBUTION NETWORK

According to the structure of power distribution networks as shown in Figure 1, we assume that there are m transformers that supply power to at least a charging station over the city. Let $B \in R^m$ with B_k representing the capacity of transformer k. Suppose there are n_i charging stations in region i and the number of charging stations in a city is $\bar{n} = \sum_{i=1}^{n} n_i$. Let $R^{tc} \in \{0,1\}^{m \times \bar{n}}$ represent the relation between transformers and charging stations, where $R^{tc}_{k,j} = 1$ if k-th transformer supplies power to charging station j; otherwise, it is 0.

Let Le^t be a length $\bar{n}$ column vector, and Le^t_j describes the charging power load at charging station j during slot t. Let Lo^t be a length m column vector, and Lo^t_k describes the power load from consumers except e-taxis on transformer k during slot t. To avoid overloading the transformers, resulting in temperature rise and power distribution network instability, we constrain that $R^{tc}Le^t + Lo^t \leq B$, where $R^{tc}Le^t$ is a length m column vector, representing the charging load from e-taxis on each transformer during slot t. The above equation describes the constraints of charging load at each charging station during each time slot to ensure the reliability of power systems.

Discussion: The structures of the local power distribution network can be either radial or meshed [28]. In this work, we take the radial network as an example to describe how the power demand from e-taxis and other users influence the local distribution network. To prevent an overload of the distribution network, certain constraints from the distribution network exist. For example, if a charging station and end users share a power line, their total power load should not exceed the line capacity. Similar constraints can be derived for a meshed network using power flow equations.

5 E-TAXI SYSTEMS

We first discretize the spatial and temporal dimensions. One day is partitioned into multiple time slots, where a time slot is indexed by t. Let $\hat{t}$ be the current time slot and we consider future T time slots for coordinating e-taxis. The entire area of a city is divided into n regions based on the power grid as described in Section 2.1.

5.1 State of E-taxi Systems

We discretize the remaining energy of an e-taxi into $\hat{L}$ levels. Let RE^t be the remaining energy of an e-taxi at the beginning of slot t. We use a linear model to describe how the remaining energy of e-taxis changes over the time [29] [30]. If an e-taxi works during time slot t, $RE^{t+1} = RE^t - \hat{L}_1$; otherwise, $RE^{t+1} = RE^t + \hat{L}_2$, where $\hat{L}_1$ ($\hat{L}_2$) is the levels that the remaining energy changes if an e-taxi works (charges) during slot t. We assume that an e-taxi does not consume energy during a time slot if it only waits for a free charging port in a charging station. We note that there are several factors influencing the battery discharging process of e-taxis, e.g., air density, vehicle mass, and traveling time [31]. Our solution can also integrate more sophisticated discharging models beyond linear ones.

There are three states of an e-taxi: working on the road for searching or delivering passengers, waiting in a charging station for a free charging port, and connecting with a charging port. To simplify the description, we call e-taxis with one of these states as working, waiting, and charging e-taxis. The state of an e-taxi system is defined as how many e-taxis with the different remaining energy levels are in one of three states in spatial-temporal dimensions. We define several notations to describe the state of an e-taxi system, i.e., $V_i^{l,t}, O_i^{l,t}$, and $D_j^{l,t}$, and they are introduced one by one.

Let $V_i^{l,t}, O_i^{l,t}$ be the number of vacant and occupied e-taxis with remaining energy level l in region i at the beginning of time slot t before scheduling. By taking advantage of the GPS and communication devices installed in e-taxis, we update $V_i^{l,\hat{t}}, O_i^{l,\hat{t}}$ with real-time data, e.g., GPS locations and occupancy status, where $\hat{t}$ is the current time slot. We define $D_j^{l,t}$ as the number of e-taxis with remaining energy l in station j at the beginning of slot t, which includes the e-taxis that wait or charge the battery during slot $t-1$.

Decision variables: There are two types of e-taxi coordination decisions for the unoccupied e-taxis: how many e-taxis are dispatched between regions for serving passengers (i.e., taxi dispatch), and how many e-taxis are scheduled to the different charging stations (i.e., charging scheduling). We define $X_{i,j}^{l,t} \in \mathbb{N}$ as the number of e-taxis with remaining energy level l are scheduled from region i to charging station j at the beginning of time slot t. The range of l is $[1, \hat{L}]$, meaning e-taxis with any remaining energy level can be scheduled for charging. In detail, we use $x_{i,j}^{l,t} \in \mathbb{N}$ to denote the number of current unoccupied working e-taxis with remaining energy l that are dispatched from region i to station j during slot t. Let $xd_{j,j'}^{l,t} \in \mathbb{N}$ be the number of e-taxis with energy l in station j that are scheduled to station j'. Given $x_{i,j}^{l,t}$ and $xd_{j,j'}^{l,t}$, $X_{i,j}^{l,t}$ is represented as: $X_{i,j}^{l,t} = x_{i,j}^{l,t} + \sum_{j'=1}^{\bar{n}} R_{i,j'}^{rc} xd_{j',j}^{l,t}$, where $R^{rc} \in \{0,1\}^{n \times \bar{n}}$ is a matrix that represents the relation between regions and charging stations, where $R_{i,j}^{rc} = 1$ if station j locates at region i; otherwise, it is 0.

We use $Y_{i,i'}^{l,t} \in \mathbb{N}$ to denote the number of e-taxis with energy l that are dispatched from region i to i' for serving passengers during slot t. Let $y_{i,i'}^{l,t} \in \mathbb{N}$ denote the number of currently unoccupied working e-taxis with energy l that are dispatched from region i to i' during slot t. We define $yd_{j,i}^{l,t} \in \mathbb{N}$ as the number of e-taxis with energy l in station j that are scheduled to region i, where these e-taxis wait or charge the battery during slot $t-1$ in station j. Given $y_{i,i'}^{l,t}$ and $yd_{j,i}^{l,t}$, we represent $Y_{i,i'}^{l,t}$ as: $Y_{i,i'}^{l,t} = y_{i,i'}^{l,t} + \sum_{j=1}^{\bar{n}} R_{i,j}^{rc} yd_{j,i'}^{l,t}$.

It is noted that all the unoccupied e-taxis, i.e., working on the road without passengers, charging the battery, or waiting for a free charging port, are considered in the charging scheduling and taxi dispatch decisions. To simplify the description, we define X^t and Y^t as the scheduling decisions for charging and serving passengers during slot t, where $X^t = \{x_{i,j}^{l,t}, xd_{j,j'}^{l,t}\}_{1\le l\le \hat{L}, 1\le i\le n, 1\le j,j'\le \bar{n}}$ and $Y^t = \{y_{i,i'}^{l,t}, yd_{j,i}^{l,t}\}_{1\le l\le \hat{L}, 1\le i,i'\le n, 1\le j\le \bar{n}}$.

In this work, we consider the e-taxis that are in any one of three states for charging or serving passengers. It means that e-taxis are instructed to terminate the charging process or leave the waiting queue for serving passengers or charging the battery in another charging station. We have the following constraints:

$$\sum_{j=1}^{\bar{n}} x_{i,j}^{l,t} + \sum_{i'=1}^{n} y_{i,i'}^{l,t} = V_i^{l,t}, \quad \sum_{j'=1}^{\bar{n}} xd_{j,j'}^{l,t} + \sum_{i=1}^{n} yd_{j,i}^{l,t} = D_j^{l,t} \quad (1)$$

5.2 E-Taxi Supply and Passenger Demand

Given the historical dataset of passenger trip records, we can estimate the dynamic passenger demand in spatial-temporal dimensions, i.e., how many passengers request taxi service in a region during a time slot. Let r_i^t be the number of passengers that request taxi service during time slot t in region i.

Taxi supply: We define $S_i^{l,t}$ as the number of e-taxis with remaining energy l that can serve passengers in region i during time slot t after taxi dispatch and charging scheduling. We have the following equations to describe how $V_i^{l,t}, O_i^{l,t}$ and $S_i^{l,t}$ change between time slot t and $t+1$.

$$S_i^{l,t} = V_i^{l,t} + \sum_{j=1}^{\bar{n}} R_{i,j}^{rc} D_j^{l,t} - \sum_{j=1}^{\bar{n}} X_{i,j}^{l,t} + \sum_{i'=1}^{n} (Y_{i',i}^{l,t} - Y_{i,i'}^{l,t}) \quad (2)$$

$$V_i^{l,t+1} = \sum_{i'=1}^{n} Pv_{i',i}^t S_{i'}^{l+\hat{L}_1,t} + \sum_{i'=1}^{n} Qv_{i',i}^k O_{i'}^{l+\hat{L}_1,t} \quad (3)$$

$$O_i^{l,t+1} = \sum_{i'=1}^{n} Po_{i',i}^t S_{i'}^{l+\hat{L}_1,t} + \sum_{i'=1}^{n} Qo_{i',i}^t O_{i'}^{l+\hat{L}_1,t} \quad (4)$$

where $Pv_{i',i}^t, Po_{i',i}^t, Qv_{i',i}^t, Qo_{i',i}^t \in [0,1]$ describe the mobility patterns of taxis for different pairs of regions during time slot t. $Pv_{i',i}^t (Po_{i',i}^t)$ is the probability that an unoccupied taxi from region i' at the beginning of slot t will travel to region i and become unoccupied (occupied) by the end of time slot t. Similarly, $Qv_{i',i}^t (Qo_{i',i}^t)$ describes the probability that an occupied taxi from region i' at the beginning of t-th slot travels to region i and becomes vacant (occupied) by the end of time slot t. The historical data is used to learn the taxis' mobility patterns by frequency theory of probability. We constrain that: $\sum_{i=1}^{n} Pv_{i',i}^t + Po_{i',i}^t = 1$, $\sum_{i=1}^{n} Qv_{i',i}^t + Qo_{i',i}^t = 1$.

Discussion: In this work, the taxi mobility pattern is learned from the historical data, which can be sometimes inaccurate due to the uncertain travel delays. To address this issue, we can build the model of the taxi mobility patterns by assuming Pv, Po, Qv, and Qo follow the different distributions extracted from the historical data. Then the problem is to determine the e-taxi charging and dispatch decisions with the probability distributions of the taxi mobility patterns. Since the main technical task of this work is not to schedule e-taxis with uncertain traveling delays, we will leave the studies with uncertain travel delays for future work.

In Eq. (2), the number of e-taxis in each charging station with the different remaining energy level, i.e., $D_j^{l,t}$, is determined by the dynamic charging supply and the scheduled charging requests during the previous slot. Therefore, the taxi supply and passenger demand model, and the charging supply and request model couple with each other by the dynamic scheduling decisions of charging.

5.3 Charging Supply and Request Model

In this section, we first formulate the dynamic charging supply constrained by the power distribution network, and the charging requests determined by the charging decisions. Then we model how to derive the number of e-taxis with the different remaining energy at the beginning of slot t when given the charging requests and supply for slot $t-1$.

Charging supply: The charging supply means the maximum number of e-taxis that can be charged simultaneously during time slot t at j-th charging station, denoted as e_j^t. Suppose there are p_j charging ports at j-th charging station. To avoid the overload on network transformers, the number of e-taxis that can be charged simultaneously is constrained by the capacity of transformers, i.e., B. We use P to denote the charging power of e-taxis. Then the maximum power load from j-th station during time slot t is $Le_j^t = e_j^t * P$. Given the limited number of charging points at station j and the power load constraint (i.e., $R^{tc}Le^t + Lo^t \leq B$), we have the following equation:

$$R^{tc}e^t P + Lo^t \leq B, \quad e_j^t \leq p_j \tag{5}$$

where e^t is a length $\bar{n}$ column vector.

Charging requests: The charging requests represent the number of e-taxis requesting the charging service at the station j during slot t. We assume that the charging stations are deployed for only e-taxis [20, 30] and the charging requests at each station are only determined by the charging decisions.

Since the charging supply may be not sufficient to satisfy the charging requests, i.e., $e_j^t < \sum_{l=1}^{\hat{L}} \sum_{i=1}^{n} X_{i,j}^{l,t}$, only part of e-taxis are selected to connect with the charging ports. We define $u_j^{l,t}$ as the number of e-taxis that are charged at the station j during slot t with energy l before charging. We constrain them as

$$u_j^{l,t} \leq \sum_{i=1}^{n} X_{i,j}^{l,t}, \quad \sum_{l=1}^{\hat{L}} u_j^{l,t} \leq e_j^t \tag{6}$$

Finally, at the beginning of slot $t+1$, the e-taxis with remaining energy l at the station j consist of the e-taxis with remaining energy l after charging during slot t and the e-taxis with remaining energy l that are not charged during slot t. Then we have the following function to derive $D_j^{l,t+1}$: $D_j^{l,t+1} = u_j^{l-\hat{L}_2,t} + \sum_{i=1}^{n} X_{i,j}^{l,t} - u_j^{l,t}$.

5.4 Power-System-Aware E-taxi Coordination

In this work, we want to schedule e-taxis for charging and serving passengers to match the dynamic passenger demand and reduce the negative impact on power systems. The objective consists of maximizing the utility of the e-taxi system and optimizing the performance measurement metrics of power systems.

5.4.1 Constraints. The traveling distance of an e-taxi is bounded during a time slot due to the limited speed and traveling time. So an e-taxi cannot be scheduled to a far charging station or region. We define two constraint parameters, i.e., $ds_{i,i'}^t \in \{0,1\}$ and $dc_{i,j}^t \in \{0,1\}$. If an e-taxi can reach region i' from region i within slot t, $ds_{i,i'}^t = 0$; otherwise, it is 1. If an e-taxi can reach charging station j from region i within slot t, $dc_{i,j}^t = 0$; otherwise, it is 1. These two constraint parameters are obtained based on the traveling time between two locations and the length of a time slot. For example, the e-taxi fleet can acquire the traveling time from the center location of region i starting at slot t to that of region i' by sending requests to map service providers, e.g., Google Map. If the received traveling time is longer than a time slot, $ds_{i,i'}^t = 1$; otherwise, it is 0. Finally, we constrain that

$$X_{i,j}^{l,t} dc_{i,j}^t = 0, \quad Y_{i,i'}^{l,t} ds_{i,i'}^t = 0 \tag{7}$$

The sustainable operation of e-taxis is a major concern for e-taxi systems. E-taxis consume energy when driving and they should avoid using up energy on the road. We assume that all e-taxis follow the scheduling decisions and constrain that all low energy e-taxis must be scheduled for charging. We have another constraint:

$$S_i^{l,t} = 0, \quad 1 \leq l \leq \hat{L}_1 \tag{8}$$

5.4.2 Objectives. The primary objective of an e-taxi system is to maximize its utility by scheduling e-taxis for charging or serving passengers [32]. The utility is equal to the total revenue from serving passengers minus the cost of e-taxi systems.

E-taxi fleet utility: In order to increase the revenue from serving passengers, an e-taxi system usually allocates the taxi supply across the city to match the passenger demand in spatial-temporal dimensions. However, the supply that an e-taxi system can provide may not satisfy the passenger demand during the peak hours, e.g., 17:00~19:00, in some regions. We define the number of passengers that are served in region i during slot t as $\min\{r_i^t, \sum_{l=1}^{L} S_i^{l,t}\}$. Here, it is supposed that a passenger can be served as long as there is an unoccupied e-taxi in the same region during the same slot. The passenger may wait in the taxi stations on roads [26] or send the service request by mobile phones, e.g., Uber and Lyft.

The average revenue coming from serving a passenger varies in spatial-temporal dimensions, e.g., drivers can earn more money when picking up passengers in an airport. Let Re_i^t be the average revenue from picking up a passenger in region i during slot t, which is predicted based on the historical data by, e.g., linear regression or neural network. The total revenue during the future time horizon (from current time slot $\hat{t}$ to $\hat{t}+T-1$) is formulated as: $J_{revenue} = \sum_{t=\hat{t}}^{\hat{t}+T-1} \sum_{i=1}^{n} \min\{r_i^t, \sum_{l=1}^{\hat{L}} S_i^{l,t}\} * Re_i^t$, where r_i^t is the number of passengers that request taxi service during time slot t in region i, and $S_i^{l,t}$ as the number of e-taxis with remaining energy l that can serve passengers in region i during time slot t after taxi dispatch and charging scheduling.

The cost of e-taxi systems consists of the payment of electric power that e-taxis consume and the idle driving on the road due to coordination decisions. We assume the power of charging is constant in the spatial-temporal dimensions. However, the price per kWh (i.e., electricity rate) changes in the spatial-temporal dimensions, e.g., the rate may be high in the central areas and it is low in the sub-urban areas, or the electricity rate increases during the period when there is a lot of power load. The total cost of electricity is formulated as: $J_{payment} = \sum_{t=\hat{t}}^{\hat{t}+T-1} \sum_{j=1}^{\bar{n}} C_j^t * \sum_{l=1}^{L} \sum_{i=1}^{n} X_{i,j}^{l,t}$, where C_j^t represents the cost of consuming energy if an e-taxi charges in station j during time slot t, which is equal to electricity rate $*$ power of charging $*$ length of a time slot. The units of electricity rate, power of charging, and length of a time slot are \$/kWh, kW, and hour, respectively.

Due to scheduling for charging or taxi dispatch, the e-taxis idly drive on the road, which is also the cost of the e-taxi system. Given the city structure, we use $\mu_{i,i'}$ to describe the driving distance from region i to i', where $\mu_{i,i'} = \mu_{i',i}$. Let $\varphi_{i,j}$ be the driving distance from region i to charging station j or from station j to region i. We define $\nu_{j,j'}$ as the driving distance from the charging station j to j'. The total idle driving distance due to scheduling decisions is: $J_{idle} = \sum_{t,l} \big(\sum_{i,j} (x_{i,j}^{l,t} + yd_{j,i}^{l,t})\varphi_{i,j} + \sum_{i,i'} y_{i,i'}^{l,t} \mu_{i,i'} + \sum_{j,j'} xd_{j,j'}^{l,t} \nu_{j,j'} \big)$.

Let β be the cost of power when an e-taxi drives idly per unit distance, and it is equal to electricity rate $*$ energy consumption per unit distance. In summary, the utility of an e-taxi system is formulated as: $J_{utility} = J_{revenue} - J_{payment} - \beta * J_{idle}$.

Power System Operational Cost: The other objective of an e-taxi system is to minimize the influence on the power distribution network, i.e., reducing the city-level and region-level power load ramping and shaving peak power load.

Power load ramping reduction: The power load in region i during slot t is the sum of power load from end users and charging stations in region i during slot t, formulated as $U_i^t = \hat{U}_i^t + \sum_{j=1}^{\bar{n}} \left(R_{i,j}^{rc} * P \sum_{l=1}^{\hat{L}} u_j^{l,t}\right)$, where U_i^t represents the power load in region i during time slot t and $\hat{U}_i^t$ denotes the power load from users except e-taxis in region i during time slot t. Therefore, the load ramping in region i between slot t and $t+1$ is $|U_i^{t+1} - U_i^t|$. The total amount of the region-level load ramping over T consecutive time slots is: $J_{region} = \sum_{i=1}^{n} \sum_{t=\hat{t}}^{\hat{t}+T-2} |U_i^{t+1} - U_i^t|$.

The city-level load ramping from slot t to $t+1$ is $|\sum_{i=1}^{n} U_i^{t+1} - \sum_{i=1}^{n} U_i^t|$. The amount of city-level load ramping over T consecutive time slots is: $J_{city} = \sum_{t=\hat{t}}^{\hat{t}+T-2} | \sum_{i=1}^{n} U_i^{t+1} - \sum_{i=1}^{n} U_i^t|$. Thus, the total amount of city-level and region-level load ramping is: $J_{ramping} = J_{region} + J_{city}$.

Peak shaving of power load: The effectiveness of shaving peak power load is measured relative to how much energy the customer typically used on other days preceding the current day during hours similar to the current hours. We use UB^t to denote this typical amount of energy the e-taxi fleet uses during slot t.

During slot t, the e-taxi fleet reduces the total power load from UB by $\max\{0, UB - \sum_{i=1}^{n} U_i^t\}$. Hence the amount of power load reduction for shaving power load is: $J_{peak} = \sum_{t=\hat{t}}^{\hat{t}+T-1} \max\{0, UB^t - \sum_{i=1}^{n} U_i^t\}$.

5.4.3 Optimization problem. In summary, we formulate the optimization problem of e-taxis' scheduling as:

$$\max_{X^{\hat{t}:\hat{t}+T-1}, Y^{\hat{t}:\hat{t}+T-1}} \quad J = J_{utility} - \gamma(J_{ramping} + \gamma_1 J_{peak}), \quad \text{s.t. } (1) \sim (8) \tag{9}$$

where $X^{\hat{t}:\hat{t}+T-1} = \{X^{\hat{t}}, ..., X^{\hat{t}+T-1}\}$, $Y^{\hat{t}:\hat{t}+T-1} = \{Y^{\hat{t}}, ..., Y^{\hat{t}+T-1}\}$ represent the coordination decisions from slot $\hat{t}$ to $\hat{t}+T-1$. γ is the weight parameter to balance maximizing the utility of e-taxi systems and minimizing the negative impact on the distribution networks. γ_1 is a parameter to balance the weight between reducing power load ramping and shaving peak load. By adding the slack variables to remove the min and max function in the objective function, the optimization problem is a multi-objective mixed-integer linear programming problem, which can be solved by, e.g., branch-and-bound [33] and cutting-plane [34]. In the evaluation, the global optimal coordination decisions can be obtained in less than one minute using a multi-core PC by a solver, Gurobi [35].

Since the locations and remaining energy of the e-taxis are dynamic and uncertain over time, we design a model predictive control (MPC) based algorithm to adjust coordination decisions with real-time status information. Alg. 1 shows the pseudo-code of the MPC algorithm. At the beginning of each time slot, the algorithm updates the real-time information, e.g., locations and remaining energy, using the sensors and communication modules installed in the e-taxis. Given the historical passenger mobility data and power demand data, linear regression is used to estimate the future passenger demand. Since the electric company provides its estimation of future power demand [17], we directly use these prediction results in this work. The algorithm obtains the decisions for the future T slots by solving Eq. (9), and the coordination decisions of current slot $\hat{t}$ are applied to the e-taxis. Our MPC-based algorithm tries to match e-taxis' scheduling with the remaining energy of e-taxis, passenger mobility model, and distribution of charging stations during the future time slots. MPC has already been widely used as a framework to adapt control decisions to the real-time system status. However, the optimization problem is formulated based on the specific e-taxi coordination problem studied in this work. The variables, constraints, objectives, and system models are unique.

Algorithm 1: *E-taxi coordination algorithm with real-time information*

Require: Duration of one time slot: t_1 minutes; time horizon T time slots; e-taxi charging power P; number of charging ports p_j; transformer capacity B; average revenue Re_i^t; parameters $R^{tc}, Lo^t, R^{rc}, \hat{L}, \hat{L}_1, \hat{L}_2, \beta, TR, TR_i^t, UB, \gamma, \gamma_1$

Ensure: Control decision: $x_{i,j}^{l,t}, xd_{i,j}^{l,t}, y_{i,i'}^{l,t}, yd_{j,i}^{l,t}$, $i, i' \in [1, n]$, $j \in [1, \bar{n}]$, $l \in [1, \hat{L}]$, $t \in [0, 24 * 60/t_1]$

1: **while** At the beginning of each t_1-minutes time slot **do**
2: Update current time slot as $\hat{t}$, sensor information for initial positions and energy status of e-taxis $V_i^{l,\hat{t}}$, $D_i^{l,\hat{t}}$ and $O_i^{l,\hat{t}}$; Update the driving distance constraint parameters $dc_{i,j}^t$, $ds_{i,i'}^t$, and electricity rate C_j^t; Update the passenger demand and estimated power load of end users based on historical data and real-time sensor information.
3: Solve the e-taxi coordination problem, Eq. (9) to get the charging scheduling decision.
4: Send current time slot's coordination decisions: $x_{i,j}^{l,\hat{t}}, xd_{i,j}^{l,\hat{t}}, y_{i,i'}^{l,\hat{t}}, yd_{j,i}^{l,\hat{t}}$.
5: **end while**
6: **return** Coordination scheduling decisions

6 POET WITH TIME-OF-USE PROGRAMS

In the previous section, we propose an e-taxi coordination algorithm where the e-taxi fleet co-optimizes the operational cost of power systems and the e-taxi service quality. This coordination algorithm demonstrates the potential benefit to power systems by coordinating e-taxis. Whereas, in the real world, such a coordination may not be practical when the fleet is a self-interested entity. In practice, one widely used mechanism for power systems to reduce peak load is the Time-Of-Use [36] electricity pricing. To induce power-system-friendly charging activities by e-taxis, it is essential in practice to design the TOU program for e-taxis. The power system can model that the e-taxi fleet determines the charging and dispatch decisions by solving the following optimization problem:

$$\max_{X^{\hat{t}:\hat{t}+T-1}, Y^{\hat{t}:\hat{t}+T-1}} \quad J = J_{revenue} - J_{payment}, \quad \text{s.t. } (1) \sim (8) \tag{10}$$

Let $F(X^{\hat{t}:\hat{t}+T-1})$ be a function describing the operational cost of power systems given the charging decisions of e-taxis, i.e., $X^{\hat{t}:\hat{t}+T-1}$. The dynamic electricity price in spatial-temporal dimensions (i.e., C_j^t) is obtained by solving the following optimization problem

$$\text{argmin}_{C_j^t} \quad F(\text{argmax}_{X^{\hat{t}:\hat{t}+T-1}} J_{revenue} - J_{payment}) \tag{11}$$

Some intuitions of designing the TOU program are: (i) the electricity price can affect e-taxis' coordination by directly changing the profit of an e-taxi fleet; (ii) the dynamic electricity price in spatial

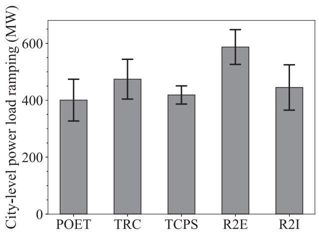


Figure 6: City-level power load ramping

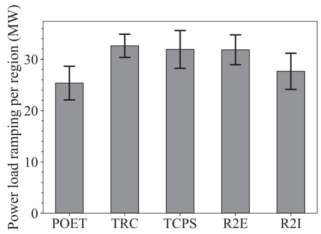


Figure 7: Region-level power load ramping

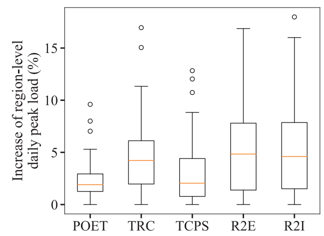


Figure 8: Peak load increase per region

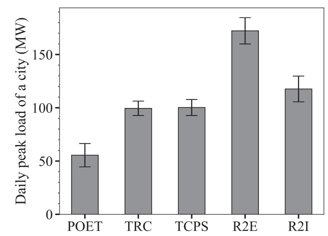


Figure 9: Daily peak charging load

dimension can help to balance the charging load across the regions and reduce the region-level load ramping or peak power load; (iii) the time-varying price can contribute to indirectly controlling the power load during a day, such as high price to decrease the charging load during the period with high power load from other end users. In this work, we provide a preliminary study of TOU's impact on an e-taxi fleet to achieve the potential of optimizing power system metrics. We leave a more detailed and novel design of TOU programs for future work.

7 EVALUATION

7.1 Methodology

To evaluate POET in a real-world scenario, we use the dataset described in Section 2.1 to conduct the trace-driven simulation. We assume that all the taxis in the dataset are e-taxis and the passenger mobility pattern does not change when the e-taxis are deployed in the city. We extract the passenger mobility information during each time slot from the historical trips of passengers. The electricity company provides the forecast of the hourly power load in each region. We use half of the forecast as the actual power load and the other part as the predicted power load from end users. POET is compared with several solutions.

- Taxi service with regular charging (TRC) [30]: it determines where, when and how long the e-taxis are charged. It aims to maximize the number of served passengers and minimize the idle waiting time for charging and the idle driving time to the charging stations.
- Taxi service considering power systems (TCPS): it first uses TRC to determine the charging and dispatch decisions. Then it reallocates the charging demand determined in the first step and then it re-computes the charging decisions to minimize the region-level load ramping and shave region-level peak load.
- Reactive to e-taxi energy (R2E) [23]: given current slot $\hat{t}$, the e-taxis are scheduled for charging if their remaining energy is below 15%. These e-taxis with low energy are scheduled to the different regions to minimize the region-level power load ramping and shave region-level peak load, i.e., $\min \sum_{i=1}^{n} |U_i^{\hat{t}} - U_i^{\hat{t}-1}|$. This method does not optimize the city-level load ramping and peak load since it only determines the charging load distribution in the spatial domain.
- Reactive to e-taxi idling (R2I): given current slot $\hat{t}$, it considers the idle e-taxis for charging. This method assigns a part of idle e-taxis to charge, aiming to minimize the region-level and city-level load ramping and shave peak power load, i.e., minimizing this objective function at each current slot $\hat{t}$, $\sum_{i=1}^{n} |U_i^{\hat{t}} - U_i^{\hat{t}-1}| + |\sum_{i=1}^{n} U_i^{\hat{t}} - \sum_{i=1}^{n} U_i^{\hat{t}-1}| + \gamma_1 \max\{0, UB - \sum_{i=1}^{n} U_i^{\hat{t}}\}$, where the power load of a region or the city in slot $\hat{t}-1$ is known.

In the evaluation, the default values of γ and γ_1 are 0.05 and 1. UB is the historical average daily peak power load of the city. Several metrics are used to measure the performance. (i) City-level load ramping: it is the city-level load ramping during a day, defined as $\sum_{t=start}^{end-1} |\sum_{i=1}^{n} U_i^{t+1} - \sum_{i=1}^{n} U_i^{t}|$. (ii) Power load ramping per region: it is the load ramping for any region i during a day, defined as $\sum_{t=start}^{end-1} |U_i^{t+1} - U_i^{t}|$. For the two metrics, the start time slot is 9:00 and the end time slot is 19:00. The reason is that the power load of users except e-taxis during this time period does not change a lot and the load ramping due to the e-taxis is demonstrated more clearly. (iii) Increase of region-level daily peak load: it is equal to (daily peak load of the region i with e-taxis - daily peak load of the region i without e-taxis) / daily peak load of the region i without e-taxis. (iv) Profit per day: the amount of money that the e-taxis earn per day minus the payment for charging. The electricity rate is set as \$0.21 per kWh. We use Gurobi [35] to solve the optimization problem, where the branch-and-bound algorithm is implemented to find the global optimal solution for the mixed-integer linear programming problem.

7.2 Results

The evaluation result shows that compared with TRC that focuses on optimizing the taxi service quality, our solution POET reduces the impact on the power systems significantly with little sacrifice on the profit of the e-taxi fleet. The main results are as follows:

- POET reduces the city-level power load ramping compared with other solutions between 4.5% and 31.8%.
- POET reduces the power load ramping of a region compared with other solutions between 8.3% and 22.3%.
- POET decreases the daily peak charging load of a city between 44.2% and 67.8% compared with other solutions.
- POET achieves the second highest profit for the e-taxi fleet and reduces the profit by 1.4% compared with the highest profit.

7.2.1 Power load ramping. Figure 6 shows the total load ramping of the city by the five charging solutions. The main observation is that POET decreases the city-level load ramping by 15.5%, 4.5%, 31.8%, and 10.0% compared with the other four solutions respectively. It is clear that purely reactive to the remaining energy of e-taxis can significantly raise the city-level load ramping due to potential concentrated charging. For example, passenger demand increases from

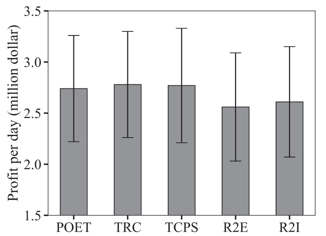


Figure 10: Profit of e-taxi systems

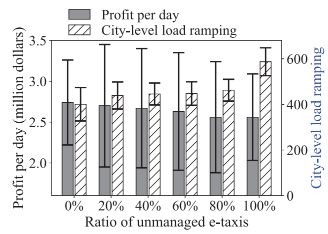


Figure 11: Impact of uncoordinated e-taxis on POET

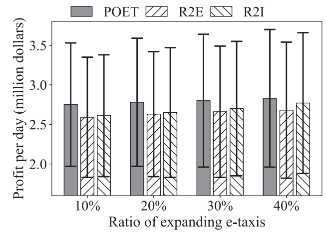


Figure 12: E-taxi profit with fleet expansion

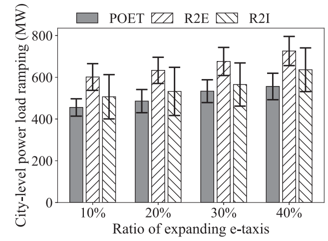


Figure 13: City-level load ramping with fleet expansion

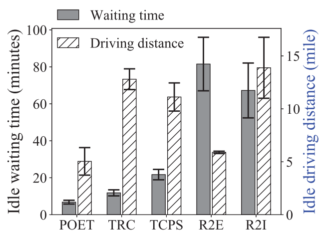


Figure 14: Idle waiting time and driving distance

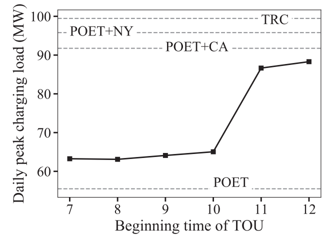


Figure 15: POET under Time-of-use pricing

6:00 to 10:00 and decreases from 11:00 to 16:00. Most e-taxis have near full energy at the beginning of the daytime and reach the threshold of low energy during lunchtime. Figure 7 shows the local load ramping per region by the five solutions. POET outperforms the other four solutions with the least power load ramping of a region, e.g., it decreases this value by 22.3%, 20.6%, 20.4%, and 8.3% compared with TRC, TCPS, R2E, and R2I. The performance of R2I (i.e., second lowest load ramping) demonstrates that explicitly considering the metrics of power systems and conducting the partial charging are useful to reduce the impact on the power systems. By comparing the performances of POET and R2I, we conclude that optimizing the city-level load ramping during several consecutive time slots is effective in reducing the ramping, which further decreases the operation cost for power network operators.

7.2.2 Region-level daily peak load & daily peak charging load. Figure 8 shows the distribution of the increase of the region-level daily peak load. It is observed that POET increases the daily peak load of most regions by less than 5.0%, while TRC, R2E and R2I sometimes increase the region-level daily peak load by more than 15.0%. Since TCPS also considers the reduction of region-level peak load, it achieves the second best performance in terms of the increase of region-level daily peak load. R2E only schedules e-taxis for charging when they have low energy (e.g., <15%) and R2I limits the number of e-taxis for charging to shave power load. Due to such logic of R2E and R2I, they accumulate a large amount of e-taxis with low energy for charging, resulting in the increase of peak load.

Figure 9 shows the daily peak charging load of a city by five solutions. We can observe that POET reduces the daily peak charging load by 44.2%, 44.6%, 67.8%, and 52.8% compared with the other four solutions. By comparing the performances of TRC and R2I, it is concluded that scheduling a sufficient number of e-taxis to charge the battery proactively is helpful to reduce the peak charging load. Because R2I selects a small number of e-taxis with sufficient energy for charging in order to shave peak load even though it considers all the idle e-taxis, resulting in the concentrated charging activities of accumulated low energy e-taxis and high peak charging load. TRC and TCPS have similar performance because they have the same logic to determine how many e-taxis should be charged during a time slot. TCPS takes a step further to assign the e-taxis to different regions to optimize the region-level power system performance.

7.2.3 Profit. A primary metric of an e-taxi system is its profit. Figure 10 shows the money that the e-taxi system earns minus the payment for electrical power per day, and there are three observations. The first is that the profit reduces only 1.4% per day when changing the scheduling solution from TRC to POET. Since there is a trade-off between maximizing the profit of e-taxi systems and minimizing the costs of power systems, it is natural that POET misses a part of the profit. The second is that the profit of the e-taxi system increases if the scheduling solutions adapt to the variation of passenger demand in the temporal dimension. For example, the four solutions (i.e., POET, TRC, TCPS and R2I) that consider the passenger demand outperform R2E that determines when to charge based on the remaining energy of e-taxis. Specifically, compared with R2E, the e-taxi system earns 0.18 million more dollars per day by taking POET. The last observation is that dispatching e-taxis for matching the passenger demand in the future several time slots is useful to increase the profit, e.g., compared with R2I, the e-taxi fleet's profit increases by 5.0% and 6.5% by POET and TRC.

7.2.4 Impact of uncoordinated e-taxis. Given the scale of the taxi system for a large city, some e-taxis may not fall into the category of being centrally coordinated to optimize the service quality and operational cost of power systems simultaneously. Figure 11 shows the daily profit of an e-taxi fleet and the city-level load ramping by POET with different ratios of unmanaged e-taxis, where the unmanaged e-taxis charge their battery when the remaining energy is below 15% and select the charging station with the minimum driving time plus waiting time. The main observation is that the profit decreases and the city-level load ramping increases with the increase of unmanaged e-taxis. For example, the daily profit decreases by 6.6% and the city-level load ramping rises by 15.4% when the ratio of unmanaged e-taxis changes from 0% to 80%.

7.2.5 E-taxi fleet expansion. We envision that the future fleet of e-taxis is likely larger than the currently available fleet, partly due to the time spent on charging the batteries. Figures 12 and 13 show the e-taxi fleet profit and the city-level load ramping by POET, R2E, and R2I with different expansion ratios of the current fleet. There are two main observations: (i) our solution POET consistently outperforms the other two solutions with the different ratios of

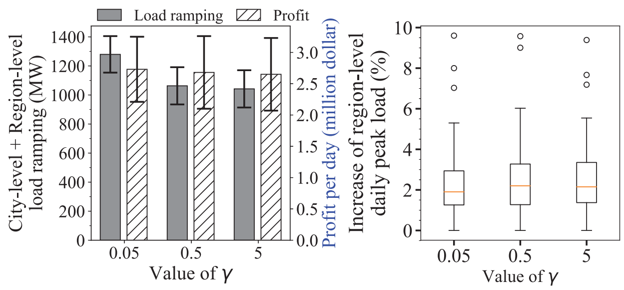


Figure 16: Impact of the weight on optimizing distribution network performance (γ)

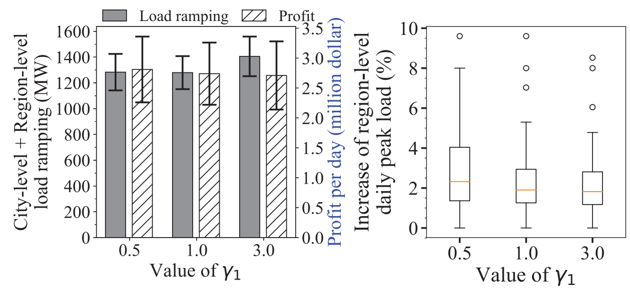


Figure 17: Impact of the weight on shaving peak load (γ_1)

expanding e-taxis: e.g., when expanding the e-taxi fleet by 40%, the daily profit by POET is 150 thousand and 60 thousand dollars more than that by R2E and R2I respectively; (ii) the daily profit and the city-level load ramping increase with the expansion of the e-taxi fleet. E.g., the city-level load ramping of POET rises by 13.7% when the fleet expands by 10%; Still, POET reduces the city-level load ramping significantly compared with R2E and R2I.

7.2.6 Idle waiting time and driving distance. Figure 14 shows the average idle waiting time for a free charging port and the average idle driving distance to charging stations of an e-taxi per day. We have several observations from the figure. The first one is that POET, TRC and TCPS introduce shorter waiting time compared with R2E and R2I. Because both R2E and R2I introduce the concentrated charging activities when many e-taxis are close to using up energy during a short time period as explained previously. The second observation is that R2I introduces the longest idle driving distance. The reason is that e-taxis are frequently scheduled to the charging stations for partial charging (i.e., only charged for a time slot) by R2I. Although POET, TRC and TCPS also conduct partial charging, they optimize the idle driving distance in the objective function and the e-taxis may be charged at the same region after dropping off passengers with little idle driving distance.

7.2.7 Comparison of Co-optimization and TOU. In the previous parts, we evaluate and show the performances of POET, which is an ideal case that the fleet is willing to work for the power system. In this part, we would like to study how much the e-taxi fleet can contribute to the power system under a Time-Of-Use program. We first evaluate POET under two real-world time-of-use programs in New York [37] and California [36], called POET+NY and POET+CA, respectively. As shown in Figure 15, the time-of-use program is useful to reduce the daily peak charging load of an e-taxi fleet, such as decreasing it from 99.46 MW to 91.75 MW and 95.8 MW respectively, but the decrease is not significant. We then customize the existing time-of-use program to evaluate whether the peak charging load can be reduced more significantly.

We use the electricity price data from a real-world TOU program [36], where there is a time window with high electricity prices to shave the peak load. In this experiment, the time window is set as four hours. The electricity price is \$0.29 per kWh before the time window, \$0.43 during the time window, and \$0.32 after the time window. We change the beginning time of the time window from 7 am to 12 pm, and plot the daily peak load in Figure 15. There are three main observations. (i) The TOU program can significantly reduce the daily peak load compared with TRC, e.g., nearly 36.4% reduction when the TOU starts at 7 am. (ii) The second observation is that when the beginning time of TOU changes from 10 am to 11 am, the daily peak load increases by 33.2% because the daily peak load usually exists between 10 am and 11 am, which is not included in the time window when the program starts at 11 am. (iii) The TOU demand response programs can help to reduce the daily peak load of e-taxi fleets, but there is still a gap from using the ideal coordination algorithm POET.

7.2.8 Impact of γ and γ_1 on POET. Figure 16 shows how the value of γ influences the performance of POET. It is observed that when the weight on optimizing power system metrics rises, the city-level and region-level power load ramping decreases, the e-taxis' profit reduces, and the daily region-level peak load does not change a lot. Figure 17 shows how the value of γ_1 affects the performance of POET. The main observation is that when increasing the weight (γ_1) on shaving peak load, the daily region-level peak load decreases, the load ramping increases, and the e-taxis' profit reduces. According to Figure 16 and Figure 17, we can observe the trade-off between shaving peak load and reducing power load ramping. Some possible scenarios of the trade-off are (i) when the power load from users except e-taxis decreases, some e-taxis should be charged to reduce the load ramping, which conflicts with shaving the power load; (ii) when the power load from users except e-taxis increases in the future time slots, some e-taxis should be charged now to reduce the load ramping, also conflicting with power load shaving.

8 DISCUSSION

Future electric vehicles: With the advancements of battery technology, the battery capacity and EV driving distance will increase [5, 38]. However, charging the higher-capacity battery fully using the same time will require higher charging power, e.g., Tesla supercharging 150 kW. As a result, the power load variation of power systems can rise even more dramatically. Meanwhile, more EVs will be on the road besides e-taxis, so the demand for EV charging will also increase, introducing an even higher burden on the power systems. Therefore, it is expected that the challenges for power systems will become even severer in the future.

Implementation of POET: To make the data-sharing between power systems and e-taxi fleets feasible, one practical scenario is to have the e-taxi fleets participate in demand response (DR) programs, where power systems provide incentives for e-taxis to address real-time power system needs. The design of new DR programs that would allow effective collaboration between e-taxi fleets and power systems is left for future work. Nonetheless, this paper demonstrates great potential of such collaboration in greatly benefiting power systems at little cost of e-taxi fleets, and mechanisms to tap into such benefits are of great interest for future studies.

Competitive scenarios of power systems and electric vehicles: This work demonstrates the potential benefit to power systems by coordinating e-taxis in a cooperative setting. However, in the real world, power systems and electric vehicle fleets may play competing roles instead of fully cooperative ones. The power systems may design the incentive mechanisms or dynamic electricity prices to impact the charging behaviors in practice. Some lessons can be learned from this work for the power systems in a non-cooperative setting: (i) the power system can impact the electric vehicle fleets' charging behaviors by time-of-use or incentive mechanisms to optimize its operational cost while still ensuring the service quality of electric vehicles; (ii) the power system would need to have a model of how the electric vehicle fleets react to the incentive mechanisms or time-of-use programs when designing the incentive mechanisms or time-of-use programs; (iii) the information sharing between power systems and electric vehicle fleets is useful to improve the efficiency of potential incentive mechanisms/demand response programs.

9 RELATED WORK

EV charging behaviors coordination: The coordination of electric vehicle fleets charging behaviors [23, 30, 31, 39–41] focuses on recommending electric vehicle fleets when, where and how long to charge the battery for improving the fleet service quality or reducing the cost of charging. [30] proposes a proactive partial charging strategy for electric taxis to provide flexible time and duration of charging for matching the passenger demand in spatial-temporal dimensions. This work differs from [30] in (i) designing the cross-system coordination framework with data sharing to explore the possibility of using the flexibility of electric vehicles to optimize the power systems instead of only considering electric vehicle fleets, and (ii) modeling the power system needs and how the charging behaviors affect the performance of power systems in a centralized vehicle coordination problem. [23] develops an electric taxi charging scheduling framework to inform the electric taxi drivers when and where to charge the battery. Whereas, these related studies only consider the performance of e-taxis, e.g., reducing e-taxi waiting time at charging stations or matching passenger demand [23, 30, 31, 39–41], which ignore the negative influence of e-taxis' charging behaviors on the stability and reliability of power networks. Furthermore, we utilize the flexibility and mobility of e-taxis to provide demand response services, co-optimizing the power grid and the transportation service quality.

Grid integration of EVs: Load management systems of EVs [14, 42–47] are proposed to ensure the stability and increase the efficiency of the power grid under the dynamic charging behaviors of EVs. [43] presents a reputation-based system to allocate power to EVs in the smart grid, which considers the power demand and deadlines of EVs. [14] proposes a stochastic optimization-based scheme to ensure both the stability of the grid and the quality of services of electric vehicles by managing the charging rate and balancing demand. [46] recommends the charging behaviors of EVs based on the dynamic changes of time-varying electricity price. [47] proposes an integrated price-based demand response program for the energy market to support the stability of the power grid. These works focus on optimizing the performance of power grids, while our work co-optimizes the e-taxi fleet and power grids with a detailed and realistic model of the transportation system with e-taxis, and evaluated based on real-world data.

Joint modeling of power systems and electric transportation systems: [48, 49] investigates the interaction between autonomous mobility-on-demand (AMoD) fleets and the power network, showing that the coordination between AMoD and the power systems can optimize the power generation cost and the AMoD system's performance simultaneously. While both of these works formulate static optimization problems for both the electric vehicle fleets and power systems, this paper focuses on designing a dynamic coordination algorithm for e-taxi fleets during daily operations. [50] provides retail pricing mechanisms and designs iterative wholesale market-clearing algorithms to maximize the social welfare in coupled electric vehicles and power grids, where the drivers make battery charging decisions only, differing from the e-taxi fleet considered in this paper where both charging and serving passengers are key decisions. [51] studies the fast charging station recommendation problem for electric vehicles to promote the stability of the coupled power-transportation system. Different from this paper, it considers private electric vehicles that do not need to serve passengers. [52] designs a fuzzy logic controller at the energy storage systems, connecting power grids and electric bus networks, to stabilize the grid and achieve the required frequency of buses. This work differs from [52] in utilizing the flexibility of electric taxis to co-optimize power and transportation system objectives. [53] proposes a rebalancing and vehicle-to-grid coordination strategy for transportation systems consisting of autonomous vehicles, while it assigns the vehicles to parking facilities to provide vehicle-to-grid services. [54] explores an integrated pricing strategy for road tolls and electricity prices to coordinate the load levels of the power distribution network and transportation network. It does not consider dynamically coordinating EVs' charging behaviors to improve the service quality of EV fleets.

10 CONCLUSION

We investigate how the charging load from e-taxi fleets impacts the power grid with real-world datasets. The data-driven analysis shows that the charging behaviors of e-taxis can lead to an increased power load ramping of a city as well as local regions within it, and the increase of peak power load. To address this problem, we propose an e-taxi coordination algorithm – POET – to co-optimize the operations of taxi service and power grids by exploiting the flexibility of e-taxi charging while serving passengers. Trace-based simulation demonstrates that, compared with the existing e-taxi charging solution that focuses on optimizations of taxi service quality, POET significantly decreases the power load ramping of local regions by 22.3% and reduces the daily peak charging load by 44.2% while achieving almost the same taxi revenue.

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