SAC: Solar-Aware E-Taxi Fleet Charging Coordination under Dynamic Passenger Mobility

Yukun Yuan, Yue Zhao, and Shan Lin

***Abstract*— As electric vehicles (EV) gradually replace traditional fuel vehicles and provide transportation services in cities, e.g., electric taxi/bus fleets, solar-powered charging stations with energy storage systems have been deployed in urban areas to provide charging services for EV fleets [1]. The mixture of solar-powered and traditional charging stations brings efficiency challenges to charging stations and reliability challenges to power systems. In this paper, we explore e-taxis' mobility and charging demand flexibility to co-optimize service quality of e-taxi fleets and system cost of charging infrastructures, such as under-utilization of solar power and reliability issues of the power distribution network due to reverse power flow. Specifically, we propose SAC, an e-taxi coordination framework to dispatch e-taxis for charging or serving passengers under spatio-temporal dynamics of renewable energy and passenger mobility. We formulate the e-taxi fleet coordination problem as a multi-criterion mixed-integer linear programming problem. We evaluate our solution with a comprehensive dataset for e-taxi systems and charging infrastructures including 726 e-taxis, 7,228 regular fuel taxis, 37 working charging stations, and 62,100 collected taxi trips per day. Our data-driven evaluation shows that SAC significantly outperforms existing solutions, reducing the total reverse power flow per day by up to 95.3%, while maintaining e-taxi service quality with very small overhead.**

I. Introduction

As battery technologies become mature, electric vehicles (EVs) have obtained significant attention and are regarded as an alternative to fuel vehicles due to their advantages, e.g., environment-friendliness, quietness, and less frequent maintenance [2]. For example, the EU plans to phase out fuel vehicle sales by 2035, and many other countries also have pitched similar plans [3]. Meanwhile, various types of EV fleets have already been progressively expanded in urban cities. For instance, an increasing number of Tesla taxis trickled into New York City in 2020 [4]. Some other cities, e.g., London, Shenzhen, and Singapore [5], are also electrifying their taxi fleets.

To address the challenge of charging large-scale EV fleets, charging stations have been increasingly deployed in urban areas. Besides the traditional charging stations drawing energy from power systems, there is a trend towards installing solar-powered charging stations that, while still connected to the grid, harness environmentally friendly renewable energy. To best utilize the solar-powered charging stations, EV fleets charging activities play a key role. For example, as the local power distribution systems may have limits on the reverse power flows from excess solar generation [6], [7] (as reflected in, e.g., limited hosting capacity), unorganized e-taxi charging may lead to unnecessarily curtailed solar power at certain charging stations due to under-utilization and limits on reverse power flows, while drawing power from the grid to charge at other charging stations. With spatiotemporal dynamics of solar energy and passenger demand, it is very challenging to coordinate an e-taxi fleet to efficiently utilize solar power for charging while fulfilling the dynamic passenger demand.

Previous works have explored designs for EV charging scheduling at a solar-power charging station [8], modulating solar array output based on fairness [9], and scheduling numerous distributed energy resource [10]. However, little work has been done to jointly consider solar power generation and passenger mobility, and co-optimize the service of an e-taxi fleet and the social cost of the charging infrastructures. This work presents the first study for coordinating an e-taxi fleet that optimizes the service quality of e-taxi fleets while minimizing the system cost of charging infrastructures.

In particular, the proposed framework, called Solar-Aware-Charging (SAC), schedules e-taxi fleets with two objectives: (i) serving passengers efficiently, and (ii) reducing the cost of charging infrastructures. Although the e-taxi company sacrifices its utility to consider the system cost of charging infrastructures, the incentive mechanism, such as [11], can be implemented by the owner of charging infrastructures to compensate the e-taxi company and induce it towards achieving social optimum. We use the number of served passengers to measure the service quality, and we consider the following solar-aware metrics to measure the cost of solar-powered and battery-equipped charging infrastructures: (i) reverse power flows from the solar-powered charging stations, (ii) energy losses due to charging or discharging energy storage systems at the stations, and (iii) the amount of power drawn from the local distribution system to supply e-taxis in addition to using the solar power. SAC aims to maximize an e-taxi fleet's utility while utilizing e-taxis' charging demand flexibility to maintain high efficiency of charging stations. SAC allows the e-taxi fleet and solar-charging stations to work cooperatively to maximize the social welfare for both the transportation and energy system metrics.

The **contributions** of this work are as follows.

- To the best of our knowledge, it is the first work to coordinate an e-taxi fleet for optimizing charging cost with both conventional and renewable energy while maintaining the taxi service quality.

This work was supported in part by the National Science Foundation under Grant ECCS-2025152, CNS-1952096 and CNS-1553273 (CAREER).
Y. Yuan, Y. Zhao and S. Lin are with the Department of Electrical and Computer Engineering, Stony Brook University, USA.

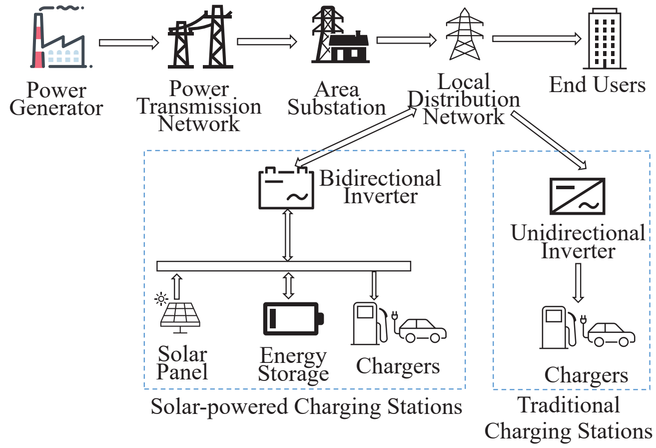

Fig. 1: Illustration of power systems with both solar-powered and conventional charging stations

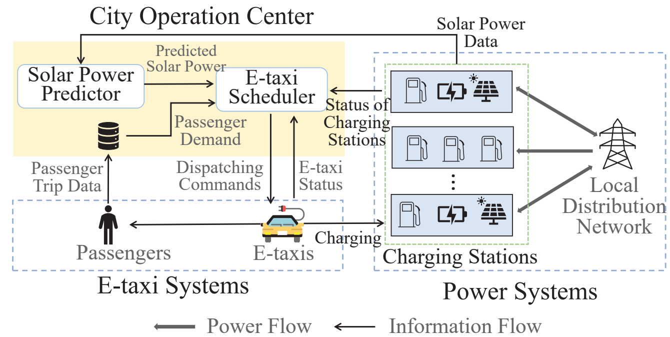

Fig. 2: SAC Framework Design

- We propose SAC, an e-taxi fleet coordination framework to dispatch e-taxis for either charging or serving passengers under spatio-temporal dynamics of renewable energy and passenger mobility. We formulate the e-taxi fleet coordination problem as a multi-criterion mixed-integer linear programming problem.
- We evaluate the proposed solution, SAC, with a comprehensive real-world dataset consisting of 726 e-taxis, 7,228 regular fuel taxis, 37 working charging stations, and total 62,100 collected taxi trips per day. Our data-driven evaluation shows that our solution significantly reduces the total reverse power flow per day by 94.8% while only reducing the number of served passengers by 2.3% compared to the solution focusing on optimizing the e-taxi service quality.

II. Background

Figure 1 demonstrates the architecture of power systems with both solar-powered and traditional charging stations. The entire city is partitioned into multiple local regions by the power systems. The users in a local region are powered by the same area substation. In each local region, there are two types of users, i.e., regular end users and charging stations. Based on the source of power, charging stations are classified into conventional charging stations and solar-powered charging stations. The former type of charging stations is powered by local power distribution networks, and the latter one is powered by both solar panels and local distribution networks.

There are four main components in a solar-powered charging station [12], [13], i.e., solar panel, energy storage systems, chargers, and bidirectional inverter. The solar panel converts solar radiation into solar energy, which can be used to charge the electric vehicles (EVs), be stored in the storage systems, or be fed to the local distribution network. When the solar energy is not fully utilized by e-taxis, the extra power can be stored for the future charging demand as long as the battery is not full. EVs are charged when connecting with the chargers, and the energy may come from the solar panel, the storage systems, or the local distribution network. The bidirectional inverter transmits the AC power coming from the distribution network to the DC power used in a charging station or in the opposite direction.

We assume that the solar-powered charging station with storage works by the following policy. (i) If the generated solar energy is more than the power demand due to e-taxi charging, and the energy storage is full, the extra energy is fed to the local distribution network. (ii) If the generated solar energy is more than the power demand due to e-taxi charging, and the energy storage is not full, the extra energy is stored in the energy storage. (iii) If the generated solar energy is less than the power demand due to e-taxi charging and the storage cannot provide sufficient energy to meet the charging demand, the energy from the solar panel, the local distribution network, and the storage is used to charge the EVs. (iv) If the generated solar energy is less than the power demand due to e-taxi charging and the storage can provide sufficient energy to meet the charging power demand, the energy from the solar panel and the storage is used to charge the EVs.

III. SAC Overview

In this work, we design a solar-aware charging coordination framework, called SAC, to schedule e-taxis for charging and serving passengers under the scenario that both solar-powered charging stations and conventional charging stations are available. The design of SAC is shown in Figure 2. The e-taxi scheduler is implemented in the city transportation center to coordinate the activities of e-taxis, i.e., dispatching e-taxis for charging or picking up passengers. The objectives of the e-taxi scheduler are (i) maximizing the number of served passengers, (ii) reducing the idle driving distance due to dispatching, (iii) minimizing the reverse power flow and the energy loss due to charging or discharging the energy storage systems, and (iv) reducing the power drawn from the local power distribution network to the charging stations and thereby increasing the local usage of solar power.

It is assumed that e-taxis report their real-time status and passenger trip data to the city operation center to improve the utility of e-taxi systems. Meanwhile, the charging stations share their information with the city operation center, i.e., the amount of generated solar energy, the remaining energy of energy storage, and the number of vehicles in each charging station, in order to facilitate the e-taxi scheduler to reduce the cost in power systems due to charging.

Two control loops exist in this system. The first loop is in the e-taxi system. During the daily operation, the e-taxi scheduler determines the dispatching commands for either serving passengers or charging the battery. When the e-taxis are moving the passengers, the passenger trip data is collected and uploaded to the city operation center. The future passenger demand is predicted using the stored passenger trip data and is fed to the e-taxi scheduler for making better dispatching decisions. The second loop connects the e-taxi system and the power system. The e-taxi scheduler determines when and which charging stations the e-taxis should use to charge the battery. The charging stations upload their real-time remaining energy in the storage systems as well as the real-time charging demand to the e-taxi scheduler. The former data helps the scheduler to detect whether the generated and stored power is sufficient for charging e-taxis the amount of reverse power flow if any. The latter data is used to estimate the available charging resource for e-taxis. The external weather forecast data and the solar power generation data are input to the solar power predictor to estimate the amount of future solar power.

IV. Charging Station Model

In this section, we propose the model of solar-powered charging stations with storage systems and conventional charging stations. Specifically, we formulate in more detail the policy of a solar-powered charging station given the charging demand and the solar power generation (cf. Section II).

A. Solar-powered Charging Station with Storage

It is assumed that there are M_s solar-power charging stations with storage and M_t conventional charging stations in a city. We use C_j to describe the storage capacity at charging station j. A day is discretized into multiple time slots, and we use k to represent a time slot. Let g_j^k be the maximum solar power output by the solar panel at solar-powered station j during slot k. Let r_j^k be the amount of remaining energy in the storage of the station j at the beginning of slot k. We define γ_c (γ_d) as the maximum charging (discharging) rate of the storage system.

Let e_j^k denote the energy charging or discharging rate of the storage system in the station j during the slot k. If $e_j^k > 0$, the storage system is charged; otherwise, it is discharged. The unit of e_j^k is kilowatt. The remaining energy changes between slot k and $k+1$ as:

$$r_j^{k+1} = r_j^k + e_j^k * K \tag{1}$$

where K is the length of a time slot, e.g., 5 minutes. Given the maximum charging or discharging rate, the actual charging or discharging rate should be bounded as:

$$-\gamma_d \leq e_j^k \leq \gamma_c \tag{2}$$

The amount of stored energy should not violate the storage capacity, which is formulated as

$$0 \leq r_j^k \leq C_j \tag{3}$$

Let d_j^k represent the charging demand from EVs in the station j during slot k. The unit of d_j^k is also kilowatt. According to the policy that each charging station follows, e_j^k is related to the amount of solar power, the charging demand, and the amount of stored energy.

If the solar power is more than the power demand for charging, i.e., $g_j^k \geq d_j^k$, the amount of extra solar power that should be stored is $g_j^k - d_j^k$. Meanwhile, the actual power charging rate of the storage system should be no more than the maximum charging rate γ_c. The stored energy $e_j^k * K$ should not exceed the remaining storage capacity $C_j - r_j^k$. We have $e_j^k = \min\{g_j^k - d_j^k, \gamma_c, (C_j - r_j^k)/K\}$.

If the solar power is less than the charging demand, i.e., $g_j^k < d_j^k$, some extra energy is discharged from the storage. The discharging rate of the storage system is bounded by the maximum discharging rate γ_d. Meanwhile, the amount of discharged power, i.e., $|e_j^k| * K$, should not exceed the amount of stored energy r_j^k. According to the two constraints, we have $e_j^k = -\min\{d_j^k - g_j^k, \gamma_d, r_j^k/K\}$. In summary, e_j^k is modeled as:

$$e_j^k = \begin{cases} \min\{g_j^k - d_j^k, \gamma_c, (C_j - r_j^k)/K\} & \text{if } g_j^k \geq d_j^k \\ -\min\{d_j^k - g_j^k, \gamma_d, r_j^k/K\} & \text{otherwise} \end{cases} \tag{4}$$

Given the charging demand (d_j^k), the solar power (g_j^k), and the charging or discharging rate of the storage system (e_j^k), the power demand from station j on the local power distribution network during slot k is:

$$D_j^k = e_j^k + d_j^k - g_j^k$$

If $D_j^k > 0$, the power is drawn from the local distribution network to the charging station; otherwise, the power is fed into the local distribution network.

Given the bidirectional inverter j associated with the solar-powered charging station j, we use B_j^+ and B_j^- to represent the capacity of this inverter to transmit power from the local distribution network to the charging station or in the opposite direction. Then the power flowing through the inverter in either direction should be constrained as:

$$-B_j^- \leq D_j^k \leq B_j^+ \tag{5}$$

B. Conventional Charging Stations

Let $\tilde{D}_j^k$ be the amount of energy that the j-th conventional charging station consumes due to charging the e-taxis during the slot k. It is noted that $\tilde{D}_j^k \geq 0$ and a conventional charging station is only powered by the local distribution network. Since the j-th inverter associated with a conventional charging station j is unidirectional, let $\tilde{B}_j$ be the capacity of this inverter. We also constrain that

$$\tilde{D}_j^k \leq \tilde{B}_j \tag{6}$$

Compared with the conventional charging stations, the solar-powered ones utilize the renewable energy reducing the greenhouse gas emissions and the energy loss during transmission. However, the distributed solar power may result in reverse power flows that lead to reliability issues of the power distribution system [14]. Thus, ideally, one would like e-taxis to be scheduled to charge at the solar-powered stations in a way that matches the solar power generation. On the other hand, the locations of solar-powered charging stations and the number of congested e-taxis at these stations affect the service quality of e-taxi fleets. For example, a solar-powered station may be far away from the central business area, where there is high passenger demand, or the waiting time is long at some solar-powered stations. Hence it is challenging to schedule e-taxis for optimizing service quality while minimizing cost of charging infrastructures. In the next section, we propose our formulation of e-taxi systems and the optimization problem of e-taxi coordination.

V. E-Taxi Systems

A. E-taxi Systems States and Decisions Variables

The entire city area is partitioned into N regions. We assume that there are $M = M_s + M_t$ charging stations in the city. Without loss of generality, it is assumed that the first M_s charging stations are solar-powered and the last M_t charging stations are only powered from local distribution networks. Let $R_{i,j} \in \{0, 1\}$ describe the relation between region i and charging station j. $R_{i,j} = 1$ if the j-th station locates in region i; otherwise, it is 0. We define three states of an e-taxi: working on the road for serving passengers, waiting in the queue of a charging station for an available charging point, and charging the battery. If an e-taxi is within one of the three states, we say that it is a working, waiting, or charging e-taxi. Let t represent the current time slot, and k is used to describe any time slot from t to $t + T - 1$. In this work, we consider the e-taxi dispatch problem for the future T time slots.

The remaining energy of an e-taxi is discretized into L levels. Let RE^k be the remaining energy of an e-taxi at the beginning of the time slot k. According to the state of an e-taxi during slot k, we have the following model to describe the change of remaining energy between RE^k and RE^{k+1}. If an e-taxi waits for a charging point during slot k, $RE^{k+1} = RE^k$. If an e-taxi charges the battery during slot k, $RE^{k+1} = RE^k + \tilde{L}$, where $\tilde{L} > 0$ is the number of levels that the remaining energy increases. If an e-taxi works on the road and it moves from region i to region i' during slot k, $RE^{k+1} = RE^k - L^k_{i,i'}$. $L^k_{i,i'}$ represents the number of levels that the remaining energy decreases if an e-taxi moves from region i to i' during slot k.

The states of an e-taxi system are defined as the number of e-taxis with the different remaining energy and the different states in spatial and temporal dimensions. Several notations are defined to describe the states of an e-taxi system.

Let $V^k_{i,l}, O^k_{i,l}$ denote the number of unoccupied or occupied e-taxis with remaining energy l at the beginning of slot k in region i. If the current time slot is t, $V^t_{i,l}$ and $O^t_{i,l}$ are updated by the real-time data (e.g., occupancy status and GPS locations) from the installed devices (e.g., GPS sensors and communication modules) in the e-taxis. It is noted that the unoccupied e-taxis include the idle working e-taxis in region i, and waiting or charging e-taxis in station j during slot $k - 1$, where station j locates in region i.

Decision variables: The e-taxi schedule may dispatch an occupied e-taxi for charging or serving passengers at the beginning of slot k. We define $X^k_{i,i',l} \in \mathbb{N}$ as the number of e-taxis with remaining energy l that are dispatched from region i to i' for serving passengers at the beginning of slot k. Since the e-taxis with any remaining energy are considered for working, the range of l is between 1 and L.

$Y^k_{i,j,l} \in \mathbb{N}$ is defined to describe the number of e-taxis with remaining energy l that are dispatched from region i to charging station j for charging at the beginning of slot k. The range of l is also $[1, L]$ and any unoccupied e-taxis can be scheduled for charging. Due to the limited number of e-taxis in each region, we constrain that

$$\sum_{i'=1}^{N} X^k_{i,i',l} + \sum_{j=1}^{M} Y^k_{i,j,l} = V^k_{i,l} \tag{7}$$

B. E-taxi Systems State Transition Model

Based on the historical passenger trip data, the future passenger demand in spatial-temporal dimensions can be estimated, i.e., how many passengers will request the taxi service in a future time slot k in region i, denoted as r^k_i.

Let $S^k_{i,l}$ represent the number of unoccupied e-taxis with remaining energy l that can move passengers in region i during slot k after dispatching. We have the following model to describe the state transition of an e-taxi system between slot k and $k + 1$:

$$\begin{aligned} S^k_{i,l} &= \sum_{i'=1}^{N} X^k_{i',i,l} \\ V^{k+1}_{i,l} &= \sum_{i'=1}^{N} Pv^k_{i',i} S^k_{i',l+L^k_{i',i}} + \sum_{i'=1}^{N} Qv^k_{i',i} O^k_{i',l+L^k_{i',i}} \\ &\quad + \sum_{j=1}^{M} R_{i,j} U^{k+1}_{j,l} \\ O^{k+1}_{i,l} &= \sum_{i'=1}^{N} Po^k_{i',i} S^k_{i',l+L^k_{i',i}} + \sum_{i'=1}^{N} Qo^k_{i',i} O^k_{i',l+L^k_{i',i}} \end{aligned} \tag{8}$$

where $Pv^k_{i',i}, Po^k_{i',i}, Qv^k_{i',i}, Qo^k_{i',i} \in [0, 1]$ describe taxis' mobility patterns between two regions during the time slot k. $Pv^k_{i',i}(Po^k_{i',i})$ is the probability that an unoccupied e-taxi travels from region i' at the beginning of slot k to i by the end of slot k and it becomes unoccupied (occupied). Similarly, $Qv^k_{i',i}(Qo^k_{i',i})$ describes the probability that an occupied taxi travels from region i' at the beginning of k-th slot to region i and it becomes vacant (occupied). The taxis' mobility patterns are learned by applying frequency theory of probability to the historical e-taxi trajectory data, and we constrain that: $\sum_{i=1}^{N} Pv^k_{i',i} + Po^k_{i',i} = 1$, $\sum_{i=1}^{N} Qv^k_{i',i} + Qo^k_{i',i} = 1$.

In the above model, $U^{k+1}_{j,l} \in \mathbb{N}$ represents the number of e-taxis with remaining energy l in charging station j at the beginning of time slot $k + 1$. It is related to the number of e-taxis that are dispatched to station j and the number of available charging points in station j. We will discuss how to derive $U^{k+1}_{j,l}$ according to the charging supply request in each charging station.

C. E-taxi Energy Transition Model in Charging Stations

The charging request in a charging station means the number of e-taxis with different remaining energy that want to charge the battery at a charging station j. It is determined by the decision variables of dispatching for charging. The number of e-taxis with remaining energy l that request charging service in station j during slot k is: $\sum_{i=1}^{N} Y^k_{i,j,l}$.

The charging supply in a charging station represents the number of e-taxis that are charged simultaneously in a charging station j, denoted as n^k_j. Let p_j be the number of charging points installed in charging station j and let P

denote the e-taxi charging rate. For a traditional charging station, we have

$$n_j^k \leq \min\{p_j, \tilde{B}_j/P\}$$

For a solar-powered charging station, the number of e-taxis that are charged simultaneously is constrained by the capacity of a bidirectional inverter and the number of installed charging points, i.e.,

$$-B_j^- \leq e_j^k + n_j^k * P - g_j^k \leq B_j^+, \quad n_j^k \leq p_j$$

Due to the limited number of charging request, we have

$$n_j^k \leq \sum_{i=1}^N \sum_{l=1}^L Y_{i,j,l}^k$$

Given charging supply, i.e., n_j^k and charging request, i.e., $\sum_{i=1}^N \sum_{l=1}^L Y_{i,j,l}^k$, a question is which e-taxis should be charged if the charging request is more than the charging supply. In this work, we formulate the order of e-taxis for charging in a station j as the variables, i.e., $u_{j,l}^k$ is the number of e-taxis with remaining energy l that are charged in station j during slot k. We constrain that $\sum_{l=1}^L u_{j,l}^k = n_j^k$ and $u_{j,l}^k \leq \sum_{i=1}^N Y_{i,j,l}^k$. Then at the beginning of slot $k+1$, the number of e-taxis with the different remaining energy l in station j is formulated as:

$$U_{j,l+\tilde{L}}^{k+1} = u_{j,l}^k + \sum_{i=1}^N Y_{i,j,l+\tilde{L}}^k - u_{j,l+\tilde{L}}^k \tag{9}$$

D. Optimization Problem

In this work, e-taxis are scheduled to optimize the service quality of e-taxi fleets while minimizing the system cost of the charging infrastructure. These two types of objectives are formulated as follows.

1) Utility of E-taxi Systems: Since the primary task of e-taxi systems is to serve as many passengers as possible, we use the number of served passengers as a metric to measure the utility of e-taxi systems. The number of served passengers over all the N regions from slot t to $t+T-1$ is

$$J_{served} = \sum_{i,k} \min\{r_i^k, \sum_{l=1}^L S_{i,l}^k\}$$

The dispatch of unoccupied e-taxis makes them drive idly on the road, which is the cost of dispatching. Based on the road network of a city, we use $\mu_{i,i'}$ to describe the idle driving distance from region i to i'. $\lambda_{i,j}$ is defined to denote the idle driving distance from region i to charging station j. Therefore, the total idle driving distance because of dispatching decisions from slot t to $t+T-1$ is

$$J_{idle} = \sum_{k=t}^{t+T-1} \Big(\sum_{i,i'} \mu_{i,i'} \sum_{l=1}^{L} X_{i,i',l}^k + \sum_{i,j} \lambda_{i,j} \sum_{l=1}^{L} Y_{i,j,l}^k \Big)$$

The above objective function considers the idle driving distance to a charging station or another region.

2) System Cost of the Charging Infrastructure: During the daily operation of solar-powered charging stations, the cost due to the reverse power flows is formulated as:

$$J_{reverse} = \sum_{k=t}^{t+T-1} \sum_{j=1}^{M_s} \max\{0, -D_j^k\} * K$$

The charging or discharging behaviors of the storage systems result in the energy loss formulated as:

$$J_{loss} = \sum_{k=t}^{t+T-1} \sum_{j=1}^{M_s} \alpha * |e_j^k| * K$$

where $\alpha \in (0,1)$ is the energy loss ratio if the power is charged to or discharged from the storage systems.

As discussed in Section IV-A, during the daytime, e-taxis should ideally take full use of the solar power to charge. During the nighttime, the stored energy should also be fully used to be ready to operate in the next day with solar power. Therefore, the third energy-related cost metric is defined as the energy drawn from the power distribution system:

$$J_{energy} = \sum_{k=t}^{t+T-1} \sum_{j=1}^{M} \max\{0, D_j^k\} * K$$

3) 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., $ds_{i,i'}^k \in \{0,1\}$ and $dc_{i,j}^k \in \{0,1\}$. If an e-taxi can reach region i' from region i during the time slot t, $ds_{i,i'}^k = 0$; otherwise, it is 1. If an e-taxi can reach the charging station j from region i during the time slot t, $dc_{i,j}^k = 0$; otherwise, it is 1. We note that traffic conditions may change during the day. The constraint parameters $ds_{i,i'}^k$ and $dc_{i,j}^k$ can reflect such changes. For example, during the slot k with heavy (light) traffic, e-taxis cannot (can) reach region i' from i within a time slot, and $ds_{i,i'}^k = 1$ ($ds_{i,i'}^k = 0$). Therefore, our formulation can incorporate real-time traffic conditions in a city. Finally, we constrain that

$$X_{i,i',l}^k dc_{i,i'}^k = 0, \quad Y_{i,j,l}^k ds_{i,j}^k = 0 \tag{10}$$

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:

$$S_{i,l}^k = 0, \quad 1 \leq l \leq L \tag{11}$$

4) Optimization Problem Formulation: In summary, we formulate the optimization of the centralized e-taxi scheduler as:

$$\max_{X,Y} J = J_{served} + \beta_1 J_{idle} + \beta_2 (J_{reverse} + J_{loss} + J_{energy}) \tag{12}$$

where $\beta_1, \beta_2 < 0$ are the weight parameters to balance the different objectives due to the trade-off among them.

After adding the slack variables to remove the min and max function in the objectives, this optimization problem is a mixed-integer linear programming problem. This problem can be solved by branch-and-bound [15], which is widely used in the existing solvers, e.g., Gurobi and optimization toolbox of Matlab.

VI. Evaluation

A. Data Description

We use three datasets to conduct the data-driven evaluation for e-taxis in Shenzhen. The first dataset is the **charging station data**. There are 37 active charging stations deployed in the city. At each charging station, there is a potentially different number of identical charging points, e.g., from 10 to 100. The charging station data includes the GPS location and the number of charging points of each charging station.

The second dataset includes **taxi trajectory data**. Each taxi, i.e., either a fuel taxi or an e-taxi, has a GPS device and

TABLE I: Specification of the e-taxi model in the dataset [16]

Battery capacity	57 kWh
Charging rate	30 kW
Maximum distance	300 km

a communication module such that it can upload its real-time information twice per minute. The real-time information of a taxi includes the plate number, time stamp of uploading, GPS location, and occupancy status. The dataset includes the data for both fuel taxis and e-taxis. In our evaluation, we use the number of passengers that the fuel taxis servers to estimate the passenger demand of e-taxis that may miss the passengers due to charging.

The third dataset is the **passengers' transaction data**. Each record in this dataset represents a taxi trip, including when and where the passenger is picked up and dropped off and the taxi plate number. Based on the second and third dataset, we estimate the passenger demand for e-taxis in each region of the city during the different time intervals.

B. Methodology

We use the dataset introduced as above to conduct a trace-driven simulation to evaluate the performance of SAC. The city is divided into regions based on the locations of charging stations, i.e., every charging station is regarded as the center of a region and the boundary of two regions has the same distance to the center of these two regions. We define the length of a time slot as 20 minutes. The passenger mobility model in spatial-temporal dimensions is extracted from the passengers' transaction data. The future time horizon is defined as six time slots, and the weight $\beta_1 = \beta_2 = -0.1$. The specification of the e-taxi model in the dataset is shown in Table I.

Given the number of fuel taxis and e-taxis in the dataset, we use the passengers served by fuel taxis to estimate the passenger demand of e-taxis between any two regions in each time slot. Since solar-powered charging stations have not been deployed in the city, we set up whether a charging station is powered by solar according to its surrounding environment. If a charging station is in an open parking lot, it is assumed to be powered by the solar, and the size of the solar array is equal to the area size of the parking lot. If a charging station is in a building, it is assumed to draw energy solely from the power system. In total, 16 charging stations are assumed to be powered by the solar. The size of storage systems in each solar-powered charging station is set up as 2.4 MWh storage per 1-MW solar system [17].

We compare our solution, i.e., solar-aware charging (SAC) with the following existing solutions to show its effectiveness. (i) **p^{2}Charging** [18]: this solution focuses on determining when, where and how long e-taxis are charged. This solution aims to maximize the number of served passengers while minimizing the idle driving time to charging stations and the idle waiting time at charging stations. (ii) **REC** [19]: this method only schedules e-taxis for charging when their remaining energy is below 15%, and an e-taxi is dispatched to a charging station introducing the minimum waiting time

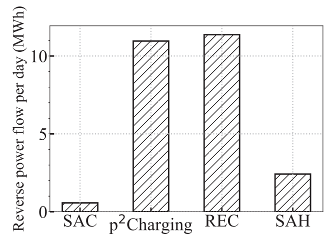

Fig. 3: Reverse power flow comparison

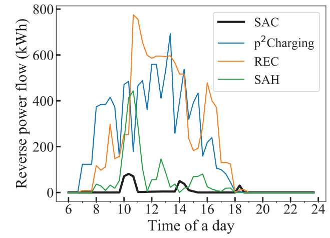

Fig. 4: Reverse power flow over time

at the station and idle driving time to the station. (iii) **Solar-Aware Heuristic (SAH)**: it is a heuristic solution aiming at taking full use of the generated solar power. This baseline also schedules e-taxis to charging stations only when their remaining energy is below 15%. Suppose the current time slot is denoted as t, an e-taxi is scheduled to the charging station to minimize $\sum_{j=1}^{M_s} |g_j^t - d_j^t|$, where g_j^t is the current generated solar power in station j and d_j^t is the charging demand in station j. If there is no solar power during slot t, e.g., nighttime, this method schedules e-taxis to minimize the power drawn from the power distribution system by using the stored energy as much as possible.

We use the following metrics to demonstrate the performance of different solutions. (i) **Reverse power flow per day (per slot)** is equal to the total amount of reverse power flow from solar-powered charging stations to the local power network during a day (a time slot). (ii) **Energy loss** is equal to the total amount of loss due to energy charged to or discharged from energy storage systems during a day. The ratio of energy loss is set as 10% due to the typical 90% efficiency of bidirectional inverters [20]. (iii) **Power drawn from the power distribution system** is defined as the amount of energy that all the charging stations consume from the local power network. (iv) **number of served passengers per day**. (v) **Idle driving distance per day** is defined as the distance that e-taxis drive idly for charging or finding the next passengers.

C. Results

As the evaluation results show, our solution SAC reduces the cost of charging stations significantly with little loss on the service quality of e-taxi fleets compared with p^{2}Charging that is designed to optimize e-taxi service quality. In detail, we summarize the main results as follows:

- SAC decreases the reverse power flow per day by 94.8% with little overhead, i.e., reducing the number of served passengers by 2.3% and increasing the idle driving distance per day by 9.0% compared with the solution only optimizing the e-taxi service quality.
- SAC decreases the reverse power flow per day by 78.7% while increasing the number of served passengers by 75.7% compared with the solar-aware heuristic solution only focusing on matching the solar power.
- SAC decreases the energy loss due to charging and discharging storage systems by up to 65.4% compared with the other three solutions.

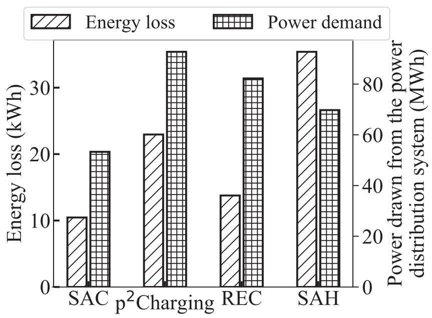

Fig. 5: Energy loss and power demand

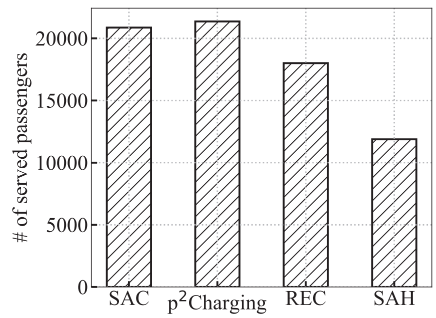

Fig. 6: # of served passengers per day

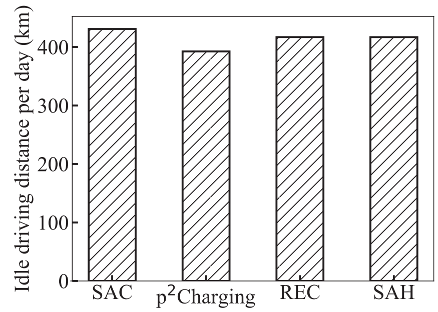

Fig. 7: Idle driving distance of an e-taxi per day

1) Social Cost: Figure 3 shows the total reverse power flow from the solar-powered charging stations to the local power distribution network during a day by the four charging scheduling methods. Figure 4 shows the reverse power flow during each time slot of a day by the different charging strategies. The main observation is that SAC decreases the reverse power flow per day by 94.8%, 95.3%, and 78.7% compared with the other three methods respectively. It is clear that the solutions that match charging with the solar power significantly reduce the reverse power flows, e.g., SAC and SAH outperform p^{2}Charging and REC. Although SAH tries to match the solar power, it introduces more reverse power flow than SAC due to potential less coordinated dense charging. For example, passenger demand increases from 6:00 to 10:00 and decreases from 10:00 to 16:00. Most e-taxis have near full energy at the beginning of a day, e.g., 6:00, and are close to using up energy during lunchtime, e.g., after 12:00. Therefore, there exists a large amount of reverse power flow before lunchtime, which is also shown in Figure 4. Meanwhile, REC also generates more reverse power flow than p^{2}Charging because it is reactive to remaining energy even though both of them do not consider how to match the solar power.

The left bars of Figure 5 show the energy loss at the solar-powered charging stations due to charging and discharging energy storage systems. First, SAC reduces the energy loss by 54.4%, 39.5% and 65.4% compared with p^{2}Charging, REC, and SAH. The reason is that SAC makes near full use of the solar power and reduces the amount of energy charged into the storage, which is shown in Figures 3 and 4. Secondly, SAH introduces the maximum energy loss. The reason is that this method does not fully utilize solar power during the daytime due to reactive to remaining energy and concentrated charging. During the nighttime, this method also wants to fully utilize the stored energy, resulting in a lot of energy loss.

The right bars of Figure 5 also demonstrate the power drawn from the power distribution system by the charging stations. The first observation is that the power demand on the local distribution network decreases by 42.5%, 35.2%, and 23.4% when changing the solution from p^{2}Charging, REC, or SAH to SAC. We also observe that making full use of solar power can significantly decrease the power drawn from the power distribution system. For example, both SAC and SAH have lower power demands from the distribution system that p^{2}Charging and REC.

2) Performance of e-taxi service: An important objective of an e-taxi fleet is to provide good service quality for passengers. Figure 6 shows the number of served passengers per day by the four solutions, and there are several observations. The first one is that the number of served passengers reduces by 2.3% when changing the scheduling solution from p^{2}Charging to SAC, where p^{2}Charging focuses on optimizing the service quality. As we trade-off between optimizing the service quality of e-taxi fleets and reducing the power system cost, it is reasonable that SAC misses a small percentage of potential passengers but significantly reduces the power system cost. The second observation is that scheduling e-taxis with the consideration of future passengers is useful to serve more passengers. For example, compared with reactive to e-taxis' remaining energy (REC), 10.5% and 11.3% more passengers are served by SAC and p^{2}Charging respectively. The last observation is that naively incorporating the objective of matching the solar power with charging can significantly influence the service quality of e-taxi fleets. For example, although both REC and SAH are reactive to e-taxis' remaining energy, the latter solution may miss some passengers since the e-taxis are assigned to a group of solar-powered charging stations introducing longer idle waiting time for a free charging point.

Figure 7 shows the total idle driving distance of e-taxis per day by the four solutions. The main observation is that SAC introduces 9.8%, 10.6%, and 4.1% more idle driving distance compared with p^{2}Charging, REC and SAH. Since SAC frequently schedules e-taxis for charging and serving passengers, it is reasonable that more idle driving distance is introduced.

VII. Related Work

In this section, we classify the related work into two categories: (i) EV charging activities coordination, and (ii) EV scheduling at solar-powered charging stations. The first category focuses on coordinating the charging locations of EVs, and the latter one studies how to schedule e-taxis' charging at a particular station.

EV charging activities coordination: As the number of EVs increases, some solutions [19], [21], [18], [22], [23] are proposed to recommend EVs where to charge for minimizing the charging cost. [21] designs a charging recommendation system to minimize the total idle time under fairness constraints for an e-taxi fleet. [23] guides a group of EVs to decide the traveling path for optimizing traveling time, payment for charging, energy consumption, and range anxiety given the source and destinations of EVs. [19] proposes a real-time charging scheduling framework to recommend when and where to charge, guaranteeing bounded waiting time for e-taxis. However, these related works concentrate on reducing the cost of charging without optimizing the service quality of electric vehicle fleets [19], [21], [22], [23] or reducing the cost of charging infrastructures [19], [21], [18], [22], [23].

EV scheduling at charging stations: In reality, drivers may park EVs at the charging stations for park-and-charge, and configure when to pick up EVs. With this operation mode, the scheduling solutions [24], [25], [8], [26] are proposed to meet the time requirement of drivers while minimizing the charging cost. When the picking up and dropping off time of EVs are known, [8] uses linear programming to determine the amount of energy delivered to each vehicle during a time slot for maximizing the utilization of solar energy while maintaining similar energy among EVs. [24] studies how to assign charging rate to EVs to satisfy their charging demand before their deadlines with minimum payment in a solar-powered charging station. [25] conducts both experimental and theoretical analysis of different scheduling algorithms at charging stations and shows their performance. Firstly, these studies [24], [25], [8], [26] research a different application scenario, i.e., park-and-charge, and this work studies the urban e-taxi fleet service. Secondly, these works focus on optimizing the performance of EVs at a charging station, while our work aims to optimize the performance of e-taxi fleets and the cost of an entire charging infrastructure.

VIII. Conclusion

We explore e-taxis' mobility and charging demand flexibility to co-optimize the e-taxi fleets' service quality and the system cost of the charging infrastructures. We propose an e-taxi coordination framework, i.e., SAC, to schedule e-taxis for picking up passengers or charging under dynamic renewable energy and passenger mobility patterns in spatial-temporal dimensions. We evaluate the effectiveness of SAC with real-world multi-source data. Trace-driven simulation results show that our solution can decrease the daily reverse power flow by up to 95.3% while maintaining e-taxi service quality with very little overhead, significantly outperforming existing solutions.

References

[1] J. WEAVER, "Off grid solar powered electric vehicle charging in NYC", https://pv-magazine-usa.com/2018/12/26/new-york-citys-solar-powered-electric-vehicle-charging-stations/.

[2] HEARST AUTOS RESEARCH, "Electric Cars: Pros and Cons", https://www.caranddriver.com/research/a32758614/electric-cars-pros-and-cons/.

[3] Reuters Staff, "Fossil fuel-based vehicle bans across the world", https://www.reuters.com/article/climate-change-britain-factbox/fossil-fuel-based-vehicle-bans-across-the-world-idINKBN27Y19F.

[4] ByJohnna Crider, "Another Look At A Tesla Taxi In New York City", https://cleantechnica.com/2021/03/18/another-look-at-a-tesla-taxi-in-new-york-city/.

[5] Taxi Singapore, "HDT Electric Taxi", https://www.taxisingapore.com/taxi-companies/hdt-electric-taxi/.

[6] J. von Appen, M. Braun, T. Stetz, K. Diwold, and D. Geibel, "Time in the sun: The challenge of high pv penetration in the german electric grid", *IEEE Power and Energy Magazine*, 2013.

[7] M. Aachiq, T. Oozeki, Y. Iwafune, and J. G. S. Fonseca Jr, "Reduction of pv reverse power flow through the usage of ev's battery with consideration of the demand and solar radiation forecast", in *2013 IEEE International Electric Vehicle Conference (IEVC)*, 2013.

[8] S. Lee, S. Iyengar, D. Irwin, and P. Shenoy, "Shared solar-powered ev charging stations: Feasibility and benefits", in *2016 Seventh International Green and Sustainable Computing Conference (IGSC)*.

[9] S. Lee, S. Iyengar, D. Irwin, and P. Shenoy, "Distributed rate control for smart solar arrays", in *Proceedings of the Eighth International Conference on Future Energy Systems*, 2017, pp. 34–44.

[10] S. Kuppannagari, R. Kannan, and V. Prasanna, "Approximate scheduling of ders with discrete complex injections", in *Proceedings of the Tenth ACM International Conference on Future Energy Systems*, 2019.

[11] Y. Zhou, R. Kumar, and S. Tang, "Incentive-based distributed scheduling of electric vehicle charging under uncertainty", *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 3–11, 2018.

[12] S. Park, A. Pröbstl, W. Chang, A. Annaswamy, and S. Chakraborty, "Exploring planning and operations design space for ev charging stations", 2021.

[13] H. Zhao and A. Burke, "An intelligent solar powered battery buffered ev charging station with solar electricity forecasting and ev charging load projection functions", in *2014 IEEE IEVC*, 2014, pp. 1–7.

[14] M. Khatibi and S. Ahmed, "Impact of distributed energy resources on frequency regulation of the bulk power system", in *2019 IEEE Conference on Power Electronics and Renewable Energy (CPERE)*.

[15] E. Balas and P. Toth, "Branch and bound methods for the traveling salesman problem", 1983.

[16] G. Wang, W. Li, J. Zhang, Y. Ge, Z. Fu, F. Zhang, Y. Wang, and D. Zhang, "sharedcharging: Data-driven shared charging for large-scale heterogeneous electric vehicle fleets", *ACM IMWUT*, 2019.

[17] Solar Energy Technologies Office, "Solar-Plus-Storage 101", https://www.energy.gov/eere/solar/articles/solar-plus-storage-101.

[18] Y. Yuan, D. Zhang, F. Miao, J. Chen, T. He, and S. Lin, "pˆ 2charging: Proactive partial charging for electric taxi systems", in *ICDCS*. IEEE, 2019.

[19] Z. Dong, C. Liu, Y. Li, J. Bao, Y. Gu, and T. He, "Rec: Predictable charging scheduling for electric taxi fleets", in *RTSS*. IEEE, 2017.

[20] T. S. Biya and M. R. Sindhu, "Design and power management of solar powered electric vehicle charging station with energy storage system", in *2019 ICECA*, 2019.

[21] G. Wang, Y. Zhang, Z. Fang, S. Wang, F. Zhang, and D. Zhang, "Faircharge: A data-driven fairness-aware charging recommendation system for large-scale electric taxi fleets", *ACM IMWUT*, 2020.

[22] L. Yan, H. Shen, Z. Li, A. Sarker, J. Stankovic, C. Qiu, J. Zhao, and C. Xu, "Employing opportunistic charging for electric taxicabs to reduce idle time", *ACM IMWUT*, 2018.

[23] A. Sarker, H. Shen, and J. Stankovic, "Morp: Data-driven multi-objective route planning and optimization for electric vehicles", *ACM IMWUT*, 2018.

[24] M. E. Kabir, C. Assi, M. H. K. Tushar, and J. Yan, "Optimal scheduling of ev charging at a solar power-based charging station", *IEEE Systems Journal*, vol. 14, no. 3, pp. 4221–4231, 2020.

[25] F. Kong, Q. Xiang, L. Kong, and X. Liu, "On-line event-driven scheduling for electric vehicle charging via park-and-charge", in *2016 IEEE Real-Time Systems Symposium (RTSS)*, 2016.

[26] Y. Zhang and L. Cai, "Dynamic charging scheduling for ev parking lots with photovoltaic power system", *IEEE Access*, 2018.