SOURCE: Towards Solar-Uncertainty-Aware E-Taxi Coordination under Dynamic Passenger Mobility

Yukun Yuan, Yue Zhao, and Shan Lin

Abstract— **As more fuel-based vehicles are replaced by electric vehicles (EVs) for providing transportation services in cities, e.g., electric taxi or bus fleets, solar-powered charging stations have been progressively deployed in the cities to provide charging services for EV fleets. The emerging solar-powered charging stations bring opportunities for EV fleets to reduce charging cost and carbon footprint by utilizing cheap and environment-friendly solar energy. The uncertainty and dynamics of solar power, however, raise challenges in making full use of solar power on time for EV fleets, e.g., e-taxis, while at the same time serving passengers efficiently. In this work, we design SOURCE, a solar-uncertainty-aware coordination algorithm for e-taxis under spatial-temporal dynamics of uncertain solar energy and passenger mobility. We evaluate our solution with a comprehensive dataset for an existing e-taxi system 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 our solution significantly improves the usage rate of solar power by 17.6% with similar passenger waiting time compared to the solution that co-optimizes service quality and usage of solar power without considering the solar power uncertainty.**

I. INTRODUCTION

As battery technologies become more mature and economical, electric vehicles (EVs) have attracted significant attention and are considered as an alternative to conventional internal combustion engine (ICE) vehicles due to being cheaper to maintain, quieter, and more environment-friendly [1]. For instance, sixteen countries, e.g., Britain and Netherlands, have officially targeted to phase out ICE vehicles and increase the number of EVs [2]. Meanwhile, urban cities have already increasingly expanded various types of electric vehicle fleets. For example, London's famous black cabs have launched the electric version in 2019 and plan to accelerate the process of retiring the gasoline taxis [3]. Some other cities, such as Shenzhen, Oslo, and Singapore have been electrifying their taxi fleets for several years [4].

To provide widely accessible charging resources for large-scale EV fleets, a large number of charging stations have been progressively installed in the urban areas [5]. In addition to the conventional charging stations powered by the grid, solar-powered charging stations [6] that harvest solar energy while connecting to the grid as the backup energy source have been increasingly popular. Notably, e-taxi fleets can play an important role in better utilizing solar power at solar-powered charging stations. For instance, uncoordinated e-taxi charging activities may result in the under-utilization or even curtailment of solar power at certain stations, while drawing energy from the power grid to charge at other charging stations. It is however non-trivial for e-taxi fleets to "seek" solar power. Firstly, seeking solar power may cause missed deadlines for picking up passengers, which increases passenger waiting time and decreases taxi service quality. Secondly, the future solar power is inherently uncertain under dynamic weather conditions [7]. The underestimation or overestimation of future solar power in spatial-temporal dimensions can hinder the effectiveness of seeking solar power and serving passengers. Therefore, it is challenging to efficiently coordinate e-taxis to utilize solar power and serve passengers on time with the uncertainty of solar power.

Existing works have investigated designs for EV charging scheduling [8], [9] or charging rate control [10] at a solar-powered charging station, providing deadline and renewable aware demand response by electric vehicles at charging stations [11], and coordinating e-taxis to seek solar power and serve passengers simultaneously [12] albeit ignoring the uncertainties in the system. Little work has considered the *solar power uncertainty* when jointly utilizing solar power and serving passengers by e-taxi fleets. This work is the first to investigate jointly optimizing e-taxi service quality and solar power utilization under uncertain solar power.

Specifically, we propose SOURCE, a SOlar-Uncertainty-awaRe Coordination algorithm for E-taxi fleets, aiming to (i) serve passengers on time, and (ii) reduce the cost due to under/delayed-utilization of solar power. We note that both objectives are parts of social welfare, one for the transportation system and the other for the power system. As such, SOURCE aims for social welfare optimization. Notably, while the e-taxi fleets are directly compensated for serving the transportation system, in practice, additional mechanisms (e.g., favorable charging prices) are needed to compensate/incentivize them for serving power system objectives. Such incentive design is out of the scope of this work. The e-taxi service quality is measured by the passenger waiting time, i.e., the delay of picking up passengers given the soft deadlines of picking up, and we model the inefficiency of seeking solar power by the amount of missed solar power. The uncertainty of solar power in spatiotemporal dimensions is modeled by a probability distribution, and we formulate the e-taxi coordination problem as a stochastic control problem. Since it is generally intractable to obtain the control decisions of the infinite horizon stochastic control problem, we propose an efficient solution to obtain the coordination policy using stochastic model predictive control.

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

This work was supported in part by the National Science Foundation under Grant ECCS-2025152, CNS-1952096 and CNS-1553273 (CAREER).
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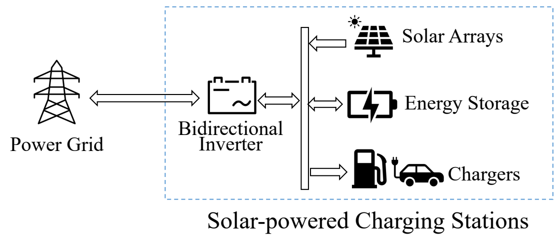

Fig. 1. Illustration of solar-powered charging stations

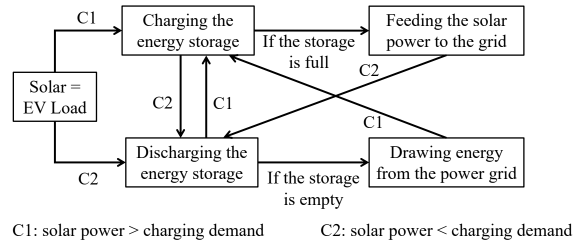

Fig. 2. State of a solar-powered charging station

- To the best of our knowledge, this is the first work to address the uncertain solar power when coordinating an e-taxi fleet to make full use of the solar power, while maintaining the e-taxi service quality. In detail, we model the solar power as a set of solar power consumption tasks, and assign e-taxis to execute both passenger serving tasks and solar power consumption tasks.
- We propose an e-taxi fleet coordination algorithm for seeking uncertain solar power or picking up passengers on time under spatial-temporal dynamics of solar power and passenger mobility. In detail, we formulate the e-taxi fleet coordination problem under uncertain solar power as an infinite horizon stochastic control problem, which is intractable in general, and then design a tractable solution based on stochastic model predictive control.
- We evaluate the proposed stochastic model predictive control based solution with a comprehensive real-world dataset consisting of 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 our solution significantly increases the usage rate of solar power by around 17.6%, while increasing the passenger waiting time by less than one minute compared to the solution co-optimizing the usage of solar power and service quality without considering the uncertainty of solar power.

II. Background & Motivation

Figure 1 illustrates the architecture of solar-powered charging stations that are powered by the solar arrays and the power grid. A solar-powered charging station consists of four components, i.e., solar arrays, energy storage, chargers, and a bidirectional inverter. The solar arrays use the sunlight as a source of energy and generate the direct current electricity. The generated energy may be used to charge the EVs, be stored in the storage, or be fed back to the power grid. The energy storage is charged or discharged based on the relation among generated solar power, EV charging demand, and stored energy. EVs are charged when connecting with the chargers and the energy is drawn from the solar arrays, the storage, or the power grid under different conditions. The bidirectional inverter transmits the power from the power grid to the chargers or from the solar arrays to the power grid.

Figure 2 shows the state transition of a solar-powered charging station under a rule-based strategy. When the solar system output is equal to the EV charging demand, no action is taken on the storage or the grid. If the solar power is less than the charging demand, the station first discharges the storage to charge the EVs until the storage becomes empty. Then the station draws energy from the power grid to charge the EVs. If the solar power is more than the charging demand, the station first charges the storage to store the extra energy until the storage becomes full. Then the charging station feeds the solar power back to the power grid in the form of the reverse power flow.

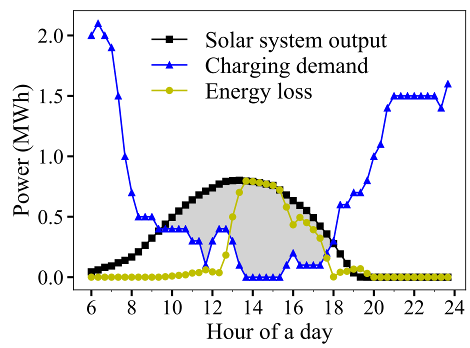

Fig. 3. Charging demand & solar output at a charging station

We show the charging power demand, the solar system output, and the potential energy loss during a day in Figure 3 to better understand their relation. The real-world e-taxi trajectory data is used to extract the charging power demand, and the solar array output at a charging station is estimated based on the existing comprehensive datasets. The energy loss includes the nearly 10% energy loss [13] when charging or discharging the storage and the reverse power flow. The storage capacity at the solar-powered charging station is determined based on the assumption that 2.4 MWh storage is installed for 1-MW solar systems [14]. Please refer to Section V-A for the details of these datasets and the method to estimate the solar system output.

From Figure 3, it is observed that there exists a mismatch between the current charging demand and the solar system output. The solar system output is higher at noon than in the morning and afternoon. However, the e-taxi drivers prefer to charge the battery in the early morning and night as in the current data sets. Particularly, the solar power is under-utilized from 10:00 to 18:00 as highlighted in gray. It is noted that the storage is full and the unused solar power is fed back to the power work regarded as energy loss after 14:00. Based on the state transition of a solar-powered charging station with on-site storage, the unused solar power is stored and then retrieved to charge the e-taxis at night. The daily energy loss due to charging or discharging the storage is nearly 9.4

MWh, which can charge 164 e-taxis from empty to full in our model. Moreover, the reverse power flow fed back to the power grid decreases the stability and efficiency of the power network [15]. Figure 3 demonstrates ample opportunities for e-taxis to seek solar power and consume it on time so that energy loss and reverse power flow are reduced. Meanwhile, e-taxis need to serve passengers during the daytime, which makes seeking solar power on time challenging.

III. Problem Formulation

A. System Model

Firstly, we discretize the spatial-temporal dimensions. A day is discretized into multiple time slots, indexed by k, and we use t to represent the current time slot. The entire city area is partitioned into N regions. Suppose there are m charging stations in a city. It is assumed that the first m_s charging stations are powered by solar power and power systems. We use $\rho \in \{0,1\}^{m\times N}$ to describe the locations of m charging stations, where if charging station j locates in region i, $\rho_{j,i}=1$; otherwise, it is 0. The remaining energy of an e-taxi is discretized into L levels.

Suppose there are M e-taxis in the city. We define four statuses of an e-taxi: (i) vacant: an e-taxi is idly driving on the road and searching the next passenger; (ii) waiting for charging: an e-taxi is waiting in the queue of a charging station for a free charging point; (iii) charging: an e-taxi is charging its battery at a charging station; (iv) occupied: an e-taxi is delivering passengers to the destination. The state of an e-taxi is described by a tuple with three parameters, i.e., (status, location, remaining energy in the battery).

Given the state of M e-taxis, we define $V^k \in \mathbb{N}^{N\times L}$ and $O^k \in \mathbb{N}^{N\times L}$ to represent the distribution of unoccupied and occupied e-taxis with the different remaining energy over the city at the beginning of slot k. $V^k_{i,l}$ ($O^k_{i,l}$) is the number of unoccupied (occupied) e-taxis with remaining energy l in region i at the beginning of slot k. It is noted that an e-taxi is called unoccupied if it is vacant, being charged, or waiting for a free charging point.

State: The state of the e-taxi system and the charging stations consists of the distribution of current unoccupied and occupied e-taxis with the different remaining energy over the city, i.e., $x^k \triangleq (V^k, O^k)$.

In this work, we assume that an unoccupied e-taxi can be scheduled for either charging or serving passengers. For example, if an e-taxi is waiting at a charging station, it can be scheduled to another charging station for charging or a region for serving passengers. An e-taxi can stop charging and go to a region for serving passengers or potentially another charging station for continuing to charge. Based on this assumption, we define the control actions of e-taxis next.

Action: The control decisions at slot k consist of scheduling e-taxis for charging $u^k \in \mathbb{N}^{N\times m\times L}$ and dispatching e-taxis for serving passengers $v^k \in \mathbb{N}^{N\times N\times L}$. $u^k_{i,j,l}$ represents the number of e-taxis with remaining energy l that are scheduled from region i to station j for charging at time k. $v^k_{i,i',l}$ represents the number of e-taxis with remaining energy l that are dispatched from region i to i' for serving passengers at time k. We use $\pi(x^k)=(u^k,v^k)$ to denote the policy of the e-taxi fleet given the state at time k. Since only the limited number of unoccupied e-taxis are considered for charging or serving passengers, we constrain that

$$\sum_{j=1}^{m} u^k_{i,j,l} + \sum_{i'=1}^{N} v^k_{i,i',l} = V^k_{i,l}.$$

Because the traveling distance of an e-taxi is bounded during a time slot, an e-taxi should not be scheduled to a far region or charging station. Given the traveling time between two locations, e.g., the center of a region and a charging station, we define two types of constraint parameters, i.e., $dc^k \in \{0,1\}^{N\times m}, ds^k \in \{0,1\}^{N\times N}$. If an e-taxi can reach the charging station j from region i during slot k, $dc^k_{i,j}=0$; otherwise, it is 1. If an e-taxi can reach region i' from region i during slot k, $ds^k_{i,i'}=0$; otherwise, it is 1. We constrain that

$$u^k_{i,j,l}dc^k_{i,j}=0, \quad v^k_{i,i'}ds^k_{i,i'}=0. \tag{1}$$

During runtime, e-taxis need to execute three sets of tasks.

Passenger serving tasks: The number of passengers requesting taxi service in region i during slot k can be estimated from the historical passenger trip data, denoted as D^k_i. A passenger serving task is defined for a request of taxi service, which is described by a two-parameter tuple, i.e., (pick-up deadline, location). The two parameters are defined as follows. *Pick-up deadline*: the beginning of the time slot when a passenger requests taxi service. Since a passenger may request the taxi service randomly during a time slot, we require that an e-taxi should be ready in the pick-up region at the beginning of the time slot to reduce the waiting time of passengers. *Location*: the region where a passenger requests taxi service.

Charging tasks: Given the remaining energy of an e-taxi, we define a charging task for this e-taxi to avoid running out of energy on the road, which is characterized by a three-parameter tuple, i.e., (release time, charging duration, deadline for start charging). We define the three parameters as: *Release time*: the earliest time slot after current slot t when an e-taxi is vacant and can be scheduled for charging. If an e-taxi is occupied at t, the release time is when it drops off the passengers; otherwise, it is the current slot t. *Charging duration*: how long each e-taxi should be charged. In this work, we assume that an e-taxi can conduct partial charging and the charging duration is set as a time slot. *Deadline for starting charging*: it is the timestamp when an e-taxi will use up the remaining energy if it does not charge the battery. If an e-taxi is not scheduled for charging before this deadline, it will use up energy on the road.

The solar power is generated continuously at each solar-powered charging station during the daytime. Once it is outputted from the solar array, ideally, some e-taxis should use it for charging to reduce energy loss and minimize reverse power flow. We model the estimated future solar power by a set of solar power consumption tasks.

Solar power consumption tasks: Given the estimated solar power at charging station j during slot k, $e^k_j \in \mathbb{N}$ e-taxis are needed to fully utilize the generated solar power, where e^k_j is equal to the estimated solar power over the charging power rate. Correspondingly, we define e^k_j solar power consumption tasks at station j during slot k, and each task should be executed by an e-taxi. It is noted that there is a mapping between the amount of solar power and the number of solar power consumption tasks in spatial-temporal dimensions. Each task is characterized by a tuple with two parameters, i.e., (time for charging, location), where the time for charging is a time slot k and the location is station j.

According to the definition, the number of solar power consumption tasks is proportional to the amount of solar power. It is uncertain during slot k since the future solar power is not known with perfect accuracy [7], especially on a cloudy day with dynamic weather conditions. Similar to [10], let $\tilde{e}_j^k$ be the number of solar power consumption tasks defined by the actual solar power at station j during slot k, and we have $\tilde{e}_j^k = (1+\epsilon)e_j^k$, where ϵ is the prediction error. It is assumed that the prediction error has two properties, i.e., the mean $\mathbb{E}[\epsilon] = 0$, and the variance $\mathbb{V}[\epsilon] = \delta^2$. The mean and variance can be obtained from the historical data as [10], [16]. Therefore, $\tilde{e}_j^k$ follows a distribution $\mathcal{F}$ with a mean e_j^k and a variance $(e_j^k)^2\delta^2$.

B. System State Transition

The dynamics of the state in two consecutive time slots, i.e., x^k and x^{k+1} is modeled by a function f as:

$$x^{k+1} = f(x^k, \pi(x^k), \tilde{e}^k), \quad \tilde{e}^k \sim \mathcal{F}.$$

Function f includes three models within a time slot, i.e., e-taxi energy consumption model, passenger serving model, and charging model. The e-taxi energy consumption model describes how the remaining energy of an e-taxi changes if it works on the road to serve passengers during a time slot. The passenger serving model gives a description of how the locations of e-taxis change between two consecutive time slots. The charging model gives details of how the remaining energy of e-taxis increases when they are dispatched to the charging stations. In the following part, we will introduce the detailed formulation of three models one by one.

1) E-taxi energy consumption model: We discretize the remaining energy of an e-taxi into L levels. Let re^k denote the remaining energy of an e-taxi at the beginning of slot k. Let $L_{i,i'}^k$ be the number of levels that the remaining energy decreases if an e-taxi travels from region i to region i' within the time slot k. The remaining energy transition of an e-taxi between slot k and $k+1$ if it travels from region i to region i' within the time slot k is modeled as: $re^{k+1} = re^k - L_{i,i'}^k$.

2) Passenger serving model: Given the distribution of unoccupied e-taxis at the beginning of slot k, i.e., V^k, and the control decisions v^k and u^k, the number of vacant e-taxis that are ready for picking up passenger in spatial-temporal dimensions changes. Let $S_{i,l}^k$ be the number of vacant e-taxis with remaining energy l that are ready for picking up passengers in region i within slot k after dispatch, and it is modeled as $S_{i,l}^k = \sum_{i'=1}^N v_{i',i,l}^k$. Then we derive V^{k+1} and O^{k+1} from V^k and O^k by the following model:

$$\begin{aligned} S_{i,l}^k &= \sum_{i'=1}^N v_{i',i,l}^k \\ V_{i,l}^{k+1} &= \sum_{i'=1}^N P_{i',i}^k S_{i',l+L_{i',i}^k}^k + \sum_{i'=1}^N H_{i',i}^k O_{i',l+L_{i',i}^k}^k + \sum_{j=1}^m \rho_{j,i} U_{j,l}^{k+1} \\ O_{i,l}^{k+1} &= \sum_{i'=1}^N \hat{P}_{i',i}^k S_{i',l+L_{i',i}^k}^k + \sum_{i'=1}^N \hat{H}_{i',i}^k O_{i',l+L_{i',i}^k}^k \end{aligned} \tag{2}$$

where $P_{i',i}^k, \hat{P}_{i',i}^k, H_{i',i}^k, \hat{H}_{i',i}^k \in [0,1]$ describe taxis' mobility patterns between two regions during the time slot k. $P_{i',i}^k(\hat{P}_{i',i}^k)$ 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 vacant (occupied). Similarly, $H_{i',i}^k(\hat{H}_{i',i}^k)$ 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: $\sum_{i=1}^N P_{i',i}^k + \hat{P}_{i',i}^k = 1$, $\sum_{i=1}^N H_{i',i}^k + \hat{H}_{i',i}^k = 1$.

In Equation (2), $U_{j,l}^{k+1}$ is the number of e-taxis at charging station j with remaining energy l at the beginning of slot $k+1$, including the e-taxis that are waiting for a free charging point and being charged. The e-taxis at charging station j are regarded as the unoccupied e-taxis and considered for charging and dispatching. $U_{j,l}^{k+1}$ depends on the charging decisions during slot k and the number of chargers installed at station j, which will be discussed in the charging model.

3) Charging model: The assumption is that the charging stations are only used for e-taxis, which is also made in [17] [18]. Therefore, the charging demand in spatial-temporal dimensions is determined by the charging decisions. The number of e-taxis with remaining energy l that are sent to charging station j during slot k is $\sum_{i=1}^N u_{i,j,l}^k$. The charging supply is the number of charging points installed in each charging station j, denoted as p_j. If the charging demand is more than the charging supply, i.e., $\sum_{l=1}^L \sum_{i=1}^N u_{i,j,l}^k > p_j$, only a part of e-taxis can be charged. We define $y_{j,l}^k$ as the number of e-taxis with remaining energy l that are charged at station j during slot k. This number is constrained by the charging demand and the charging supply, formulated as

$$y_{j,l}^k \le \sum_{i=1}^N u_{i,j,l}^k, \ \sum_{l=1}^L y_{j,l}^k \le p_j.$$

At the beginning of slot $k+1$, the e-taxis with remaining energy l at station j consist of the e-taxis with energy l that are dispatched to station j and are not charged during slot k, and the e-taxis that are dispatched to station j with remaining energy $l-\hat{L}$ and are charged during slot k. Hence, we derive $U_{j,l}^{k+1}$ by the following equation: $U_{j,l}^{k+1} = \sum_{i=1}^N u_{i,j,l}^k - y_{j,l}^k + y_{j,l-\hat{L}}^k$, where we define that the remaining energy of an e-taxi increases $\hat{L}$ levels if it is charged for a time slot.

C. Objectives

The primary objective of an e-taxi fleet is to reduce the waiting time of passengers for taxi service. The waiting time of a passenger is the delay of meeting the soft deadline of the corresponding passenger serving task, which is equal to the time difference between when the passenger is picked up and the corresponding soft pick-up deadline.

We use the Queueing model to describe the passenger pick-up process in the city. The pick-up process in N regions is modeled as a multi-queue system with N queues, and each region corresponds to a queue. We use Q_i^k to represent the queue size, i.e., the number of congested passenger serving tasks in the queue of region i at the beginning of slot k. The dynamics of Q_i^k are: $Q_i^{k+1} = \max\{0, Q_i^k - S_i^k\} + D_i^{k+1}$, where S_i^k is the taxi supply in region i during slot k, and it is equal to $\sum_{l=1}^{L} S_{i,l}^k$. We denote $g_s(v^k, Q^k)$ as the total waiting time of the congested passenger serving tasks in the queue during slot k. Given a congested passenger serving task in the queue of region i, if it is executed by an e-taxi that is dispatched from region i' to i, its waiting time during slot k is equal to the driving time from region i' to i during slot k, denoted by $\omega_{i',i}^k$. Therefore, we have the following equation to obtain $g_s(v^k, Q^k)$: $g_s(v^k, Q^k) = \sum_{i=1}^{N}\sum_{i'=1}^{N}\omega_{i',i}^k \sum_{l=1}^{L} v_{i',i,l}^k + \max\{0, Q_i^k - S_i^k\} * t$, where the first term is the total waiting time of congested passengers serving tasks that are executed by e-taxis during slot k, and the second term is the waiting time of congested passenger serving tasks that are not executed by e-taxis during slot k. t is the length of a time slot.

The secondary objective of the e-taxi fleet is to make full use of solar power. Hence, we aim to reduce the amount of solar power that cannot be consumed on time, i.e., charged to the storage or fed back to the power network. Given the charging decisions, i.e., u^k, the number of e-taxis that can execute the solar power consumption tasks at station j is $\sum_{i=1}^{N}\sum_{l=1}^{L} u_{i,j,l}^k$. The amount of solar power consumption tasks that are executed at station j during slot k is: $\max\{\tilde{e}_j^k - \sum_{i=1}^{N}\sum_{l=1}^{L} u_{i,j,l}^k, 0\}$. The total amount of missed solar power during slot k, i.e., $g_p(u^k, \tilde{e}^k)$, is:

$$g_p(u^k, \tilde{e}^k) = \sum_{j=1}^{m_s}(\max\{\tilde{e}_j^k - \sum_{i=1}^{N}\sum_{l=1}^{L} u_{i,j,l}^k, 0\} * W)$$

where W is the amount of power needed to charge an e-taxi for a time slot. We define the cost function at slot k as:

$$g(x^k, \pi(x^k)) = g_s(v^k, D^k) + \gamma * g_p(u^k, \tilde{e}^k) \tag{3}$$

where γ is a parameter to balance the two objectives.

D. Stochastic Control Formulation

To ensure the hard deadlines of charging tasks are not missed, we constrain that if an e-taxi will use up energy during slot k, i.e., remaining energy is 1, it will be scheduled for charging, formulated as

$$\sum_{j=1}^{m} u_{i,j,1}^k = V_{i,1}^k. \tag{4}$$

We seek to obtain a policy $\pi(\cdot)$ that maps the state x^k at the beginning of each time slot k to the action $\pi(x^k) = (u^k, v^k)$ that minimizes the cost for infinite horizon of future time slots. We also consider a discount factor of $\beta < 1$ for the cost of future slots. We formulate the following stochastic control problem:

$$\min_{\pi}\ \mathbb{E}_{\tilde{e}^k \sim \mathcal{F}}\ \Big[\sum_{k=t}^{\infty}\beta^{k-t} g(x^k, \pi(x^k))\Big] \tag{5}$$

$$\textbf{s.t. } x^{k+1} = f(x^k, \pi(x^k), \tilde{e}^k)\ \forall k \geq t, \quad \text{Eq. (1), (4).}$$

The set of charging tasks changes dynamically with the charging actions during the infinite future time slots. In general, the above stochastic control problem of minimizing the expected discounted cost in an infinite horizon is computationally intractable due to the multi-dimensional continuous space of the control strategy. We design an efficient solution to obtain the coordination policy in the following section.

IV. Stochastic Model Predictive Control

In this section, to address the challenge of computational intractability, we propose an efficiently tractable solution to obtain the e-taxi coordination policy based on stochastic model predictive control (SMPC).

First, we convert the infinite stochastic control problem, i.e., Equation (5) into a finite-horizon stochastic model predictive control problem. The difference between them is that the stochastic MPC approach aims to minimize the cost of missing the deadlines of passenger serving tasks and solar power consumption tasks within a finite time horizon, i.e., future T time slots. The objective function of the finite-horizon stochastic model predictive control problem is:

$$\min_{\pi}\ \mathbb{E}_{\tilde{e}^k \sim \mathcal{F}}\ \Big[\sum_{k=t}^{t+T-1}\beta^{k-t} g(x^k, \pi(x^k))\Big]. \tag{6}$$

The above stochastic MPC problem considers uncertainty since the solar power is modeled to follow a probability distribution $\mathcal{F}$. As such, it is more robust than simply using the expectation. To solve the stochastic MPC problem (6) efficiently, we generate a set of samples of the actual number of solar power consumption tasks in m_s solar-powered charging stations during future T slots with a Monte Carlo approach, where the set of samples is denoted as $\mathcal{S}$. We determine the charging and scheduling decisions for the future T time slots that minimize the cost of missing the deadlines across all the samples by solving the following optimization problem:

$$\min_{\pi}\sum_{\tilde{e}\in\mathcal{S}}\sum_{k=t}^{t+T-1}\beta^{k-t} g(x^k, \pi(x^k)) \tag{7}$$

$$\textbf{s.t. } x^{k+1} = f(x^k, \pi(x^k), \tilde{e}^k)\ \forall k \geq t, \quad \text{Eq. (1), (4)}$$

where $\tilde{e}$ is a sample in $\mathcal{S}$ for the actual number of solar power consumption tasks in m_s solar-powered charging stations during future T slots. The above optimization problem is a *mixed-integer linear programming* (MILP) problem after adding the slack variables to remove the max function in the objective function. It can be solved by many methods, e.g., branch-and-bound, implemented in existing solvers.

In summary, the coordination decisions of e-taxis are obtained by the following steps during the runtime. At the beginning of each time slot, the e-taxi coordinator updates the real-time information, e.g., locations, status, and remaining energy, using the sensors and communication modules installed in the e-taxis. Given the weather forecast, the coordinator determines the probability distribution of the future solar power consumption tasks, i.e., $\mathcal{F}$. Then a set of samples is generated according to $\mathcal{F}$, and the optimization problem (7) is solved to obtain the charging and dispatch decisions. Only the coordination decisions of the current slot t are sent to the e-taxis.

V. Evaluation

A. Dataset

The first dataset includes the information of deployed charging stations. There are 37 active charging stations deployed in the city. At each charging station, there is a potentially different number of identical charging points. The charging station data includes the GPS location and the number of charging points of each charging station. The

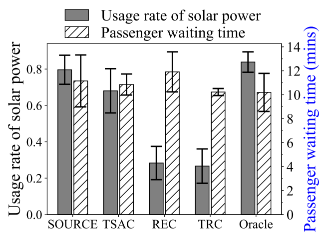

Fig. 4. Performance comparison among five solutions

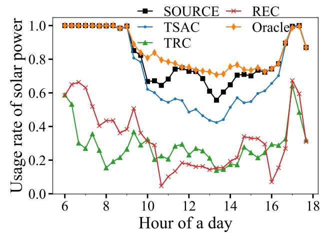

Fig. 5. Usage rate of solar power over time by five solutions

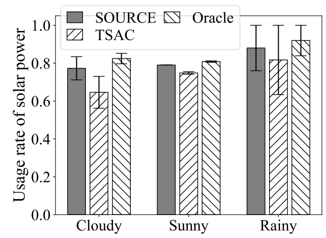

Fig. 6. Performance under different weather conditions

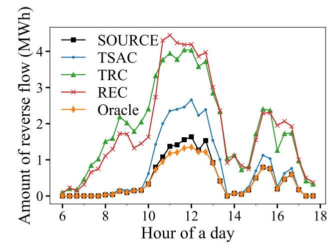

Fig. 7. Reverse power flow over a day

second dataset contains the trajectory data of taxis. Each taxi, i.e., either a fuel taxi or an e-taxi, has a GPS device and 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. There are around 6,000 fuel taxis and 700 e-taxis. The third dataset includes the passenger transaction data. Each record represents a taxi trip, including when the passenger is picked up and dropped off and the taxi plate number. Based on the second and third dataset, we can obtain the pickup and drop-off locations of each passenger, and further estimate the passenger demand for e-taxis in each region of the city during the different time intervals. The last dataset contains the six-month output data of the solar system installed in 25 homes [19]. The data for each home is collected once per minute. Each record consists of the ID of home, timestamp when collecting the data, the output of the installed solar system, and the solar array size.

The first three datasets are collected from an e-taxi fleet in Shenzhen, which uses the traditional charging stations to charge the battery. Since the solar-powered charging stations have not been deployed in the city, we assume that a part of the existing charging stations will deploy solar arrays in the future based on the surrounding environment. If a charging station is in an open parking lot, it is supposed to be a solar-powered station, and the size of the solar arrays is equal to the area size of the parking lot. Then we assume that the unit size of solar arrays in each solar-powered charging station generates the same amount of power per minute as the unit size of solar arrays installed in a home does. Based on these assumptions, we can simulate a city that has an e-taxi fleet and both traditional and solar-powered charging stations.

B. Methodology

We partition the city into regions based on the locations of charging stations, i.e., every charging station represents the center of a region, and the boundary of two adjacent regions has the same distance to the center of the two regions. The length of a time slot is set up as 20 minutes. We extract the passenger mobility model from the passengers' transaction data. The passenger demand that should be met by the e-taxis is estimated using the number of passengers served by fuel taxis. The storage capacity in each solar-powered charging station is determined by the same method in Section II.

We compare our solution, SOURCE, with several baselines to show its effectiveness. (i) Taxi service under regular charging (TRC) [17]: this solution investigates when, where and how long e-taxis are charged to maximize the number of served passengers while minimizing the cost for charging, i.e., waiting time and idle driving time. (ii) Real-time e-taxi charging scheduling (REC) [20]: an e-taxi plans to charge the battery when its remaining energy is below 15%, and the e-taxi chooses the charging station with the minimum waiting time. (iii) Taxi service under solar-aware charging (TSAC) [12]: this method uses the mean value of the distribution of future solar power consumption tasks as the only sample in $\mathcal{S}$ of problem (7), and it solves a certainty-equivalent MPC problem. (iv) Oracle: it assumes that the controller knows the actual future solar power, and then solves the problem (7). Since this assumption is ideal and unattainable in practice, the oracle provides an upper bound of the performance.

We use the following metrics to compare the different scheduling strategies. (i) Usage rate of solar power is equal to the amount of solar power that is consumed on time over the total amount of generated solar power during a day. It is used to measure the efficiency of seeking solar power. (ii) Passenger waiting time is defined as how long a passenger waits for a vacant e-taxi after sending the service request. It is used to measure the e-taxi service quality. (iii) Energy saving is defined as the amount of solar power used for charging e-taxis. The e-taxi fleet reduces the power drawn from the power grid by such an amount. (iv) Energy loss is equal to the amount of solar power that is lost due to charging or discharging the storage, or in the reverse power flow. (v) Daily idle driving distance is defined as the distance that e-taxis drive idly for charging per day.

C. Results

As the evaluation results show, our solution SOURCE can increase the utilization of solar power significantly with little cost on the service quality of e-taxi fleets compared with TRC which solely focuses on optimizing the service quality. In detail, we summarize the main results as follows:

- SOURCE increases the usage rate of solar power per day by 17.6% with similar passenger waiting time compared to the solution that does not consider uncertainty.
- SOURCE can enhance the efficiency of seeking uncertain solar power, i.e., raising the usage rate of solar power by 19.2% on cloudy days compared with the solution that does not consider the uncertainty.

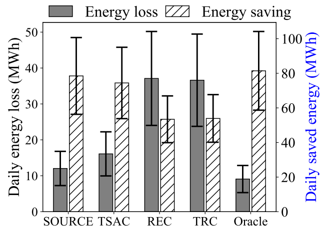

Fig. 8. Energy loss and saving by five solutions

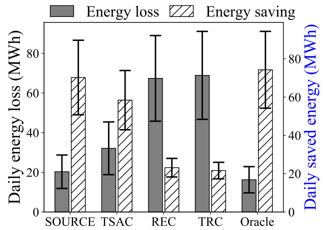

Fig. 9. Energy loss and saving without on-site storage

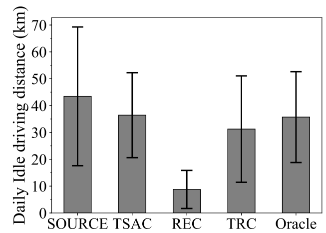

Fig. 10. Idle driving distance per day

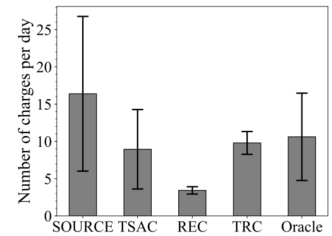

Fig. 11. Number of charges per day

- Our solution reduces the daily peak reverse power flow from solar-powered stations to the power grid by up to 63.1%, which improves the stability of the power grid.

1) Efficiency: We first show the efficiency of different charging solutions, i.e., the usage rate of solar power per day and the passenger waiting time in Figure 4. There are several observations. The first one is that SOURCE achieves the best performance (except Oracle that is unattainable in the real-world) in terms of fully utilizing solar power, i.e., improving the usage rate of solar power by 17.6%, 182.7%, and 200.8% compared to TSAC, REC, and TRC. The second observation is that by jointly seeking solar power and improving the e-taxi service quality, the efficiency of using solar power can be improved remarkably while introducing little overhead on the e-taxi service quality. For example, SOURCE and TSAC increase the usage rate of solar power by 200.8% and 155.6% while increasing the passenger waiting time by less than one minute compared with TRC that solely optimizes the e-taxi service quality. The last observation is that considering the distribution of solar power is useful to handle the uncertainty and improve the efficiency of utilizing solar power, i.e., SOURCE outperforms TSAC with an increase of the usage rate of solar power by 17.6%.

Figure 5 shows the usage rate of solar power during a day by five solutions. The first observation is that SOURCE outperforms the other three solutions, i.e., TSAC, REC, and TRC by up to nearly 12.9 times from 9 am to 4 pm. The second observation is that although TRC also frequently schedules e-taxis to charging stations for partial charging as SOURCE and TSAC do, it may miss the solar power due to preferring the conventional charging stations in the central business areas for serving passengers quickly rather than the solar-powered charging stations in the sub-urban areas. The third observation is that the usage rate of solar power decreases during noon when the output of solar systems is maximum and the number of e-taxis that can be used to utilize solar power is limited. The last observation is that when the solar system output is not sufficiently large, e.g., at the beginning or end of daytime, SOURCE and TSAC can make full use of solar power.

In Figure 6, we measure the performances of SOURCE, TSAC, and Oracle under different weather conditions, i.e., cloudy, sunny and rainy. It is observed that when the weather is cloudy, our solution SOURCE can significantly increase the efficiency of seeking solar power, i.e., outperforming TSAC, the solution that uses a deterministic estimate of solar power, with a growth of the usage rate of solar power by 19.2%. The reason is that the solar system output varies a lot, and using a set of samples based on the historical solar power on cloudy days can decrease the cost of prediction errors. The performances of SOURCE and TSAC are close to each other on sunny days since the solar power is stable and the prediction error is small.

2) Benefits: In this part, we discuss the benefits of seeking solar power to the power grid and society. Since distributed solar power can result in reverse power flows that lead to reliability issues of the power grid [21], we measure the amount of reverse power flow during a day and show the results in Figure 7. The main observation is that our solution SOURCE reduces the daily peak reverse power flow by 38.3%, 59.4%, and 63.1% compared to TSAC, TRC, and REC. It is also observed that the amount of reverse power flow by SOURCE and Oracle is close to each other except at noon, which demonstrates that using samples from the probability distribution model is useful to address the challenges introduced by solar power uncertainty.

Figure 8 shows the amount of saved energy and lost energy per day. It is clear that our solution achieves the minimum amount of energy loss and the maximum amount of saved energy other than the Oracle. For example, compared with TSAC, our solution saves more than 4 MWh energy per day that can charge 70 e-taxis from empty to full. Since the storage is expensive and there is not any standard describing the proper storage capacity at a solar-powered charging station, we consider an extreme (but indeed probable) case that there is no on-site storage for the grid-connected solar charging stations, and show the energy loss and saving in Figure 9. We observe a similar advantage of SOURCE compared with the other solutions.

3) Overhead: We use the idle driving distance per day of an e-taxi and the number of charges per day of an e-taxi to measure the overhead of different solutions. The results are plotted in Figures 10 and 11. The main observation is that SOURCE introduces the longest idle driving distance and the maximum number of charges per day. It is because that e-taxis need to frequently drive to different charging stations to seek solar power. Meanwhile, to match the samples with overestimation of solar power, more e-taxis are also scheduled for charging. Although these do not lead to much service quality loss as demonstrated earlier, these overhead may be considered a cost of the more dynamic algorithm.

VI. Related Work

Integrating EVs and Renewable Energy: As the development of EVs and renewable energy, some solutions [12], [22]–[25] are designed to integrate the EV charging and the renewable energy. [22] proposes a method to efficiently schedule EVs for charging with unpredictable renewable energy, aiming to reduce the average cost of charging. [23] introduces electric vehicles as both load and source to help to consume the renewable energy by V2G techniques, focusing on improving the operation stability and economic performance of micro-grid. [12] considers the coordination of e-taxis to use solar power and serve passengers, but it ignores the solar power uncertainty. Compared to this work, some works do not consider the uncertain solar power explicitly [12], [23], [24], and the other works focus on the charging performance of EV fleets [22], or the benefit of charging stations [25], rather than how to use solar power to provide power system benefits while reducing the impact on the service quality of the EV fleet.

EV Charging Scheduling: There are also a set of existing works that investigate how to determine when, where and how long the EVs should be charged to optimize the charging performances [18], [20] and the service quality of EV fleets [17], [26]. [26] proposes a robust e-taxi balancing method under the uncertainties of passenger demand and charging resource to improve the service quality of e-taxis. [20] develops a real-time e-taxi charging scheduling framework with guaranteed predictable and bounded waiting time for e-taxis. [18] designs a real-time charging scheduling system with shared charging infrastructure among heterogeneous EV fleets to improve overall charging efficiency. Firstly, these existing solutions research a different application scenario, i.e., EV fleets and conventional charging stations, and this work considers the e-taxi fleet and solar-powered or conventional stations. Secondly, they focus on optimizing the service quality of EV fleets and the charging cost, while this work aims to consume solar power on time while introducing little overhead on the service quality.

VII. Conclusion

We explore e-taxis' mobility and charging demand flexibility to utilize solar power and serve passengers on time. We propose an e-taxi coordination algorithm, SOURCE, to schedule e-taxis for picking up passengers or charging under dynamic uncertain solar energy and passenger mobility patterns in spatial-temporal dimensions. We evaluate the effectiveness of SOURCE with real-world multi-source data. Trace-driven simulation results show that our solution can increase the usage rate of solar power per day by 17.6% while introducing less than one-minute extra waiting time for passengers, significantly outperforming the solution that co-optimize the e-taxi service quality and the usage of solar power without considering uncertainty.

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