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Energy-aware E-taxi Fleet Coordination under Power Rationing via Dynamic Charging Rate

Yukun Yuan, Zilong Zeng, Xiaonan Zhang, Shan Lin

***Abstract*— Existing electric taxi (e-taxi) services rely on charging infrastructure to maintain their daily operations. Unfortunately, severe power system disruptions, such as power rationing, can impose harsh constraints on e-taxi charging activities and significantly affect the service quality of e-taxis fleets. To address this issue, we design a framework for Energy-Aware e-taxi fleet coordination via dynamic charging Rate (EAR), to provide a satisfactory service quality while meeting energy conservation requirements. In this framework, an e-taxi fleet coordination algorithm is designed to provide sustainable service quality during pre-rationing, rationing and post-rationing phases. The coordination problem across the three phases is modeled as separate multi-objective mixed-integer linear problems due to the distinct objectives of each phase. The proposed solution is evaluated with a comprehensive dataset for an existing e-taxi system and charging infrastructures including nearly 800 e-taxis. Our data-driven evaluation shows that EAR improves the ratio of served passengers by 37.0% during the power rationing phase compared with the state-of-the-art method, which does not consider disruptions in charging infrastructure when coordinating e-taxis.**

I. Introduction

Electric vehicle fleets, e.g., e-taxis, are highly reliant on power systems to maintain consistent service quality for passengers. Unfortunately, power systems suffer from various disruptions caused by natural disasters [1], cyber attacks [2], [3], and equipment failures [4]. These power system disruptions can have significant impacts on the capacity of charging infrastructure, limiting the energy supply for e-taxis. An example of such failures is power rationing [5]–[7], which is usually implemented as the last measure to reduce energy consumption and prevent widespread blackouts across the world [8]–[11]. For instance, in August 2022, power companies regulated EV charging activities in response to a sharp rise in electricity consumption during a heatwave in China [9]. This affected around 350k charging stations and nearly 800k EVs. In order to maintain a balance between supply and demand, only a limited level of energy supply was delivered to charging stations for e-taxis. Due to the reduced power supply, few e-taxis can charge at the maximum power rate, resulting in longer charging duration, increased frequency and competition for charging stations, and consequently, lower availability of e-taxis on the road.

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There are limited methods available to manage e-taxi fleets and maintain service quality during power rationing. Many studies focus on analyzing the impact of EV charging activities on power system stability [12]–[14]. In [15], an e-bus-based V2V energy-sharing method is proposed to charge low-power EVs during large-scale grid outages. However, this approach relies on additional energy storage resources, i.e., e-buses, and V2V energy-sharing technology, making it unpractical for large-scale e-taxi fleets. A fairness-aware e-taxi coordination algorithm designed in [16] aims to enhance service quality in local areas affected by power outages, which contrasts with the large-scale power rationing problem investigated in this work. Moreover, it does not consider dynamic charging rate, which is essential to adapt to limited charging supply. Recent studies also explore ways to optimize EV charging activities to improve charging efficiency when limited power supply is available [17]–[19]. These studies present valuable research results, but they do not address the challenges faced by e-taxi fleets.

To demonstrate the impacts of power rationing on e-taxi service, we conducted a trace-driven simulation. Preliminary results reveal a significant decline in taxi service quality, with a 31.9% reduction observed when the power supply to each charging station in a city is restricted, e.g., 30% of its maximum demand.

To maintain sustainable service quality for passengers during power rationing, we develop an Energy-Aware coordination algorithm with dynamic charging Rate (EAR) for e-taxi fleets to optimize service quality during a day with power rationing. The algorithm operates across three distinct phases of the day: pre-rationing, rationing, and post-rationing, with tailored strategies for each phase. In the pre-rationing phase, the fleet focuses on increasing the remaining energy of e-taxis while maintaining high service quality in preparation for the forthcoming rationing period. During the rationing phase, the goal shifts to maximizing the number of passengers served by dynamically adjusting the charging rates of e-taxis based on their remaining energy. Once rationing ends, the fleet returns to regular operations for optimizing service quality for passengers. As outlined, the control algorithm has unique objectives for each phase. To achieve these, separate multi-objective mixed-integer linear problems are formulated, which are efficiently solved using the Gurobi optimizer. Solutions are typically computed within a minute on a standard personal computer.

The main contributions of this work are listed as follows:

- To the best of our knowledge, it is the first study to understand the impact of short-term, large-scale power

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rationing on the service quality of e-taxi fleets and to develop strategies for the fleets to effectively respond to such disruptions.

- We develop an energy-aware e-taxi coordination algorithm that dynamically adjusts charging rates based on the remaining energy of e-taxis. The algorithm incorporates tailored strategies for three distinct phases of the power rationing, with the goal of maintaining sustainable service quality.
- Through a data-driven evaluation using a comprehensive dataset from an existing e-taxi fleet, we demonstrate that our solution delivers 37.0% higher service quality across the city during the power rationing phase, compared to the state-of-the-art method that does not account for charging system failures in e-taxi coordination.

II. Background & Motivation

A. Power Rationing

Due to extreme weather conditions, such as high temperatures, electricity demand has significantly increased, prompting the power companies to implement power rationing. Since daily electricity usage is given higher priority over charging electric vehicles, in some cities, power rationing measures are applied to vehicle charging during peak usage hours, reducing the charging rate to extend charging duration. Consequently, this can decrease the availability of fully charged e-taxis on the roads, causing inconvenience for passengers and potential revenue losses for e-taxi companies.

Let us take a look at two real-world instances of power rationing. In August 2022, China experienced a significant spike in electricity consumption due to an intense heat-wave. In response to this surge, power companies adopted a key measure to regulate EV charging activities, prioritizing household electricity needs over EV charging [9]. This initiative was initially implemented in several provinces, impacting approximately 350k charging stations and nearly 800k electric vehicles. To stabilize peak electricity consumption, charging power was adjusted during high-demand hours from 3 p.m. to 10 p.m. [20]. In the other case, the California Independent System Operator declared an Energy Emergency Alert 3 on September 6, 2022 [21], due to electricity shortages triggered by record-breaking heat and demand. To reduce the risk of widespread power outages, the California government enacted rolling blackouts.

B. Performance of E-taxi Fleets under Power Rationing

To understand how power rationing policies affect e-taxi service quality, we simulate the implementation of such a policy in a city with an active e-taxi fleet. The simulated policy is based on a real-world power rationing instance [20]. Specifically, the policy is enforced between 3 p.m. and 10 p.m., during which the power supply to each charging station is reduced to 30% of its maximum power demand. The maximum power demand is defined as the total power required when all charging poles at a station are operating at their maximum charging capacity simultaneously. The reduction in power supply and its time duration are announced city-wide one day before the policy takes effect. Please refer to Sec. V about the detailed description of datasets.

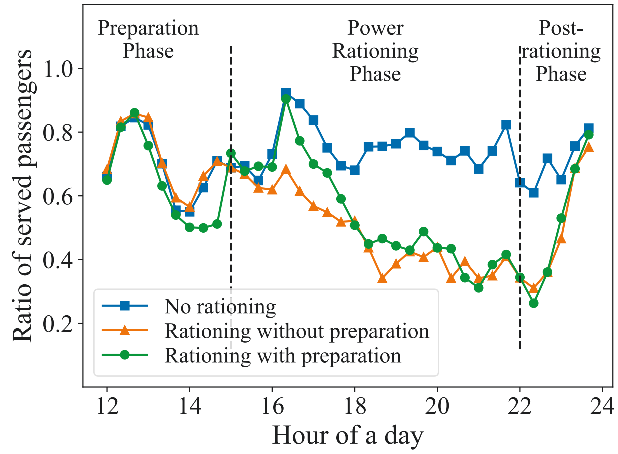

Fig. 1: E-taxi fleet service quality with power rationing.

We divide each day into three distinct phases: the preparation, power rationing, and post-rationing phases, as illustrated in Figure 1. By announcing the power rationing policy a day ahead, the e-taxi fleet can proactively prepare by maximizing the remaining energy in the EVs before the rationing phase. In this analysis, we evaluate three operational settings for the e-taxi fleet throughout a day: (i) No rationing: This scenario assumes that no power rationing policy is implemented, and the e-taxi coordinator employs the optimization algorithm described in [17] to maximize service quality. (ii) Rationing without preparation: In this case, the e-taxi fleet operates as usual, dispatching vehicles to serve passengers and charge their batteries, aiming to maximize the number of passengers served [17]. During the power rationing stage, the number of e-taxis that can be charged simultaneously is limited, ensuring that each charging e-taxi receives the maximum rate. (iii) Rationing with preparation: In this setting, the fleet adopts a different strategy during the preparation stage. The coordinator optimizes the pickup locations of e-taxis at the start of each time slot and assigns idle vehicles to charge as much as possible during those intervals.

The simulation results are shown in Figure 1. There are several key observations. (i) In the rationing without preparation scenario, service quality noticeably declines after 15:00 due to an insufficient number of available vehicles. This shortage is caused by the reduced overall charging power supply, limiting the number of e-taxis that can charge simultaneously at the stations. (ii) Early preparation before the power rationing period is beneficial for maintaining a sustainable e-taxi service throughout the rationing duration. (iii) During the preparation stage, after dispatching idle vehicles to charge their batteries, service quality may decline compared to scenarios without early preparation. This is because the reallocation of these idle vehicles results in a distribution that may not align with the passenger demand in the subsequent time slot. Driven by these observations, our goal is to ensure sustainable service quality for an e-taxi fleet both during power rationing periods and in normal conditions.

III. E-TAXI FLEET FORMULATION

A. E-taxi Systems

First, we model the spatial and temporal dimensions of the e-taxi system. We divide the city into m regions, each containing at least one e-taxi charging station. Additionally, we break down a day into multiple equally-sized time slots, each denoted by t. The current time slot is represented by t'. Our focus is on studying the charging and rebalancing problem faced by an e-taxi fleet over the next T slots, i.e., spanning from t' to $t'+T-1$.

Throughout a day's operation, the battery energy of an e-taxi varies between 0% and 100%. To simplify the analysis, we categorize the remaining energy of an e-taxi into L discrete levels. The energy level of an e-taxi at the beginning of each time slot t is represented by e^t. Then we model the changes in an e-taxi's energy between consecutive time slots. If an e-taxi is in use on the road during time slot t, its energy level at the beginning of slot $t+1$ is defined as: $e^{t+1} = e^t - e^t_{i,i'}$, where $e^t_{i,i'}$ represents the energy reduction incurred when the e-taxi travels from region i to i' during slot t. On the other hand, if an e-taxi is at a charging station, its energy replenishment depends on the availability of charging poles and the demand for charging services from other e-taxis. A subsequent model will be developed to track the energy status of e-taxis at charging stations.

With the installed sensing and communication devices on the e-taxis, fleet managers can periodically receive updates on the fleet's status. This status includes the distribution of occupied and unoccupied e-taxis across the city, along with their respective energy levels. Let $U^t_{i,l}$ and $O^t_{i,l}$ denote the number of unoccupied and occupied e-taxis, respectively, with an energy level l in region i at the beginning of slot t. Note that during time slot $t-1$, e-taxis engaged in either passenger search or battery charging are considered as unoccupied for the beginning of slot t.

Charging and rebalancing decisions: Fleet managers periodically schedule e-taxis for either recharging or passenger service based on the fleet's current status. This scheduling process includes redistributing e-taxis for charging or picking up passengers as needed. The notation $X^t_{i,i',l}$ represents the number of e-taxis with remaining energy l that are sent from region i to i' to serve passengers at the beginning of time slot t. E-taxis can be charged at different rates at charging stations, depending on the available power supply [22]–[26]. In situations where power rationing occurs, e-taxis may select from various charging power rates to accommodate supply constraints, with the goal of maximizing the number of vehicles charged. We discretize the charging power rate into M equal-length levels, and there are M available charging power rate options for e-taxis. Let $Y^{t,j}_{i,i',l}$ denote the number of e-taxis with remaining energy l that are sent from region i to i' for battery charging using the charging level j at the start of time slot t. It shows the consideration of charging e-taxis with dynamic power rate $j \in [1, M]$ based on their remaining energy $l \in [1, L]$.

Fleet state transition: Based on the actions taken by each e-taxi during time slot t, there are three categories of e-taxis: those charging, those available for serving passengers, and those delivering passengers. Let $C^t_{i,l}$, $S^t_{i,l}$, and $O^t_{i,l}$ denote the number of e-taxis with remaining energy l in region i that belong to each of three categories after be sent to charge or serve passengers. The relationship between the distribution of e-taxis before and after dispatching is

$$C^{t,j}_{i,l} = \sum_{i'} Y^{t,j}_{i',i,l},\ S^t_{i,l} = \sum_{i'} X^t_{i',i,l}. \tag{1}$$

The e-taxis dispatched to serve passengers or already occupied with them determine the distribution of occupied e-taxis at the start of time slot $t+1$. Meanwhile, the distribution of unoccupied e-taxis at the beginning of slot $t+1$ depends on the mobility pattern of the e-taxis that are in any of the three categories during slot t. In summary, we propose the following model to describe $U^{t+1}_{i,l}$ and $O^{t+1}_{i,l}$ derived from $C^{t+1}_{i,l}$, $S^{t+1}_{i,l}$, and $O^{t+1}_{i,l}$:

$$O^{t+1}_{i,l} = \sum_{i'=1}^{m} \tilde{P}^t_{i',i} S^t_{i',l+E^t_{i',i}} + \sum_{i'=1}^{m} P^t_{i',i} O^t_{i',l+E^t_{i',i}} \tag{2}$$

$$U^{t+1}_{i,l} = \sum_{i'=1}^{m} \tilde{Q}^k_{i',i} S^t_{i',l+E^t_{i',i}} + \sum_{i'=1}^{m} Q^t_{i',i} O^t_{i',l+E^t_{i',i}} + f_i(\mathbf{C}^t_{i,\cdot}), \tag{3}$$

where $P^t_{i',i}$ ($Q^t_{i',i}$) represents the likelihood of an occupied e-taxi relocating from region i' to i during slot t and being occupied (unoccupied) at the end of slot t. Similarly, $\tilde{P}^t_{i',i}$ ($\tilde{Q}^t_{i',i}$) indicates the probability of an unoccupied e-taxi traveling from region i' to i during slot t and still being occupied (unoccupied) at the end of slot t. $\mathbf{C}^t_{i,\cdot}$ is the concatenation of e-taxis sent to region i for charging with diverse energy status. The function $f_i(\mathbf{C}^t_{i,\cdot})$ characterizes the number of e-taxis with varying energy levels for given the charging e-taxis in region i during time slot t, which will be introduced later.

B. E-taxi Charging Model under Power Rationing

There has been the wide deployment of charging stations throughout the city to support the daily operations of e-taxi fleets. Suppose that region i contains q_i charging poles. Each pole is capable of delivering various charging power rates, depending on the selection made by the electric vehicles [22], [27], [28]. We use r^j to describe the charging power rate of charging level j. The effect of power rationing on charging systems is captured by the resilient total charging power rate, such as the resilient total charging power rate may be reduced to 70% of the regular total charging rate. Let α_i denote the resilient total charging rate with power rationing in region i. In order to not exceeding the resilient total charging rate, we constrain that $\sum_{i',j,l} Y^{t,j}_{i',i,l} r^j \leq \alpha_i$.

The number of e-taxis dispatched to region i for charging during time slot t is equal to $\sum_{i',j,l} Y^{t,j}_{i',i,l}$. If the number of charging poles is more than the number of e-taxis requesting charging service, each e-taxi can be charged by the requested charging power rate. Otherwise, only q_i e-taxis can be charged within a time slot. Since the e-taxis may arrive at the charging stations in a random sequence, it is challenging to model which e-taxis can be charged when the number of charging poles is not sufficient. We utilize $y_{i,l}^{t,j}$ to describe the number of e-taxis with energy level l that are charged in region i during slot t with the charging level j, which is constrained by:

$$y_{i,l}^{t,j} \leq C_{i,l}^{t,j}, \quad \sum_{j,l} y_{i,l}^{t,j} \leq q_i. \tag{4}$$

By the end of time slot t, the number of e-taxis with the energy level l at the charging station of region i is equal to $\sum_{j,i'} Y_{i',i,l}^{t,j} - \sum_j y_{i,l}^{t,j} + \sum_j y_{i,l-l^j}^{t,j}$, where l^j represents the increase of an e-taxi's remaining energy if it is charged by the level j for a time slot.

IV. Energy-aware E-taxi Coordination via Dynamic Charging Rate

In this section, we introduce an energy-aware e-taxi coordination algorithm that utilizes dynamic charging power rates to maintain sustainable passenger service under power rationing. The algorithm divides a day into three distinct phases: pre-rationing, rationing, and post-rationing. The strategies for each phase are as follows: i) Pre-rationing: E-taxis are charged to their maximum capacity in anticipation of the power rationing period, while ensuring high passenger service quality. ii) Rationing: Charging schedules are adjusted based on the remaining energy of e-taxis with modulated charging power rates to increase the availability of e-taxis on the road, which further maximizes passenger service quality. iii) Post-rationing: The e-taxi fleet resumes regular service, with a focus on optimizing the number of passengers served. The objectives, constraints, and optimization problems for each stage are described below.

Objectives: Let D_i^t be the estimated number of passengers requesting taxi service in region i during time slot k. The corresponding taxi supply, i.e., the number of e-taxis available for serving passengers after dispatch, is $\sum_{l=1}^{L} S_{i,l}^t$. The primary objective of an e-taxi fleet is to optimize the service quality, which is defined as the number of passengers that can be served:

$$J_{service} = \sum_{i=1}^{m} \sum_{t=t'}^{t'+T-1} \min\{D_i^t, \sum_{l=1}^{L} S_{i,l}^t\}. \tag{5}$$

The e-taxi dispatch system for charging and passenger service presents a challenge in terms of idle driving distance. This distance represents the amount of energy e-taxis use while not actively serving passengers, potentially leading to wasted energy and missed opportunities to pick up passengers. In addition to providing efficient passenger service, a secondary objective of the e-taxi dispatch system is to reduce dispatching costs. These costs are calculated based on the idle driving distance formulated as follows:

$$J_{cost} = \sum_{i,i'} \mu_{i,i'} \sum_{l} (X_{i,i',l}^t + \sum_{j} Y_{i,i',l}^{t,j}), \tag{6}$$

where $\mu_{i,i'}$ is the driving distance from region i to i'.

Constraints: Because of the limited traveling time and speed, the traveling distance of an e-taxi is bounded during a time interval. Therefore, an e-taxi should not be dispatched to a far region for charging or serving passengers. Let $\omega_{i,i'}^t \in \{0,1\}$ represent if an e-taxi can reach region i' from i within the time interval t or not. $\omega_{i,i'}^t = 1$ means the two regions are reachable to each other; otherwise, it is equal to 0. We constrain that

$$X_{i,i',l}^t(1-\omega_{i,i'}^t) = 0, \quad Y_{i,i',l}^{t,j}(1-\omega_{i,i'}^t) = 0. \tag{7}$$

A major concern of the e-taxis is the sustainable operation. The energy is consumed when an e-taxi operates on the road to search and serve passengers. It is crucial to ensure that every e-taxi does not use up energy on the road. To achieve this goal, we enforce strict guidelines for e-taxis with low energy levels. Specifically, we set a threshold l_{low} to define when an e-taxi is considered to have low energy. When an e-taxi reaches this threshold, it must be sent to a charging station to replenish its batteries. It is formulated as:

$$S_{i,l}^t = 0, \quad l \leq l_{\text{low}}. \tag{8}$$

Optimization problem: Given the distinct scheduling strategies proposed for each of the three phases, we formulate separate optimization problems to determine the optimal rebalancing and charging decisions.

i) Pre-rationing phase: Energy consumers are typically notified in advance about upcoming power rationing policies, including the start and end times and the percentage of the power supply reduction. Upon receiving the notification, the e-taxi fleet must prepare for the upcoming power rationing by increasing the remaining energy levels of the e-taxis. However, this preparation must be carried out without compromising the service quality during periods without power rationing. The following optimization problem is formulated to obtain the optimal service quality that the e-taxi fleet can provide before the power rationing:

$$\max_{X,Y} \quad J = J_{service} + \beta J_{cost} \tag{9}$$
$$\text{s.t. } Y_{i,i',l}^{t,j} = 0, \ \forall j < M; \quad \text{Eq. (1)} \sim \text{(4)}, \text{(7)} \sim \text{(8)},$$

where β is a negative weight parameter to balance the two objectives due to the potential trade-off between them. The constraint in the above optimization problem represents that the e-taxis do not need to perform charging activities with dynamic charging rate when the power supply is sufficient before power rationing. Let $\tilde{J}_{service}$ denote the optimal service quality obtained from Eq. (9). Another optimization problem is formulated to increase the remaining energy of e-taxis while ensuring the service quality, i.e.,

$$\max_{X,Y} \quad J = \sum_{t,j,i,i',l} Y_{i,i',l}^{t,j} \tag{10}$$
$$\text{s.t.} \quad J_{service} \geq \gamma \tilde{J}_{service}; \ Y_{i,i',l}^{t,j} = 0, \quad j < M,$$
$$\text{Eq. (1)} \sim \text{(4)}, \text{(7)} \sim \text{(8)},$$

where $\gamma \in (0,1]$ represents the allowable reduction in service quality that the e-taxi fleet can accept while preparing for the upcoming power rationing period.

ii) Rationing phase: During power rationing, the limited power supply may prevent some e-taxis from being charged if all e-taxis are charged at the maximum power rate, even when charging poles are available. We assign e-taxis to charge their batteries using a dynamic charging power rate to maximize the number of e-taxis available for sustainable passenger service during the rationing period. For instance, if two e-taxis are charged at a medium power rate, both will be available to pick up passengers. In contrast, charging a

Algorithm 1: ***Energy-aware e-taxi coordination algorithm via dynamic charging rate***

Input: Time horizon T time slots; parameters $E, \beta, \gamma, \alpha_i$.
Output: Control decision: $X_{i,i',l}^{t}, Y_{i,i',l}^{t,j}, i \in [1,m], l \in [1,L], j \in [1,M], t \in [t', t'+T-1]$.

while at the beginning of each time interval **do**
  Update current time slot as t', the distribution of unoccupied and occupied e-taxis as $U_{i,l}^{t'}$ and $O_{i,l}^{t'}$;
  Update the driving distance $\mu_{i,i'}$ and driving distance constraint parameters $\omega_{i,i'}^{t}$;
  Update the passenger demand in each region D_i^t.
  if the current time slot is in the pre-rationing phase **then**
    Solve the problem, Eq. (9) to get the optimal service quality $\tilde{J}_{service}$.
    Solve the problem, Eq. (10) to get the dispatch decisions.
  else if the current time slot is in the rationing phase **then**
    Solve the problem, Eq. (11) to obtain the decisions with dynamic charging power rate.
  else
    Solve the problem, Eq. (9) to get the dispatch decisions for resuming the e-taxi service.
  end if
  Send rebalancing and charging decisions: $X_{i,i',l}^{t'}, Y_{i,i',l}^{t',j}$.
end while
return Decisions for charging and serving passengers.

single e-taxi at the maximum power rate would leave only one e-taxi on the road. The optimization problem for an e-taxi fleet during power rationing period is defined as:

$$\max_{X,Y} \quad J = J_{service} + \beta J_{cost} \tag{11}$$
$$\text{s.t.} \quad \text{Eq. } (1) \sim (4), (7) \sim (8).$$

The optimization problems Eq. (9), (10), and (11) are the mixed-integer linear programming problems, which can be solved using existing methods, e.g., branch-and-bound and cutting-plane. In this work, these problems are solved by the Gurobi solver, achieving a solution under one minute on a standard personal computer, which is a reasonable method for the realistic application scenario.

iii) Post-rationing phase: After power rationing, the e-taxi fleet resumes regular service with full charging power supply. The e-taxi fleet aims to schedule e-taxis to maximize the service quality for passengers and reduce the dispatch cost. The optimization problem for the e-taxi scheduler after power rationing is Eq. (9).

Energy-aware e-taxi coordination algorithm via dynamic charging rate: The pseudo-code of the energy-aware e-taxi coordination algorithm during a day with power rationing is shown in Alg. 1. The main idea is that the e-taxi fleet managers adopt the different strategies described above to coordinate the e-taxis during pre-rationing, rationing, and post-rationing phases. This algorithm operates within the framework of model predictive control. At the beginning of each time slot t', the e-taxi fleet scheduler updates the fleet status and determines dispatch decisions for the next T slots. However, only the dispatch decisions relevant to the current time slot t' are deployed to the e-taxis. When the T-slot planning horizon spans two operational phases, the optimization problem is determined based on the phase in which the current slot t' resides. Because the actual implementation is based solely on the decisions corresponding to the current slot t, despite considering future slots. E-taxis with identical remaining energy and location are treated the same and are randomly directed to different charging stations or regions based on dispatch decisions.

V. Evaluation

A. Data Description

Our comprehensive dataset consists of three parts: (i) charging station data: GPS locations and number of charging poles of each charging station; (ii) taxi trajectory data: a networked GPS device is installed in each taxi such that the real-time information, e.g., GPS coordinates, occupancy status, and vehicle ID, is reported every thirty seconds; (iii) passenger transaction data: this contains the time stamps of pickup and drop-off and the taxi's plate number associated with each passenger trip.

The proposed algorithm, EAR, is compared with several baselines to demonstrate its effectiveness: (i) Oracle: this assumes the proposed solution EAR operates without power rationing, which shows the performance upper bound; (ii) reactive to passenger demand (R2D) [17]: the charging activities of e-taxis are coordinated to meet the passenger demand as much as possible in spatial-temporal dimensions; (iii) reactive to passenger demand with preparation (R2D W/ Prep.): it is a variation of R2D, which adopts a preparation strategy described in Section II-B during the pre-rationing phase. The performances of all the four solutions are measured by the ratio of served passengers for a city. The policy is simulated to be applied between 3 p.m. and 10 p.m., during which the power supply to each charging station is reduced to 30% of its maximum power demand. The settings of parameters are: $\beta = -0.1$, $T = 4$ and $\gamma = 1.0$. The length of a time slot is 20 minutes.

B. Results

Performance Comparison: Figure 2 illustrates the service quality achieved by four methods in the simulated power rationing scenario. Our method, EAR, consistently outperforms the two baselines (R2D and R2D W/ Prep.) during both the preparation and rationing phases. Specifically, EAR increases the ratio of served passengers by 5.0% and 49.9% from 1pm to 3pm, and by 37.0% and 20.7% in the power rationing phase, compared to R2D and R2D W/ Prep., respectively. A comparison between EAR and R2D W/ Prep. reveals that EAR's scheduling strategy during the preparation phase effectively maximizes the remaining energy of e-taxis, all while maintaining high service quality. Furthermore, after

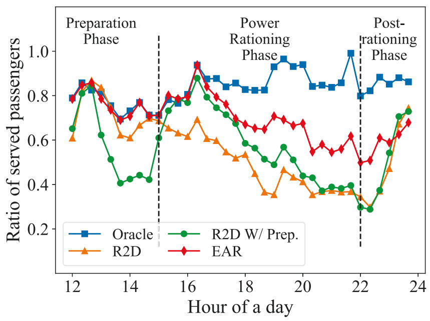

Fig. 2: Service quality comparison.

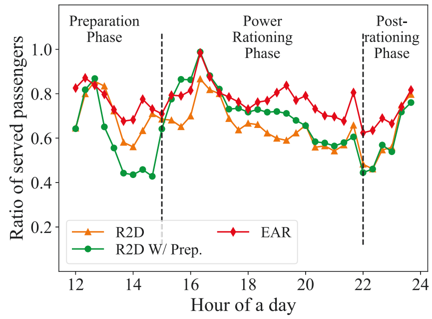

Fig. 3: Service quality under a 70% power supply reduction.

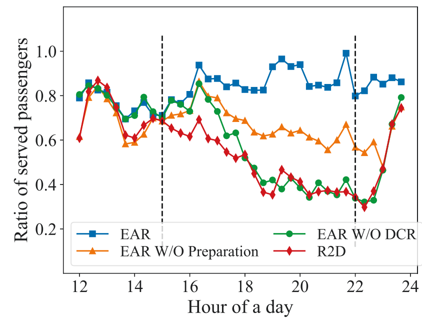

Fig. 4: Impact of each phase's strategy.

TABLE I: Service quality & overhead.

Methods	# of served passengers	Daily idle driving distance (km)	# of chargers
Oracle	19,376	17.99 (±11.43)	3.37 (±2.06)
R2D	14,994	21.8 (±11.8)	7.64 (±1.46)
R2D W/ Prep.	15,819	23.4 (±11.28)	6.29 (±1.76)
EAR	16,876	21.55 (±11.89)	5.03 (±1.74)

18:00, when the stored energy is depleted, EAR continues to provide greater availability of e-taxis on the road. This is due to its dynamic charging rate strategy, which proves more effective than that of the R2D W/ Prep. method. It is also observed that EAR delivers comparable service quality to Oracle before 16:00, highlighting the effectiveness of its scheduling strategy during the preparation phase. However, as the power supply is reduced to 30%, the performance gap between EAR and Oracle widens between 4pm and 7pm. As shown in Table I, EAR increases the total number of served passengers by 6.7% compared to R2D W/ Prep., demonstrating the efficiency of the proposed method in passenger service.

We also evaluate the service quality of EAR, R2D, and R2D W/ Prep. when the power supply is reduced to 70% of the maximum under a normal scenario. The results, presented in Figure 3, show that EAR consistently outperforms the other two methods. Meanwhile, a key observation from Figures 2 and 3 is that the performance improvement diminishes as more power supply becomes available for the e-taxi fleet. Specifically, around 19:00, EAR's performance is 71.4% better than R2D in Figure 2, whereas in Figure 3, this improvement is 23.9%.

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 four methods, which are shown in Table I. It can be observed that all four methods result in similar daily idle driving distances, as they share the same strategy of scheduling e-taxis for charging and passenger service at the start of each time slot. However, EAR introduces 34.2% fewer number of chargers compared to R2D. This is because, with EAR, the e-taxis can remain connected to charging poles at a lower charging rate, whereas in R2D, they must disconnect and reconnect later to make charging resources available for other e-taxis, leading to a higher number of required chargers.

Ablation Study: To better assess the contribution of scheduling strategies across different phases in maintaining sustainable service quality, we evaluate the performance of two variations of EAR. The first variation, EAR without Preparation (EAR W/O Preparation), aims to enhance service quality during the preparation phase without accounting for the increase in the remaining energy of e-taxis. The second variation, EAR without Dynamic Charging Rate (EAR W/O DCR), assumes that e-taxis are charged at the maximum rate whenever they are assigned to a charging station during the power rationing phase. Figure 4 presents the ratio of served passengers across four methods, revealing two key observations. (i) The preparation phase plays a crucial role in maintaining service quality during the early stages of power rationing, as EAR and EAR W/O DCR achieve similar performance at the beginning of rationing. However, beyond this initial period, the performance of EAR W/O DCR declines significantly, eventually aligning with that of R2D. For instance, at 18:00, the ratio of served passengers using EAR W/O DCR is 26.2% lower than that achieved by EAR. (ii) The dynamic charging rate strategy for e-taxis proves to be effective in sustaining higher service quality when the power rationing policy is enforced for several hours. For example, at 20:00, EAR W/O Preparation increases the ratio of served passengers by 47.3% compared to EAR W/O DCR.

VI. Related Work

EV fleet management: Two key works focus on guiding the operation of EV fleets during power system failures. In [15], an energy-sharing method utilizing e-buses for vehicle-to-vehicle (V2V) charging is proposed to support low-power EVs during large-scale grid outages. However, this approach depends on additional energy storage resources, such as e-buses, and V2V energy-sharing technology, making it unsuitable for the scenario considered in this study. Similarly, the fairness-aware e-taxi coordination algorithm in [16] is designed to improve service quality in small-scale areas affected by power outages. This focus on localized disruptions contrasts with the large-scale power rationing problem addressed in our work. Other studies have investigated managing EV fleet charging behaviors in scenarios with limited city-wide charging resources, aiming to optimize operational efficiency [19], [29]–[31]. For instance, [31] introduces a human preference-aware framework for rebalancing and charging shared electric micromobility vehicles. However, these approaches are not designed to address the challenges of maintaining service quality when the charging infrastructure is partially inoperable.

Power system stability with EVs: The rapid expansion of EVs has prompted extensive research into the effects of EV charging activities on power system stability [12]–[14], [32], [33]. For instance, [14] investigates the vulnerabilities in the power system caused by cyberattacks that manipulate EV charging behaviors, while [32] employs a hybrid analytical and Monte Carlo simulation approach to assess the reliability of power systems integrated with EVs. [33] provides a comprehensive review of various management strategies aimed at minimizing the impact of EV integration into the grid system. While these studies focus on the potential impact of EVs on power system operations, they do not address the challenges EVs face when charging infrastructure is disrupted.

VII. Conclusions

We demonstrate the degradation in service quality experienced by e-taxi fleets during short-term, large-scale power rationing when using conventional e-taxi coordination algorithms, as well as a method with prior preparation. To ensure sustainable service quality throughout a day affected by power rationing, we propose an energy-aware e-taxi coordination algorithm (EAR) that dynamically adjusts the charging rate. EAR implements tailored strategies for the pre-rationing, rationing, and post-rationing phases. Our data-driven evaluation shows a 37.0% improvement in service quality during the rationing phase, compared to the state-of-the-art method, which does not account for disruptions in charging infrastructure.

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