Understanding the Long-Term Evolution of Electric Taxi Networks: A Longitudinal Measurement Study on Mobility and Charging Patterns

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Due to the ever-growing concerns over air pollution and energy security, more and more cities have started to replace their conventional taxi fleets with electric ones. Even though environmentally friendly, the rapid promotion of electric taxis raises problems to both taxi drivers and governments, e.g., prolonged waiting/charging time, unbalanced utilization of charging infrastructures, and inadequate taxi supply due to the long charging time. In this article, we conduct the first longitudinal measurement study to understand the long-term evolution of mobility and charging patterns by utilizing 5-year data from one of the largest electric taxi networks in the world, i.e., the Shenzhen electric taxi network in China. In particular, (1) we first perform an electric taxi contextualization about their operation and charging activities; (2) then we design a generic charging event extraction algorithm based on GPS data and charging station data, and (3) based on the contextualization and extracted charging activities, we perform a comprehensive measurement study called ePat to explore the evolution of the electric taxi network from the mobility and charging perspectives. Our ePat is based on 4.8 TB taxi GPS data, 240 GB taxi transaction data, and metadata from 117 charging stations, during an evolution process from 427 electric taxis in 2013 to 13,178 in 2018. Moreover, ePat also explores the impacts of various contexts and benefits during the evolution process. Our ePat as a comprehensive measurement of the electric taxi network mobility and charging evolution has the potential to advance the understanding of the evolution patterns of electric taxi networks and pave the way for analyzing future shared autonomous vehicles.

CCS Concepts: • **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*; • **Information systems** → *Spatial-temporal systems*;

Additional Key Words and Phrases: Electric taxi, mobility pattern, charging pattern, evolution experience, shared autonomous vehicle

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1 INTRODUCTION

In the vision of smart cities, vehicle electrification has become inevitable since it contributes to significant emission reduction for better air quality and less energy consumption [1, 41]. Compared to personal cars, taxis as shared vehicles have high gas consumption and emissions due to their long daily operation time [12, 47]. For example, replacing a conventional gas taxi with an Electric Taxi (ET) creates an emission reduction impact that is equivalent to replacing eight New York City personal cars with electric vehicles [34], which provides a higher incentive for city governments to upgrade conventional gas taxis with ETs. In the recent decade, many cities around the world have initiated the process of taxi electrification, e.g., New York City, London, Beijing, and Shenzhen [38]. Among these cities, the Chinese city Shenzhen started the taxi electrification process in 2010 and achieved the largest ET network in the world by 2017 [7]. In particular, the number of ETs in Shenzhen increased from 50 in 2010 to 12,518 in 2017 [26], and it is projected to be over 18,000 by 2020, becoming an ET-only taxi network [28].

Even though ET-related research has become more and more popular, and there is an increasing number of works in this area [9, 15, 19, 22, 24, 35, 48], most of them are focused on theoretical models, e.g., charging scheduling [9, 19, 22, 35] and charging station deployment [15, 48]. A lack of data-driven investigation based on real-world operation data make it hard for these models to achieve ideal results. With the growing promotion of ETs and some smart city initiatives, real-world ET data has become available for research in recent years. Although some research [37] has been conducted to study basic charging patterns of ETs, few existing works have tried to understand long-term evolution patterns of large-scale ET networks. Nevertheless, understanding long-term evolution patterns of ET networks is essential for predicting and quantifying ET development roadblocks and benefits. The understanding of ET networks also has the potential to provide insights for future shared autonomous electric vehicles [2, 13], which can be treated as ETs without human drivers [18].

However, the unique characteristics of ETs, e.g., the long charging durations and unexpected waiting time for refueling compared with conventional gas taxis, make their operation and charging patterns very complicated regarding years of revolution. For example, the average daily operation distance of ETs in Shenzhen is 430 km, which causes frequent charging activities because of the limited battery capacity, e.g., about 3.5 times per day on average [37]. Furthermore, due to the limited charging station supply and uneven temporal charging demand, the average charging time combined with the waiting time for a charging activity is about 1.5 hours, which reduces the overall taxi business time by 13.6%. Moreover, the energy consumption of ETs varies in different contexts, e.g., the lower mileages caused by air conditioners at low temperatures. All these factors, along with a city's ET evolution process (e.g., more ETs, more charging stations, better vehicular makes/models), make it extremely challenging to understand the long-term evolution patterns of a large-scale ET network.

In this article, we perform a comprehensive measurement investigation called ePat to explore the evolution patterns of the ET network in Shenzhen based on multisource datasets. However, there are some challenges to approaching this target: (1) an intricate data cleaning process is needed due to the poor quality of the raw data; (ii) without real-world data from charging stations, an accurate charging events extraction method is required to obtain the charging events from vehicle data; and (3) a set of key and generalizable metrics is also important to reveal some unique features of ETs and should be carefully defined. With ePat, we systematically measure the mobility and charging evolution patterns of ETs, combined with the accessory charging network evolution patterns. Finally, an in-depth discussion is made on the potential applications of our measurement investigation for other cities that plan to promote large-scale ET fleets and future shared autonomous vehicles. In particular, the major contributions of this article include:

- To our best knowledge, we conduct the first work to measure and understand the long-term evolution patterns of electric vehicle networks. Our data-driven investigation has three key features: (1) a long period, i.e., more than 5 years; (2) a large number of ETs, i.e., 13,178 ETs; and (3) a large number of charging stations and points, e.g., 117 charging stations. Such a large-scale data-driven investigation enables us to understand the evolution process of the mobility and charging patterns of the ET network, which are difficult to achieve with a small-scale or short-term investigation.
- We perform a comprehensive contextualization process of ETs considering both their operation and charging activities. We design and show in a detailed way a charging activity extraction algorithm based on GPS data and charging station data, combined with manually labeled ground truth from a set of real-world field studies for parameter learning and verification, which is highly generalizable to other electric vehicle works.
- We present a measurement framework called ePat for a systematical and longitudinal context-aware measurement study for ET networks. In addition to ET data and charging station data, various contextual data are also leveraged for spatiotemporal modeling, including urban partition, weather conditions, and so forth. We report our measurement results on various metrics related to spatial, temporal, mobility, energy, CO_2 emissions, and drivers' incomes. More importantly, we explain possible causalities based on various correlation analyses.
- Based on our measurement results, we provide some in-depth discussions for the lessons learned and insights, including ET and charging network evolution patterns, along with how to apply our experiences to other cities for charging station deployment and policy guidance. Some of our data-driven insights have been provided to the Shenzhen transportation committee for a better future ET development. Some lessons learned have the potential to provide valuable experiences for a conceptually similarly evolution process for future shared autonomous electric vehicles.

The rest of the article is organized as follows. Section 2 describes the related work. Section 3 provides dataset details. Section 4 describes our ePat methodology. Section 5 elaborates our measurement results. Section 6 provides some insights and discussions, followed by a conclusion in Section 7.

2 RELATED WORK

Most investigations of ETs can be classified into two types based on the investigation periods: long-term investigation (over 1 year) and short-term investigation. For the existing research, some works are based on real-world data from large-scale fleets (over 1,000 electric vehicles), while others leverage a small dataset or simulations. Based on these two factors, we divide the ET research into four categories, as given in Table 1.

Table 1. Categories of Related Works

Electric Vehicles	Small Scale	Large Scale
Short Term	[9, 22, 32, 37]	[10, 40, 45, 46, 51]
Long Term	[16, 29, 36, 60]	ePat (Our work)

2.1 Short-Term Investigation

Small scale: Numerous studies [8, 21, 31, 33, 43, 44, 48, 49] have been carried out for dealing with real problems in the ET domain, e.g., charging station siting and deployment, charging schedule. However, most of the existing works are based on small-scale real-world ET data or utilize conventional gas taxi data to simulate ET scenarios. [9] develops a real-time scheduling approach for ET fleets based on the GPS trajectory records of 550 ETs. [22] develops an optimal charging station deployment framework based on 490 ETs' trajectory records. Compared to these research works, our dataset includes the real-time GPS records of more than 13,000 ETs.

Large scale: [50] presents an opportunistic wireless charger deployment scheme for ET fleets to minimize the total deployment cost and maximize the opportunity of picking up passengers at the chargers based on large-scale gas taxi trajectory data. [45] develops a scheduling strategy for future city-scale ETs to avoid congestion in the swapping stations by leveraging the data of the existing conventional taxi fleet. But they are based on short-term gas taxi data, which makes it difficult to uncover the operating and charging characteristics of ETs, whereas we study a 5-year real-world dataset from a large-scale ET network.

2.2 Long-Term Investigation

Small scale: There are also some existing works for the long-term investigation of the ET mobility patterns. [36] investigates 4 years of GPS trace data from 850 ETs in Shenzhen to understand the battery degradation of ETs. [60] analyzes a 2-year dataset from 34 ETs in Beijing to understand the operational status, benefits, and charging facilities. These small networks cannot fully reveal the complexity and advantage of city-scale networks. Besides, few existing works investigate mobility patterns' evolution of ETs.

Large scale: Different from the existing work, we delve into the long-term (over 5 years) mobility and charging patterns' evolution for a large-scale (over 13,000) ET network. To our best knowledge, ePat is the first work of data-driven investigation on studying the long-term mobility and charging patterns for large-scale ET networks.

2.3 Summary

Existing works mostly study the mobility and charging patterns of ETs with small-scale and short-term data, e.g., fewer than 1,000 taxis and within 1 week. Even though some works investigate the mobility patterns of ETs from a large-scale perspective, they only leverage data over several days. However, our ePat is the first work to study the long-term mobility and charging patterns for large-scale ET networks. Such a long-term data-driven investigation enables us to identify the real-world ET mobility and charging patterns' evolution, which cannot be revealed using simulation studies or small-scale data or under a short-term setting.

3 DATASET

In this section, we introduce the data collection, data cleaning, and data description of our large-scale and multisource ET datasets from the Chinese city Shenzhen.

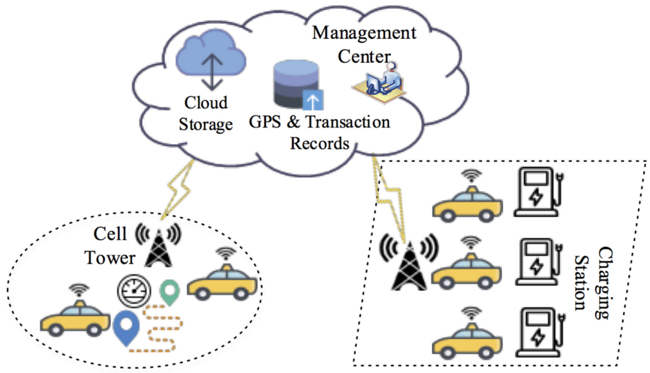

Fig. 1. Infrastructure and data collection.

3.1 Data Collection

During this project, we are collaborating with the Shenzhen Transportation Committee, which monitors the real-time operating status of all taxis in Shenzhen, which is a city with a population of more than 12 million and an area of 792 mi^2. All taxis in Shenzhen are equipped with basic taximeters, GPS devices, and communication devices. Taximeters and GPS devices record the real-time operating status and transaction activities, and all these data are uploaded periodically to servers of the Shenzhen Transportation Committee through a cellular network. The collected data is used for monitoring, accounting, and security assurance purposes. We have establish a secure and reliable transmission mechanism with the Shenzhen Transportation Committee. Figure 1 shows the ET infrastructure and data collection in Shenzhen. After some simple data filtering processes, all taxi data in the Shenzhen Transportation Committee will be transmitted to our servers via a wired connection.

3.2 Data Cleaning

After obtaining the ET data, we conducted a series of data cleaning processes, e.g., data masking, map matching, and errant data filtering. Due to the large-scale data, we utilize a 34 TB Hadoop Distributed File System (HDFS) on a cluster consisting of 11 nodes, each of which is equipped with 32 cores and 32 GB RAM to manage the data. For daily data processing, we utilize the MapReduce-based Pig and Hive since our analyses are based on log data, instead of streaming data.

We first filter some sensitive data for privacy protections; e.g., we replace each plate ID with a unique serial number. Then we match each GPS record on the Shenzhen road network, and we filter some records that are very far from all road segments caused by GPS error (e.g., 20 meters from the nearest road segment). Due to the long-term GPS data and transaction data, we have been dealing with several kinds of errant data, including duplicated data, missing data, and logical errors of data (e.g., GPS records with extremely high speed, GPS records with wrong longitudes and latitudes) to obtain the data for this project.

3.3 Data Description

After data cleaning, we obtain the datasets used for this project. The time span of these datasets is from September 2013 to July 2018, during which the percentage of ETs among all taxis increased from 2.7% to 65.2%. In total, there are five datasets including 4.8 TB of taxi GPS data, 240 GB of taxi transaction data, 117 charging stations' data, the urban partition data with 491 regions of Shenzhen, and the Shenzhen road network data. An example including some primary fields of each dataset is shown in Table 2.

Table 2. Examples of All Data Sources

GPS	plate ID	longitude	latitude	time	speed (km/h)
	TIDXXXX	114.022901	22.532104	2016-06-16 08:34:43	22
Transaction	plate ID	pickup time	dropoff time	cost (CNY)	travel distance (m)
	TIDXXXX	2015-09-03 13:47:58	2015-09-03 13:57:23	22.6	6954
Charging Station	station ID	station name	longitude	latitude	number of charging points
	30	NB0005	113.9878608	22.55955418	40
Urban Partition	Region ID	Longitude1	Latitude1	Longitude2	Latitude2
	1	114.31559657	22.78559093	114.311230763	22.78220351
Road Network	roadID	startLongitude	startLatitude	endLongitude	endLatitude
	27813	114.426971	22.604326	114.4370363	22.5904528

- **GPS Data** include over 70 billion taxi trajectory points with the size of 4.8 TB in total. Each GPS record includes 13 fields describing the status of taxis, e.g., the car ID, GPS location information (i.e., longitude and latitude), timestamp, direction, current speed, occupied flag, and plate color. The GPS data are collected by an onboard device in each ET with a cellular connection in real time. We found that 90% of continuous GPS records of ETs were uploaded within 60 seconds, leading to a detailed physical status log.
- **Transaction Data** are collected from the same time duration for auditing purposes. The size of the transaction dataset utilized is over 200 GB, including 1.45 billion transaction records. For each transaction record, it contains 18 fields describing each transaction's information, e.g., car ID, pick-up time and drop-off time, duration and distance the taxi traveled, unit price per km, metered fare, and so forth. We found that 80% of ETs have a transaction uploading interval shorter than 40 minutes, leading to a detailed trip-level status log.
- **Charging Station Data** include the locations (in terms of GPS) of each charging station, the number of charging points in each station, and opening dates for these charging stations.
- **Urban Partition Data** describe the urban partition for the population census of the Chinese city Shenzhen, which is provided by the Shenzhen government. There are 491 regions, and each region has a region ID and longitudes and latitudes of its boundary.
- **Road Network Data:** In total, there are about 135K road segments and 87K road intersections in Shenzhen. Each road segment has a road ID, road name, length, road types, and so forth.

4 METHODOLOGY

In this section, we introduce our investigation methodology by (1) contextualizing ET activities by defining operation and charging characteristics; (2) describing the detailed charging event extraction process, which lays the foundation for the later mobility and charging pattern investigation. and (3) introducing some quantification measurement metrics.

4.1 ET Contextualization

We leverage Figure 2 to illustrate how we put the operation and charging patterns of ETs into contexts from three dimensions, i.e., spatial, temporal, and energy. As shown in Figure 2, the period from t_0 to t_5 is defined as a complete operation and charging cycle of ETs.

- **Overhead after Charging $t_{picking} = t_1 - t_0$:** At time t_0, the ET is fully charged and in the full battery capacity status, and then it starts to cruise to seek passengers. At time t_1, it has

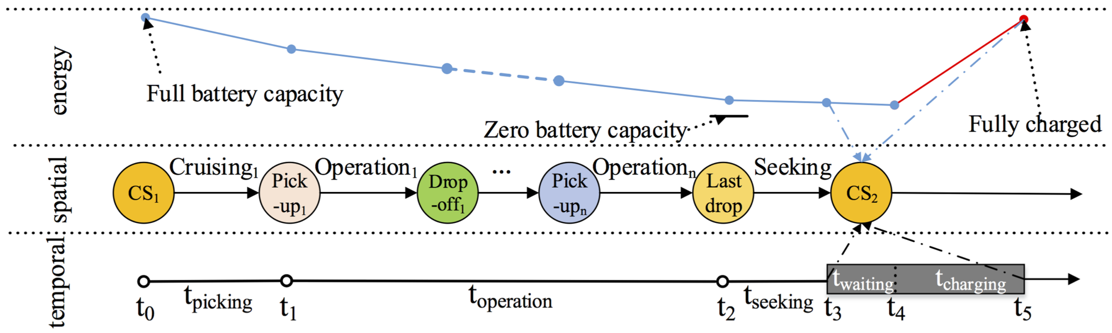

Fig. 2. Operation and charging patterns of electric taxis.

the first passenger after the charging. During this process, the battery capacity of the ET is decreasing. We denote the time from the charging station to pick up the first passenger as $t_{picking}$.

- **Normal Operation $t_{operation} = t_2 - t_1$:** Due to the limited battery capacity and high range anxiety caused by low battery capacity, ET drivers will start to seek charging stations when the battery capacity declines to a certain level [37]. Hence, we define the period from the first pickup after a charge to the last drop-off before the next charge as the $t_{operation}$. During this period, the energy level is nonincreasing.
- **Overhead before Charging $t_{seeking} = t_3 - t_2$:** After dropping off a passenger at time t_2, the ET driver will stop seeking passengers and go to a charging station. At time t_3, it arrives at a charging station, and we denote the time of seeking a charging station as $t_{seeking}$. Note that an ET driver may not go to the nearest charging station due to various factors [35], e.g., traffic conditions, and the $t_{seeking}$ varies when drivers choose different charging stations. During this period, the energy level is always decreasing.
- **Overhead for Charging $t_{waiting} + t_{charging}$:** At t_3, the ET arrives at a charging station. However, due to the limited charging points and drivers' heuristic charging station searching behaviors, there may be heavy queuing phenomena in the station at t_3, which results in long waiting time in this station. When there is a charging point available in the station at t_4, this ET will start to charge and its battery capacity increases. We leverage the $t_{waiting}$ to stand for the waiting period for an available charging point (i.e., $t_{waiting} = t_4 - t_3$), followed by the charging time in the station (i.e., $t_{charging} = t_5 - t_4$). After fully charged, this ET will start to cruise and seek for passengers again.

We define a *charging event* as the process of a driver starting to seek a charging station (i.e., t_2) until he or she finishes charging (i.e., t_5), which is $t_{seeking} + t_{waiting} + t_{charging}$. An *operation cycle* includes all pickup and drop-off activities, so the duration of an operation cycle is $t_{picking} + t_{operation}$.

4.2 Charging Events Extraction

In order to investigate the charging patterns of ETs, we need to know when and where they are charging (i.e., charging events), which means we need to know the $t_{seeking}$, $t_{waiting}$, and $t_{charging}$.

4.2.1 Guidelines for Charging Events Extraction. Figure 3 shows an example of trajectories of ETs, which is shown as a sequence of GPS records (i.e., $g_1, g_2, \ldots, g_{n+1}$) in our data. As we know, ETs will stay in the same location (i.e., charging station) for a long period (much longer than gas refueling processes) when they are charging, which is shown as a set of continuous GPS records with the same longitudes and latitudes (e.g., $g_3, \ldots, g_n$ in Figure 3).

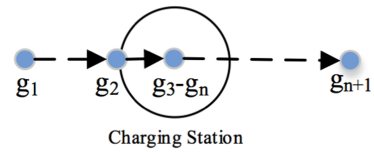

Fig. 3. An example of trajectory of ETs.

Since the GPS record uploading frequency of ETs is normally 30s to 50s in our data, which is typically enough for drivers to park their ETs at the charging spots, there should be no GPS records that are detected in charging stations before plugging in charging points if there are unoccupied charging points available in charging stations. We verify this phenomenon using our data. Hence, we consider that the time cost in charging stations before plugging in charging points is the waiting time $t_{waiting}$, which is shown as different longitudes and latitudes with g_3 but still in the charging station (e.g., the time duration between g_2 and g_3) in Figure 3.

4.2.2 $t_{charging}$ Extraction. Based on the above guidelines, in this article, we design a two-step spatiotemporal constraint-based algorithm to extract $t_{charging}$ of ETs from their trajectories (i.e., GPS records). For the first step, we extract the possible charging events (*PCE*) from ETs' GPS data based on the fact that an ET will stay for a long time ($>\tau$) at the same point (i.e., same longitude and latitude) to have a charge. For the second step, we check if the *PCE* is in a charging station, which means the location of the *PCE* should be within a certain range (e.g., $< \mathcal{D}$) of a charging station location in the charging station data.

The detailed charging events extraction algorithm is shown in Algorithm 1.

Different from conventional gas taxis, which normally spend 3 to 5 minutes for a refueling event [54], the charging duration for ETs is usually between half an hour and 2 hours [35]. Hence, in our parameter learning process, we first set the parameter τ to be a small value, i.e., 20 minutes, since few drivers will spend less than 20 minutes for a charge considering the large battery capacity of ETs and their operation characteristic. Since the longitudes and latitudes will be unchanged during the duration, the parameter d in Algorithm 1 is 0. After obtaining the initial *PCEs*, we then utilize the Kernel Density Estimation (KDE)-based method [51] to refine the *PCEs*. The Gaussian Kernel is utilized to fit all *PCEs*, and we remove the top 2.5% and bottom 2.5% values to achieve refined *PCEs*. Finally, we found that 30 minutes is usually the least time for a charge. Hence, for the temporal constraint in the first step, if an ET stayed in the same place, i.e., the same longitude and latitude in GPS records, for over 30 minutes, it is extracted as a *PCE*, which means the parameter τ in Algorithm 1 is set to 30 minutes. In addition, according to our field study and data analyses, Shenzhen ET drivers generally charge their ETs at least for 30 minutes each time due to the charging rate and battery capacity; more details will be shown in the next section.

After obtaining all *PCEs*, we merge them with the charging station data to obtain the true charging events *CEs*. Considering the sizes of charging stations and the accuracy of GPS data, the *PCEs* happening within a certain range of charging stations could be identified as true *CEs*. We manually labeled 136 real charging events from our field studies, and then we utilized the method in [54–59] to learn the parameter $\mathcal{D}$ in Algorithm 1. Finally, we found that the optimal value for $\mathcal{D}$ is 150, so we set it to 150 meters and use it for extracting all charging events. The time duration of a *CE* is the charging time $t_{charging}$ of an ET.

Except for the two-step spatial and temporal constraints, we also filter some noises to refine the obtained *CEs* based on real-world field studies.

4.2.3 Ground Truth for Validation. Since it is challenging to obtain the real-time State of Charge data of ETs, we performed a set of field studies at different charging stations in Shenzhen to obtain

ALGORITHM 1: Two-Step Spatiotemporal Constraint-Based Charging Event Extraction Algorithm

```
Input:
    A set of ETs {ET_1, ET_2, ..., ET_N}
    Trajectory data of each ET k {g_1^k, g_2^k, g_3^k, ..., g_e^k}
    Charging Station CSs {CS_1, CS_2, ..., CS_M}
Output:
    Charging Events (CEs);
Begin
  Foreach ET_k with GPS records {g_1^k, g_2^k, g_3^k, ..., g_e^k}
    For (i = 1; i + 1 ≤ e; i++)
        j = i + 1;
        While (dist (g_i, g_j) ≤ d)
            j++;
        If (timeInterval(g_i, g_{j-1}) > τ)
            i = j;
            Set g_i to g_{j-1} as a PCE;
    End
  End
  Foreach PCE
    Foreach Charging Station CS_m
      If dist(PCE, CS_m) < 𝒟
          PCE → CE;
    End
  End
End
return CEs;
```

the ground truth of some charging events, which are utilized to verify our algorithm performance and further filter some charging noises (e.g., false *CEs* in charging stations). Our field studies were conducted on July 20, 2014; Nov. 9, 2015; Nov. 11, 2015; June 20, 2017; and May 26, 2018, respectively. There are 136 ETs involved in our field studies. We recorded their charging behaviors near the charging stations and obtained the ground truth of when they arrived at charging stations, whether they were charging or just parking at those stations for rest. Based on this, we compared the *CEs* detected by our method from GPS data with the ground truth, and 130 ETs' *CEs* out of the ground truth from 136 ETs are correctly detected, yielding an accuracy of 96%.

Figure 4 shows a field study we performed on June 20, 2017, in Shenzhen. As we can see, a line of charging points are installed under a shelter, which is used for protecting the chargers; an ET was queuing at the entrance of the station since there were no charging points available at 12:25; another ET was approaching a charging point since there was a fully charged ET leaving the charging point. In this field study, we found that all of the 42 charging points in this station were occupied from 11:30 to 13:00, there were queuing phenomena since 12:26, and the longest waiting time was up to 31 minutes. Until 13:45, there was still one ET waiting there for available charging points. This long-time queuing phenomenon also reflects the unbalanced charging demand and/or insufficient charging supply.

We found that these ET drivers have a relatively stable charging pattern in charging stations, which is also verified by talking with them. Even though there are restaurants around charging

Fig. 4. A field study on June 20, 2017 in Shenzhen.

stations, ET drivers are most likely to charge their taxis when they are having lunch or dinner to avoid more potential income loss caused by a long charging time. The GPS records of the other six extracted *CEs* in our field study follow a similar pattern of normal *CEs* (but they just park there without charging), which is difficult to distinguish from true *CEs*. At the third and fourth time of field studies, we talked with those ET drivers to learn about their charging behavior patterns. We found that the false *CEs* came from the ETs whose drivers happen to live near the charging station. Based on our field studies, these particular drivers living near charging stations are very limited and can be found out based on their historical records and excluded by our field studies. As a result, we argue that our two-step spatiotemporal constraint-based algorithm using real-world GPS data is a practical approach to extract *CEs* of city-scale ETs.

4.2.4 $t_{waiting}$ Extraction. We use a similar method for $t_{charging}$ extraction to extract the waiting time $t_{waiting}$ from the GPS records. What we only need to do is to change the parameter d in Algorithm 1 into a threshold, e.g., 150 meters in our setting. In this case, the returned results will be $t_{waiting} + t_{charging}$ of *CEs*. Then we utilize the returns results and subtract the corresponding $t_{charging}$ obtained from Section 4.2.2 to get the waiting time $t_{waiting}$. The extracted $t_{waiting}$ also shows high accuracy compared to the ground truth obtained from our field studies.

4.2.5 $t_{seeking}$ Extraction. As we defined in Section 4.1, the $t_{seeking}$ is the duration between the last drop-off time before charging and the time when the ET arrives in the charging station. However, in the GPS records of ETs, they only include the occupied flag, which means when passengers get on taxis, but the times of drop-offs are unknown. Hence, we merge the *CAs* into the transaction data to obtain the $t_{seeking}$ since the drop-off times are included in the transaction records.

After extracting all these times, we then conduct a comprehensive investigation on their charging patterns.

4.3 Quantification Metrics

Mobility Evolution Measurement: We investigate the mobility pattern evolution of the ET network from both spatial and temporal perspectives. For the spatial pattern evolution, we define the ET coverage density and the daily operation distance for quantification. For the temporal pattern evolution, we utilize the $t_{picking}$ evolution pattern for quantification, which has been defined in Section 4.1.

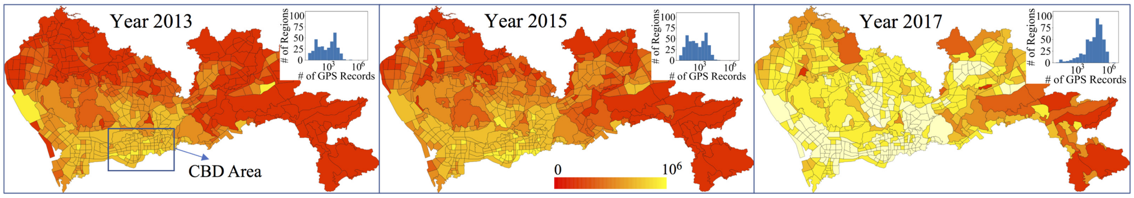

Fig. 5. The ET coverage density evolution pattern in 491 urban regions.

Charging Evolution Measurement: For the charging measurement, we investigate the $t_{waiting}$ and $t_{charging}$ evolution patterns. Besides, we define two quantitative metrics, i.e., charging network connectivity and charging station utilization rate, to quantify the charging network evolution. We also investigate the charging supply and demand evolution patterns from both temporal and spatial aspects over 5 years, from which some insights are derived.

5 INVESTIGATION RESULTS

We present our measurement results from four aspects: (1) the ET mobility evolution patterns, (2) the ET charging evolution patterns, (3) the impacts of different contexts, and (4) the benefits of ET evolution. The details are shown below.

5.1 Mobility Evolution

ET Coverage Density Evolution: We define the ET coverage density as the number of GPSs in a specific region to investigate the ET mobility patterns. We leverage the urban partition data to divide Shenzhen into 491 regions, which is provided by the Shenzhen government. As shown in Figure 5, the darker red means fewer ET activities in this region and the lighter yellow stands for more ET activities in this region. We also show the distribution of the number of GPS records in these regions in the northeast corners. We have the following observations: (1) The ET density in Shenzhen has increased significantly during the 5 years, especially from 2015 to 2017; almost all the regions have a higher ET density compared to the previous year, which was also observed from the distributions. Quantitatively, the growth of the density from 2015 to 2017 increased 25 times compared with the previous growth. (2) The ETs are gathered in the central business district (CBD) area from 2013 to 2015, but more ETs start to operate in the suburban areas after 2015. One factor may be the urbanization process in Shenzhen; e.g., more companies built and more people live in former suburban areas [3]. Another reason may be the upgrading of the charging infrastructures; e.g., more charging stations are built in suburban areas, which we will investigate in Section 5.2.

Operation Activity Evolution: In this subsection, we investigate the long-term operation evolution patterns of ETs using $t_{picking}$ and daily operation distance, which are shown by box plots as Figure 6 and Figure 7. The top and bottom of each "box" are the 25th and 75th percentiles of the data. The middle red lines are the median values. The top and bottom of each black dashed line indicate the maximal and minimal values. The top red crosses are outliers, which are values that are more than 1.5 times the interquartile range away from the top value or bottom value of the box.

Figure 6 shows the evolution of $t_{picking}$, i.e., the duration from the fully charged time to the first pickup time as shown in Figure 2. We found that the median value of $t_{picking}$ is almost stable at 10 minutes, while the maximal values have a trend of decrease. We show the daily operation distance of ETs in Figure 7. Intuitively, there are no obvious evolution patterns since the new adopted ETs can increase the average operation distance of the ET fleet despite the nature of battery degradation, which results in relatively stable average daily operation distance. However,

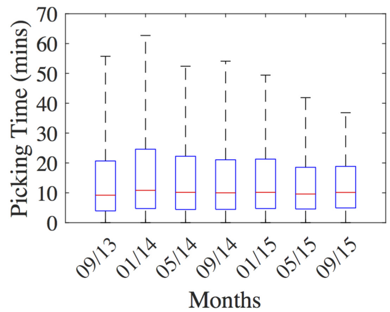

Fig. 6. $T_{picking}$ evolution.

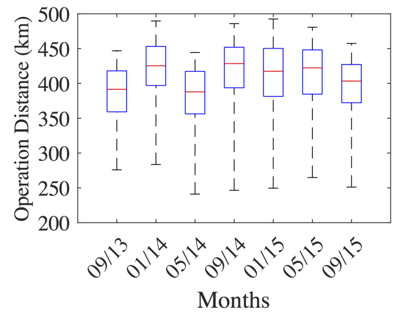

Fig. 7. Operation distance evolution.

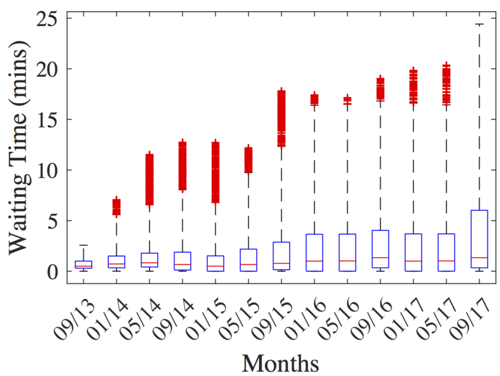

Fig. 8. $T_{waiting}$ evolution.

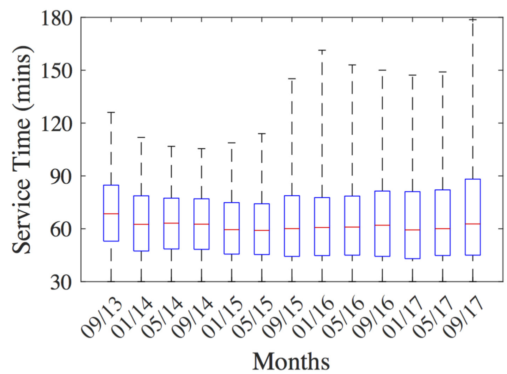

Fig. 9. $T_{charging}$ evolution.

there is a significant drop in May 2014. We carefully studied the causality, and we found that there is exceptionally severe weather in this month with heavy rain, resulting in many ETs breaking down.

5.2 Charging Evolution

We perform an in-depth investigation of the charging activity evolution for ETs, coupled with the evolution patterns of the accessory charging network.

5.2.1 Charging Activity Evolution. We leverage $t_{waiting}$ and $t_{charging}$ to investigate the charging activity evolution of ETs from the years 2013 to 2017.

As shown in Figure 8, the overall trend for $t_{waiting}$ is growing from 2013 to 2017. We then further investigate causalities behind this phenomenon, and one possible reason is that the number of ETs increased too fast, whereas the increase of charging infrastructure cannot keep up. Specifically, from 2013 to 2014, the number of ETs had increased by about 200, but the number of charging points only increased by 2, which causes waiting time increases. From 2015 to 2017, the number of ETs had dramatically increased, whereas only limited charging stations were built.

Figure 9 shows the average $t_{charging}$ evolution pattern. Even though the highest charging time has an increasing trend, the medians and the 25th and the 75th percentiles are close, i.e., about 60, 45, and 75 minutes, respectively. It indicates that most drivers have a relatively stable charging time. Since the $t_{seeking}$ is mainly related to the urban traffic conditions, which is decided by many nonmobility factors, e.g., government traffic management and urban road network evolution, we do not report it as it is difficult to find obvious evolution patterns even after an in-depth investigation.

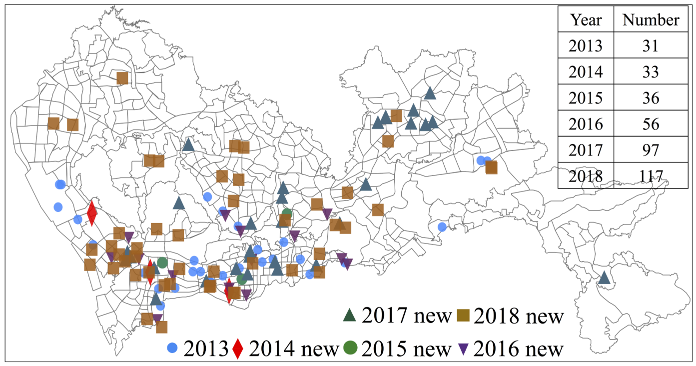

Fig. 10. Charging station deployment evolution.

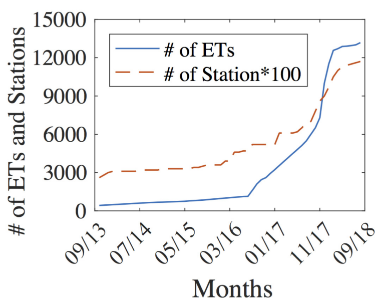

Fig. 11. Number of ETs and charging stations' evolution.

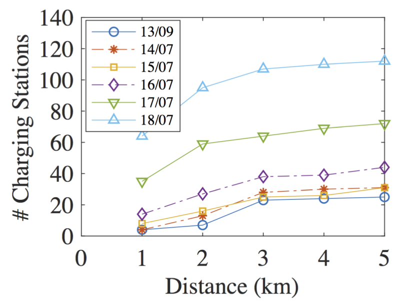

Fig. 12. Charging station distance evolution.

5.2.2 Charging Supply Evolution. In Figure 10, we visualize the evolution pattern of charging supply for ETs in Shenzhen from the years 2013 to 2018 in 491 urban regions. We found that the total number of charging stations had increased from 31 in 2013 to 117 in 2018. Intuitively, ET charging stations are unevenly distributed in Shenzhen, and the general trend of the charging station deployment is from the urban areas to suburban areas, with an accelerated deployment speed from 2013 to 2018, especially from 2016 to 2018, during which more than 60 charging stations were deployed. We further compare the increase of charging stations and ETs, which is given in Figure 11. We found that the number of ETs has not increased too much from September 2013 to June 2016, but there is a large-scale adoption after 2016. Especially at the end of 2017, there is a sharp expansion of ETs, while the growth rate of charging stations is much lower.

We further investigate the quantitative evolution patterns of the charging supply by defining the charging network connectivity, which is the average shortest distance between charging stations and their neighbor stations, shown as Equation (1):

$$Conn(net) = \frac{\sum_{i=1}^{N} SD_i}{N}, \tag{1}$$

where N is the total number of charging stations in the charging network net, and SD_i is the shortest-distance neighbor of the ith charging station.

The charging network connectivity can reflect on average how far there is another charging station for a given charging station. We first study the distribution of the distances between any two charging stations. We found that the distances between two charging stations can be as short as 200 meters and as long as 70 km based on our statistics, but most charging stations have a neighbor station within 5 km. Figure 12 shows the number of charging stations with at least another charging station within a certain distance, e.g., from 1 km to 5 km over 5 years. From Table 3,

Table 3. Charging Network Connectivity Evolution

Year	2013	2014	2015	2016	2017	2018
Connectivity	2.25	2.76	2.62	2.13	2.00	1.31

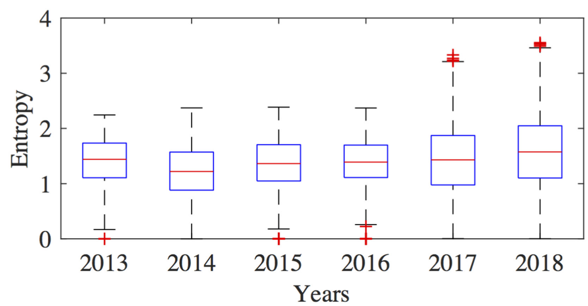

Fig. 13. Entropy of charging location evolution.

we found that the charging network connectivity has increased from 2.76 in 2014 to 1.31 in 2018, which indicates the charging network in 2018 is more resilient to cope with the long waiting phenomena in charging stations. We also found that in the recent two years most charging stations (e.g., 96 stations in 2018, i.e., more than 82% of all 117 stations) have at least one station within 2 km, making the Shenzhen ET charging network well connected. In this case, if some drivers find there are no charging points available when they arrive at a station, they can quickly go to other nearby stations.

5.2.3 Entropy of Charging Location Evolution. We introduce the charging location entropy of ET drivers to quantify the charging preferences of users, which are indicators to show if ET drivers have stable charging locations and if their charging locations are predictable. The entropy of a specific ET driver u's charging location $H(D_u)$ is shown as:

$$H(D_u) = \sum_{D_u \in S} p\left(D_u\right) \log \frac{1}{p(D_u)}, \tag{2}$$

where $p(D_u)$ is the probability of charging events happening in charging station D of driver u, and S is the collection of charging stations.

We utilize 1 month of data from each year of 2013 to 2018 to investigate the charging station selection of ET drivers. As we can see from Figure 13, about 25% of ET drivers usually charge in two charging stations, and some drivers will always charge in the same charging station as the entropy is 0. Even though the trend for the number of charging stations' usage is increasing due to more charging stations being built in the years 2017 and 2018, 75% of ET drivers only charge in fewer than four charging stations, which indicates that most ET drivers have stable charging locations and they have their preferred locations. One reason may be because some ETs are operated by two drivers (i.e., day shift and night shift), so drivers may have shifts during charging periods in the fixed charging stations.

5.2.4 Charging Demand Evolution. To understand the charging demand evolution of ETs, we investigate both the spatial and temporal charging demands of the ET network, which are shown in Figure 14 and Figure 15, respectively. As shown in Figure 14, we found that there are four charging demand peaks in each day, i.e., 3:00 to 5:00, 11:00 to 13:00, 16:00 to 17:00, and 22:00 to 23:00. Such a temporal pattern has not changed significantly in the last 5 years. Among the four charging peaks, the first and third ones are before the rush hours for picking up taxi passengers, which can make

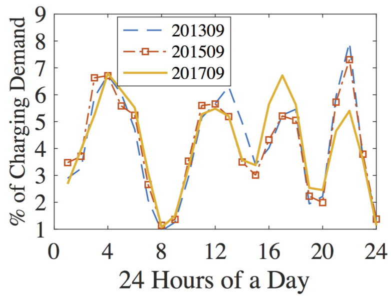

Fig. 14. Charging temporal pattern.

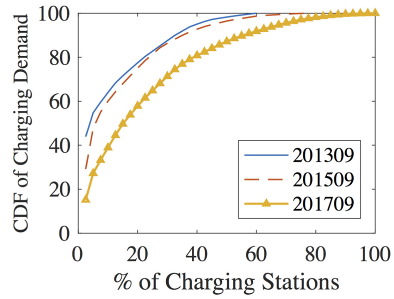

Fig. 15. Charging spatial pattern.

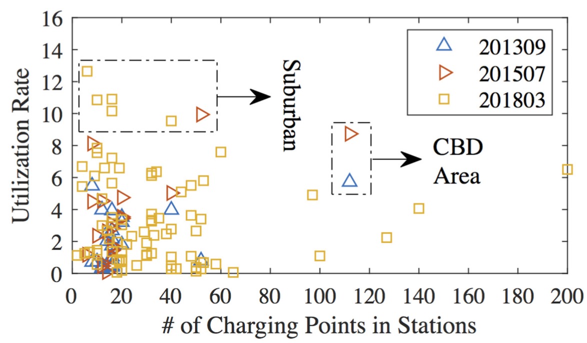

Fig. 16. Utilization rate evolution.

them have enough battery energy to pick up passengers. The second one is during lunchtime, when the electricity price is relatively low. We then investigate the electricity prices during the four peaks, and we find that all of the four peaks are in relatively low electricity price durations.

Figure 15 shows the accumulative charging demand in the charging network. Further, we found that 20% of charging stations accommodate 80% of charging demand in 2013 due to their convenient locations; e.g., most of them are located in downtown areas, where the possibility for ETs to pick up passengers after charging is high. However, such an unbalanced spatial pattern has improved since 2015 given the increased charging stations. For example, the charging demand in the top 20% of the popular charging stations accounts for only 60% of the total charging demand of the ET fleet in September 2017, which indicates that the unbalanced charging station utilization phenomenon has improved with more charging stations deployed.

5.2.5 Charging Station Utilization Rate Evolution. To further study the relationship between charging demand and supply at the station level, we define the utilization rate of a charging station i as the ratio of the daily number of charging events $CE(i)$ over the charging points $CP(i)$ in this station, as shown in Equation (3):

$$UR(i) = \frac{CE(i)}{CP(i)}. \tag{3}$$

Figure 16 shows the charging station utilization evolution during the 5 years. We found that the highest utilization rate has doubled from 2013 to 2018 as more ETs were promoted, resulting in more charging demand. However, the charging station sizes with the highest utilization rates are different, so we further investigate the geographical feature of the charging stations. We found that the highest utilization rate of 2013 happens in the largest charging station in the CBD area, which has 112 charging points. This station was also the largest charging station in 2015 and it still had a relatively high utilization rate in 2015. However, it was closed in 2016 due to some

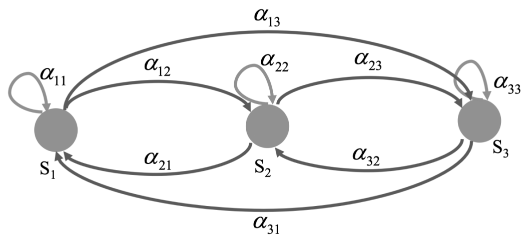

Fig. 17. Charging event transition of ETs.

security concerns. In 2018, there were five large charging stations with more than 100 charging points located in Shenzhen suburban areas to accommodate the skyrocketing ETs. Even though the utilization rates in these charging stations are not too low, they are not too high compared to some small charging stations. We found that the highest top five utilization rates' charging stations have the same common features, i.e., (1) located in suburban areas, e.g., Shenzhen airport, and (2) include fewer than 40 charging points, which is an interesting finding.

The above utilization rate evolution patterns have the potential to provide guidelines for other cities that have plans to promote large-scale ETs. For example, if it is feasible to deploy large charging stations in the urban CBD areas, then those charging stations have the potential to achieve the highest utilization rate, which can improve the charging infrastructure utilization and reduce the resource waste. If it is not feasible, more median/small charging stations with fewer than 40 charging points should be placed in some important suburban areas, e.g., airports and transportation hubs.

5.2.6 Charging Station Importance Evolution. In this subsection, we develop a PageRank-based charging station importance measurement method, which jointly considers the charging behaviors of ET drivers and charging demand in each station.

PageRank [23, 27] was originally introduced to rank search-query results, which consider a web page (i.e., a node in a network) more important if it has more incoming links [14]. However, not all in-links are equally important, and each link's score is proportional to the importance of its source node [14]. For example, if a node j with importance r_j has d out-links, then each link obtains r_j/d scores. Node j's importance is the sum of the importance scores on its total in-links, so a node is important in the network if it has more in-links from other important nodes.

In our charging network, each charging station is considered as a node, and the link is the number of transfers between two charging stations for two adjacent charges. For example, an ET charges at station S_1 at 7:00, and its next charge happens in station S_2, so there is a link from station S_1 to S_2. Similarly, a charging station is more important if it has more in-links from important charging stations, and removing an important node in the network will potentially have a high impact on its out-links. That is to say, if a charging station with high importance is disrupted by incidents, then the next to go charging stations are also vulnerable to those disruptions (e.g., resulting in a surge of charges in these stations, which potentially prolong the waiting time in them).

For example, as shown in Figure 17, if there are 100 ETs charging in station S_1 for the last time, then there are 60 of them still charging in S_1, 30 of them charging in S_2, and 10 of them charging in S_3, so the transition probabilities $\alpha_{11}, \alpha_{12}, \alpha_{13}$ are 0.6, 0.3, 0.1, respectively.

For each station j, its importance score is r_j, which is represented by

$$r_j = \sum_{i \to j} \alpha_{ij} \cdot r_i + (1 - \beta) \frac{1}{N}, \tag{4}$$

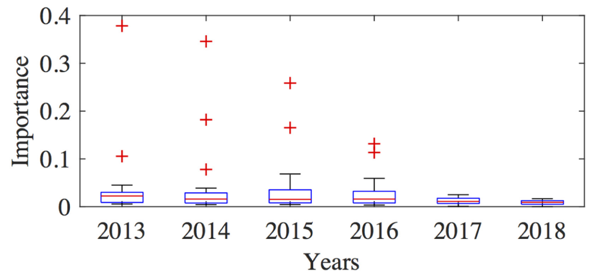

Fig. 18. Charging station importance evolution.

where α_{ij} is the ratio of prior charging events happening at station S_i and the next charging events at station S_j, and $\sum_i \alpha_{ij} = 1$; β is used to teleport out of "spider traps" and usually is in the range of $[0.8 \sim 0.9]$. We then construct a stochastic adjacency matrix $\mathbf{M}$, where $M_{ji} = \alpha_{ij}$ if there are α_i of the total prior charging events at station S_i and the next ones at station j. $M_{ji} = 0$ if there are no links from station S_i to station S_j. The sum of each column c of the adjacency matrix $\mathbf{M}$ is 1. So r_c is the importance score of station S_c. We can further construct a Google matrix $\mathbf{A}$, which is denoted as

$$\mathbf{A} = \beta \cdot \mathbf{M} + (1 - \beta)\left[\frac{1}{N}\right]_{N \times N}. \tag{5}$$

In this way, we obtain an eigenvector $\mathbf{r}$ for matrix $\mathbf{A}$ since $\mathbf{r} = \mathbf{A} \cdot \mathbf{r}$, where $A_{ji} = \beta M_{ji} + \frac{1-\beta}{N}$. Then, the importance of station S_j can be represented as

$$\begin{aligned} r_j = \sum_{i=1}^{N} A_{ji} \cdot r_i &= \sum_{i=1}^{N}\left[\beta M_{ji} + \frac{1-\beta}{N}\right] \cdot r_i \\ &= \sum_{i=1}^{N} \beta M_{ji} \cdot r_i + \frac{1-\beta}{N}\sum_{i=1}^{N} r_i \\ &= \sum_{i=1}^{N} \beta M_{ji} \cdot r_i + \frac{1-\beta}{N}, \end{aligned} \tag{6}$$

so we obtain the importance vector $\mathbf{r}$, which is

$$\mathbf{r} = \beta \cdot \mathbf{M} \cdot \mathbf{r} + \left[\frac{1-\beta}{N}\right]_N, \tag{7}$$

where $[\frac{1-\beta}{N}]_N$ is a vector of length N with all entries $\frac{1-\beta}{N}$. When we calculate the importance score vector $\mathbf{r}$, we need to compute $\mathbf{r}^{(t+1)} = \beta \cdot \mathbf{M} \cdot \mathbf{r}^{(t)}$ first and then add a constant value $\frac{1-\beta}{N}$ to each entry in the updated $\mathbf{r}^{(t+1)}$.

For a charging network with N stations, we will have N equations for their state transition and we can obtain the importance of each station by solving the N equations. If N is small, we can utilize the Gaussian elimination method to solve them. However, if the network is too large, the solutions may not converge, so we need to find some other efficient methods to solve them. In this work, we utilize a power-iteration-based method to solve this problem, which is shown in Algorithm 2, where N is the number of charging stations in the charging network; α_{ij} is the percentage of charging events happening in station S_i to subway station S_j; and r_j is the importance of subway station S_j. As shown in Figure 17, α_{21} is the ratio of passengers entering at station S_2 and exiting at station S_1, and α_{11} is the ratio of passengers entering at station S_1 and exiting at station S_1.

Figure 18 shows charging station importance in each year from 2013 to 2018. We found that there are some dominant charging stations in the first 3 years, especially in 2013, since there

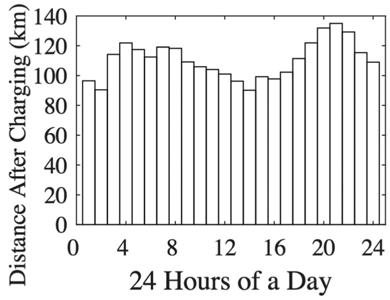

Fig. 19. Per-charge distance.

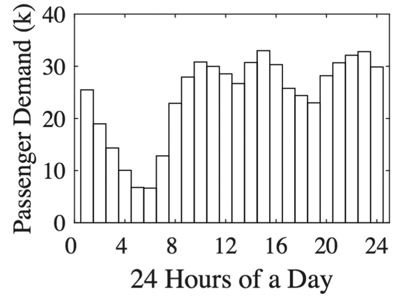

Fig. 20. Travel demand.

ALGORITHM 2: Power-Iteration-Based Method for Charging Station Importance Measurement

Input : A charging network G with N charging stations
a constant parameter β
a convergence threshold value ε
Output: Importance score vector $\mathbf{r}$

Initialize: $\mathbf{r}^{(0)} = [1/N, \ldots, 1/N]^\intercal$
repeat
  foreach $1 \leq j \leq N$ **do**
    if *there are stations connected to i* **then**
      $r_j^{(t+1)} = \sum_{i \to j} \alpha_{ij} \cdot r_i^{(t)} + \frac{1-\beta}{N}$;
    else
      $r_j^{(t+1)} = 0$;
    end
  end
until $\sum_{j=1}^{N} |r_j^{(t+1)} - r_j^{(t)}| < \varepsilon$;
$\mathbf{r}^{(t)} = \mathbf{r}^{(t+1)}$, then go to 2

were limited charging stations and only one large station was deployed in the CBD area. The most important charging station has an importance score of about 0.4, which means the charging network will be greatly influenced if it is disrupted by incidents. From 2013 to 2018, there were more and more charging stations deployed, so ETs will not only rely on some specific stations, which potentially indicates the charging network becomes healthier during the evolution process of charging stations.

5.3 Contextual Factors

5.3.1 Impact of Daytime and Nighttime. In Figure 19, we found that the operation distance of ETs is different if they are charged in different hours. For example, if an ET is charged at 3:00, it may be fully charged at 4:30 and leave, and then it travels about 120 km before next charging. We also found that the charging starting time from 3:00 to 8:00 and 20:00 to 22:00 may result in a more extended operation distance for ETs even with potential congestion at rush hours. We then explore the possible reason by considering the passengers' travel demand, as shown in Figure 20. We found that there is higher taxi demand around 9:00 and 22:00, which is alighned with the period that ETs

Table 4. Daily Operation Distance in Different Contexts

Weather	Distance (km)	Temp.	Distance (km)
Sunny	447	Mild	437
Heavy rain	413	High	421
Typhoon	406	Low	389

were fully charged and started to pick up passengers. It may indicate that ET drivers would prefer to charge before the rush hour for longer cruising distances, which can potentially reduce their income loss caused by the long charging time.

5.3.2 Impact of Temperatures and Weather. We select three temperature levels and three weather conditions to investigate their impacts on ETs' mobility patterns, i.e., high (27-34°C), low (6-8°C), mild (17-25°C), and sunny, heavy rain, and typhoon. As in Table 4, the average operation distance under mild temperatures is the longest; the average operation distance under low temperatures is the shortest. One explanation is that the energy consumption rate is the highest on cold days because of the heaters being used to heat the ETs.

Just as with the impacts of different weather, we found that the average operation distance of ETs on sunny days is longer than rainy days; the operation distance on hurricane days is the shortest. The potential reason could be that on sunny days, ET drivers may reduce the charging time for longer operation distance. On rainy days, drivers have a longer operation distance than on typhoon days. Hence, we conclude that different weather conditions have various impacts on the mobility patterns of ETs; e.g., severe weather conditions will potentially reduce the daily operation distances of ETs.

5.4 ET Benefits

Using the emissions and driver incomes as examples, we quantificationally compare the ETs with conventional gas taxis to study the evolution of ETs' benefits based on their daily mobility patterns, e.g., operation distances.

5.4.1 Emission Reduction. Based on [25], we consider the real-world traffic conditions (e.g., travel speed), daily travel distance of ETs, and daily travel time of ETs to accurately estimate CO_2 emission reduction of the ET network, which is represented by

$$E = K_c * \left[0.3T + 0.028D + 0.056 \sum_{i=1}^{k} (\delta_i * (v_{i+1}^2 - v_i^2))\right], \tag{8}$$

where E is the CO_2 emissions (g); T is the travel time of taxis (s); D is the travel distance of taxis (m); K_c is the coefficient between gasoline consumption and CO_2 emissions, which is 2,322 g (CO_2)/liter(gasoline) for Shenzhen taxis; v_i is the speed at time i (m/s); and δ_i is a tow-value indicator, taking the value 1 when accelerating ($v_{i+1} > v_i$), otherwise 0 ($v_{i+1} \leq v_i$). Thus, we estimate the monthly CO_2 reduction from September 2013 to July 2018 in Figure 21. There is more ET deployment in June 2016, which explains a major CO_2 reduction. Especially in the last 2 months of 2017, the number of ETs has increased significantly; e.g., in December 2017, the CO_2 reduction is close to 18 Mt (i.e., 1.8 million tons), which is equivalent to CO_2 emissions from 176,324 homes' energy use for 1 year according to the U.S. Environmental Protection Agency.

5.4.2 Driver Income Comparison. A key roadblock of ET deployment is that many drivers worry about their income reduction caused by the long charging time of ETs compared with refueling of conventional gas taxis. Here, we comprehensively consider the daily travel distance of taxis to

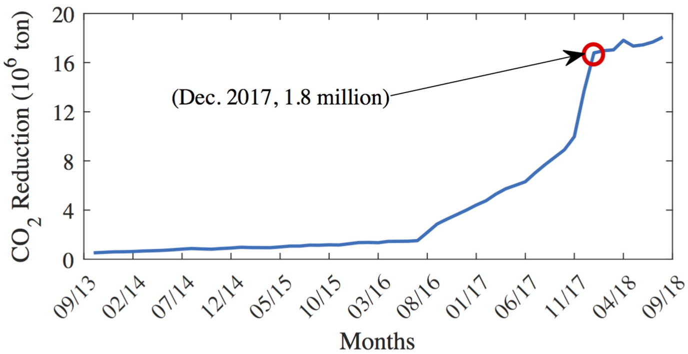

Fig. 21. CO_2 reduction evolution.

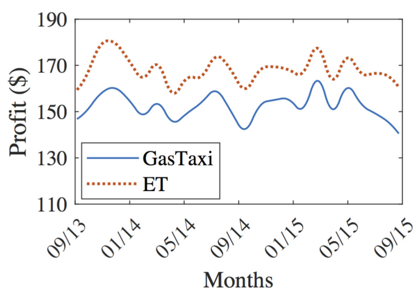

Fig. 22. Daily profit comparison of ETs and gas taxis.

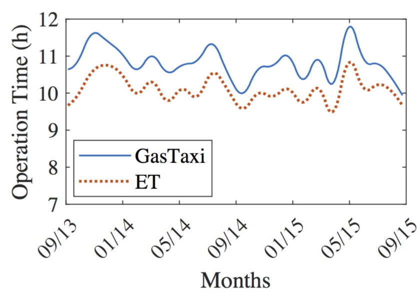

Fig. 23. Daily operation time comparison of ETs and gas taxis.

calculate the instant profits of ETs and gas taxis without considering other costs like maintenance and depreciation, which can be represented by

$$P(j) = I(j) - E(j) = I(j) - D(j) * C_r * P, \tag{9}$$

where $P(j)$ and $I(j)$ stand for the daily profit and income of driver j, respectively. $E(j)$ includes all costs, e.g., refueling costs, maintenance fees. In this article, we only consider the refueling costs because they are the major expenses for the daily operation of taxis, which depend on taxis' daily operation distance $D(j)$ and energy consumption rate C_r. For a gas taxi, the fuel consumption per 100 km is 9 liters, so the energy consumption rate C_r for gas taxis is 9 liter/100 km. Besides, the unit oil price P is $1.015/liter (2017) in Shenzhen. For ETs, the energy consumption rate C_r is 26 kWh/100 km, and the average electricity price P is $0.1/kWh in Shenzhen.

In Figure 22, we show the profits' evolution of ET drivers and gas taxi drivers during 2 years. We found that the average daily income of each ET driver is about $15 more than each gas taxi driver per day even though the ET drivers have lower income. Besides, we also found that the daily operation time of ETs is about 5% less than gas taxis, from 1.1 h to 0.26 h, which is shown in Figure 23. When considering these two figures, we found that even though the operation time decreases for ETs, the profit of ETs can potentially increase by energy savings, in addition to other benefits, i.e., fewer emissions, less noise, and more rest time for drivers during charging.

In addition to the revenue and refueling costs, some other factors should be considered to compare the long-term profits of ETs and gas taxis, e.g., depreciation and maintenance. (1) For the ETs in Shenzhen, the purchasing price is $40,400 after the subsidy from the government. If we consider the life cycle of a taxi to be 5 years, the depreciation is about $5,223/year. For the gas taxi, the purchasing price is about $14,286, so its depreciation is $2,857/year. (2) For the maintenance fee, it is about $2,571/year for an ET and $857/year for gas taxis. (3) The insurance fee for each

ET is \$1,714/year and is \$1,371/year for a gas taxi [52]. In sum, the yearly profit of an ET is \$1,054 higher than a gas taxi on average.

6 INSIGHTS AND DISCUSSIONS

In this section, we provide a few insights we obtained in our measurement study and some discussions.

6.1 Insights

Our long-term investigation has the potential to provide some insights for (1) city governments—e.g., how to deploy charging stations and address the unbalanced charging supply and demand issues; (2) taxi drivers—e.g., their profits would not reduce, although they have more time to rest; and (3) society—e.g., how to promote large-scale ET networks and the amount of quantitative emission reduction. We summarize some key insights below.

Charging Station Deployment: Charging stations play a key role in large-scale ET promotion. Insufficient charging infrastructure will result in a longer waiting time for charging points, as shown in Figure 8. However, even though enough charging points are deployed, the unbalanced temporal or spatial charging demand and supply reduce the efficiency of the overall charging network. We found that the uneven supply and demand phenomena can be improved by building more charging stations in the right locations, as shown in Figure 15. Based on our investigation of Figure 16, we found that those large charging stations in urban CBD areas have the best chance of achieving a higher utilization rate, which can improve the charging infrastructure utilization and reduce the charging resource waste. *Hence, if it is feasible to deploy large stations in urban CBD areas for other cities, it would be beneficial for promoting their large-scale ET networks; if it is hard to place large stations in CBD areas for some reasons (e.g., land resources unavailable), more median/small charging stations with fewer than 40 charging points may be placed in some important suburban areas (e.g., airports and transportation hubs), to improve the overall charging efficiency.*

Charging Behavior Patterns: There is a stable temporal charging pattern of ET drivers, as shown in Figure 14. We found a very large gap between the four charging peaks and the charging valleys, which inevitably result in the underutilized charging and the overcrowded charging during different hours. The major causality behind this phenomenon is that Shenzhen has *time-varying electricity prices*, and the charging peaks happen in relatively low price periods. Another reason is that the ET drivers may have the potential to pick up more passengers as some charging peaks are 1 hour before the rush hours. Once this phenomenon exists, it must need to build more charging stations to accommodate ETs, while it will also cause the resource waste in many hours of every day. This phenomenon will happen with a very high possibility during the ET promotion process of other cities, and it is important to address it. *One possible approach is to adjust the electricity prices, e.g., setting lower electricity prices during the valleys and higher prices for the peaks for ETs only. For taxi drivers, our investigation can guide them to charge to minimize their* $t_{waiting}$ *and reduce the possible income loss; e.g., they can charge from 23:00 to 3:00 as there is the lowest electricity price in Shenzhen.*

Charging Contexts: The following three contexts are explored for their impacts on ET mobility patterns:

- **Nighttime:** *There is no obvious observation that indicates that the cruising mileage of ETs decreases significantly during the night,* as shown in Figure 19, even though we thought that the cruising mileage should drop because of the use of headlights compared to the daytime. The reason may be that typically there is no severe traffic congestion during nights, which results in extended cruising range compared to the daytime, even with the energy consumption of headlights [4].

- **Temperature and Weather:** Even though adverse temperatures and weather will decrease the daily operation distance of ETs, e.g., about 4% on hot days and 9% on hurricane days, the reduction is still less than operation distance reduction of gas taxis under the same situations based on our investigation. We do not report the details of gas taxis because we focus on the ET patterns in this article. *This finding can help better promote ETs, since the ETs may achieve a higher energy efficiency even in adverse contexts.*

ET Benefits: Even though the overall daily operation time of ETs has reduced compared to gas taxis, the profits of ET drivers are potentially higher than gas taxis' due to the low electricity prices (e.g., ET drivers' daily profits are about $20 higher than gas taxi drivers'). This finding may lead to a higher incentive for drivers to accept electric vehicles. Most importantly, the overall emission reduction can be beneficial for public health and air quality (e.g., CO_2 reduction by adopting ETs in Shenzhen was about 1.8 million tons in December 2017), which is important for a sustainable society.

A Balance between ET and Station Evolution: The relationship between electric vehicles and charging infrastructure (i.e., both charging stations and charging points) is interdependent on lots of factors. If the charging points and charging stations are not enough, it is challenging to promote electric vehicles. However, if the charging infrastructure is much more than necessary in a city with only a small number of electric vehicles, many charging points will be idle, leading to low utilization rates. As a result, a balance needs to be achieved between the number of electric vehicles and the number of charging stations and charging points. *One possible solution to achieve the balance could be designing an intelligent charging recommendation system for the ET network under a centralized management mode. In this case, we can know information of all ETs and charging stations in the ET network, and then we can recommend ETs to charging stations for minimizing their charging overhead and balancing the utilization rates of charging stations at the same time. With the charging recommendation system, we can potentially know how many charging stations/points are enough for the ETs to avoid low-efficient charging resource deployment.*

6.2 Limitations and Future Work

Single City Investigation. In this work, we only utilize ET data from Shenzhen to study the ET evolution process. Due to certain features of Shenzhen (e.g., the most crowded city in China with the fastest economic growth, a tropical city with mild winters), the results we have in Shenzhen may not be applied in all other cities. However, we argue that our investigation along with electric vehicle operation models [9, 19, 22, 24, 39, 42] can help other cities to predict and understand their ET evolution process by considering their own city features.

Driver-Specific Investigation: In this work, we are mainly focusing on investigating the aggregate mobility patterns and charging patterns' evolution of the Shenzhen ET fleet while lacking individual driver-level findings. There are still some interesting directions we need to study; e.g., if ET drivers will be more experienced for seeking charging stations and passengers after years of ET operation, can we inversely learn ET drivers' charging preferences from data and characterize the dynamics of such preferences over time, which will potentially provide some guidelines for new ET drivers to operate ETs? In the next step, we will try to investigate the driver-specific mobility [30, 53] and charging patterns' evolution, and we strive to build a model to quantify their behavior evolution over time.

Impact of Battery Evolution: With the development of battery technologies, the battery capacities and energy efficiency of ETs will also increase, but it does not impact our charging events' extraction. Potential impacts of large battery capacity and high energy efficiency are on the per-charge distance, operation distance, and charging time. Hence, in this work, we did not investigate the long-term evolution of per-charge distance. During the evolution process, we found that although there are gas taxis replaced with ETs with large battery capacities, the battery of old ETs also degrades. Hence, with the mixed new ETs and old ETs with different energy efficiency, it is challenging to analyze some evolution patterns related to the battery capacities. As shown in Figure 7, we found that the daily operation distance was stable before the year 2015, and the reason is that there is not much of an increase of new ETs. However, there were a large number of ETs adopted after 2016, so we did not investigate the pattern after 2016. From Figure 9, we also found a similar pattern: the charging time is stable before 2015 and increases after 2016, which is caused by large-scale new ETs' adoption with larger battery capacities. Therefore, we have considered the impact of battery evolution for our analysis. In the future, we will try to distinguish the new ETs from the old ETs and divide them into different groups, and we will try to measure the mobility and charging patterns that related to the ET battery.

From our measurement study, we found that ET drivers always have their charging plans, e.g., charging during shifts and lunchtime as shown in Figure 14, so the battery capacity may not impact their charging events. The charging station is mainly related to the charging demand, i.e., when, where, and how many ETs need to charge, which may not be influenced by the evolution of battery, even with the battery upgrade or degradation.

Impact of Political Factors: In this work, we did not consider the impacts of political factors (e.g., tax, subsidy) on the ET network evolution. Even though tax and subsidy will impact the adoption of ETs, we found they have little impacts on the mobility and charging patterns of ETs. Moreover, the ET promotion of Shenzhen is initiated by the government; i.e., Shenzhen planned to replace all its gas taxis by ETs by the end of 2020 [28]. Hence, we did not emphasize these factors.

6.3 Impacts

Current Impacts. Based on ePat, our understanding of mobility and charging patterns of ET fleets at the city scale can be valuable to charging infrastructure providers, ET drivers, and government managers. For example, a charging infrastructure provider can build more efficient charging stations near the road segments frequently traveled by ETs. Further, taxi drivers may also potentially reduce their charging overhead because there are more charging points available in a short distance. Moreover, the Shenzhen government agency will benefit from mobility and charging pattern understanding as well because they may evaluate their current ET development for better future upgrading. We have reported our insights from our investigation to the Shenzhen transportation committee for better charging station deployment and ET adoption, including some recommended charging station locations and the possible electricity price mechanism for ET charging. These insights were well received, but it will take some time to see the actual results. Even though the government officials think our results provide valuable technical insights, the real-world deployment is extremely complicated and mostly dependent on policies. As a result, instead of deciding on the development and evolution strategy, our next objective is to utilize our framework to quantify the benefit of a predefined evolution strategy.

Potential Impacts. (1) A good charging station deployment strategy is also beneficial for promoting large-scale ET networks. Our investigation can guide other cities to deploy the charging stations more efficiently and economically, achieving successful ET promotion. For example, we can guide them on where to deploy charging stations and how many charging points are appropriate for each charging station. More specifically, urban CBD areas would be the best places for large cities if the land resources are available for them. Some median/small charging stations with fewer than 40 charging points in some important suburban areas are also good choices for charging station deployment. We can also estimate how many charging points are sufficient for other cities based on the Shenzhen model and their taxi operation patterns. (2) Our investigation can help people learn the quantitative benefits of ETs and accept this new thing, which can potentially promote other electric vehicles, e.g., electric cars. (3) Based on the current prediction [18], shared autonomous vehicles [5, 6, 11, 17, 20] are most likely to be electric vehicles, which will be cruising around a city to pick up and drop off passengers or parking until dispatched. These features make shared autonomous vehicles very similar to ETs, except for the human driver factors. Hence, our investigation on the ET evolution process is extremely valuable to predict and quantify the impact of future shared autonomous vehicles. For example, our results on various metrics may be reapplied to shared autonomous vehicles with some modifications targeting human driver factors, future parking, and charging models. (4) Charging events' extraction is the basis for some electric-vehicle-related work, e.g., charging station deployment, charging recommendations, and charging load rebalancing. Our two-step spatiotemporal constraint-based charging event extraction algorithm has the potential to provide guidance for other researchers to extract charging events from vehicle data since it is challenging to obtain the data from the charging infrastructure. (5) Our charging station importance measurement method also has the potential to generalize to other networks, e.g., subway network or cellular network, since they have some similar characteristics. (6) Our work can also provide some guidance for the charging demand prediction since we have investigated the relationships between the number of ETs and charging infrastructure, which represents the demand and supply, respectively.

7 CONCLUSION

In this article, we conduct the first longitudinal measurement study to understand the long-term evolution of ET networks. Our study is from the comprehensive mobility and charging perspective to investigate the long-term evolution patterns. We utilize the real-world data collected from the Shenzhen ET network, which includes more than 13,000 ETs and 117 charging stations. We design a generic two-step spatiotemporal constraint-based charging activity extraction algorithm based on GPS data to explore ETs' charging activities, which can lay the foundation for other ET-related works, e.g., charging recommendation and charging station deployment. We provide a few insights regarding the evolution process of charging station deployment and utilization, ET coverage density, operation, and mobility patterns under various contexts. We also quantify the emission reduction and driver income benefits of the ET network based on their mobility patterns. For the immediate benefit, understanding long-term evolution patterns of the Shenzhen ET network provides valuable experiences for Shenzhen and other cities to further promote ETs. For the long-term benefit, our work may be used to predict the evolution process of future shared autonomous vehicles and quantify their benefits due to their similar characteristics to ETs.

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