Enhanced Real-Time Charging Station Recommendation System For Load Base Electric-Vehicle Taxis

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Abstract:
Electric Vehicles (EV) have less air pollution and are more environment friendly, and due to their contribution to carbon dioxide reduction, EVs are becoming increasingly popular nowadays. The government also encourage and supporting the usage of electric vehicles for the public. The electric vehicle - taxis have been introduced into the public transportation systems to increase EV market distribution. Different from regular taxis that can refuel in minutes, EV taxis' recharging cycles can be as long as one hour. Due to the long cycle, the bad decision on the charging station, i.e., choosing one without empty charging piles, may lead to a long waiting time of more than an hour in the worst case. Therefore, choosing the right charging station is very important to reduce the overall waiting time. Considering that the waiting time can be a non negligible portion to the total work hours, the decision will naturally affect the revenue of individual EV taxis. The current practice of a taxi driver is to choose a station heuristically without a global knowledge. However the heuristically choice can be a wrong one that leads to more waiting time. The proposed system provides a real-time charging station recommendation system for EV taxis via large-scale GPS data mining. By combining each EV taxi's historical recharging events and real-time GPS trajectories, the current operational state of each taxi is predicted. Based on this information, for an EV taxi requesting a recommendation, recommend a charging station that leads to the minimal total time before its recharging starts.

Keyword : Electric vehicle (EV), charging station, recommendation

I. INTRODUCTION

Data mining, or knowledge discovery, is the computer-assisted process of digging through and analyzing enormous sets of data and then extracting the meaning of the data. Data mining tools predict behaviors and future trends, allowing businesses to make proactive, knowledge-driven decisions. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations. Data mining derives its name from the similarities between searching for valuable information in a large database and mining a mountain for a vein of valuable ore. Both processes require either sifting through an immense amount of material, or intelligently probing it to find where the value resides.

Although data mining is still in its infancy, companies in a wide range of industries - including retail, finance, health care, manufacturing transportation, and aerospace - are already using data mining tools and techniques to take advantage of historical data. By using pattern recognition technologies and statistical and mathematical techniques to sift through warehoused information, data mining helps analysts recognize significant facts, relationships, trends, patterns, exceptions and anomalies that might otherwise go unnoticed. For businesses, data mining is used to discover patterns and relationships in the data in order to help make better business decisions. Data mining can help spot sales trends, develop smarter marketing campaigns, and accurately predict customer loyalty. Specific uses of data mining include:

- **Market segmentation -** Identify the common characteristics of customers who buy the same products from the company.
- **Customer churn -** Predict which customers are likely to leave the company and go to a competitor.
- **Fraud detection -** Identify which transactions are most likely to be fraudulent.
- **Direct marketing -** Identify which prospects should be included in a mailing list to obtain the highest response rate.
- **Interactive marketing -** Predict what each individual accessing a Web site is most likely interested in seeing.
- **Market basket analysis -** Understand what products or services are commonly purchased together; e.g., beer and diapers.

II RELATED WORKS

Zhiyong Tian, Yi Wang, Chen Tian, Fan Zhang, Lai Tu, Chengzhong Xu [1] describe major obstacle to the wide acceptance of Electric Vehicles (EV) is the lack of a wide spread charging infrastructure. To solve this, the Chinese government has promoted EVs in public transportation. The operational patterns of EV taxis should be different from Internal Combustion Engine Vehicles (ICEV) taxis: EVs can only travel a limited distance due to the limited capacity of the batteries and an EV taxi may re-charge several times throughout a day. Understanding the status (e.g., operational patterns, driver income and charging behaviors) of EV taxis can provide invaluable information to policy makers. The main contributions of this paper include: 1) Overall, the travel and occupied time/distance are comparable between EV and ICEV taxis. They derive the net profits of both EV and ICEV taxis, and found that an EV taxi can earn almost as much as an ICEV taxi although the EV taxi spend more time on charging. The implication is that commercial operation of an EV taxi fleet can be profitable in metropolitan area, when specific policies give advantages to EV taxis.

Zhongjing Ma Duncan Callaway Ian Hiskens [2] developed a novel decentralized charging control strategy for large populations of plug-in electric vehicles (PEVs).They consider the situation where PEV agents are rational and weakly coupled via their operation costs. At an established Nash equilibrium, each of the PEV agents reacts optimally with respect to the average charging strategy of all the PEV agents. Each of the average charging strategies can be approximated by an infinite population limit which is the solution of a fixed point problem. The control objective is to minimize electricity generation costs by establishing a PEV charging schedule that fills the overnight demand valley. They showed that under certain mild conditions, there exists a unique Nash equilibrium that almost satisfies that goal. Moreover, the paper establishes a sufficient condition under which the system converges to the unique Nash equilibrium. The theoretical results are illustrated through various numerical examples.

Lingwen Gan Ufuk Topcu Steven Low [3] proposed decentralized algorithms for optimally scheduling electric vehicle (EV) charging. The algorithms exploit the elasticity and controllability of electric vehicle loads in order to fill the valleys in electric demand profiles. They first formulate a global optimization problem, whose objective is to impose a generalized notion of valley-filling, and study the properties of optimal charging profiles. Then they give two decentralized algorithms, one synchronous (i.e., information update takes place in each iteration) and one asynchronous (i.e., EVs may use outdated information with bounded delay in some of the iterations) to solve the problem.

Hua Qinand Wensheng Zhang [4] proposes a method to estimate the probability in which each reservation will be really carried out (called success probability of the reservation hereafter), and use the reservation information according to its success probability. The success probability is estimated based on the following ideas: When a reservation is made, the stability (i.e., the chance that it will not be changed or cancelled) is firstly estimated through comparing the waiting time caused by this reservation with the waiting time caused by other optional reservations. The larger is the difference, the higher is the stability. Furthermore, the historical data is used to model the mapping between the stability of reservations and the success probabilities. With themapping, the success probability of a reservation can then be quantified based on both stability and the mapping between stability and success probability.

Francesco Malandrino, Claudio Casetti, Carla-Fabiana Chiasserini [5] investigates how equilibrium in such a market can be reached. They also address the issue of computational complexity, showing that, through their model, equilibria can be found in polynomial time. They evaluated their model in a realistic scenario, focusing on its ability to capture the advantages of the availability of an Intelligent Transportation System (ITS) supporting the EV drivers. The model also mimics the anticompetitive behavior that charging stations are likely to follow, and it highlights the effect of possible countermeasures to such a behavior. It is now an established tenet of transportation technology that Electric Vehicles (EVs) will, at some point in the future, replace vehicles propelled by fossil fuel. Environmentally friendly by definition, EVs enjoy favorable attention by industry and governments alike..

III. DATA PREPROCESSING AND BEHAVIOR ANALYSIS

A. EV Taxi Specifications & Charging Station Deployment

The specifications of the EV taxis in Shenzhen indicate that the distance which is fully charged EV can travel is shorter than that of a fully fueled ICEV (according to the fuel economy and the tank capacity specifications of the ICVE taxis in Shenzhen, a fully fueled ICVE can travel approximately 600 km). Meanwhile, the distribution of deployed charging stations for public Evs. There are two kinds of charging stations deployed in Shenzhen. A majority of the stations are exclusively for EVtaxis while a few are shared by EV taxis and electric buses. Neither type of stations are open for private cars. Since electric buses usually have fixed schedule and recharge at a certain fixed time at late night, the available charging stations and piles for EV taxis can be considered as static resource. They will be negligibly affected by other type of electric vehicles. Although the charging stations are mostly only for EV taxis, they are still in severe shortage to supply all EV taxis. Both above battery specifications and the current charging station deployment can lead to EV drivers' long time cost for recharging and can be obstacles in promoting the usage of EV. Infrastructure constructions and battery technology improvement can be an option. However, the initial cost of additional infrastructure is considerably large and the construction may also be limited by some constrains such as land use and power grid. The battery technology also needs further breakthrough to be widely applied in EVs. Therefore, the status quo of the EV specifications and charging station deployment raise the emergency of an efficient charging recommendation solution

Fig: 2 Distribution of charge station

B. Individual EV Taxi Recharge Events Detection

It can assume that an EV taxi that is recharging or waiting for recharging at any charging station should stay almost still and close to the station for a long period of time. This should also be reflected in the GPS trace data of every EV. Therefore, based on such assumption, we detect an EV taxi's recharging events by fusing taxi GPS and charging station data

Model	Dist./Charge	Max. Speed	Capacity	Charging Cycle
BYD e6	300Km	160Km/h	72KWh	1h

Fig: 3 Specification of EV taxis in Shenzhen

It founds that there exists cases of EV taxis parking at positions nearby a charging station not for recharging but identified as a recharging event by our detection method. The GPS records of them follow a similar pattern like normal charging events, which is difficult to distinguish. So at second and third time of the field investigation, we talked with those EV taxi drivers to learn about their recharging behavior patterns during the field investigations. We found that the misjudge samples come from the taxis whose drivers happen to live near the charging station. These portions of drivers are very limited and can be found out by long time observation with a few more field investigations.

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D.Behavior Analysis and Opportunities for a Recommendation System

It describes the temporal distribution of collected EV taxis' recharging events. Besides, we concern more concerned about the temporal feature of individual EV taxi recharging events. Based on the recharging event data set, we can analyze every individual EV taxi's recharging events by grouping the data records by the field ofCarID. It observes that most EV taxi drivers are likely to recharge at some fixed time slots and we randomly select one EV taxi to illustrate this observation. Where one bar indicates the frequency that this EV taxi intends to recharge at a certain time throughout the whole month. It is obvious that the period when this EV taxi driver intends to recharge concentrates around 11:40. This observation is very common among EV taxi drivers in the statistical resultsin Shenzhen, which is beneficial for us to capture their recharging intentions.

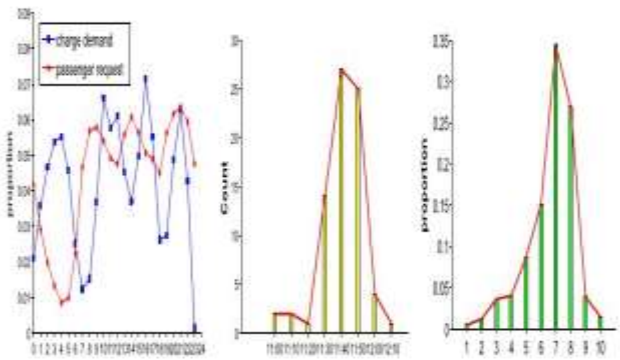

Fig: 4 a) Hour of Day(00:00) b) Time c) Charging Station

This spatio-temporal analysis proves that EV taxis' long time cost at charging stations results from the fact that EV taxi drivers always rush to the same charging stations during the same period. This is partly because they do not have access to the real-time loads of the charging stations (i.e., the number of vehicles using the stations) and it also results from the lack of accurate recommendation system. In conclusion, the preliminary observations and analysis of recharging behavior patterns suggest the necessity of the charging station recommendation system. Therefore, we propose a real-time recommendation system for EV taxi drivers. Note that although our observations are achieved from the data set collected in Shenzhen, none of them are dependent on special characteristics of Shenzhen, and all of the spatio-temporal patterns are likely to hold in any EV taxi system under other circumstances.

E. Real-time recommendation system

It performs the EV taxi state inference, focusing on recharging intention formulation. Specifically, it investigates EV taxi drivers' recharging intentions from two perspectives:

- At a time t, how to identify whether an EV taxi v has a recharging intention.
- If v has a recharging intention, which charging station it chooses to go.

Thereafter, we will combine EV taxi drivers' recharging intentions and the occupancy of charging piles in each station to calculate waiting time at each charging station. Finally, based on the calculated waiting time, we propose a model for our real-time recommendation system. Therefore, charging stationswhere cost time is minimal can be recommended for EV taxi drivers who use the system, improving their operational time on roads.

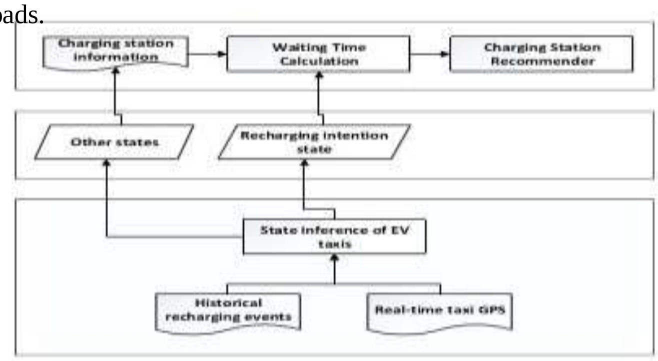

Fig: 3 Framework for Real-time Recommendation System

As a recommendation system, the solution presented in this paper is a user centric approach, rather than a global scheduling. Recommendation is computed upon users' requests. The recommendation workflow runs with incrementally update when a new recommendation request comes or a new real time GPS record comes from an involved taxi. As an EV reports its GPS record every 30 seconds, in case that the new GPS record shows a change of an EV's state or intention, the recommendation decision can be recalculated and issued within 30 seconds. As a driver should usually request a recommendation much earlier than 30 seconds before he arrives at a charging station, the 30 seconds computing round based on the real time data should be acceptable for updating the recommendation decision.

F. Recharging Intention Identification

There is another factor that may influence EV taxi drivers' recharge intentions: the travel distance after the last recharging event. This can be computed by analyzing the sum of Cruise distance and Distance between two consecutive recharge events in the taxi transaction data set. Although we mainly focus on time slots when predicting states of EV taxis, it follows from our observation that an EV taxi driver do not drive to a charging station for recharging if he did not travel a long distance after the last recharging event. Thus we take this distance data set into consideration when predicting their states to avoid the occurrence of this exception.

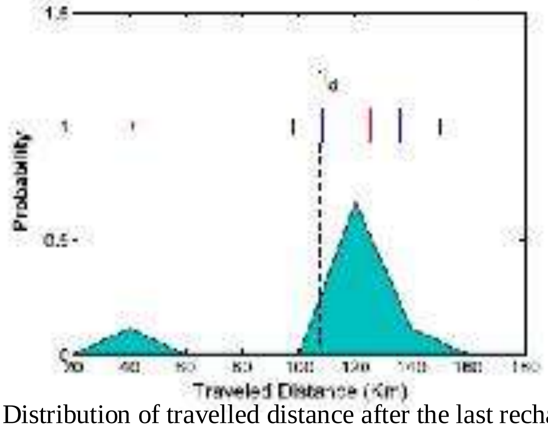

Fig: 5 Distribution of travelled distance after the last recharging event

F. Charging Station Selection

After identifying whether an EV taxi v has a recharging intention at t, we should also predict which charging station v is most probably heading to. Specifically, for v we firstly obtain a list of charging stations v choose to recharge and rank those charging stations by the frequency v has visited. It denotes v's ordered list as $sta=(s_1,s_2,...,s_m)$ where s_i refers to a charging station. This ordered list reveals an EV taxi drivers preference to different charging stations and for every $s_i \in sta$, we denote c_i as the count that s_i has been visited by v for recharging.

Besides the preference to charging stations, we should also consider v's position at t since the investigations through EV taxi drivers indicate that the drivers always prefer to drive to nearby charging stations instead of remote ones, thus for every $s_i \in sta$, $c_i / dist(p_m,s_i)$ Then we choose the charging station with the highest score as the EV taxi's station selection.

Taxi GPS traces can be exploited to investigate EV taxi drivers' recharging behavior patterns. In this paper, we have studied EV taxi drivers' recharging intention identification based on the activities of over 800 EV taxis in Shenzhen. To understand recharging intentions of EV taxi drivers, we first propose a method to detect their recharging events and then analyze their historical recharging behavior patterns by utilizing the detected recharging events data and field investigations through EV taxis drivers. The investigations are mainly focused on two perspectives: 1) EV taxi drivers usually have recharging intentions at a fixed period; 2) although over 50 charging stations are deployed in Shenzhen, most of EV taxi drivers choose 6–8 stations among them regularly. Based on our verifications for these investigations, we combine historical recharging event data and real-time taxi GPS data to identify drivers' recharging intentions, including when and where they will choose for recharging.

In this paper, we present a real-time recommendation system for them by linking charging stations' operational condition information to reduce their cost time for recharging. The system first predicts EV taxi drivers' recharging intentions.

Then, given the current location and time of an EV taxi that sending a recharging request, the system can recommend a charging station for the EV taxi driver, to which the driver's overall cost time for recharging is most likely to be minimal. Our extensive analysis on the real data set shows that our system can reduce the cost time by 50% in Shenzhen. Although the research is based on the study case in Shenzhen, we claim that most of our preliminary observations will be commonly observable among EV taxi drivers in general, and the theoretic model of our system is irrelevant to the city, which make it evident that our system is universally applicable in any city or country considering the adoption of EV taxi system.

IV.RESULTS

The following **Table 6.1** describes experimental result for existing system analysis. The table contains search Vehicle, mapping Vehicle and average mapping clustering details are shown.

S.NO	Search Vehicle	Mapping Vehicle	Average of Mapping Clustering Vehicle [%]
1	200	155	77.5
2	250	220	88.00
3	300	272	90.66
4	350	322	92.00
5	400	383	95.75
6	450	429	95.33
7	500	468	93.60
8	550	523	95.05
9	600	578	96.33
10	650	633	97.74

Table 1 Map reduces Model- Existing System

The following **Figure 1 a and b** describes experimental result for existing system analysis. The fig contains search Vehicle, mapping Vehicle and average mapping clustering details are shown

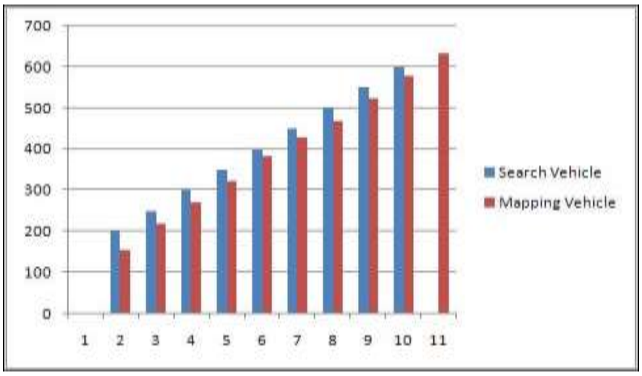

Figure 1 a

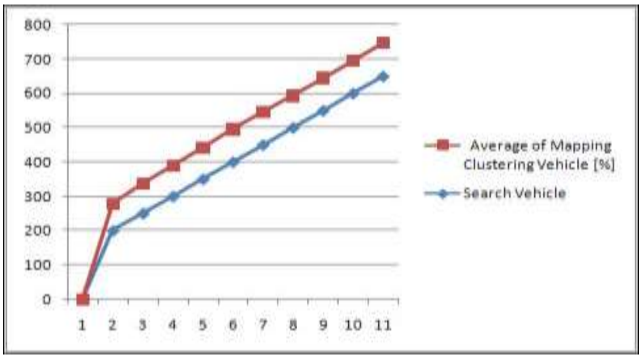

Fig 1 a and b Map reduces Model

REFERENCES

[1] Z. Tian et al., "Understanding operational and charging patterns of electric vehicle taxis using GPS records," in Proc. IEEE 17th Int. Conf. ITSC, 2014, pp. 2472–2479.

[2] Z. Ma, D. Callaway, and I. Hiskens, "Decentralized charging control for large populations of plug-in electric vehicles," in Proc. 49th IEEE CDC, 2010, pp. 206–212.

[3] L. Gan, U. Topcu, and S. Low, "Optimal decentralized protocol for electric vehicle charging," in Proc. IEEE 50th CDC-ECC, 2011, pp. 5798–5804

[4] R. Freire and et al., "Integration of Renewable Energy Generation with EV Charging Strategies to Optimize Grid Load Balancing". *Conference on Intelligent Transportation Systems*, 2010

[5] F. Malandrino, C. Casetti, and C.-F. Chiasserini, "A holistic view of its-enhanced charging markets," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1736–1745, Aug. 2014.

[6] J. Zhao, C. Tian, F. Zhang, C. Xu, and S. Feng, "Understanding temporal and spatial travel patterns of individual passengers by mining smart card data," in Proc. IEEE 17th Int. Conf. ITSC, 2014, pp. 2991–2997

[7] F. Zhang, D. Wilkie, Y. Zheng, and X. Xie, "Sensing the pulse of urban refueling behavior," in *Proc. ACM Int. Joint Conf. Pervasive UbiquitousComput.*, 2013, pp. 13–22

[8] C. Chen et al., "Real-time detection of anomalous taxi trajectories from GPS traces," in Mobile and Ubiquitous Systems: Computing, Networking, and Services. New York, NY, USA: Springer-Verlag, 2012, pp. 63–74 [9] F. Zhang et al., "Spatio-temporal segmentation of metro trips using smart card data," IEEE Trans. Veh. Technol., to be published.

[10]D. Zhang et al., "Understanding taxi service strategies from taxi GPS traces," IEEE Trans. Intell. Transp. Syst., vol. 16, no. 1, pp. 123–135, Feb. 2015