International Journal of
Scientific Engineering and Technology Research

ISSN 2319-8885
Vol.06,Issue.32
November-2017,
Pages:6668-6673

www.ijsetr.com

Persistent Charging Station Recommendation System for Electric-Vehicle Taxis

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Abstract: The 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. 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. Understanding the status (e.g., operational patterns, driver income and charging behaviors) of EV taxis can provide invaluable information to policy makers. Based on this information, for an EV taxi requesting a recommendation, we can recommend a charging station that leads to the minimal total time before its recharging starts. Extensive experiments verified that our predicted time is relatively accurate and can reduce the cost time of EV taxis.

Keywords: Electric Vehicle (EV), Charging Station, Recommendation, Taxis.

I. INTRODUCTION

Electric vehicles (EVs) offer significant potential for increasing energy efficiency in transportation, reducing greenhouse gas emissions, and relieving reliance on foreign oil. Currently, several types of EVs are either already in the U.S. market or about to enter, and electrification of transportation is at the forefront of many research and development agendas. On the other hand, the potential comes with a multitude of challenges including those in the integration into the electric power grid. EV charging increases the electricity demand, and potentially amplifies the peak demand or creates new peaks. EV taxi may recharge several times throughout a day. What's more, each charging event usually costs much longer time compared with an ICEV refueling event: every recharging lasts for more than one hour, even with the fast charging mode. As environment reservation becomes a prominent issue around the world, electric vehicles (EVs) are poised to aim mass acceptance from the general public. Electric vehicles offer many benefits over traditional ones, such as high energy efficiency, low greenhouse gas emissions potential to run on locally produced renewable energy (e.g., wind and solar power) and so on. EVs are gaining popularity in market, for not only short-distance commuting but also long-distance journeys.

II. RELATED WORK

A. Evaluations on State Prediction

To evaluate our prediction on EV taxis' states, we firstly collect the real states of every EV taxi as the ground truth. Thus many EV taxi drivers will have recharging intentions, beneficial for evaluating on state prediction, especially on recharging intention identification. The predicted states of the whole EV taxis in Shenzhen can be obtained by exploiting algorithm and we select several typical EVs to illustrate the comparisons between our predicted states and real states. Note that for to-station states, we still need to predict which charging station is selected for recharging. We propose our predicted charging station selections and make a comparison with the real selections, obtaining that the accuracy of integral recharge intention identification, including to-station state and charging station selection.

B. Evaluations on Recommendation Results

As mentioned previously, most of the EV taxis in Shenzhen have two drivers for each vehicle. Normally, the two drivers set up an agreement on when and where to hand over the EV taxi. Since the agreement constraint, an EV taxi driver usually chooses the charging station near the agreed place for his shift convenience, instead of our recommended charging stations even though it can save his cost time. Therefore, we choose time 11:30 A.M. around noon recharging peak period to evaluate our recommendation results. Another setting factor to consider is that we only choose a part of EV taxis from the whole fleet as the evaluation objectives for our recommendation system, different from the load balance problem involved the whole EV taxi fleet. Actually, when more drivers use our system, the system can acquire more exact real-time information to enhance the recommendation performance but incline to become a global optimization system. Therefore, we choose 80 EV taxis from the whole fleet supposed to be installed our recommendation system as the evaluation objectives.

C. EV Taxi Specifications & Charging Station Deployment

The studying case used to understand EV taxis' behavior patterns is in Shenzhen, China. The amount of EV taxis is around 1000 until 2014. Considering the total amount of taxi fleets in Shenzhen, the percentage of EV taxis is less than 10%. A number of charging stations have been built and deployed in Shenzhen, offering fast charging piles for EV taxis. In this sect ion, we propose the solution to the real-time recommendation system. The framework of the real-time recommendation system is shown in Fig. 1. We firstly perform the EV taxi state inference, focusing on recharging intention formulation. Specifically, we investigate EV taxi drivers' recharging intentions from two perspectives:1) at a time t, how to identify whether an EV taxi v has are charging intention; 2) 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. Finally, based on the calculated waiting time, we propose a model for our real-time recommendation system. Therefore, charging stations where cost time is minimal can be recommended for EV taxi drivers who use the system, improving their operational time on roads. It chooses to recharge and rank charging stations by the frequency this taxi has visited. 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.

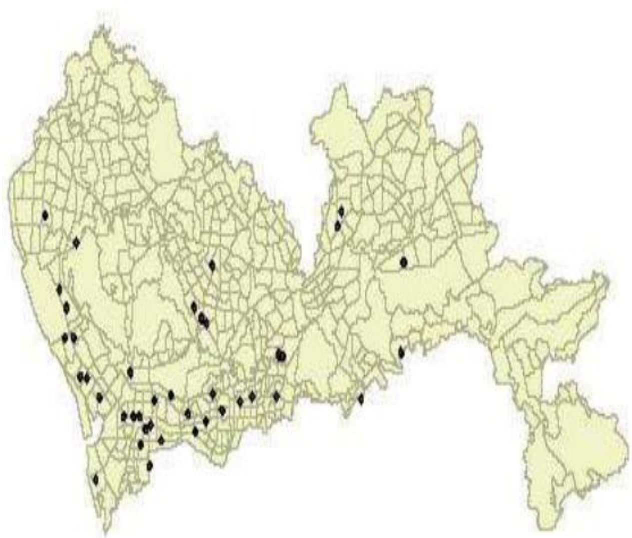

Fig.1. Distribution of charge stations in Shenzhen (one dot per station).

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. In conclusion, the preliminary observations and analysis of recharging behavior patterns suggest the necessity of the charging station recommendation system.

III. REAL-TIME RECOMMENDATION SYSTEM

A. Recharging Intention Identification

The first objective of recharging intention identification is to identify whether an EV taxi v has a recharging intention at a time t. The identification is accomplished by combining historical recharging event data and real-time taxi GPS data. As we know, there exist three states for EV taxis: to-station, recharging and operating and to-station corresponds to EV taxis' recharging intentions. Therefore, for any time interval Ik, we can count the number of times different states occurred, then the probability of v's in to-station state (i.e., having recharge intention) in Ik can be approximated with the following empirical probability. The state may change in an interval as well, e.g., an EV taxi begins to recharge after it arrives at a charging station, which means this process contains to-station and recharging states. If the duration of to-station is longer than recharging, then we regard this EV taxi's state as to-station in the interval. However, 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 as shown in Fig.2. 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.

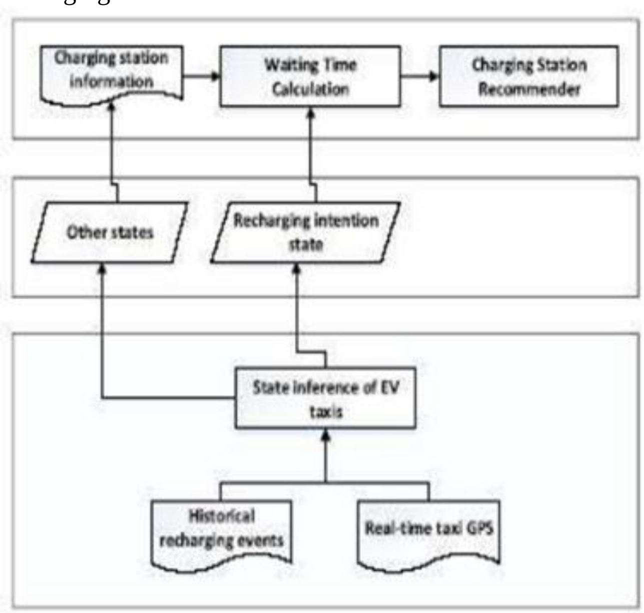

Fig.2. Solution framework of our real-time recommendation system.

B. 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 charging stations v choose to recharge and rank those charging stations by the frequency v has visited. We denote v's ordered list as sta= s1, s2, . . . ,sm, where sirefers to a charging station. This ordered list reveals an EV taxi drivers preference to different charging stations.

EV taxi drivers indicate that the drivers always prefer to drive to nearby charging stations instead of remote ones, thus for every si∈sta, we denote dist(pm, si) as the distance between v's current location at t and charging station si, where pm comes from trj and indicates v's location at the moment closest to t with the highest score as the EV taxi's station selection.

C. Recommendation System Model

Based on the results of EV taxi state inference achieved from Algorithm 1, we design the real-time recommendation system as follows. For an EV taxi v0 which sends a recharging request at t, the system recommends a charging station s0 wherev0 can obtain the minimum value of cost time where S is the set of charging stations while s refers to a charging station. Tv0(s)and Wv0 (s) refer to the functions of travel time and waiting time, respectively ForWv0 (s), we firstly find those EV taxis having recharging intentions for s, and then partition them into two groups. Actually, our recommendation system will continue to monitor EV taxis after sending recommendations to respond their requests. Specifically, for those EV taxis following our recommendations, their states including where to recharge and how soon reaching a charging station are available, which is taken into account when recommending for a new EV taxi.

IV. EXPERIMENTS AND RESULTS

A. Evaluations on State Prediction

To evaluate our prediction on EV taxis' states, we firstly collect the real states of every EV taxi at 08/01/2014 11:30 A.M.as the ground truth. This time is selected since it's the peak time of recharge indicates as shown in Figs.3 and 4. Thus many EV taxi drivers will have recharging intentions, beneficial for evaluating on state prediction, especially on recharging intention identification. The predicted states of the whole EV taxis in Shenzhen can be obtained by exploiting algorithm 1 and we select several typical EVs to illustrate the comparisons between our predicted states and real states, as shown in Table I. Comparison results of over 800 EV taxis between our predicted states and real states show that the overall accuracy of our state prediction is 94.7%, among which the accuracy of to-station state prediction is 92.2%, 96.8% for recharging. 95.3% for operating. Note that for to-station states, we still need to predict which charging station is selected for recharging. Based on score shown in Equation (2), we propose our predicted charging station selections and make a comparison with the real selections, obtaining that the accuracy of integral recharge intention identification, including to-station state and charging station selection, is 84.7%.

TABLE I: Sample Evaluations On State Prediction Out of The Whole EV Fleet

Car ID	Historical Probabilities			Real-time GPS	Predicted State	Real State
	Recharging	To-station	Operating			
v_1	0.32	**0.52**	0.16	$\nexists sp \subset trj$	to-station	to-station
v_2	0.30	0.05	**0.65**	$\nexists sp \subset trj$	operating	operating
v_3	**0.74**	0.00	0.26	$\exists sp \subset trj$ **and** $p_m = \hat{p}_m$	recharging	recharging
v_4	0.22	0.13	**0.65**	$\exists sp \subset trj$ **and** $p_m \neq \hat{p}_m$	operating	operating

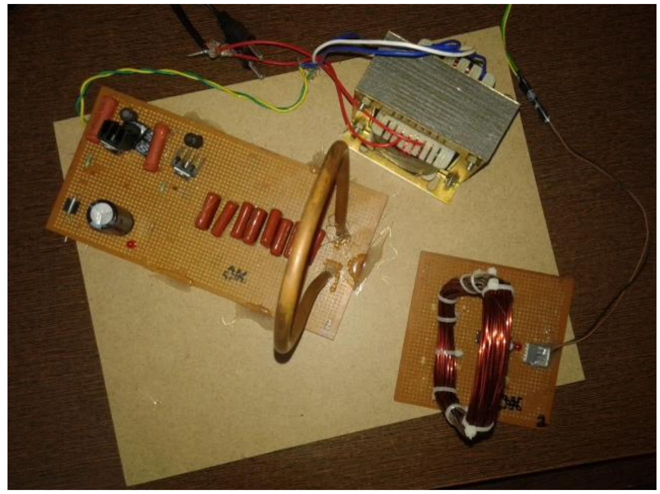

Fig.3. Hardware setup for WPT Module.

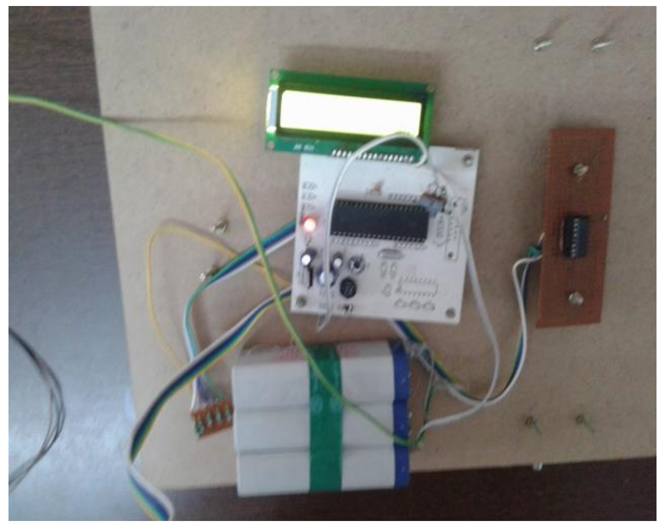

Fig.4.Hardware setup for Electric Vehicle section(Robot).

TABLE II: Sample Evaluations Of Real Resultsversus Recommended Results

Car ID	CS ID	RTT	PTT	RWT	PWT
ev_1	B	12	10	0	0
ev_2	D	6	5	20	15
ev_3	A	5	5	15	0
ev_4	E	15	14	0	0
ev_5	C	20	18	21	25

B. Evaluations on Recommendation Results

As mentioned previously, most of the EV taxis in Shenzhen have two drivers for each vehicle. Normally, the two drivers set up an agreement on when and where to hand over the EV taxi. Since the agreement constraint, an EV taxi driver usually chooses the charging station near the agreed place for his shift convenience, instead of our recommended charging station seven though it can save his cost time. Therefore, we choose time11:30 A.M. around noon recharging peak period to evaluate our recommendation results. Another setting factor to consider is that we only choose a part of EV taxis from the whole fleet as the evaluation objectives for our recommendation system, different from the load balance problem involved the whole EV taxi fleet. Actually, when more drivers use our system, the system can acquire more exact real-time information to enhance the recommendation performance but incline to become a global optimization system. Therefore, we choose 80 EV taxis from the whole fleet supposed to be installed our recommendation system as the evaluation objectives. Before evaluating our recommendation results, we verify the precision of our recommendation system. Assuming that for an EV taxi v0, our system can recommend a charging stations for it; meanwhile, by exploiting recharging event detection method, v0's real charging station selection ˆs can be known. We choose the instances of s = ˆs and regard their real charging station selections as the ground truth, then we compare our recommended results with the ground truth on travel time and waiting time. A part of comparison results are shown in Table II, where CS denotes charging station, RTT denotes real travel time, RWT denotes real waiting time, PTT denotes predicted travel time and PWT denotes predicted waiting time the above four concepts of time use the minute as the unit.

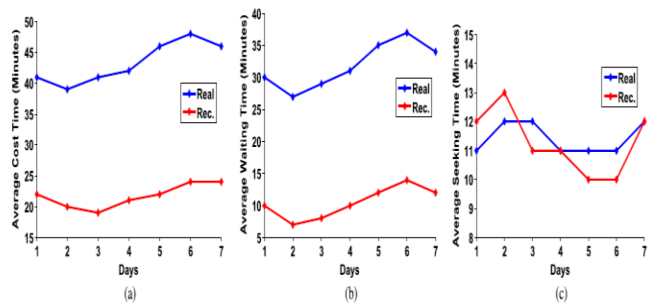

Fig.5. Comparisons between recommended and real results. (a) Comparisons on average cost time; (b) comparisons on average waiting time; (c) comparisons on average travel time.

Our predicted results based on the recommendation system are close to real results except ev3 whose real waiting time at A is 15 minutes while our prediction is 0 minutes. This occurs since another EV taxi drops off passengers after the time A is recommended to ev3 and then reaches A earlier than ev3 for recharge. Because our system only predicts EV taxis' states at the moment recommendation occurs and later state change is not observed by the system. This kind of exceptions is seldom in our application scene, thus overall recommendation results will be affected little. We evaluate our recommended results from three perspectives: overall cost time, travel time and waiting time as shown in Fig. 5. We trace those 80 EV taxis as evaluation objectives for a week and then make a everyday comparison. Fig. 5(a) shows overall cost time comparisons between real condition and recommended condition among from those 80 EV taxis as evaluation objectives, indicating our recommendation system can reduce the cost time by half. Since cost time is composed of travel time and waiting time, thus we propose evaluations on them, respectively. Fig. 5(b) shows comparisons on average waiting time, similar with cost time while Fig. 5(c) displays comparisons on average travel time. Overall, the reduction of cost time by using our recommendation system is mainly achieved by the huge reduction in the waiting time instead of travel time, indicating that EV taxis usually don't choose their near by charging stations of less waiting for recharging due to lack of global information about EVs and charging stations.

We also divide the typical 80 evaluation objectives into several subsets and, respectively evaluate their performances. We still use v0's example to illustrate the rule of division. Assuming that for an EV taxi v0, our system can recommend a charging station s for it, meanwhile, by exploiting recharge event detection method, v0's real charging station selection ˆscan be known. When s = ˆs, it means the driver of v0 finds a optimal charging station (minimum cost time) by himself. As for s ≠ˆs, the driver of v0 may choose a charging station nearest from him (minimum travel time) or with no waiting delay (waiting time equals 0). The performance result is shown in Table III. It can be found that it's reasonable to take travel time and waiting time together into account rather than consider these two factors independently when searching for an optimal charging station.

TABLE III: Division And Performance Of Overall Evaluation Objectives

Category	Condition	Proportion	RTT	RWT	PTT	PWT	Saving Time
optimal	$s = \hat{s}$	10%	12	10	10	12	0
nearest	RTT_{min}	20%	7	35	15	5	22
no waiting	$RWT = 0$	20%	38	0	7	7	24
remaining	the other	50%	14	31	12	13	20

C. Comparisons with Other Recommendation Strategies

In order to evaluate our recommendation system further, we compare it with different recommendation strategies. There commendation strategies to be compared include the result without recommendation (No-R for short), with Nearest-Recommend (Nearest-R for short) and Shortest-Recommend (Shortest-R for short). No-R means no external recommendation strategy is applied at all, reflecting the current situation in Shenzhen. Then Nearest-R strategy means an EV taxi is always recommended to its nearest charging station; and finally, Shortest-R strategy always recommends an EV taxi to the charging station where the waiting time equals 0 regardless of its probable long distance from this EV taxi. Notice that the waiting time in Shortest-R strategy can be computed as the way that in our real-time recommendation system. We collect the real charging stations that the 80 evaluation objectives choose for recharging and analyze the change of waiting time at those charging stations under different recommendation strategies as shown in Fig.6. Compared with No-R strategy, Nearest-R makes the waiting time of charging station A and B increase sharply.

This trend is caused by the fact that A and B is located in the downtown area of Shenzhen, thus many EV taxis are close to them. Although Nearest-R reduces travel time since it always recommends an EV taxi to its nearest charging station, the waiting time increases tremendously which makes Nearest-Run favorable. On contrary, the waiting time achieved from our recommendation system clearly outperforms both, and it is even close to the Shortest-R. In the Shortest-R, although the waiting time is reduced, EV taxis are directed to charging stations far from their current locations, leading to two drawbacks: large travel time is incurred by the long-distance travel, and whether the taxis can reach those stations is unknown due to the low state of charge (SoC) of batteries. Actually, for EV taxi drivers, time spent on waiting at charging stations is much more than that on driving to charging stations, therefore, EV taxi drivers are more concerned about waiting time. Obviously, saving more time on waiting can make EV taxi drivers pick up more passengers, thus they don't care about more electricity consumption to find a proper charging station in this case. Therefore, we mainly focus on waiting time among these different recommendation strategies.

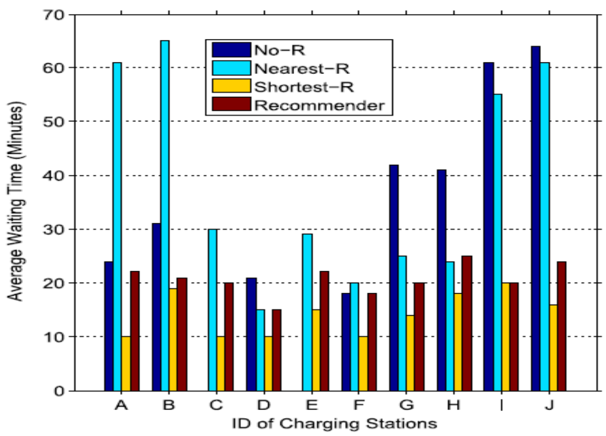

Fig.6. Comparisons of waiting time at selected charging stations.

D. Evaluations on Utilization of Charging Piles

Through the publicly available information of the charging stations, we can obtain the total number of charging piles at each station. Recharging efficiency also can be displayed by the utilization of the charging piles since when the amount of recharge requests is constant, smaller number of occupied posts means larger number of EV taxis waiting at charging stations. Thus a proper recommendation for EV taxis should make more charging piles occupied, improving the level of charging piles utilization. We use the ratio of the number of occupied charging piles over the number of total piles to reflect the utilization of charging piles. The utilization ratio is evaluated with the periods ranging from 9:30 A.M.–13:30 P.M., which can avoid work shift conditions (mentioned in Section IV-B) and cover the noon recharging peak period. We choose 30 minutes as the size of the interval because recharge events always take up to hours. The average charging piles utilization across all charging stations during 9:30 A.M.–13:30 P.M. is presented in Fig.5.The total number of charging piles in Shenzhen is about700, i.e., 5% improvement on charging pile occupancy means about 35 charging piles turn into occupied state from non-occupied, easing the seriousness of queuing delay. As shown in Fig7, the utilization achieved by our recommendation system outperforms No-R and Nearest-R almost in all periods.

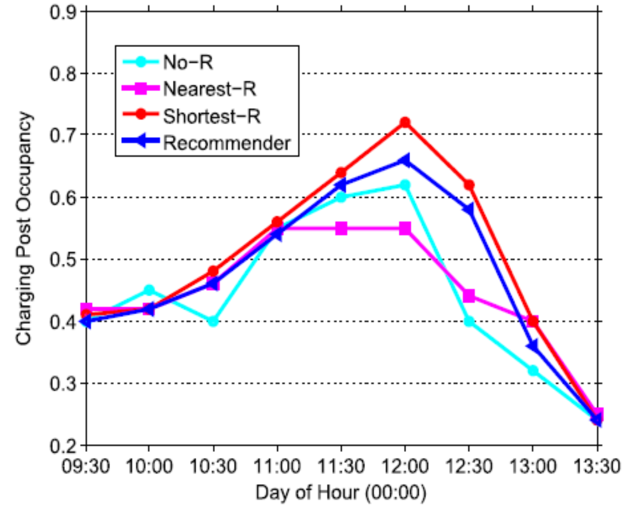

Fig.7. Evaluations on utilization of charging piles.

V. CONCLUSION

In this paper, implemented a real-time recommendation system by linking charging stations' and its operational condition information to reduce the waiting time for recharging of electronic vehicle. The proposed methodology initially predicts the EV taxi drivers' recharging intentions. Then, give the current location and time of an EV taxi that sending are charging request, the system can recommend a charging station for the EV taxi driver, to which the driver's overall waiting time for recharging is most likely to be minimal. The proposed system provides a real-time charging station recommendation system for EV taxis by mining large-scale GPS data and taxis operation data. In addition to that the waiting time calculation along with the distance for the recharging stations and cost is also carried out. Mining large GPS traces has been investigated for tracking the traffic towards there commended recharging stations. A novel scheme needs to be developed to identify the peak and normal time periods to identify and calculating waiting time to provide the charging recommendations.

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