Electrical Vehicle Charging Station Deployment based on Real World Vehicle Trace

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Abstract. The fast development of smart-grid technologies and applications calls for new means to meet the transportation and environment requirements of the next trend of mainstream vehicles. Electric vehicle (EV), which has been regarded as an important replacement for present gasoline-based vehicle, is expected to greatly reduce the carbon emissions meanwhile offer acceptable transportation ability. However, most of present market-level electric vehicle heavily rely its capacity-constrained battery which can only support limited driving range. Although there have been many pioneer works focusing on ameliorating the driving experience of EVs through tuning the placement of charging infrastructure, most of them do not consider the heterogeneity of vehicle movement in different scenarios. In this paper, starting from a fine-grained analysis of a real-world vehicle trace, a charging station placement algorithm considering the installation cost, traffic flow and battery capacity, called *EVReal*, is proposed. In comparing its performance with other representative algorithms, *EVReal* outperforms the others in various metrics.

1 Introduction

Electric vehicles (EVs) have been viewed as the potential solution to greenhouse gas emission problem for several decades. EVs are worthy to be considered as a replacement of current gasoline-based vehicles for several reasons (e.g., environment friendliness, fuel economy). However, EVs also have driving range problems (typically 60 to 120 miles on a full charge), long recharge time (takes 30 min to charge up to 80%), and expensive batteries replacement [16]. To make EVs penetrate faster into consumers under the context of current charging infrastructure limitations, researchers have proposed various algorithms to optimize the placement strategy of charging stations, which can be categorized into charging demand based methods and traffic flow based methods.

In the charging demand based methods, vehicles' charging demands are generally analyzed with various models (e.g., queue theory, driver preference, parking positions) [4, 5, 13–16]. Then the decision is made to maximally fulfill the deduced demands of certain road network. The common problem with these algorithms is that the charging demand deduced by the proposed means cannot depict the actual charging scenario of the whole road network due to several factors (e.g., timeliness, traffic pattern) [7,12]. Therefore, some algorithms based on fine-grained analysis of traffic flow were proposed. The traffic flow is measured based on EVs' origin-destination pairs (O-D pairs). The traffic flow of a O-D pair is defined as the number of vehicles that travel along the paths included in the O-D pair during a certain period of time [6, 12]. In these works, the vehicle parameters (e.g., vehicle density on certain road segment, mobility pattern) are extracted from the movement of vehicles, and the placement of charging stations is designed to maximally capture (i.e., cover) the traffic flows [7, 10, 12]. In these representative works based on traffic flows, [10, 12] provide comprehensive models considering various aspects of traffic flow and road network, but they only validate their works with very small scenarios (50 positions).

To provide a comprehensive EV charging station placement strategy with fine-grained analysis of vehicle mobility, we propose *EVReal*, a charging station placement method based on real world vehicle movement records. Its design is based on the trace analysis of a 28-day vehicle trace in Rome. Then in the model design, the properties and constraints of the vehicles are combined to formulate an optimization problem. Finally, the performance of *EVReal* is evaluated using the trace from various perspectives. In summary, our contributions are threefold:

(1) Our study on a real world trace [3] presents a comprehensive analysis of vehicles' mobility parameters related to the placement of charging stations and their possible influence on the performance of a charging system.
(2) We propose a charging station placement method aiming at maximizing the coverage of vehicle activities under constraints from the trace analysis.
(3) We have conducted extensive trace-driven experiments to validate the performance of *EVReal* from various perspectives.

To our knowledge, this work is the first to formulate a charging station placement optimization problem driven by the observations of vehicles' real-world movement characteristics. Related work is presented in Section 2. Section 3 presents the analysis of a vehicle mobility trace. Section 4 presents the detailed design of *EVReal* model. Then Section 5 evaluates the performance of *EVReal*. Section 6 concludes this paper with remarks on our future work.

2 Related Work

Charging demand based algorithms. Deploying charging stations based on deduced charging demands has been extensively studied. Bae *et al.* [4] proposed to determine the suitable deployment of charging stations through analyzing the spatial and temporal dynamics of charging demand profiles at potential charging stations using the fluid dynamic model. Zheng *et al.* [16] formulated an optimization problem trying to maximize the number of EVs charged in the charging stations while minimizing the life cycle cost of all the stations. Eisel *et al.* [5] aimed at dealing with customers' range anxiety (i.e., fear of being unable to reach destination due to insufficient charging opportunities on road) through a model that transforms customers' preference in charging positions into planning of station locations. The problems with these works are that the mobility cannot be modeled with independent sources.

Traffic flow based algorithms. To better capture the charging dynamics of vehicles, several traffic flow based methods were proposed. Lam *et al.* [7] formulated the station placement as a vertex cover problem, proved its NP-hardness and proposed four solutions. Sánchez-Martín *et al.* [10] proposed to deploy charging stations at the positions with many parking events and suitable parking time length with the minimum deployment cost. Wang *et al.* [12] determined constraints (e.g., driving range, traffic volume) from EV traffic statistics, and formulated and solved a multi-objective location optimization problem to maximize the coverage of EV traffic. They conducted simulation experiments on a 33-node road network. Although these works have turned their focuses to capturing the vehicles' activities, they either validate their design on small road network (e.g., a road network with 34 intersections) [7, 10, 12].

EVReal utilizes various vehicle mobility related parameters , which are extracted from a real world vehicle trace, in forming the objective function and corresponding constraints. Therefore, *EVReal* enables the charging system to have higher serving performance.

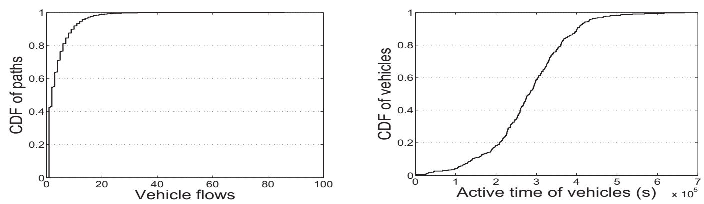
3 Trace Analysis

In this section, we present our trace analysis on the Rome trace [3]. There have been many works using taxis to analyze traffic flows [3, 9, 17–19]. We use their insights to support our taxi trace based data analysis. The Rome trace lasts for 30 days from Feb 1, 2014 to Mar 2, 2014. Each taxi reports its location records (timestamp, ID, GPS position) every 15 seconds. We filtered out positions with precision larger than 20 meters, and taxis with few appearances (< 500). We extracted intersections, where vehicles make significant movement changes, as landmarks. Finally, the Rome trace has 315 taxis and 4638 landmarks. When a vehicle stays at one landmark for more than 5min, we call this position *anchor position* that cut the vehicle's trace into several trajectories. Each trajectory is represented as a sequence of landmarks with corresponding arrival timestamps.

3.1 Traffic Flows Deduced from Vehicle Trajectories

When a vehicle follows certain trajectory, it generates traffic flow to the landmarks consisting the trajectory. During the driving process, there may be multiple vehicles driving on the same landmarks. Correspondingly, for each trajectory, we define the number of vehicles driving on the consisting landmarks at the same time as its traffic flow. The traffic flow is crucial because it represents vehicle activity, and is closely related to the possible charging load at the landmark [7, 20]. The distribution of traffic flow is not balanced. For illustration, we measured the cumulative distribution function (CDF) of the traffic flows of all trajectories as shown in Figure 1(a). We see that most of the trajectories (more than 90%) have vehicle flows lower than 15. The largest traffic flow is higher than 80. About

40% of the trajectories have traffic flows lower than 2. The results demonstrate that the vehicles' activities are highly concentrated at certain popular areas (landmarks). Therefore, properly planning charging stations at these landmarks to maximize captured traffic is necessary. Meanwhile, almost half of the trajectories cover areas with low vehicle flows, which means several "unpopular" landmarks also need consideration.



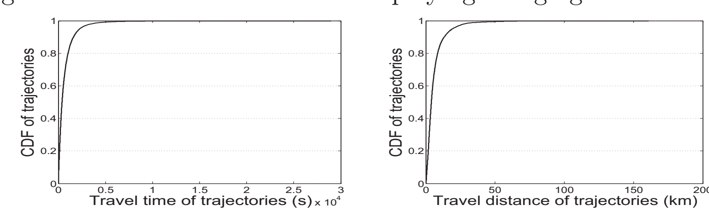
(a) Vehicle flows. (b) Active time of vehicles.

Fig. 1: Properties related to charging load.

3.2 Vehicle Active Time

The charging ability of the system should be consistent with the number of active vehicles [4,16]. Most previous works only consider transient traffic load. But the temporal dynamics of vehicle activities also need to be considered. We define the active time of a vehicle as the total time it spends in transiting. Then we draw the CDF of the active time of all the vehicles as shown in Figure 1(b).

Around 50% of the vehicles have total active time between 200,000s and 400,000s. But around 20% of vehicles having active time less than 200,000s and around 15% of vehicles having active time more than 400,000s. These results demonstrate the fluctuation of the vehicles' active time. Thus, comprehensively collecting the traffic flows is crucial for deploying charging stations.



(a) Travel time of trajectories. (b) Distance of trajectories.

Fig. 2: Properties of trajectories.

3.3 Properties of Vehicle Trajectory

In this section, we present the analysis of the properties of trajectories. Range anxiety, which is the EV drivers' concern that they might not reach a planned destination due to a discharged battery, needs consideration in placing the charging stations [5,8,11]. Thus, considering the EV users' habitual travel distance is necessary to increase the charging station accessibility and relieve EV drivers' range anxiety. We define the distance of a travel as the number of landmarks the trajectory covers, and the duration as its time span. In urban scenario, vehicles are likely to drive short trajectory. To confirm this, we measured the CDF of the distance and the duration of vehicles' travel as shown in Figure 2(a) and Figure 2(b). We see that the travel times of 90% of vehicles are less than 5min, and the travel distances of 90% of vehicles are less than 20km. These observations inspire us that: when a vehicle needs charging, (1) its distance to the nearest charging station should fit in the distances of majority of travels to avoid range anxiety; (2) its time spent in reaching the nearest charging station should be shorter than most vehicles's travel times.

4 System Design

In this section, we present the details of *EVReal*. In formulating the problem of optimizing deployment of charging stations, *EVReal* utilizes the analysis fruition of Section 3 and consider other additional constraints as follows:

- Vehicle flows are highly concentrated within certain ranges (Figure 1(a)). Therefore, our objective is to maximize the totally captured vehicle flows.
- Vehicles' active time in urban scenario fluctuate (Figure 1(b)). Correspondingly, we collect the traffic flow of every vehicle's O-D pair as candidates, and use a binary vector to represent whether a traffic flow should be covered.
- Vehicles in urban scenario usually travel short distance and duration (Figure 2(a) and Figure 2(b)). We set the amount of energy that can be recharged at each station to be nonnegative. That is, the vehicles will get charged as long as a charging station is available at the position.
- Besides the parameters that directly affect the charging coverage, we also consider the installation cost per station, total budget, battery capacity, etc.

The indices for the parameters and variables are listed in Table 1. The parameters are listed in Table 2. The variables are listed in Table 3. The meaning of the parameters and variables are presented in Section 4.1. The formulation of our optimization model is presented in Section 4.2.

4.1 System Preliminaries

We view the target road network as an undirected graph $G = (N, A)$, where N and A represent the set of all landmarks, $N = \{i|i = 1, 2, \dots, n\}$, and the set of edges, $A = \{(i, j)|i, j \in N, i \neq j\}$, respectively. Given two candidate landmarks, i and j, we define d_{ij} as the distance of the shortest path connecting these two landmarks. For each traffic flow, we use r to denote its origin landmark, and s to denote its destination landmark. The collection of the origin landmarks is denoted with R, and the collection of the destination landmarks is denoted with S. We define VR as the driving range, which is the vehicles' maximum driving distance after a full charge. For a subset of landmarks $\hat{N} \subset N$, if a vehicle can reach at least one landmark $j \in \hat{N}$, then $\hat{N}$ is reachable by the vehicle with VR. Therefore, for a road network, if $\hat{N}$ is reachable by any vehicle with VR, the charging stations can capture all vehicle movements on the road network. For convenience, we summarize the notations as in Table 1.

Table 1: Table of notations.

Index	Description	Index	Description
i	Index of candidate sites, $i \in \hat{N} \subset N$	s	A destination landmark in the network, $s \in S \subset N$
r	An origin landmark in the network, $r \in R \subset N$	a	Index of arc set A, $a = (i, j) \in A$

Let f^{rs} be the traffic flow from r to s if there are vehicles following the O-D pair in the records. Ideally, the more traffic flows that the model can capture, the more power load the charging station can offer, and the higher residential power the vehicles can maintain. However, the installation cost of charging station C_i at landmark i, and the total budget m constrains the deployment of charging stations. Thus, to tune the performance of the station deployment with acceptable cost, we further consider parameters: the sequence of landmarks composing the path from r to s, P^{rs}; the distance between landmark i and landmark j, d_{ij}; and the flag denoting whether recharging opportunity should be offered on the path from r to s, δ_i^{rs}. The combination of these parameters formulates the objective of capturing as many traffic flows as possible, but is constrained by the battery capacity, β, which determines VR; the constraint denoting the restraining effect on the length of path, M; and the total budget for deployment, m. For clarity, we summarize the parameters as in Table 2.

Table 2: Table of parameters.

Item	Description	Item	Description	Item	Description
C_i	The installation cost of a charging station, $i \in N$	f^{rs}	Traffic flow from r to s	P^{rs}	A sequence of landmarks on the shortest path from r to s
β	Onboard battery capacity (unified in travel distance), *i.e.*, vehicle range	f^{rs}	Traffic flow from r to s	d_{ij}	Distance between landmark i and landmark j
M	A sufficiently large number denoting restraining effects	δ_i^{rs}	$\delta_i^{rs} = 1$ if node i is in the sequence of nodes P^{rs}, $\delta_i^{rs} = 0$ otherwise; this is an outcome of the deviation paths that are exogenously generated	VR	The maximum distance that an EV can drive after it is fully charged to battery capacity, denoted by β

We use $X = \{X_i | i = 1, 2, \ldots, n\}$ to represent the decision vector indicating whether a landmark should be installed with a charging station. Due to the constraints, it is possible that not all vehicle flows will be captured. Correspondingly, we use $Y = \{X^{rs} | r \in R, s \in S\}$ to select the vehicle traffic that will be captured by the final strategy. The charging system should maximally keep the remaining driving capacity of vehicles positive whenever the vehicle reaches a landmark installed with charging station. Meanwhile, the power recharged at a charging station should be capped with the maximum battery capacity of the vehicle. Thus, in formulating the constraints, we use $B = \{B_i^{rs} | i = 1, 2, \ldots, n,\ r \in R, s \in S\}$ to denote the remaining driving range of a vehicle when it arrives at landmark i on the path from r to s. Similarly, let $l = \{l_i^{rs} | i = 1, 2, \ldots, n,\ r \in R, s \in S\}$ be the vector denoting the amount of residual power of a vehicle when it arrives at landmark i on the path from r to s. For clarity, the variables that can be manipulated in finalizing the model are summarized in Table 3.

Table 3: Table of variables.

Item	Description	Item	Description
X_i	$X_i = 1$ if a charging station is located at landmark i; $X_i = 0$ otherwise	B_i^{rs}	Remaining range at landmark i on the path of O-D pair $r - s$
Y^{rs}	$Y^{rs} = 1$ if the path between r and s can be completed (taken); $Y^{rs} = 0$ otherwise	l_i^{rs}	Amount of energy recharged at landmark i on the path of O-D pair $r - s$

4.2 Model Formulation

Our goal, which is to maximize the captured traffic flow, is formulated as:

$$\max \sum_{r,s} Y^{rs} f^{rs} \tag{1}$$

Additionally, we consider following constraints. First, the power recharging of an EV can only be accomplished at landmarks equipped with a charging station. Therefore, through combining the parameter δ_i^{rs} (the flag denoting whether recharging opportunity should be offered on the shortest path from r to s) with the variable l_i^{rs} (the amount of energy recharged at landmark i on the path from r to s), we set a constraint corresponding to the EVs' charging behavior. Due to the EVs' mobility, the traffic flow is time-varying and depends on various factors [12]. Thus, we set a constraint to guarantee that the sum of the remaining power (range) and the power recharged at landmarks is no larger than the maximum battery capacity. Besides, the battery consumption should be consistent with the distance between landmarks. As for the budget m, the total cost of the charging system is consistent with the sum of the costs of all charging stations C_i determined by the decision vector X. In summary, the constraints are:

$$B_i^{rs} + l_i^{rs} \leq M(1 - Y^{rs}) + \beta, \ \forall r, s; i \in P^{rs} \tag{2}$$

$$B_i^{rs} + l_i^{rs} - d_{ij} - B_j^{rs} \leq M(1 - Y^{rs}), \quad \forall r, s; i, j \in P^{rs}; (i, j) \in A \tag{3}$$

$$-(B_i^{rs} + l_i^{rs} - d_{ij} - B_j^{rs}) \leq M(1 - Y^{rs}), \quad \forall r, s; i, j \in P^{rs}; (i, j) \in A \tag{4}$$

$$\sum_{r,s} l_i^{rs} \delta_i^{rs} \leq M X_i, \ \forall i \in \hat{N} \tag{5}$$

$$\sum_{i} C_i X_i \leq m \tag{6}$$

$$X_i = \{0, 1\}, \forall i \in N \tag{7}$$

$$Y^{rs} = \{0, 1\}, \forall r, s \tag{8}$$

$$B_i^{rs} \geq 0, l_i^{rs} \geq 0, \ \forall r, s; i \in P^{rs} \tag{9}$$

(2) assures that the total onboard electricity each vehicle carries will not exceed the EV battery capacity ($B_i^{rs} + l_i^{rs} \leq \beta$) if the path of that O-D pair is taken to electrify; otherwise no restriction exists when $Y^{rs} = 0$. (3) and (4) work simultaneously to ensure that the energy consumption conservation $B_i^{rs} + l_i^{rs} - d_{ij} - B_j^{rs} = 0$ holds for all links traversed on the path which is taken to deploy adequate stations ($Y^{rs} = 1$). Otherwise, if $Y^{rs} = 0$, then $B_i^{rs} + l_i^{rs} - d_{ij} - B_j^{rs} \leq M$, namely no restraining effects. (5) implies a logic that recharging is only available at node i if there is a charging station. Budget is indicated by (6). (7), (8) and (9) are nonnegativity constraints on remaining power B_i^{rs} and recharged power l_i^{rs}, and binary definition on charging station placement vector X and traffic flow selection vector Y. The problem is a Binary Integer Programming (BIP) problem. We refer to an existing toolbox (e.g. GLPK [2], Cbc [1]) to obtain the integer-feasible solution to the problem.

5 Performance Evaluation

We used the Rome [3] trace for evaluation. The experiments are deployed on a trace-driven vehicular network simulation platform, called CGod. Unless otherwise specified, the experiment setting is the same as in Section 3. We first elaborate the charging station placement results in Section 5.1. Then we briefly explain the comparison methods and the metrics for illustration in Section 5.2. Finally, we present the experimental results and analysis in Section 5.3.

5.1 Charging Station Placement

In determining the charging positions, we made assumptions as follows:

- The cost of installing a charging station at any landmark is identical, namely the number of charging stations represents the restriction of budget.
- All the vehicles are homogeneous, having the same vehicle range and fully charged at origins.
- All the drivers are homogeneous. Namely, they will seek charging station when their residual power is below 10% of their battery capacity.

Table 4: Deployment of charging stations under different budget scenarios.

sites	Deployment of charging stations (Landmark ID)		sites	Deployment of charging stations (Landmark ID)	
	VR=50km	VR=100km		VR=50km	VR=100km
1	3197	2558	7	5, 136, 262, 374, 741, 2957, 3197	-
2	14, 3197	-	8	5, 86, 136, 374, 382, 485, 615, 3197	-
3	14, 136, 3197	-	9	5, 136, 262, 374, 485, 741, 1782, 2980, 3197	-
4	14, 136, 374, 3197	-	10	5, 86, 136, 374, 485, 741, 1097, 1782, 2980, 3197	-
5	86, 136, 374, 382, 3197	-	11	5, 9, 136, 262, 374, 484, 485, 570, 624, 2980, 3060	-
6	136, 262, 374, 741, 2957, 3197	-			

We extract the traffic flows as defined in Section 3, and obtained a road network with 2514 landmarks and 27807 edges connecting these landmarks, and EV traffic flows with 16443 O-D pairs. Then we applied the model on the network with the landmarks as the candidate charging sites and the O-D pairs for consideration. Two vehicle ranges are tested for comparison (i.e., VR=50km and VR=100km). For each range, we first solve the problem with one charging station, and then solve problems by gradually increasing the number of stations until all the travel demand are covered. This is to find the suitable budget for the planning of the charging stations given the road network and traffic flows.

Table 4 presents the detailed deployment of charging stations. Obviously, given limited battery capacity, the more charging stations deployed, the more traffic flows can be captured. Table 5 gives more details on this phenomenon. Moreover, we also observe that vehicle battery capacity (i.e., driving range) would indirectly affect the deployment of charging stations. For example, when budget only allows us to place one charging station, the landmark selected for installing charging station is different for VR=50km and VR=100km. When the vehicle range is 50km, all the flows are not captured until 11 stations can be placed at locations as indicated in the table. In contrast, when VR=100km, one station located at Landmark 2558 can cover all the traffic flows in the network. This is mainly because for most urban trips, their lengths are within the vehicle range (100km). Therefore, we assign VR=50km in the following experiments. In Table 5, we can see the total number of traffic flows captured under various deployment of charging stations. As the number of charging stations is increased, we observe a diminishing marginal benefit in terms of coverage of flows.

Table 5: Coverage of flows under different budget scenarios.

sites	Captured traffic flows		sites	Captured traffic flows		sites	Captured traffic flows	
	VR=50km	VR=100km		VR=50km	VR=100km		VR=50km	VR=100km
1	640619	645047	5	644386	-	9	644975	-
2	642058	-	6	644786	-	10	645010	-
3	643048	-	7	644875	-	11	645047	-
4	643830	-	8	644959	-			

5.2 Settings of Performance Comparison

We compared *EVReal* with two representative charging station placement methods. The first one is random placement method (*Random* in short), which randomly chooses landmarks for deployment. The second one is a traffic density constrained, drivers' interest based method which considers both quantitative and qualitative attributes of the target road network [5] (*MaxInterest*). In *MaxInterest*, the landmarks with the highest average vehicle densities and long vehicle staying time are treated as candidate charging places. The metrics are:

- *Average charging station power load*: Power load distribution on charging stations. It is calculated by averaging the total power that vehicles recharged in different hours during a day.
- *Average vehicle residual power*: The vehicles' average residual power under different hours during a day. It illustrates the methods' ability in keeping the vehicles' operability on road network.
- *Average number of necessary charges*: The average number of charges for keeping each vehicle operable per day under different number of charging stations. We define a necessary charge is needed when a vehicle's residual power is lower than 10%. It illustrates the methods' ability in capturing vehicles' traffic flows.
- *Average travel time to the nearest charging stations*: The average travel time to the nearest charging stations when a necessary charge is needed. It is used to measure the methods' performance in properly distributing the charging stations considering the reachability of vehicles.

5.3 Experimental Results

We conducted two kinds of experiments. In one experiment, given that the number of total charging stations is 11, we measured the average power load of charging stations and the average residual power of vehicles under different hours during a day. In the other experiment, we varied the total number of charging stations from 1 to 11 and measured the average number of charges and the average travel time to the nearest charging station a vehicle needs per day.

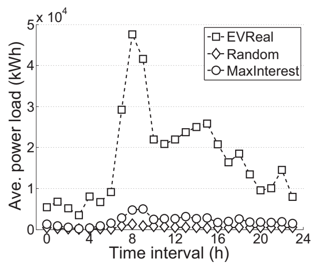


Fig. 3: Average station power load.

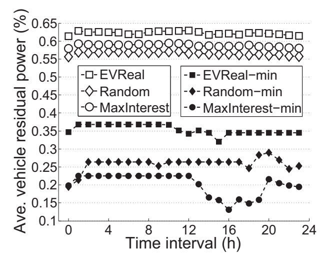


Fig. 4: Average vehicle residual power.

Average Charging Station Power Load Figure 3 shows the measured average charging station power loads. We see the results follow: *MaxInterest*>*EVReal*>*Random*. The power load of *EVReal* is higher than the others at all times. Note that the results are obtained with 11 landmarks installed with charging stations. This means the determined positions for placing charging infrastructure of *EVReal* can serve more vehicles than others with comparative power load pressure.

MaxInterest has the second highest power load. This is because it focuses on satisfying the charging need of most vehicles by placing charging stations at vehicles' most visited places. During rush hours, these charging stations can fulfill the need of most vehicles. But during normal hours (e.g., 14:00∼16:00), *MaxInterest*'s power load is much lower than the one of *EVReal*. To illustrate the difference of the methods in fulfilling vehicles' charging needs, we further measure the vehicles' residual power in Figure 4. *Random* always achieves the lowest power load on landmarks. This is because vehicles have highly biased preference on visiting landmarks. Randomly placing charging infrastructure on landmarks can hardly meet the charing requirement of most vehicles.

Average Vehicle Residual Power Figure 4 shows the average vehicles' residual power in different hours during a day. We see that the results follow: *EVReal*>*MaxInterest*>*Random*. We also measured the minimum vehicle's residential power, which follows: *EVReal-min*>*Random-min*>*MaxInterest-min*.

EVReal has the highest vehicle residual power. This is because the charging stations determined in *EVReal* can timely fulfill the charging need of vehicles. The residual power of vehicles can be kept at relatively stable level within different hours. Besides, there are two obvious drops at around 8:00 and 16:00, which correspond to the peaks in Figure 3. This means that the rush hours with active vehicle movements can affect the vehicle residual power. *MaxInterest* has the second highest vehicle residual power. This is because *MaxInterest* aims to place charging stations at landmarks that can maximize the charging need of most vehicles. *Random* has the lowest vehicle residual power. The reason is that most vehicles cannot be charged timely. Furthermore, we measured the average number of charges that vehicles can have under different number of charging stations, as shown in Figure 5. *EVReal* can still maintain the vehicles' residual power at around 35% under the worst case. *Random* achieves the second highest minimum vehicle's residual power. *MaxInterest* results in the lowest minimum metric. This is because *MaxInterest* concentrates on the areas with dense vehicle movements, so some vehicles in non-dense areas cannot be sufficiently charged.

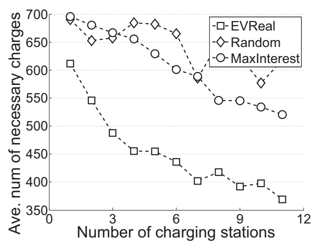


Fig. 5: Average number of charges.

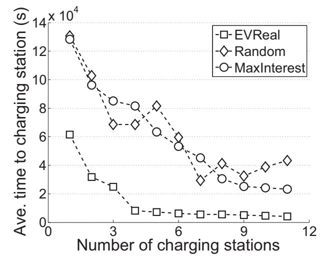


Fig. 6: Average time to charging station.

Average Number of Necessary Charges Figure 5 shows the average number of the vehicles' necessary charges under various number of charging stations. We see the results follow: *Random>MaxInterest>EVReal*.

EVReal has much lower number of necessary charges, and the gap increases along with the increasing of the number of charging stations. This is because *EVReal* aims to cover most of the traffic flows. As for *MaxInterest* and *Random*, their performance is comparative with *EVReal* only when the total number of charging stations is small. The reason is similar to that explained in vehicles' residual power.

Average Travel Time to Nearest Charging Stations Figure 6 shows the average travel time to the nearest charging station under various number of charging stations. We see the results follow: *MaxInterest≈Random>EVReal*.

Vehicles in *EVReal* always have much shorter travel distances to the nearest charging stations. This is because *EVReal* aims to maximize the covered vehicle flows in balanced manner. Note that when the number of charging stations is larger than 4, the improvement of the metric becomes smaller than before. This is because when VR=50km, *EVReal* can use 5 charging stations to fulfill the charging needs. In contrast, *MaxInterest* results in locating the charging stations at popular places (e.g., downtown area). Therefore, vehicles need to travel longer distances to these positions. *Random* cannot guarantee reasonable placement of charging stations, leading to bad reachability in charging.

6 Conclusion

Electric vehicle is expected to fulfill the blueprint of zero pollution meanwhile offering acceptable transportation ability. However, most current market-level EVs have limited driving range. Multiple pioneer works focusing on tuning the placement of charging stations have been proposed. They fail to support the continuous movement of the EVs due to lack of vehicle mobility analysis. In this paper, we establish *EVReal*, which considers various factors which are critical for the planning of charging stations based on a real-world trace. Driven by our trace analysis, we determined the parameters that need consideration, and formulated an optimization model composed by these parameters. Compared with other representative methods, *EVReal* outperforms in distributing power load, vehicle residual power, the number of charges needed and travel time to the nearest charging station. In the future, we will explore more in the effect of traffic events (e.g., jam, accident) in placing charging stations.

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