Optimizing Electric Vehicle Charging with Charging Data Analytics

Tayyibah Khanam, Ivanshu Kaushik, Mohammad Saad Alam, Sanchari Deb, and Yasser Rafat

Abstract Electric vehicles are considered as viable replacements to gasoline cars since they help in reducing harmful emissions and stimulate power generation through renewable energy sources, hence contributing to sustainability. However, one of the significant obstacles in the mass deployment of electric vehicles is the charging time anxiety among users and thus, the subsequent large waiting times for available chargers at charging stations. Data analytics, on the other hand, has revolutionized the decision-making tasks of management and operating systems since its arrival. In this paper, we attempt to optimize the choice of EV charging stations for users in their vicinity by minimizing the summation of time taken to reach the charging stations and the waiting times for available chargers. The proposed framework utilizes real-time data and historical data from all operating charging stations in the city to assist the user in finding the best suitable charging station for their current situation and can be implemented in a mobile phone application.

Keywords Electric vehicles · Charging infrastructure · Data analytics · Waiting times

T. Khanam (✉) · M. S. Alam
Department of Electrical Engineering, Aligarh Muslim University, Aligarh, India
e-mail: tayyibahkhanam@zhcet.ac.in

M. S. Alam
e-mail: saad.alam@zhcet.ac.in

I. Kaushik
Department of Electronics Engineering, BITS Pilani, Pilani, India
e-mail: f20180520@pilani.bits-pilani.ac.in

S. Deb
Electric Power-Train Group, VTT Technical Research Center, Espoo, Finland

Y. Rafat
Department of Mechanical Engineering, Aligarh Muslim University, Aligarh, India
e-mail: yasser.rafat@zhcet.ac.in

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1 Introduction

With the evolving need for sustainable mobility, expansion of the Electric Vehicle (EV) market has emerged as a viable solution. However, EVs are still a rare sight in developing countries like India, mainly because of the challenges faced by users in the adoption of electric vehicles as their primary modes of transport. The introduction of EVs has brought about a need for adequate charging stations with efficient charging strategies for mass-market adoption. Remaining Useful Time (RUL)/range anxieties, cost anxieties and charging time anxieties remain the top three issues which can't be negotiated from a consumer point of view. Thus, for mass-market adoption, these anxieties must be addressed by governmental policies and EV management firms.

Data, on the other hand, is heterogeneous and abundant in the transport sector, thus giving rise to transport 'big data'. In this digitalized era, mobile phone applications have revolutionized the managing and organizing tasks for several users across the globe, majorly by leveraging transport big data. Some common features available in the existing EV charging mobile applications [1] are

(1) Locating charging stations from a worldwide database.
(2) Filtering out stations by—specific locations or routes, types of chargers, legend names etc.
(3) Providing real-time status of chargers.
(4) Trip Planning and booking time slots for EV charging in advance.

Li [2] in his study has extensively used EV trajectory data and data from several other sources to optimally place new charging stations in urban cities, intending to minimize the average time to the nearest charging station, and the average waiting time for an available charging point. Similarly, several studies in the recent past have attempted to optimize EV charging through different approaches such as—switching to green energy charging sources [3], EV Charging station layout to reduce excess driving distances and energy overheads [4] and minimizing charging costs and power balancing [5]. However, existing frameworks, especially the existing mobile phone applications, don't optimally assist the EV users in finding the most suitable charging station concerning time constraints in the present Charging Pile Network (CPN) of cities. Thus, the objective of this paper is to address charging time anxieties by assisting an EV user find the most optimal choice of an EV charging station in his/her vicinity, which simply translates to 'reducing the time taken to find an EV charger'. Thus, we propose the framework of an additional feature capable of working on a mobile phone application that not only saves time but can also reduce the overall travel costs in the future.

The proposed methodology is based on comparative analysis of all possible suitable chargers filtered by user inputs. A comparative analysis is conducted on all potential EV chargers from the user's perspective based on real-time datasets. The rest of the paper is structured as follows—the methodology in Sect. 2 describes the data as well as solution framework with the help of a pseudocode and a flowchart. While Sect. 3 generalizes the results obtained, Sect. 4 discusses the potential limitations from the author's point of view. Finally, Sect. 5 concludes the paper's objectives.

2 Methodology

Suppose an EV user travelling on a particular route needs to charge his/her EV shortly. The mobile application comes into play when the user needs to find a charger with lowest travelling time as well as soonest possible available. We begin by describing the types of data required by our framework, followed by the solution framework itself in the following sections.

2.1 Data Description

Initial one-time data procured by our framework and stored in the database:

(1) Location of each Charging Station
(2) Total number of Chargers in each station
(3) Type of each charger.

User data is collected as 'filters' applied by the user to better sort out chargers that can potentially be considered by the user, rest of the chargers are then excluded from our study at this stage. In our framework, users are provided with the facility of filtering out charging stations according to the current maximum possible driving range of their EV and further filter out the charger type capable of charging their EVs (Table 1).

Real-time data is also expected to flow in our ideal framework through various data collecting devices such as sensors and smart meters, following which this data can be stored in the database. Here, real-time data consists of the current status of every charger—whether available or occupied and if occupied, the percentage charged of the EV getting currently charged.

Historical data of each charger can be ingested and stored in the database, essential for the calculation of 'waiting times'. Through sensor devices installed in each charger, we intend to record the time taken to charge an EV from a% to b% (where b is usually full charge = 100%) in smaller percent intervals (such as 10% in our study) for each EV previously charged.

Table 1 Key notations and terminologies

Notations	Descriptions
n	Number of charging stations
S_n	'nth' charging station
P_k	Number of charging points in each charging station 'Sk'
P_{km}	'mth' charger of 'kth' charging station

2.2 Solution Framework

Filtering out Potential Chargers: Based on the filter inputs provided by the user (the type of charger and maximum driving range), our framework pulls out a set of potential charging stations whose chargers need to be considered while picking out the most optimal charger and hence the most optimal charging station.

For instance, the user specifies the range of seeking a charging station as “d” kilometres with a charger type ‘B’. In this case, our framework filters out all operating charging stations with type ‘B’ chargers in the range of “0 to d” kilometers. Let the set of filtered charging stations be SC = $\{S_1, S_2, \ldots, S_x, \ldots S_b\}$ (where b = [0, n]) each at a distance of dC = $\{d_1, d_2, \ldots, d_x, .., d_b\}$ kilometers respectively. Thus, the set of charges being considered in our study is PC = $\{P_1, P_2, \ldots, P_x, \ldots P_b\}$ where $P_k = \{P_{k1}, P_{k2}, P_{k3} \ldots\ldots\}$ for k = 1, 2, …x, …b.

Calculation of Travel Times: Irrespective of which station is the nearest, second nearest (and so on) to the user, the time taken to reach a particular station plays a much more important role in our study since our goal is to minimize the time taken by an EV user to find a charger as explained previously. The time taken to reach a station depends on the distance as well as the current traffic congestions of that route and thus at this stage, our framework is expected to utilize the Google Maps Distance Matrix API [6] to calculate the set of travel times $dt_C = \{dt_1, dt_2, \ldots, dt_x, \ldots dt_b\}$ for each charging station where dtx = time taken to reach station ‘x’ in current traffic conditions (Fig. 1).

Once the API calculates travel times for individual charging stations, we sort these travelling times in ascending order. For this analysis, let’s assume the sorted output is $dt_1 < dt_2 < \ldots. < dt_b$, where Station 1 requires minimum travel time.

Total Time to charge: Since our framework procures real-time status of each charger across $S_1, S_2, \ldots S_b$, current occupancy status (occupied/available) of chargers in each charging station is made available to the user. Ideal case scenario would be the availability of chargers in the nearest charging station i.e. S_1. However, in reality, preoccupancy of all chargers in a charging station is highly likely to happen once the mass adoption of EVs takes place in the near future.

In this situation, the user can do either one of the two things.

Option 1: Either the user can decide to go to the next nearest charging stations in the order of S_2 then S_3 and so on till S_b.

OR

Option 2: The user can go to the nearest charging station i.e. S_1 and wait for any one of the chargers to be available.

This is where our framework will come into play by performing a comparative time minimization analysis on the set of Total Times (TC) of all occupied/available chargers in the set of considered chargers PC. Here, TC = $\{T_1, T_2, \ldots, T_x, \ldots T_b\}$ where $T_k = \{T_{k1}, T_{k2}, T_{k3} \ldots\ldots\}$ for k = 1, 2,….x, …b. Hence, $\mathbf{T_{xy} = dt_{x} + wx_{y}}$. Our job here is to find the charger y corresponding to station x for which Txy is minimum.

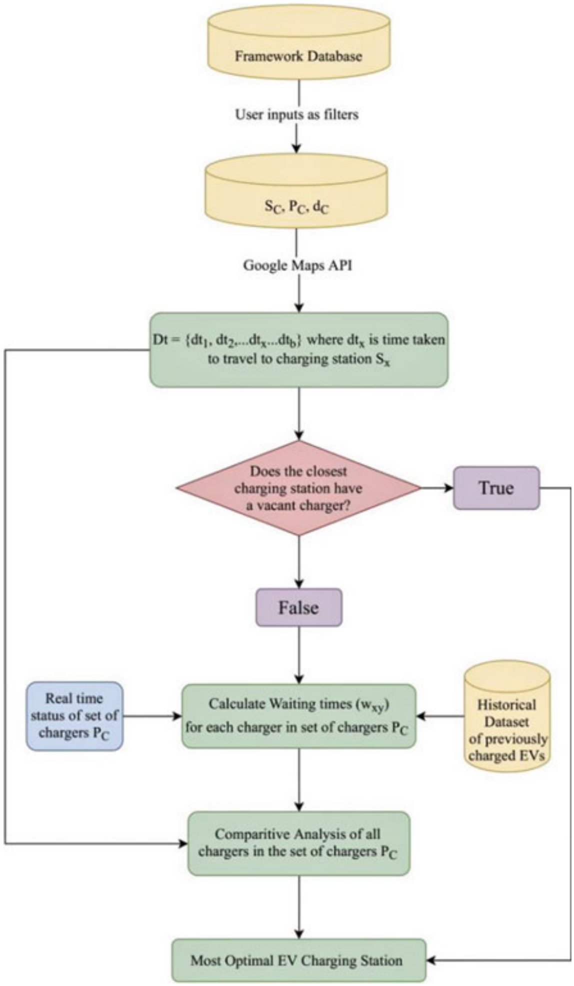

Fig. 1 Flowchart of the methodology utilized in this study

Calculation of Waiting Times: Since the Google Maps API provides us with information on the least travelling times among the set dtC, our job is now restricted to find the waiting times 'w_{xy}' for each charger 'y' in the charging station S_x to finally minimize T_{xy}.

To find w of a charger, historical data of previously charged EVs stored in our database is utilized. Suppose at a particular time when the user seeks assistance from his/her mobile application to charge an EV, an occupied charger P11 (charger 1 of station S_1) has charged an EV by "g%". Using historical charging data, we aim to find out the time taken by the charger P11 to charge rest of the "(100-g) %" at the car getting charged presently as follows—

(1) Firstly, the percent battery level (g %) of the EV currently getting charged at P11 is recorded and sent to the processor.
(2) From historical data, the times taken by EVs getting previously charged at charger P11 to charge from g% to 100% are retrieved from the databases. Due to lack of datasets, we have considered 5 EVs in our study.
(3) Next, we perform a supervised machine learning algorithm—Regression to predict a continuous outcome (which is the waiting time 'w_{11}' in this case) based on the values of predictor variables which are averages of the historic time data sets. We particularly perform Polynomial Regression of 5th degree since it can suit all types of EV charging profiles while preventing overfitting and underfitting to finally give reasonable outcomes. Briefly, the goal of Polynomial Regression model is to build a mathematical equation that predicts waiting time of the present car getting charged as a function of the waiting times of the previously charged cars at the same charger. The waiting time "w11" thus calculated is sent to the output generating framework (Figs. 2 and 3).
(4) The two critical parameters for evaluating the waiting time regression algorithm are Least squared errors (LSE) and total waiting times. Although the total waiting times predicted by both Linear Regression Model (simply averaging) and Polynomial Regression Model are comparatively close in the case of many chargers, the Linear Regression model generally has a very high LSE, thus making it inappropriate for practical purposes.

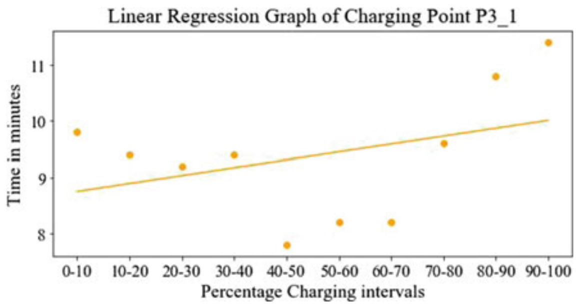

Fig. 2 Linear regression (simple average method) for charger P_{31}

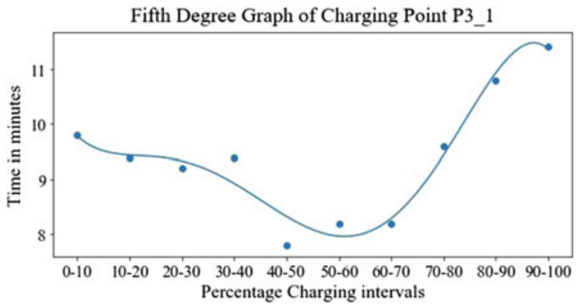

Fig. 3 Polynomial regression graphs for charger P_{31}

(5) Similarly, waiting times for all chargers in the set of chargers P_C is calculated as (w_{11}, w_{12}, w_{13}…) for chargers at S_1, (w_{21}, w_{22}, w_{23}…) for chargers at S_2 and so on till S_b.

Comparative Analysis on Total Times: The final comparative code on Total Times is run using inbuilt functions in python on the set of times Txy to find the minimum T_{xy}. Let us assume that T_{xy} assumes minimum at 'x = q' and 'y = r' where charger 'r' with type 'B' belongs to 'qth' charging station from the set of charging stations SC such that

$$\boldsymbol{Min(T_{xy}) = Min(dt_x + w_{xy}) = (dt_q + w_{qr})}$$

The pseudocode for the proposed framework is described below

Inputs: Current Location, Historical Data, Real-time Data, User Inputs

Outputs: Most optimal charger and Charging Station, Total Waiting Time

Description:

```
1: function FindWaitingTime (Percentage Charged) {
   Use Polynomial Regression on Historical Data to estimate waiting time
   return waiting_time
end
}
2: function FindTimeAndDistance (Current Location, Final Location) {
   Use the Google Maps API to find the Distance and Time required
to reach Final Location from Current Location
   return travel_time, travel_distance
end
}
3: In the main function { for
every station in the city:
    Compute the travel time and distance using FindTimeAndDistance
          () for every charger in that station:
              Compute waiting time using FindWaitingTime ()
                    TotalTime ← waiting_time +
                    travel_time store TotalTime
return charger and charging station with minimum
TotalTime }
```

Thus, our framework assists the user for the most optimal choice of a charger, which would be charger 'r' belonging to charging station 'q' at that particular time instant considering the current status of chargers across the city and the current traffic conditions. Google Maps API can further be utilized for best route guidance and so on to the most optimal charging station.

3 Results

To verify our framework code, we tested our framework using one-time data of 27 EV charging stations in the city of Mumbai. Since real-time data sets and historical data sets are not available in EV charging stations of Indian cities, the rest of the data was assumed for this study. With user location at (19.112705, 72.888662) and maximum driving range of the user as—20 km, the most optimal charger was charger P_{31} corresponding to charging station S_3 (TATA Power Charging Station) with a Total Time to Charge = T_{31} = 27.263 min.

4 Limitations

The regression method helps in the prediction of the waiting time of the current charger based on its historic charging profile. However, many research articles have stated that EV charging till 100% is not the best practice as it reduces battery life and affects battery health too [7]. Due to this reason, several users might disconnect the charger before reaching 100% based on personal perception, which can't be assumed or generalised. Similarly, an EV user might disconnect the charger at any time before 100% due to his/her time constraints, which can again not be generalized but is assumed to happen rarely. Hence, this approach might result in the deviation of actual waiting times than the calculated ones and hence affect the decision making of the EV user.

Further, EV Charging profiles are expected to differ with different types of vehicles such as bus, truck, car, two-wheeler, bicycle etc. Hence, while calculating waiting times of existing type 'H' vehicle getting charged, historical data of previously charged type 'H' vehicles only need to be considered. Further, within the same vehicle type, charging profiles can also differ due to the differences in battery elements and manufacturer specifications. Due to lack of data sets and rarity of EV users in Indian cities, this issue was passed over in this study but can be entertained in future when EVs are adopted widely by users to give accurate results.

5 Conclusion

In this study, we have proposed a framework which attempts to analyze the most optimal charger and hence charging station considering time as the deciding factor. While travel times to charging stations depend on traffic conditions and route lengths, we have attempted to minimize the 'total time to charge' by optimizing the variables of importance through Polynomial Regression. The evaluation results demonstrate that our framework could successfully reduce the total time to charge by 20–30% by assisting the users. While it is possible that the most optimal charging station recommended by our framework might be ecologically unsustainable (corresponding to chargers having much higher travel times and distances), we expect our framework to successfully work in a city with mass EV adoptions among users which directly results in an interconnected and stronger CPN.

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