Departure Time Prediction Using Smartphone Data for Delayed-Full Charging BMS Algorithm

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ABSTRACT

Battery degradation, a gradual loss of capacity and performance due to frequent charging and discharging cycles, is a significant challenge to the widespread adoption of electric vehicles (EVs). This study proposes a BMS algorithm that delays full charging under selective conditions and completes charging immediately just before use to reduce battery degradation rate caused by fully charged state time. Our goal is to predict the charging end time based on an individual's departure time by capturing digital behavioral markers extracted from smartphone data, while minimizing reduction in driving range due to undesired predictions. Preliminary experiment was conducted with 41 subjects to assess the feasibility of the proposed approach. Our results demonstrate that the mobile passive features are capable of learning the departure behavior pattern, achieving an average mean absolute error (MAE) of 0.2336.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

Delayed-Full Charging (DFC); Battery Management System (BMS); Departure Time Prediction; Digital Phenotyping

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1 INTRODUCTION

In recent years, the remarkable advancements in lithium-ion battery technology and the rapid expansion of the electric vehicle (EV) market [5] have brought the critical concern of battery degradation. Battery degradation entails the progressive reduction in capacity and performance over time, resulting from repetitive charging and discharging cycles [1, 8]. Specifically, the available capacity diminishes relative to the initial capacity, primarily attributed to adverse side reactions induced by high electric potential difference during the battery's fully charged state time ($t_{100\%}$) [7]. Mitigating this degradation holds significant implications for the widespread adoption and viability of EVs in the era of carbon neutrality [6].

Battery life can be improved by active control of $t_{100\%}$ via battery management system (BMS). By delaying full charging until certain threshold of time and fully charges the battery just before use, battery degradation caused by long $t_{100\%}$ can be reduced. For reliable implementation of BMS algorithm, it is necessary to predict the charging end time (unplug time, t_{unplug}). An accurate prediction of t_{unplug} can minimize the probability of the undesired prediction, i.e., when the predicted time is later than the actual departure time, limiting the driving range of EVs.

t_{unplug} is determined by the EV user's departure time, which can be analyzed through human behavior modeling. Mobile and wearable devices possess the capability to capture multifaceted aspects of human behavior in various situations, uncover social patterns in daily activity, infer relationships, and locate socially significant places [4]. By leveraging personal data, it may be feasible to quantify an individual's pre-departure behavior via digital phenotyping [11]. Consequently, through the utilization of contextual data derived from smartphone sensors, it is possible to extract relevant digital behavioral markers associated with the pre-departure behavior.

In this paper, we introduce a pioneering methodology for predicting the daily departure time of EV users through the utilization of mobile passive data. To the best of our knowledge, our work represents the first attempt to predict departure time by quantifying pre-departure behavior. Previous studies [2, 3] have investigated the use of smartphone location sensor data to analyze mobility traces of individuals for predicting departure time. However, it is limited that they mainly focused on identifying movement patterns indicative of location change or incorporating time-related information relevant to departure time choice, rather than obtaining cues from behavior characteristics of human. We conducted a preliminary experiment using smartphone data collected from 41 subjects, and extracted features of behavioral patterns related to physical activity and smartphone activity preceding departure. By developing a personalized departure time prediction model, we were able to obtain valid results with a reliable performance.

2 DELAYED-FULL CHARGING BATTERY MANAGEMENT SYSTEM ALGORITHM

This study focuses on departure time (t_{unplug}), which serves as a critical parameter of our proposed "delayed-full charging (DFC)" BMS algorithm. The DFC BMS algorithm employs a strategy wherein full charging is deliberately delayed under specific usage conditions. Subsequently, the algorithm predicts the t_{unplug} and ensures that the battery reaches full charge just prior to the use of EV. The intervention of the algorithm is contingent upon certain selective conditions determined by an Artificial Intelligence (AI) model. These conditions include: (1) the model should learn the user's repetitive behavioral patterns, along with the achievement of reliable prediction performance for t_{unplug}; and (2) the demonstration of a substantial enhancement in the battery lifespan, achieved through a high expected improvement in the effect on $t_{100\%}$.

At the initial stage of the intervention, the charging is paused once the battery reaches a specific state of charge (SOC) typically in the range of 70-80%. This SOC threshold is identified as the point where the battery degradation rate experiences a significant increase. Subsequently, the AI model trained on mobile passive data predicts t_{unplug}, and the battery is then fully charged up to 100% SOC shortly before the predicted t_{unplug}, with an additional time margin (t_{margin}) applied. Here, the margin refers to the amount of time needed to eliminate all the defective cases that model predicted t_{unplug} later than actual value. Since t_{margin} and $t_{100\%}$ exhibit a trade-off relationship, it is necessary to minimize both variables simultaneously in order to improve battery degradation. The algorithm can be optimized by determining these parameters in such a way that maximizes the average reduction in degradation rate and ensures that the probability of defective intervention remains below a target threshold (10 parts per million, ppm), utilizing a selective coupling-based degradation model [10].

Figure 1 (a) shows the successful implementation of the DFC algorithm which effectively reduces the unnecessary $t_{100\%}$ associated with repetitive charging patterns, while avoiding restriction of EV driving range by last-minute full charge before the end of the charging cycle. The algorithm has learned the charging pattern of overnight and work hours, and successfully applies the DFC. As shown in the Figure 1 (b) however, when the actual t_{unplug} deviates from the predicted value, the battery may not be fully charged at the start of the EV driving session, resulting in a defective intervention that limits the driving range. The DFC algorithm must mitigate the degradation rate due to the $t_{100\%}$ factor while minimizing the probability of such undesired predictions to an acceptable level.

3 DEPARTURE TIME PREDICTION

As t_{unplug} signifies the EV usage upon departure from the current location, it is determined by the user's departure time. We anticipate

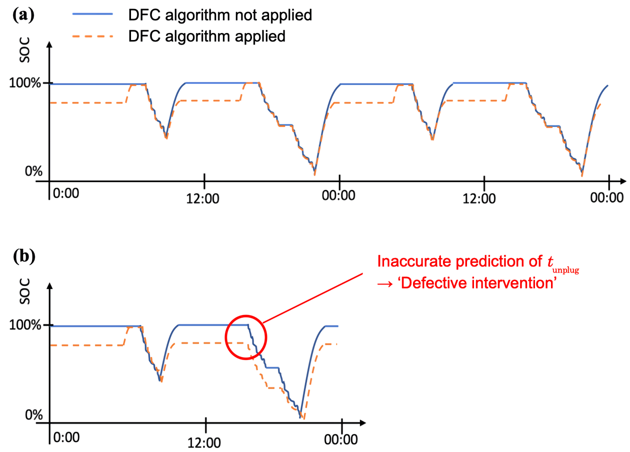

Figure 1: Examples of virtual application of DFC BMS Algorithm. (a) Desired case: It effectively reduces the unnecessary $t_{100\%}$ when charging overnight or at work, and fully charges just before t_{unplug}. (b) Undesired case: EV is not completely charged before departure, limiting subsequent EV driving range due to the inaccurate prediction of t_{unplug} (defective intervention) around 4:00 p.m.

the existence of the pre-departure behavior patterns that can be identified by digital behavioral markers extracted from smartphone data. In this study, we conducted a preliminary experiment with 41 participants over a period of 30 to 90 days. We define a specific scenario of individual's daily commuting on weekdays, exclusively considering subjects aged between 30 and 60 years. This scenario focuses predominantly on the initial trip of the day, which is assumed to be from home to work or another destination.

Mobile passive data: we consider the behavioral aspects of physical activity and smartphone activity before departure. The ground-truth is the time in hours of the last sample of the first 'HOME'-labeled series in the GPS data for each day. Mobile passive sensing data, i.e., activity transition, step detector, significant motion, app usage, call logs, screen unlock are utilized for pre-departure behavior modeling. Time domain features, e.g., time interval between two consecutive samples and frequency domain features, e.g., number of samples are engineered. To infer sleep-awake time, we used the time in hours of the initial detection of the day by each sensor. These features are then extracted with 4-hour time window 30 minutes prior to each label sample in order to identify the behavior characteristics before departure time.

Model Evaluation: We develop a personalized model to predict the daily departure time of each subject, using Catboost (Categorical Boosting) algorithm [9]. CatBoost is a Gradient-Boosting Decision Tree (GBDT) algorithm that incorporates categorical feature handling through an Ordered Boosting approach, enabling it to effectively capture valuable information from high-cardinality categorical variables. It encompasses techniques such as symmetric trees, random permutations, and gradient-based regularization to prevent overfitting. We used 5-fold cross-validation for robust evaluation of model performance and better utilization of data. For

Table 1: Prediction results of departure time

Model	MAE (h)	MAPE (%)
Baseline	0.3154	4.2785
Our Model	0.2336	3.1278

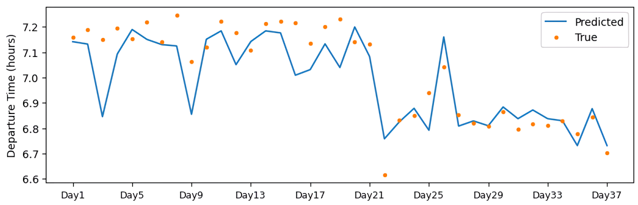

Figure 2: Predicted and true departure time by days

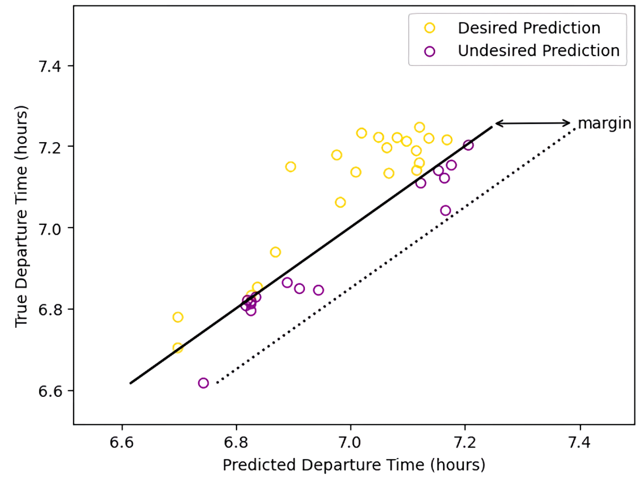

Figure 3: Margin estimation to eliminate undesired predictions

evaluation metrics, *Mean Absolute Error (MAE), Mean absolute Percentage Error (MAPE)* are used. We establish the baseline model as the average departure time of training set for each phase of evaluation. In addition, we also examine the prediction uncertainty of the model to estimate the margin that effectively removes undesired predictions prior to the algorithm optimization through charge/discharge degradation experiment.

Results: As shown in Table 1, the proposed model outperforms the baseline model, verifying that departure time inferred from the passive data is superior to simply averaging the values. The achieved MAE of 0.2336 in hours by our model implies that the departure time can be predicted with an average error of 15 minutes. Figure 2 depicts the best subject case (MAE = 0.0351) of predicted and actual departure times by days. It is evident that the predicted values are tracking the patterns of the actual values, indicating that departure time patterns can be learned from mobile passive data based on human behavior. Figure 3 depicts the desired and undesired prediction results by contrasting the amount of departure time deviation between predicted and actual values for the same subject. With a margin of 9 minutes (0.15 hours), the algorithm can guarantee driving range through effective intervention.

4 DISCUSSION AND FUTURE DIRECTIONS

In this paper, we introduced a novel approach for predicting departure time for DFC BMS algorithm. Departure time is predicted by training a personalized model using digital behavioral markers extracted from mobile passive data. We demonstrated the feasibility of our work and obtained promising results, with an average MAE of 0.2336 through a preliminary experiment utilizing the physical activity and smartphone activity data of 41 subjects. However, it is important to note that our initial work addresses a confined scenario of weekday daily commuting using a small dataset of subjects and limited smartphone sensors. We also used a simple machine learning model approach (CatBoost) to capture the personalized departure time prediction of each individual.

For future work, we will conduct a user study involving approximately 500 EV users over a span of two years to obtain robust and reliable results. To do this, we will first define a set of data sources that effectively represent behavioral context of pre-departure. The dataset includes diverse mobile passive sensors encompassing physical activity, smartphone activity, and social activity (e.g., call logs) as well as additional information such as personal characteristics (e.g., demographics), and environmental factors (e.g., meteorological data). We will quantify the pre-departure behavior and identify key features that advance or delay the departure time. Furthermore, various aspects of departure scenarios including travel as well as time series patterns (weekday and weekend) will be explored. Our ultimate objective is to enhance the accuracy of the departure time prediction model through the utilization of mobile passive data, thereby facilitating effective mitigation of battery degradation rate and maximizing the utilization of the EV driving range in conjunction with the DFC BMS algorithm.

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REFERENCES

[1] Peter M. Attia and et al. 2022. "Knees" in lithium-Ion battery aging trajectories. *Journal of The Electrochemical Society* 169, 6 (2022).
[2] Ron Biton, Gilad Katz, and Asaf Shabtai. 2015. Sensor-based approach for predicting departure time of smartphone users. In *2015 2nd ACM International Conference on Mobile Software Engineering and Systems*. IEEE.
[3] Andrew Bwambale, Charisma F. Choudhury, and Stephane Hess. 2019. Modelling departure time choice using mobile phone data. *Transportation Research Part A: Policy and Practice* 130 (2019), 424–439.
[4] Nathan Eagle and Alex (Sandy) Pentland. 2006. Reality Mining: Sensing Complex Social Systems. *Personal and Ubiquitous Computing* 10, 4 (2006), 255–268.
[5] Bloomberg New Energy Finance. 2022. Electric Vehicle Outlook 2022.
[6] G. Harper and et al. 2019. Recycling lithium-ion batteries from electric vehicles. *Nature* 575, 7782 (2019), 75.
[7] Peter Keil and et al. 2016. Calendar aging of lithium-ion batteries. *Journal of The Electrochemical Society* 163, 9 (2016).
[8] Y. Preger and et al. 2020. Degradation of commercial lithium-ion cells as a function of chemistry and cycling conditions. *Journal of The Electrochemical Society* 167, 12 (2020), 120532.

[9] Liudmila Prokhorenkova, Gleb Gusev, Alexey Vorobev, Anna Dorogush, and Andrey Gulin. 2018. CatBoost: Unbiased Boosting with Categorical Features. In *Advances in Neural Information Processing Systems 31*. 6638–6648.

[10] J. Song and et al. 2021. Pathways towards managing cost and degradation risk of fast charging cells with electrical and thermal controls. *Energy & Environmental Science* 14, 12 (2021), 6564–6573.

[11] John Torous, Jukka-Pekka Onnela, Matcheri Keshavan, Laura Calderone, Elizabeth Gregory, Emily Steinhart, Robin Friedman, Shalini Y Gipson, Daniel Fulford, Rebecca Kasper, et al. 2016. New tools for new research in psychiatry: a scalable and customizable platform to empower data-driven smartphone research. *JMIR mental health* 3, 2 (2016), e5165.