Chapter 1: Introduction

1.1 Introduction

Electric vehicles (EVs) are the key to future urban mobility and affordable power. However, controlling their charging behavior is still a practical problem of when do drivers keep driving their vehicles with very low battery levels? This behavior known as low-SOC driving (State-of-Charge < 20%) is likely to be due to underlying issues such as range anxiety, poor charging infrastructure, or variable usage patterns.

In this project we will perform a human-in-the-loop analysis of low-SOC EV behavior using the UrbanEV dataset. Specifically we will use a combination of descriptive statistics, visualization, and lightweight machine learning to understand temporal and behavioral trends, predict whether a post-low-SOC charging event will occur, and provide interpretable insights to guide future EV power management and user decision support systems. Ref. Zhao et al. (2022) "Low-SOC travel prediction accuracy is only 38.4% at best: an analysis of its irregularity." Applied Energy 313. Although this work provides descriptive statistics of low-SOC behavior, it is your project to extend their work by performing machine learning to discover actional patterns in low-SOC behavior.

1.2 Background of the Problem

EV adoption is high worldwide, but operational EV operation presents challenges. Low-SOC driving (drivers using vehicles to operate SOC < 20%) incurs risks, including battery damage, emergency charging and grid damage. Despite its impacts, empirical studies on low-SOC behavior are limited. Most existing literature focuses on:

1. Route optimization (e.g., minimizing energy consumption).
2. Charging station recommendations (e.g., location-based services).
3. Aggregate energy demand forecasting (e.g., city-level charging load prediction).

However, there is a lack of deep exploration of low-SOC driving behaviors, such as low-SOC driving frequency, timing, and post-low-SOC charging behaviors. Ref. (Zhao et al. 2022) reported that the accuracy of low-SOC behavior prediction models is only 38.4%, and more empirical studies are needed. In this project, we will explore to use real-world data to characterize low-SOC events and its implications. Through the integration of lightweight machine learning models (e.g., classification + SHAP interpretation), we aim to bridge descriptive analysis and predictive insights.

1.3 Statement of the Problem

Current EV charging behaviour models and policies for infrastructure assume a mainstream usage where low-SOC driving is not an edge case. Without proper analysis, the following questions become unknown:

- How often do low-SOC driving events take place?
- Are low-SOC events concentrated at certain times/pools of users?
- Do low-SOC events always lead to charging, or are there delays?
- How do factors such as public charging density and time of day affect low-SOC behaviour?

- Can we use machine learning models to forecast post-low-SOC charging behaviour and discover high-risk user groups?

Failing to account for these issues could result in poor infrastructure policies, user dissatisfaction and increased risk of battery degradation.

1.4 Research Questions

The study investigates the following questions:

1. When do low-SOC driving events occur? (i.e., temporal distribution at the hourly, daily, or weekly level).
2. What are the driving characteristics (e.g., energy consumption, distance travelled) of low-SOC and normal-SOC trips?
3. What is the probability of immediately charging after a low-SOC event and what factors influence this?
4. Can we use SHAP-based interpretability analysis to explain which of the key features contribute to machine learning predictions?
5. How are geographical and environmental factors (e.g., charging station density, urban versus rural) correlated with low-SOC behaviour?

1.5 Objectives of the Research

This research aims to:

1. Define and separate low-SOC driving events (SOC < 20%) from the UrbanEV dataset.
2. Study the temporal distribution (hourly, daily, weekly) of low-SOC events.
3. Study the energy consumption, distance, and charging behavior of low-SOC and normal-SOC trips.
4. Predict post-low-SOC charging behavior using lightweight machine learning algorithms (e.g., XGBoost).
5. Interpret model decision making using SHAP values to explore the characteristics of low-SOC behavior.
6. Discover high-risk user clusters and visualize the spatial–temporal pattern to support policy and infrastructure design.

1.6 Scope of the Study

The study is confined to:

1. Data: Analysis of UrbanEV dataset. It is a six-month public dataset including data of thousands of EVs.

2. Analytical Methods:

    - Methods: Descriptive statistics (e.g., histograms, boxplots, heatmaps).

    - Machine learning techniques:

        - Classification models (e.g., XGBoost) for predicting post-low-SOC charging behaviors.
        - SHAP based interpretability analysis on models.
3. Temporal patterns and behavioral analysis of low-SOC driving, lightweight predictive modeling

4. No extra data (e.g., weather, POI) are added on top of UrbanEV public dataset.

1.7 Significance of the Study

This research contributes to:

1. Background information:
    - Descriptive analysis of an exploratory phenomenon: low-SOC EVs. A poorly understood class of observations.
    - Innovation in methodology: descriptive analysis combined with interpretable machine learning.
2. Practical Implications:
    - Infrastructure providers can learn where to place more charging stations (e.g., high-density areas with frequent low-SOC delays).
    - The dynamic user alert service can learn (e.g., low-SOC alert with charging suggestions).
3. Policy Impact:
    - Energy policy makers can learn how to mitigate low battery degradation risks and balance the grid demand.
    - Input evidence for future research on predictive models and behavior-based EV management systems.

1.8 References

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