Simultaneous Scheduling of Electric Vehicle Charging and Daily Activities

Senlei Wang[a*], Janody Pougala[b], Tim Hillel[a]

[a] UCL Behaviour and Infrastructure Group, London, UK
senlei.wang@ucl.ac.uk, tim.hillel@ucl.ac.uk
[b] EPFL, Lausanne, Switzerland
janody.pougala@epfl.ch
* Corresponding author

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 29, 2024

Keywords: Electric vehicles, charging demand, activity-based modelling, optimization

1 INTRODUCTION

Wider adoption of Electric Vehicles (EV) promises major benefits in terms of reductions in CO2 and air pollution. However, access to charging infrastructure presents a major barrier to mass adoption and continued use of EVs. Wealthy residents of single-family homes with access to at-home charging are over-represented among early EV adopters. Meanwhile, lower-income households and residents of apartment buildings or multi-unit dwellings are less likely to have access to home charging. Public charging infrastructure at service stations, workplaces and other public places (e.g., shopping malls and grocery stores), which allows people to charge their vehicles away from home, is therefore crucial to support wider EV adoption. The spatial and temporal variations in demand for this charging infrastructure are, therefore, heavily dependent on the scheduling of daily activities.

Charging scheduling has attracted much attention in the literature as it helps to effectively manage limited charging infrastructure and power grid capacity, thereby relieving EV users' charging anxiety. There have been several works focusing on the optimization of charging infrastructure delivery, assuming exogenous vehicle demand (Mukherjee & Gupta, 2015; Pasha et al., 2024). Some studies focus on maximizing the grid-side benefits, such as minimizing the grid operation cost and balancing the load in the power distribution (Dean et al., 2023; He et al., 2012). Other works have prioritized user benefits, aiming to minimize charging costs and waiting times whilst maximizing the average state of charge (SOC) (An et al., 2023; Yin et al., 2021). More recent studies incorporate environmental considerations into EV charging scheduling, designing a framework to maximize the use of renewable energy or minimize greenhouse gas emissions (Babaei et al., 2024; Yang et al., 2024). However, these studies tend to make oversimplified assumptions about individual behavior that can result in suboptimal solutions.

Rather than focusing on network optimization, some studies have analyzed individual consumer preferences for charging patterns, including details on charging times, public charging locations, and charger types (Fang et al., 2020; Hardman et al., 2018; Visaria et al., 2022). These studies typically use stated choice experiments to elicit the charging preferences of existing and potential EV owners. However, these studies treat the demand for vehicle charging as direct, therefore omitting the inherent link with daily scheduling behavior.

This study aims to fill the gaps by incorporating EV charging into activity scheduling to capture the inherent links and tradeoffs between charging and activity scheduling. This study contributes to the literature on modeling EV charging behavior in two ways. Firstly, we propose and develop a framework for simultaneous scheduling of charging and daily activities. The activity scheduling choices include activity types, starting time and duration, and location. The charging scheduling choices are charging location, charging starting time and duration, and charging mode. This approach is able to capture the trade-offs between charging and non-charging activities. Secondly, this study models charging behaviors at various locations to capture charging demand evolution. Charging mode is jointly considered in scenarios including home charging, work charging, and other public charging (e.g., at shopping malls) at a service station. Moreover, different types of charging modes (i.e., slow, fast, and rapid charging) are considered, and charging behaviors for different charging modes are modeled.

2 Methodology

Scheduling of daily activities is a complex process that combines multiple choices. The OASIS, which is an optimization-based activity scheduling framework, is able to simulate activity schedules by considering all choice dimensions simultaneously (Pougala et al., 2023). The modeling framework is characterized by its ability to schedule multiple choices, including activity types, start times, durations, modes, and locations (Pougala et al., 2022). It represents continuous time and explicitly models behaviors that influence decision-making, such as preferences and flexibility. The framework captures trade-offs in timing, locations, and modes of engaging in activities and incorporates a range of possible activities as opposed to a predefined set. Building on top of the OASIS framework, new components have been developed to model EV charging.

The behavioral principle is that individuals schedule their day to maximize the overall utility derived from the activities they complete. We define it as the sum of a utility U_f in Equation (1) associated with the whole schedule and utility components capturing the activity-travel-charging behavior:

$$U_f = U + \sum_{a=0}^{A}(U_a^{parti} + U_a^{activi\ start} + U_a^{activi\ duration} + U_a^{charging} + \sum_{b=0}^{A-1} U_{(a,b)}^{travel}) \tag{1}$$

Where:

- U is a generic utility that captures aspects that are not related to any activities.
- U_a^{parti} captures the utility of participating in different activities.
- $U_{a_n}^{activi\ start}$ captures the perceived penalty created by deviations from the preferred activity starting time.
- $U_{a_n}^{activi\ duration}$ captures the perceived penalty created by deviations from the preferred activity duration time.
- $U_{(a,b)}^{travel}$ captures the perceived penalty associated with travel between locations.
- The charging utility $U_a^{charging}$ captures the perceived penalty associated with charging decisions.

Charging-related decisions include their battery's SOC, charging location, charging mode, charging starting time and duration. The charging utility captures the perceived penalty associated with low battery SOC levels, charging or not charging at activities (e.g., at home, work, shopping) or at public service stations, and charging duration for different charging modes.

We derive the objective function from Equation 1. The choice of activity and charging schedule is explicitly modeled as a mixed integer optimization problem. The mixed integer optimization problem is formulated and solved using CPLEX mathematical programming modeling for Python.

3 Results and Discussion

We model the charging of an individual worker, Claire, from the Swiss Mobility and Transport Micro census which was used in the original model by Pougala et al. (2022). Without access to home charging, she relies on non-home charging infrastructure and has the option to choose from various locations, such as work and other public places (e.g., shopping malls) and service stations, while considering different charging modes (slow, fast, or rapid chargers). We use a simulation approach with each of the 50 model runs, representing a different day (See Figure 1). This simulates Claire's charging and activity behaviors over this period, capturing variability in behavior and charging patterns, which is crucial for understanding the dynamics in making charging decisions based on the model outcome.

Figure 2 illustrates the relationship between activity participation and charging scheduling at locations. How often charging happens in conjunction with different activities is revealed and could be useful for planning the charging infrastructure. It indicates the need for charging infrastructure at the places where there is a high rate of charging occurrences. Furthermore, the EV user's preferences for charging speed are based on charging locations. For example, as shown in Figure 3, there is a tendency to charge faster when away from home. The charging behavior could inform where to invest in faster-charging technologies and identify locations where slower charging options are insufficient.

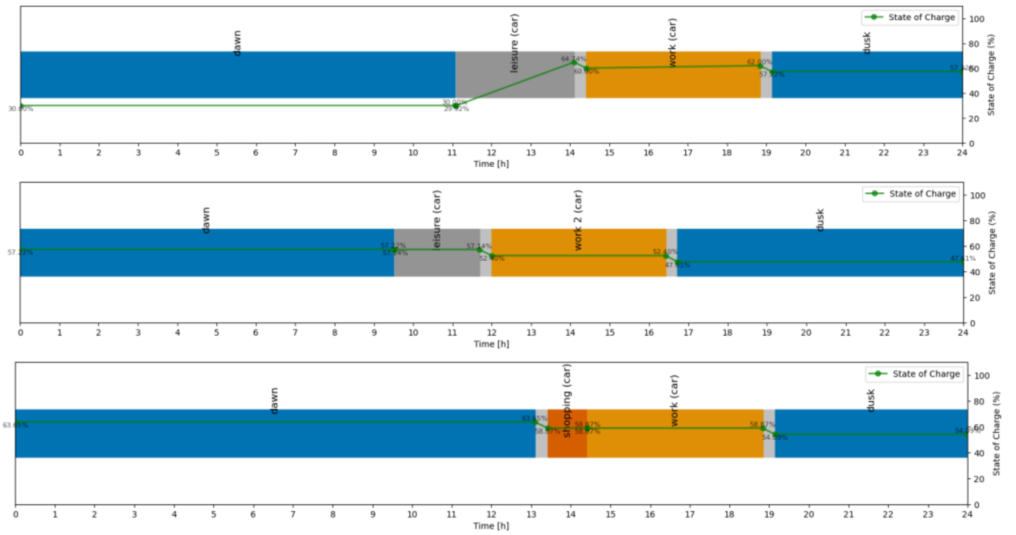

Figure 1- An example of SOC changes during travel and recharges at an activity location for three consecutive weekdays

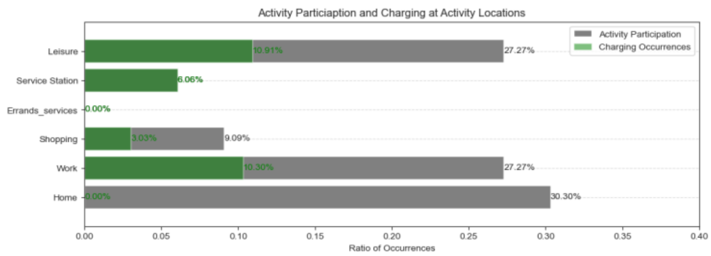

Figure 2- Charging location decisions during the 50 weekdays

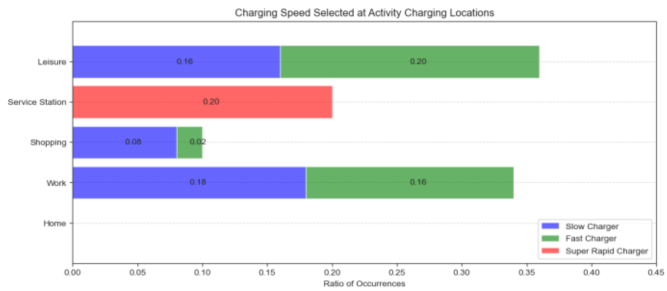

Figure 3- Charging mode decisions during the 50 weekdays

4 Conclusions

Having such a model allows us to realistically understand charging and travel behaviors with a high level of temporal and spatial resolution. It also enables the evaluation of the effects of alternative management strategies (e.g., Time-of-Use tariff, infrastructure build-out) on individual charging and travel behavior. A better understanding of EV drivers' charging behavior, including charging locations and mode choices, will inform guidance for EV use, charging infrastructure planning, and power grid capacity management and upgrades. EV charging data is currently scarce, as the charging market is still emerging and small—particularly concerning fast and super-rapid charging. This study introduces a new activity-based framework to estimate charging behavior. One limitation, however, is the lack of behavioral data for the calibration of the assumed model parameters.

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