DecarboN8

Place-based decarbonisation for transport

Understanding electric vehicle charging behaviours

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Decarbon8: Report on the project "Understanding EV charging behaviors"

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Executive Summary

The UK Government has announced its intention to ban the sales of internal combustion cars and vans from 2035. Ofgem's Decarbonisation Action Plan states that GB electricity network operators should have a network that can power 10 million electric vehicles by 2030. It is widely recognized and acknowledged that stress on current electricity networks can be alleviated with smart technologies, which enable smart demand management using advanced predictive analytics, such as accurate forecasting algorithms, and prescriptive analytics, such as advanced load balancing and optimization algorithms.

To successfully utilize analytical models for charging electric vehicles at scale it is essential for these models to inherently capture vehicle users' interaction with charging infrastructure, both personal and public. Hence the need for understanding charging behaviors and the factors that influence these behaviors. The aim of this project is to utilize public and home charging data to develop a finer understanding of charging behaviours and influencing factors, and explore algorithmic frameworks that embed these behaviors in realizing large scale smart charging solutions.

Analysis of charging data from 18 public charging stations in Durham revealed that there is a strong connection between usage of charge points and other nearby amenities such as shops, schools, restaurants etc. This shows that placement of charge points has significant consequences for future urban planning.

A simulation study, embedding advanced forecasts of electric vehicle power demand, on distribution transformers' impact in a scenario with partial control of home charging shows that a minimum of 60% of users need to be controlled charged to remain within transformer capacity and avoid overloading blackouts.

Clustering analysis of home charging data from Electric Nation project trial 1 shows that, without price interference, vehicles are charged mainly starting from evening to overnight. However, intermittency in charging behavior also makes sizeable proportion of charging data. Similar observations could be made using choice analysis.

Accommodating the behavioral aspects in online scheduling of vehicle charging is necessary for efficient charging at scale. Preliminary experiments with a new approach to embed clustering analysis within online scheduling framework shows more power demand could be satisfied with same amount of resources.

With ongoing COVID pandemic the nature of work and people mobility is bound to change and exhibit a more dynamic yet volatile nature in future. Given this, a sustainable transition to electric vehicles, much needed to tackle climate crisis, requires a substantial amount of research in analytics technologies. For sustainable vehicle charging at scale charging behaviors should be dynamically embedded within optimization models.

1 Analyzing public charging: lessons from Durham charging data

Understanding charging behavior at public charging stations is of paramount importance to effectively manage the EV charging demand and to facilitate the transition to EVs. With charging data becoming available at scale with improved EV adoption empirical research in this direction is also increasing, see [Helmus et al., 2020, Wolbertus et al., 2018]. Many techniques have been employed to analyze charging data to find models that could explain the charging behaviours at public charge points. A tempting idea is to use choice modeling approaches to explain charge point choices made by EV users. Such approaches are often combined with other objectives such route or activity scheduling, see [Luo et al., 2017, Daina et al., 2017]. Modeling charge points as choices implicitly assumes EV users are goal driven and visit charge points mainly to charge their vehicles. However, there is enough evidence in literature that public charge point utilization can be very low. There are two possible reasons 1) poorly placed charge point 2) charge point hogging. Of course, in many cases, they both contribute equally for ineffective charge point utilization. Moreover, the way EV users interact with charging facilities may vary from city to city. We analyze the charging data from public charge points in Durham.

Abstract of Findings

Using plug-in data from 19 public charging stations and amenities in Durham, clustering, coupled with quantile regression analysis was used. Instead of focusing on the conditional average, we explain the effects of various factors, including availability of other amenities, on the entire distribution of the plug-in duration. Results show that both demand for charging and other amenities surrounding the charging station play an important role. More specifically, these effects are different at different quantiles of plug-in distribution.

2 Analyzing home EV charging

Charging at home is found to be the most preferred for most EV drivers, there is considerable emerging evidence for this, see [Lee et al., 2020]. This implies most charging needs may need to be satisfied at home. Moreover, with COVID/pandemics new work cultures are emerging at fast pace with a large workforce based out of their homes. This implies charging behaviors at home need to be well understood to enable a sustainable transition to electric vehicles. We first present findings of a simulation study that analyzes impact of different type of level of controls on distribution transformers by using forecasts in a mixed proportion vehicle ownership setting (Section 2.1). In Section 2.2, we present findings from cluster analysis of home EV charging and in Section 2.3 we give evidence from preliminary findings of gains that can be achieved by embedding behavioral aspects in prescriptive models.

2.1 Impact Evaluation on Distribution Transformers

Smart or controlled charging of EVs is widely argued as a solution to offset the impact of EV penetration on both transmission and distribution networks. However, to what extent a centralized controlled charging is viable is an open question. In fact, different types of control can be considered; for example, from an EV user's point of view, a complete control on charging may not be acceptable, while some degree of freedom in EV charging even during peak hours, although costly, may be more preferable. Such a control policy will have massive revenue and power generation ramifications. On the other hand, from a purely distribution-capacity point of view, a control policy that restricts the numbers of users to charge during peak hours is of greater benefit. We dub these two policies as consumption and user control policies and study the impacts on a specimen distribution transformer by utilizing the advanced forecasts from our previous work ([Roy et al., 2021]).

2.1.1 Findings

In our simulation study, we found that user control is a more effective approach than consumption control to limit the additional bulk load caused by EV charging during peak hours as increasing the level of control decreases the bulk load only in case of user control. In fact, if the level of control is increased beyond 60%, then the total connected load remains within the feeder capacity. On the contrary, consumption control is found to be more effective if the DNOs wish to limit the charging duration of EVs within the peak-hours window. For low to mid-ranged battery capacity EVs, any level of control beyond 40% contains the charging duration within the peak-hours window, while for higher-ranged battery capacity EVs, charging duration gradually falls within the desired limits beyond 60% level of control. The number of EVs in each cluster are different and are chosen proportionately to that in EV nation trial [Roy et al., 2021]. We find that the total connected load on feeders with a mixed distribution of EVs from different clusters remains significantly less than the load on feeders with EVs from purely low or mid-ranged clusters, indicating that networks with EVs having low to mid-ranged battery capacities would generate higher additional load due to EV charging and hence, DNOs should lay more emphasis on such networks than on similarly structured networks with EVs having relatively high-ranged battery capacities if limiting the bulk load is of prime concern. However, if limiting the EV charging duration is the major concern, then focus should be on feeders with EVs having high-ranged battery capacities than on feeders with EVs having low to mid-ranged battery capacities. In a real-world scenario, DNOs might need to restrict not only the additional bulk load due to EV charging but also the charging duration itself, suggesting that a mixed strategy involving both consumption and user controls at a suitable level of control would be desirable under such circumstances.

For more details of forecasting methodologies employed and simulation set-up, see [Roy et al., 2021]. A preliminary version of the work is accepted as an abstract in ACM E-Energy 2021 conference.

2.2 Understanding home EV plug-in behaviors

Charging choices, at home, differ from charging choices of EV users at public charging facilities. The main difference being in case of public charging decisions are taken at an hourly scale. Instead, home charging choices usually are longer in charging session length and EV users are more likely to plan them on day scale with fewer sessions that last at least a few hours. We used the daily plug-in data from Electric Nation Trial1 to understand how EV users plug-in behaviors.

2.2.1 Methodology

- Daily plug-in data is encoded as a number of charging sessions each characterized by start times and duration.
- We used hierarchical clustering to identify daily plug-in patterns.

2.2.2 Findings

Clustering analysis shows that there are predominantly three types of charging behaviors:

- *Long Duration Overnight.* The events in this cluster, largest among all clusters, correspond to charging decisions that start late afternoon to late evening with duration ranging between 9 to 15 hours.

- *Highly Intermittent.* The events in this group spread roughly a third of the daily charging during the day splitting into 2-3 short duration charge sessions covering morning, afternoon and evening times. The rest of two-thirds of daily charging happens in a long overnight charge session lasting on average around 10 hours.

- *Short Morning Long Evening.* The events in this cluster have short (between 1 to 3 hours) during morning to mid- morning charging, followed by long charging sessions lasting between 9 to 15 hours which start late in evening to midnight.

Figures (1-3) and (4-6) show session-wise histograms of plug-in start time and duration, respectively, for all three clusters. Among these behaviors, the observed data shows that first type, that is, long duration overnight, is most prevalent. However, contrary to popular belief in the existing studies EV users do not plug-in everyday. In fact, the data shows that less than half of participants plugged-in on most days during the trial.

2.3 Online EV charging scheduling

Efficient algorithms need to be designed in order to achieve real-time adaptive charging to charge EVs at scale in a cost effective manner. Online scheduling algorithms aim to schedule EVs to charge on-the-fly without the information of future plug-in. A number of algorithms have been proposed for workplace and public charge station online charge scheduling, see [Nakahira et al., 2017]. However, the charging behaviors at home are considerably different from that compared to public charge points.

Algorithmic Idea

Building on the clustering analysis of home charging data, we study novel way to combine predictive and prescriptive models. More specifically, we propose an algorithm which takes into account the observed charging behavior, which is encoded as probabilities of charging according to a pattern characterized by a cluster. Our algorithm after observing a user's plug-in behaviour for a predefined amount of time (plug-in behavior in initial time slots of the day), schedules users by taking residual demand of users and threshold capacities in each time slots into account.

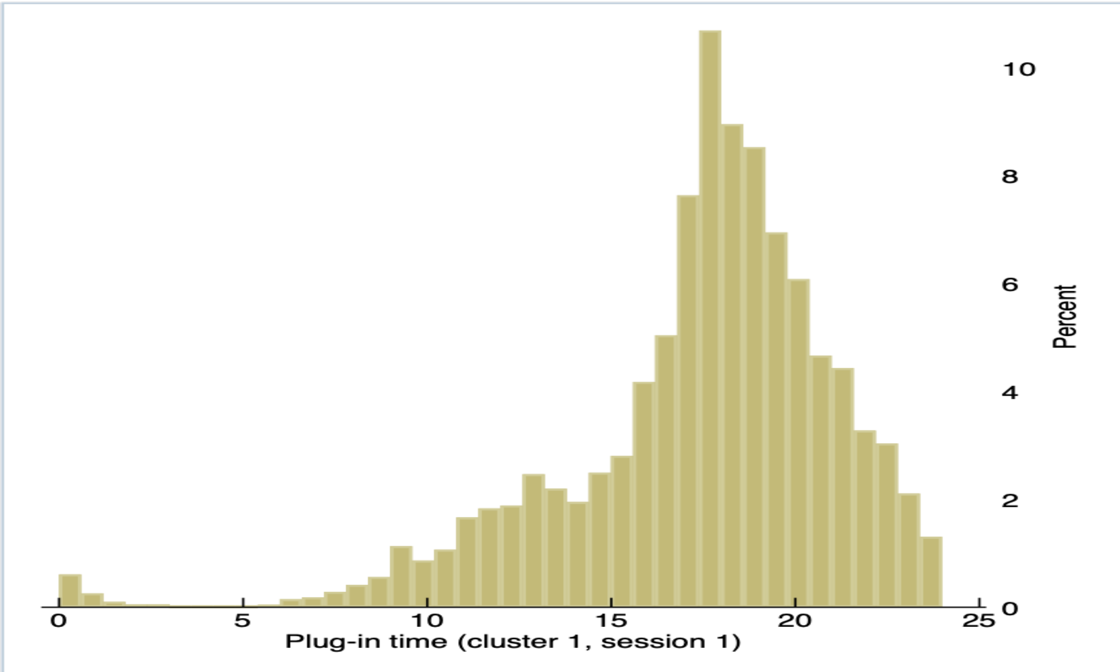
Findings

Below we present some preliminary findings of comparison of proposed *learning based online heuristic* with *demand driven online greedy heuristic.* Experimental set-up is as follows:

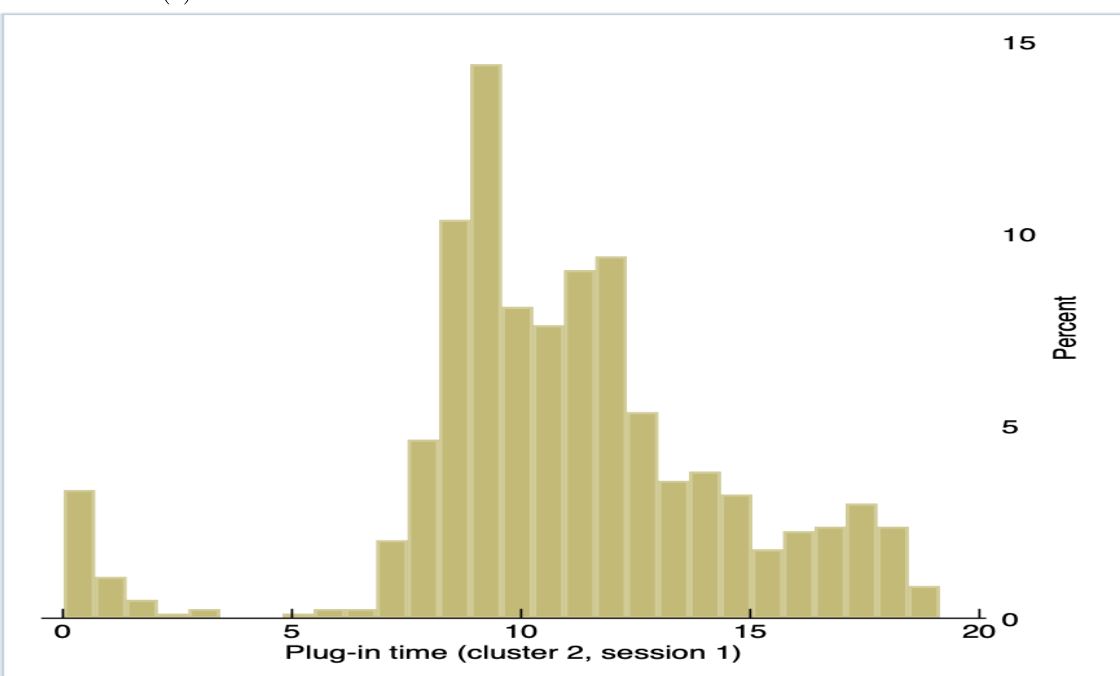
- 10 user profiles have been generated where user profile defines demand for each user(two scenarios: 50 and 75 users), and probability that user will charge according to a cluster (which is taken as same for all users in preliminary experiments). Demands (kWh) were randomly sampled from observed consumption in Trial 1 of EV Nation project. Similarly, cluster choice probabilities are estimated from data.

- cluster profiles are generated which define for each charging slot in a day (24, 48 or 96): threshold capacity (available kWh). Each cluster is encoded as a binary vector (of size 24, 48, or 96), where a 1 corresponding to a slot indicates that users in this cluster will plug in this slot.

- For every combination of user and cluster profiles plug-in behavior for 1 day is simulated. To accommodate the variability within a cluster while simulating plug-in behavior randomness was introduced

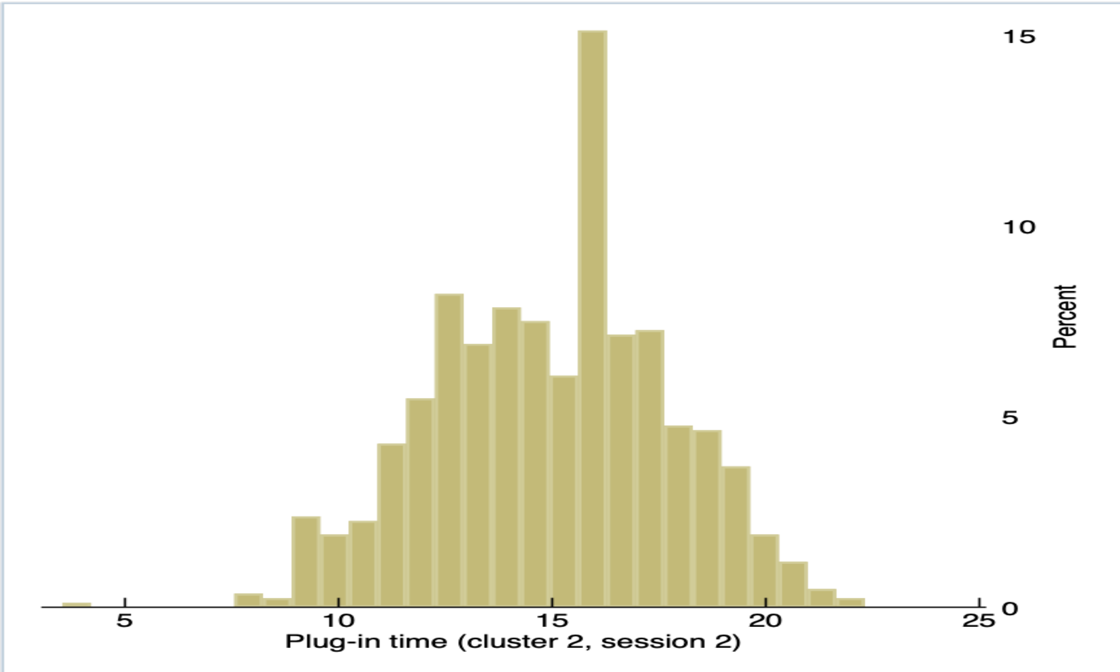


(a) Cluster 1 session 1

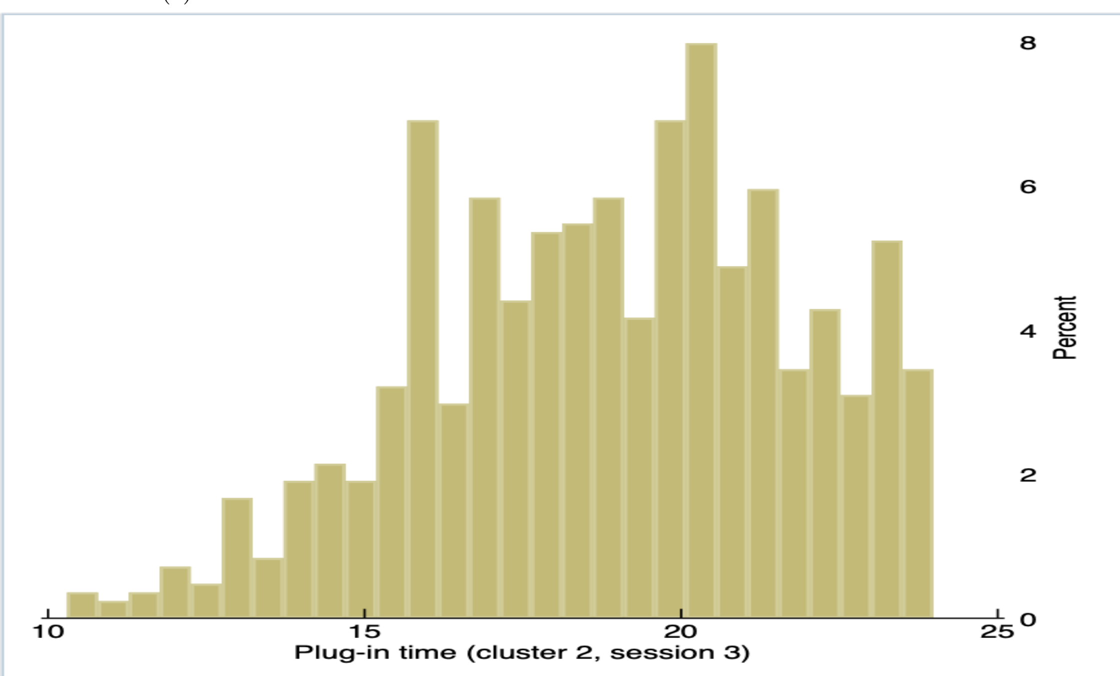


(b) Cluster 2 session 1

Figure 1: Clusters - start time distributions

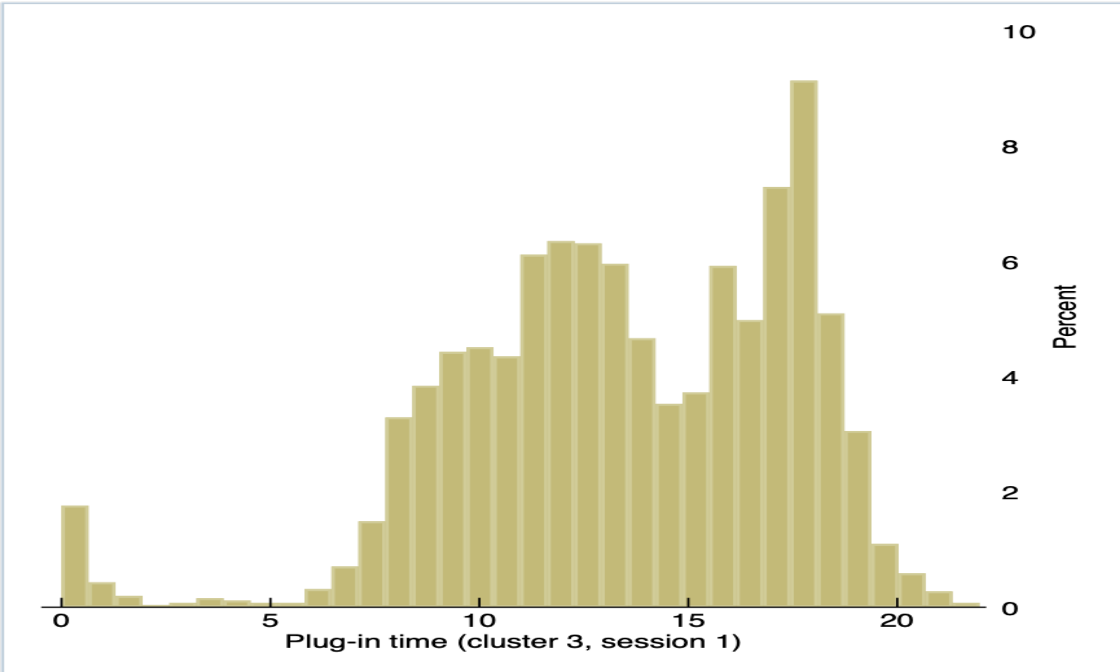


(a) Cluster 2 session 2

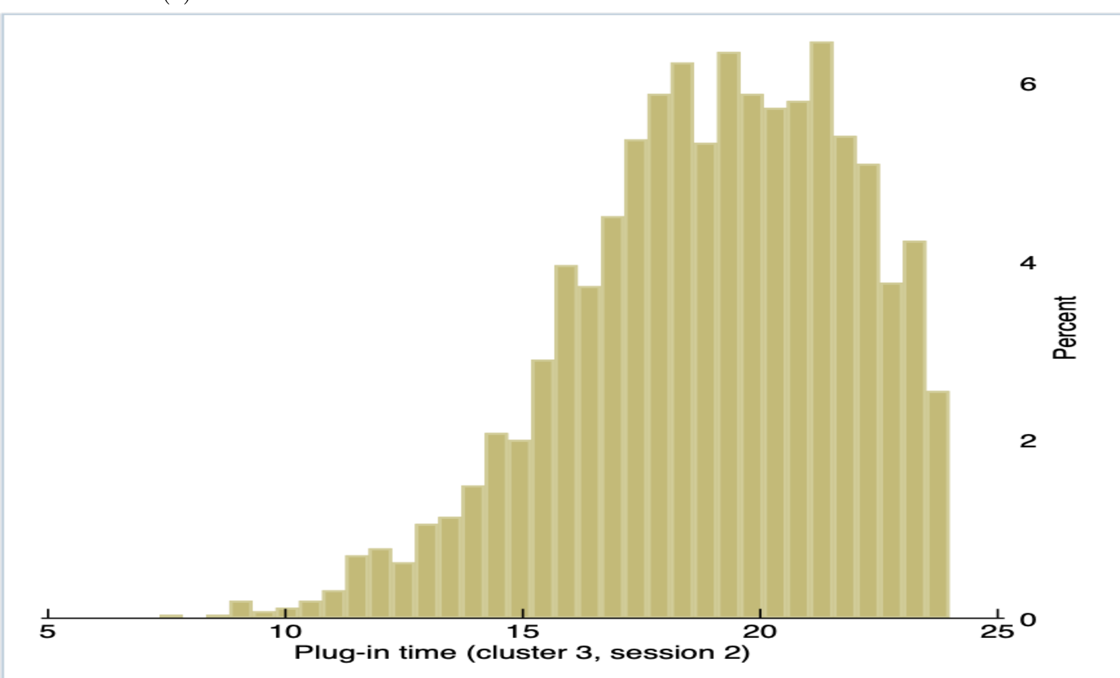


(b) Cluster 2 session 3

Figure 2: Clusters - start time distributions

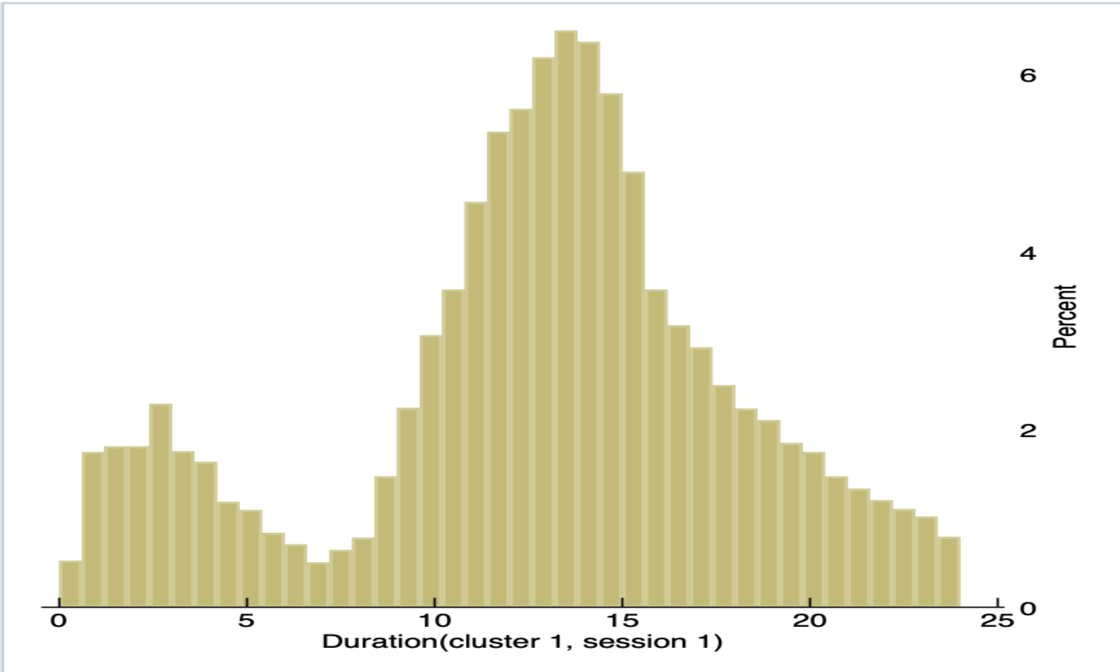


(a) Cluster 3 session 1

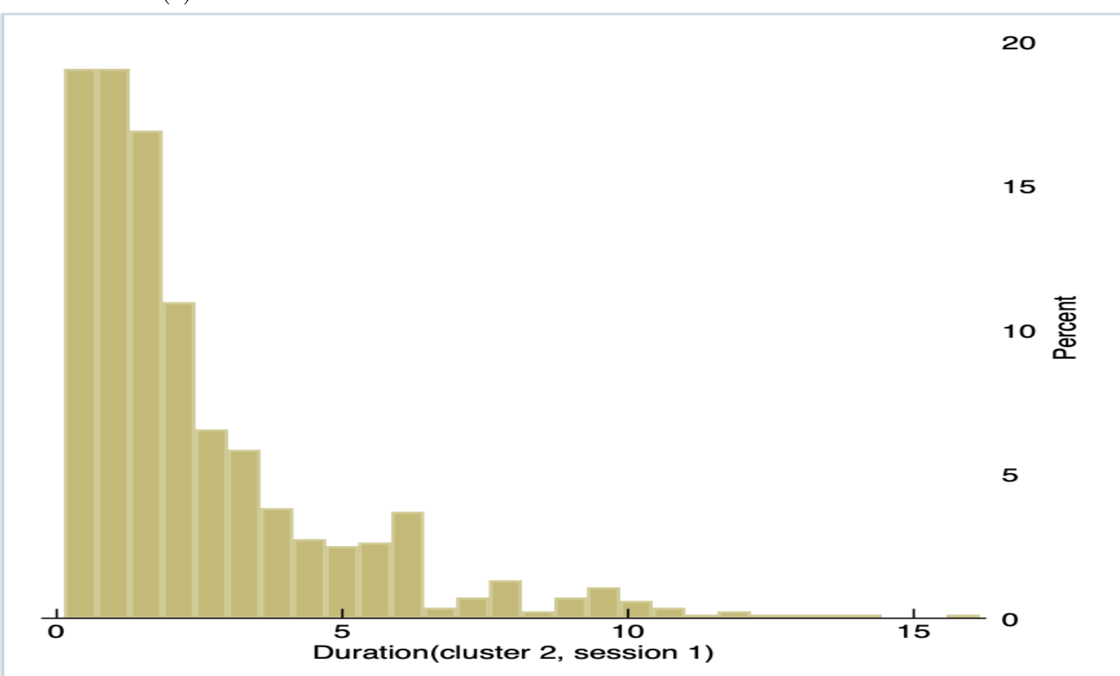


(b) Cluster 3 session 2

Figure 3: Clusters - start time distributions

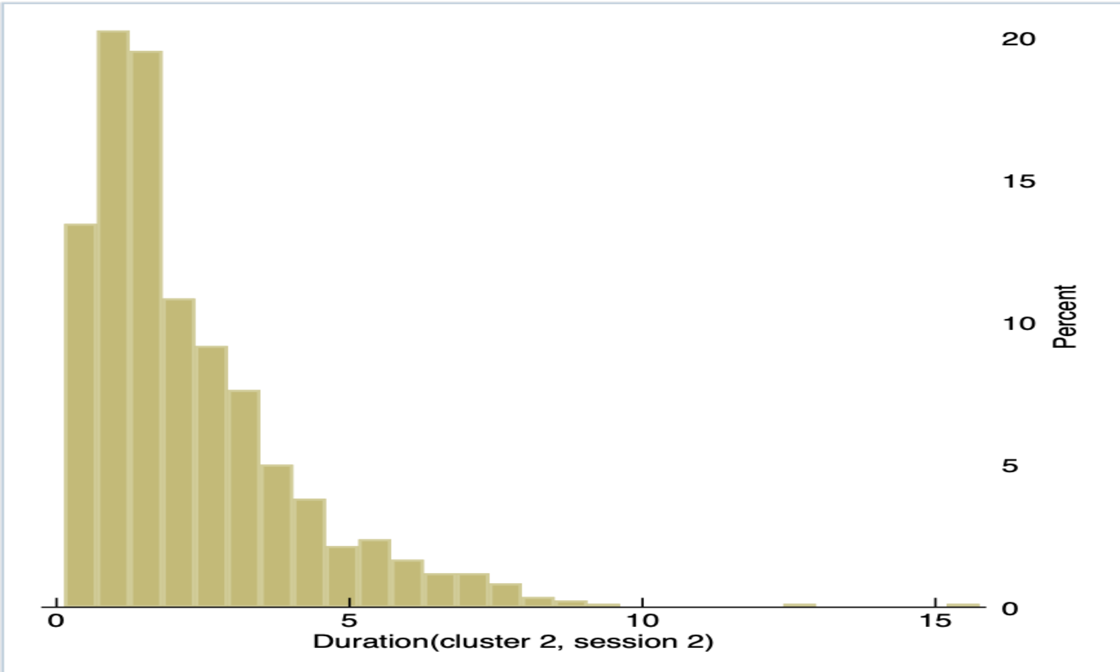


(a) Cluster 1 session 1

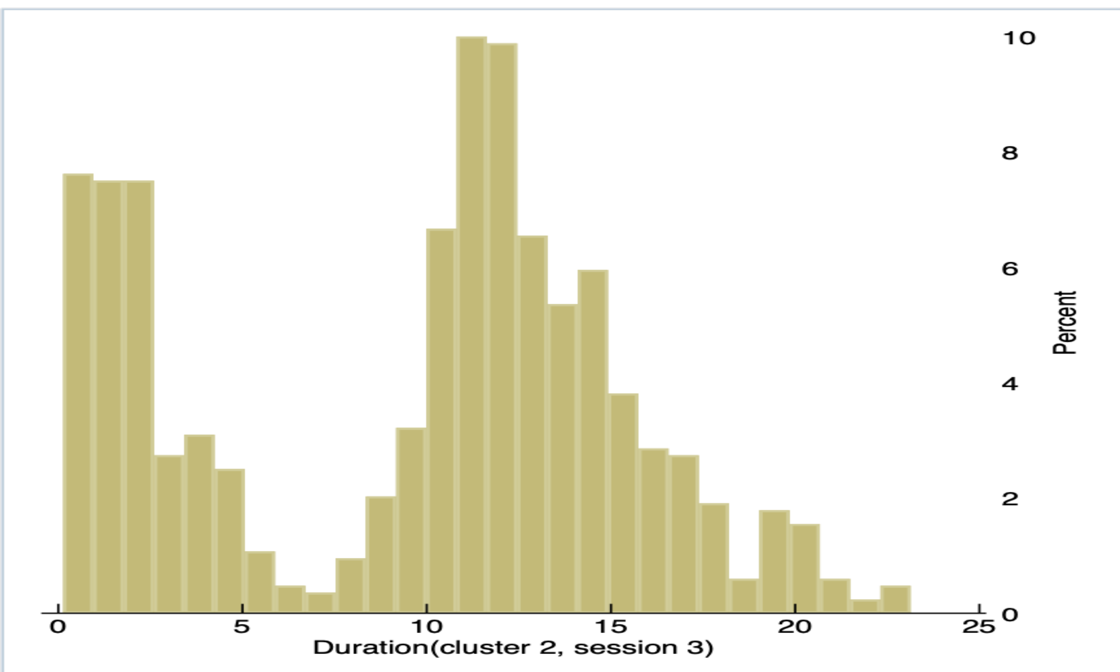


(b) Cluster 2 session 1

Figure 4: Clusters - duration distributions

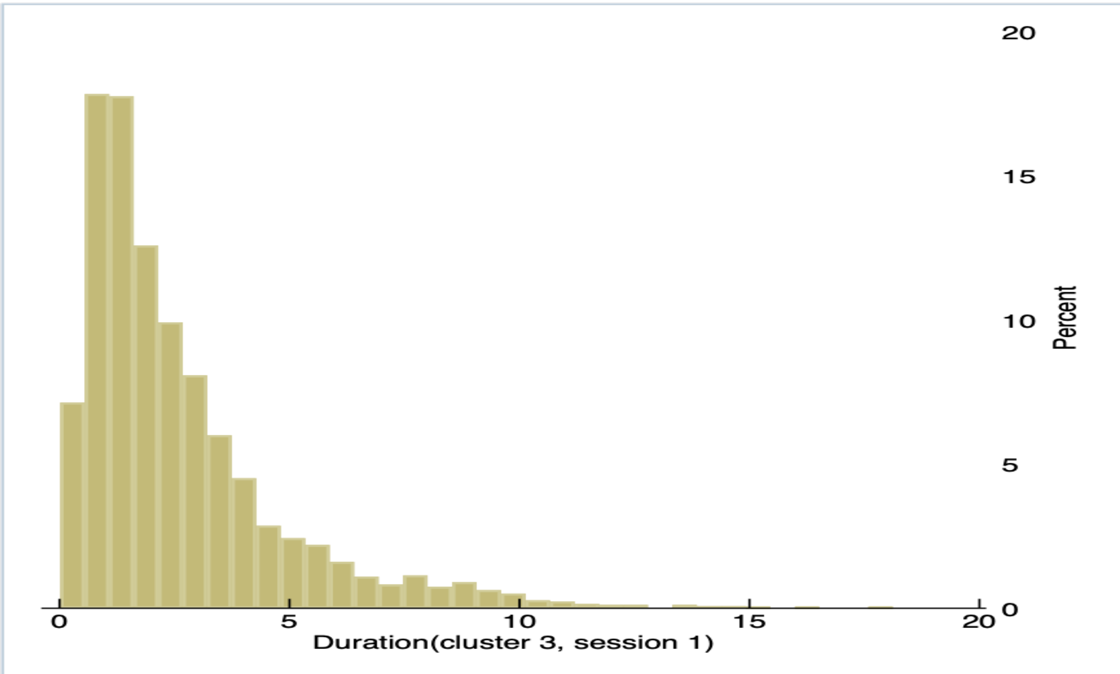


(a) Cluster 2 session 2

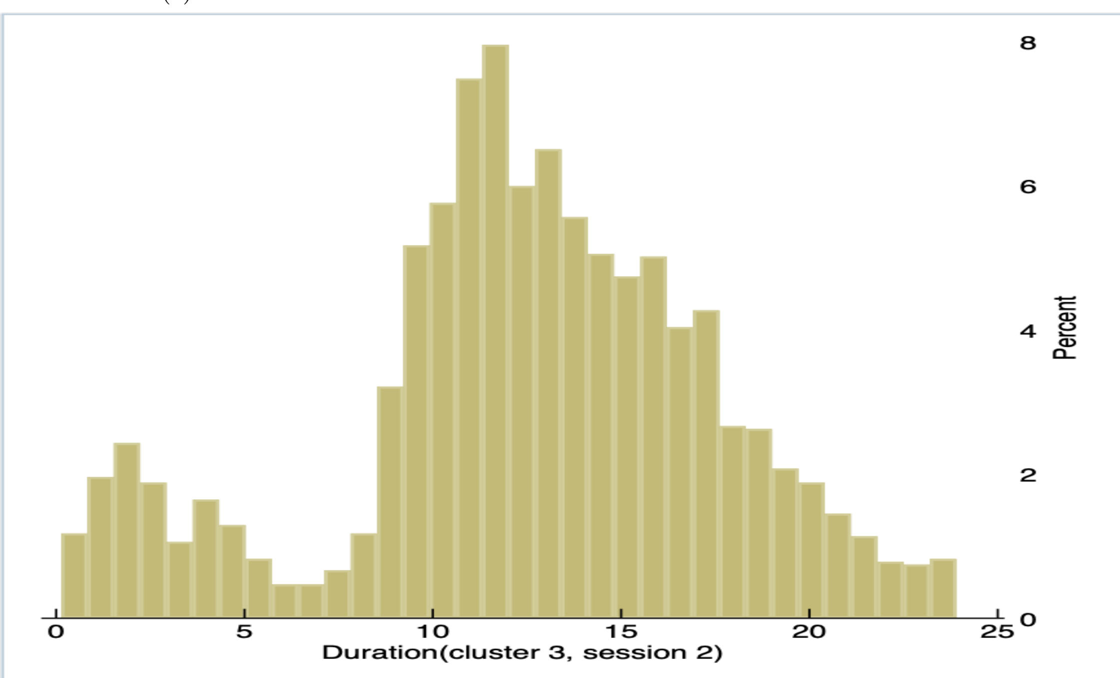


(b) Cluster 2 session 3

Figure 5: Clusters - duration distributions



(a) Cluster 3 session 1



(b) Cluster 3 session 2

Figure 6: Clusters - duration distributions

within simulation. We characterize this with cluster efficiency parameter where *high* implies a plug-in behavior closer to identified clusters. Greedy and learning based heuristics are applied to schedule EVs for charging. Since it is online optimization all charging demand may not be satisfied, hence we compare the average unsatisfied demand over all days and over all users.

- Two cluster capacity scenarios are constructed by employing a scaling factor to assess the impact of capacity on algorithm performance.
- Learning based heuristic is characterized by length of the learning phase, l and h in the below tables.

	cluster efficiency		
	low	medium	high
low-capacity			
l	10(1)	10	10
h	10	10(1)	10(1)
high-capacity			
l	8(2)	10(2)	9(2)
h	10(1)	10(4)	8(1)

Table 1: number of cases out of 10 where learning based online heuristic matched or improved performance over demand-driven greedy heuristic for 50 users, 96 (15min intervals) time slots; numbers in brackets are strict improvements

	cluster efficiency		
	low	medium	high
low-capacity			
l	10(1)	10	10
h	10	10(1)	10(1)
high-capacity			
l	7(4)	8(5)	9(2)
h	9(1)	8(1)	10(1)

Table 2: number of cases out of 10 where learning based online heuristic matched or improved performance over demand-driven greedy heuristic for 75 users, 96 (15min intervals) time slots; numbers in brackets are strict improvements

Tables 1-2 show that learning based heuristic matches or outperforms the greedy heuristic, especially, with more EV users. Moreover, low learning phase is enough compared with more cases where the proposed approach outperforms.

Extensive simulations to test the effectiveness of our algorithms under various scenarios and a rigorous validation is still work in progress. Given that greedy heuristic does not take capacity in to account, its performance is impressive. While learning based heuristic improves over greedy but in few cases it does not yield a better outcome, this can be ascertained to clustering inefficiency.

Research outputs in preparation

1. Findings from Section 1 are in prepartion for submission to a journal [Dokka et al., 2022].

2. Findings from Sections 2.2 and 2.3 are in preparation as: Dokka, T. and Anwar, S. and Yarahmadi, A. (2021).Data driven online scheduling of EV home charging. In preparation.

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