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Author(s)
Vermeulen, I; Helmus, JR; Lees, M; van den Hoed, R

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Simulation of Future Electric Vehicle Charging behavior

- Effects of transition from PHEV to FEV -

I Vermeulen[2] JR Helmus[1] * M Lees [2] R van den Hoed[1]

1) University of Applied Science Amsterdam, Weesperzijde 190 1097 DZ Amsterdam,

2) University of Amsterdam, Science Park 904 1098XH Amsterdam, uva.computationalscience.nl

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ABSTRACT: The Netherlands is a frontrunner in the field of public charging infrastructure, having a high number of public charging stations per electric vehicle (EV) in the world. During the early years of adoption (2012-2015) a large percentage of the EV fleet were Plugin Hybrid Electric Vehicles (PHEV)due to the subsidy scheme at that time. With an increasing number of Full Electric Vehicles (FEVs) on the market and a current subsidy scheme for FEV only, a transition of the EV fleet from PHEV to FEV is expected. This is hypothesized to have effect on charging behavior of the complete fleet, reason to understand better how PHEVs and FEVs differ in charging behavior and how this impacts charging infrastructure usage. In this paper, the effects of the transition of PHEV to FEV is simulated by extending an existing Agent Based Model. Results show important effects of this transition on charging infrastructure performance.

Corresponding author: J.R.Helmus@hva.nl +31 6 2115 60 41

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1. INTRODUCTION

The Netherlands is known to be one of the frontrunners in EV adoption and public charging infrastructure rollout (1, 2). During early years of EV adoption (2012-2015), both PHEVs and FEVs were subsidized, leading to large uptake of EVs by mostly lease drivers (1–4). Due to the limited supply of EV models and almost equal tax advantage at that time, most uptake was due to PHEVs and only limited uptake was due to FEVs (such as Tesla and Nissan Leaf) (5–7). In the year 2018 it is expected that many car manufacturers will launch FEVs on the European market. This, combined with the ending of many lease contracts, Charging Point Operators (CPOs) and policy makers expect a transition of the Dutch EV fleet from PHEV to FEV in the near future. This is suppored by EV sales trends in the Netherlands which shows that the last year more than 90% of EV sales have been FEVs.

This leads to the question of whether the current public charging infrastructure is capable of accommodating the new composition of the EV fleet. To answer this question a simulation model that incorporates the differences in charging behavior between small and large battery sized vehicles is required (8, 9), thereby representing PHEVs and FEVs respectively.

Many simulation models exist today on the topic of EV(9–16). However, to the best of our knowledge, those models are generally not validated or only validated using small amounts of data (9, 17–19). Furthermore, these models do not incorporate differences in charging behavior related to battery size.

Therefore, in this research we examine the effects of the transition of EV users from PHEV to FEV on charging behavior using real world data (20). From this analysis a behavior transition equation is developed to transform any PHEV user type to an equivilent FEV user. Simulations with different FEV transitions were performed in an Agent Based Model (ABM) that includes real world charging data. From this conclusions regarding the effects of charging infrastructure performance were drawn (6, 21, 22).

2. LITERATURE OVERVIEW

Research on the influence of battery size on the charging behavior of EV users is still scarce. Zoepf et al. (23) conducted research concerning PHEVs with some aspects of fuel consumption versus

battery use for varying battery sizes. They concluded that fast chargers are of little added value for users with a small battery.

Wei et al. (24) present a tool to estimate fast charging demand and sample results on a current and future EV scenario. Their results show the interaction of battery size, frequency of charging, and energy needed per charging transaction.

While energy per charging transaction increases with battery size, the overall electricity demand per vehicle decreases with larger batteries. This is due to less charging transactions with more kWh charged per transaction. A reason for this may be that that larger battery FEVs tend to reach their destinations more often which leads to less transactions, while if needed the transaction size is larger due to the larger battery size.

They use long-distance data and provide a table with interaction between battery size and number of charge scenario results. They consider battery sizes of 80, 150 and 300 miles and show that the demand in kWh from fast charging per vehicle decreases as the battery size increases. The results show how battery size may interact with charging behavior, particularly the share that will be fastcharged versus regular charging; but does not shed light on the actual charging behavior on public (slow) chargers which is focus in this study.

Franke and Krems (8) performed a study that focuses on user-battery interaction of EV users based on the concepts of how mobile phone users charge their phones. While this research provides results on how EV users cope with battery size it does not provide insights usable in simulations.

Tal et al. (25) present a survey of more than 3500 PHEV owners conducted in California in May and June 2013. Their findings include the following. There is a low correlation between (i) the need for charging and (ii) actual charging transactions for low battery PHEVs mainly due to public charging availability as reported by the drivers. PHEV drivers with higher battery capacity and FEV drivers charge more often and are more positive on charging opportunities in locations where low battery PHEVsdid not charge. They suggest that users with a low battery PHEV may not have a high enough incentive to charge their car often.

Concluding, while interest is clearly being shown in the influence of battery sizes and car types on the behavior of EV users, little research is done in this area. Moreover, a real understanding of the effects of battery size on total charging infrastructure performance has not been found in literature so far.

3. METHOD

This research builds upon the Simulation of Electric Vehicles Activity (SEVA) model, a data driven agent-based simulation model (currently under peer review). At initialization of this simulation model, the behavior of the agents in terms of connection and disconnection distributions is generated from transaction data of the agents themselves (26). The dataset contains more than 5.6 million recordson public charging points in 4 big cities in the Netherlands and the Metropolitan Region Amsterdam (MRA) (26). To assure generalization, special user types such as car sharing cars and taxis are filtered out at the initialization of the model. Next, each EV user needs to have at least 20 transactions en a local area and at least 10 at one Charging Point (CP).

The geospatial behavior of an agent is captured by defining clusters nearby of charging points, where the agent displays a similar activity pattern. Each cluster has a geospatial center based on the weighted average of the transactions at the CPs in a cluster. Note that both the centers and the clusters are uniquely defined for each agent.

To simulate the change in behavior due to a change in batteries, a clear understanding is needed as to how the connection and disconnection distributions change. It is also arguable that the clusters of an agent may change as their batteries change. A user might have fewer or more regular charging locations depending on its battery size. However, it also seems likely that a user would keep some, if not all, of its centers, as the user still drives the same routes and visits the same locations when it gets another car.

To decide exactly which aspects of the agents are crucial in capturing the change of battery size, a data analysis focused on the differences in batteries was performed. Next, based on behavioral properties on charging data, three types of EV-types were distilled from the data: (1) PHEV, (2) small battery FEV (low FEV) and (3) large battery FEV (high FEV). The differences in charging behavior were made explicit for modelling by drawing distributions on connection and disconnection to charging points and location-based behavior.

In the next step, a Factor Transform (FT) function was developed to apply the EV transition to behavior properties. Subsequently, the FT function was implemented in the ABM to simulate transformations of the current EV fleet from PHEVs and small Battery FEVs to large battery FEVs. Finally, simulations were performed with different transition probabilities to reveal insight in to different future scenarios. From the data derived from simulations effects on typical Key Performance Indicators (KPIs)

of charging infrastructure were analyzed (27). This led to conclusions and recommendations for policy makers and CPOs.

4. RESULTS

4.1. Battery Size Analysis

To identify differences in behavior between PHEV and FEV and the effect of battery size, a distinction between these types of EVs is required. A large amount of the EV users in the dataset can be classified as either owning a PHEV or a FEV with a classification method that relates maximum transaction size to EV car type (28). The classifier considers the largest transaction volume and charging speed of an EV user and compares this with known properties of EV models to classify a user. In case of doubt the user gets the label "unknown". These unknown EVs are filtered out in this analysis and the simulation model.To determine the battery sizes of the EV users in the dataset the transaction volumes (in kWh) within the dataset were used. For each user, this may be calculated by taking the maximum transaction volume, assuming that a user will at least once charge from 0% to 100% SOC, yet some caution is required. Different cars can be used with the same charging card ID, because a charge card is not bound to a car but to a user. For instance, an EV user may incidentally use its charging card to e.g. a hired car or EV from a colleague.

Therefore, it was decided not to set the battery size of a user the maximum kWh observed in all charging transactions, but a percentile to filter out the top percentage of the transactions. A deeper analysis revealed that the 98th percentile there was a good balance between filtering outliers while not filtering too many regular transactions.

Based on the results of the classifier and the battery size calculation, the spread of battery size of PHEV and FEV of (2,172) users present in the simulation model can now be displayed, see Figure 1 (PHEV) and Figure 2 (FEV). The FEV users are clearly split into two groups, one with low and one with high battery capacity, while the PHEV users are all close to a mean of 10 kWh. The outlier of 30kWh may be a wrongly identified FEV (e.g. the BMW i3 with large battery).

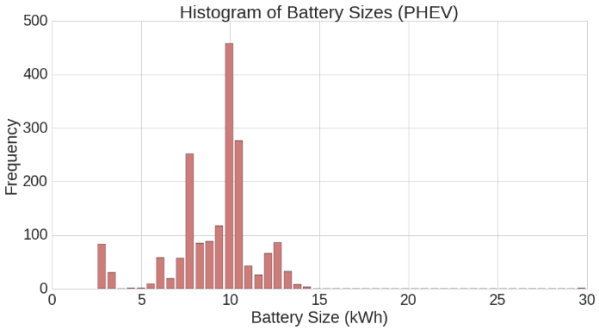


Fig. 1 The spread of battery capacity for all (1727) PHEV users present as valid agents in the SEVA model.

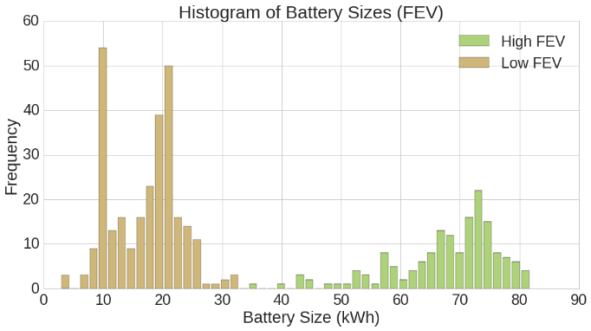


Fig. 2 The spread of battery capacity for all (445) FEV users present as valid agents in the SEVA model.

While there are no models available with battery sizes between 33 kWh (BWM i3) and 70 kWh (Tesla Model S) in the period up to December 2016 we do see some occurrences of battery sizes between those values in Figure 2. This is caused by users that mostly charge their car before the battery is fully empty. Given that the actual battery size is unknown in the available dataset and that the behavioral properties of the EV users relate to the transaction volume rather than the battery size, we decided not to rescale the Figures 1 and 2 to known EV battery sizes.

Based the current results, the users were split in the dataset into three groups based on their car type and battery size. Namely PHEV (1727 users), low FEV (283 users) with low battery capacity (up to 33 kWh) and high FEV (162 users) with high battery capacity (over 33 kWh). The low FEV group includes models such as Nissan Leaf; the category over 33kWh includes Tesla's.

3.2. Geospatial Charging Behavior for Different Battery Sizes

In this section the differences that can be found between PHEVs, low FEVs and high FEVs are described and tested on significance. First the differences in geospatial behavior is analyzed. This contains the differences in number of centers that this user type on average has, which can be related to the number of locations where

EV users typically charge. Next, the clusters size being the number of CPs of a center is analyzed. Last, given that the cluster size relates to the distances of CPs in the cluster, the walking preparedness is also considered in this analysis. This is defined as the maximum distance between two CPs in a cluster.

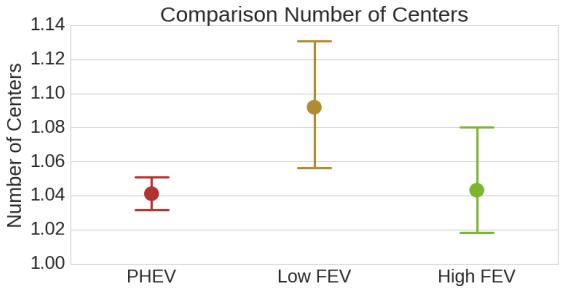


Fig. 3 Comparison of number of centers between the three battery categories

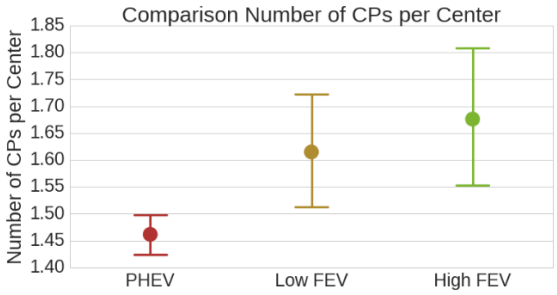


Fig. 4 Comparison of number of Charging Points per center between the three battery categories

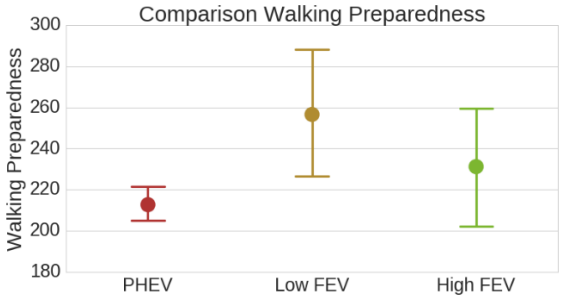


Fig. 5 Comparison of walking preparedness between the three battery categories

In Figures 3 to 5 the mean and 95% confidence intervals of the number of centers, number of CPs per cluster and walking preparedness is shown.

For each combination seen in these figures we performed a twosample independent t-test assuming unequal variances between the two samples. The p-values resulting from these tests can be found in Table 1, where significant P values are emphasized in green.

Possible explanations for the found differences are the following. As PHEVs have less incentive to charge often, they are not required to search alternative CPs when their preferred CP is occupied. This could be a reason that the walking preparedness and the number of CPs per cluster are lower for PHEVs. The low FEVs have more centers than the other two categories, possibly because in this category the need to charge is highest, thus they seek alternative charge locations.

	FEV (low) & PHEV	FEV (high) & PHEV	FEV (low) & FEV (high)
Number of centers	**0.001**	0.902	0.085
Number of CPs per center	**0.004**	**0.001**	0.493
Walking preparedness	**0.000**	0.212	0.297

Table 1 For the three geospatial variables in the first column a two-sided t-test for each combination is carried out.

From this we conclude that regarding geospatial behavior, most differences are present between low battery FEV and PHEV. Given that the simulation is setup to transform the PHEVs to high battery FEV, the only factor to transform is the number of CPs per center.

3.3. Temporal Charging Behavior for Different Battery Sizes

The temporal charging behavior is based on the connection and disconnection distribution of an agent given per cluster of CPs. Before analysis, a cutoff on extremely short sessions less than 5 minutes and long connection durations of 5 days and disconnection duration of 40 days was performed to filter outliers and/or errors. Afterwards, the mean behavior per unit time was calculated by polynomial fit.

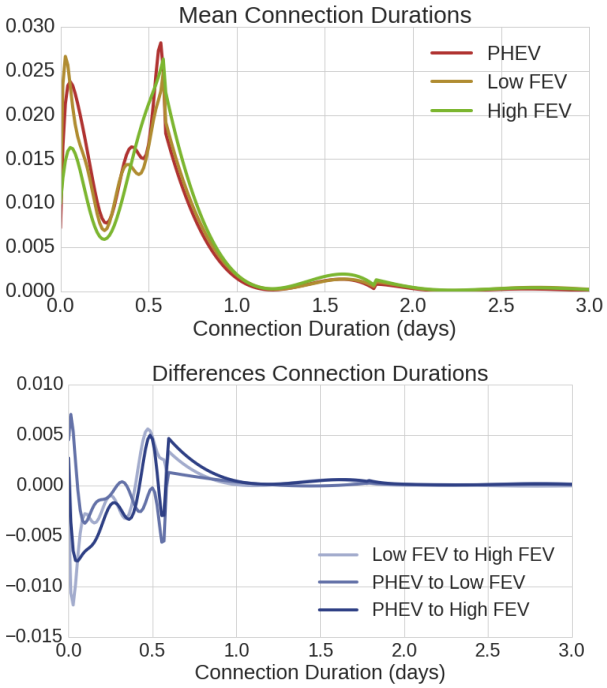


Fig. 6 The mean connection duration distributions for the different battery groups, where (a) shows the fitted distributions and (b) the differences between those distributions.

In Figure 6 the mean connection duration distributions for each of the battery categories are displayed. From this it is found that the high FEV users have a much lower first peak around 0.05 days (first hour), which suggests that high battery users are less likely to connect for (very) short durations. This may be explained by the idea that high battery EVs have a longer driving range and as such do not need to stop and charge for a short time in between driving and may prefer to wait and charge for a more solid duration. It can also be observed that low FEV and PHEV categories have a peak at both 0.35 and 0.55. We hypothesize that the 0.35 peak is due to the users charging at work (roughly 8 hours), while the 0.55 peak might point to users charging at home overnight (roughly 13 hours) also found in (27, 29). This peak is absent in the high FEV group, which may indicate that large battery FEVs may not specifically charge at work as much as PHEVs and low battery FEVs.

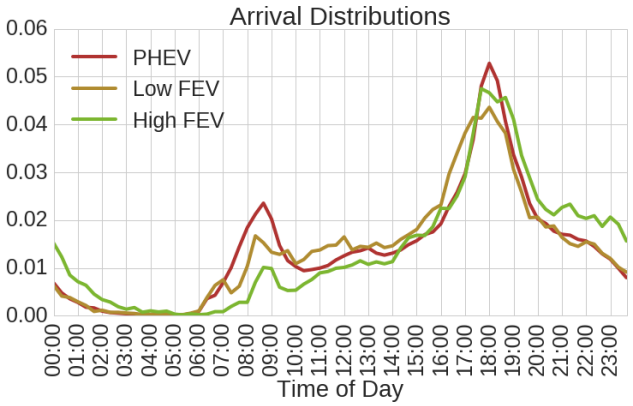
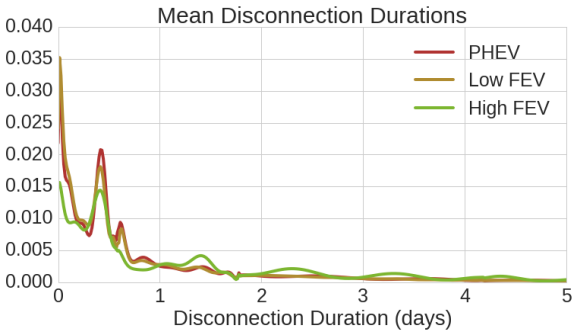


Fig. 7 The arrival time distributions for the three different groups

The arrival time distributions indeed indicate a lower number of high FEV users that start their charging session at typical daytime or office hours.



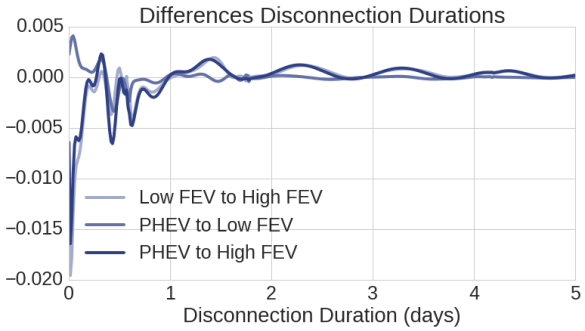


Fig. 8 The mean disconnection duration distributions for the different battery groups, where (a) shows the fitted distributions and (b) the differences between those distributions.

In Figure 8 the mean disconnection duration, being the time between two subsequent sessions, distributions is displayed. Note that the high FEVs shows longer disconnection durations. High FEVs are found to have 49% of their disconnections longer than more than a day, while both PHEVs and low FEVs this is only 30%. The figure shows peaks at 0.4, 1.4 and 2.4 in the high FEV pattern, indicating a disconnection of roughly nine hours plus zero to two days. This indicates that high FEV users tend to skip transactions and connect at the same time a day or more later. This corresponds with the finding that high FEVs have a lower mean number of weekly sessions than the other categories.

For the lower battery categories, the highest peak is for very small disconnection durations of less than an hour. This may indicate that those users most often charge again right after reaching their destination. A deeper analysis of the differences between the distributions using the Hellinger distance showed, that the high battery FEV tend to differ more from the other two categories by disconnection than by connection duration. Low FEVs and PHEVs are very similar in both disconnection and connection patterns. Next, high FEVs differ from the other two groups by less charging transactions, which on average are longer and less frequent.

3.4. Transformation of EV user behavior

Having a clear insight in the differences in charging behavior, a transformation function can be developed that enables transforming a user from one category to another. And then implementing this in the simulation model to evaluate how this plays out in the utilization of charging infrastructure. The SEVA model used in this research, simulates the behavior of an agent mainly by the use of the disconnection and connection duration distributions. The combination distributions of both results in arrival patterns and the number of weekly sessions. Therefore, the

connection and disconnection distributions are the main subject to the transformation.

However, in this research, we choose not to consider the differences in center characteristics with the transformation for a reason. Namely, the differences, although significant, are a lot smaller than other differences and the manipulation of centers is not straightforward, since they are directly pulled from the dataset with the clustering of CPs.

For the Factor Transformation (FT) we use the fitted means for the connection and disconnection distributions as seen in Figure 6 and Figure 7. The transformation can be defined by the following equation:

$$w_i = \begin{cases} v_i \cdot \dfrac{t_i}{o_i} & \text{if } o_i > 0 \\ 0, & \text{otherwise } i = 0. \end{cases}$$

Eq. 1 Factor Transformation function

Here w_i is the new value bin i will take, v_i is its old value and t_i and o_i are the values in bin i for the target distribution and the origin distribution respectively. The term $\frac{t_i}{o_i}$ can be seen as the transform factor of the *i*-th bin. For each user transformation from PHEV to high FEV, t would represent the high FEV (dis)connection duration distribution and o the PHEV distribution.

4. SIMULATION SETUP

4.1. Extension of SEVA model

To implement the transformation of an agent from one battery category to another, the SEVA model needs several upgrades. First, agents should now have an attribute containing information on whether the agent is a PHEV, low FEV or high FEV. Second, a transform probability which defines for each agent the probability of transforming from PHEV to FEV is added as parameter of the model.

To implement the transaction volume in the model for a session of an agent, the whole population of a single battery category is used as predictive information on transaction volume for an agent within this group.

The transaction volume is modelled as follows. For the whole category a heatmap of probability of transaction given the connection duration is setup, see Figure 8. During simulation the model samples a charged amount belonging to the simulated connection duration according to the probabilities at this connection duration.

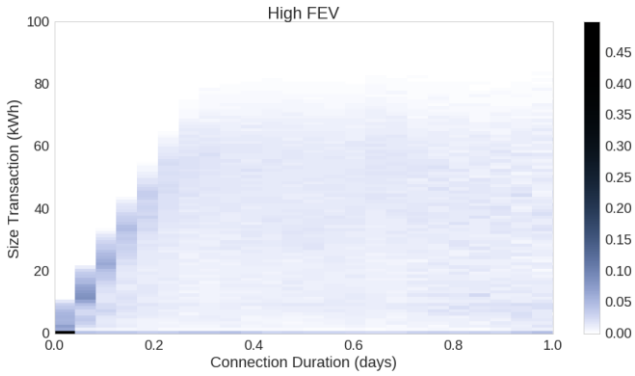


Fig. 9 Heatmap of transaction volume versus connection duration

4.2. Simulation metrics

The purpose of this study is to observe the change in demand on the charging infrastructure given the transition of battery size. Previous research revealed important key performance indicators on charging infrastructure for various stakeholders (27, 30). The following indicators were chosen to analyze from the simulation results; (1) Average connection duration per CP per week;(2) Average number of unique users per CP per week; (3) Average number of charging transactions per CP per week; (4) Average kWh charged per CP per week.

4.3. Simulation procedure

The simulation procedure is setup to research the effects of on the demand on the charging infrastructure as a transition takes place from a population fully consisting of PHEVs to one fully consisting of large battery FEVs. As such, the simulation contains the 1727 PHEV agents and is performed in five simulation runs of one year with those agents, keeping track of the system measures. Each simulation run every agent has a probability to be transformed to a high battery FEV at the start of the simulation. This percentage varies from 0% to 100% with a step size of 20%.

5. SIMULATION RESULTS

The values of the system measures in the case study are plotted against the probability to transform in Figure 10-14. The error bars indicate the variance over al CPs and all runs.

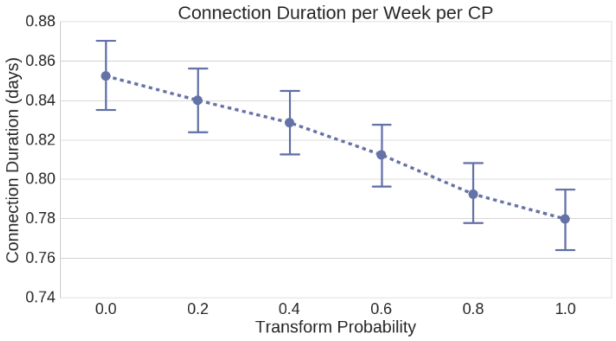


Fig. 10 Weekly connection duration related to transform probability

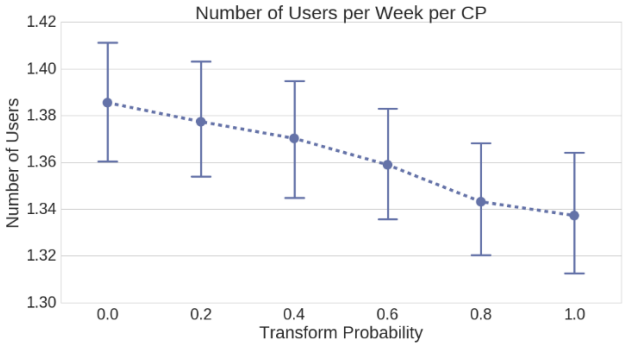


Fig. 11 Weekly number of users related to transform probability

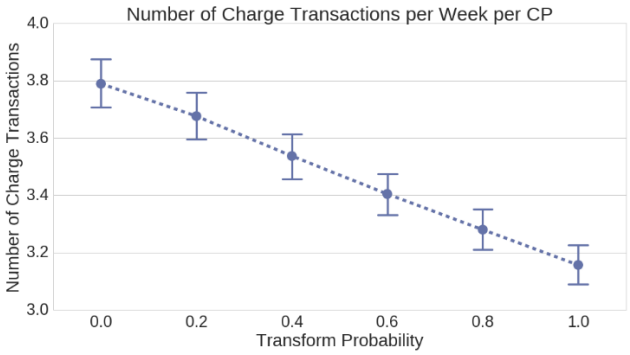


Fig. 12 Weekly number of transactions related to transform probability

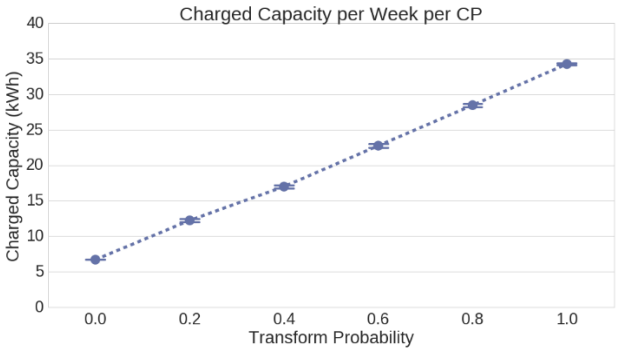


Fig. 9 Weekly transaction volume related to transform probability

There is a significant decrease (17%) in the number of charging transactions per week and the connection duration per week, which is as expected. This also confirms that the FT of disconnection and connection distributions does capture the difference in the number of charge transactions per week. The number of users per week also decreases, but not significantly over the scope of this transformation (0.7%). This decrease is not as strong as expected, which can be explained by the fact that the model does not decrease the number of CPs to choose from with the transformation. Each CP still has the same chance of being selected as it had before the transformation. The increase shown could be due to an agent having to deviate from its first choice less often, since CPs are less often occupied. Lastly, the total and the average per CP per week on charged kWh increase significantly (80% and 70% respectively) for every step. The reason for this may be found in the idea that PHEVs tend to use their full battery each day and their transactions is limited by battery size rather than daily trip size, whereas FEVs do not have this limitation.

6. CONCLUSION

This study presented a simulation model for the transition of EV user charging behavior. The model is an extension of the existing SEVA model (currently under peer review). The transformation of EV user charging behavior due to increase of battery size was performed based on data analysis of actual EV users' transactions.

From this case study we see the utility of the CPs, and thus of the charging infrastructure, increases as the battery size of the population increases. The connection times per CP decreases, while the kWh charged at those same poles increases. This would indicate that, as a transition to higher batteries takes place, first the efficiency of charging infrastructure increases, and second less charging infrastructure would be needed to facilitate the EV population.

The number of unique users per CP and the decrease in connection times would also be positive for EV users, as this implies that the CPs are available more often. Yet, the current transformation function could be improved on the CP selection process, which may affect this metric as well.

There are some drawbacks as well. As we have seen, high FEVs charge more at night times and this could cause a higher peak on the energy demand as a higher fraction of the population starts charging at night. However, this peak might be shifted towards a later time using smart charging as generally not the entire night is

needed for a full recharge. Implementation of smart charging in a future research and extension of this model would therefore be a logical next step.

Overall, the results of the case study indicate a decrease in demand on the charge infrastructure as battery sizes increase and the number of EVs stays the same, which is beneficial for most involved stakeholders.

AKNOWLEDGEMENTS

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CONTRIBUTIONS

JRH, ML initialized and designed this research, IV conducted the research and analysis, IV wrote the code, JRH and ML supervised the research, JRH and IV wrote the paper, ML and RvdH edited the paper.

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