Charging demand analysis in the face of overwhelming uncertainty

Gunnar Flötteröd[1]

[1]Department of Communication and Transport Systems Linköping University, Sweden
& The Swedish National Road and Transport Research Institute

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SHORT SUMMARY

A quantitative method to studying charging station demand under a minimum of scenario/modeling assumptions is presented. The approach enables a quantitative analysis in situations where scenario uncertainty renders a traditional simulation study infeasible. Case study results for a sketch version of the Skellefteå region in Sweden illustrate the approach.

Keywords: Transport network modeling, Electrification, Operations research applications

1 INTRODUCTION

The broad adoption of electric vehicles requires the design and placement of corresponding charging stations, drawing much attention to quantitative charging demand studies. Examples from the previous hEART conference comprise the data-driven charging demand analysis of Hajhashemi et al. (2023) and the Swedish simulation study of Arabani et al. (2023). Stochastic simulation is the mainstream analysis tool when addressing uncertain futures and nontrivial model structures (Williams et al., 2024; Harris et al., 2023). Mainstream driving/charging simulations require parameterizing a possibly large number of internal sub-models (travel behavior, charging behavior, ...), which may be challenging if the parameters of the scenario under consideration are uncertain. This calls for a Monte-Carlo analysis, the extent of which is bound by computational facilities (Punzo, 2015).

The present work adopts a probabilistic model to charging demand analysis. It differs from mainstream simulation approaches in that the model can be evaluated even with an absolute minimum of information (a set of possible charging stations, the charging logic at each station, the energy consumption and travel time when moving from one station to another). In the minimum-information case, the model predicts a uniform distribution over all physically feasible driving/charging patterns. Adding travel behavioral assumptions, which is possible in an incremental manner, focuses the predicted driving/charging behavior on patterns that are compatible with these assumptions.

The model relies on a discrete state space of driving/charging patterns over which a target probability distribution of modeling assumptions is defined. The Metropolis-Hastings algorithm (Hastings, 1970) is used to draw driving/charging patterns according to this distribution. Since the resulting number of possible driving/charging patterns may be huge and difficult to sample from representatively, importance sampling (e.g., Ross, 2012, Chapter 9.6) is used to over-sample driving/charging patterns that are of interest to a given analysis question; this over-sampling is then corrected for in the statistical analysis such that unbiased predictions are obtained.

2 METHOD

The presented method considers private car charging in that it assumes that travel occurs in daily round trips that are anchored at a home location. Adaptations for demand segments with different travel structures (e.g. freight) are possible within the same framework.

Consider a set of parking locations $1, \ldots, L$ and discretize within-day time into uniform intervals (time bins) $1, \ldots, K$. A round trip is an alternating sequence of parking and driving episodes that starts and ends at the round trip's home location. The finite length $J_x \in \{1, \ldots, J^{\max}\}$ of round trip x represents the number of parking resp. driving episodes in that round trip. A round trip x is a three-tuple $x = (l_x, d_x, c_x)$, as subsequently defined.

- $l_x = (l_{x,1}, \ldots, l_{x,J_x})$ is the sequence of visited parking locations; $l_{x,i} \in \{1, \ldots, L\}$ for $i = 1, \ldots J_x$. The first location $l_{x,1}$ is called the home location. Adjacent locations must be different, meaning that $l_{x,i} \neq l_{x,i+1}$ for all $i = 1, \ldots, J_x - 1$ and, since the round trip is completed by returning from the last location back home, $l_{x,1} \neq l_{x,J_x}$. The requirement of alternating locations may be relaxed; it is adopted here to remove energy-wise uninteresting short trips within a given location from consideration.

- $d_x = (d_{x,1}, \ldots, d_{x,J_x})$ is the sequence of planned departure time bins, with $d_{x,i} \in \{1, \ldots, K\}$ being the planned departure time bin from parking location $l_{x,i}$. Departure time bins are strictly increasing in that $d_{x,i} < d_{x,i+1}$ for all $i = 1, \ldots, J_x - 1$. The departure time bins represent a desired time structure that may or may not be compatible with a given physical reality of finite travel speeds.

- $c_x = \{c_{x,1}, \ldots, c_{x,J_x})$ is the sequence of planned charging actions, meaning that $c_{x,i} \in \{0, 1\}$ indicates if charging is planned at location $d_{x,i}$ or not. If charging actually occurs at a given location depends on the availability of a charger.

This defines a finite, yet possibly very large state space of possible round trips. Given L locations and K time bins, a round trip of size J has $\text{size}_{\text{chg}}(J) = 2^J$ possible charging configurations, $\text{size}_{\text{dpt}}(J) = \binom{K}{J}$ possible departure time bin combinations, and

$$\text{size}_{\text{loc}}(J) = \begin{cases} L & \text{if } J = 1 \\ L \cdot (L-1) & \text{if } J = 2 \\ L \cdot (L-1) \cdot (L-2) & \text{if } J = 3 \\ L \cdot (L-1)^{J-2} \cdot (L-2) \cdot \sigma(J, L) & \text{if } J > 3 \end{cases} \tag{1}$$

possible location sequences, with $\sigma(J, L)$ an available but somewhat unwieldy expression taking values between one and $(L-1)/(L-2)$. The size of the state space (total number of possible round trips) is hence $\sum_{J=1}^{J^{\max}} \text{size}_{\text{loc}}(J) \cdot \text{size}_{\text{dpt}}(J) \cdot \text{size}_{\text{chg}}(J)$.

In the complete absence of travel behavioral information, all possible round trips may be considered equally realistic. However, given that the number of possible round trip configurations grows rapidly over the round trip length J, this alone would imply the assumption that longer round trips are (much) more likely to arise than shorter ones. A convention is hence adopted that a most uninformed round trip distribution is (i) uniform over all round trip lengths $1, \ldots, J^{\max}$, and (ii) given the round trip length J uniform over all round trip configurations of that length. This is ultimately a modeling decision, and different specifications may be adopted. It is achieved by assigning the following "uninformed" probability to round trip x of length J_x:

$$p_{\text{uninf}}(x) = (\text{size}_{\text{loc}}(J_x) \cdot \text{size}_{\text{dpt}}(J_x) \cdot \text{size}_{\text{chg}}(J_x))^{-1}. \tag{2}$$

Let the round trip probability distribution $p_{\text{model}}(x)$ represent all modeling assumptions made about driving/charging behavior. (An example may be a higher probability for overall shorter travel times in combination with longer parking episodes at relevant activity locations.) Since these modeling assumptions are by definition deviations from the uninformed round trip distribution (2), specifying round trips according to given model p_{model} amounts, apart from normalization, to postulating a target distribution $p_{\text{uninf}} \cdot p_{\text{model}}$ over all round trips.

Let $h(x)$ map round trip x onto an performance measure of interest. (This could, for instance, be the amount charged at a given parking location.) We are interested in the expected performance measure h over a given round trip target distribution, i.e. $\mathrm{E}\{h(X)\}$ with random variable (round trip) X distributed according to the target distribution. Given a machinery to draw R independent realizations $x^{(1)}, \ldots, x^{(R)}$ of X, we can approximate the expectation of interest by an average over the performance measures of these realizations: $\frac{1}{R}\sum_{r=1}^{R} h(x^{(r)}) \stackrel{R\to\infty}{\longrightarrow} \mathrm{E}\{h(X)\}$. The variance of this estimator falls with R, but a relatively high variance may still arise if round trips relevant to h are unlikely to arise in the target distribution. This is addressed using importance sampling: Let the nonzero importance weight $q(x)$ be the larger the more relevant round trip x is for performance measure h. Sampling $x^{(1)}, \ldots, x^{(R)}$ from a (normalized version of) $p_{\text{uninf}} \cdot p_{\text{model}} \cdot q$ yields the asymptotically unbiased variance-reduced estimator

$$\frac{\sum_{r=1}^{R} h(x^{(r)})/q(x^{(r)})}{\sum_{r=1}^{R} 1/q(x^{(r)})} \quad \stackrel{R\to\infty}{\longrightarrow} \quad \mathrm{E}\{h(X)\}. \tag{3}$$

The Metropolis-Hastings (MH) algorithm is used to draw round trips according to $p_{\text{uninf}} \cdot p_{\text{model}}$ or, with importance sampling, according to $p_{\text{uninf}} \cdot p_{\text{model}} \cdot q$. This implies that it is sufficient to specify the involved distributions up to a normalizing constant, which avoids enumerating all possible round trips for computing this constant. Deploying the MH algorithm in the given setting requires defining an irreducible proposal distribution on the state space of all possible round trips. The important but rather technical specification of this distribution is omitted due to space restrictions; it basically consists of randomly inserting/removing driving/parking episodes into a given round trip, or randomly changing aspects location, departure time, charging) of that episode. See Ross (2012, Chapter 12) for an introduction to the MH algorithm and Flötteröd and Bierlaire (2013) for a related approach in the context of route choice set sampling.

3 RESULTS AND DISCUSSION

This section presents one out of many possible adaptations of the proposed method to driving/charging analysis.

Figure 1(left) shows a map of the Swedish municipality Skellefteå. The red circles indicate seven possible parking locations, with circle sizes loosely corresponding to parking location sizes. Network distances between locations range from 5 km to 50 km. Further scenario parameters are displayed in Table 1. Even in this relatively small scenario, there are more than 200 million possible round trips. To illustrate that the proposed approach enables meaningful analyses without requiring a complete state space enumeration, a sample size of one million (less than 5 ‰ of the state space) is used in all experiments. For brevity, all analysis is limited to first-order statistics, and all reported results approximate expected values over the possible round trips of a single vehicle, meaning that one needs to scale up these numbers by the considered driver population size in order to obtain grand totals. The (single-threaded) computing time is on a 1.8 GHz i7 CPU in the order of minutes.

A simple, deterministic simulator is adopted that translates a round trip into a within-day sequence of realized driving/charging episodes. Omitting details due to space restrictions, the simulator moves a vehicle once through its round trip, keeping track of time-of-day dependent battery levels and realized location arrival/departure times. The simulator ensures that battery capacity is not exceeded but even moves vehicles with negative battery levels. Further constraints are therefore added as modeling assumptions. The corresponding target weights are composed

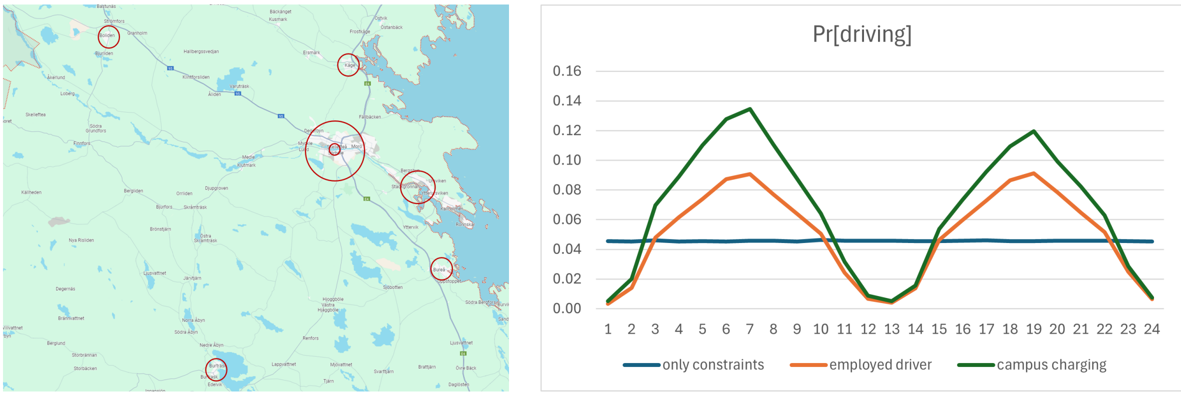

Figure 1: Study region (left, adopted from Google maps), driving episodes (right).

Table 1: Scenario parameters

Parameter	**Value**
location distance	from underlying road network
driving speed	60 km/h
travel time between locations	location distance / driving speed
energy consumption	0.2 kWh/km
charging rate	11 kW
battery capacity	60 kWh
number of locations L	7
number of time bins K	24
max. round trip length $J^{\max}$	4

of products of the following terms:

$$p_{\text{nonneg}}(a) = e^{\min\{a,0\}} \tag{4}$$

$$p_{\text{close}}(a,b) = e^{-|a-b|} \tag{5}$$

where (4) approaches zero as a gets increasingly negative and (5) approaches zero as the distance between a and b increases. Based on this, the following constraints are formulated, using self-explaining variables: (i) Desired and realized departure times coincide; modeled by a product of terms $p_{\text{close}}(\text{desiredDeparture}, \text{realizedDeparture})$. (ii) A round trip is completed within 24 h; modeled by $p_{\text{nonneg}}(24\,\text{h} - \text{realizedDuration})$. (iii) Battery load profile is 24 h-periodic; modeled by $p_{\text{close}}(\text{batteryBeforeMidnight}, \text{batteryAfterMidnight})$. (iv) Battery level is non-negative; modeled by $p_{\text{nonneg}}(\text{batteryLevel})$. The product of these terms constitute the first investigated model p_{constr}, meaning that round trips are sampled according to $p_{\text{uninf}} \cdot p_{\text{constr}}$ with p_{uninf} defined in (2).

Figure 1(right) displays, over hours of the day, the probability that a round trip implies that the vehicle is driving (not parked). The "only constraints" curve is flat, which reflects the fact that no time-of-day specific modeling assumption has been made. Figure 2 offers further summary statistics, all over hour-of-day. Parking occurs almost uniformly over all available locations. The expected amount charged grows with the travel distance that is needed reach a charging location; it is largest for the countryside villages Burträsk and Boliden. Expected charging values are smaller than the charging rate because they include the possibility of not charging. The time structure of these curves merely represents the fact that the home location has the by definition earliest departure time and hence is most likely to be visited early and late during the day.

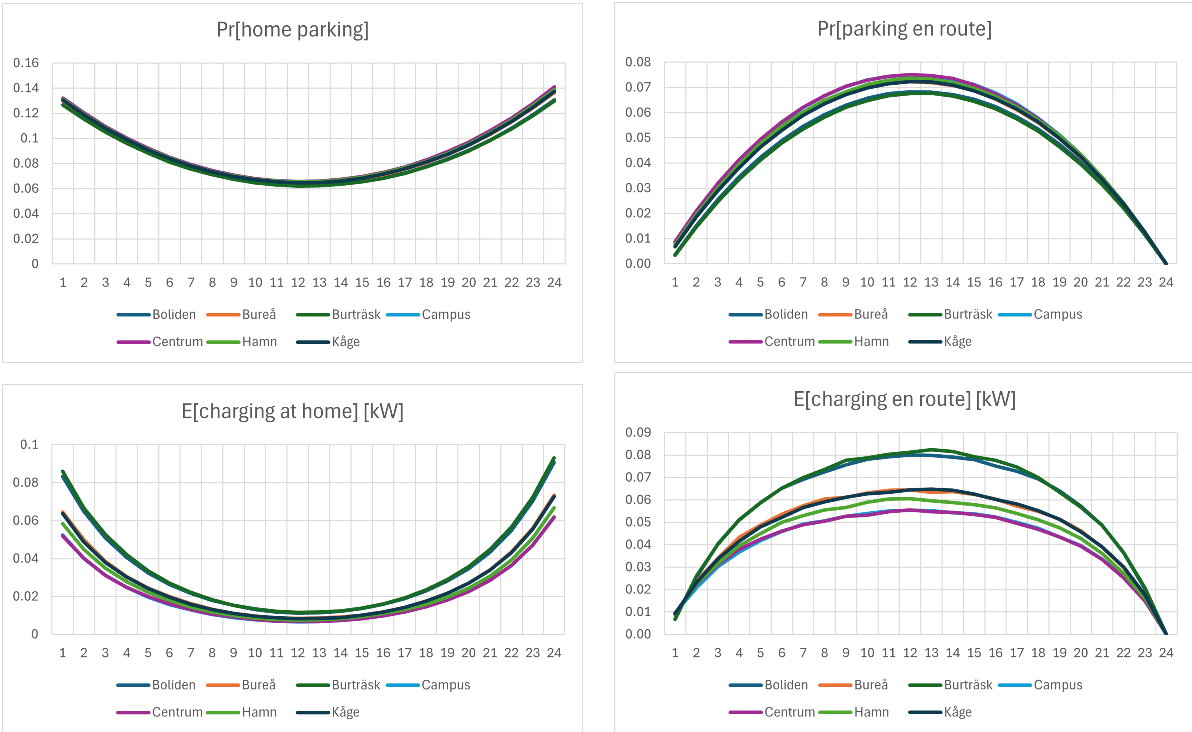

Figure 2: Uniformed model

The uninformed time structure is far from realistic. A behavioral assumption is hence added that captures an employed driver who spends at least 8 consecutive hours between 20:00 and 6:00 at home and at least 8 consecutive hours between 6:00 and 20:00 at an out-of-home work location. The following construction (one out of may possible) achieves this:

$$i_x^* = \underset{i=1\ldots J_x}{\operatorname{argmax}} \left\{ \text{duration} \left(\text{parkingInterval}_{x,i} \cap \text{targetInterval} \right) \right\} \tag{6}$$

$$p(x) = \min \left\{ 1.0, \left(\frac{\text{duration} \left(\text{parkingInterval}_{x,i_x^*} \cap \text{targetInterval} \right)}{\text{minimumDuration}} \right)^{10} \right\} \cdot \phi(l_{x,i_x^*}). \tag{7}$$

Equation 6 identifies the parking episode within round tip x that has the largest time overlap with a given target interval (20:00-6:00 for being at home, 6:00-20:00 for being at work). Equation 7 consists of two factors. The first factor evaluates the ratio of the realized parking duration over the required minimum duration (limited to one and raised to the 10th power to strongly downweight too short parking episodes). The second factor is a location-specific weight, which in the given case study is loosely derived from the number of available home and work opportunities, as shown in Table 2. This is an over-simplified travel behavioral model. It merely captures, with relative ease, a basic scenario-specific assumption, which as well could arise as a qualitative statement in a stakeholder/expert discussion. Round trips are now sampled according to $p_{\text{uninf}} \cdot p_{\text{constr}} \cdot p_{\text{home}} \cdot p_{\text{work}}$, with the latter two terms representing the newly added travel behavioral assumptions. Figure 1(right) shows that the resulting "employed driver" travel pattern exhibits distinct morning and evening peak hours. Figure 3 indicates that home and en-route parking occur consistently with the chosen location preferences and that the traveler is likely to park (and possibly charge) at home over night and at work during the day. En-route charging for relatively unattractive locations peaks in the late morning and early evening because of intermediate stops before and after the work episode.

Now we are interested in round trips that charge, throughout the day, at least 10 kWh on campus. For this, we specify the importance distribution $q \sim p_{\text{nonneg}}(\text{amountChargedOnCampus}_x -$

Table 2: Location weights

Location	**Home weight** ϕ_{home}	**Work weight** ϕ_{work}
Boliden	1.00	1.00
Kåge	1.00	1.00
Center	5.00	5.00
Campus	0.01	2.00
Hamn	0.01	2.00
Bureå	1.00	1.00
Burträsk	1.00	1.00

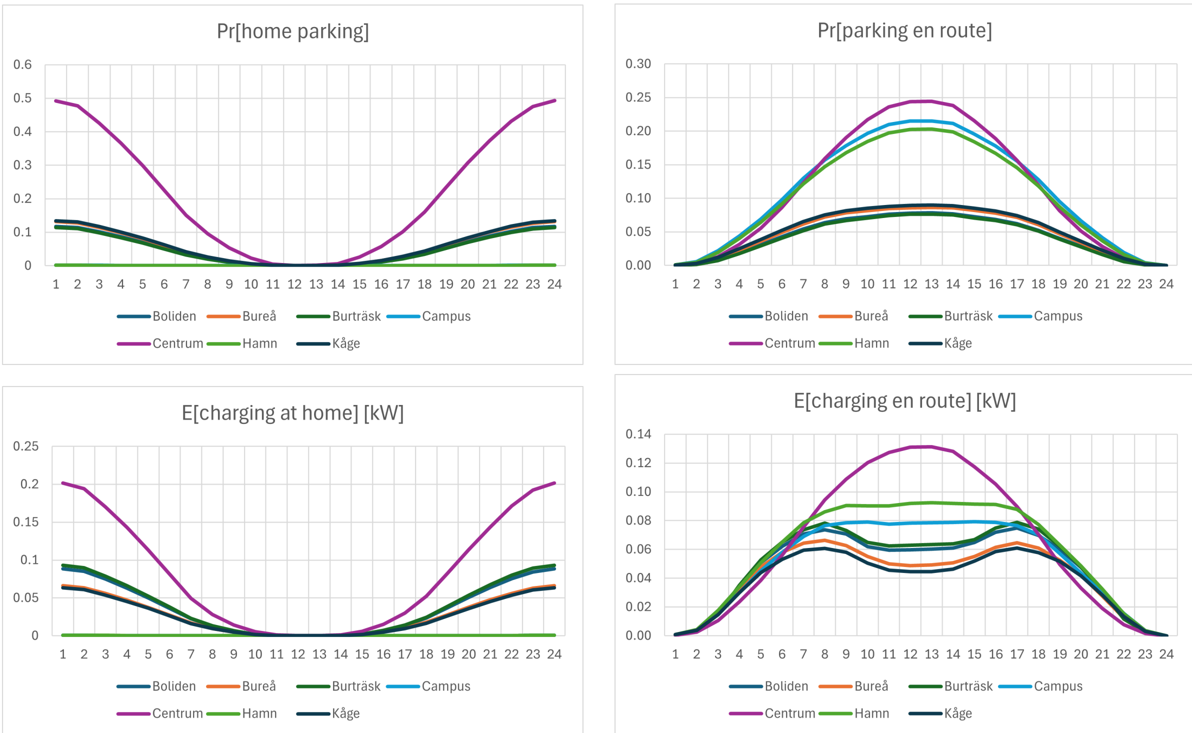

Figure 3: Employed drivers

10 kWh). Round trips are hence sampled from the un-normalized distribution $p_{\text{uninf}} \cdot p_{\text{constr}} \cdot p_{\text{home}} \cdot p_{\text{work}} \cdot q$, and the resulting statistics are corrected for the importance sampling using (3). All subsequently presented results are obtained by only considering round trip realizations that charge at least 10 kWh on campus, meaning that they truthfully reflect the driving/charging behavior of an employed driver *given* that this driver charges at least 10 kWh on campus. Figure 1(right) reveals that the probability of driving episodes for "campus charging" is larger than without this criterion, which can be explained by longer travel inducing a larger demand for (campus) charging. Figure 4 indicates, unsurprisingly, that round trips of interest now almost exclusively charge on campus, which also is the by far preferred out-of-home parking location. The largest share of round-trips now has Centrum as its home location, where many possible travel patterns originate that contain one or two energy-demanding short trips to countryside destinations before/after engaging in a long on-campus charging episode of interest.

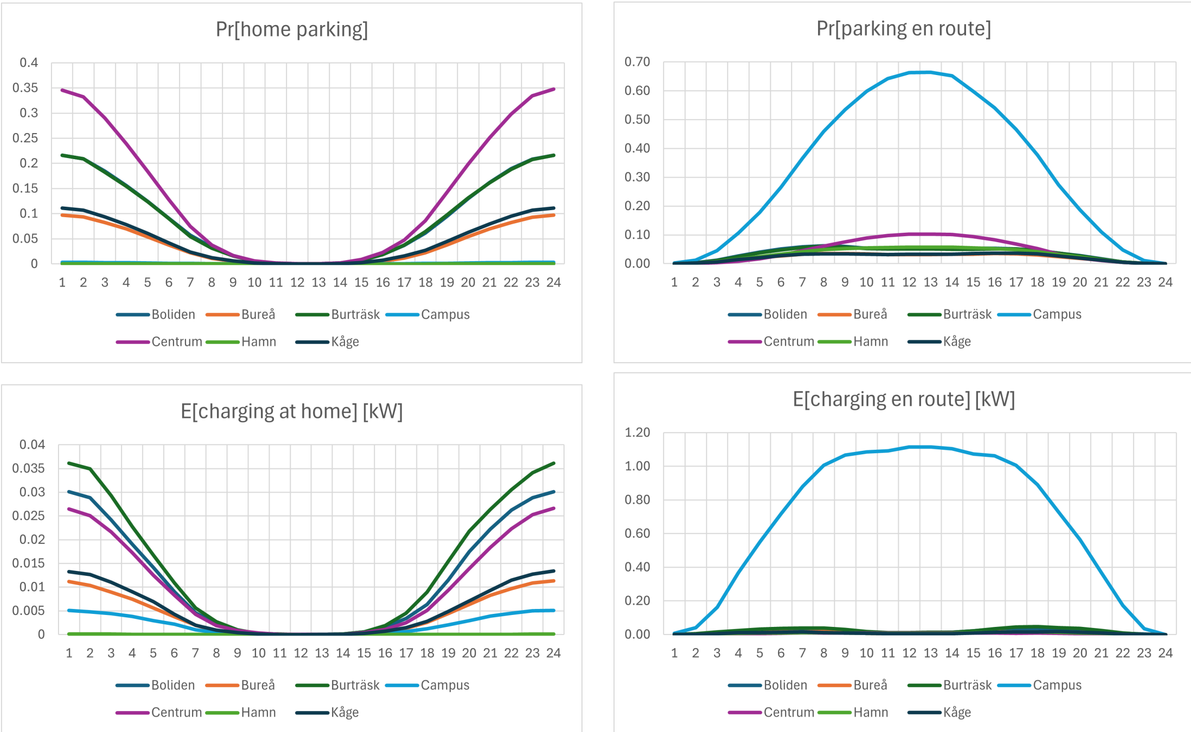

Figure 4: Employed on-campus chargers only

4 SUMMARY

The presented case study illustrates that the proposed method allows to quantitatively study charging station demand even in extremely uncertain scenarios. The proposed approach consists of incrementally adding modeling assumptions that *constrain* the possibly huge space of feasible driving/charging patterns rather than imposing very specific modeling assumptions. The possibility to incrementally add modeling assumptions renders the method suitable for interactive planning support.

A completely different application of the proposed method should also be mentioned. Multi-agent transport simulations such as MATSim (Horni et al., 2016) may require the construction of home-based round trips from often available yet relatively uninformative origin/destination matrices (Matet et al., 2023). Setting the sampling weights of the proposed method proportional to the the frequency with which the travel episodes of a round trip arise in a given origin/destination matrix immediately addresses this problem. Further modeling assumptions can be included in the same manner as illustrated above.

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