VEHICLE ENERGY CONSUMPTION IN PYTHON (VENCOPY): PRESENTING AND DEMONSTRATING AN OPEN SOURCE TOOL TO CALCULATE ELECTRIC VEHICLE CHARGING FLEXIBILITY

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Motivation

Target: Generic profiles that **estimate the flexibility** of an electric fleet of **various sizes** and electricity consumptions

Mobility patterns are different across Europe implying different load shifting characteristics of future EV fleets

Technical assumptions

- **Battery size**: ~30 kWh
- **Consumption**: 17.7-21.6 kWh / 100 km
- **Charging availability**: 3.5-60 kW (avrg. 3.5-17.6 kW / charger)

Higher morning peak for Germany & Denmark
Wider evening peak for Finland
Swiss people drive more during midday
Different weekend distance peak amplitudes …
… , times and distributions.
Modeling pipeline and structure of the talk

- Fleets
- Mobility surveys
- Technical Assumptions
- Electric vehicle fleet flexibility
- Energy system investment and operation
Modeling pipeline and structure of the talk

- Mobility surveys
- Technical Assumptions
- Fleets
- Electric vehicle fleet flexibility
- Energy system investment and operation
## Explanation of the datasets – increased consciousness about personal data protection makes analysis more difficult

<table>
<thead>
<tr>
<th>Dataset</th>
<th>MiD 2008 (public use file)</th>
<th>MiD 2017 (B2 regional dataset)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Household</strong></td>
<td>(N=25,922) 102 variables</td>
<td>(N=156,420) 49 variables</td>
</tr>
<tr>
<td><strong>Vehicles</strong></td>
<td>(N=34,601) 53 variables</td>
<td></td>
</tr>
<tr>
<td><strong>Person</strong></td>
<td>(N=39,722) 124 variables</td>
<td>(N=316,361) 107 variables</td>
</tr>
<tr>
<td><strong>Trips</strong></td>
<td>(N=50,500) 121 variables</td>
<td>(N=960,619) 157 variables</td>
</tr>
<tr>
<td><strong>Travels</strong></td>
<td>(N=36,182) 50 variables</td>
<td></td>
</tr>
</tbody>
</table>

Procedure of cleaning and processing the dataset of the MiD2017

**Trips (N=960,619)**
157 variables
17 variables

- Trips by MIV (N=525,033)
  - Start and arrival hour available (N=484,630)

- No multi-modal trips (N=405,411)
  - Detailed trip length available (N=463,045)
    - Start hour <= arrival hour (N=471,777)

- Filter out implausible combinations of triplengths (N=405,407)

- Merge single trips to daily travel diaries (N=143,699)

The influence of weighting trips is minor compared to the changing mobility patterns from 2008 to 2017

N=143,699  N=17,863
Modeling pipeline and structure of the talk

- Fleets
- Mobility surveys
- Technical Assumptions

Electric vehicle fleet flexibility

Energy system investment and operation
Vehicle Energy in Python (VencoPy) – resulting profiles

Grid

Battery

SOC Max
SOC Min

Demand

Uncontrolled charging

Controlled charging

Consumption
Grid connection
SOC Max
SOC Min
Comparing consumption and uncontrolled charging on the background of the data bases MiD2008 vs. MiD2017

Morning and evening peak of electricity consumption reduced, evening peak flat. However, this doesn’t affect evening peak of uncontrolled charging.
Comparing SOC flexibility on the background of the data bases MiD2008 vs. MiD2017

Similar shape of mobility-demand enforcement constraints for the SOC. However, SOC Max significantly shifted up.
Conclusion and outlook

• **Mobility patterns** that are widely measured by national travel surveys **change** implying methodological challenges for estimating future electric vehicle fleet load shifting potential.

• Germans now travel less in the early morning and more during the course of the day. Weekend travels are shifted by 1-2 hours to later hours but increased in distance.

• For estimated electric vehicle fleet flexibility, these changes imply **lower morning** and **flatter day consumption** of EVs, however **evening peaks of uncontrolled charging are not affected**. Estimations of available battery SOC for load shifting shows higher potential at night hours between 9pm and 5am in the morning.

Outlook

• We’re working on validating our estimation methodology with real-world pilot project EV mobility, connection and charging data.
Background Literature


Mobility patterns change over time and between fossil fuelled and electrically driven vehicles

<table>
<thead>
<tr>
<th></th>
<th>MiD2008</th>
<th>MiD2017</th>
<th>EV studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Number of trips in 1/(cap*d)</td>
<td>3.4</td>
<td>3.1</td>
<td></td>
</tr>
<tr>
<td>Average trip distance km/(cap*d)</td>
<td>38</td>
<td>39</td>
<td>61 (UK) vs. 43 (UKNTS) [Neaimeh et al. (2017)]</td>
</tr>
<tr>
<td>Share of active days in %</td>
<td>90</td>
<td>85</td>
<td>83</td>
</tr>
</tbody>
</table>
VencoPy – Estimating an electric vehicle fleets flexibility

Grid
Hourly electricity production costs

- $P_{\text{charge,avail}}(t)$
- $C_{\text{charging}}(t)$
- $\eta_{\text{GTV}}$

Charging (controlled + uncontrolled)

Interface grid – vehicle fleet battery

Fleet battery

- $L_{\text{min}}(t)$
- $L_{\text{max}}(t)$

Electric drive power

Interface battery – electric motor

Technical assumptions for this analysis

Battery size: 50 kWh
Consumption: 20.0 kWh / 100 km
Charging availability: 3.7 kW

In the following not differentiating between weekend and workday
The MiD 2017 dataset

**Meta properties**
- Collection period: May 2016 – October 2017
- 316k persons, 156k households, almost 1 Mio. trips
- 3 German-wide surveys, 55 local surveys
- How representative is the MiD? Non-response study yielded no significant differences between responders and non-responders

**Comparisons**
- The influence of weights (averaged vs. weighted) on consumption profiles
- The influence of weekdays (with weights) on consumption profiles

**Calculation of weights**
- Basis for the weights is the household size
- Selection probability and household features distribution
- For extrapolation, weights have to be multiplied with additional factor
  - Households: 262
  - Person: 260
  - Trips: 268
Steps of VencoPy

1. Trip distance, grid connection profiles and assumption read-in
2. Calculation of estimated individual profiles for vehicle demand side flexibility
3. Filtering of individual profiles
4. Aggregation to a fleet level
5. Normalization
6. Plotting and output
Differentiating independent variables

<table>
<thead>
<tr>
<th>Criterium</th>
<th>Independent variable</th>
<th>Source</th>
<th>Arguments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging Place</td>
<td>Home, work, shopping etc.</td>
<td>Babrowski et al. (2014), Corchero et al. (2014)</td>
<td>- Strong influence on load curve characteristic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>- Locational influence on charging behaviour</td>
</tr>
<tr>
<td>Area type</td>
<td>Metropole, urban, rural</td>
<td>Babrowski et al. (2014)</td>
<td>- Different distribution grid resiliencies</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>- Different EV penetration rates</td>
</tr>
<tr>
<td>Daytype</td>
<td>Weekend, weekday</td>
<td>Babrowski et al. (2014)</td>
<td>- Different mobility patterns</td>
</tr>
<tr>
<td>User group</td>
<td>Commuter, part-time workers, student, pensionist etc.</td>
<td>Fischer et al. (2019), Gaete et al. (2020, forthcoming)</td>
<td>- Charging locations depend on user group and thus charging characteristic</td>
</tr>
<tr>
<td>Car model</td>
<td>Battery size, consumption, charging rate</td>
<td>Fischer et al. (2019)</td>
<td>- Battery size, electric consumption and maximum charging rates influence charging</td>
</tr>
</tbody>
</table>