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

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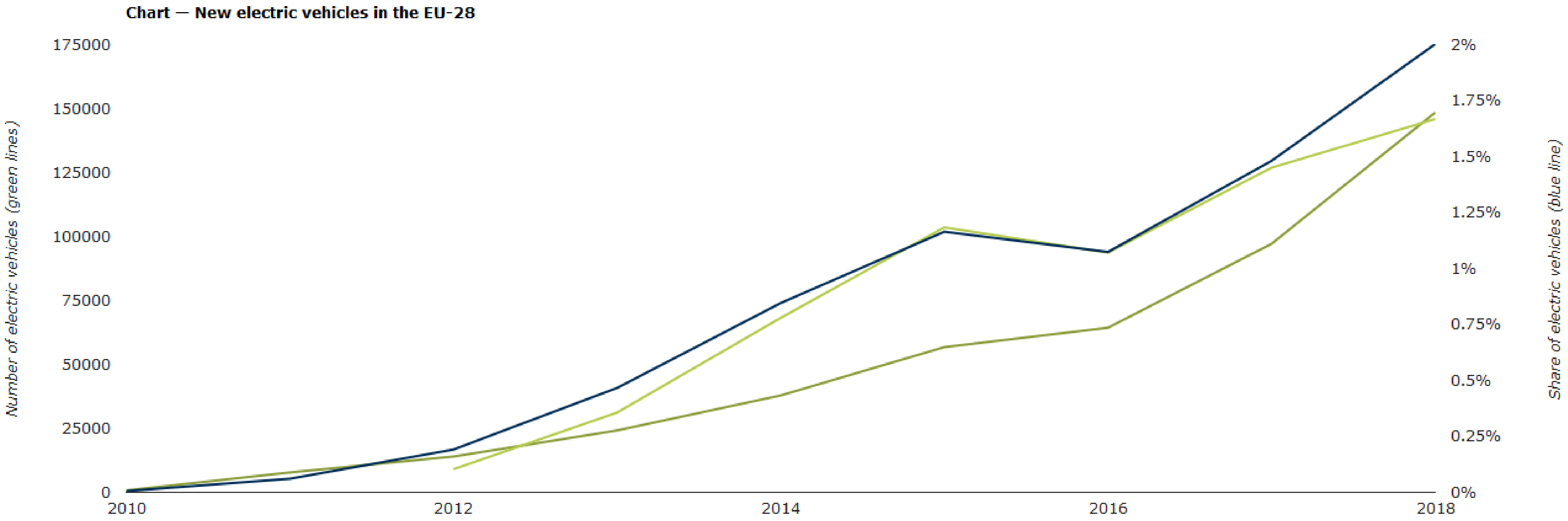
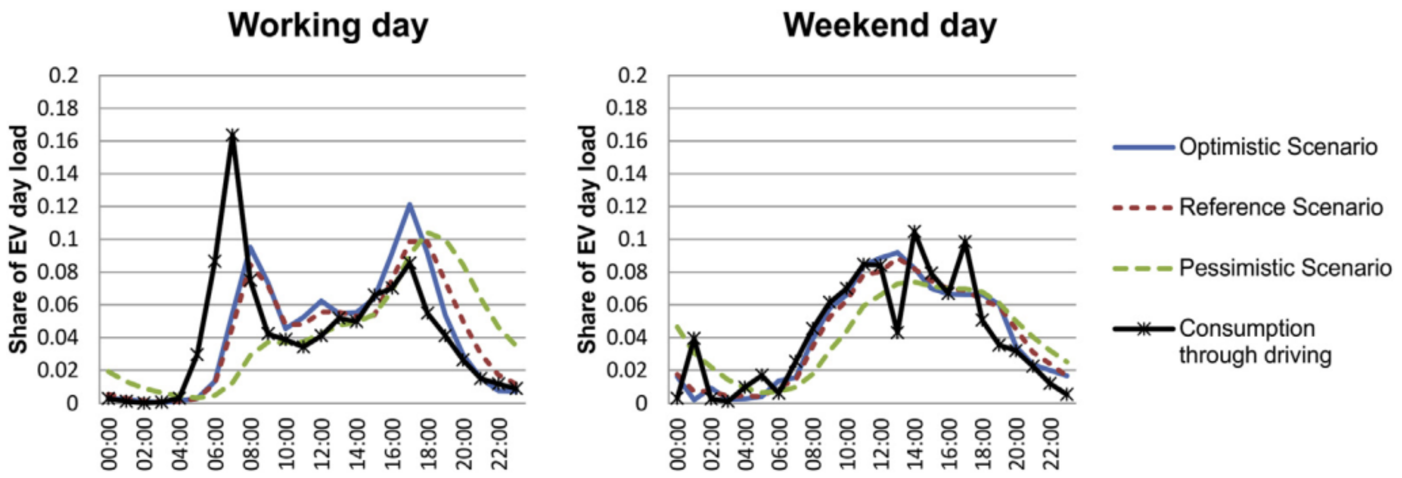
Motivation



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

https://www.eea.europa.eu/data-and-maps/indicators/proportion-of-vehicle-fleet-meeting-4/assessment-4

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

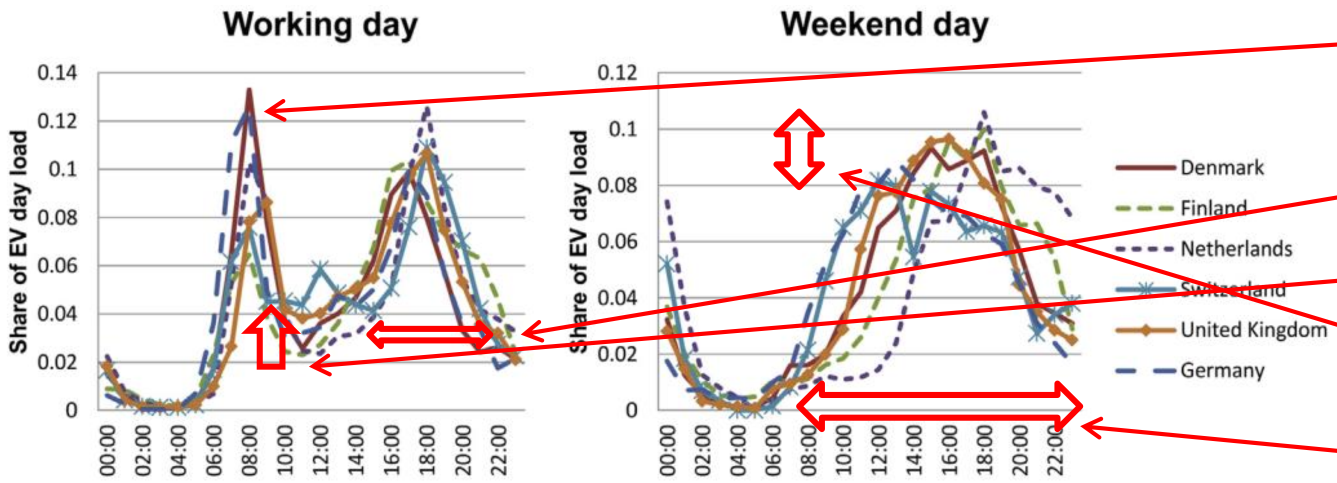


Technical assumptions

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

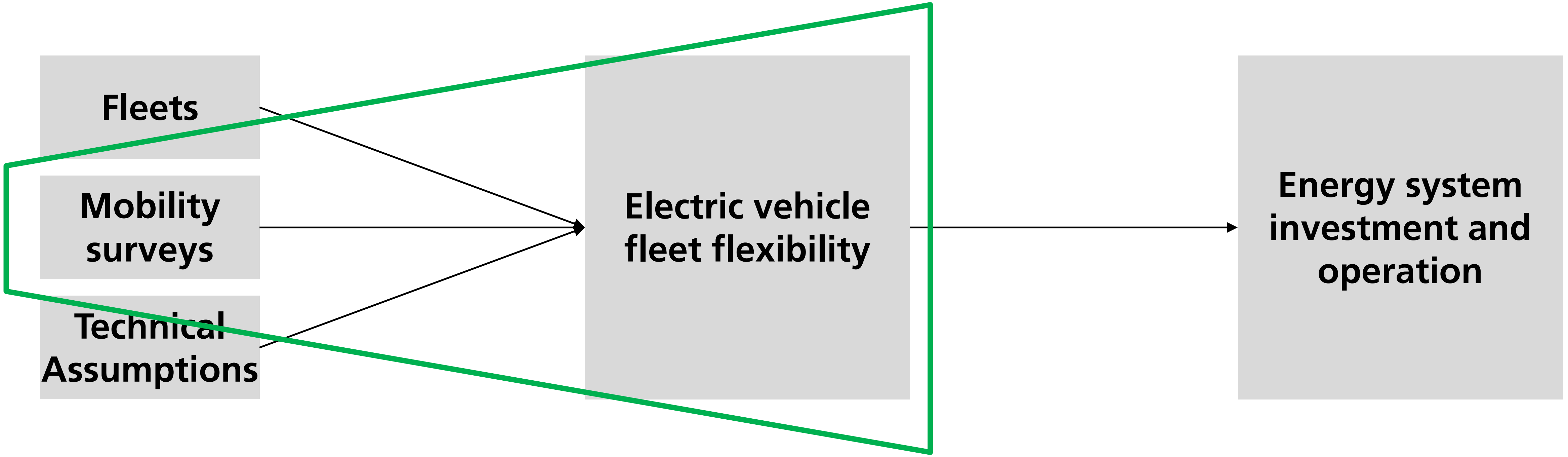
Wider evening peak for Finland

Swiss people drive more during midday

Different weekend distance peak amplitudes …

… , times and distributions.

Modeling pipeline and structure of the talk



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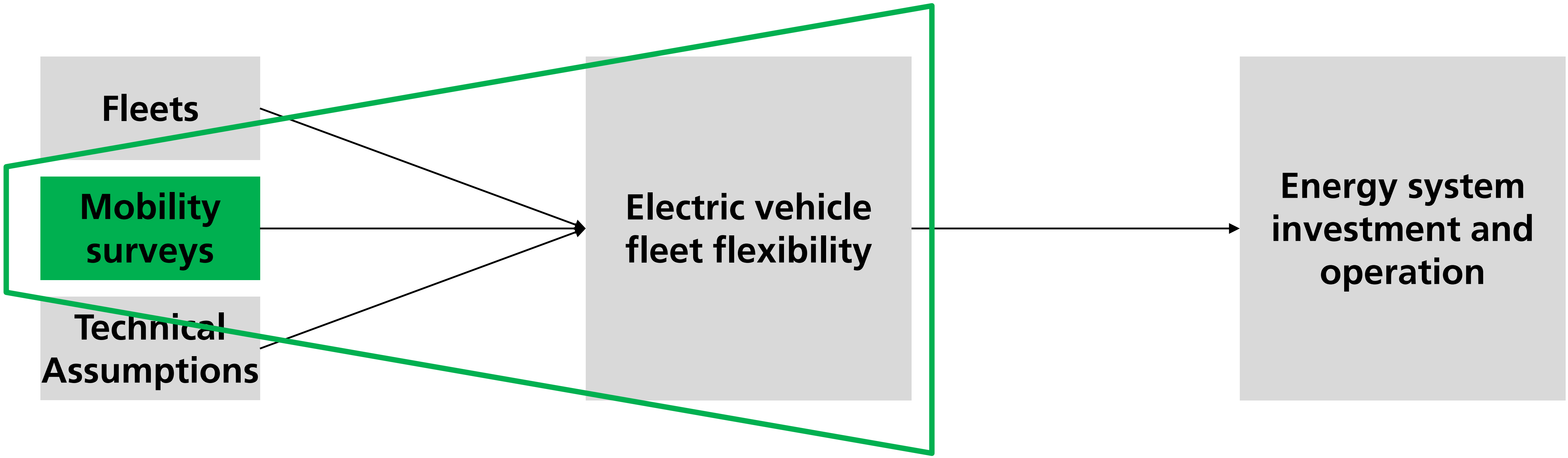


Explanation of the datasets – increased consciousness about personal data protection makes analysis more difficult

MiD 2008 (public use file)

Household (N=25,922)
102 variables

Trips (N=50,500)
121 variables

Vehicles (N=34,601)
53 variables

Travels (N=36,182)
50 variables

Person (N=39,722)
124 variables

MiD 2017 (B2 regional dataset)

Household (N=156,420)
49 variables

Trips (N=960,619)
157 variables

Vehicles

Travels

Person (N=316,361)
107 variables

Full codeplans available in German from http://www.mobilitaet-in-deutschland.de/pdf/2_MiD2017_Codeplaene.zip

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)

Start hour <= arrival hour (N=471,777)

Detailed trip length available (N=463,045)

No multi-modal trips
(N=405,411)

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

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

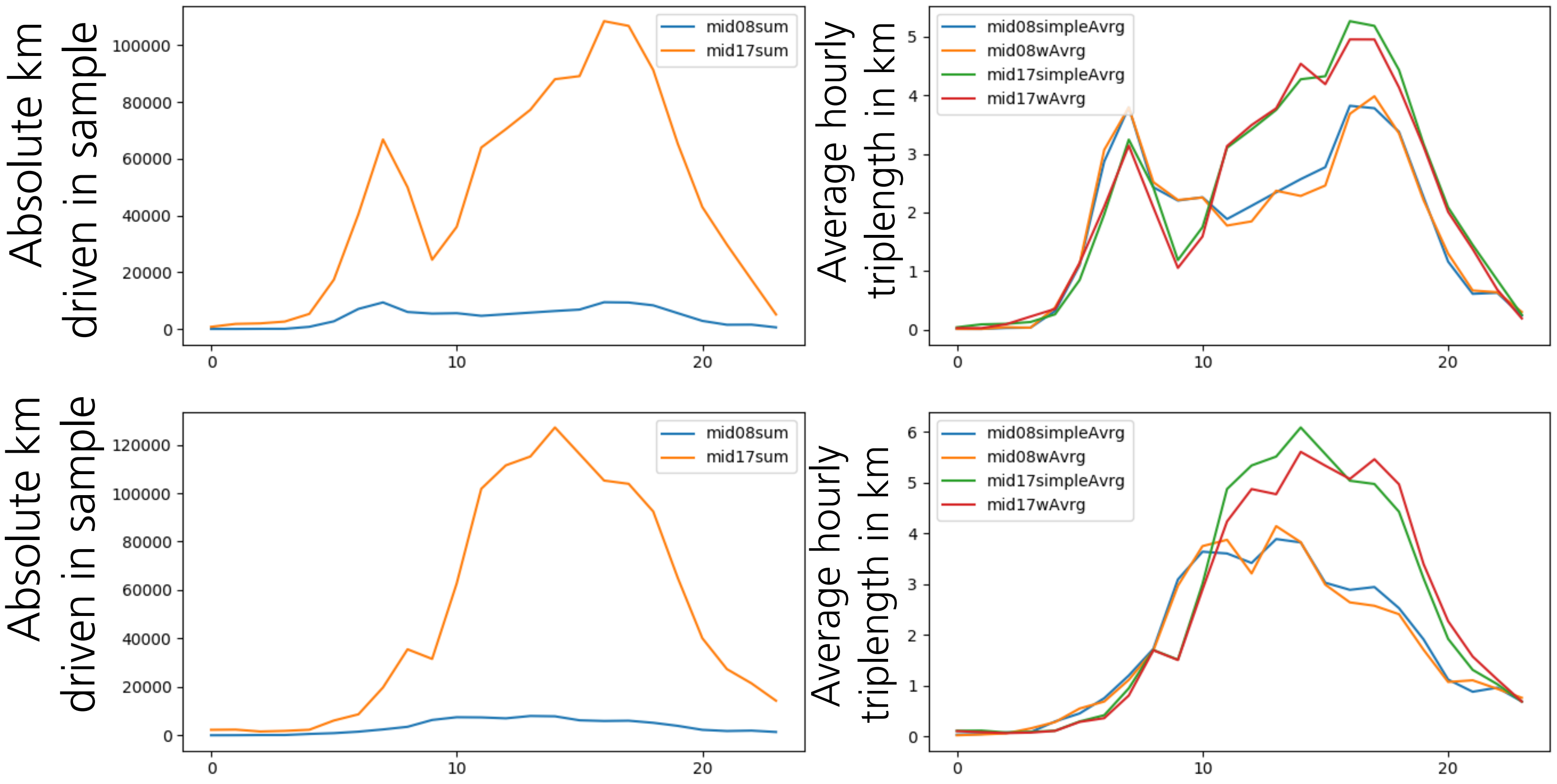
Codeplans available in German from http://www.mobilitaet-in-deutschland.de/pdf/2_MiD2017_Codeplaene.zip

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

N=143,699 N=17,863

TUESDAY

SATURDAY



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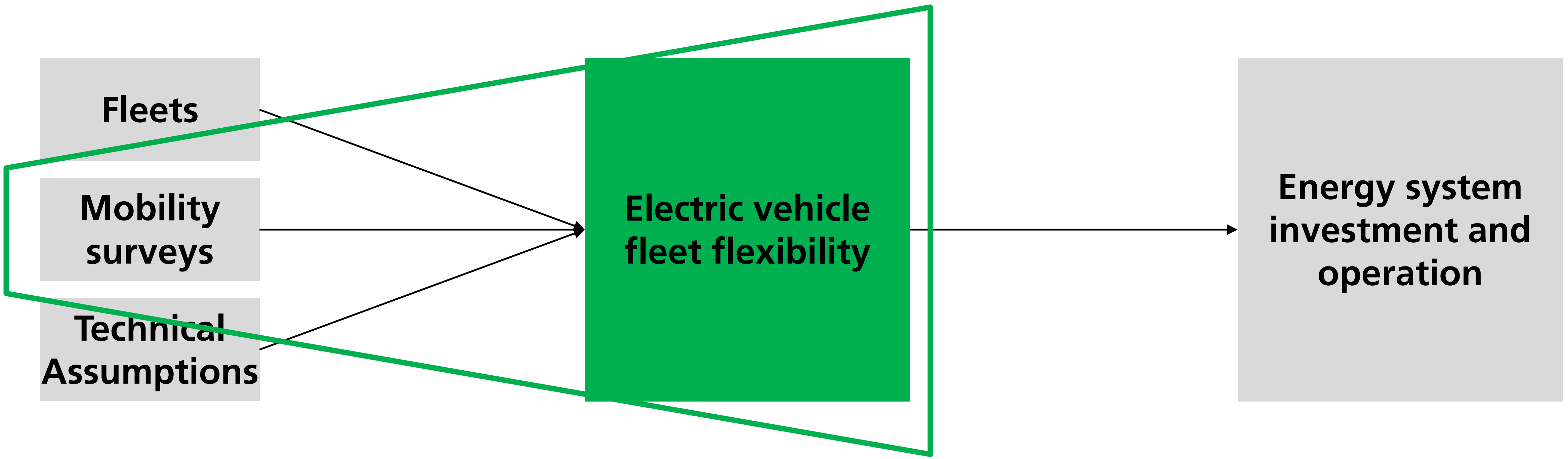


Vehicle Energy in Python (VencoPy) – resulting profiles

Grid

Battery

SOC Max
SOC Min

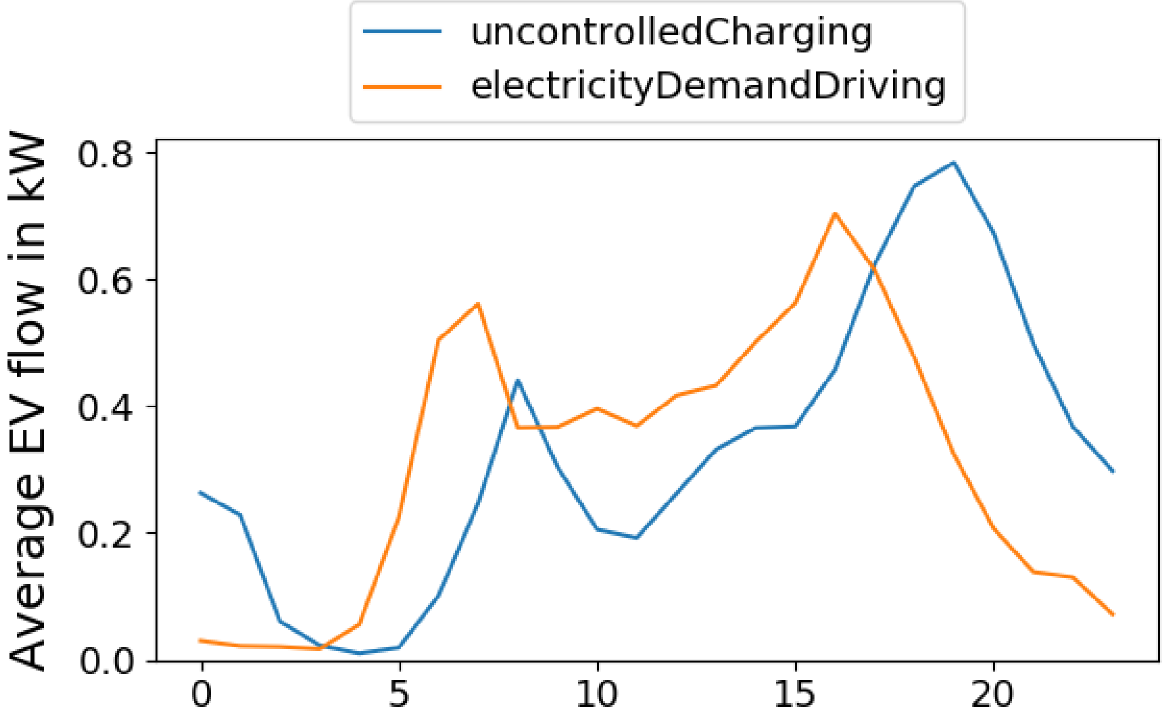
Demand

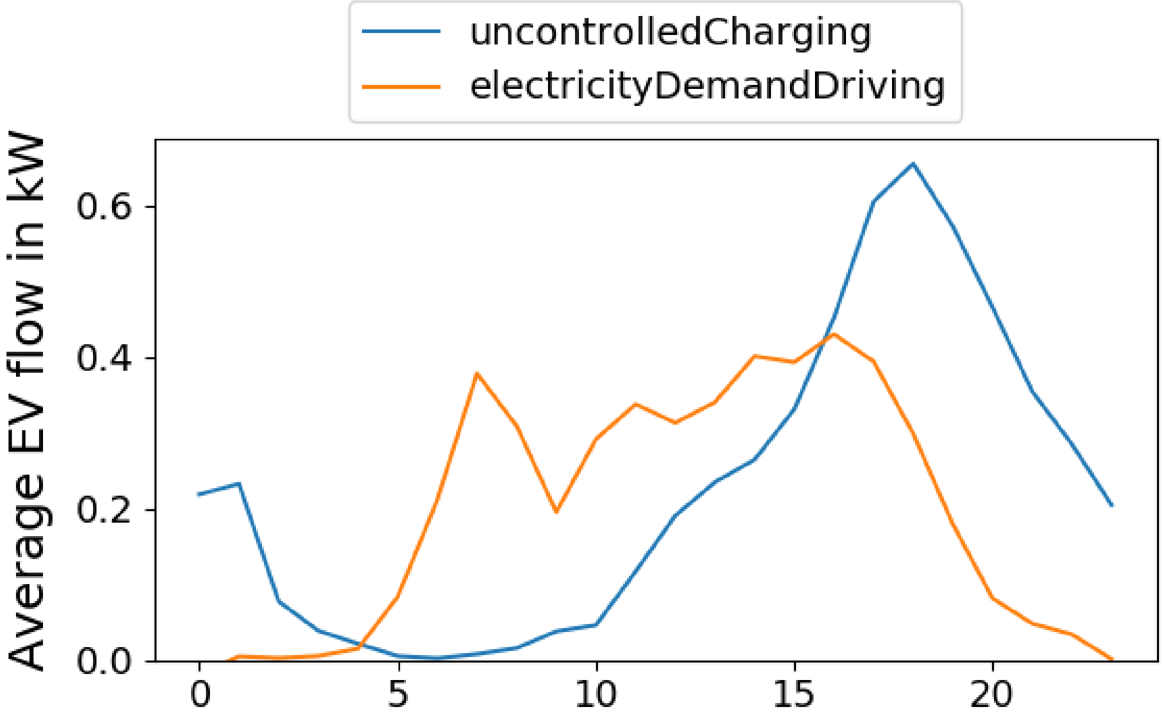
Uncontrolled charging

Controlled charging

Consumption
Grid connection
SOC Max
SOC Min

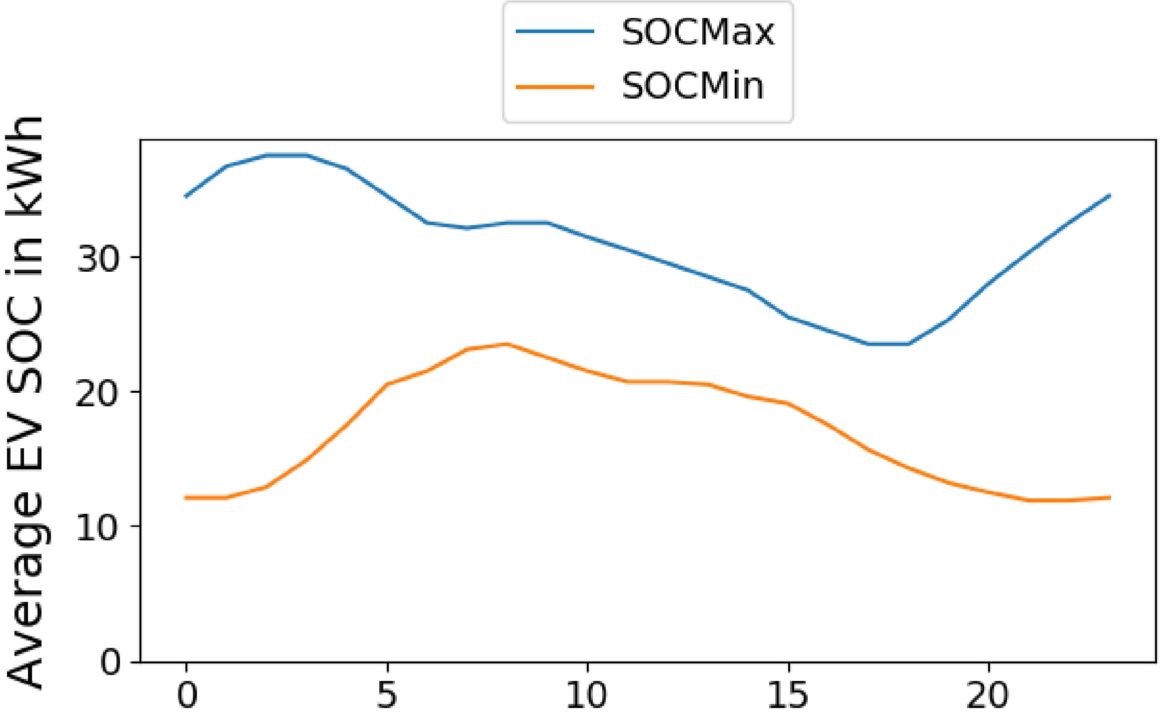
Comparing consumption and uncontrolled charging on the background of the data bases MiD2008 vs. MiD2017

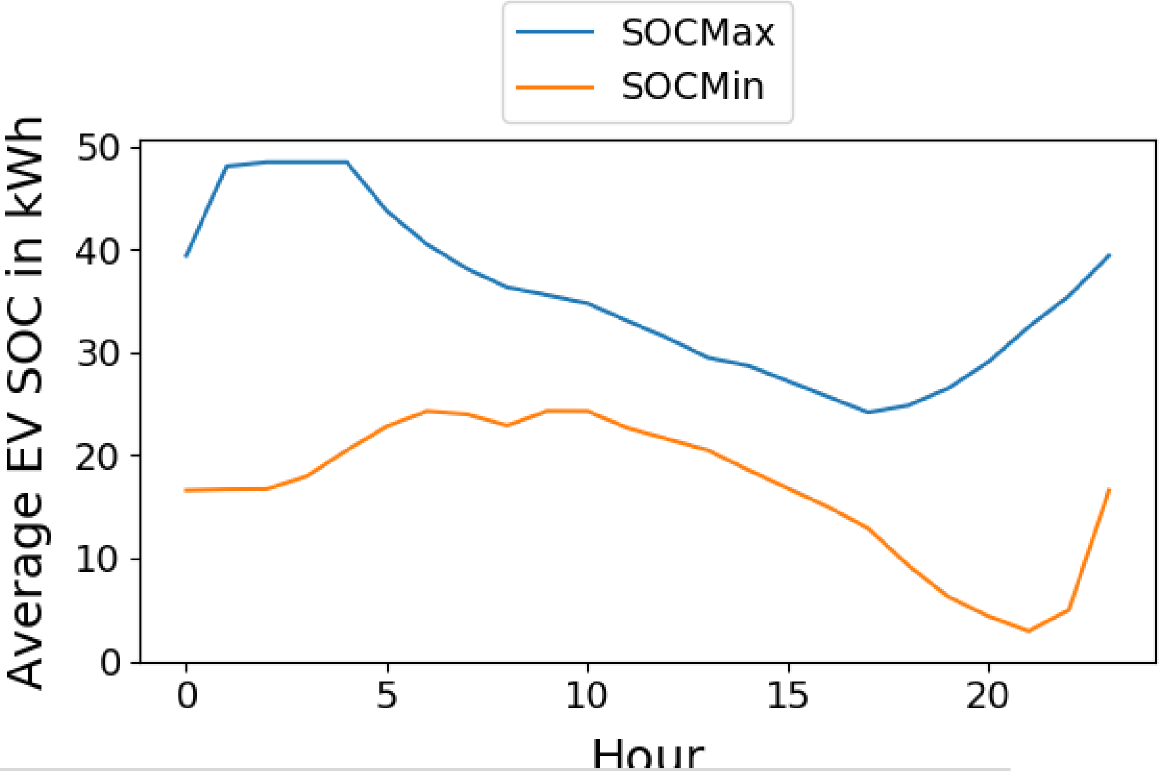




Morning and evening peak of electricity consumption reduced, evening peak flat. However, this doesn‘t affect evening peak of uncontrolled charging.

Comparing SOC flexibility on the background of the data bases MiD2008 vs. MiD2017





Similar shape of mobility-demand enforcement constaints 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

Follmer, R., Gurschwitz, D. Jesske, B., Quandt, S., Nobis, C. and Köhler, K. (2010). *Mobilität in Deutschland 2008* – Nutzerhandbuch. Online: http://mobilitaet-in-deutschland.de/pdf/MiD2017_Nutzerhandbuch.pdf

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Neaimeh, M., Salisbury, S.D., Hill, G.A., Blythe, P.T., Scoffield, D.R., Francfort, J.E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. https://doi.org/10.1016/j.enpol.2017.06.033

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Schaeuble, J., Kaschub, T., Ensslen, A., Jochem, P. & Fichtner, W. (2017). Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany. In: *J Clean Prod 150,* 253-266. https://doi.org/10.1016/j.jclepro.2017.02.150

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

	MiD2008	MiD2017	EV studies
Average Number of trips in 1/(cap*d)	3.4	3.1	
Average trip distance km/(cap*d)	38	39	61 (UK) vs. 43 (UKNTS) [Neaimeh et al. (2017)]
Share of active days in %	90	85	83

VencoPy – Estimating an electric vehicle fleets flexibility

Grid
Hourly electricity production costs

- $P_{charge,avail}$ (t)
- $C_{uncontr}$ (t)
- η_{GtV}

Charging (controlled + uncontrolled)

Interface grid – vehicle fleet battery

Fleet battery

L_{min} (t)
L_{max} (t)

- P_{drive} (t) **Electric drive power**

Interface battery – electric motor

Final energy demand for driving

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

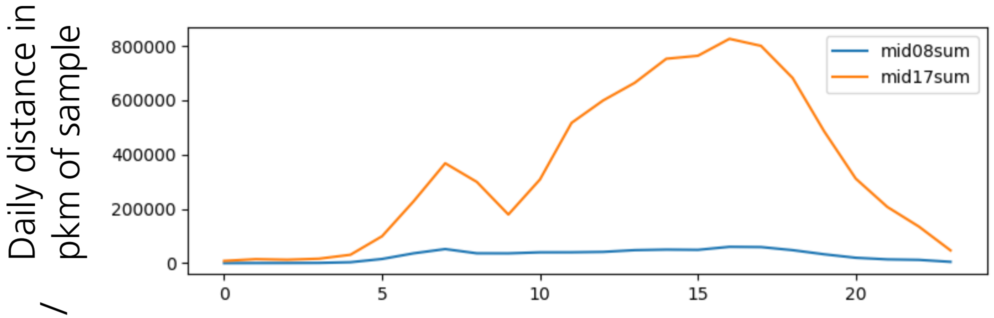
Image source
https://static.thenounproject.com/png/116156-200.png

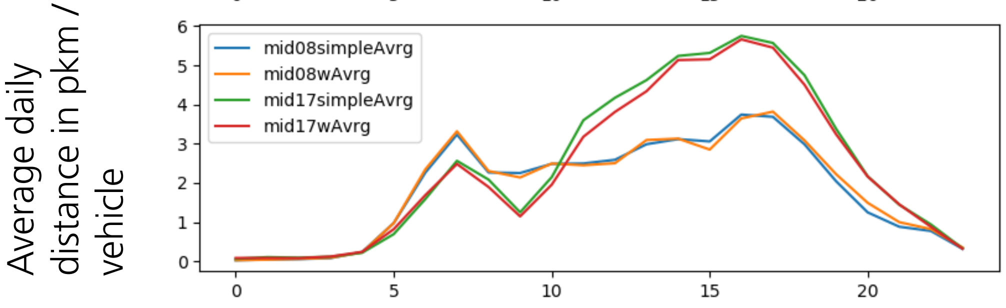
The MiD 2017 dataset

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

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

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





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

Criterium	Independent variable	Source	Arguments
Charging Place	Home, work, shopping etc.	Babrowski et al. (2014), Corchero et al. (2014)	- Strong influence on load curve characteristic - Locational influence on charging behaviour
Area type	Metropole, urban, rural	Babrowski et al. (2014)	- Different distribution grid resiliencies - Different EV penetration rates
Daytype	Weekend, weekday	Babrowski et al. (2014)	- Different mobility patterns
Season	Temperature (continuous)	Fischer et al. (2018) citing Lindgren et al. (2016), Brown et al. (2018)	- Influence of temperature on vehicle electricity consumption
User group	Commuter, part-time workers, student, pensionist etc.	Fischer et al. (2019), Gaete et al. (2020, forthcoming)	- Charging locations depend on user group and thus charging characteristic
Car model	Battery size, consumption, charging rate	Fischer et al. (2019)	- Battery size, electric consumption and maximum charging rates influence charging