Exploring EV charging patterns, flexibility potential, and grid impacts

Federica Bellizio (Empa), Siobhan Powell & María Parajeles (ETH Zurich)

sweet swiss energy research for the energy transition

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Agenda

1. Motivation
2. María – *Mobility-based quantification of EV fleets charging power and flexibility* (10 min)
3. Federica - *Flexibility quantification and prediction: The Dutch and Swiss analysis* (10 min)
4. Siobhan – *Techno-economic analysis of V2G profitability: The case of Switzerland* (10 min)
5. Conclusion
6. Questions and answers (15 min)

Motivation

- **Transport demand** is especially **flexible** due to its low active utilization (high percentage of time parking), allowing for **smart integration of transport and electricity sectors**.

Modeling

Charging data is not always available or universally representative:

Alternative modeling approaches.

Validating

Quantifying and predicting the available flexibility is crucial to fully exploit it:

Data-driven approaches

Accessing

New policies and regulations are needed to fully access the available flexibility

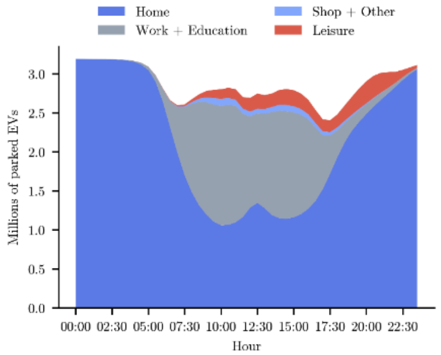
- We discuss our work towards **modeling, validating, and accessing** charging demand and flexibility from the transport sector.

Mobility-based quantification of EV fleets charging power and flexibility

Modeling Work So Far:
From Agent-based Transport Simulations to Georeferenced Driving Energy Requirements

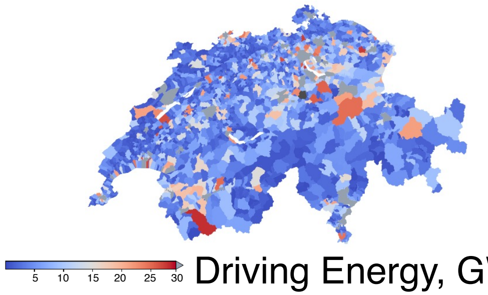
Nationwide Transport Simulation [1]

- Parking geographic location

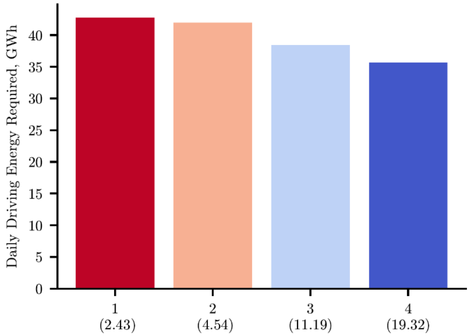


Daily distribution of parking location by type

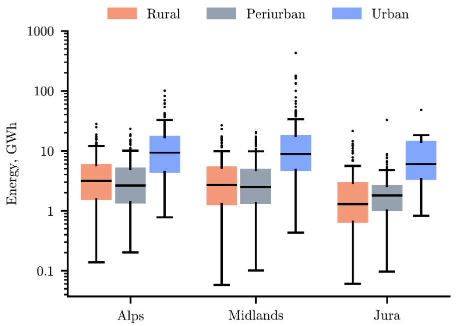
Vehicle-specific Driving Energy Estimation [2]



Driving Energy, GWh



Daily national driving energy by mean ambient temperature



Driving energy needs grouped by region and urbanization

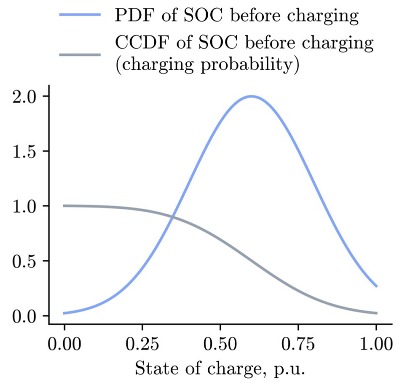
Extend to *weekly* mobility and energy needs patterns using open statistical data

[1] A. Horni, K. Nagel, and K. Axhausen, Eds., Multi-Agent Transport Simulation MATSim. London: Ubiquity Press, Aug 2016.
[2] M. Parajeles Herrera, M. Schwarz, and G. Hug, “Spatio-Temporal Modelling of Large-Scale BEV Fleets Charging Energy Needs and Flexibility” SEST 2024.

Estimating Charging Power:
Base-Case Charging Profiles Formulation

Generation of weekly charging profiles

- Charging infrastructure considered widely available: 7-22 kW depending on parking location.
- Charging decision subject to:
  - $SOE < X,\ X \sim \mathcal{N}(\mu, \sigma)$,
    and additional heuristic considerations regarding:
    - minimum battery level,
    - enough energy for consecutive trips,
    - equal start and end SOE.



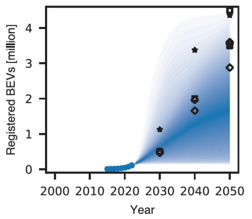
- EV trails: My Electric Avenue, Switch EV, The EV Project, Pecan Street
- Tuncated normal distribution: $\mathcal{N}(0.6, 0.2)$ [3]

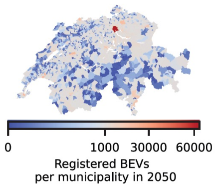
Generation of yearly charging profiles

- Generation of charging profiles for each typical weather period.
- Electrification percentages per year applied per municipality.

TP	Mean Temp., deg. C	Months
1	2.43	December
2	4.54	January, February, March, November
3	11.19	April, May, October
4	19.32	June, July, August, September

- Distribution of typical periods in the year





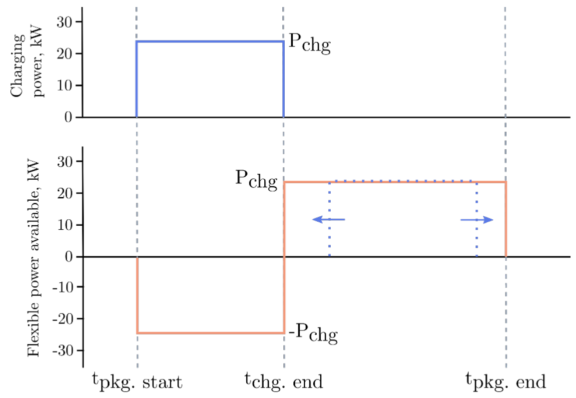
- Probabilistic projections per municipality [4]

[3] G. Pareschi et al., “Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data,” *Appl. Energy*, vol. 275, p. 115318, Oct. 2020.
[4] N. Zielonka, X. Wen, and E. Trutnevyte, “Probabilistic projections of granular energy technology diffusion at the subnational level,” PNAS Nexus, Sep. 2023.

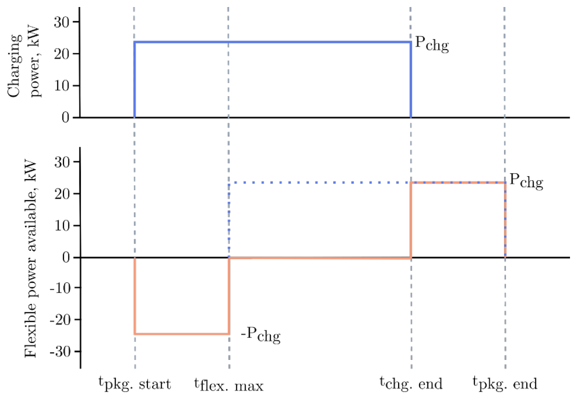
Estimating Charging Flexibility:

Power And Energy Flexibility Bounds Formulation

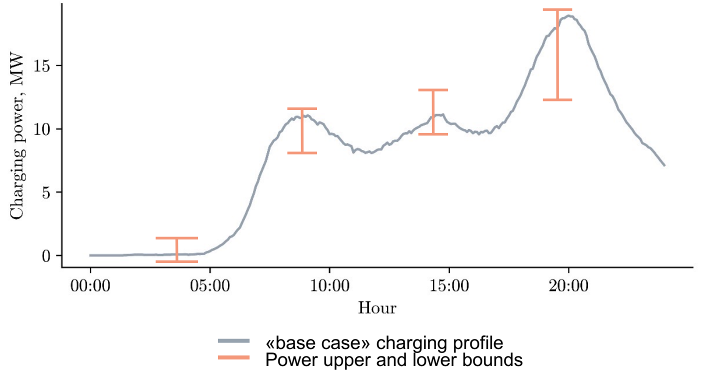
- Estimation of charging power and energy flexibility, with respect to the base case charging patterns, subject to:
  - $1\ hour\ \leq t_{parking} \leq 15\ hours$
  - $t_{parking} > t_{charging}$
  - $SOC_{final,\ without\ flexibility} = SOC_{final,\ with\ flexibility}$
  - $E_{flexible} = \begin{cases} (t_{chg.\ end} - t_{pkg.\ start}) \cdot P_{chg.}\ , if\ t_{parking} \geq 2 \cdot t_{charging} \\ (t_{chg.\ end} - t_{flex.\ max}) \cdot P_{chg.}\ , if\ t_{parking} < 2 \cdot t_{charging} \end{cases}$



$t_{parking} > 2 \cdot t_{charging}$

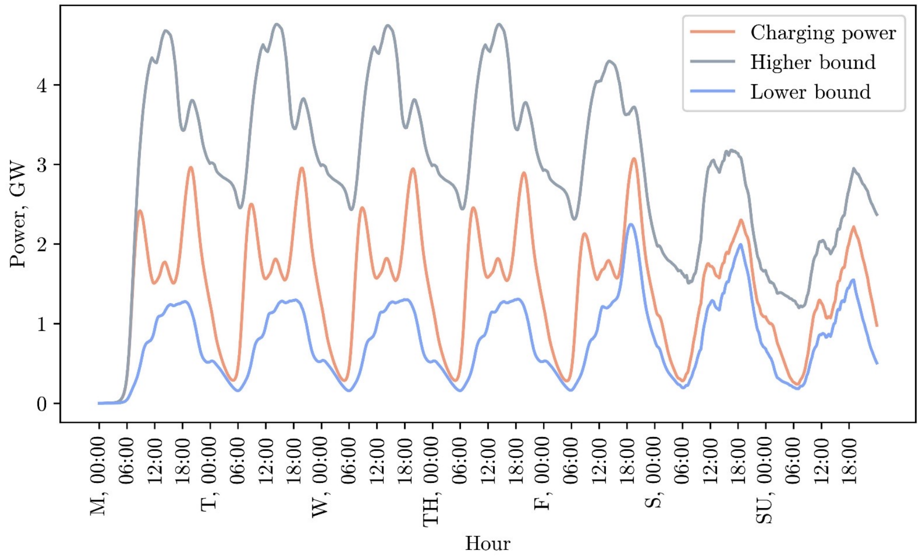


$t_{parking} < 2 \cdot t_{charging}$

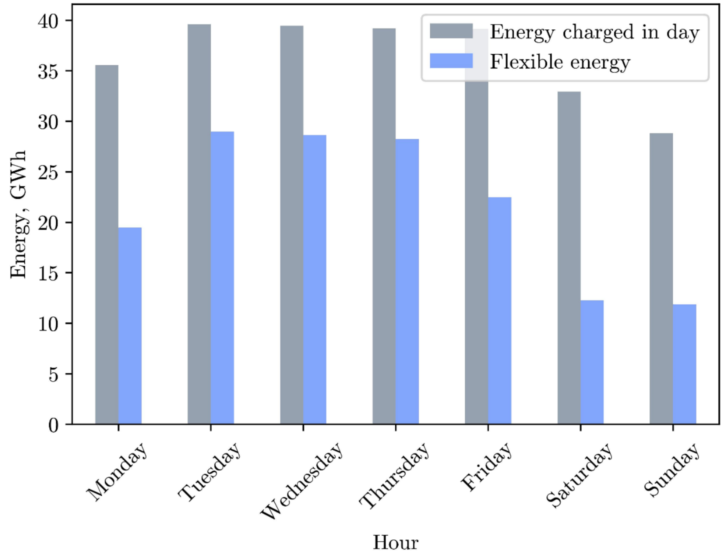


Charging power and flexibility bounds

Estimating Charging Power and Flexibility:
Power And Energy Flexibility *Nationwide* Bounds



Nationwide charging power and flexibility bounds during a cold week

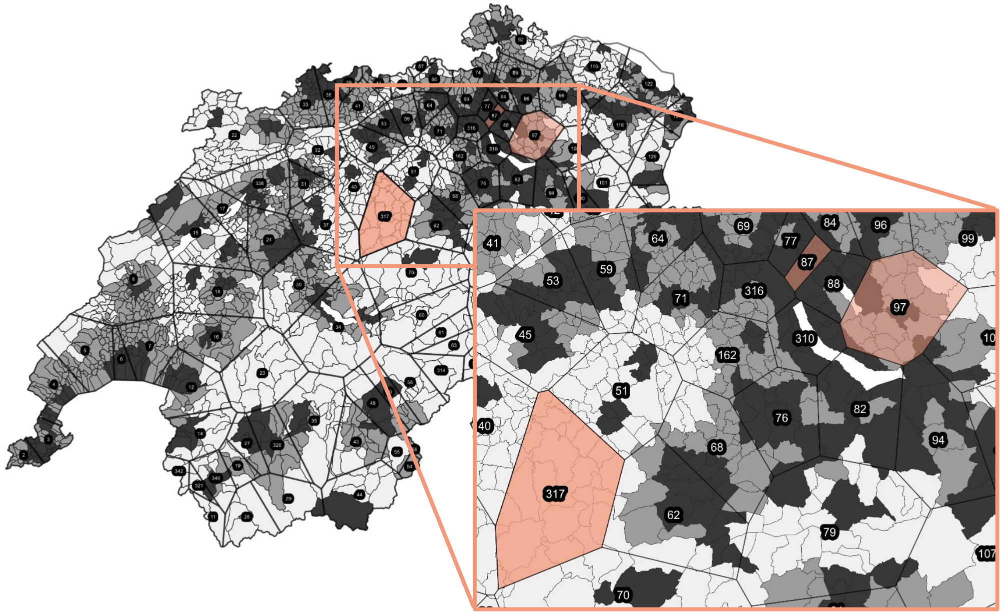


Nationwide flexible energy during a cold week

- **Upwards** power flexibility is estimated on an average of 1.28 GW, with a maximum of 2.6 GW.
- **Downwards** power flexibility is estimated on an average of 0.5 GW, with a maximum of 1.7 GW.

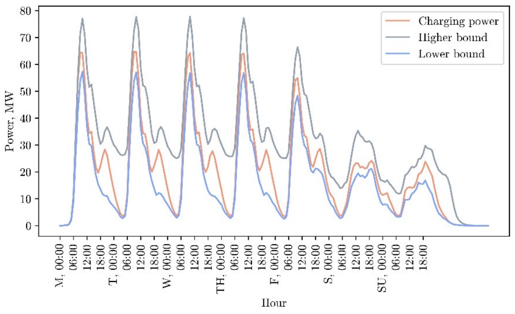
- Increase of 16.5% of peak charging power on cold days with respect to warm days.
- 62% of energy charged during the week is flexible, whilst only 34% is flexible on weekends.

Estimating Charging Power and Flexibility:
Power And Energy Flexibility *Localized* Bounds

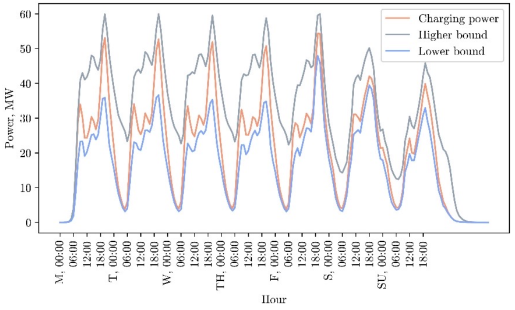


Urban Periurban Rural

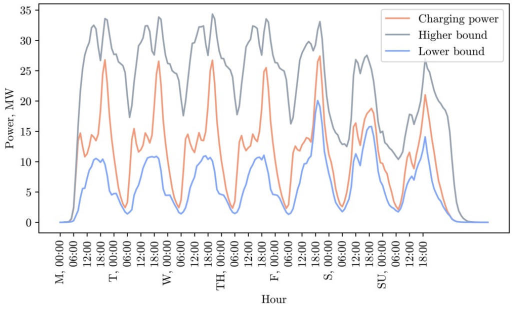
Charging power and flexibility bounds for area **87 (mostly urban)**



Charging power and flexibility bounds for area **97 (mostly periurban)**



Charging power and flexibility bounds for area **317 (mostly rural)**



Outlook:
Integration into Energy Systems Models

Work in progress

Generation of **geographic and time-specific** charging profiles, power, and energy flexibility bounds for 2030, 2040, and 2050.

Integration of the information **into Nexus-e's optimization model**:

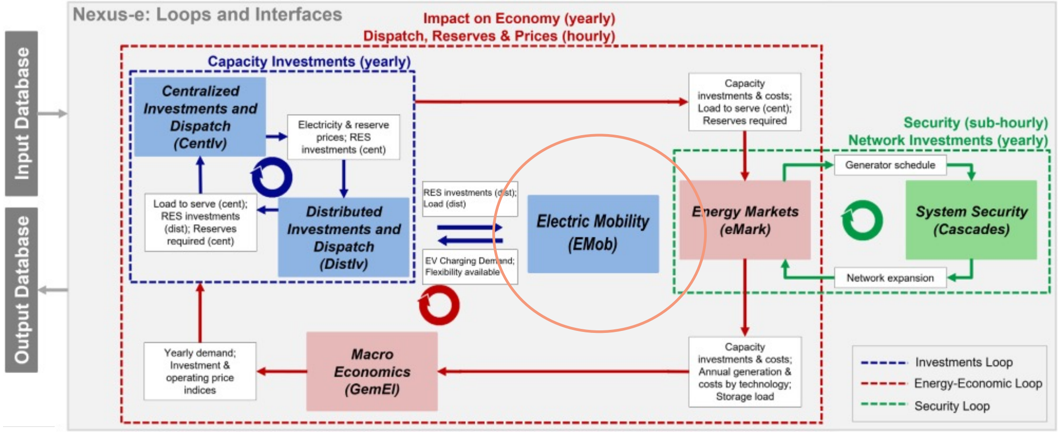
•Bounds differ in space and time

•Overnight charging flexibility captured by modeling weekly charging patterns

Run updated simulations to **study** the **use of the flexibility available** in the investment and operation decisions at the transmission level.

Module implementation planned

Nexus-e



Implementation of the transport electrification model as a **stand-alone module** in Nexus-e:

- with varying underlying assumptions,
- and interaction with the distributed investment and operation decisions.

Flexibility quantification and prediction: The Dutch and Swiss analysis

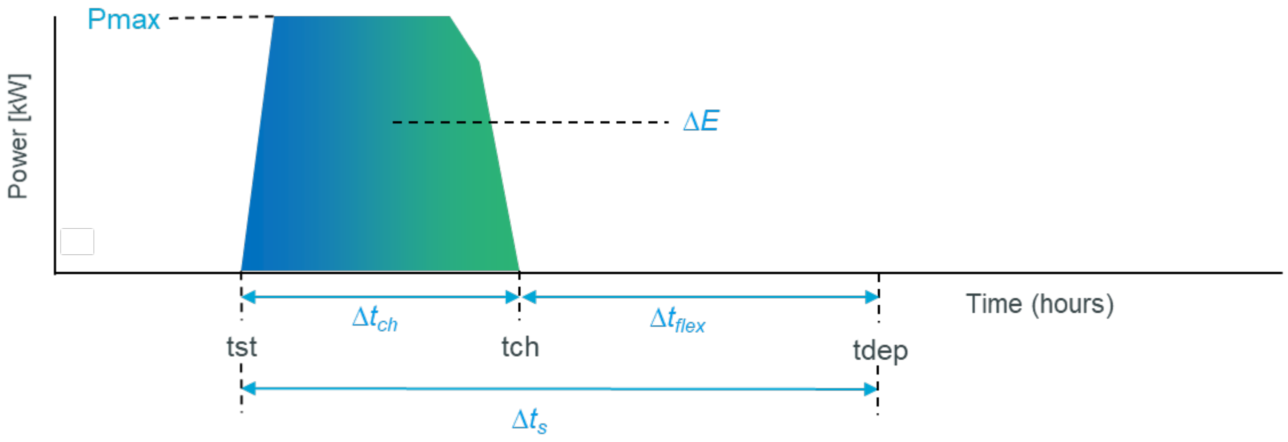
How can we quantify and predict the flexibility?

- Mobility-based modeling requires validating multiple assumptions about charging (human) behaviors
- EV mobility data are scarce, often not publicly available and owned by single operators, such as charge-point (CP) operators
- Exploiting flexibility remains a challenge even when data is available, as managing charging sessions requires information on human behaviors.
- We conduct data analysis from EV charge-points in the Netherlands and in Switzerland to investigate how to quantify and predict available flexibility in real-world scenarios.

Flexibility quantification

- Large dataset available: ~10,000 public CPs in the Netherlands, ~2.5 million charging sessions over 1 year

- Flexibility $\Delta f = \Delta E \times \Delta t_{flex}$ with $\Delta t_{ch} = \frac{\Delta E}{Pmax}$ and $\Delta t_{flex} = max\{\Delta t_s - \Delta t_{ch}, 0\}$



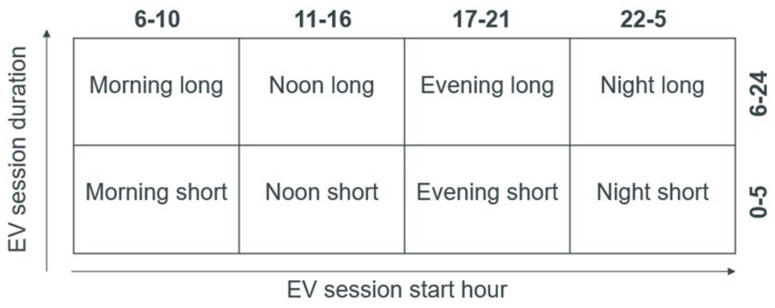
To predict:
- Session duration (Δt_s)
- Energy consumption (ΔE)

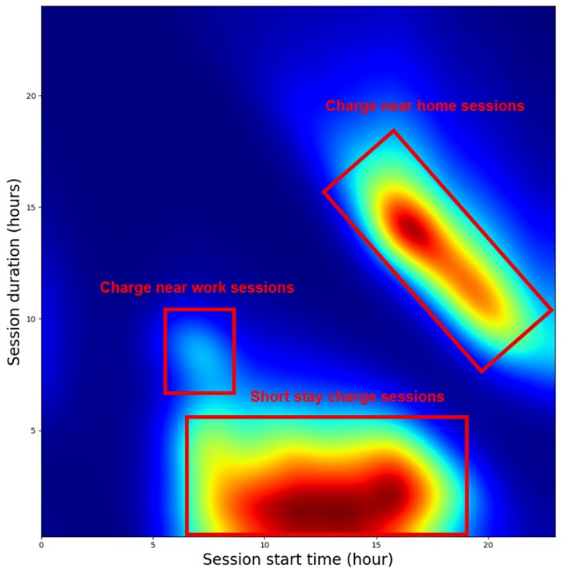
- Two informed data-driven approaches: CP cluster- and user-based approach

[5] Bellizio, F., Dijkstra, B., Fertig, A., Van Dijk, J., & Heer, P. (2024). Machine Learning Approaches for the Prediction of Public EV Charge Point Flexibility. SSRN. DOI: https://dx.doi.org/10.2139/ssrn.4751908

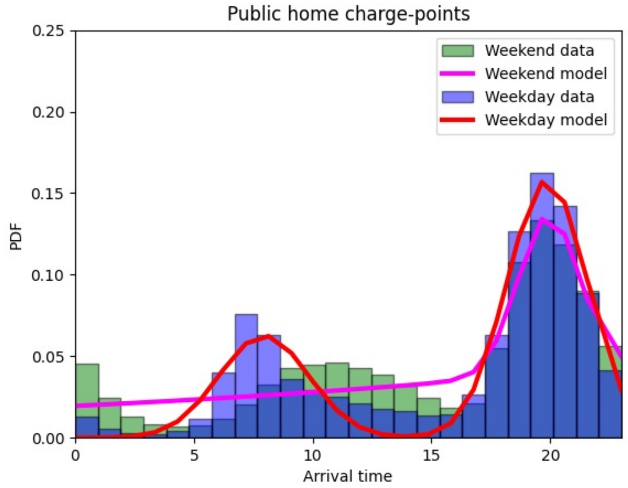
Machine leaning-based predictive models

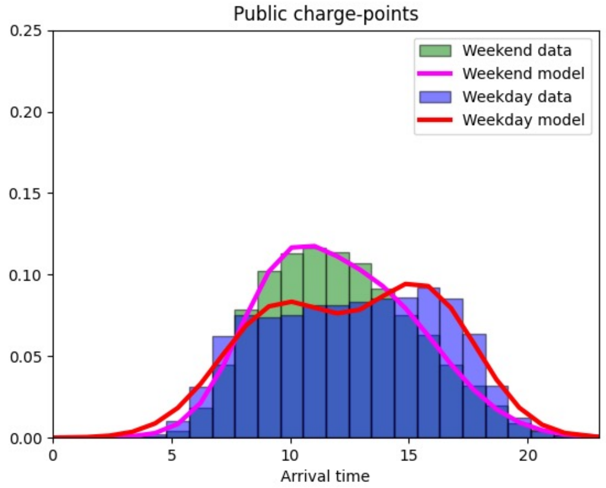
- CP clusters: Hybrid, Work, Short-stay, Home
  - ➢ XGBoost model per cluster

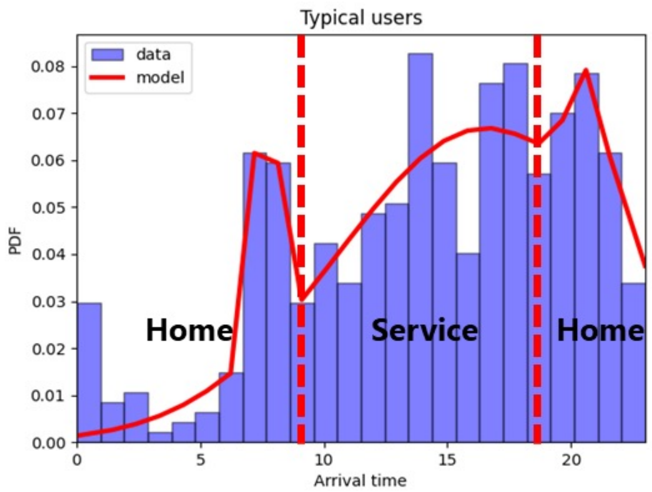




- EV user archetypes
  - ➢ Long short-term memory (LSTM) model per EV







[3] G. Pareschi et al., “Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data,” *Appl. Energy*, vol. 275, p. 115318, Oct. 2020.

The training dataset

- Input features:
  - EVSE max power *
  - EVSE average energy demand *
  - EVSE average duration *
  - Session starting hour *
  - Day of week, month, year *
  - Week of year
  - Month of year
  - Weekend or not
  - Holiday or not
  - Temperature, Precipitation, Humidity, Sunshine, Wind speed (based on postal code)
  - User moving mean, max and min of the target feature

EVSE related features

Session related features

Weather related features

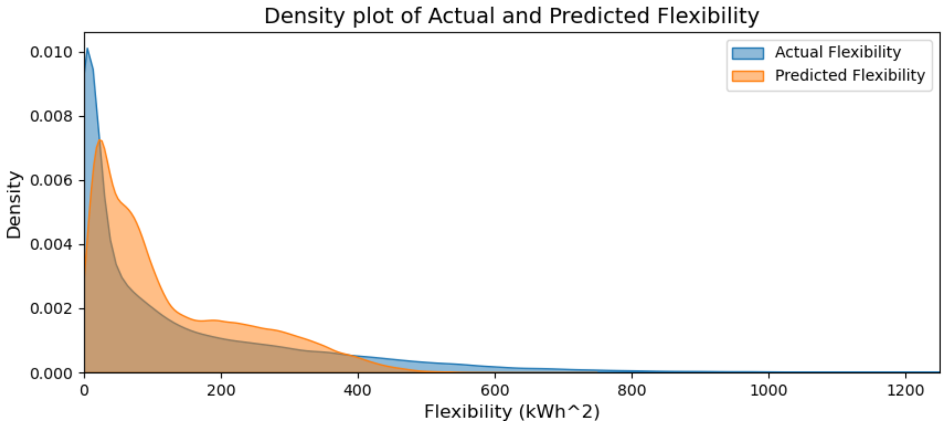
User related features

- Target features: Session energy demand and duration

The Dutch analysis: predictive performance

- CP cluster-based approach

Cluster	Aggregated model			Cluster approach models		
	MAE	MSE	SMAPE (%)	MAE	MSE	SMAPE (%)
0	3.363	21.311	48.72	3.320	21.181	50.06
2	3.812	26.476	48.17	3.806	25.992	50.12
7	2.933	17.511	50.18	2.809	17.101	51.47
5	3.119	18.466	46.25	3.100	18.618	48.27
6	3.602	23.228	47.03	3.641	23.685	49.22
3	2.088	8.663	58.82	1.572	7.255	46.51
10	3.826	27.224	51.00	3.789	26.389	52.92
9	2.340	9.977	51.49	2.074	9.508	48.68
20	3.017	18.099	48.60	2.869	17.670	49.44
13	4.117	29.489	47.75	4.119	28.549	49.95
Overall	3.382	21.654	48.86	3.305	21.212	49.89



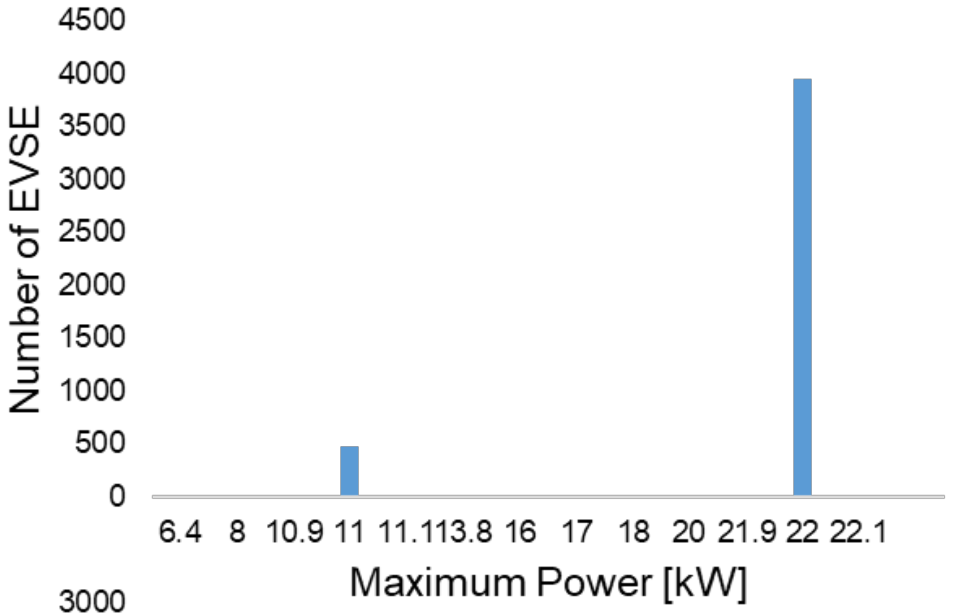
Accurate predictions of aggregated flexibility → Relevant info to system operators for planning and operation

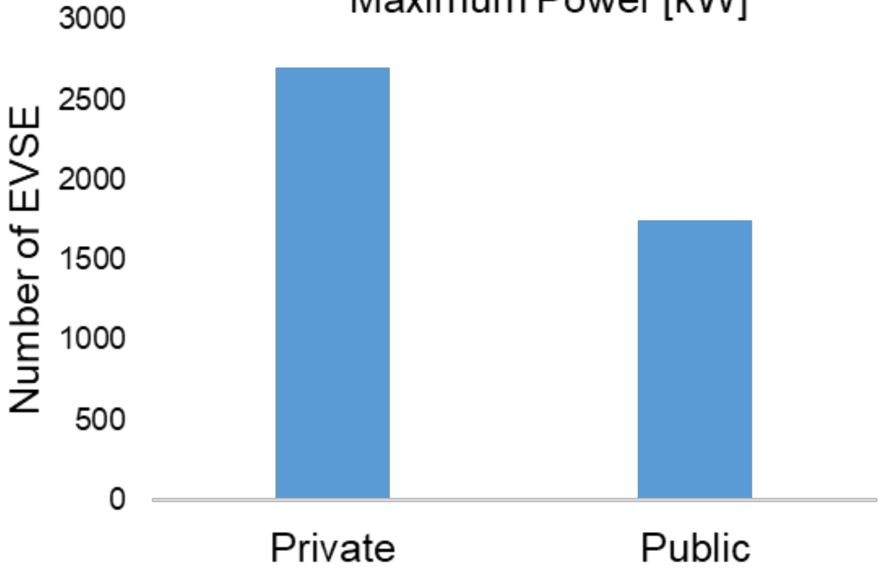
- User-based approach
  - Fleet of 10 EVs sampled from user archetypes
  - Training/Testing: 1/1/2022 – 31/7/2022
  - Validation: 1-31/8/2022
  - MAE: 2.6h → 21% improvement

The Swiss analysis: charging data

- Initial dataset:
  - 9’511 EVSE IDs
  - 1’048’575 sessions
  - 2022/03/30 and 2024/04/11

- Data-preprocessing: EVSE IDs with more than 30 sessions, sessions with energy [0.25, 150] kWh and duration [0.25, 200] h, 22kW max power
  - 4’444 EVSE IDs
  - 466’905 sessions

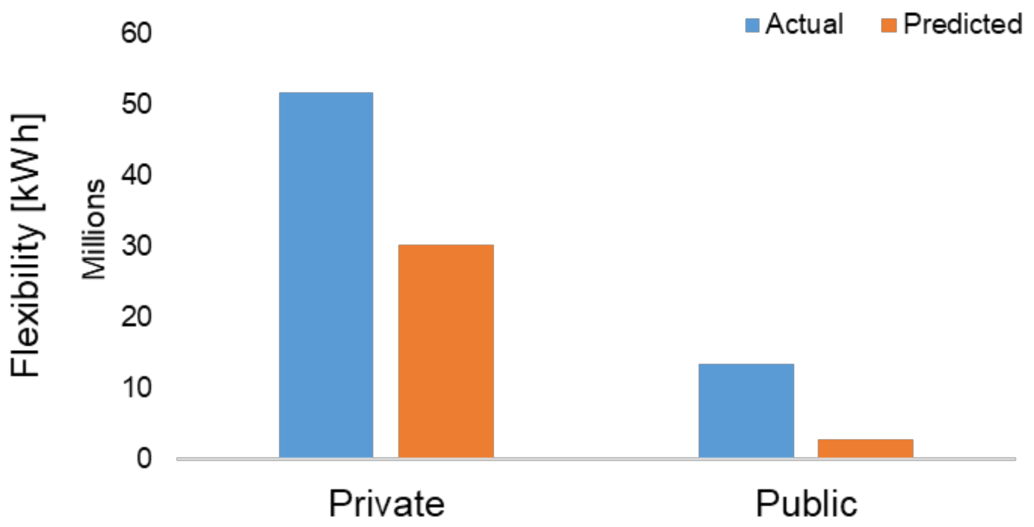


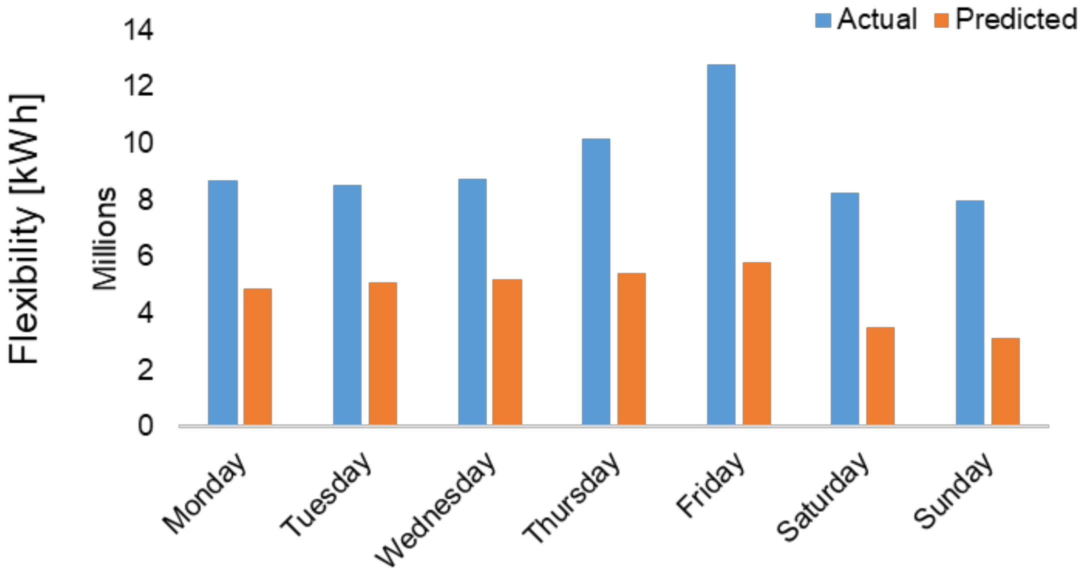


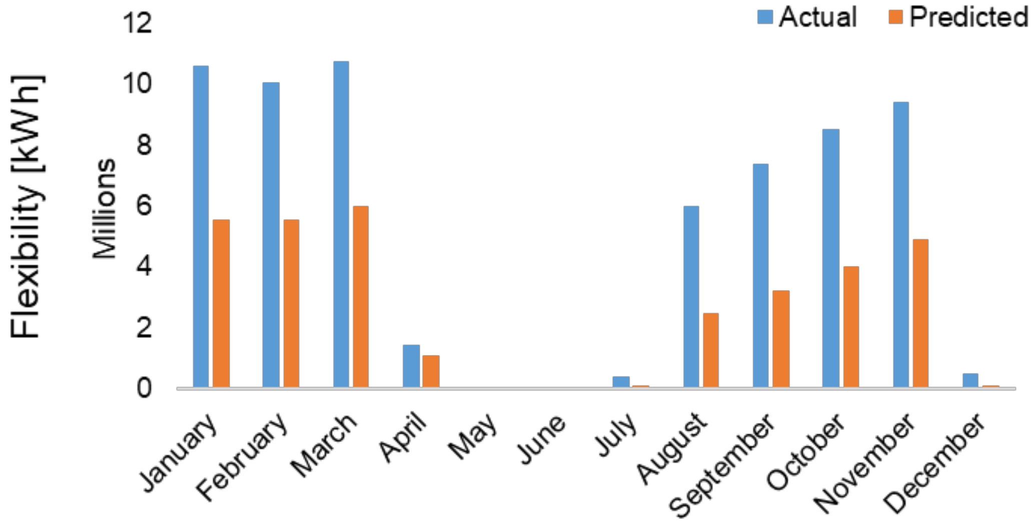
The Swiss analysis: predictive performance

- Mean Absolute Error (MAE):
  - ➢ Energy demand: 10.2 kWh
  - ➢ Duration: 2.9h

- Assumptions for calculation:
  - ➢ Max power: 11kW







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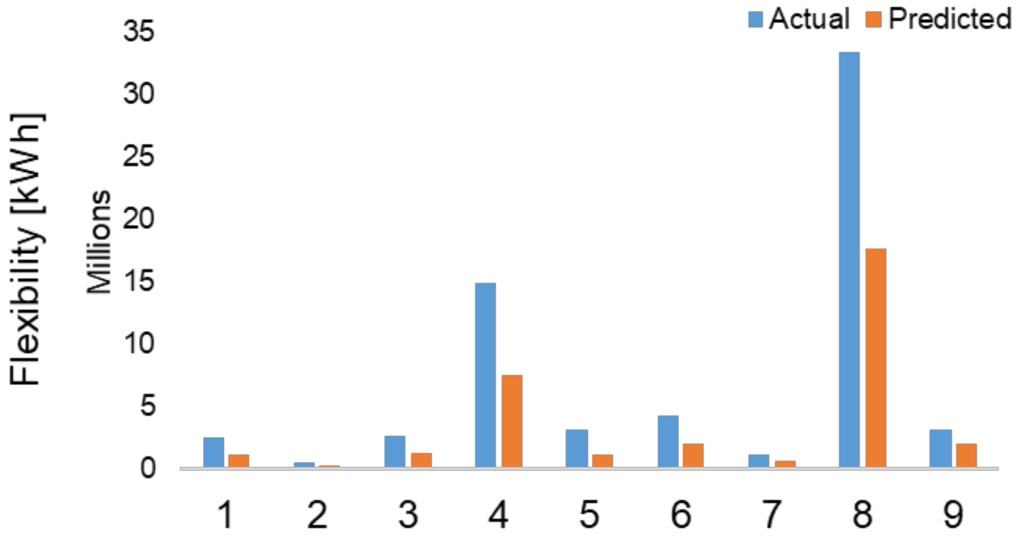
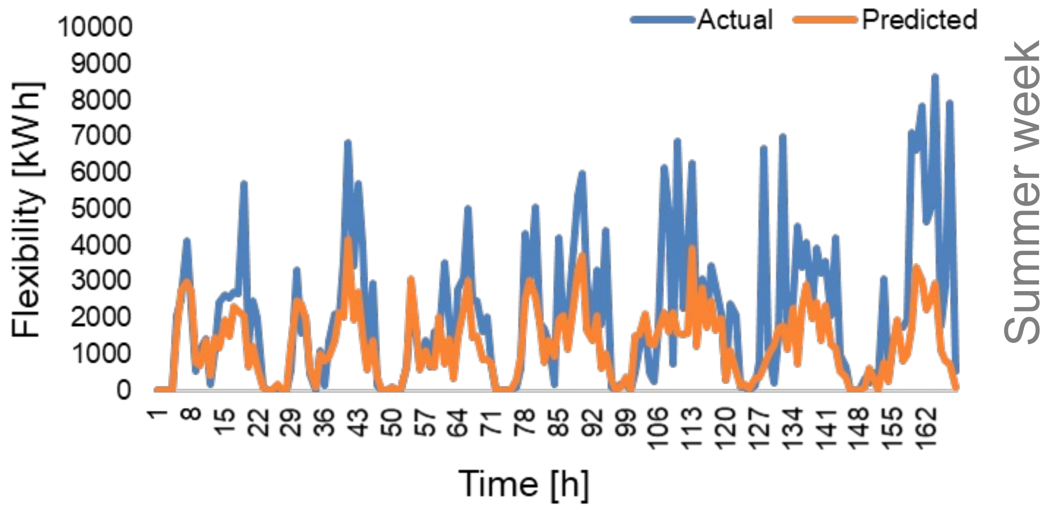
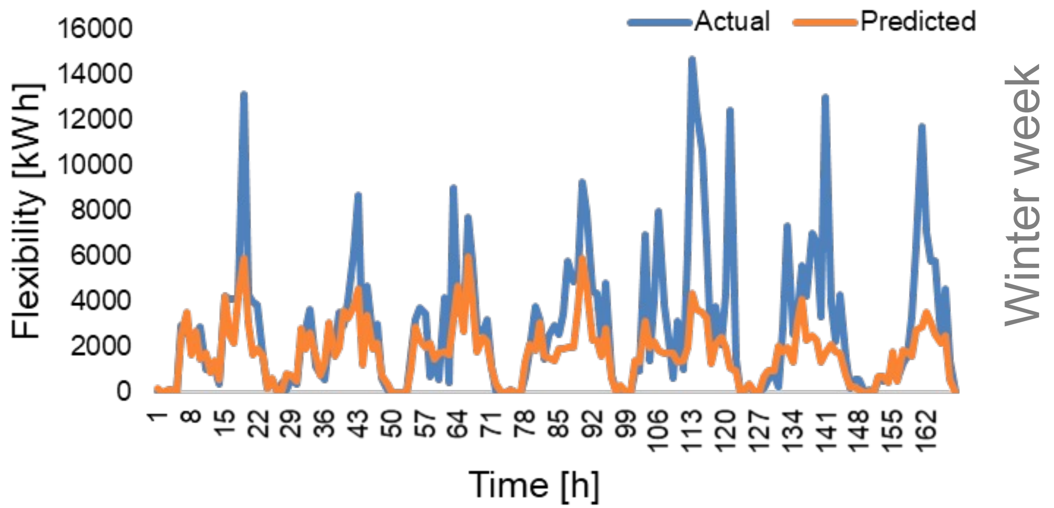
The Swiss analysis: predictive performance



Zurich city





Techno-economic analysis of V2G profitability: The case of Switzerland

Andersen, Daniel and Powell, Siobhan, Policy and Pricing Tools to Incentivize Distributed Electric Vehicle-to-Grid Charging Control. Available at SSRN: https://ssrn.com/abstract=4918051

How can we access this flexibility?

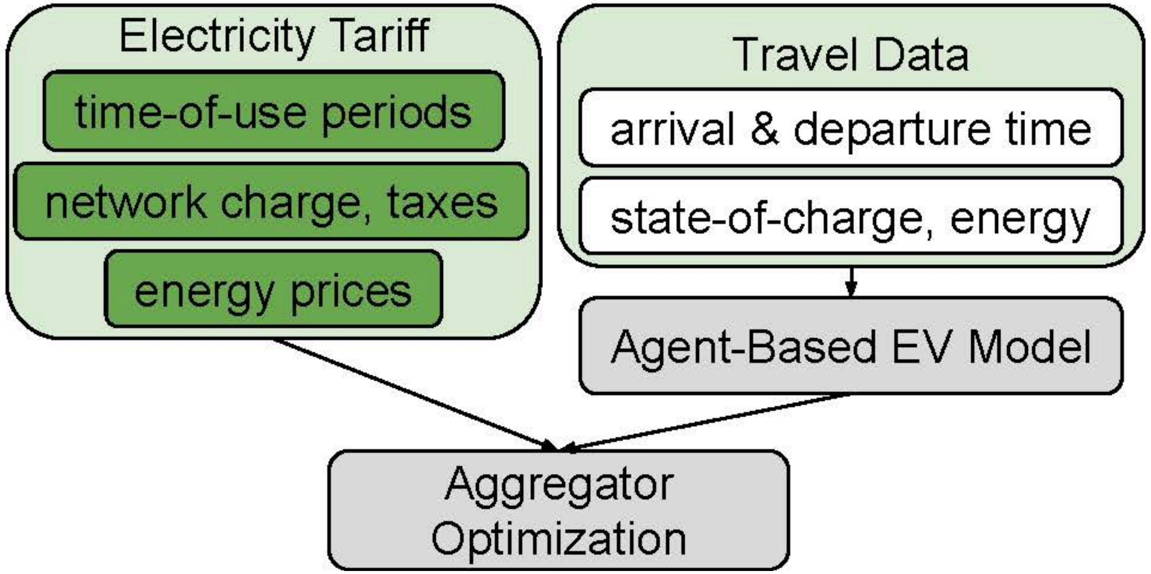
- Great that we have so much flexibility potential!
- But, accessing that flexibility depends on regulations, tariffs, costs, …
- While V1G is likely profitable, the literature is unclear on the techno-economics of V2G [6]
  - High station costs
  - “Double taxation” of discharged energy, different than other forms of storage [7]
  - Minimum aggregation levels to participate in markets [8]
  - Other non-technical barriers [7]

We conduct a techno-economic analysis to understand the profitability of V2G in Switzerland and identify potential solutions for policymakers and regulators to support V2G deployment.

[6] Sovacool, Benjamin K et al (2020). “Actors, business models, and innovation activity systems for vehicle-to-grid (V2G) technology: A comprehensive review”. In: *RSER* 131, p. 109963.
[7] Gschwendtner, Christine et al (2021). “Vehicle-to-X (V2X) implementation: An overview of predominante trial configurations and technical, social and regulatory challenges”. In: *RSER* 145, p. 110977.
[8] Heilmann, C (2021). “Factors influencing the economic success of grid-to-vehicle and vehicle-to-grid applications – A review and meta-analysis”. In: *RSER* 145, p. 111115.

Testing Policy and Regulation Impacts on V2G Profitability
Case Study: Workplace Aggregator

Aggregator Optimizes for Electricity Tariff

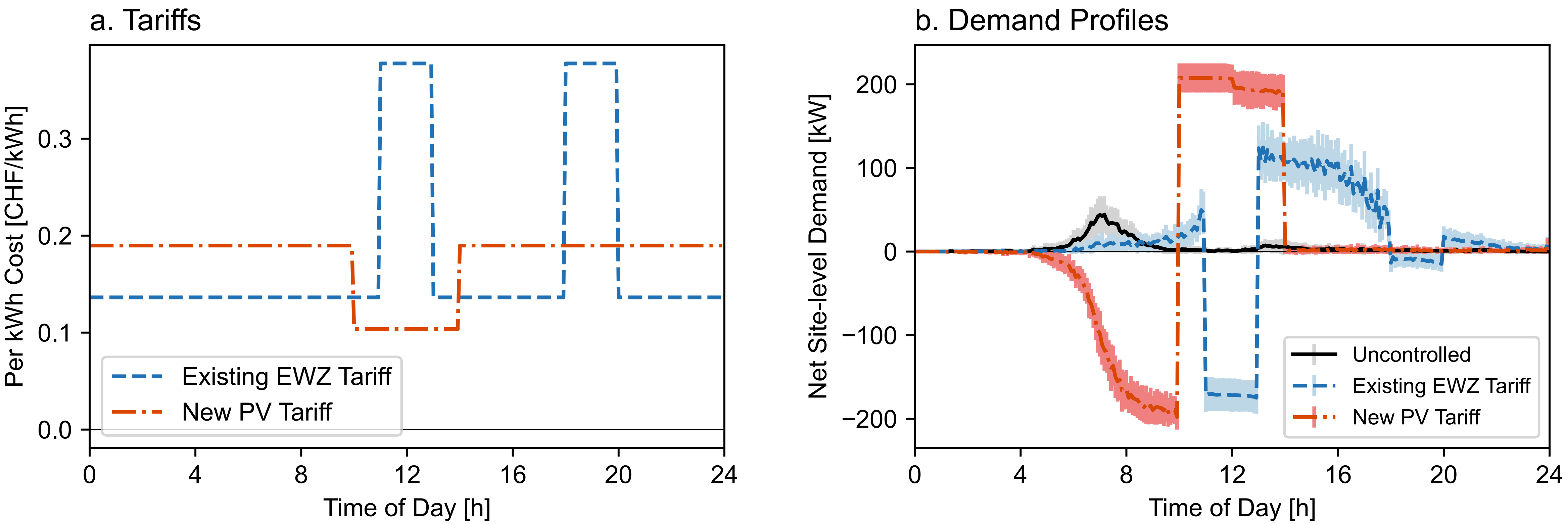


Key Assumptions:

- 80 kWh battery
- 11 kW workplace chargers
- 50 EVs for 25 chargers
- Re-run simulations 50 times
- Drivers have access to home charging
- Travel data from MZMV [9]
- Optimization ensures the same total energy is delivered by departure as with uncontrolled

PATHFNDR [9] BFS and ARE (2023). Mikrozensus Mobilität und Verkehr 2021.

Tariffs and Charging Profiles



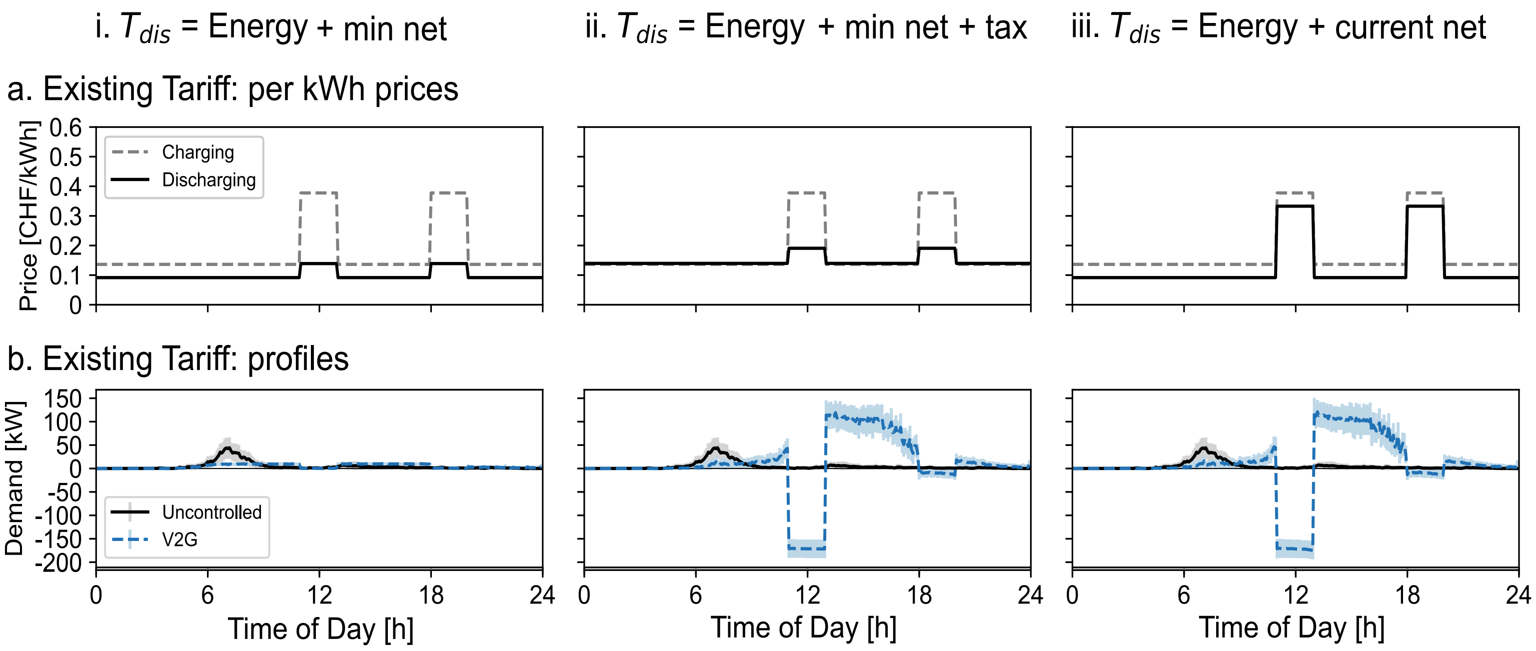
Minimum Spread Between Charging and Discharging Prices

Criteria for V2G:

$$T_{dis,max} > \frac{1}{\eta^2} T_{ch,min}$$

Scenarios for Discharging Price:

- ‘Tracked Net’ network charge
- ‘Min Net’ network charge
- ‘Current Net’ network charge
- (No) tax reimbursed



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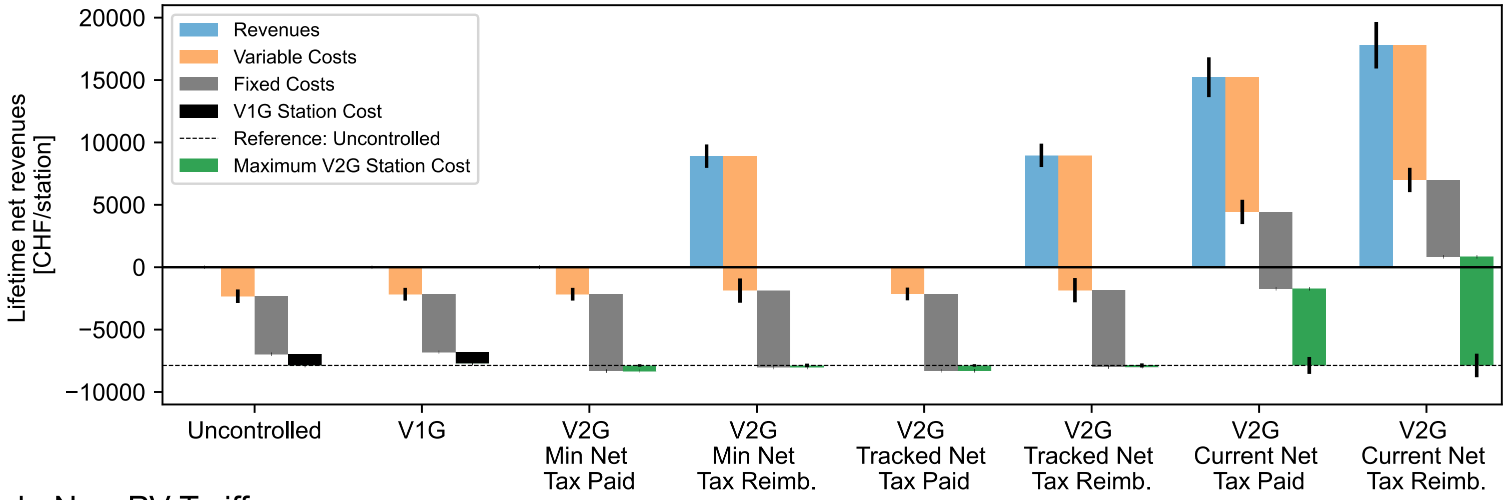
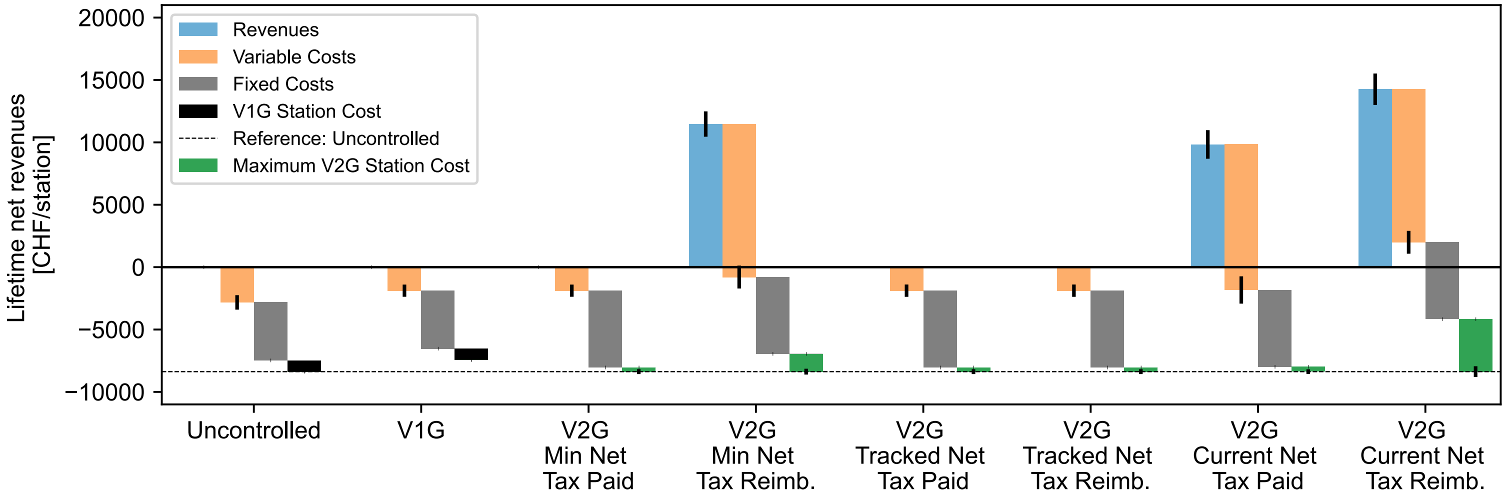
Minimum Spread Between Charging and Discharging Prices

a. Existing EWZ Tariff



b. New PV Tariff



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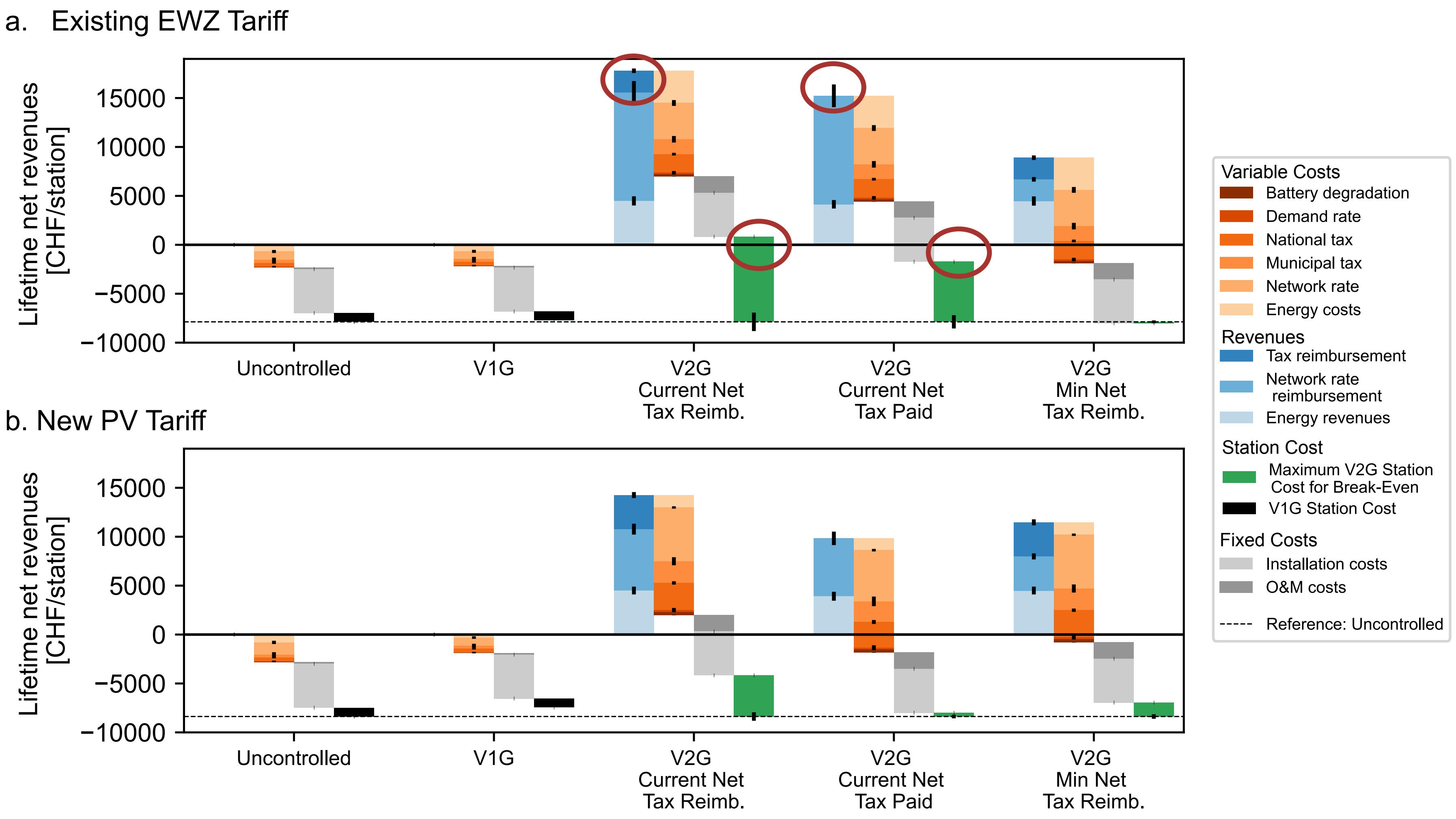
Regulation on “Double Taxation” vs. Station Subsidies



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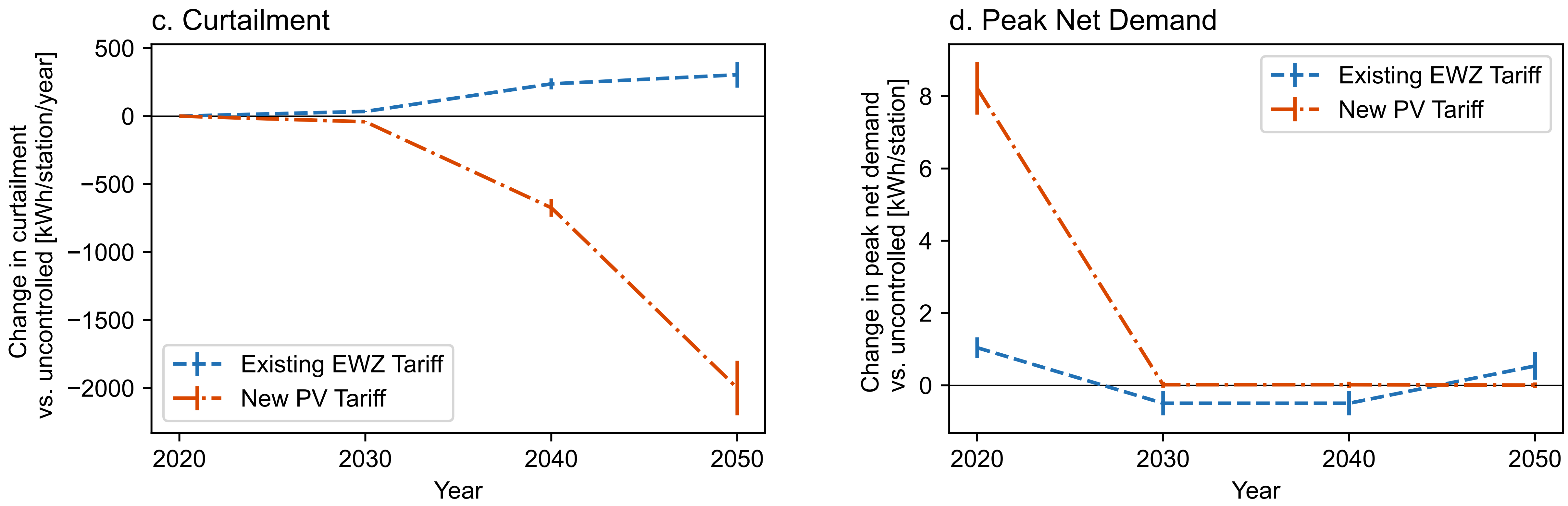
What is the Impact?
Estimated Impact on Curtailment and System Peak



The better tariff depends on the year and system.

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Conclusion

Summary of Key Conclusions

Charging and Flexibility across space and time

1. Spatial and temporal trackability help us identify region and time-specific complementarities or mismatches that must be handled for successful transport and electricity sector integration.
2. Geographical representativeness is crucial in planning for the future charging infrastructure and potential new flexibility markets.

Flexibility quantification and prediction

1. Data-driven approaches result in conservative flexibility prediction compared to actual quantification.
2. Accounting for user-specific behaviors enhances the accuracy of flexibility predictions.
3. The highest EV flexibility is observed in the Zurich region.

Policies and utilization

1. Techno-economics may be challenging; station subsidies may be needed for some types of flexibility.
2. To incentivize V2G, regulations should remove “double taxation” and increase tariff price spreads.

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- Team at SusTec, PSL, UESL, and the ESC

Questions?

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