Stanford University

CTU CZECH TECHNICAL UNIVERSITY IN PRAGUE

ML for Generative Modelling of EV Charging Load Profiles

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NEURAL INFORMATION PROCESSING SYSTEMS

Climate Change AI

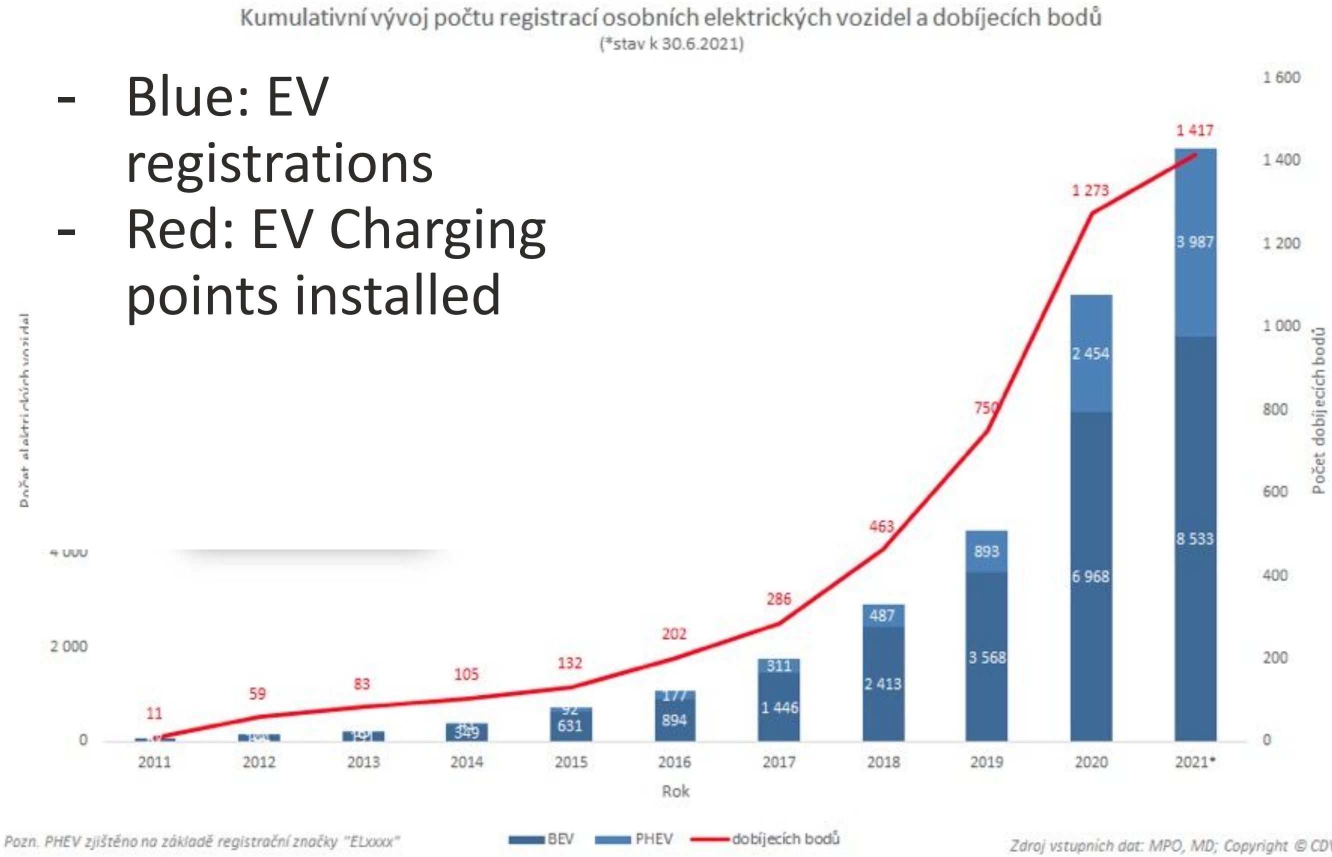
Motivation and context

Motivation

- Electric vehicles are becoming more common, with them comes demand for chargers and charging itself
- However, infrastructure for charging is not easy or quick to build
- Conflicting trends:
  - Charging demand is accelerating
  - It is more and more difficult to build charging stations
- Can we better characterise EV charging?
  - To build infrastructure more efficiently
  - To detect systemic challenges in capacity
  - To utilize EV charging potential in grid balancing

Current situation: in some places, potentially reaching an inflection point

- Blue: EV registrations
- Red: EV Charging points installed

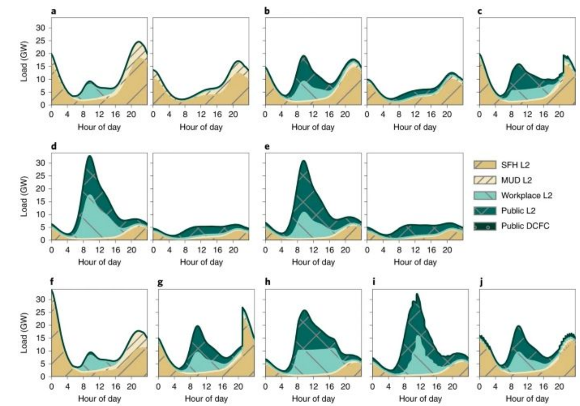


Better EV charging patterns understanding needed for efficient infrastructure development

Building on previous work at Stanford

- Building on paper in Nature Energy: *“Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption”* by Powell, S. et al.
- First characterisation of EV charging demand between public and private EV chargers, with breakdown to sources of demand
- Focus geography: California

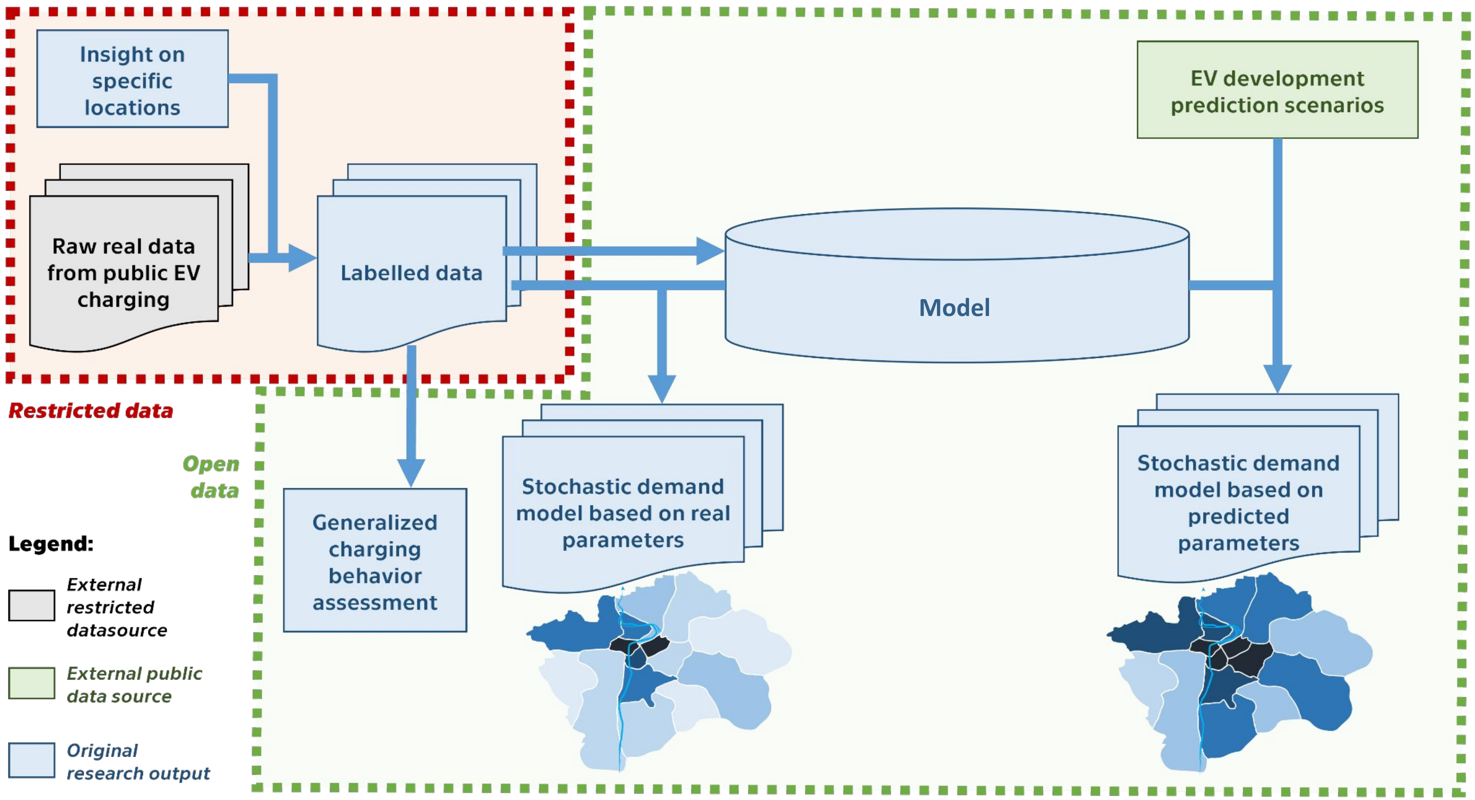
Fig. 2: Profile of aggregate EV charging demand illustrated for each infrastructure and control scenario.



a,**b**,**d**,**e**, The uncontrolled profiles for a typical weekday (left) and weekend (right) are shown for Universal Home access (**a**); High Home access (**b**); Low Home, High Work access (**d**) and Low Home, Low Work access (**e**). **f**–**j**, The weekday profile is shown for one example of each type of control: midnight SFH timers with Universal Home access (**f**); 9 p.m. SFH timers with High Home access (**g**); workplace peak minimization with Low Home, High Work access (**h**); workplace average emissions minimization with Low Home, Low Work access (**i**); and random SFH timers between 8 p.m. and 2:30 a.m. with High Home access (**j**) (Methods). Profiles are illustrated for full electrification for the US states in WECC to show the maximum modelled demand. Demand is aggregated in local time for this illustration, but in the simulation the two time zones are reflected and there is a 1 h delay between the timers set on Pacific and Mountain Time. **c**, Business As Usual is a special case of High Home access with a mixture of residential timers at 8 p.m., 9 p.m., 10 p.m. and midnight and peak minimization workplace control. The weekday and weekend profile for each scenario is repeated to compile the full year’s charging demand. L2 stands for Level 2 charging and DCFC stands for Direct Current Fast Charging.

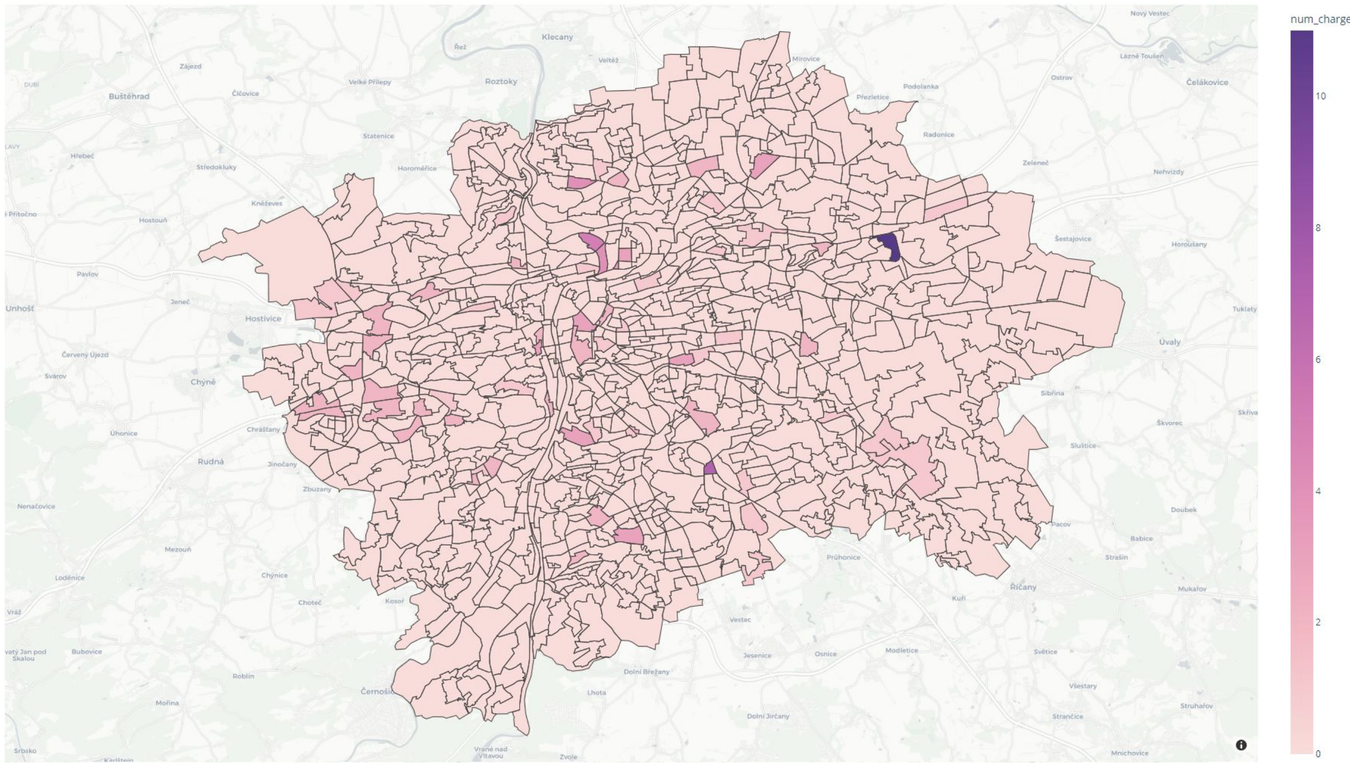
Data pipeline

General work data flow scheme



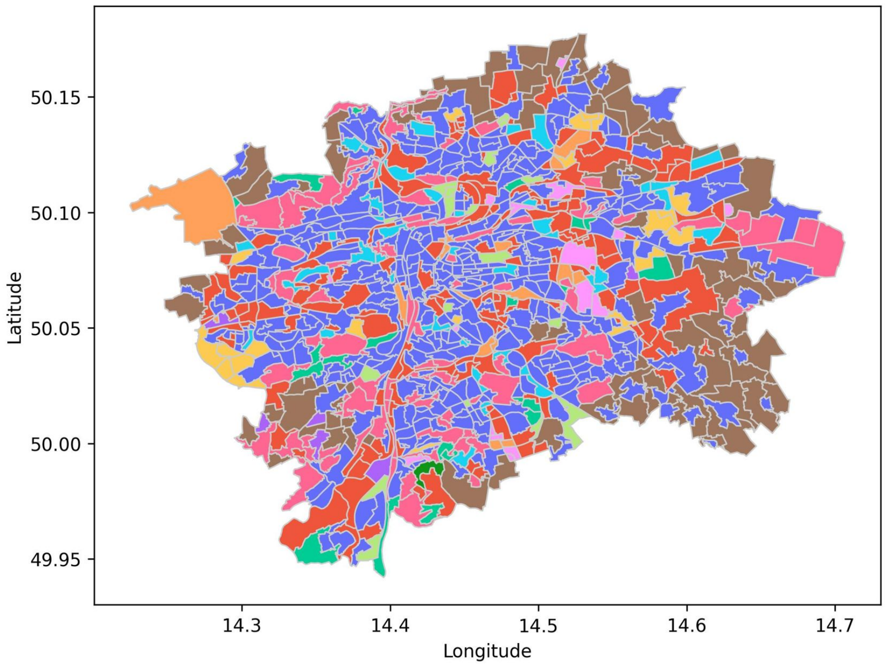
Data showcase: Charging points

Charging point count per ZSJ / BAU



Data showcase - Area typology

Typology per ZSJ - Basic Administrative Unit (BAU)

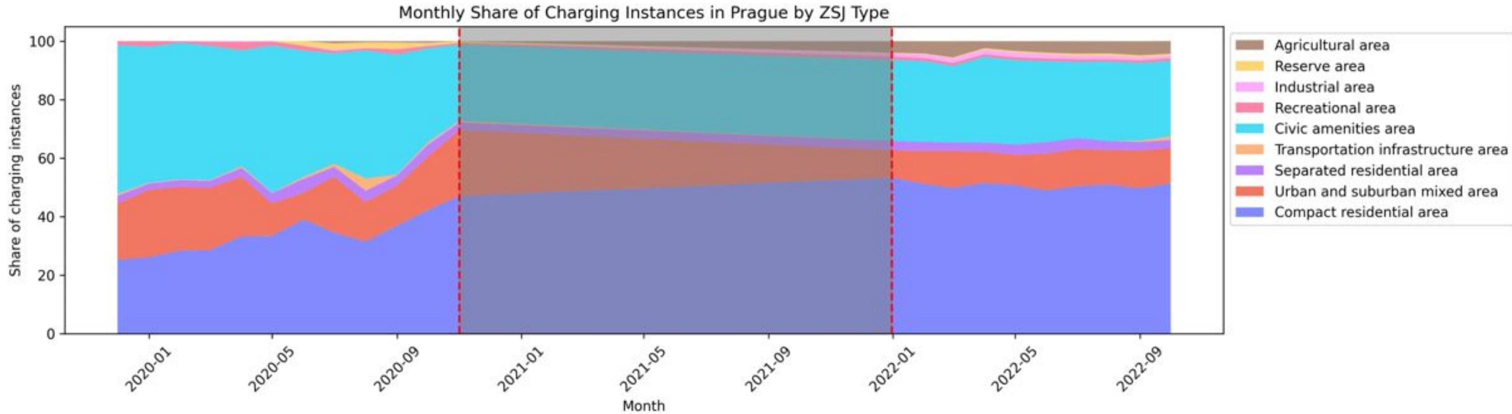


Basic Administrative Unit (ZSJ) Categories		
Original Czech name	English translation	Colour
Obytná plocha v kompaktní zástavbě	Compact residential area	Purple
Městská a příměstská smíšená plocha	Urban and suburban mixed area	Red
Obytně rekreační plocha	Residential and recreational area	Teal
Odloučená obytná plocha	Separated residential area	Violet
Dopravní areál	Transportation infrastructure area	Orange
Areál občanské vybavenosti	Civic amenities area	Blue
Rekreační plocha	Recreational area	Coral
Ostatní účelová plocha	Urban and suburban mixed area	Lime
Průmyslový areál	Industrial area	Pink
Rezervní plocha	Reserve area	Yellow
Zemědělská plocha	Agricultural area	Brown
Lesní plocha	Forest area	Green

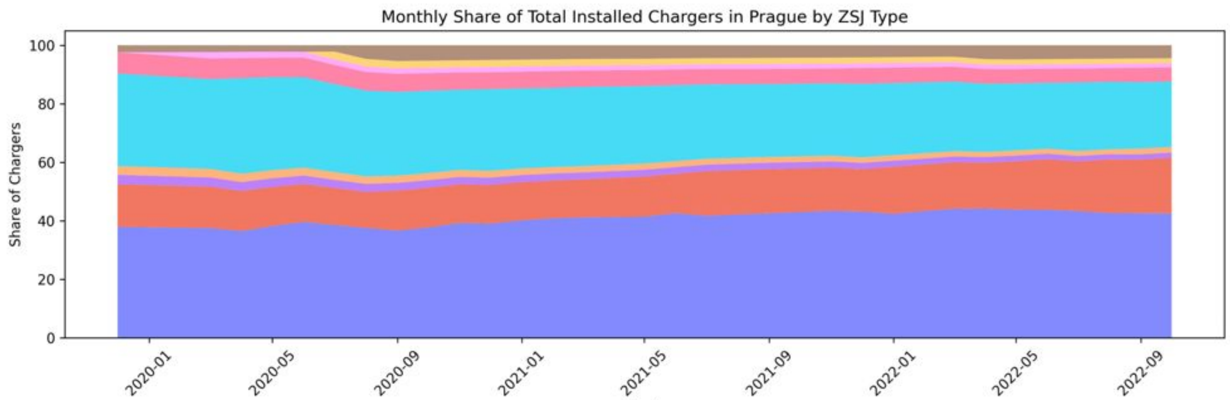
Results

Charging and chargers share development per type in the dataset (2020-2022)

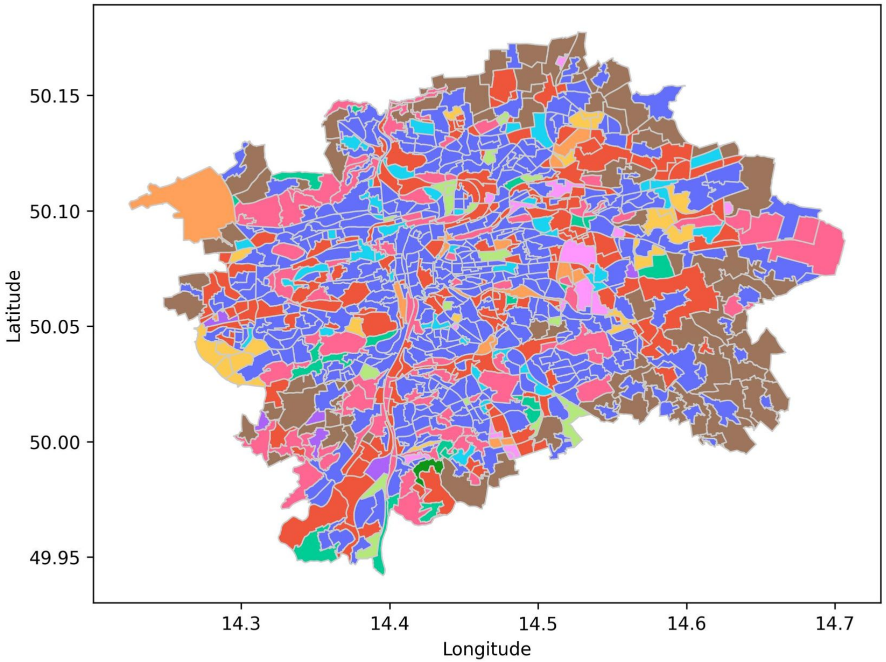
Share of charging sessions per BAU type

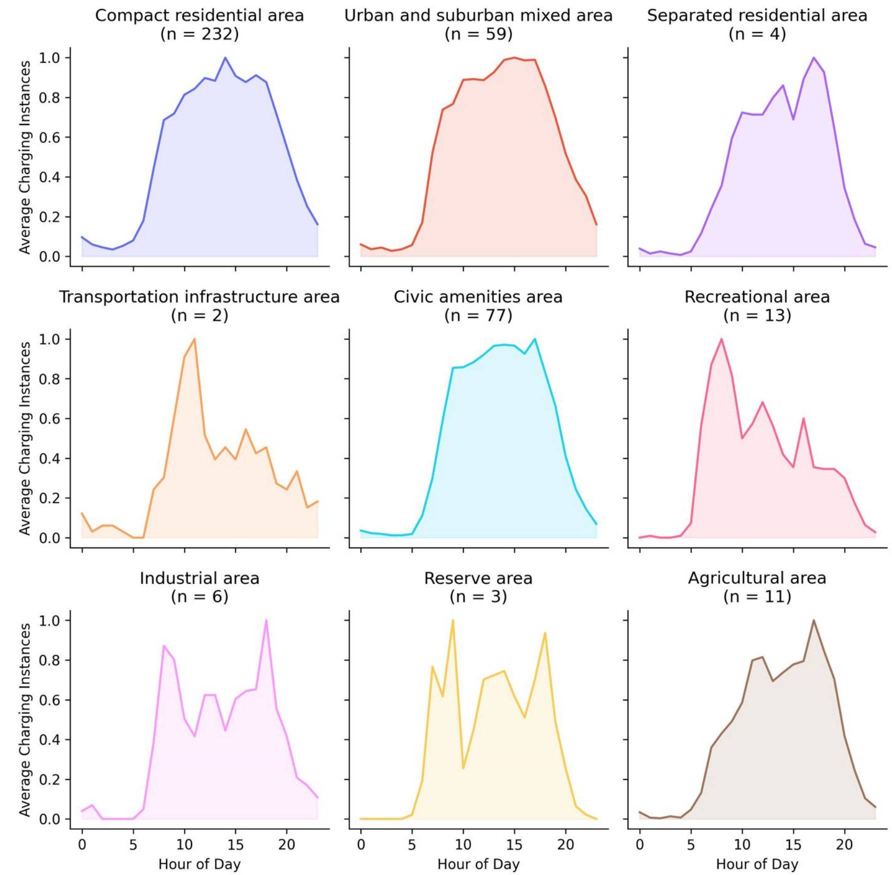


Share of charger points per BAU type



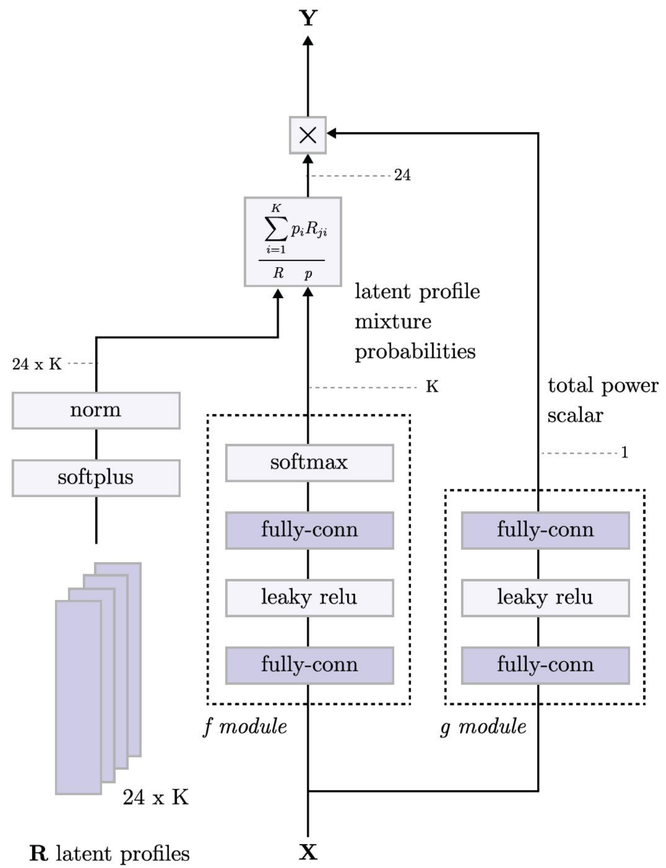
Consumption modelling: EV charging

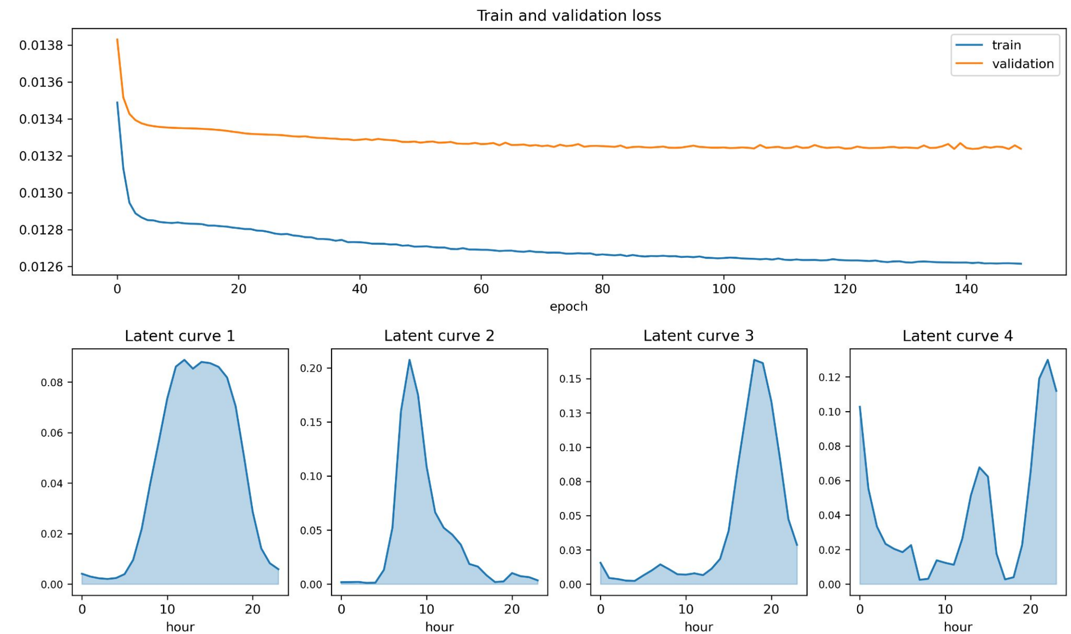




Source: Miltner et al. 2024, pending peer review

Machine learning based generative AI approach to EV charging demand curves based on data





Limitations and next steps

Limitations

- Limited timeframe of currently analyzed dataset
- Currently narrowly defined geography used for demonstration
- Some features not explored or unavailable, such as population movement or EV adoption per location

Next Steps

- Expanding timeframe of dataset
- Improving explainability by visualising effect of individual inputs onto resulting load curve shape
- Expanding the robustness of our findings through validation on data from different geographies
- Connecting the dots:
  - *Where and when will we reach infrastructure (wire, transformer, …) capacity due to EV charging?*
  - *Can we use the capacity of EVs plugged in to public chargers to balance the grid?*

Conclusion

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1. Location of public EV chargers greatly affects their load curve shapes during the day

2. We can use generative AI to reliably predict EV load curves even in locations where EV chargers are not yet present

3. This can help Distribution System Operators (DSOs) in efficiently planning infrastructure expansion

Thank You

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