CTU FEL Prague

Master thesis

EV vehicles

and charging demand

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March 28, 2025

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Publisher
First printed in May 2019 by CTU FEL

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Introduction

LLM generated slop *give historical context on how automobiles came to be and used and how gas stations infrastacturue had to be created. And how EV chargers are very similar to the spread of ICE vehicles.*

The invention of the automobile in the late 19th century revolutionized human mobility, enabling unprecedented freedom to traverse long distances. However, this breakthrough hinged not only on the internal combustion engine (ICE) itself but also on the parallel development of a critical support system: gasoline stations. Just as early motorists relied on scattered fuel depots to power their journeys, the rise of ICE vehicles necessitated a standardized, accessible network of refueling infrastructure to sustain their adoption. This symbiotic relationship between vehicles and their energy infrastructure became a cornerstone of modern transportation, shaping urban planning, economic systems, and global energy policies.

Today, as societies pivot toward sustainability, electric vehicle (EV) are heralding a similar paradigm shift. Yet their widespread adoption faces a challenge mirroring the early days of automobiles: the need for reliable, equitable, and efficient charging infrastructure. While EVs eliminate tailpipe emissions, their practicality depends on overcoming "range anxiety" and ensuring charging availability aligns with user behavior—issues that gas stations largely resolved for ICE vehicles over a century of iteration. Predicting EV charger usage, therefore, is not merely a technical exercise but a good step in designing infrastructure that mirrors the ubiquity and convenience of gas stations. And helps smoothen transition.

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1.1 Climate change

Climate change and its effect on humanity. And how traditional ICE vehicles are harmfull. But also that it might be controversial. Show pie chart of emmisions. Creates motivation for EVs.

What about underdeveloped world

1.2 Electric vehicles

Invented in parallel with ICE. Not feasible. But now they are. Has same birth pains as ICE. Need infrastructure. How they are greener. Show their increase.

1.3 EU mandate

mention EU "law" that forbids production of new ICE vehicles. That sets a hard bureaucratic need on the transition and makes it concrete

1.4 Public Electric Charging Locations

Show how chargers look, work. Their types. How lots of areas have no access to private CP. And due to mandated rise in EVs chargers will not be enough.

1.4.1 EV Charging Location Placement problem

Talks about how placement of chargers is not cheap. And also its hard to determine which one to place. Also talk about grid scaling and the ability to flatten the electric demand with more strategic placement of chargers. Therefore its really good to have some model with good time resolution.

Related research 2

This section mentions relevant literature that focuses either on the very same issue. Or topics close to predicting EV charger demand. There are not that many papers focusing on our specific issue however there is a lot of knowledge ihdden inside of them. The papers analyzed in this chapter provide insight into how similar issues were tackled. And on what does the research focus on.

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First, from an outside perspective. Issues and topic of the papers will be explored. What outcome were they focused on. And then an inside look, into what research approaches they took and what methods were used.

Because this is spatial data science. Most of the papers are very practical in a sense that they work with real datasets. And each country and even city has different data gathering culture and data availabilty. The research is tightly connected to what data is available. No relvant paper for our issue was found focusing on Prague.

2.1 Issue addressed

- EV charger demand prediction
- EV charger use anaylsis
- Charging infrastructure planning and optimization
- Digital twin

2.2 Research approaches

Starting from simple statistics. Then menitoning agent simulations. And end with ML.

Research applies itself to all sorts of EV stuff. Starting from understanding coverage of existing EV chargers.

2.2.1 Understanding EV Charger Use by Data

bad quality text

To understand why certain chargers are being utilized the way they are. Research utilizes traditional and bayesian statistics. As the person that plans ev chargers it is good to have insight into what influences charging demand. That is, why a certain charger is utilized. And what factors contribute to it. So far, we dont care about expansion of the infrastrcture. But could provide insights that allow to place new chargers more strategically. [1] gathered Points of Interest near every charger of interest (more explanation in data chapter) from Open Street maps. And extracted features like shops, restaurants, public transport offices et cetera. And aggregated them by count by category. Then for each charger computed its utilization. Which is its average daily power consumption. Then used linear regression to test which of the category of PoIS contributed to the consumption. The study had some statisficaly significant results. They also trained neural network model for capturing non linear relationships. This allowed to point at any place on map with available. However it does not work with other chargers in the area and does take into account charger density.

[1]: Hecht et al. (2024), 'Global Electric Vehicle Charging Station Site Evaluation and Placement Based on Large-Scale Empirical Data from Germany'

[2] uses log-Gaussian Cox process. Which is a statistical model that can handle dependence between points on a map (EV chargers) .

[2]: Dong et al. (2019), 'Electric Vehicle Charging Point Placement Optimisation by Exploiting Spatial Statistics and Maximal Coverage Location Models'

i think

2.2.2 Simulating EV Charger Use

simulations starting from agent simulations (with digital twins), which are not that data-validated. Moving into simmulating smaller parts but more data based.

[3] [4] [5] [6] [7]

[3]: Brady et al. (2016), 'Modelling Charging Profiles of Electric Vehicles Based on Real-World Electric Vehicle Charging Data'

[4]: Ul-Haq et al. (2018), 'Probabilistic Modeling of Electric Vehicle Charging Pattern in a Residential Distribution Network'

[5]: Zhang et al. (2024), 'An Urban Charging Load Forecasting Model Based on Trip Chain Model for Private Passenger Electric Vehicles'

[6]: Zhang et al. (2023), 'Charging Demand Prediction in Beijing Based on Real-World Electric Vehicle Data'

[7]: Powell et al. (2022), 'Scalable Probabilistic Estimates of Electric Vehicle Charging given Observed Driver Behavior'

[Using ML for prediction]

Using ML for prediction

ML for predictions, not explainable. Just learning on data

2.3 Infrastructure Planning

Charger placement, optimization problem how to cover certain areas. ILP and others used

2.4 Czechia and Prague Relevant Research

No research paper has been found with theme of EVs and Czechia/Prague. So only relevant stuff is gonna be mentioned

[8] [9] [10]

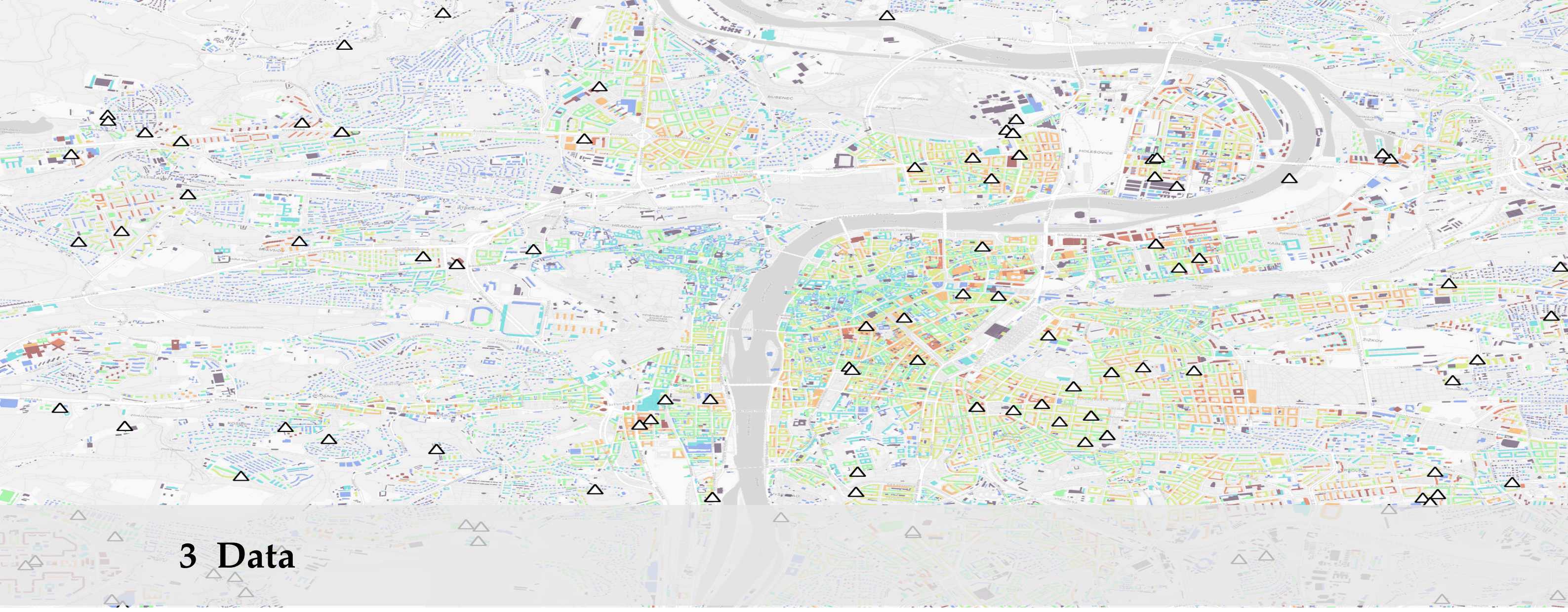
[8]: Pekárek (2017), 'A Model of Charging Service Demand for the Czech Republic'

[9]: Elomiya et al. (2024), 'An Advanced Spatial Decision Model for Strategic Placement of Off-Site Hydrogen Refueling Stations in Urban Areas'

[10]: Uglickich et al. (2025), 'Poisson-Based Framework for Predicting Count Data'

2.5 Discussion

Mention how the relevant research is helpful for us. Also how noone has studied Prague and that it has different data landscape. And so we have to do a new approach.



3 Data

Mention all the available data forming our data landscape which determines whats possible. Those data are split into two groups. Target data which we would like to learn to predict. And then factors which we hypothesize that this data may explain our target variables. And also show it off. I am not sure if feature engineering fits into here.

Also talk about different data types. Spatial, temporal, spatio-temporal

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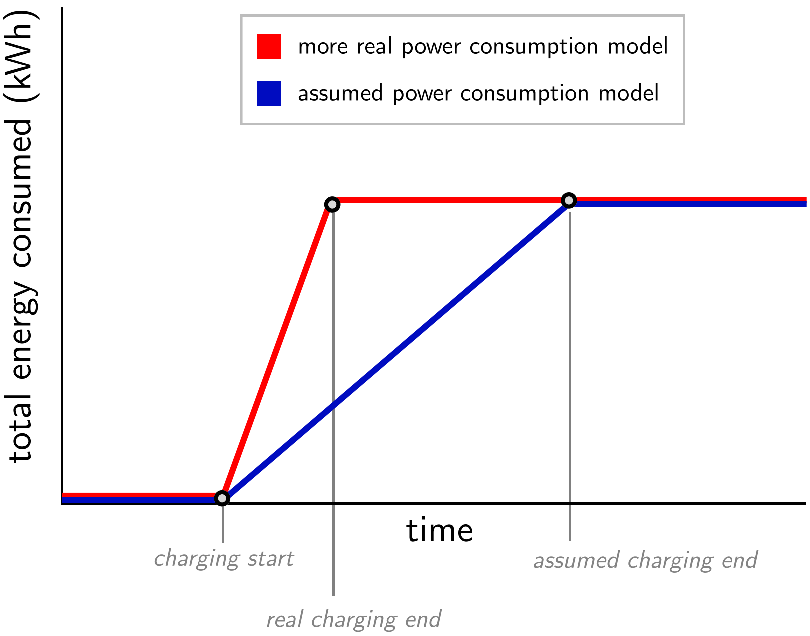
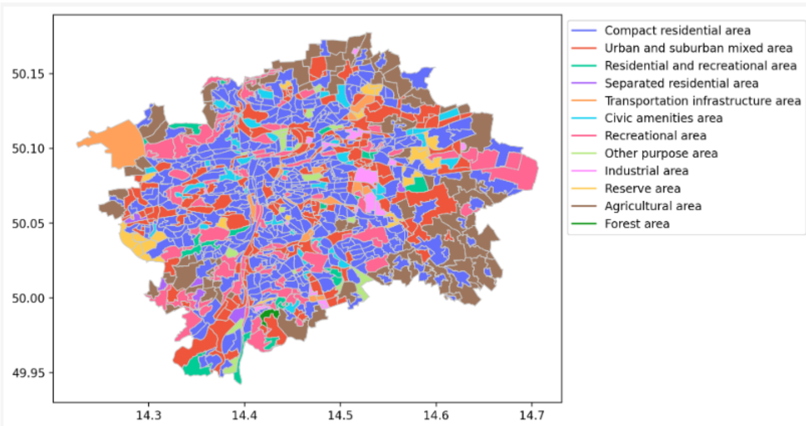
3.1 EV Chargers and Charging Sessions

Explanation of the charging sessions dataset. Chargers in Prague. Modelling assumption. And showing lots of pretty plots and pictures.



3.2 Population numbers (ZSJ)

Title image is a map of Prague with all chargers denoted as triangles in available datasets. The layer below displays all buildings in Prague with color being the number of floors



Compact residential area
Urban and suburban mixed area
Residential and recreational area
Separated residential area
Transportation infrastructure area
Civic amenities area
Recreational area
Other purpose area
Industrial area
Reserve area
Agricultural area
Forest area
50.15
50.10
50.05
50.00
49.95
14.3
14.4
14.5
14.6
14.7

3.3 Points of Interest

3.4 People Mobility

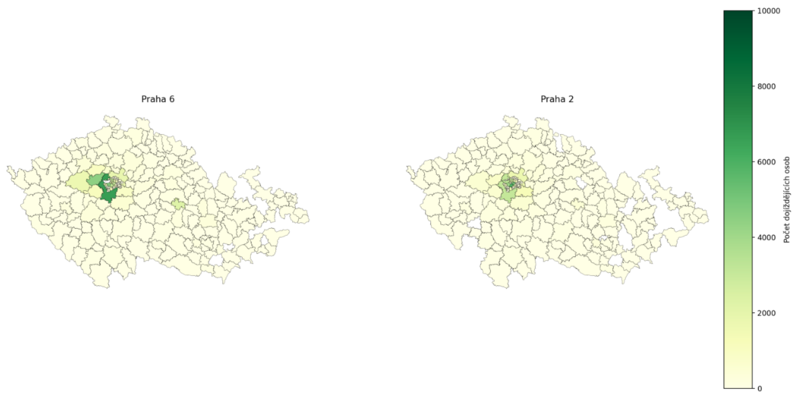


Figure 3.1: Chapter content overview.

3.5 Mobility Survey - cesko v pohybu

Figure 3.2: Chapter content overview.

—

Talks about what was extracted from datasets in 3

3.6 Spatial data

3.6.1 ZSJ Type and Population

3.6.2 Points of Interest

Has statistically significant results for certain PoI [1][2] ([2] uses Gaussian cox model, [1] uses Neural networks and linear regression)

[1] states that radius of relevant PoIs is 2000metres. The research stated that the distance is sensible. One solution is to just count all the PoIs in the radius but as they are more far away from the CP their relevance might decrease. The [1] thus uses importance factor for pair of PoI and CP.

$IF(PoI_i, CP_k) = max(r - d_{\text{sphere}}(PoI_i, CP_k), 0)$

Buildings (OsmPoisPbf)

Public Ammenities (OSMOX)

how osmox works

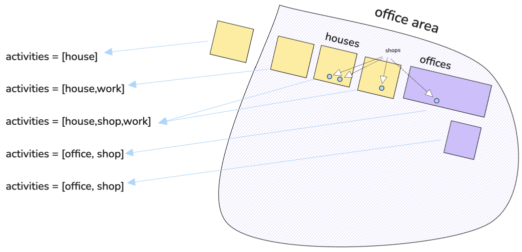
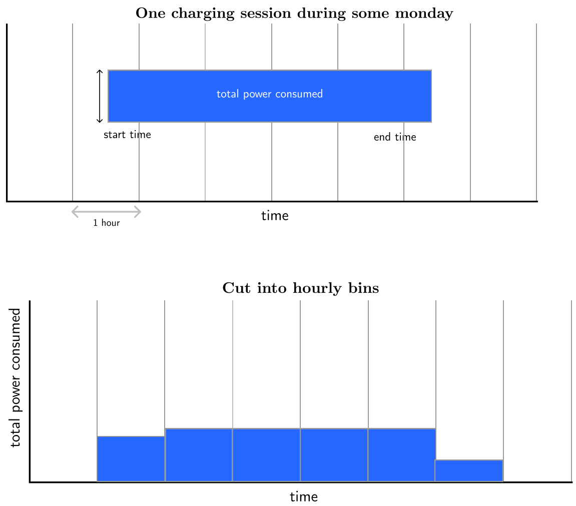
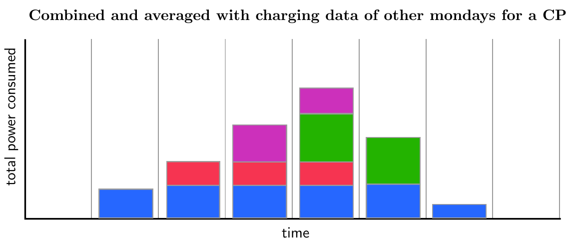


Figure 3.3: osmox

3.7 Charging profiles




Combined and averaged with charging data of other mondays for a CP
total power consumed
time

4 Research and implementation

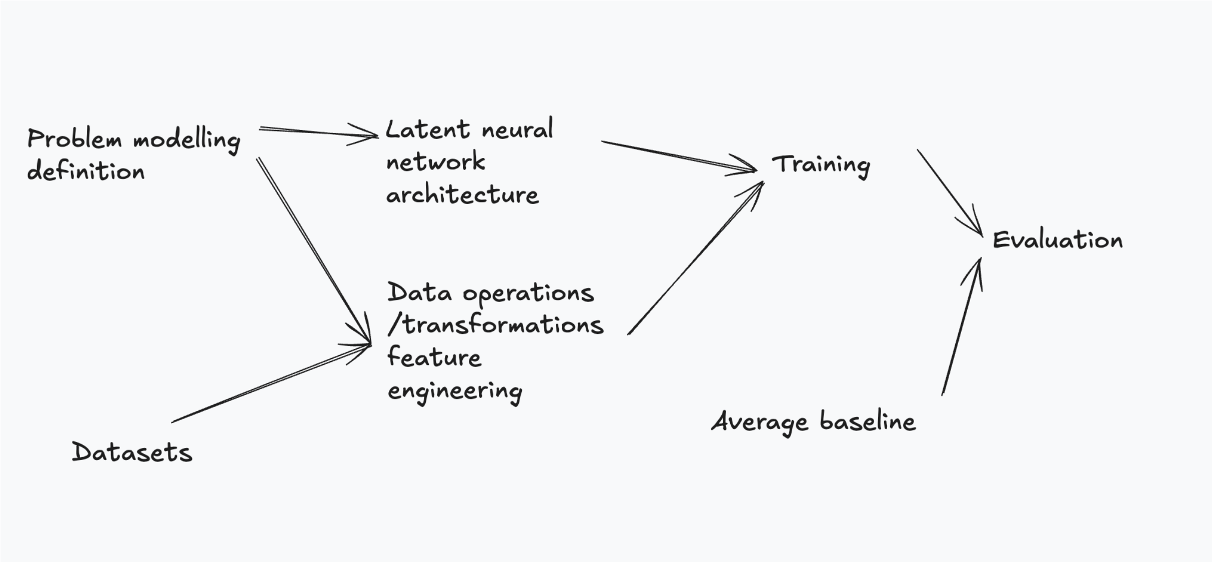


Figure 4.1: Chapter content overview.

The issue introduced in 4

4.1 Methodology

Given existing sessions data and data landscape from 3. Predicting power demand for various factors for any location in prague as mentioned in chapter 4. Utilizing existing data. So machine learning plus addition of some more insight.

So we are interested in predicting average profile for given charger given some temporal characteristic. Like month or day of the week.

4.2 Latent Nerual Network Architecture

mention relevant literature for the latent network from litera-true research

mentions operations done to the data plus anaylsis of statistical impact of features on result

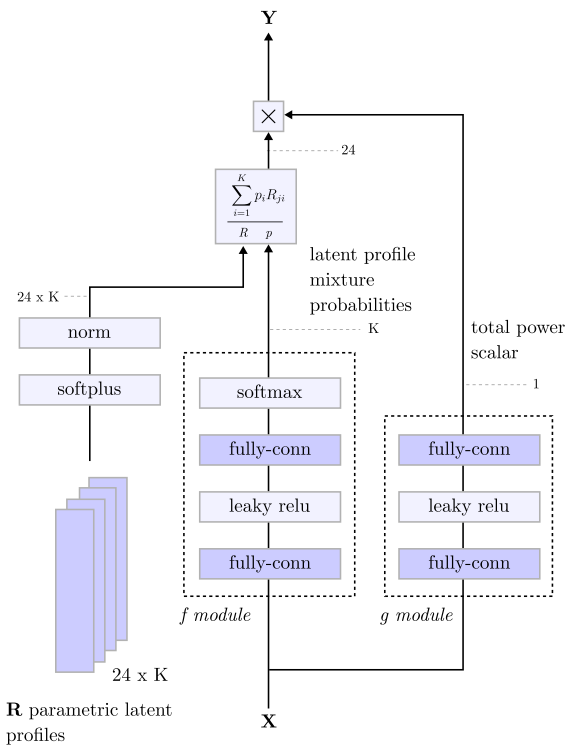


Figure 4.2: Latent neural network architecture. Light blue rectangles denote NN layers without trainable parameters. While blue denotes layers with parameters learned by SGD.

4.3 Input data transformation

Standardization mainly.

4.4 Training

train test split, mention to be sure that we are learning on unseen data. So mby how there are multple chargers for one point

4.5 Baseline

To be able to tell if our results have some value. Are we better than average ? Because noone has done it for prague and even our greenfield problem formulation.

Results | 5

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model trained on data with results

5.1 Training Results and Loss

5.2 Latent profiles interpretation

Conclusion 6

How good we think we have been. And what did this work provide.

6.1 Future work

What to do next to improve the model. What datases to be included.

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