

CTU FEL Prague

Master thesis

**EV vehicles
and charging demand**

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April 18, 2025

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 infrastructure 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.

1.1 Climate change

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

What about underdeveloped world

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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

Writes 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.

1.5 Goals of the thesis

Writes about what we/i aimed to achieve in this work and what was done

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 hidden 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.

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 availability. The research is tightly connected to what data is available. No relevant paper for our issue was found focusing on Prague.

2.1 Issue addressed

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

2.2 Research approaches

Starting from simple statistics. Then monitoring 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

To understand why certain chargers are being utilized the way they are. Research utilizes traditional and Bayesian statistics. As the person that plans charging point (CD) 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 don't care about expansion of the infrastructure. But could provide insights that allow to place new chargers more strategically.

[1] gathered counts of types of point of interest (CD)¹ near every charger of interest² from Open Street maps. 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 point of interest (CD) contributed to the consumption. The study had some statistically significant results. They also trained neural network model for capturing non linear relationships. User can use the model to select any point where a charging point (CD) might be placed and see its estimated utilization and evaluate worthiness of placement. However it does not work with other chargers in the area and does not take into account charger density. The paper has identified that certain categories of point of interest (CD)³ are correlated with charger demand.

[2] uses log-Gaussian Cox process. Which is a statistical model that can handle

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

1: types like shops, sport areas, schools, offices

2: Search radius of 2000m around each charger with linear decrease in importance in relation to distance

3: CD data obtained from OpenStreetMaps

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

4: <workplace population, traffic flow, commerce description here>

dependence between points on a map (EV chargers). It has identified that workplace population and traffic flow are positively related to demand of charging point (CD) while commerce is in a negative relation.⁴

Simulation vs Model

Model is concerned with representing a system of interest. Purpose of it is so it matches its real system in some behaviour while being simpler than reality. There are many ways how to construct models. From simplest small replicas (small car models to use in wind tunnel) to complicated mathematical and software ones.

Simulation is then a use of model to try to replicate some real system of interest to gain insights how a real system might behave.

An example can be a toy car and a ramp which would be our model. Then pushing the car off the ramp to see how far it is able to land. This is much less expensive than pushing real cars of larger ramps.

[3]

2.2.2 Simulations and EV Charger Use

Traffic models are used to estimate charging point (CD) demand. They are a mathematical model of real-world traffic. And they can estimate charging demand by introducing EV vehicle agents into the simulation. Those agents navigate replica of real road network. While also being able to emulate traffic jams, alternative path finding. Negative of these models is that they are harder to develop, fine tune to match real situation. And performance costly. But once developed and validated with real-world. They can be highly utilized.

Micro,Macro,Meso-Scopic

Traffic models can be separated into three groups according to [4][5]([6] also writes about splitting simulation models into 3 groups with a more theoretical view):

- ▶ **Microscopic** - Simulation of individual agents/vehicles. Can be as detailed as emulating accelerating, lane changing, turning. Higher fidelity is useful for example when designing intersection with light signals optimizing for traffic or pedestrian flow. But the model can also have less detailed fidelity for vehicles. Which simplifies the simulation and enables larger area of interest. Like cities or even countries.
- ▶ **Mesoscopic** - Provide less fidelity than microscopic. Improve
- ▶ **Macroscopic** - Work with aggregate information. Work more on analytical model and proven mathematical relationships between traffic flow. Improve

[7]: Community (2025), MATSim

Slight foreshadowing but this approach was not taken in this thesis however it was considered.

Matsim [7] is Agent based model (ABM). It's OpenSource software licensed under GPLv2, implemented in Java. And started in 2004 in Zurich. It falls into category of microscopic models due to it being able to simulate individual agents. The model simulates simplified version of vehicle movement and traffic which is needed to correctly simulate entire city including congestions. The simulation usually concerns only one day. To create such a model the following are needed:

- ▶ **Road/communication Network** - Spatial data for area of interest regarding: roads, intersections, tram or train tracks etc. Obtained from technical data published by governments or third party map providers. (Mainly OpenStreetMaps)

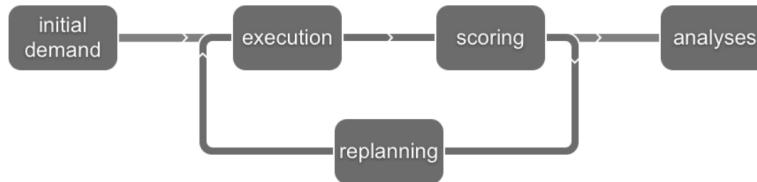


Figure 2.1: Stages of matsim simulation. [8]

- ▶ **Population** - Agents with their day plan, where are they going to live and commute to work. Those are generated with help of expert knowledge and travel diaries survey.
- ▶ **Facilities** - Locations where activities can be performed. Obtained from third parties like OpenStreetMaps.

The agents plan assigns unique daily schedule for each agent in the population. See 2.1 This established the initial demand. During the execution step, Matsim simulates agents commute and tries to satisfy the agents schedule. The agent might fail to be on schedule due to road or public transport congestion from other agents. After finishing the simulation the agents actual daily schedule is scored. Penalizing arriving at work late or being stuck for too long in traffic giving agents lower score. While agents who got where they wanted quickly and without traffic jams get better score. During replanning agent schedule can be modified so it either adjusts the agents schedule, like less time spent home or taking a different route to work. When the simulation is sufficiently optimized the results of it can be then used for various analysis as the output of the model is detailed log of agent activities.

To create the agents schedule, day intentions need to be provided to the model. Those can be either manually crafted. With the increased availability of census data, data driven approach can be taken. This trades away the possibility to experiment with different kinds of populations and policies⁵ but simplifies the process of creation where only data is needed and not expert knowledge on human behavior. [9] models multiple probability densities for what activity will an agent do, how long it will take and what activities are available in the area. This utilizes several datasets. New schedules can be generated from the model by sampling from the distributions.

Finally, moving to use of Matsim for EV scenarios. [10] studies the impact of EVs on the electric grid and electricity production in Croatia. By having a simulation of power production network for the whole country as well. They first have a simulation regarding the current state and how that impacts the electrical grid. This sets the baseline and also allows to correctly calibrate the model. Then they increase the EV adoption and see what is the hourly energy consumption of EVs and their impact on the grid.

Stochastic models provide a way for modeling charging behavior of electric vehicles by capturing randomness and uncertainty in travel patterns. They work with more simplified representation of reality compared to traffic models⁶. These models typically employ probability distributions to characterize variables such as departure times, travel distances, parking durations, and charging decisions. By sampling from these distributions using techniques like Monte Carlo simulation, they generate synthetic power demand profiles.

[11] presents an example of stochastic modeling applied to EV charging behavior. Their approach uses a non-parametric copula function to model the dependence structure between six variables: departure time, number of journeys, and total distance traveled across two consecutive days. For this they utilize real-world GPS data collected from electric vehicles. Their model simulates complete journey schedules for individual vehicles and implements a probabilistic charging decision model at each destination, conditioned on the state of charge, parking

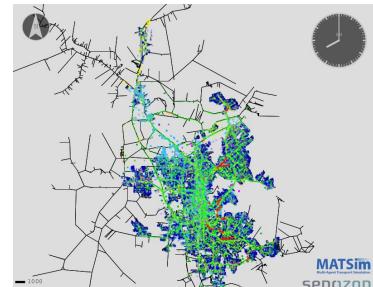


Figure 2.2: Matsim, Joinville example. Model intended to help the city encumbered by high traffic volumes.

<https://matsim.org/gallery/joinville/>

5: like examining effect of different school start times on traffic

[9]: Drchal et al. (2019), 'Data-Driven Activity Scheduler for Agent-Based Mobility Models'

[10]: Novosel et al. (2015), 'Agent Based Modelling and Energy Planning – Utilization of MATSim for Transport Energy Demand Modelling'

Talk about arup

6: Of course traffic models have large parts of stochasticity inside themselves

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

time, and journey number. The approach captures the variability in charging behavior by incorporating factors such as battery characteristics and probabilistic charging point availability.

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

probably skip, the paper is too hard

Paper: [12]

- ▶ tests policy changes
- ▶ estimate ev charging pattern based on residents activity patterns
- ▶ utilizes markov chain to estimate next trip departure time and travel distance
- ▶ does not have charging data, so from simulation of a day it guesses how much the ev needs to be charged
- ▶ graphical model with good diagram/description

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

Paper: [13]

- ▶ groups drivers hierarchically by charging behaviour
- ▶ utilization of actual charging data, charging sessions data. In the session, driver id is available. So drivers charging behaviour can be observed.
- ▶ utilize monte carlo simulation. Sample from learnt prob distributions.
- ▶ validated against real data
- ▶ $P(s, z, G) = P(s|z, G) P(z|G) P(G)$
- ▶ [12]
- ▶ [14]
- ▶ [15]

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

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

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

mention difference forecasting vs modelling

2.3 Forecasting

ML for predictions, not explainable. Just learning on data

2.4 Infrastructure Planning

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

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

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

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

[19]: Shang et al. (2021), 'Estimating Building-Scale Population Using Multi-Source Spatial Data'

2.5 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

[16] [17] [18]

2.6 Data sources and transformations

estimate population

Predicts density of each building per $100m^2$ living area. With $R^2 = 94\%$. [19]

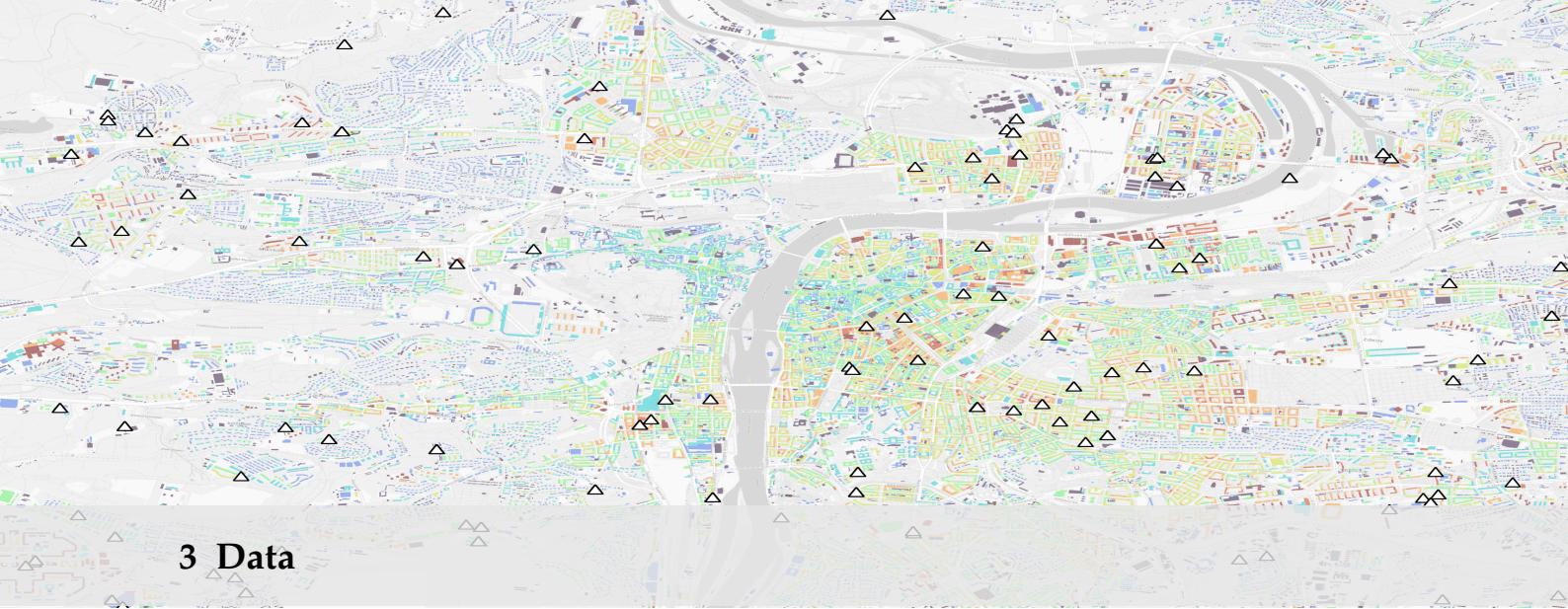
2.7 Discussion

From observed papers regarding simulation to obtain some estimate of charging demand. Either, in absence of data, expert knowledge is utilized to create simulations. Which lean more on engineering complexity. Due to need to simulate some percent of city/country population. But they might not always be feasible to develop as well as calibrating. Which is to ensure the simulation matches real world. But then they have large utility and flexibility. For example examine policy changes.

When data is available, turn to more data based methods is more common. Instead of microscopic simulations. Stochastic properties of people are obtained from the data or estimated to match the data.

2.8 Research gaps

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

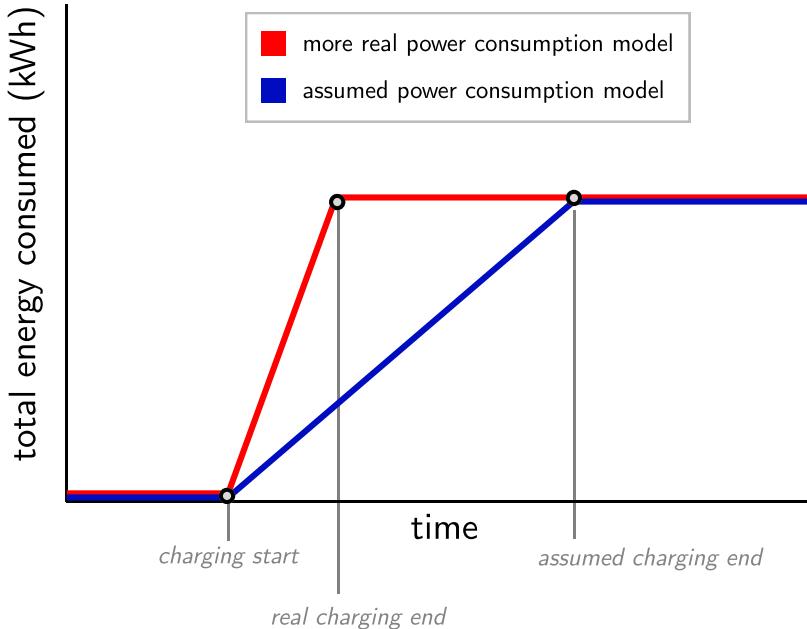
Mention all the available data forming our data landscape which determines what's possible. Those data are split into two groups. Target data which we would like to learn to predict. And then factors which we hypothesize that this data may explain our target variables. And also show it off. I am not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

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

3.1 EV Chargers and Charging Sessions

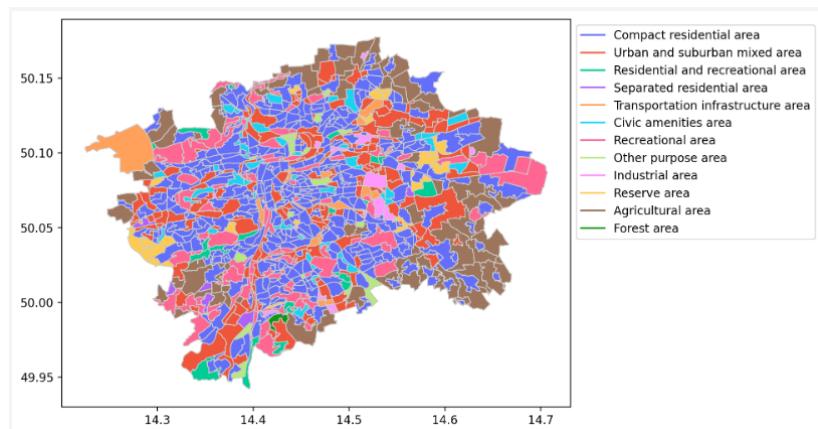
Explanation of the charging sessions dataset. Chargers in Prague. Modelling assumption. And showing lots of pretty plots and pictures.

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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



3.3 Points of Interest

3.4 People Mobility

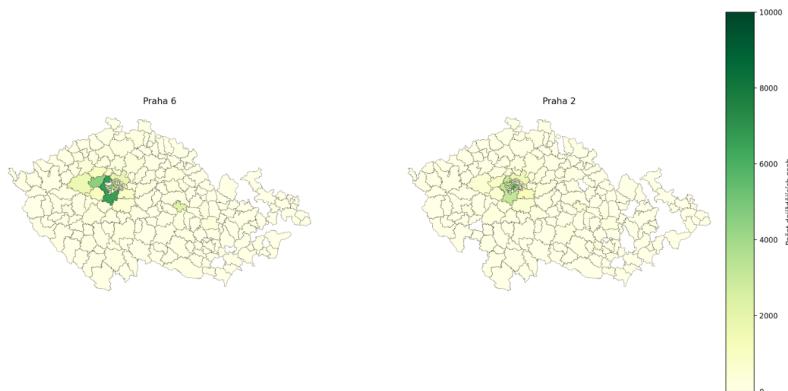


Figure 3.1: Chapter content overview.

3.5 Mobility Survey - cesko v pohybu

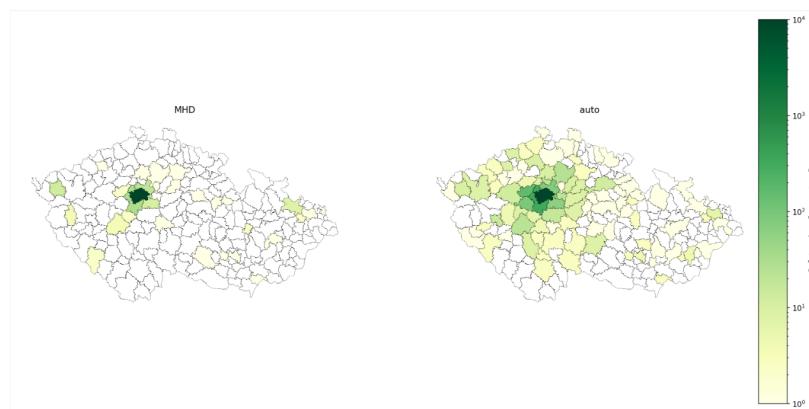


Figure 3.2: Chapter content overview.

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.

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

Buildings (OsmPoisPbf)
Public Ammenities (OSMOX)
 how osmox works

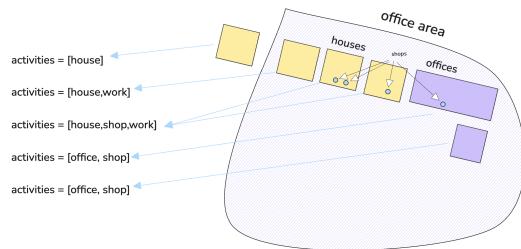
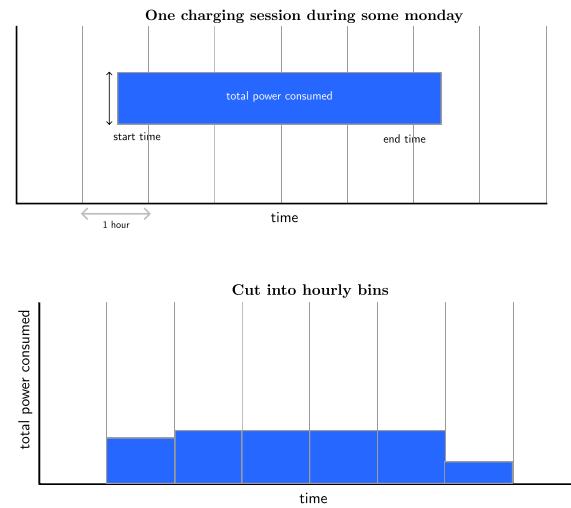


Figure 3.3: osmox

3.7 Charging profiles



3.8

4

Research and implementation

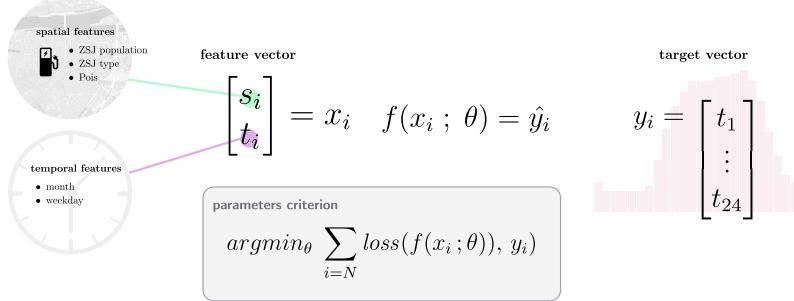


Figure 4.1: Problem approach overview

In this chapter, problem will be formulated together with model development and training. As a soluton to problem introduced in . That is, be able to predict potential demand for a new charging point (CD) placed anywhere in the city of Prague. As a solution a latent profile nerual network will be discussed which should be able to predict charging demand while also offer interpretability to its results.

4.1 Problem statement

Given existing charging sessions data and data landscape as described in 3. We are interested in predicting power demand for any new potential charger location in Prague as mentioned in chapter 4. Utilizing existing data.

- ▶ define the data variables
- ▶ formulate the problem
- ▶ state possible solutions
- ▶ introduce latent profiles neural network model
- ▶ mention training procedure in all the detail, because everyone does this
- ▶ data normalization
- ▶ train test data split (based on location, to avoid double positions)
- ▶ loss function
- ▶ parameter tuning

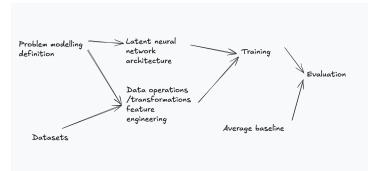


Figure 4.2: Chapter content overview.

4.2 Architecture of the Latent Nerual Network

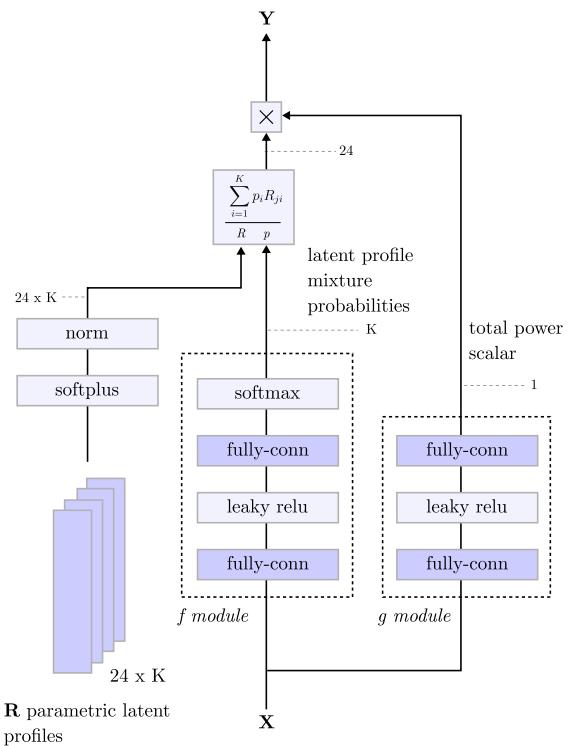


Figure 4.3: Latent neural network architecture. Light blue rectangles denote NN layers without trainable parameters. While blue denotes layers with parameters learned by SGD.

4.3 Input data transformation

Standardization mainly.

4.4 Training

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

In this chapter. Prediction model results will be discussed. An quantitative comparison to other models is provided.

To evaluate the quality of the model and its potential benefits.

5.1 Quantitative comparison to other models

Table 5.1: Comparison of model performance metrics including Mean Absolute Error (MAE) and Mean Squared Error (MSE) with their normalized and power variants.

Model	MAE	MAE norm	MAE power	MSE	MSE norm	MSE power
ChargingProfileModel	86.3404	0.0447	1553.9763	33729.4410	0.0057	7748441.2767
LinearRegression	107.9335	0.0962	2181.7242	41590.8896	2.9124	10658337.9148
TrainAverageModel	87.9659	0.0435	1629.9461	33973.4273	0.0057	7853195.2634
ValidationAverageModel	87.9659	0.0435	1629.9461	33973.4273	0.0057	7853195.2634
XGBoost	92.4132	0.0456	1639.3703	42282.8242	0.0065	7993035.6818

5.2 Qualitative latent profiles analysis

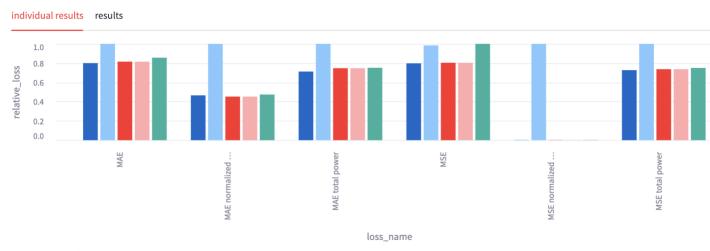
Inspection of the outputted latent profiles in prague together with hypothesising if that at least makes sense. Show the latent profile contribution on the training dataset because it interesting to see what it learned from the data and not necesarily rating its prediction power.

5.3 Tool for visualisation of prediction results

To be able to inspect the prediction results in spatial context a tool was also developed with use of Streamlit[20]. The dashboard is in a form of a webapplication. It consists of two screens. First one allows inspection of overall model losses as visible in 5.1. In bar charts and tabular formats. Where the bar chart shows all the types of losses relatively to each other.

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[20]: (2021), *Streamlit • A Faster Way to Build and Share Data Apps*



model	MAE	MAE normalized profile	MAE total power	MSE	MSE normalized profile	MSE total power
ChargingProfileModel	86.3404	0.0447	1553.9763	33729.4410	0.0057	7748441.2767
LinearRegression	107.9335	0.0962	2181.7242	41590.8896	2.9124	10658337.9148
TrainAverageModel	87.9659	0.0435	1629.9461	33973.4273	0.0057	7853195.2634
ValidationAverage Model	87.9659	0.0435	1629.9461	33973.4273	0.0057	7853195.2634
XGBoost	92.4132	0.0456	1639.3703	42282.8242	0.0065	7993035.6818

Figure 5.1: Data dashboard website showing bar chart with relative losses of the models

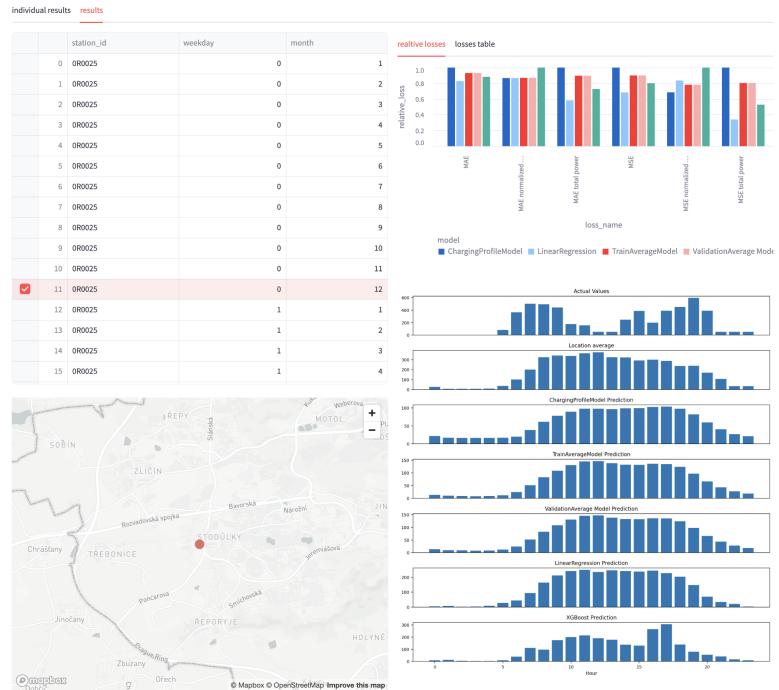


Figure 5.2: Data dashboard website showing table with data from validation data set with one selected row. Of which the prediction is computed from the main model and the other models for comparison.

The second screen displays table of all charging location together with day of the week and month. The individual rows of the table are selectable. When selection happens location of the charger in map is shown and prediction from the model together with other models used for comparison is computed and its results are shown in a bar chart graph. Together with losses against the original label y value.

6

Conclusion

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

what was achieved in regards of the beginning goals

6.1 Future work

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

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- [1] Christopher Hecht et al. 'Global Electric Vehicle Charging Station Site Evaluation and Placement Based on Large-Scale Empirical Data from Germany'. In: *eTransportation* 22 (Dec. 1, 2024), p. 100358. doi: [10.1016/j.etran.2024.100358](https://doi.org/10.1016/j.etran.2024.100358). (Visited on 02/28/2025) (cited on pages 5, 13).
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