CTU FEL Prague

Master thesis

EV vehicles

and charging demand

Bc. Jakub Zíka

April 30, 2025

CTU FEL

CTU FEL Prague

Colophon
This document was typeset with the help of KOMA-Script and LaTeX using the kaobook class.
The source code of this book is available at:
https://github.com/fmarotta/kaobook
(You are welcome to contribute!)

Publisher
First printed in May 2019 by CTU FEL

Contents

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.

Motivation - Electromobility and Climate Change 1

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

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 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.

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 relevant 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

To understand why certain chargers are being utilized the way they are. Research utilizes traditional and Bayesian statistics. As the person that plans charging connector (CP) 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 counts of types of point of interest (CD)[1] near every charger of interest [2] 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 statisficaly 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 connector (CP) 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 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

[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'

dependence between points on a map (EV chargers). It has identified that workplace population and traffic flow are positively related to demand ofcharging connector (CP) while commerce is in a negative relation. [4].

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

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

Trafic models are used to estimate charging connector (CP) demand. They are a mathematical model of real-world trafic. And they can estimate charging demand by introducting EV vehicle agents into the simultion. 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,Meno-Scopic

Traffic models can be separated into three groups according to [4][5]([6] also writes about splitting simmulation 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 isuUsable 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 simmulation 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 mathematcial 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 simluate individual agents. The model simmulates simplifed version of vehicle movement and traffic which is needed to correctyl 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 reagarding: roads, intersections, tram or train tracks etc. Obtained from technical data published by goverments or third party map providers. (Mainly OpenStreetMaps)

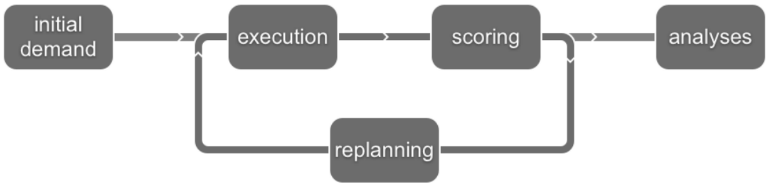


Figure 2.1: Stages of matsim simulation. [8]

- **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 estabilished the initial demand. During the execution step, Matsim simulates agents commute and tries to satisft 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 lover score. While agents who got where they wanted qucikly and without trafic 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 modle is detailed log of agent activities.

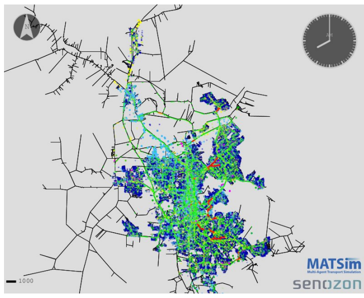


Figure 2.2: Matsim, Joinville example. Model intended to help the city encumbered by high traffic volumes. https://matsim.org/gallery/joinville/

To create the agents schedule, day intentions need to be provided to the model. Those can be either manually crafted. With the increased availabiliy of census data, data driven approach can be taken. This trades away the possibility to experiment with different kinds of populations and policies[5] 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 utilizies several datasets. New schedules can be generated from the model by sampling from the distributions.

5: like exmaining effect of different school time start on traffic

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

Finaly, moving to use of Matsim for ev scenarios. [10] studies the impact of EVs on the electric id and electricty production in Croatia. By having a simmulation of power production network for the whole country as well. They first have a simmulation 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.

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

Talk about arup

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 fo reality compared traffic models[6]. 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.

6: Of course trafic models have large part of stochasticity inside themselves

[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

[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 simmulation 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 hiearrchicaly 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]: 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'

- [12]
- [14]
- [15]

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

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

2.6 Data sources and transformations

estimate population

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

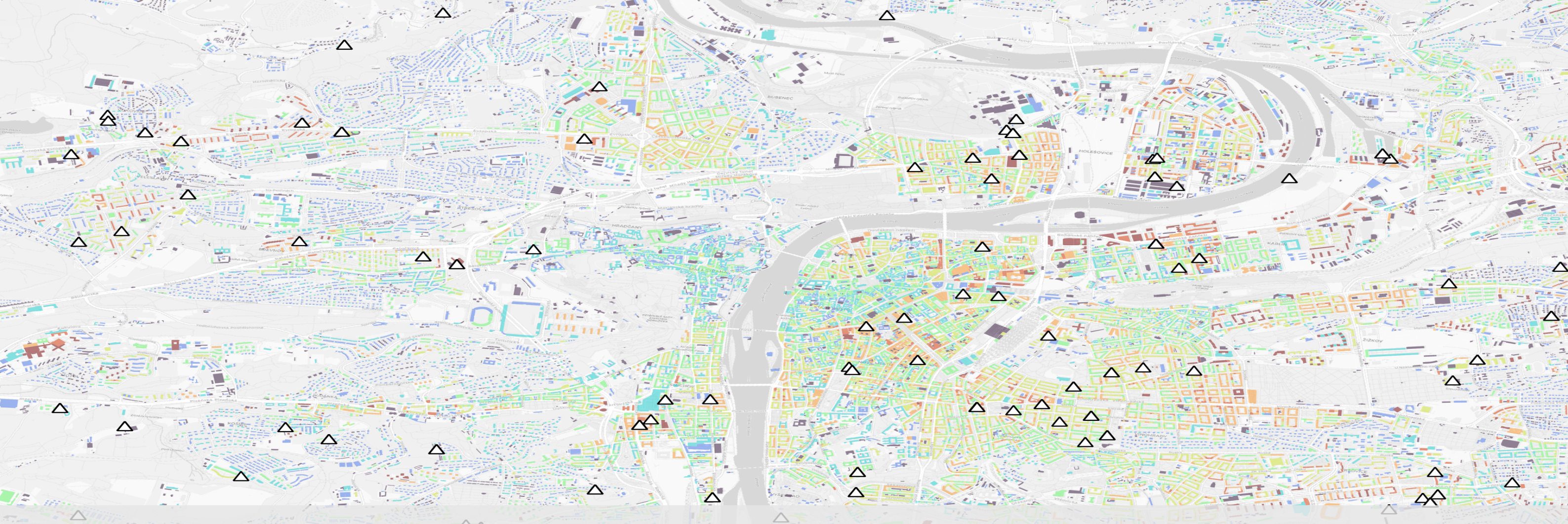
2.7 Discussion

From observed papers regarding simulation to obtain some estimate of charging demand. Either, in absence of data, expert knowledge is utilized to create simmulations. Which lean more on engineering complexity. Due to need to simmulate 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 flexibilty. 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.



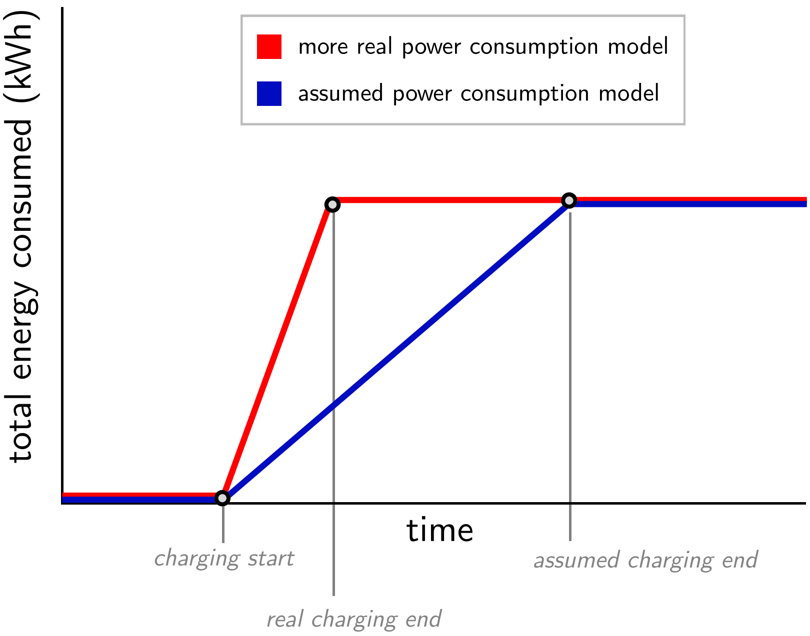
3 Data

Mention all the available data forming our data landscape which determines 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

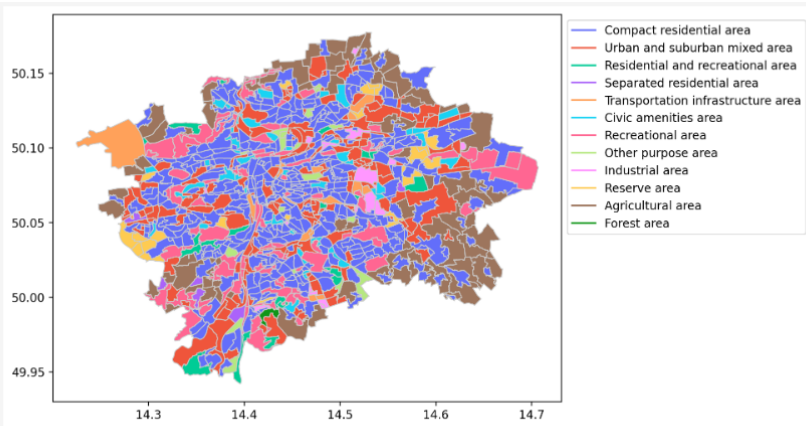
3.1 EV Chargers and Charging Sessions

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

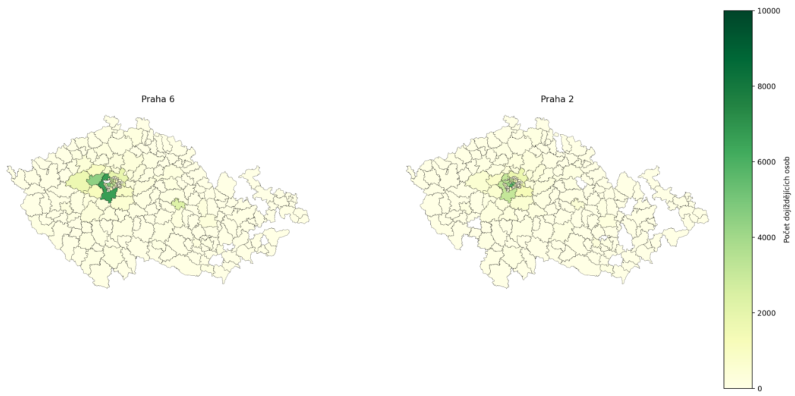


Figure 3.1: Chapter content overview.

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

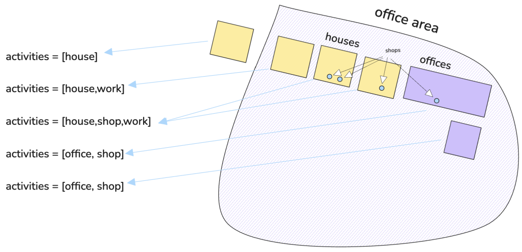
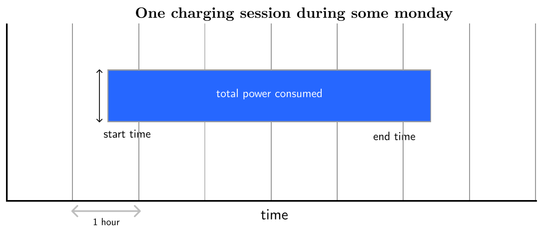
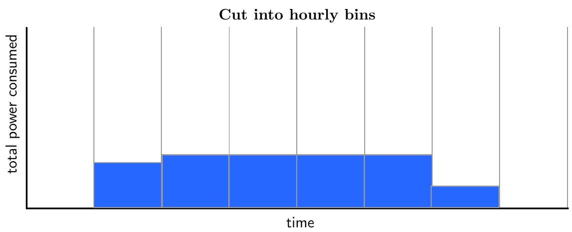


Figure 3.3: osmox

3.7 Charging profiles





3.8

Research and implementation 4

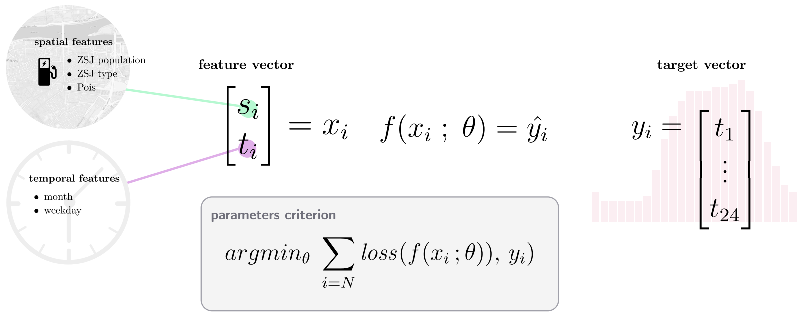


Figure 4.1: Problem approach overview

In this chapter, the problem will be formulated, and then an approach of solving it will be presented. The choice for the ML model will be discussed as well as its interpretable structure. A way of processing the data, splitting it into training and validation sets will be presented. And then a way to evaluate the model in comparison to other ML models will be described.

4.1 Problem statement

We will be interested in estimating average power consumption with temporal pattern (APC) from some set of features. And will like to know if our data-driven approach is viable.

To formulate how the model will look like, the model f_θ will execute the following mapping:

$$f_\theta : X \to Y$$

Where X will be the set of all feature vectors and Y will be the set of all targets. The available data are split into training test and validation sets. The first available at training time with goal of the training algorithm to minimize the empirical risk.

$$\begin{aligned} train:\ \mathcal{T} &= ((x_i, y_i) \in X \times Y |\ i = 1, \ldots, P) \\ test:\ \mathcal{S} &= ((x_i, y_i) \in X \times Y |\ i = 1, \ldots, R) \\ validation:\ \mathcal{V} &= ((x_i, y_i) \in X \times Y |\ i = 1, \ldots, O) \end{aligned} \tag{4.1}$$

$X \in \mathbb{R}^M$ and $Y \in \mathbb{R}^{24}$. And $|A| = |B| = P$.

The model function f will have trainable parameters θ. And we will be interested in finding such θ that minimizes the empirical risk:

$$loss_{total}(f, \theta) = \frac{1}{P} \sum_{(x,y)\in\mathcal{T}} \alpha \cdot a_x + \beta \cdot b_x \tag{4.2}$$

Where:

$$\begin{aligned} a_x &= loss_{power}(\left\|f(x_i;\theta)\right\|_1, \left\|y_i\right\|_1) \\ b_y &= loss_{norm}(\frac{f(x_i;\theta)}{\left\|f(x_i;\theta)\right\|_1}, \frac{y_i}{\left\|y_i\right\|_1}) \end{aligned} \tag{4.3}$$

where $loss_{power}$ and $loss_{norm}$ will be individual loss functions. Because we will be interested in model performance in estimating total daily power consumption (TDPC) and normalized daily power consumption (NDPC). This will match with the chosen NN model architecture that will be discussed further in this chapter.

The use case of the model is to answer the EV charger planners' question: what will be the charger's power consumption if he decides to place a new charging station (CS) at a new place in Prague? And he is interested in its behavior given the temporal pattern[1].

1: e.g., how would a new charger at place x perform on Thursdays of February

4.2 Model features and feature engineering

The feature vector of the model consist of **temporal** and **spatial** parts. Features regarding the charger's capabilities should be present as well, but that will be a limitation of the current chargers dataset that we will work with. The most useful will be the charger's maximum power output. Since that will most certainly influence the charger's average consumption. From this absence, the normalized daily power consumption (NDPC) will also be in our interest to estimate. Since the total power consumed might not have that big of an influence on it.

The feature items will fall into two categories divided by the data type. Either they will be categorical or numerical. If they will be categorical, they will be transformed with one-hot encoding. That is, given a category with n items to transform the feature into n binary features, where each binary feature will correspond to one of the possible values. For each observation, exactly one of these binary features will have the value 1, indicating the presence of that categorical value, while all others will be 0.

For example, if we have a categorical feature "day of week" with 7 possible values (Monday through Sunday), one-hot encoding transforms this into 7 binary features: "is_Monday", "is_Tuesday", etc. If an observation occurs on Wednesday, then the "is_Wednesday" feature would be 1, while all other day features would be 0. This transformation allows the model to properly handle categorical variables without imposing an arbitrary ordinal relationship between category values.

In our case, categorical features like the day of the week, month, and location characteristics will be one-hot encoded before being fed into the model. This will ensure that the model can effectively learn from these categorical variables without the constraints of numerical ordering.

Numerical features, on the other hand, will be standardized by subtracting the mean and dividing by the standard deviation to ensure all features will be on a comparable scale. This normalization process will prevent features with larger scales from dominating the learning process and will help achieve faster convergence during model training.

The feature vector will be constructed in the following way:

$$x_i = \begin{bmatrix} s_i^T \\ t_i^T \end{bmatrix} \tag{4.4}$$

spatial features s_i will be a vector of spatial features which contents will be described in 4.1 together with how this feature will be encoded.

$$s_i = \begin{bmatrix} s_i^1 \\ \vdots \\ s_i^R \end{bmatrix} \tag{4.5}$$

temporal features t_i will be a vector of temporal features which contents will be described in 4.2 together with how this feature will be encoded.

$$t_i = \begin{bmatrix} t_i^1 \\ \vdots \\ t_i^P \end{bmatrix} \tag{4.6}$$

Table 4.1: Overview of spatial features used in the feature vector.

Index	Name	Type	Value from	Additional processing
s_1	ZSJ population	numeric	charger in ZSJ polygon	normalization by the polygon area
$s_{2:10}$	ZSJ type	categorical	charger in ZSJ polygon	one-hot encoding
s_{11}	ZSJ number of addresses	numeric	charger in ZSJ polygon	normalization by the polygon area
s_{12}	Number of people commuting into the district from inside Prague	numeric	charger in the district polygon	normalization by the polygon area
s_{13}	Number of people commuting into the district from outside of Prague	numeric	charger in the district polygon	normalization by the polygon area
$s_{14:162}$	Points of Interest	numeric	number of PoIs by euclidean distance	importance calculation (value of single PoI is 1 if its distance from charger is 0, 0 if it is of distance 2km or further)

Table 4.2: Overview of temporal pattern used in feature vector.

Index	Name	Type	Value from	Additional processing
$t_{1:7}$	day of the week	categorical	average power consumption with temporal pattern (APC)	one-hot encoding
$t_{8:19}$	month	categorical	average power consumption with temporal pattern (APC)	one-hot encoding

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

4.3 Architecture of the Latent Neural Network

The formulation of the machine learning problem provides us with ability of many solutions. Mainly from the class of nerual networks.

Neural networks are computational models. They consist of layers of interconnected nodes or "neurons" that process information. A typical neural network contains an input layer that receives data, one or more hidden layers that perform computations, and an output layer that produces the final result. Each connection between neurons has an associated weight that is adjusted during the training process. Information flows through the network via activation functions, which introduce non-linearity and allow the network to learn non-linear patterns. The training process involves feeding the network with labeled examples and using optimization algorithms, typically variants of gradient descent, to minimize a loss function by adjusting the weights. Backpropagation is the primary algorithm used to calculate gradients and update weights efficiently.

This leads us to the proposed neural network with latent profiles. Diagram of the network is visible at 4.2. Before diving into the detailed network architecture a high level overview. The goal of the network is to construct for its internal use K [2] latent profiles. Which is a matrix R where $R \in \mathbb{R}^{24 \times K}$. And then estimate with use of f module their mixture into the resulting L1 normalized profile.

2: K is hyperparameter

Then there is the g module. Whose purpose is to estimate the overall day power consumption. Where the output of it is multiplied with the already mixed latent profiles.

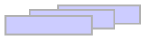
The network utilizes the following layers:

Trainable layers:

- **Fully connected (Linear transformation)**
  $\mathrm{Linear}_m^n(x) = Wx + b$
  $\mathrm{Linear}_m^n : \mathbb{R}^n \to \mathbb{R}^m \ , \ W \in \mathbb{R}^{m \times n} \ , \ b \in \mathbb{R}^m$
  W, b are learnable

  ...

- **Latent vectors (Embedding)**
  $\mathrm{LatentVec}_K = R$
  $\mathrm{LatentVec}_K : \emptyset \to \mathbb{R}^{24 \times K}$
  R is learnable



  ...

Non-parametric operations:

- **Softplus (Smooth activation)**
  $f(x) = \ln(1 + e^x)$
  $f : \mathbb{R} \to \mathbb{R}^+$

  ...

- **Normalization**
  $\mathrm{Norm}(x) = \frac{x}{\|x\|_2}$
  $\mathrm{Norm} : \mathbb{R}^n \to \{y \in \mathbb{R}^n : \|y\|_2 = 1\}$
  input dimension matches output dimension

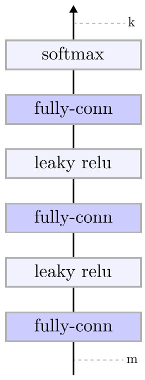
  ...

- **Leaky-relu**
  $$\mathrm{LReLU}(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases}$$
  $\mathrm{LReLU} : \mathbb{R} \to \mathbb{R} \ , \ \alpha$ is a hyperparameter

  Extension of ReLU. In this work there is no clear motivation for its use over tanh or ReLU.

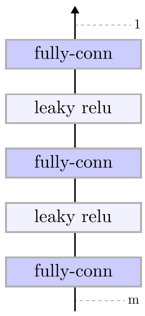
Those layers joined together form 3 modules. Each of which has assigned purpose by the way the are constructed and what is their possible output value range.

Non-parametric operations:



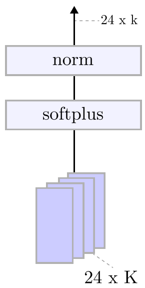
- **f module (Latent profile probabilities)**
  $f : \mathbb{R}^d \rightarrow \mathbb{R}^K$
  $f = \text{Softmax} \circ \text{Linear}_K \circ \text{LeakyReLU} \circ \text{Linear}_{64} \circ \text{LeakyReLU} \circ \text{Linear}_h$
  Where d is feature size, h is hidden size, and K is latent profiles count
  Outputs normalized weights for latent profiles

  Purpose of this module is to predict the contribution of individual profiles into the resulting output normalized profile. In other words, this module is tasked with estimating the day rhythm of the charger without the actual total power. The input is feature vector, and it is transformed by two linear layers and ReLUs. The output is vector of K values and is transformed by softmax to ensure the sum of its values equals 1.



- **g module (Total power)**
  $g : \mathbb{R}^d \rightarrow \mathbb{R}$
  $g = \text{Linear}_1 \circ \text{LeakyReLU} \circ \text{Linear}_{32} \circ \text{LeakyReLU} \circ \text{Linear}_{h_g}$
  Where d is feature size and h_g is hidden size for g module

  This module predicts just the total power for the given temporal pattern and location. It consists of 3 linear layers joined with LReLU. Its input is a feature vector and outputs just one scalar. With which combined output of h and f is multiplied at the end to obtain the prediction.



- **h module (Latent profiles)**
  $h(\mathbf{x}) = f(\mathbf{x}) \cdot R^T$
  $p : \mathbb{R}^d \rightarrow \mathbb{R}^T$
  Where $R \in \mathbb{R}^{T \times K}$ is the normalized latent profiles matrix
  T is time granularity (24), K is latent profiles count

  Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Outputs of h and f modules are then combined like so:

$$\begin{aligned}&\mathrm{Combine}(R, p) = \sum_{i=1}^{K} p_i\, R_i \\ &\mathrm{Combine} : \mathbb{R}^{24\times K} \times \mathbb{R}^{K} \longrightarrow \mathbb{R}^{24}\end{aligned} \tag{4.7}$$

This is then multiplied by the scalar from g module which finally gives us the resulting prediction.

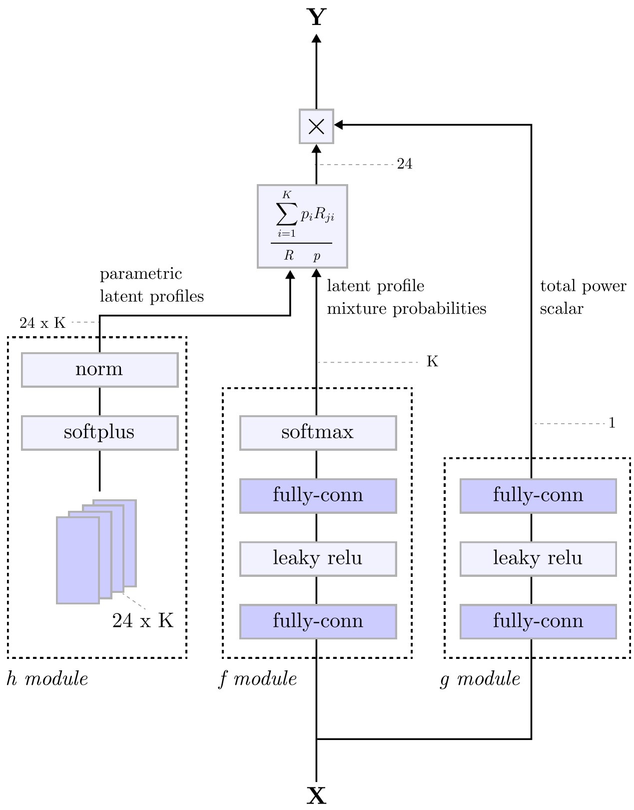


Figure 4.2: Latent neural network architecture. Light blue rectangles denote NN layers without trainable parameters. While blue denotes layers with parameters learned by SGD. Notation borrowed from Fleurets book "Little book of deep learning"

4.4 Training

4.5 Baseline

To be able to tell if our results will have some value. Will we be better than average? Because no one 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 evaulate 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

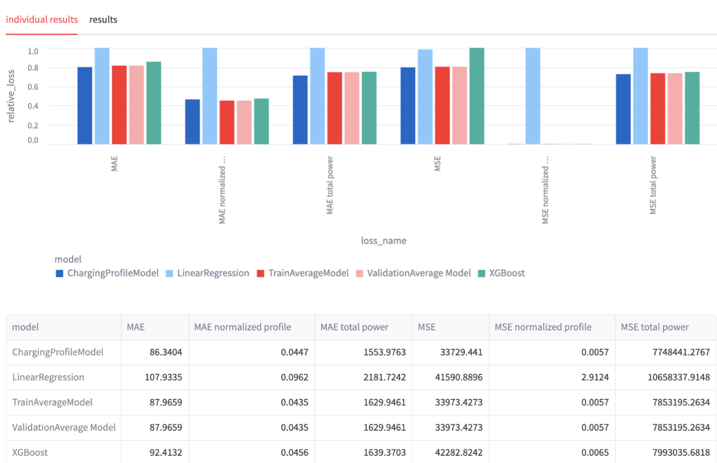
5.2 Qualitative latent profiles analysis

Inspection of the outputed latent profiles in prague together with hypotethising 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.

[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	33729.441	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

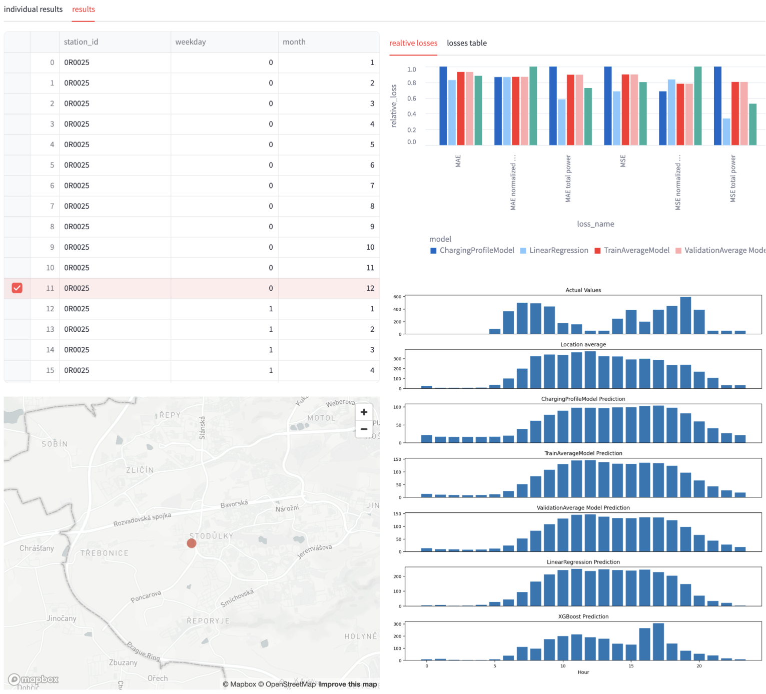


Figure 5.2: Data dashboard website showing table with data from validation data set with one selected row. Of which the prediction is computed from the main model and the other models for comparison.

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 haapens 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 agains 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 datases to be included.

List of Figures

List of Tables

Bibliography

Here are the references in citation order.

[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. (Visited on 02/28/2025) (cited on pages 5, 13).

[2] Guanpeng Dong et al. 'Electric Vehicle Charging Point Placement Optimisation by Exploiting Spatial Statistics and Maximal Coverage Location Models'. In: *Transportation Research Part D: Transport and Environment* 67 (Feb. 2019), pp. 77–88. DOI: 10.1016/j.trd.2018.11.005. (Visited on 01/28/2024) (cited on pages 5, 13).

[3] Anu Maria. 'Introduction to Modeling and Simulation'. In: *Proceedings of the 29th Conference on Winter Simulation*. 1997, pp. 7–13 (cited on page 6).

[4] *Traffic Analysis Tools: Types of Traffic Analysis Tools - FHWA Operations*. URL: https://ops.fhwa.dot.gov/trafficanalysistools/type_tools.htm (visited on 04/13/2025) (cited on page 6).

[5] *Home | Austroads*. URL: https://austroads.gov.au/ (visited on 04/13/2025) (cited on page 6).

[6] Mirosław Lachowicz. 'Microscopic, Mesoscopic and Macroscopic Descriptions of Complex Systems'. In: *Probabilistic Engineering Mechanics*. Special Issue: Stochastic Methods in Mechanics — Status and Challenges 26.1 (Jan. 1, 2011), pp. 54–60. DOI: 10.1016/j.probengmech.2010.06.007. (Visited on 04/13/2025) (cited on page 6).

[7] Matsim Community. *MATSim*. MATSim. Mar. 31, 2025. URL: https://matsim.org/ (visited on 04/13/2025) (cited on page 6).

[8] Andreas Horni, Kai Nagel, and Kay Axhausen, eds. *Multi-Agent Transport Simulation Matsim*. London: Ubiquity Press, Aug. 2016, p. 618 (cited on page 7).

[9] Jan Drchal, Michal Čertický, and Michal Jakob. 'Data-Driven Activity Scheduler for Agent-Based Mobility Models'. In: *Transportation Research Part C: Emerging Technologies* 98 (Jan. 1, 2019), pp. 370–390. DOI: 10.1016/j.trc.2018.12.002. (Visited on 04/15/2025) (cited on page 7).

[10] T. Novosel et al. 'Agent Based Modelling and Energy Planning – Utilization of MATSim for Transport Energy Demand Modelling'. In: *Energy*. Sustainable Development of Energy, Water and Environment Systems 92 (Dec. 1, 2015), pp. 466–475. DOI: 10.1016/j.energy.2015.05.091. (Visited on 04/13/2025) (cited on page 7).

[11] John Brady and Margaret O'Mahony. 'Modelling Charging Profiles of Electric Vehicles Based on Real-World Electric Vehicle Charging Data'. In: *Sustainable Cities and Society* 26 (Oct. 2016), pp. 203–216. DOI: 10.1016/j.scs.2016.06.014. (Visited on 01/13/2024) (cited on page 7).

[12] Azhar Ul-Haq, Carlo Cecati, and Ehab El-Saadany. 'Probabilistic Modeling of Electric Vehicle Charging Pattern in a Residential Distribution Network'. In: *Electric Power Systems Research* 157 (Apr. 2018), pp. 126–133. DOI: 10.1016/j.epsr.2017.12.005. (Visited on 01/15/2024) (cited on page 8).

[13] Siobhan Powell, Gustavo Vianna Cezar, and Ram Rajagopal. 'Scalable Probabilistic Estimates of Electric Vehicle Charging given Observed Driver Behavior'. In: *Applied Energy* 309 (Mar. 2022), p. 118382. DOI: 10.1016/j.apenergy.2021.118382. (Visited on 12/29/2023) (cited on page 8).

[14] Jin Zhang et al. 'Charging Demand Prediction in Beijing Based on Real-World Electric Vehicle Data'. In: *Journal of Energy Storage* 57 (Jan. 2023), p. 106294. DOI: 10.1016/j.est.2022.106294. (Visited on 01/16/2024) (cited on page 8).

[15] Lei Zhang et al. 'An Urban Charging Load Forecasting Model Based on Trip Chain Model for Private Passenger Electric Vehicles: A Case Study in Beijing'. In: *Energy* 299 (July 15, 2024), p. 130844. DOI: 10.1016/j.energy.2024.130844. (Visited on 03/28/2025) (cited on page 8).

[16] Jan Pekárek. 'A Model of Charging Service Demand for the Czech Republic'. In: *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis* 65.5 (Oct. 2017), pp. 1741–1750. DOI: 10.11118/actaun201765051741. (Visited on 01/19/2024) (cited on page 8).

[17] Akram Elomiya et al. 'An Advanced Spatial Decision Model for Strategic Placement of Off-Site Hydrogen Refueling Stations in Urban Areas'. In: *eTransportation* 22 (Dec. 1, 2024), p. 100375. DOI: 10.1016/j.etran.2024.100375. (Visited on 02/09/2025) (cited on page 8).

[18] Evženie Uglickich and Ivan Nagy. 'Poisson-Based Framework for Predicting Count Data: Application to Traffic Counts in Prague Areas'. In: *Journal of Computational Science* 85 (Feb. 1, 2025), p. 102534. DOI: 10.1016/j.jocs.2025.102534. (Visited on 02/09/2025) (cited on page 8).

[19] Shuoshuo Shang et al. 'Estimating Building-Scale Population Using Multi-Source Spatial Data'. In: *Cities* 111 (Apr. 1, 2021), p. 103002. DOI: 10.1016/j.cities.2020.103002. (Visited on 04/09/2025) (cited on page 8).

[20] *Streamlit • A Faster Way to Build and Share Data Apps*. Jan. 14, 2021. URL: https://streamlit.io/ (visited on 04/17/2025) (cited on page 23).