# Simulaad project

## Optimization of Smart Charging strategies

Robert van den Hoed
Youssef El Bouhassani
Peter van Bokhoven
Jan Dam
Ruud Noordijk
Nazir Refa

Amsterdam University of Applied Sciences · TKI Urban Energy Topsector Energy · MRA elektrisch · Amsterdam elektrisch · enpuls · Pitpoint Clean Fuels · Elaadnl · Rijkswaterstaat · Royal HaskoningDHV Enhancing Society Together

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- Clustering charging sessions
- Prediction of connection times
- Testing prediction & optimization


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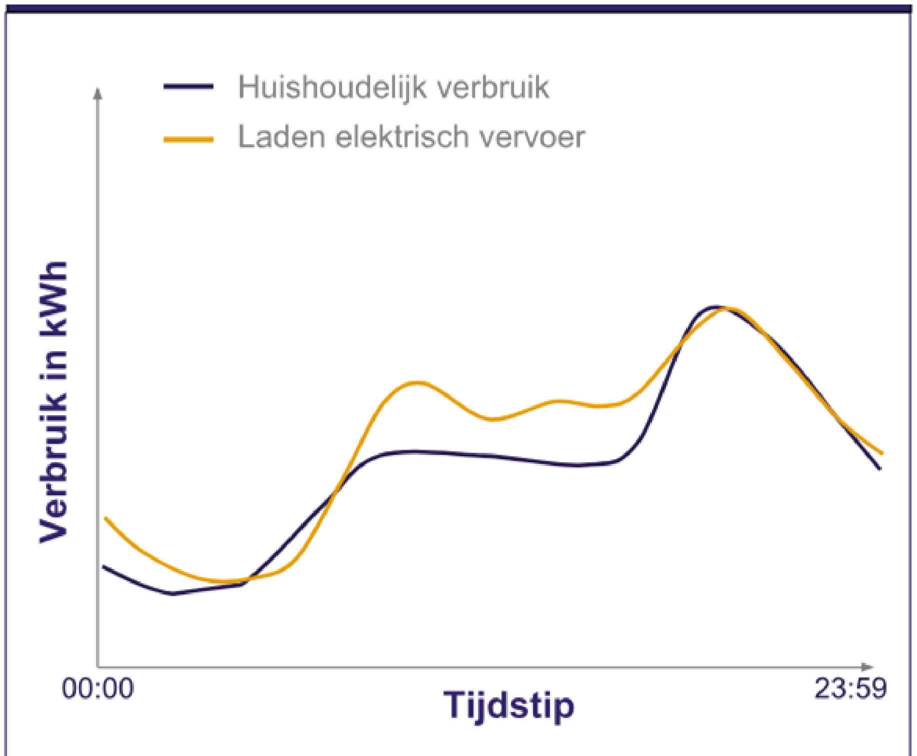
# Smart Charging can be used to meet EV power demands in an optimal way.

*Objective Simulaad: can we optimize charging using historical data?*




## The dataset spans almost the entire Netherlands with the four largest cities as outliers.

### G4 / MRA data

**Amsterdam**
**Den Haag**
**MRA**
**MRR**
**Rotterdam**
**Utrecht**

Sessions: 2,177,351
RFIDs: 56,988
Charging stations: 4,428

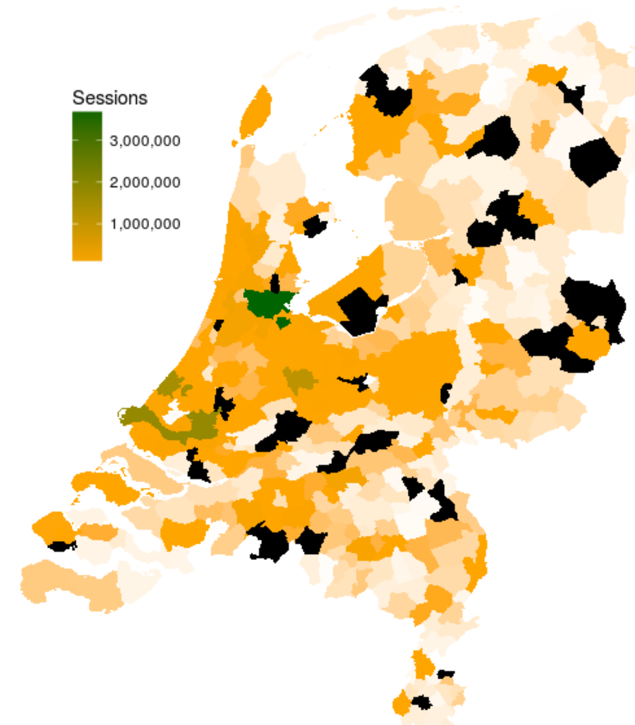
**Data mainly from large cities**

### EVNETNL data

**Noord-Brabant**
**Gelderland**
**Other**

Sessions: 605,440
RFIDs: 33,907
Charging stations: 1,538

**Data mainly from rural areas**



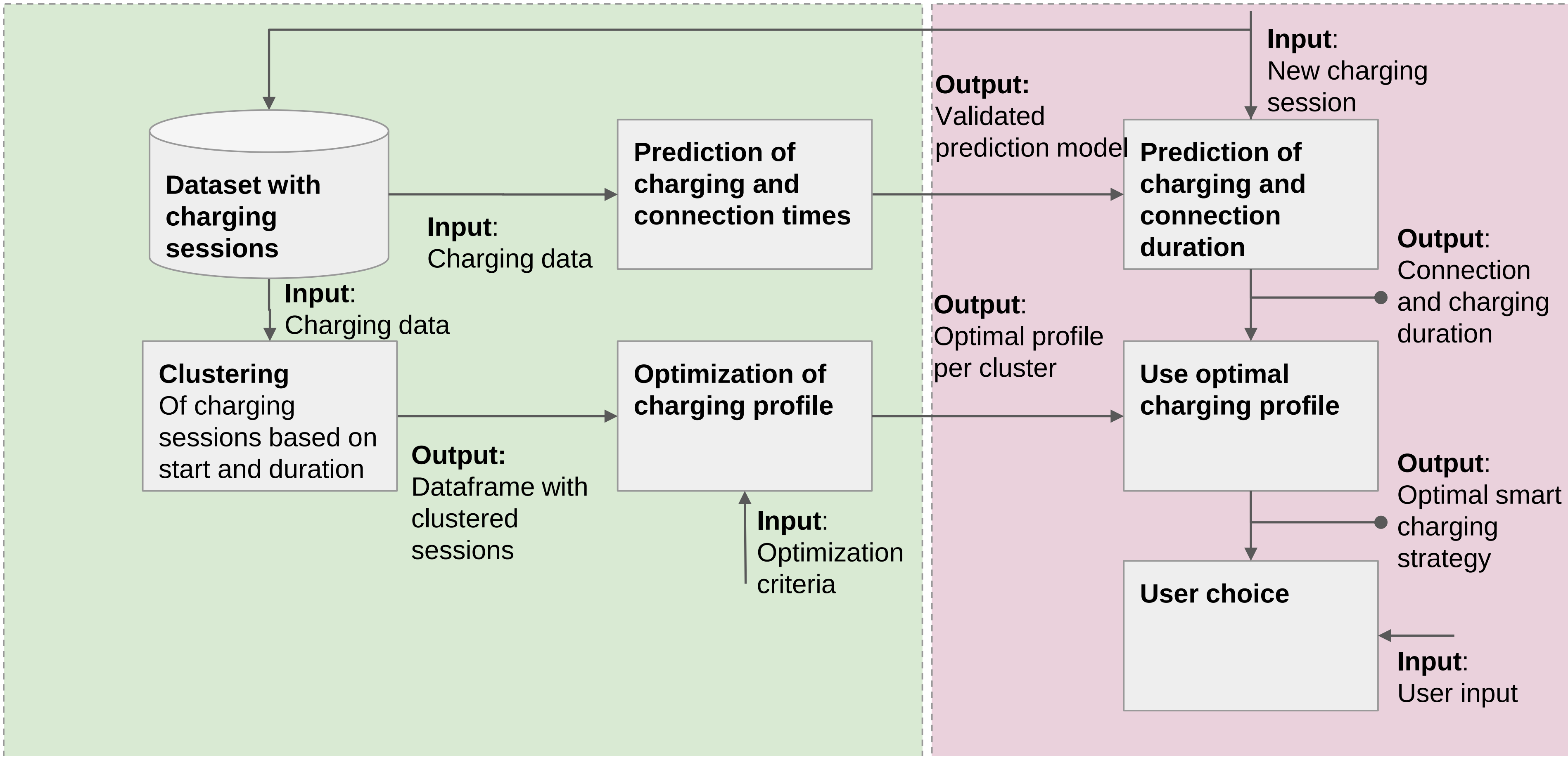

**Data per municipality**

## Offline in batch

The model is trained on a regular basis. This is necessary because training the model takes a lot of time.

## Online real-time

The models are used in real-life at the charging point. The used has an over-run option



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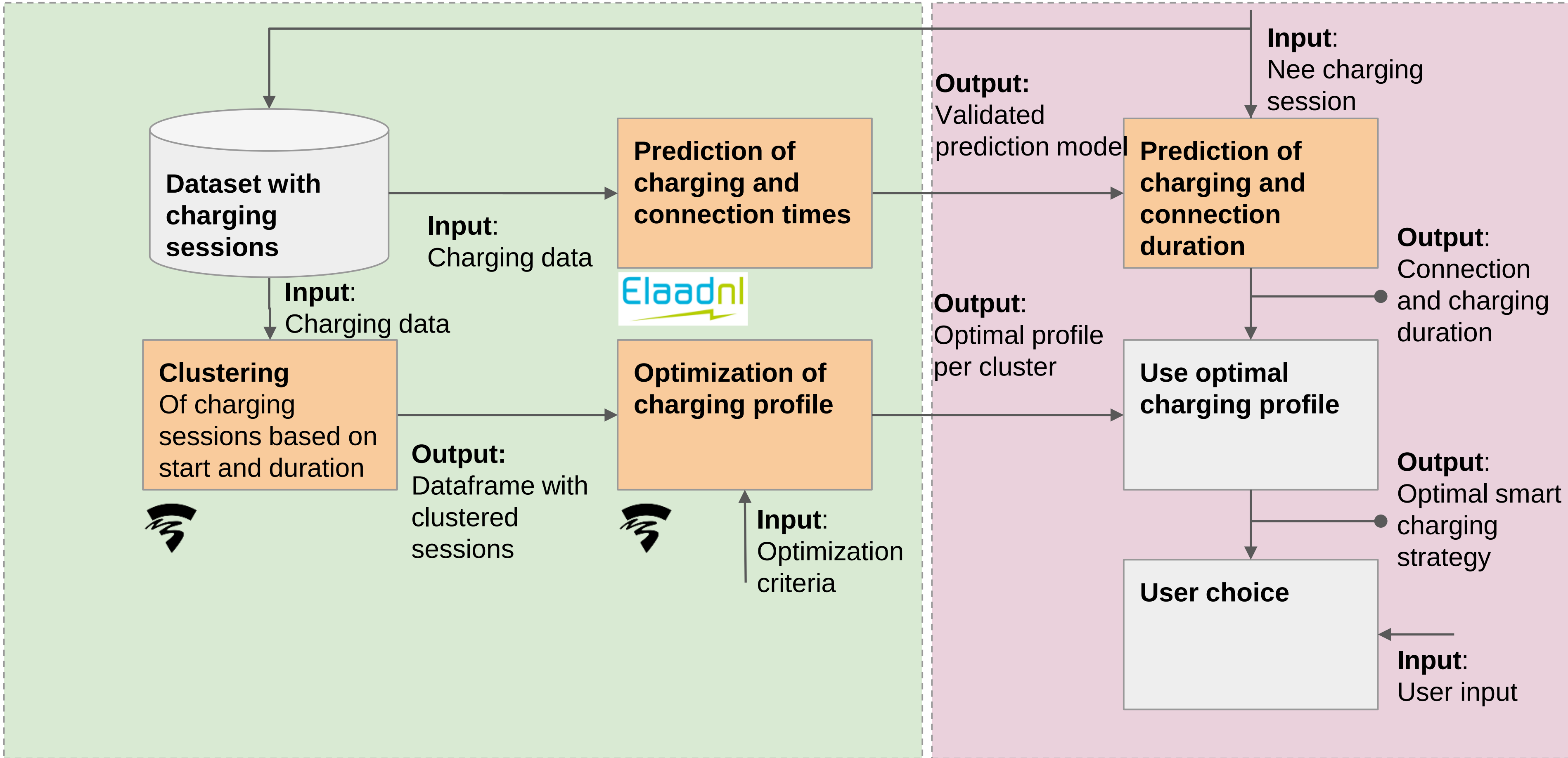

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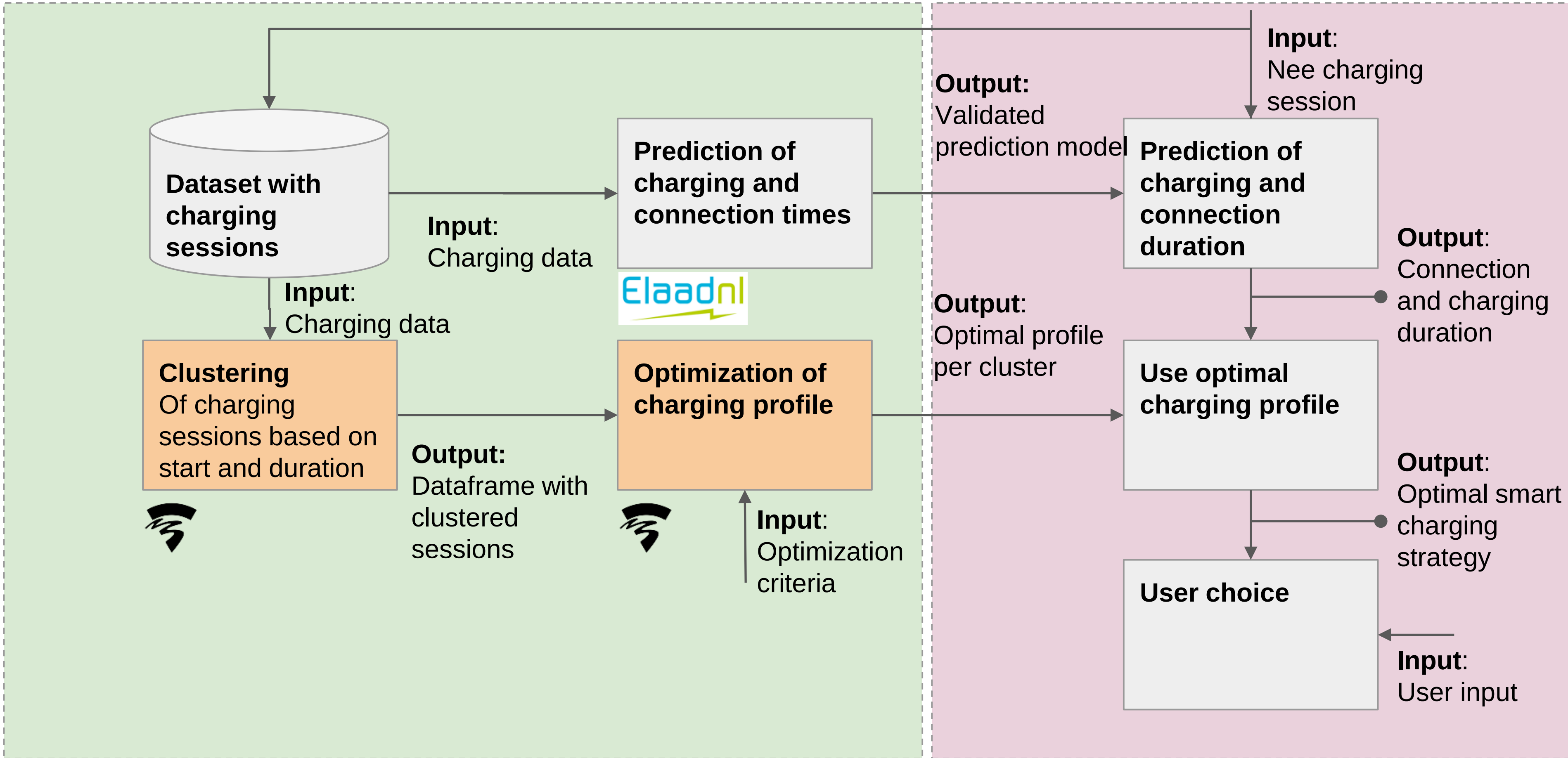
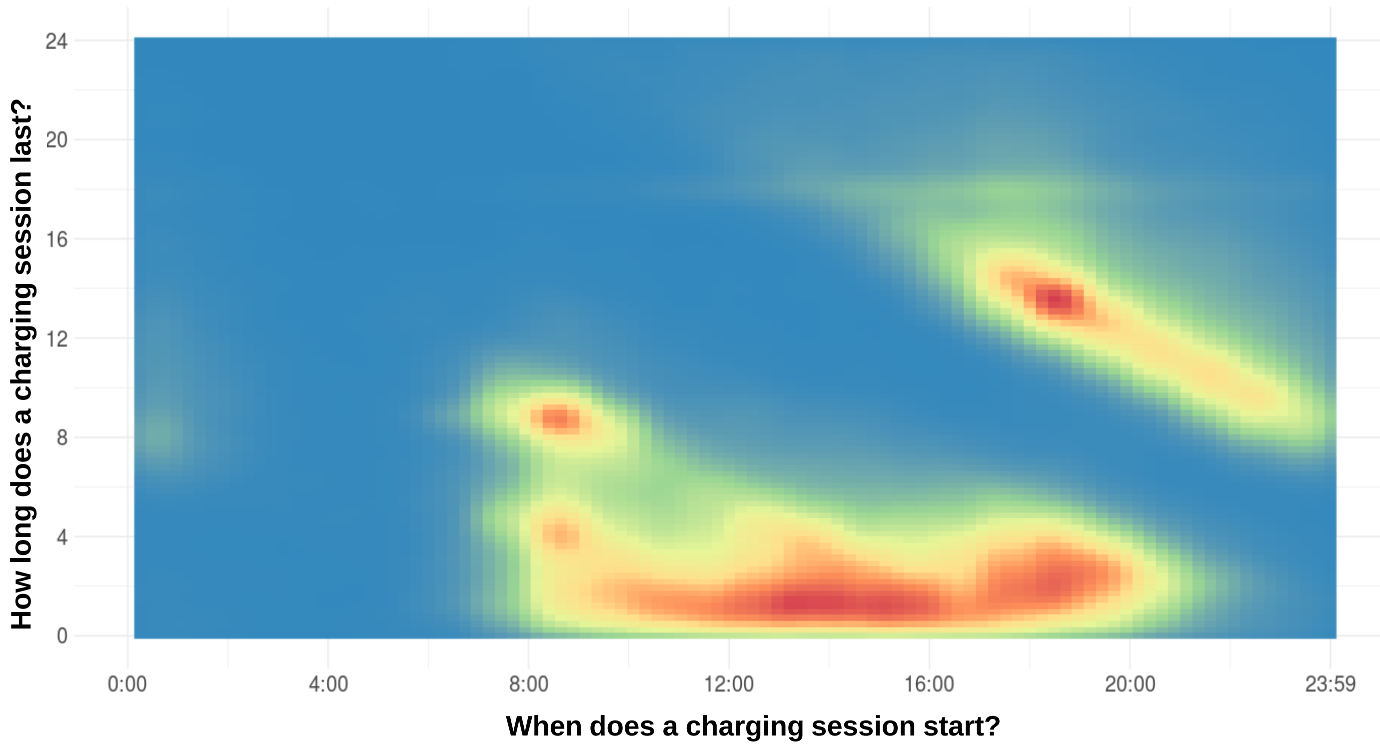
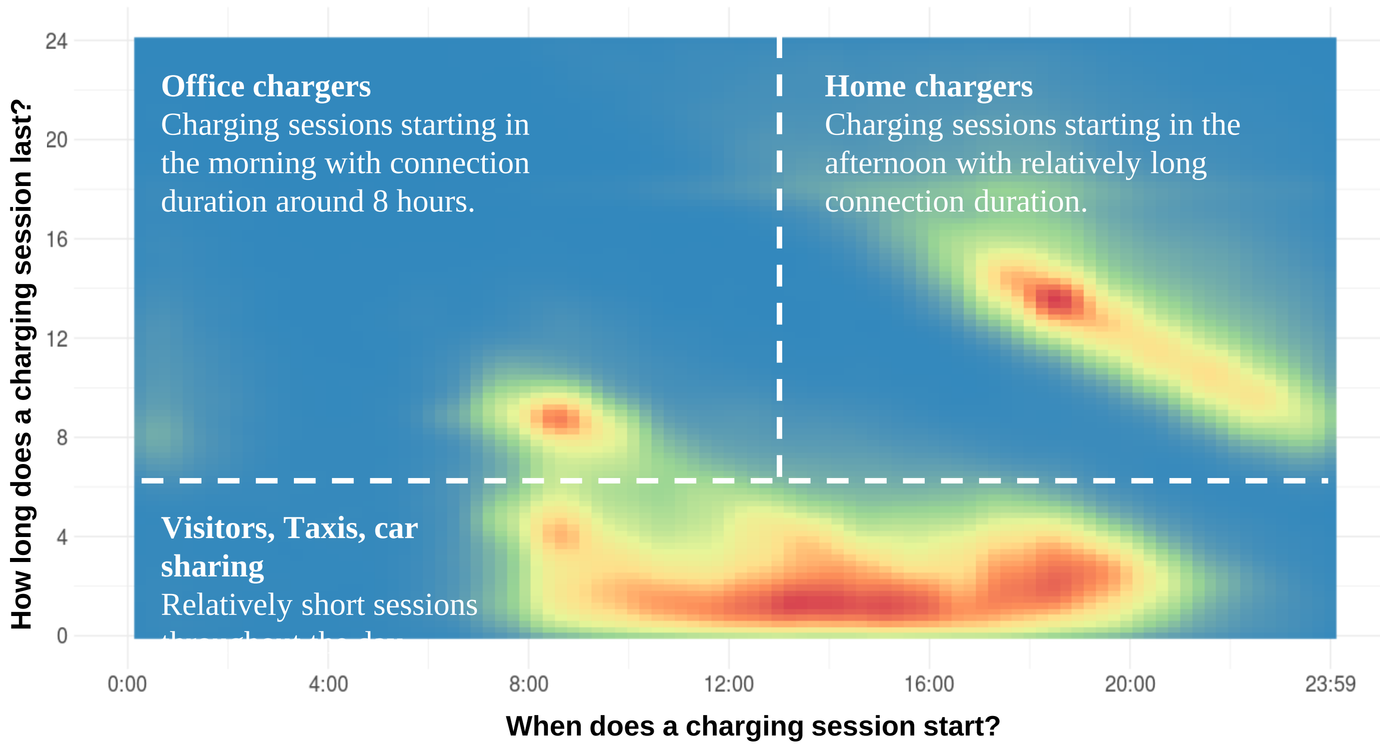


## Clustering: Charging sessions can be divided on two axes: (i) start connection time, and (ii) connection time.



# The division allows separating between typical user groups

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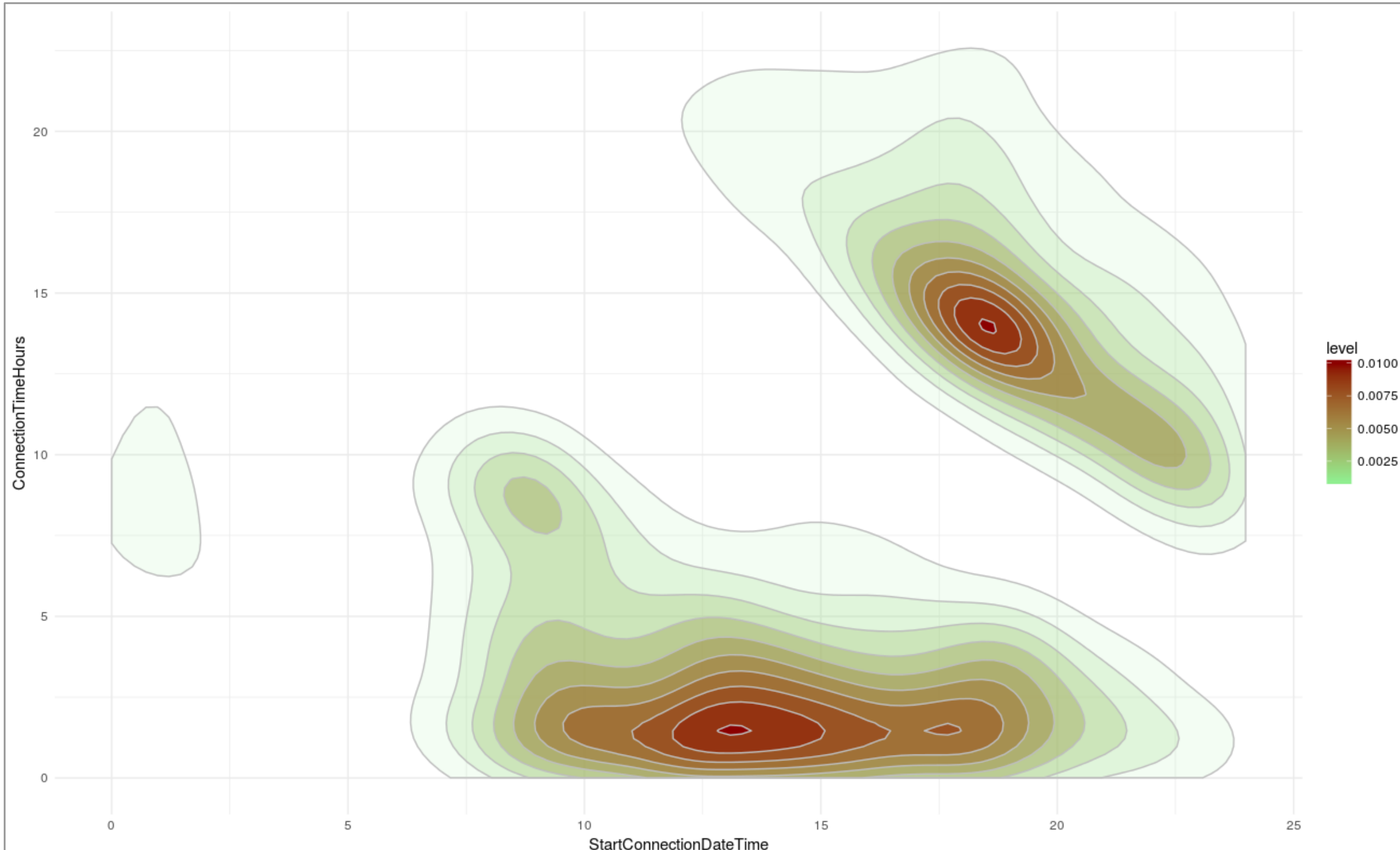
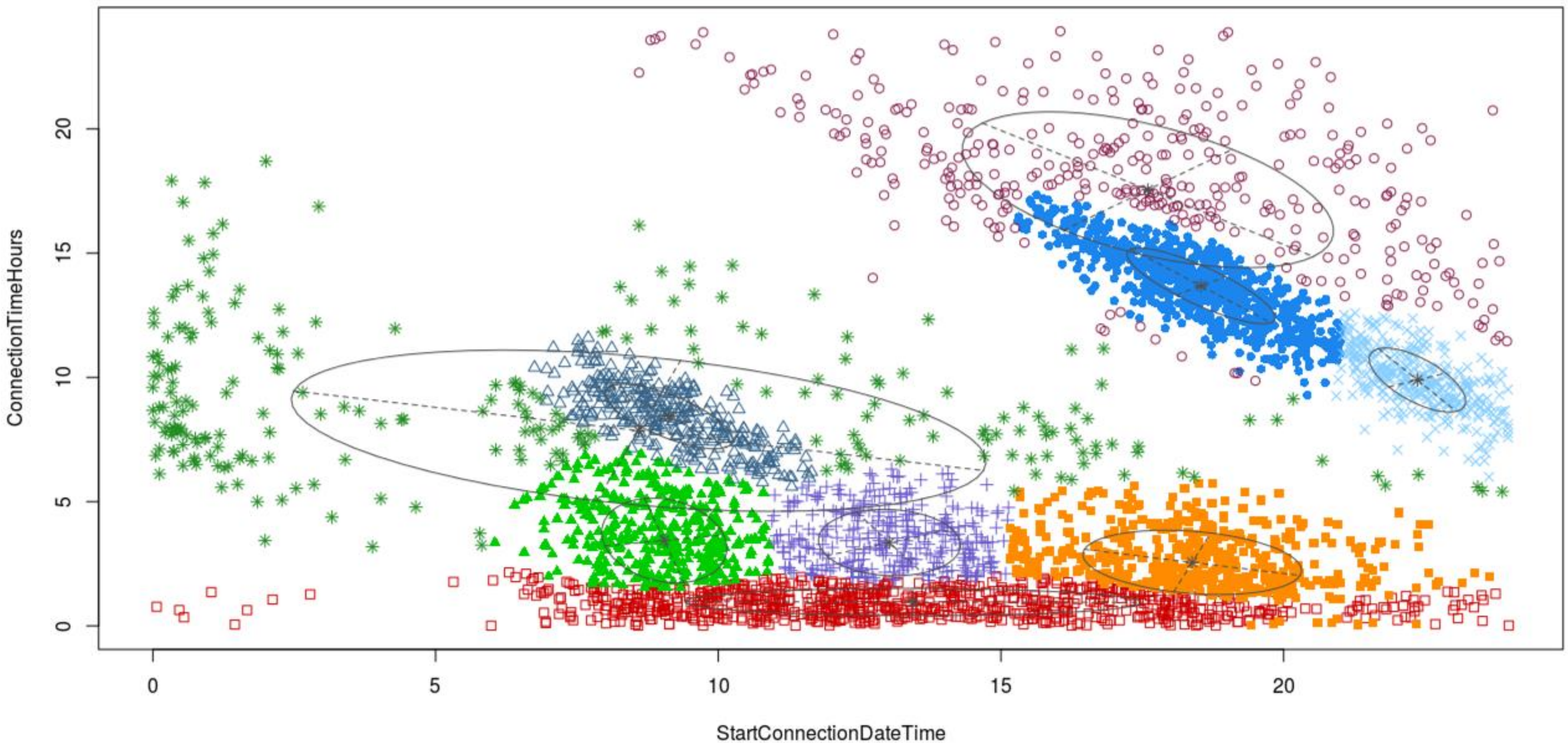
**The heatmap can also be visualised as a height map. This gives a better indication of the density of points in the plot.**



**Gaussian Mixture Models (GMM) were used for clustering charging sessions in 7-9 clusters → optimization can be suggested per cluster.**



# The goal is to find the influence of Smart Charging on net congestion, sustainability and cost of charging.

## SMART CHARGING STRATEGIES

**Postpone strategy**
A session is postponed. The shift is a percentage of the potential to Smart Charge.

**Cut and divide strategy**
A session is cut into smaller sessions and distributed over the total connection time.

**Slower charging strategy**
The maximum power for a charging session is reduced so the speed of charging is lower.

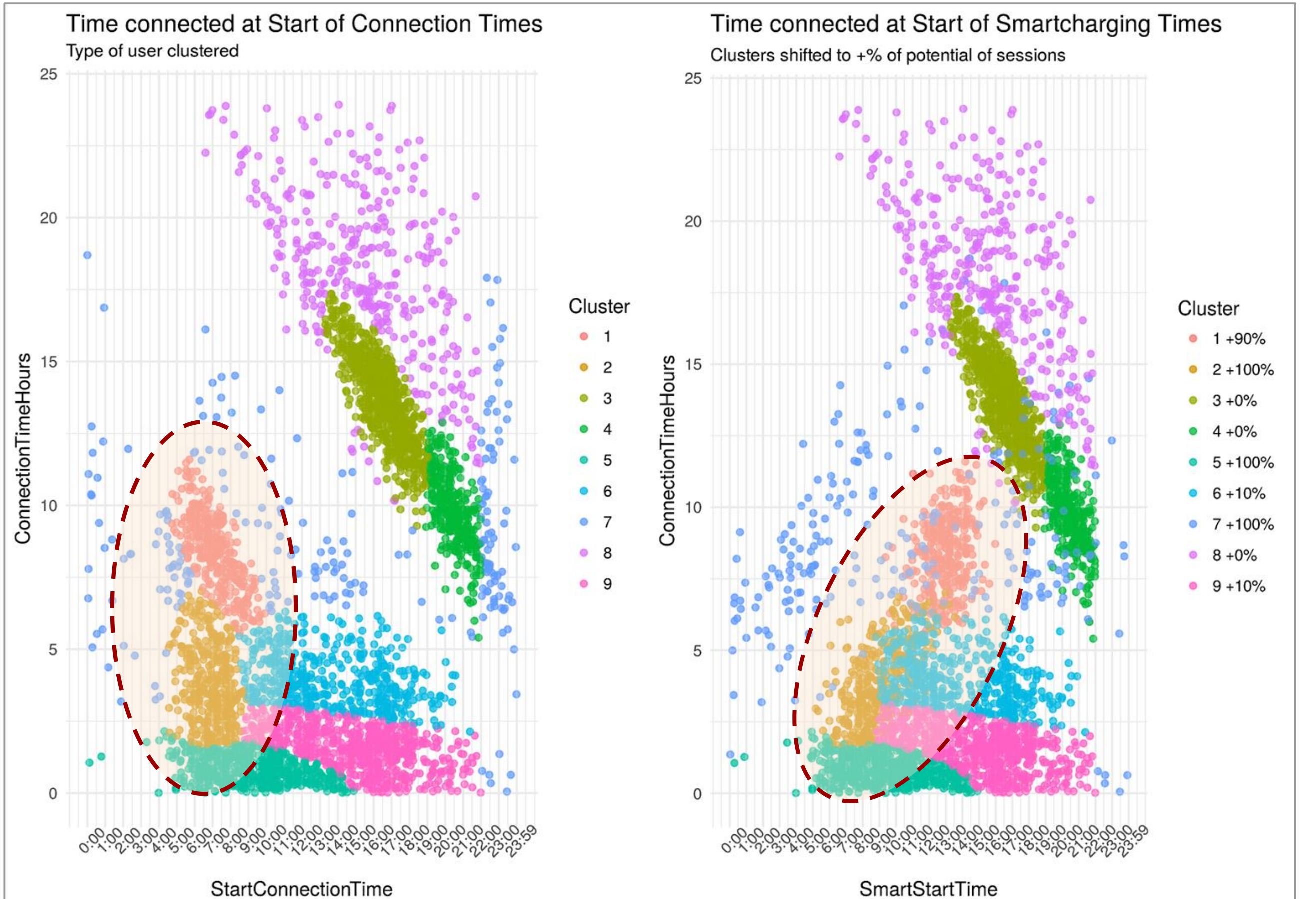
## PERFORMANCE INDICATORS

**Net congestion**
How can Smart Charging be used to reduce peak load.

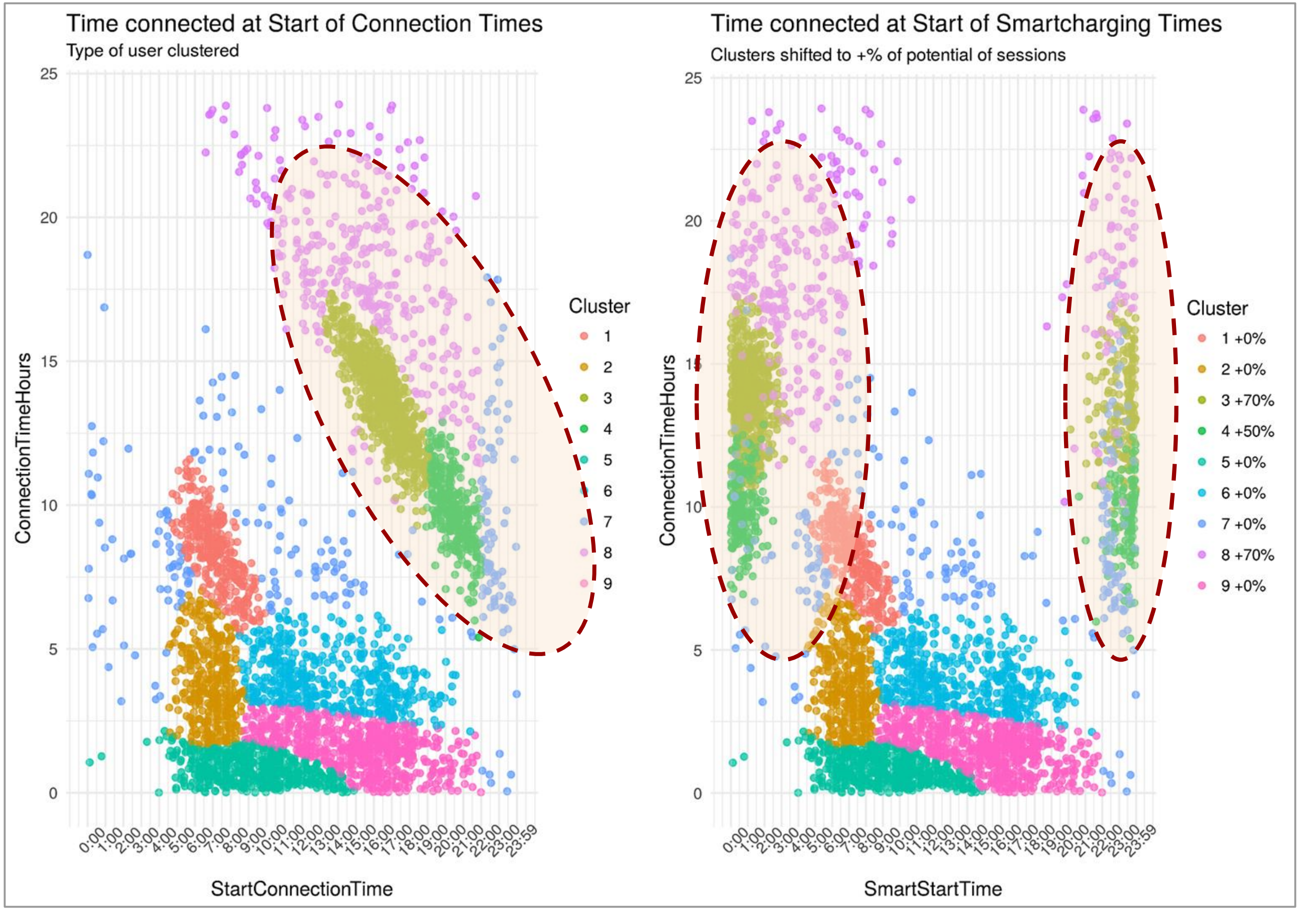
**Charging sustainably**
How can Smart Charging be used to use more sustainable energy sources.

**Cheaper charging**
How can Smart Charging be used to optimize for APX prices.

# When optimized for sustainable energy (solar), morning sessions are shifted the most

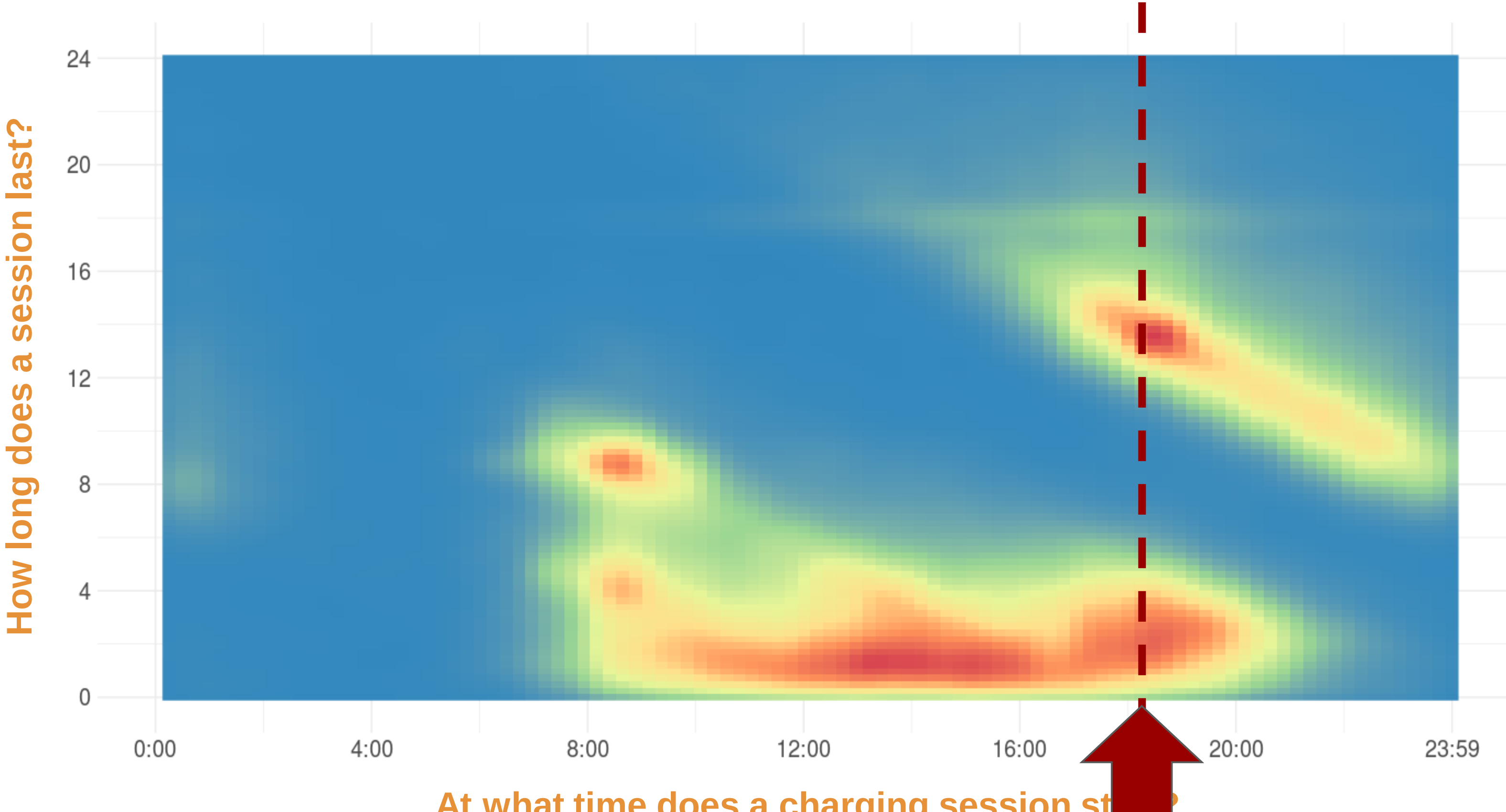


# When optimizing for power demand, the evening sessions are shifted the most.



## But how to predict how long a session will last?

*Requires sophisticated prediction models.*



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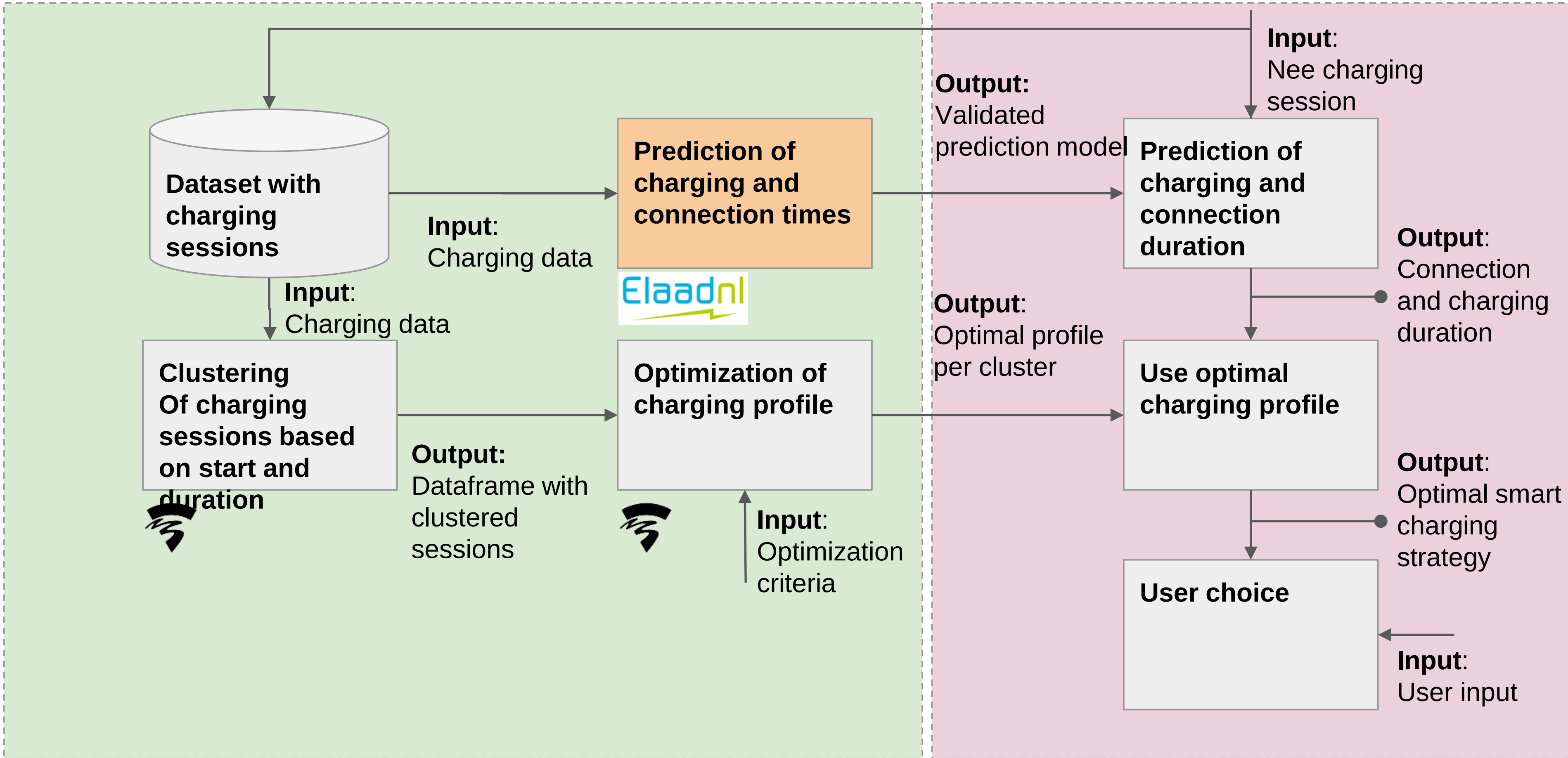
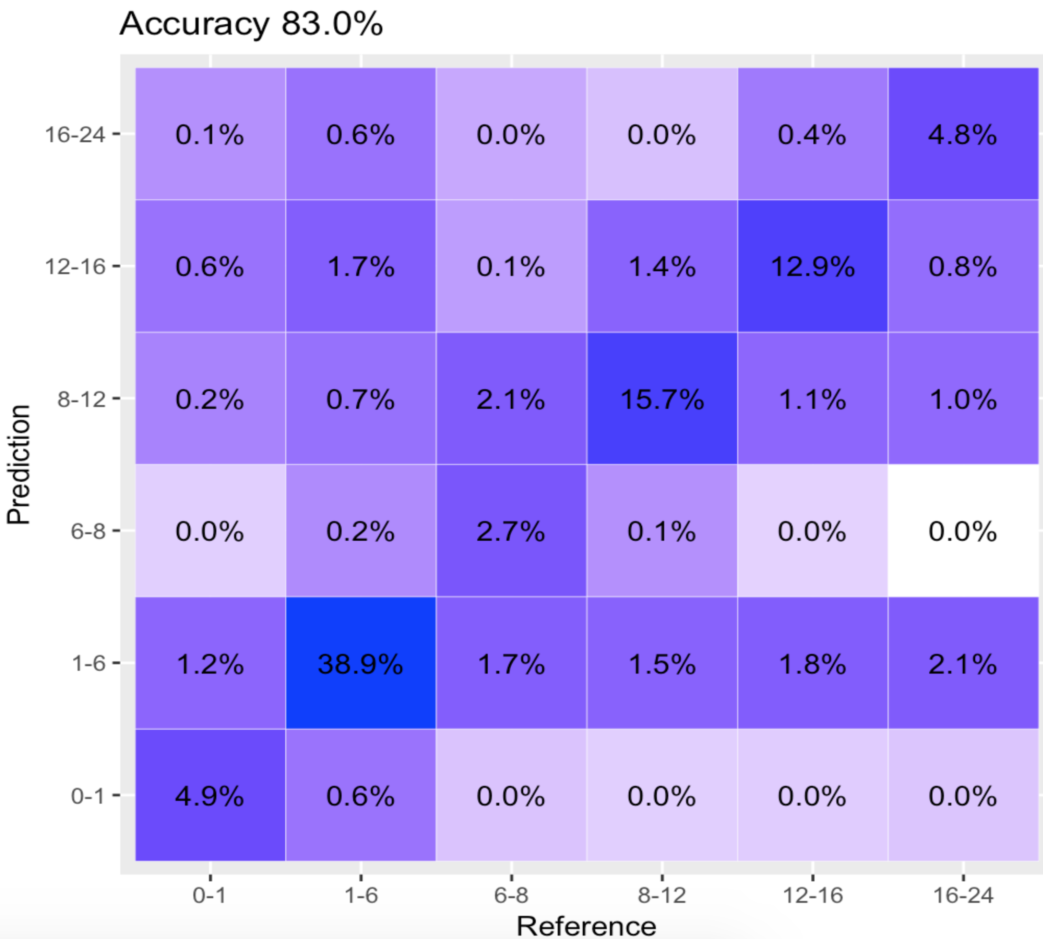


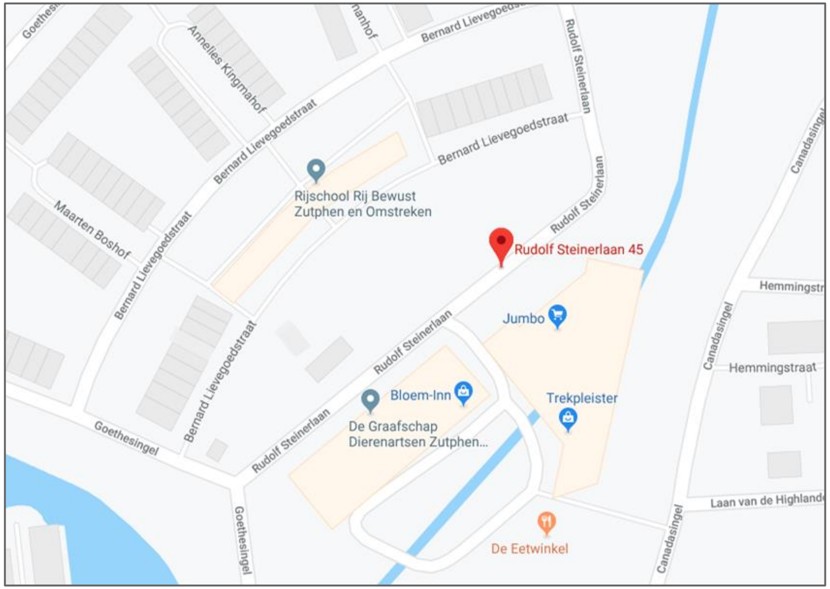
| | Averages | Weighted averages | GLMs | Classification (Linear) | Classification (Non-linear) |
|---|---|---|---|---|---|
| **Why?** | The average connection time of historical charging sessions should be an indication of the average connection time now. | Some charging sessions are more significant than other. Charging sessions should be weighed higher if they are significantly more important | The average connection time is a poor measure. Connection time is influenced by different factors which should be modeled. | GLMs attempt to predict the exact connection time. Another approach is to predict the time window (class) to which a charging sessions belongs. | Linear classifiers can not take complex non-linear boundaries into account. |
| **How?** | Calculate average transaction times based on historical sessions related to RFID, time and charge point | Within the maximum boundaries rate sessions based on different formulas | Fit a multivariable regression model to calculate the transaction times in the future | Use a flexible, easy and widely used classification model Random Forests to predict 2 time windows | Use neural networks to encapture non-linear correlations to predict 2+ time windows |
| **Result** | **Average error:** 2.1 - 4.8 hours | **Average error**: 1.8 - 3.5 hours | **R-squared:** 0.49 **Average error:** 2.6 hours | 2 classes: >6 and <6 hours **Accuracy** 78% | 5 classes: ≤6, ≤8, ≤12, ≤16, >16 **Accuracy** 78% - 82% |

# 1 Results prediction of connection times by identifying 6 classes.



## 2 Select at random a single session of a single RFID at a specific location

To test our pipeline, first 1 session is selected from our dataset and analyzed. Information session:



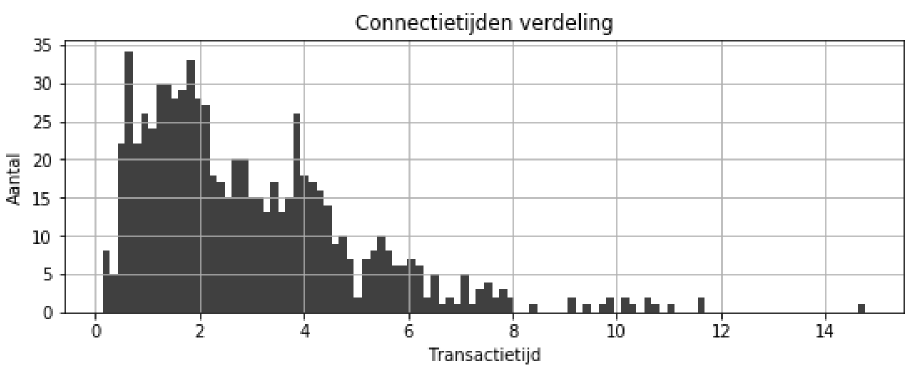


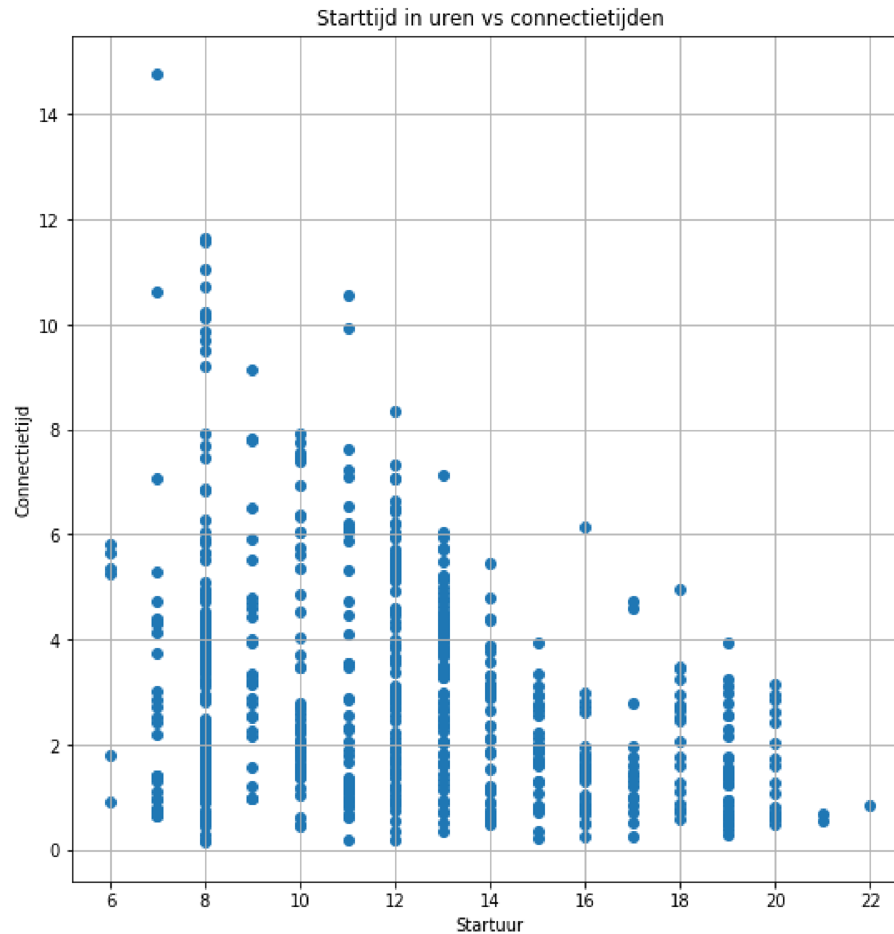
**Address**
Rudolfsteinerlaan, 7207 PV, Zutphen, Nederland

**Charging point**
EVNETNL.
Liander

**Actual Start:** 2019-08-16 08:48:59
**Actual End:** 2019-08-16 14:43:52
**Connection duration** = 5.91 hours
**Charging time** = 1.18 hours
**SCP** = 69%

# 2 Analyse connection times and charging times at this location

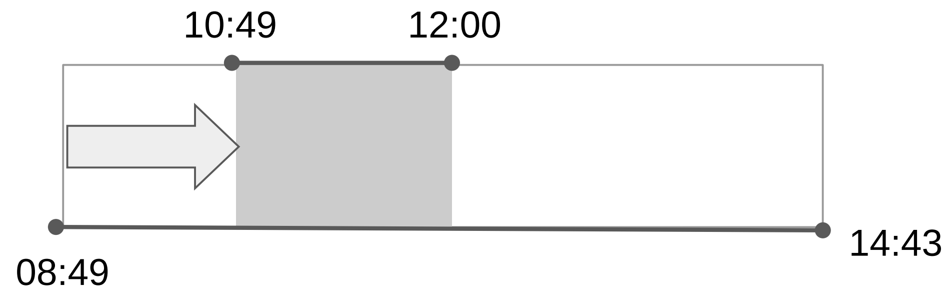


# 4 Make a prediction & propose a smart charging optimization

- The predicted class is correct (1-6hrs).
- Classification limits smart charging potential.

| ACTUAL SESSION | PREDICTED AND OPTIMIZED |
|---|---|
| **Class 2** (01-06 hours) | **Class 2** (01-06 hours) |
| **Start time** 08:49 | **Start time** 10:49 |
| **Delta start time** 0 hours | **Delta start time** ~ 2 hours (5,91-1,18)*0,4*60 = 114 minutes |



# 5 Results multiple sessions: scale up from 1 to 900

## General information

**Date**
Wednesday 30th october 2019

**# Sessions**
900

**First session**
00:02:01

**Last session**
23:58:06

**# RFID's**
832

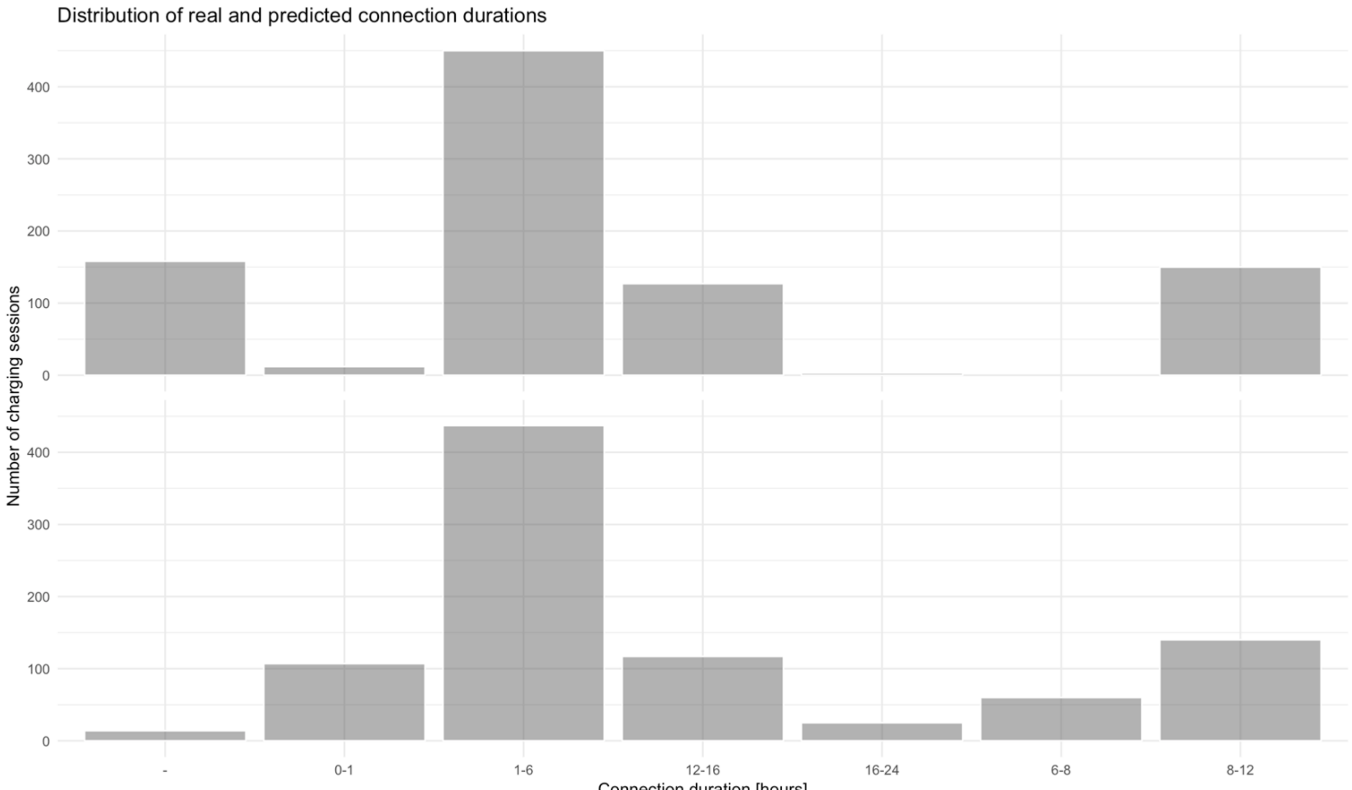
**Average connection time**
~ 6.43 hours

**Average usage**
~ 15.62 kWh

**Average historical # sessions per user**
~ 91 (minimum: 1, maximum: 1526)

# 5 Results multiple sessions

The image below shows the predicted connection time classes (on top) vs the real connection time classes (bottom). We see a spike in predicted times in the second class (1-6). Also some of the sessions cannot be predicted because we do not have enough data from a user to predict accurately what the connection time will be.



# Conclusions

1. **Prediction is necessary** - for unlocking smart charging potential.

2. **Predictions is hard** – particularly on public charging stations and for users with limited sessions.

3. **Prediction can be powerful**– in combination with clustering techniques for CPOs and grid operators.

# Taking all the optimization criteria into account is quite a challenge!