SIMULAAD

Applying prediction and optimisation models for smart charging (WP4)

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Content

1 - Project definition & objectives

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1.1 - Problem definition

The Netherlands has one of the most extensive public charging infrastructures for electric vehicles worldwide.

This increasingly creates opportunities and challenges to optimize the supply of and demand for sustainable energy in combination with the grid capacity.

Smart charging strategies play a necessary precondition for the large-scale rollout of electric driving, knowledge that is also eminently applicable in other countries worldwide.

Knowledge is lacking in regards to which conditions and which smart charging strategies are effective to achieve those goals.

One of the main challenges in smart charging is predicting charging session length and charging time. Without that knowledge, smart charging cannot be accurately optimized at the start of a session. After all, this can lead to short sessions that are incorrectly postponed; or long sessions that unjustly charge a lot.

1.2 - Objectives

Objective:
Apply and validate the developed prediction and optimization models for enabling smart charging.

Results:

- A report on the quality and accuracy of prediction models
- Application and validation of the prediction model on a real-world dataset
- Practical recommendations

2 - Context & previous work

2 Smart charging

The demand for electricity required to charge EVs will increase significantly, as the vast majority of the Dutch households is expected to acquire one (or multiple) EVs when the transition unfolds. Given the current charging patterns, the increased electricity demand will be concentrated in the morning and the evening.

This increased demand coincides with the same peak moments for household electricity consumption, especially the evening peak roughly between 17.00h and 20.00h. Moreover, there are other significant developments in the field of the energy transition that have a serious impact on the low-voltage electricity grid.

The adaptation of heat pumps (4,5 kW) and solar panels (for example 10 panels of 300 Wp represent 3 KW at peak solar). The combined developments account for a peak impact that the low-voltage electricity grids are not fully designed for. Smart Charging can help balance those grid peak loads.

Currently some Smart Charging is applied in the form of load balancing, meaning that every active EV gets an equal amount of energy. This is often not optimal and can be done in a smarter way. Postponing some of the sessions could result in less peak usage during peak hours in the morning and evening.

2 - Previous work

In our previous report[1] we already analyzed different prediction methods and created an optimization model. As a summary we can list some key findings:

- Prediction of connection times / energy usage
  - Neural networks and random forests are best in predicting connection times and energy usage. Multiple variables are found to take into account in our models. Prediction accuracy for different methods range from 60% - 80%.

- Optimization of smart charging sessions
  - Optimization of charging sessions is done per cluster. For each cluster of charging sessions identified using Gaussian Mixture Models and optimum postpone strategy is determined. The optimum depended heavily on optimisation criteria an cluster.

1 https://www.elaad.nl/uploads/files/Final_report_TKI-1_definitieve_versie_190214-1.pdf

3 - Modelling

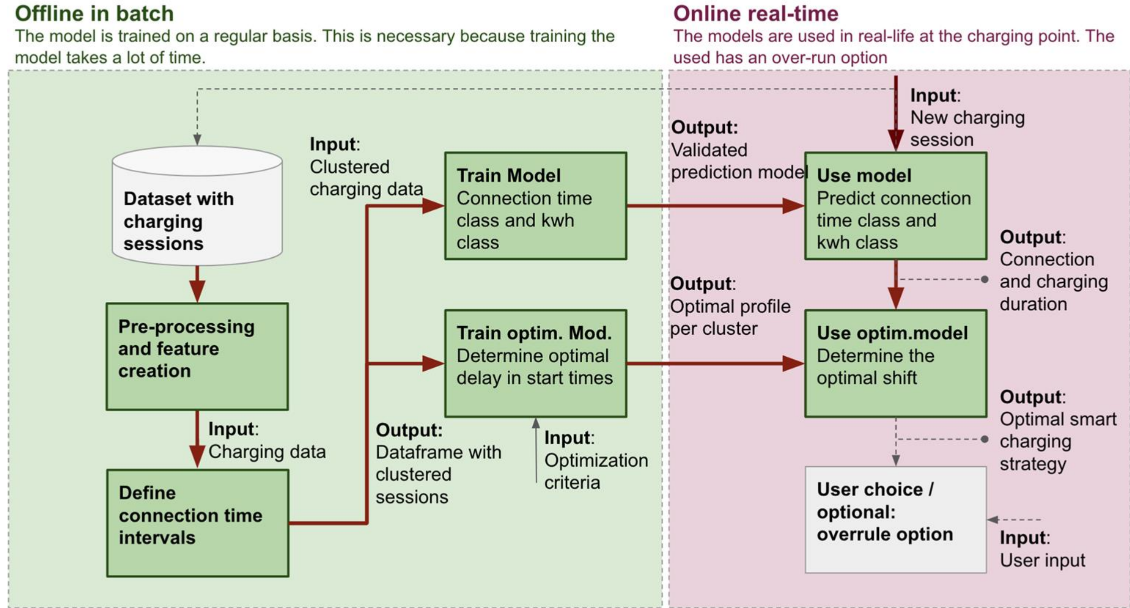
3.1 - Approach

In our previous project we defined an approach including an offline and an online part. In the offline part historic data is processed, the models are trained/built and they are saved for later use. In the online part the goal is to use these models to (i) predict connection/charging times of new charging sessions & (ii) provide optimization recommendations..

In previous work we already built the building blocks (green blocks) for this pipeline. In this project we will build the pipeline so that we can run the pipeline for multiple sessions and calculate the 'result'. This means that we are going to build the red lines in the illustration on the right. The overrule option is not built during this project.

If we run this pipeline for multiple charging sessions we can answer questions like: how many of these sessions are shifted, how many kWh's are shifted, which users, which time are the sessions shifted most? To which time?

The difficulty in this project is that the different building blocks are built on different data platforms due to data access in the previous project. We must make sure that all of the functionality is working together, well documented and ready to deploy on other platforms.

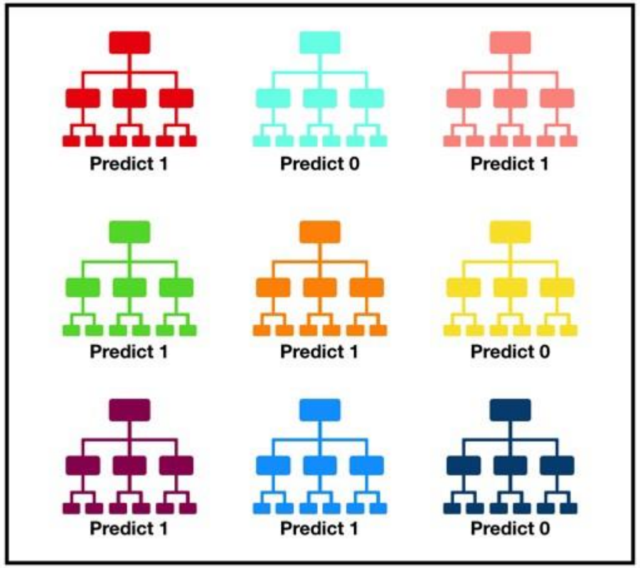


3.2 - Forecasting

In previous work we already implemented a Random Forest model for prediction of transaction times and energy usage. In this project we used grid search for tuning parameters. We used the Caret package in R for this. When training a random forest we can use many parameters and setting these parameters could have a big impact on the outcome. In the end we want to have the best settings for the best possible outcome.

To understand which parameters we tuned, let's first briefly describe random forests. Very short: random forests consists of a large number of individual decision trees that operate as an ensemble[1]. To predict an outcome, majority voting is used. In the image on the right 3 trees predict 0, 6 trees predict 1, hence the predicted outcome is 1 by majority vote.

Further explanation can be found in the link below. The parameters we optimized are the number of trees in the forest, number of mtrys (number of variables available for splitting at each tree node) and maximum number of nodes (levels in decision tree).



1 https://towardsdatascience.com/understanding-random-forest-58381e0602d2

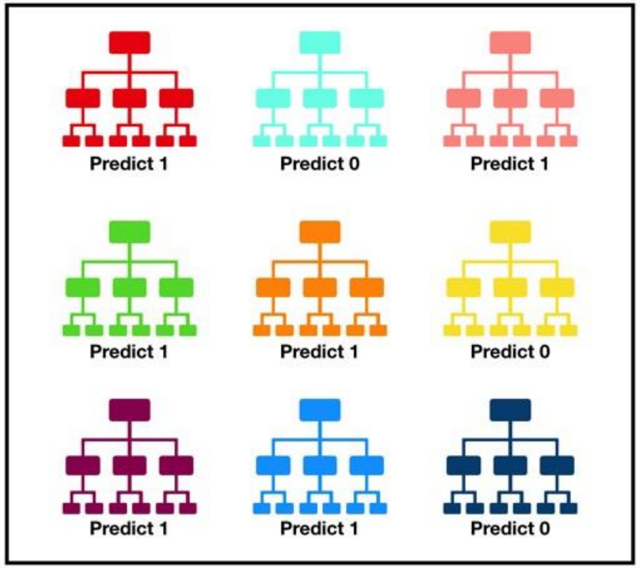
3.2 - Forecasting

We used over 30 variables in our random forest, but the model states that the most important features were:

- [time] the quarter of an hour of start of the session and the start hour
- [previous sessions] data about last session, second last session, moving average of 5 sessions and average on all previous sessions
- [utilization] the max connection time / energy usage, the standard deviation of the previous connection times / energy usage[2].

The predicted outcome where transaction time classes:

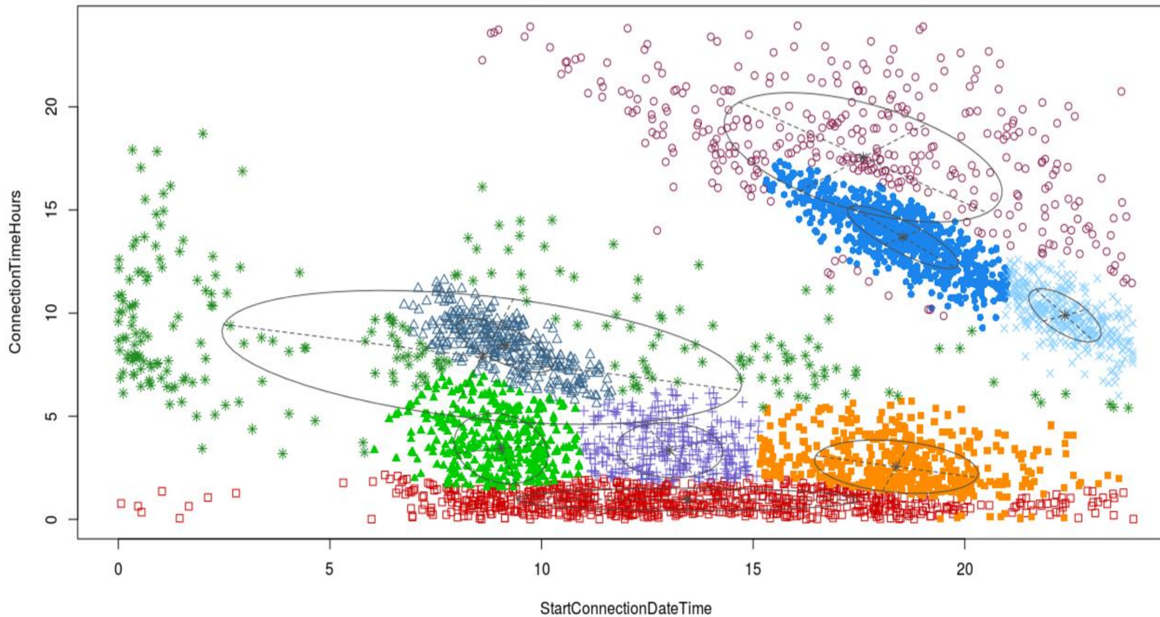
- 0 - 1 hour (class: shopping)
- 1 - 6 hours (visitors; short stay at work)
- 6 - 8 hours (work charging)
- 8 - 12 hours (short overnight charging)
- 12 - 16 hours (long overnight charging)
- 16 - 24 hours. (overnight/weekend charging)



The classes of 6 hours and up are most interesting for smart charging. For energy usage we used classes of 10 kWh, meaning 0 - 10, 10 - 20, .., until 100. 2ttps://www.hva.nl/kc-techniek/gedeelde-content/contentgroep/simulaad/blog/blogs/feature-importance.html?origin=Z%2BrzIdWjSW%2BhVXHmoGrNMg

3.2 - Optimization

The goal with optimization is that we cluster sessions in several groups by analyzing history data. In this project we apply postponing as optimization technique. After clustering we determine the optimal shift per cluster based on the the kpi to reduce peak loads. In previous work (see link underneath) we applied cluster techniques to differentiate sessions and group/cluster them in smart ways, these clusters are shown on the image.

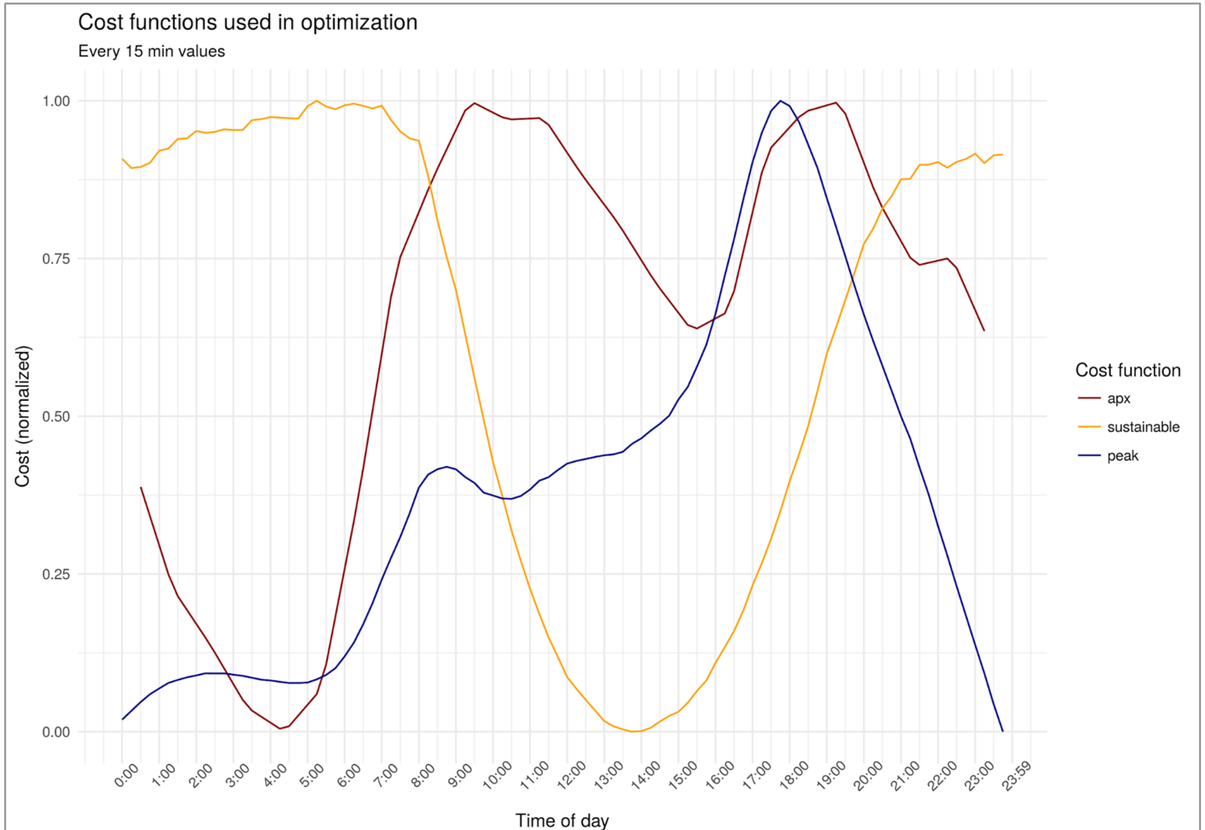


We applied Gaussian Mixture Models to define 8 clusters of charging sessions.

Each cluster has its own potential for applying smart charging regimes.

[1] https://www.elaad.nl/uploads/files/Final_report_TKI-1_definitieve_versie_190214-1.pdf

3.2 - Optimization: cost functions



As stated before, we use peak reduction (blue line) as KPI in this project. The image on the left show the different costs functions used to determine the optimal shift per cluster.

It is important to realise that the different cost function might be conflicting, meaning that we cannot optimize for everything at the same time and tradeoffs have to be made.

The data sources on which these cost functions are based can be found in the previous report.

In this case, sessions from the morning will be shifted to the afternoon and sessions from the evening are shifted to the night.

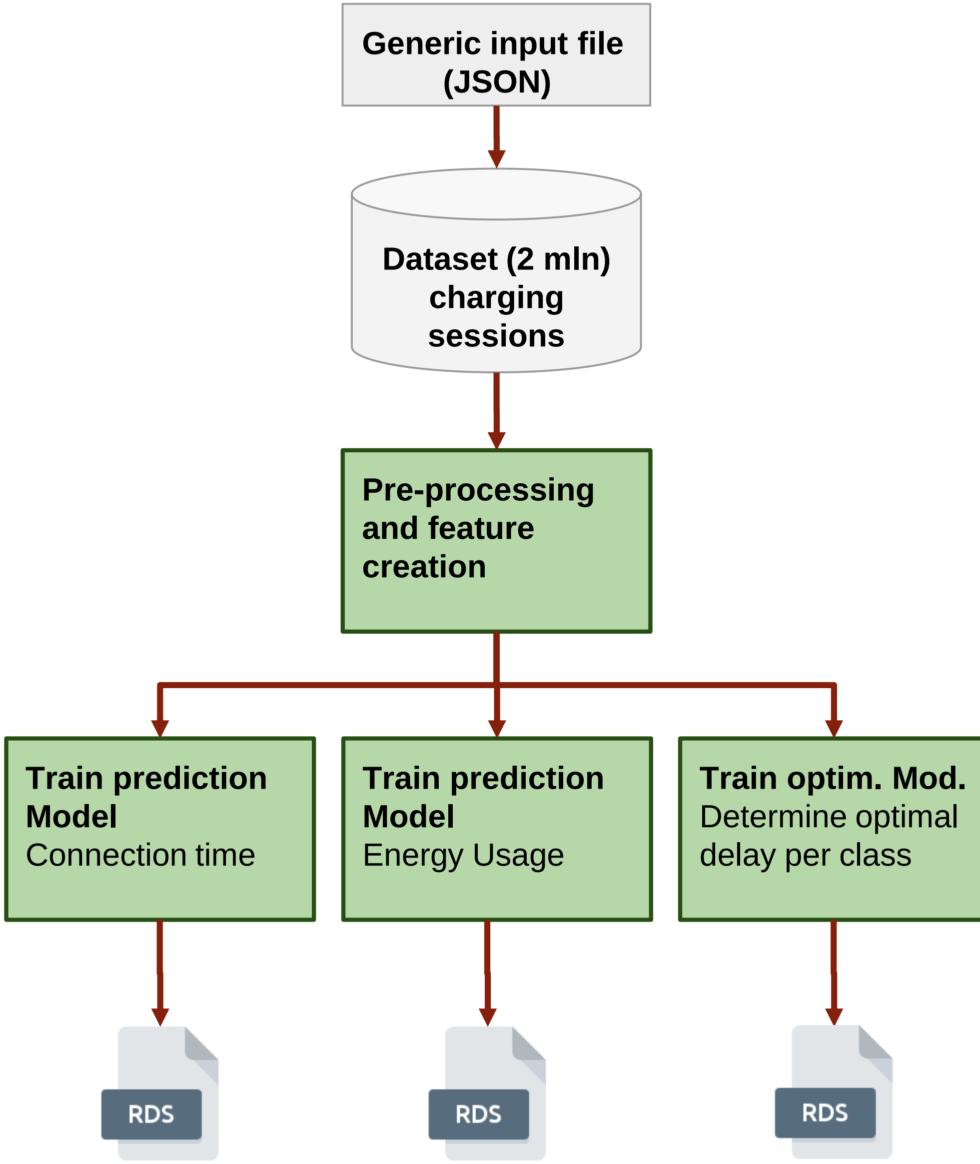
3.4 - Pipeline (offline part)

For this study we created a **generic input file t**hat enables both HVA as ElaadNL to develop models based on their respective datasets.

In this input file we set some of the **input parameters** that are needed to run our models such as: credentials, minimal number of transactions (that enables prediction), maximum transaction time (24 hours), connection time classes, usage classes, the optimization kpi and the mapping function.

The **mapping function** consists of the naming of the most important fields in our databases. For example the starttime, endtime and charged energy is named differently in the databases of ElaadNL and HvA. Therefore we need a mapping function.

Next the data is loaded, renamed into generic naming and the variables that are used in our models are created. Then this data is used as input for our random forest. These models are trained and tested before they are stored as an .RDS file (R Data Structure) for later use.



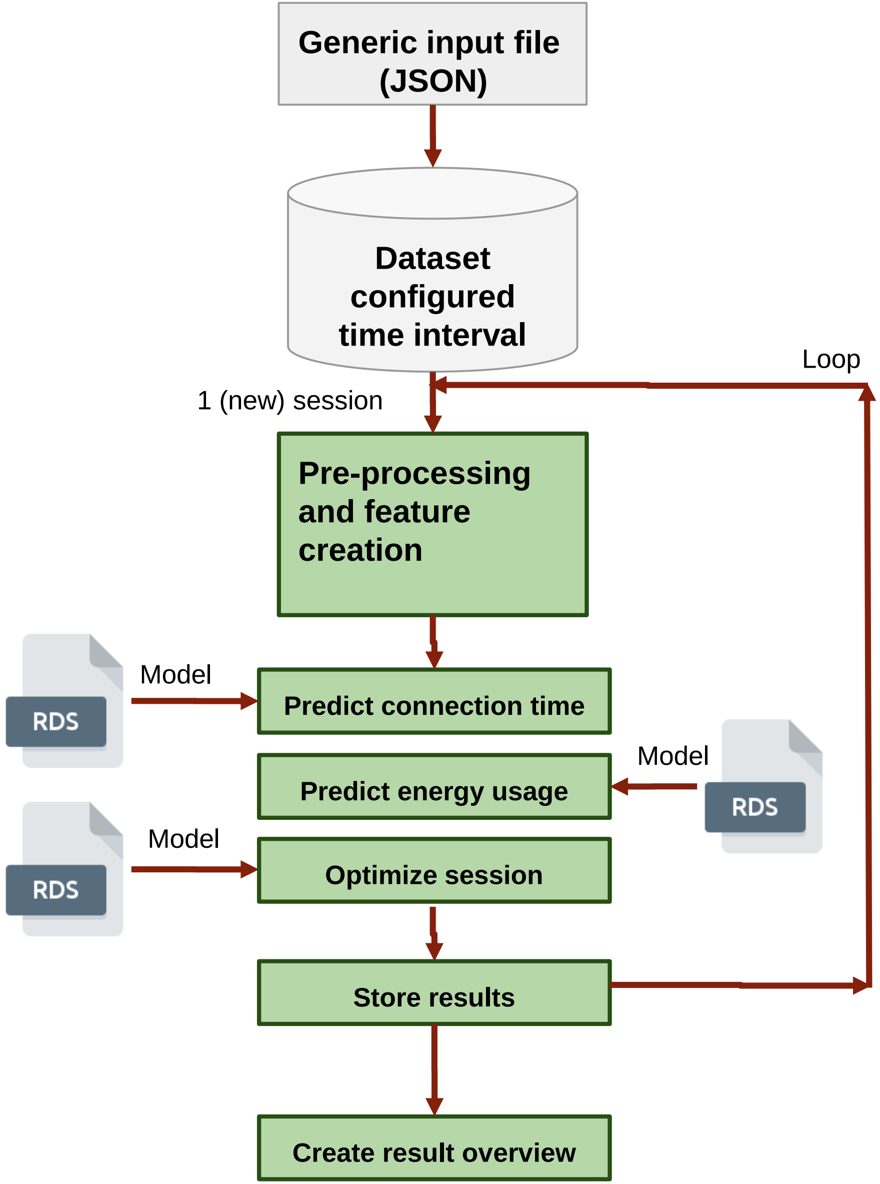
3.4 - Pipeline (online part)

The proposed model is ‘online’; but is not implemented online (model was not yet integrated by one of our partners).

We built our pipeline in such a way that we can analyse multiple sessions at once, for example all sessions of one day, week, month, year or custom time interval.

The dataset from the configured time interval is loaded and then a loop is started to load individual sessions from the dataset. Individual sessions are analyzed and the results are stored. The loop then runs for the next session. At this moment these sessions are not real/live sessions, but sessions within a time period that are in our history database.

When all the sessions are analyzed and the results are stored, a report can be created or the results of all the sessions can be analyzed.



4 - Results

Evaluating the accuracy of the prediction model on real-world data

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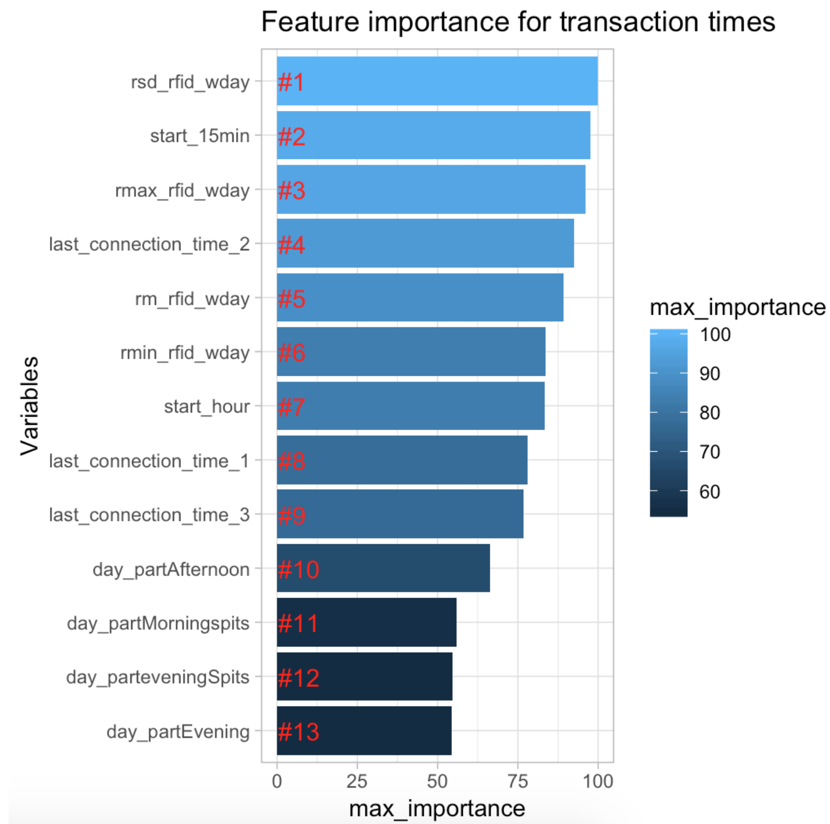
Results prediction: predicting (i) transaction times and (ii) energy usage

Prediction model "transaction times"
Average test accuracy = 83% ± 4%. This implies that in 83% of the sessions we predict the correct class, and in 17% of the sessions we predict a different class. The Matthews correlation coefficient (MCC) is 0.49, which is on average. MCC generalizes better but is far from optimal here (MCC = 1). The top feature based on importance are shown on the right. The confusion matrix and some important conclusions are discussed on the next slide.

Prediction model "energy usage"
Although the outcome of these prediction are classes, the input for our optimisation model should be numeric. As result to pass through our optimization model we took the middle (average) of the intervals. For example, if the predicted connection time class is 2, the input for our optimization model is 3.5. The most important features are similar to the features on the right.

Explanation features
Some of the features are hard to interpret. Some explanation: Day_part variables are slots of the day (morning peak, evening peak, between these 2 and night time etc.), the r in front of some variables mean 'running', these variables are based on the last 5 transactions. For instance: rsd_rfid_wday means the running standard deviation of the last transactions while having the same rfid and day of the week.



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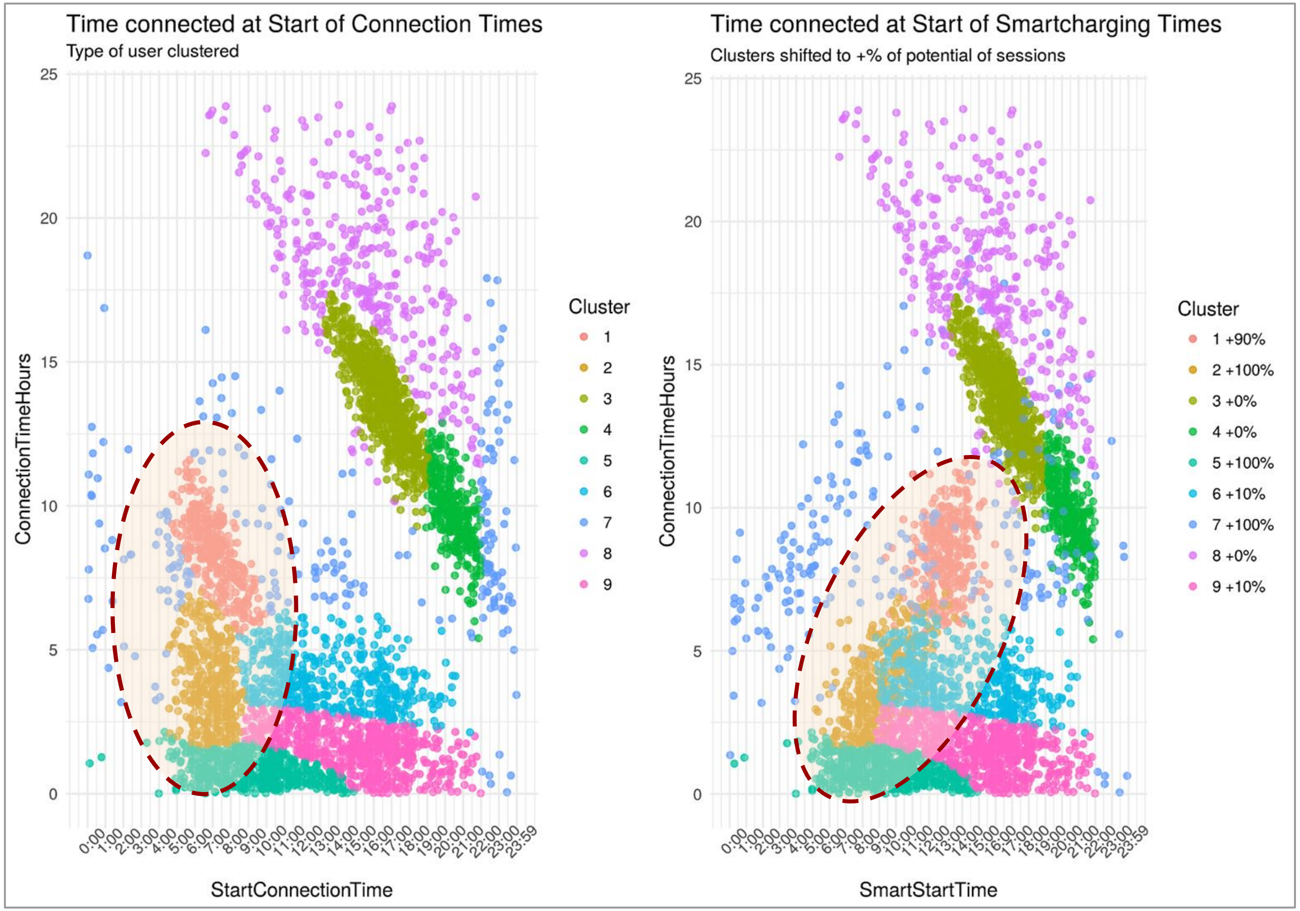
1 Results prediction: confusion matrix

Explanation
This matrix shows the correct predictions on the diagonal. All other predictions are ‘incorrect’. However, different errors can be made: beneath the diagonal we predict a shorter connection time than the real connection time. For an EV driver, this does not have negative consequences because the driver is longer connected than predicted. Above the diagonal does have a big impact because we possibly apply smart charging and the driver has a shorter connection time than predicted, which means that he can leave without being charged at all.

The goal is not only to score accuracy here, but also reduce the number of predictions where the user possibly does not charge.

Preliminary conclusions
We see that the most correct predictions are in the 1-6 class. In this class we also have the most training/test cases. Still, the 1-6 class has a large interval, which can lead to errors in optimization later (5 hours or 1,5 hour is a big difference. The same holds for the 16-24 class.

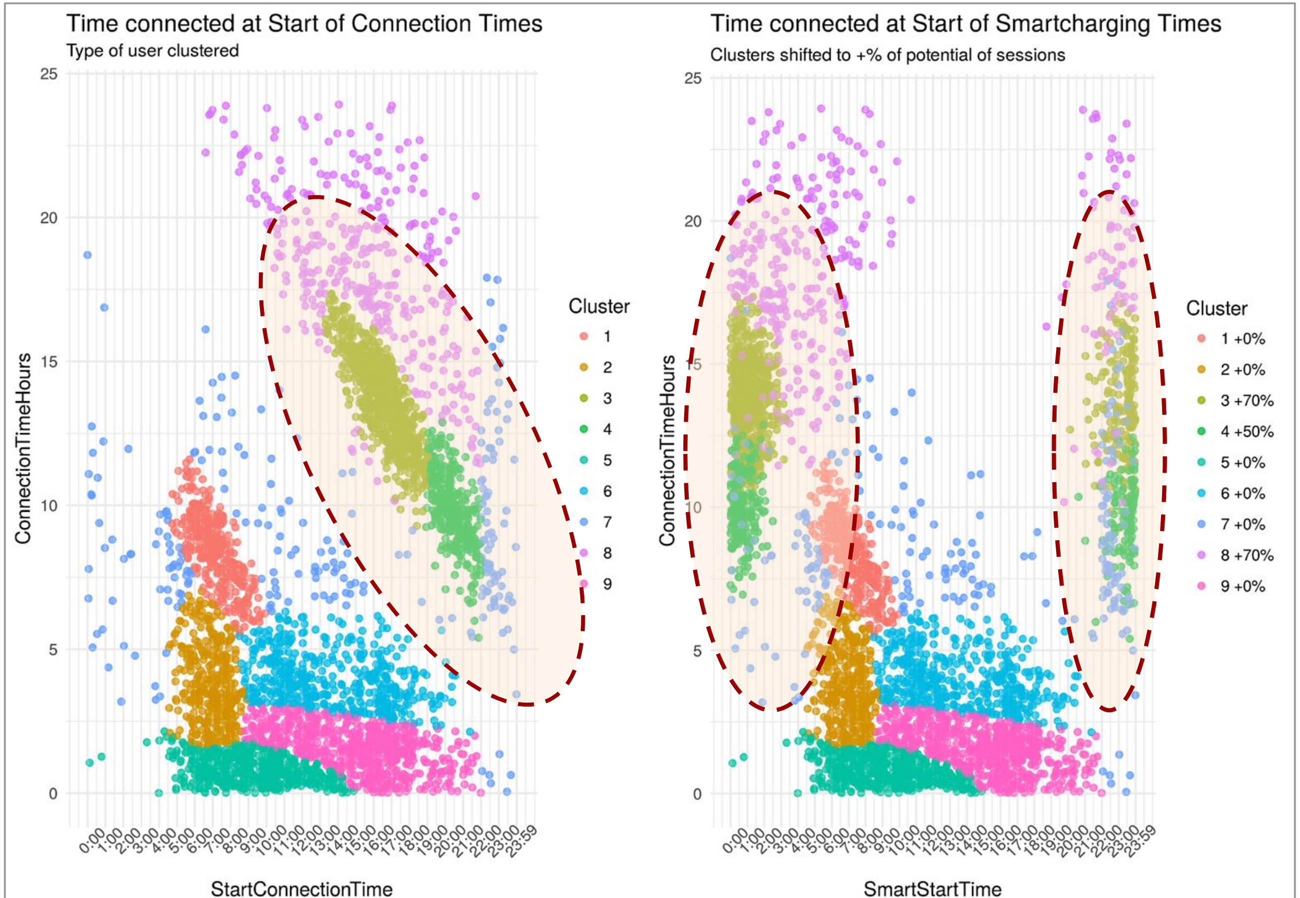
1 Results optimization: sustainable energy



For optimization we have 3 results slides. Each slide shows the result when running the optimization model on multiple historic sessions.

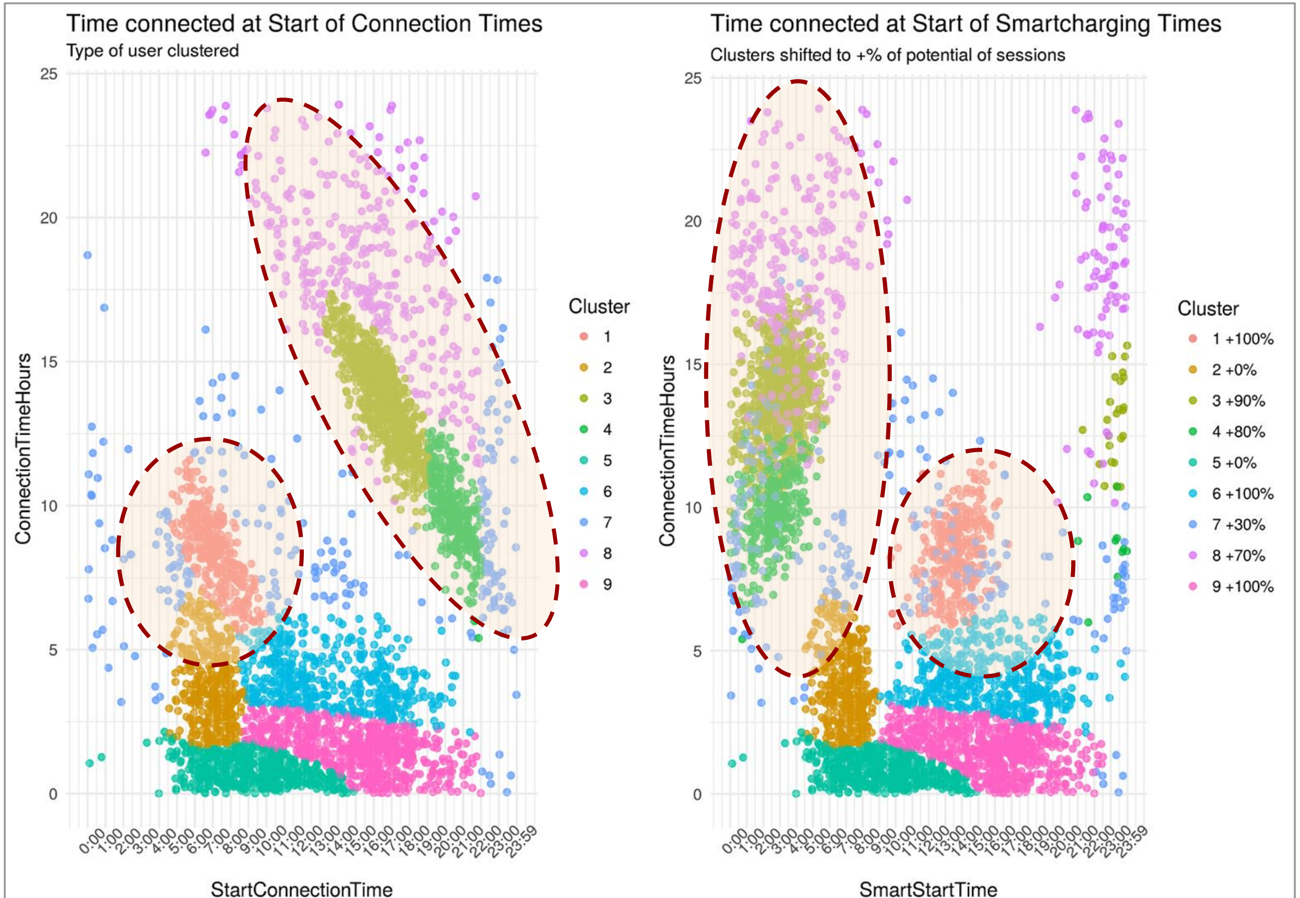
Optimize for sustainable energy results in sessions shifted from the morning to the afternoon, as shown in the image on the left.

1 Results optimization: energy demand / grid



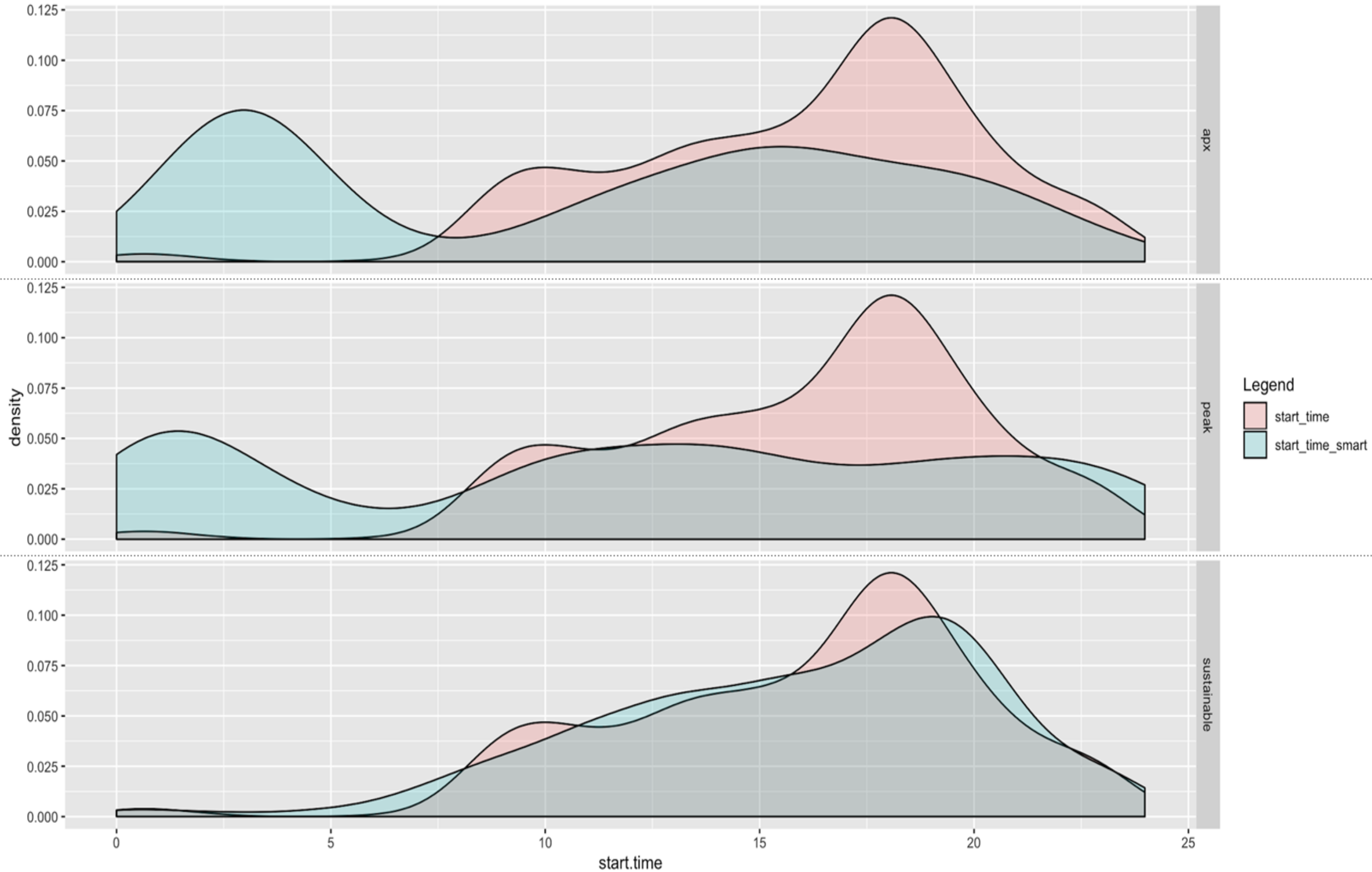
Optimizing for sustainable energy results in sessions shifted from the evening to the night, as shown in the image on the left.

1 Results optimization: APX prices



Optimizing for APX prices results that sessions in the morning and in the evening will be shifted as shown in the image on the left.

The distribution of starting times of charging sessions with and without postponing for each cost function.



1.APX-optimizing shifts evening sessions to the night

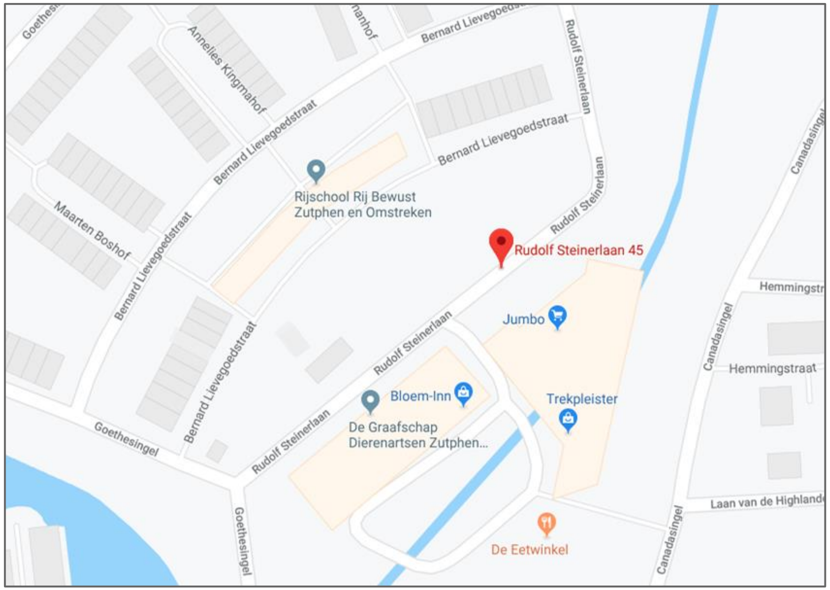
2.Grid-optimizing shifts evening sessions to the night

3.Renewable-optimizing shifts day sessions to later that day - creating an undesired peak at 17-18hrs

:erdam Elaadnl

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%

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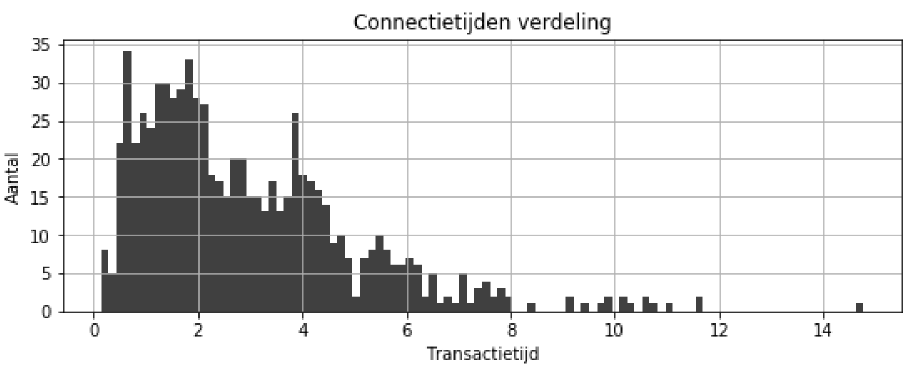
3 Analyse relevant historical data on this charging station (e.g. connection/charging duration)

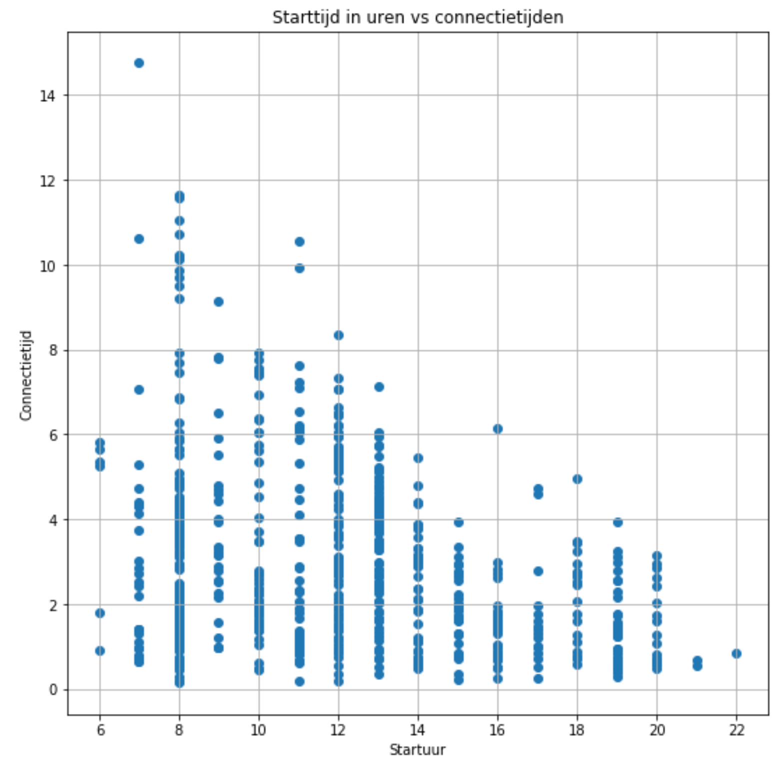
Historical data
Historical charging data on the particular charging station adds to predictive power of a particular charging session.

Underneath graphs on (i) connection times and (ii) starting time x connection times show the following:

- Connection times vary widely; with a bulk from 0-2 hours (visitors) but also peaks around 4 hours. There are limited sessions after 8 hours.
- Start times: starting times are scattered throughout the day; where connection times tend to be longer (on average) when starting times are earlier.

All in all the graphs show the wide diversity and variance in start and connection times; illustrating the difficulty of prediction.





4 Results 1 session

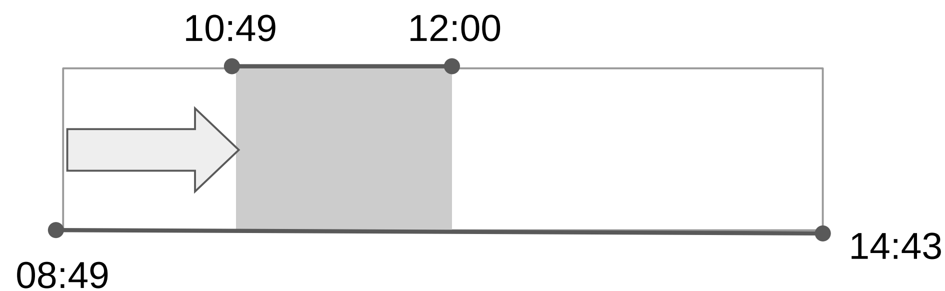
Results show that the predicted class is correct. Still there is some error, because the real connection time is not a class and we take the average as input for prediction.

Our final output of our prediction for this class is 3.5 hours, in real time this was around 6 hours so there is still an error here of 2.5 hours.

From our optimization model, we saw that the optimal shift is 40% of the smart charging potential. In this example this means that our test session is postponed for 2 hours towards the afternoon.

This also matches with our KPI (sustainable energy), because on average sun and wind generate more energy in the afternoon.

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: from 1 to 900 sessions

In this section we increase the amount of sessions to 900 to validate the quality of models. A selection was made to analyse all (900) sessions that took place on 1 day: Wednesday 30st october 2019. The objective is not to analyze as many sessions as we can, but to validate our pipeline and show that we can implement this in real life in a later stadium.

<u>Characteristics of the selection:</u>

Date
Wednesday 30th october 2019

 # Sessions
900

First session
00:02:01

Last session
23:58:06

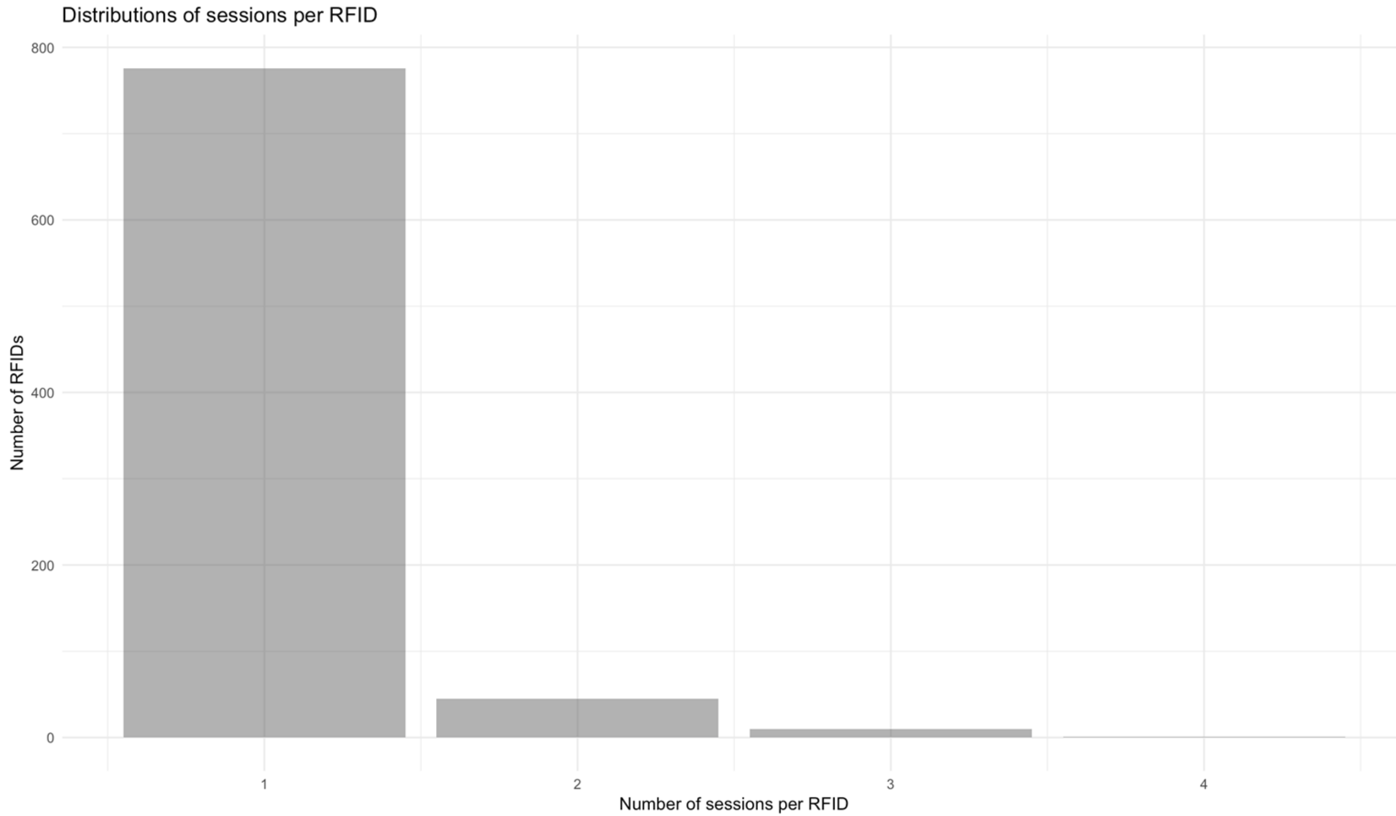
 # RFID's
832

Average connection time
~ 6.43 hours

Average usage
~ 15.62 kWh

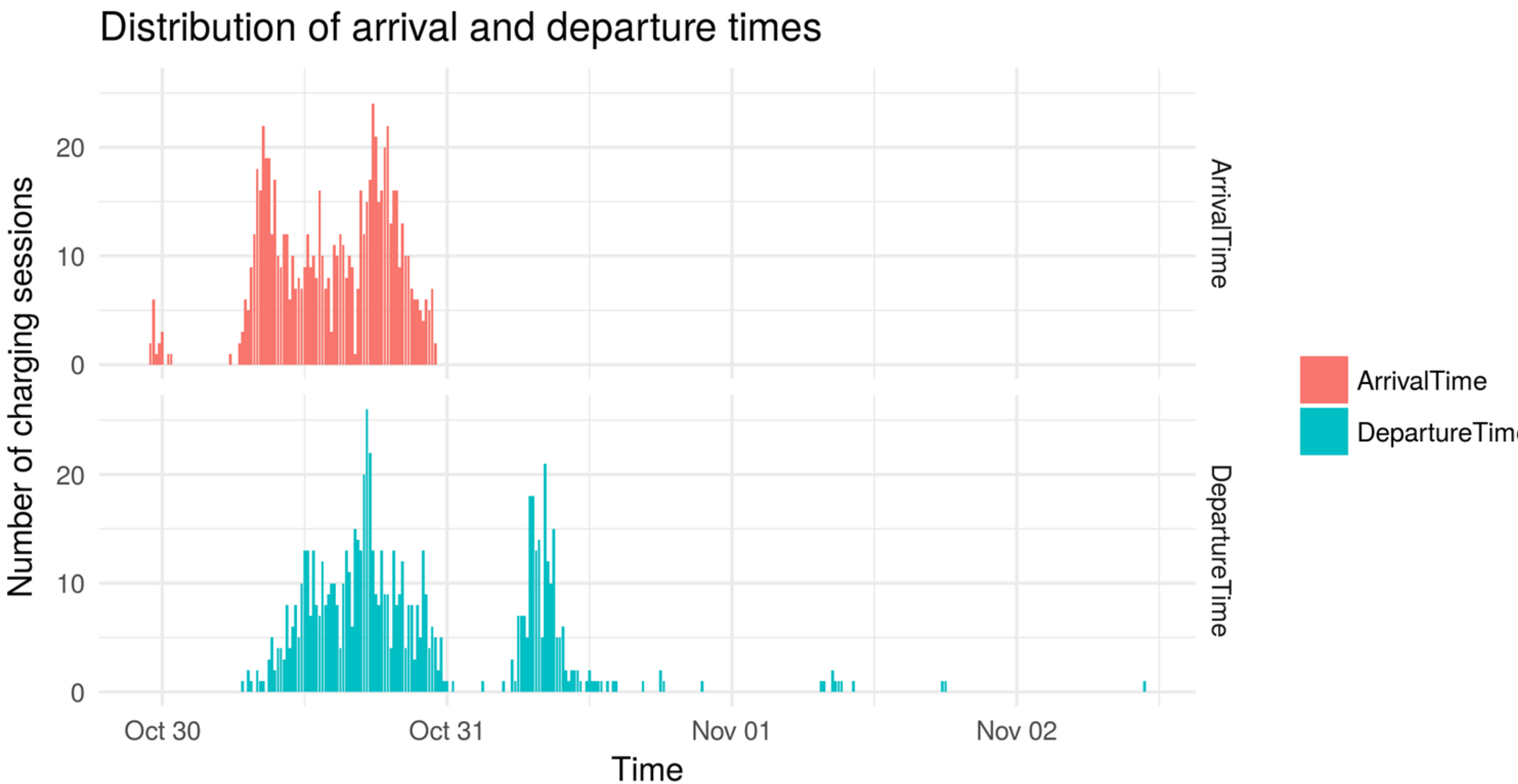
Average historical # sessions per user
~ 91 (minimum: 1, maximum: 1526)

5 Results multiple sessions: analysis



In the image above we see that around 780 of the RFIDs that charged during our test period have only 1 session in that day. Only a few RFIDs charge more than once. 5 of the RFIDs (<1%) connect their car 3 times or more.

5 Results multiple sessions: analysis

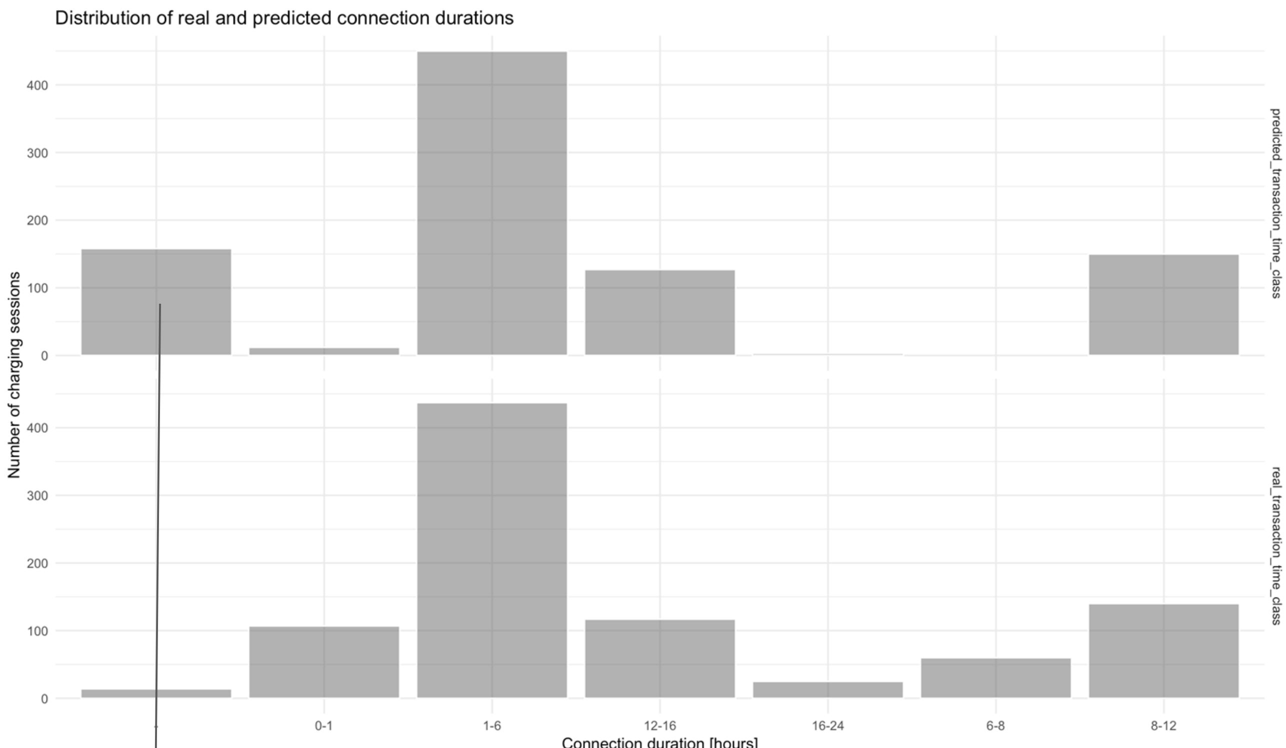


A majority of Oct30-sessions end on the same day. A share of approximately 15-25% are connected overnight. The latter has a large potential for smart charging (postpone strategy).

5 Results multiple sessions: predicting connection times

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 (left column) due to limited data of the respective RFIDs (<3 sessions).

All in all, classes of 1-6, 8-12 and 12-18 show similar distributions, indicating a fair prediction result.



'unpredictable' sessions due to limited sessions of RFID (<3)

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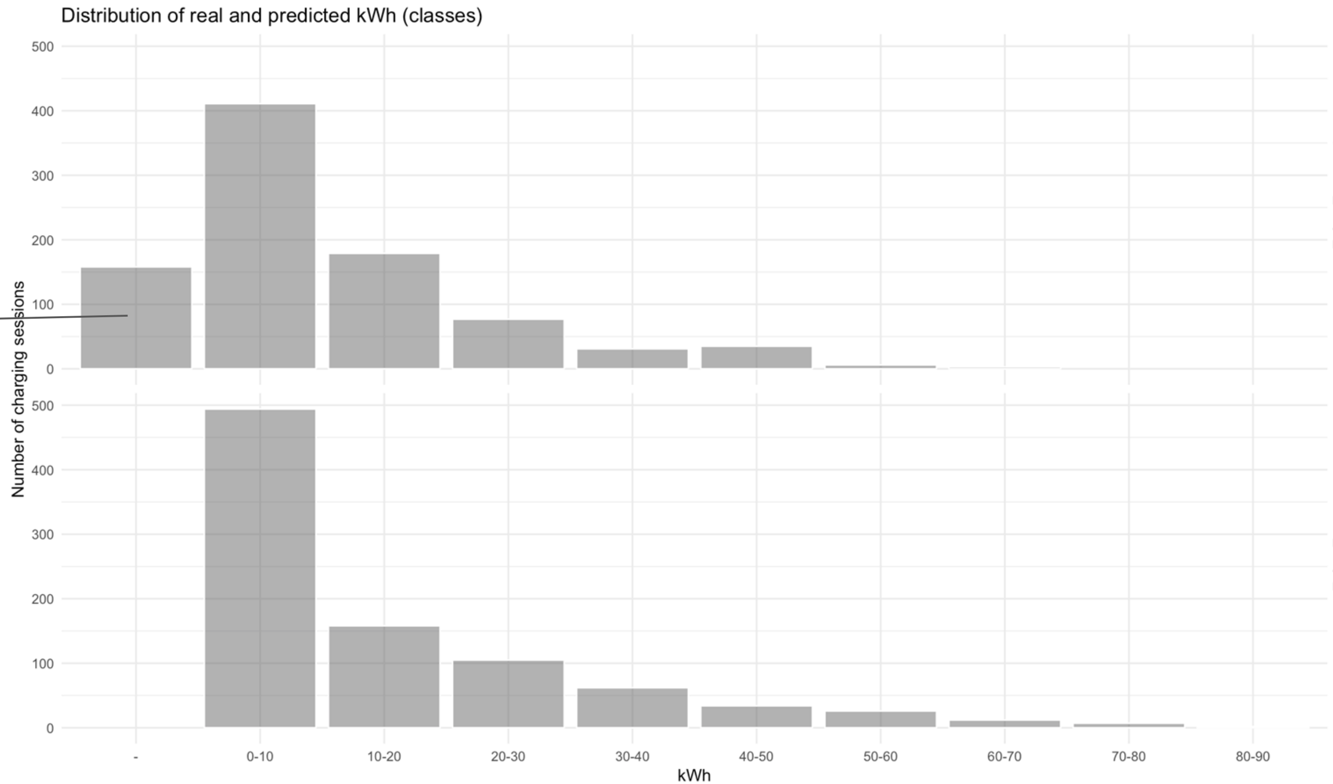
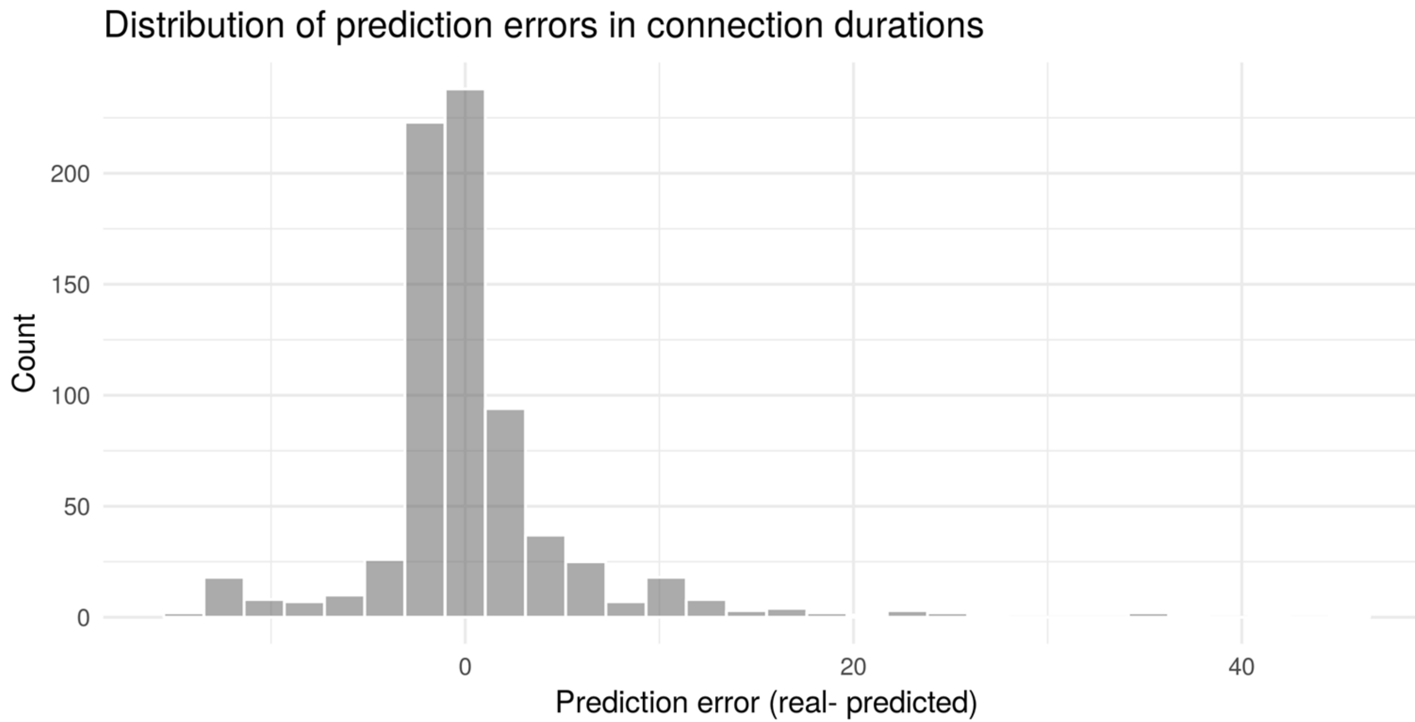
5 Results multiple sessions: predicting energy usage

‘unpredictable‘ sessions due to limited sessions of RFID (<3)



Similarly the distributions in (i) *predicted* and (ii) *real* energy usage have a high similarity; which suggests a fairly high accuracy of the prediction model.
In total 160 sessions (18% of total) can not be predicted due to limited historical data for these RFIDs.

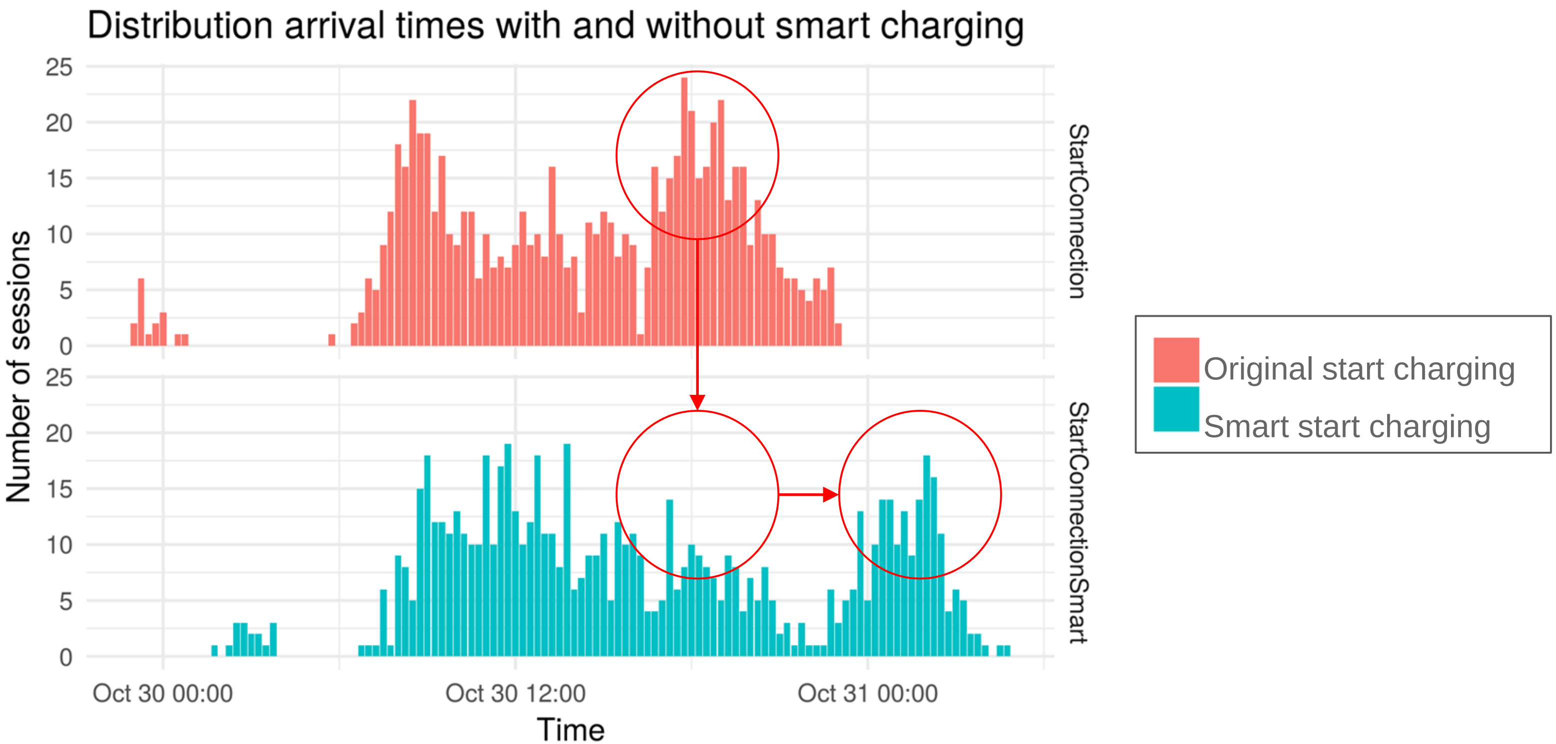
5 Results multiple sessions



The error (in hours) that we calculated above is the real connection time - based on the middle of the predicted class. For example, real transaction time is 4.29 and the predicted class is 1-6. The error would be 4.29 - 3.5 = 0.79 hour. This distribution is distributed around 0, which is a good thing because otherwise we would have a bad prediction model.

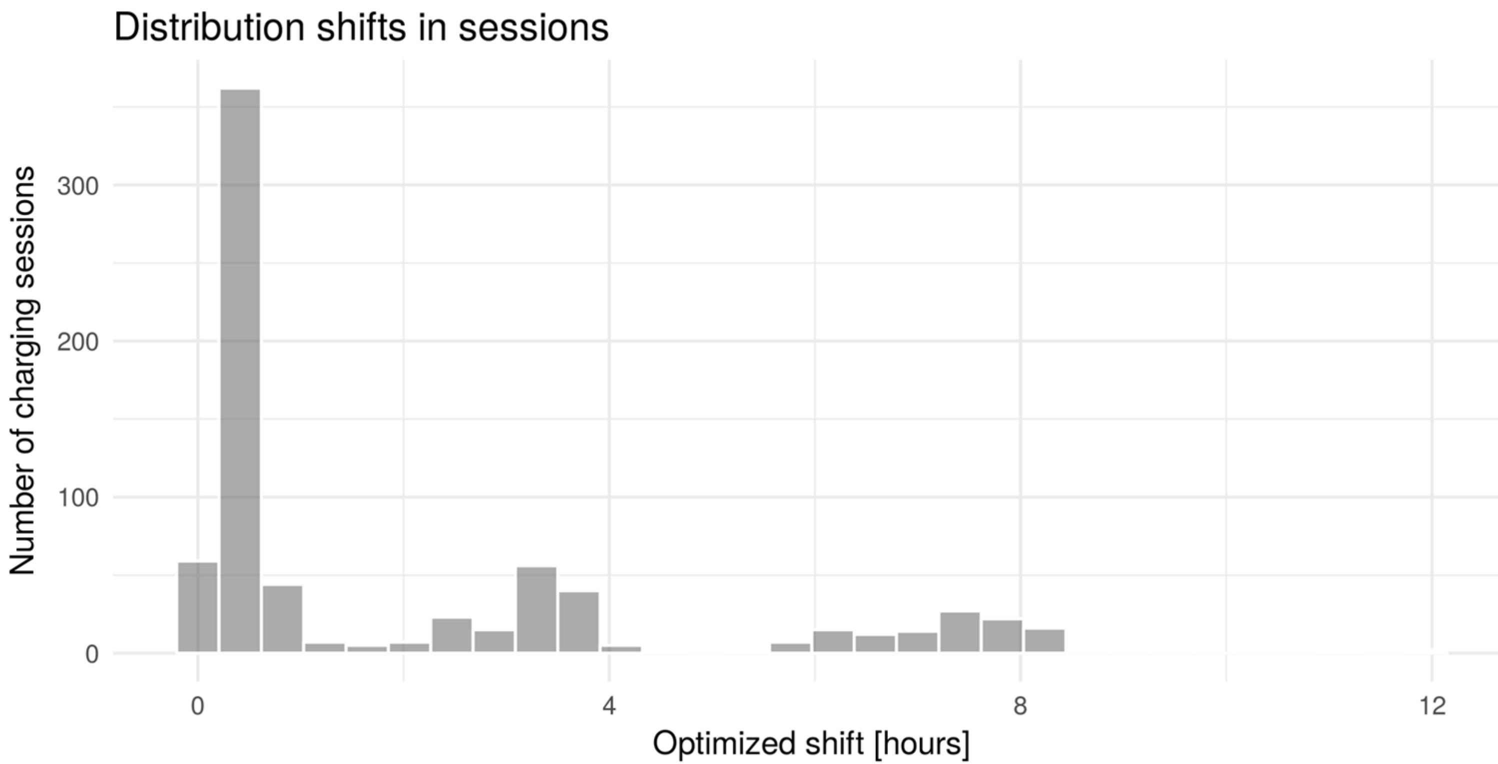
The majority of connection times are predicted to be within 2 hours of the real connection times. About 10-15% of all sessions has a larger deviation.

5 Results multiple sessions



Above image shows that the peak load could be reduced during the peak and these sessions are shifted to the night. The red circles illustrate this behaviour.

5 Results multiple sessions



Above image show that the majority of sessions is not shifted, because they could not be predicted or were predicted to be in class 1 (0-1hours).
Also, a lot of sessions are part of class 2 (1-6hours), limiting the smart charging portential (with a peak of postponing with 30-60minutes). ,
Further peaks in postponed charging are around 3-4 hours and around 6-8 hours.

Conclusions

1. **Predicting is necessary:** Predicting connection and charging times for electric vehicles is key for unlocking smart charging potential. The better you predict, the more flexibility in charging is created. This can enhance charging profiles significantly.
2. **Predictions are hard:** Predicting connection times is particularly complex for (i) public charging stations given its multitude of users and its wide diversity of charging behavior, and (ii) in particular for EV drivers with limited amount of sessions. With a classification technique & random forest an accuracy of 83% was reached.
3. **Predictions can be powerful:** when combined with clustering techniques to develop a fully automated optimization chain. This study has shown that evening peaks could be postponed significantly by applying prediction and optimization models.
4. **Cost functions conflict:** applying different costs functions can be done, but when applying multiple cost functions together they conflict because of different composition, strategies and goals.
5. **Smart charging pipelines in operation:** this project shows that a pipeline can be built to shift sessions using the peak reduction KPI.

Recommendations & Future work

1. **Prediction techniques:** It is recommended to further explore artificial intelligence applications in increasing predictive power. Particularly prediction of transaction time and energy usage should be improved.
2. **Optimization scheme**: The pipeline of predicting and optimization should be further extended to larger data sets for further validation.
3. **Optimization techniques/KPIs**: Extend the model such that multiple optimization techniques (cut & divide, postponing and charging speed) and KPIs (APX, sustainable energy, peak reduction) can be combined .
4. **Process of data sharing**: The intended collaborative opportunities between AUAS and Elaad were not reached as access to G4/MRA data remained limited (a.o. due to sensitivity in GDPR regulation). This lead to inefficiencies in a.o. writing codes, validating results and enabling analysis on the large dataset. For future projects upfront consent for sharing data for all data partners is highly recommended.
5. **Development**: Code is developed in R which is not optimal for an production environment. This should be changed to another language such as Python.