DEI Final Public Report
Smart Charging on Transformer Level Pilot

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Summary

Motivation
This DEI-project concerns a new idea for smart charging where EV chargepoints within a single distribution grid are connected. This way it is possible to measure and control the consumption of a group of chargepoints instead of a single one. This approach makes smart charging more effective, allows for more EVs to be charged simultaneously without need for costly grid extensions and allows for EVs to charge much faster on average.

Goal
The goal of this project is to validate a new smart charging technology using field data. Here the electrical energy demand of the EVs is collected through chargepoints to be able to use the available cable- and transformer capacity for EV charging more efficient and thus to prevent congestions in the distribution grid. This should potentially be the solution for the capacity and congestion problems of DSOs.

Activities
Activities mainly consisted of the experimental development of new software. This includes a new smart charging platform, data exchange between grid operator and charge point operators regarding available transformer capacity.

Further, a mobile app has been developed to assist end users in interacting with charging infrastructure. The availability of chargers and the expected charging speed are predicted through data analytics and machine learning tools. Also, users can request priority through the app if they are in a hurry. Finally, a test setup was created in which a number of pilot tests were conducted. The data obtained from the pilot was subsequently analysed.

Conclusions
The main conclusion from this project is that it is technically possible to apply smart charging at transformer level. In addition, a pilot has shown that although EVs take longer to charge on average, the adverse effects on end users are very limited. Finally, flexible connection values are currently not yet legally possible. The law can be amended in such a way that this will be possible in the future.

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1. Introduction

1. Involved parties

Stichting ElaadNL

ElaadNL is the knowledge and innovation centre in the field of smart charging infrastructure in the Netherlands. Through their mutual involvement via ElaadNL, the grid operators prepare for a future with electric mobility and sustainable charging. It is our mission to make sure that everyone can charge smart. We monitor the EV-charging infrastructure and coordinate the connections between public charging stations and the electricity grid.
Starting in 2009 the E-laad Foundation established a network of more than 3,000 public charging stations for electric cars across the Netherlands. In 2014 the foundation split up its activities into two separate platforms: ElaadNL and EVNetNL. EVnetNL is now responsible for managing the existing charging points together with municipal partners. ElaadNL continued the foundations efforts to expand research and stimulate innovation regarding smart charging and the use of sustainable energy for electric vehicles.

Eco-Movement B.V.

Eco-Movement is the foremost and most complete data provider of charging stations in Europe. To this end, Eco-Movement collects, corrects and enriches charging station data to provide valuable P.O.I. information for local, national and supranational governments, as well as to EV drivers. This data includes geospatial information along with various hardware configurations (cables, sockets, connectors, etc). In addition, Eco-Movement provides real-time availability of charging stations, as well as predicted availability, which is especially useful for navigational purposes. As the EV infrastructure matures and smart-charging capabilities develop, Eco-Movement's excellent position as a provider of P.O.I. data to consumers will help support EV drivers with reliable and accurate information regarding real-time and predicted charging speeds.

GreenFlux Assets B.V.

GreenFlux is a supplier of Platform As A Service (PAAS) solutions for electric vehicle charging. GreenFlux provides a cloud-based platforms that consists of three main functionalities:

- With the operator functionality, our customers can directly couple charging stations, enabling them to do operational management, fault analysis, retrieve data from the charging station and provide smart charging services.
- With the service provider functionality, our customers can provide EV-drivers with RFID cards and App-plugins. Data can be exchanged with other partners enabling roaming services.
- With the billing functionality, many pricing schemes for EV charging become possible and wholesale and retail billing is supported.

2. Problem introduction

In the Netherlands, small-scale consumption connections, including all connections for normal (non-fast-charging) charge points, have a connection with a constant contract capacity. The Charge Point Operator has thus obtained the right to use the maximum power associated with the connection at all times.

To make a connection, a connection fee is charged once and in addition a yearly fee is charged for maintaining the connection. The periodic connection tariff is intended to cover the costs incurred by grid operators for connecting customers and producers to the electricity grid. The connection fee therefore applies to both producers and consumers.

A three-phase connection with 25 Amps per phase (3 x 25A) is generally used for connecting charge points for electric vehicles, since this is the most cost-effective. This connection can theoretically deliver 17.3 kW of power. However, the grid dimensions are based on an average simultaneous consumption of a maximum of 4kW, with the actual average simultaneous power for a 3 * 25A connection between 1 and 1.5 kW. Since charge points on a 3 x 25A connection require a much higher capacity (up to 11 kW for a three-phase charger) than the average of 4 kW and, require continuous connection for a long time, the grid capacity is under pressure. For this reason, grid operators and Charge Point Operators are investigating ways of creating more flexibility in the grid load via *Smart Charging*. For a grid operator, Smart Charging means that grid users adjust their grid load (usually only consumption, but with Vehicle to Grid also returning energy) according to the needs of the grid operator. This can be done through congestion management, by applying flexible rates or by setting flexible capacity profiles to the charge points. If the network operator can guarantee supply through the use of Smart Charging, CPOs may be able to install more charge points on a cable or transformer than if this were not the case, making this an attractive concept for CPOs, as well.

The various options a grid operator has to keep the grid load within the capacity limits are shown in the table below.

Congestion management	**Flexible rates**	**Flexible capacities**
Changing the production based on transaction in the energy market	Indirect change in production based on incentives in rates, based on time or bandwidth	Purchase of flexibility services through contracting of variable threshold value during the day
Response is mandatory	Parties can decide themselves whether they want to contribute to flexibility issues	Contribution is inherent to chosen contract form
Fine for not complying	Reward for complying	No fines or rewards

Congestion management is not realistic for CPOs, as they cannot guarantee that a customer will be available when the DSO requires it. Flexible rates and flexible capacity can both lead to the desired result for charge points. Active control of charging speed is an obvious measure for meeting requests from the DSO in a transparent manner without billing the driver of the electric vehicle.

3. Proposed solution

Smart charging is current being used primarily at individual locations with several charge points, in both private and semi-public locations such as industrial areas or in parking garages on a single grid connection. It is however also possible to set up smart charging at the level of a low voltage cable and/or the MV-LV transformer. This offers more freedom to the CPO to decide at which charge point the capacity is reduced. For the grid operator it does not matter at which connection(s) the capacity is reduced, as long as it happens on the cable where the peak load occurs.

This smart charging method can be set up by administratively adding up several charge points that are practically connected to a different grid connection but are connected to the same LV cable or transformer and then calculate the available capacity on the level of the neighbourhood's local transformer. This way not the maximum consumption per connection is considered, but the maximum consumption of a group of chargers within the transformer capacity. This new approach requires new control technology and a new form of contracts from the grid operator. This approach is unique and has never been used before.

There are several approaches for smart charging depending on the party that initiates it. For this project we consider the approach of the distribution grid operator who wants to prevent congestion through smart charging of EVs. The starting point here is that the available grid capacity determines the capacity that is available for charging. This smart charging can be arranged in the following ways:

1. Variable prices for use of the grid
2. Variable capacity agreements. The dynamic application of this involves a form of digital control (via a third party).
3. Direct control
4. Self-controlling devices
5. (Organization of) a marketplace for capacity trading

This project investigates a solution based on option 2. Based on variable capacity agreements, the customers (in this case the CPOs) receive a different capacity during the day per time period from the grid operator. The available capacity is larger when more capacity is available on the grid or transformer and less when also less capacity is available. The optimal, intelligent design of smart charging can be achieved using a dynamic interpretation. The available capacity is based on the measured load on the cable/transformer is communicated to the CPO.

These agreements and technical design were always performed at the level of the single grid connection. In this project this will be done for the first time at a higher level of abstraction. To this end, the capacity is distributed over charging station across different grid connections, using a new form of smart charging. The distribution of capacity from the MV-LV transformer is determined first and several small connections are added together to create one large *virtual* connection.

The advantage being that individual grid connection can become larger, the grid load will be reduced and more autonomy is gained by the CPO, which guarantees certainty of charging for EV drivers. Moreover, in many cases the charging process will be considerably faster.

2. Goal

The goal of this project is to test and prove the technical, economic and legal advantages and disadvantages of a (virtualized in the pilot) aggregation of 50 public charging points on a single MV / LV transformer in a representative pilot environment, which meets all requirements to deploy and upscale in the market after success.

Newly acquired knowledge in the pilot tests will be used to:

- Create insight and generate evidence of the extent to which the available capacity on the existing electrical infrastructure for the network operators can be increased and the extent in which this reduces network congestion.
- Generate more insight into the (technical) risks and opportunities upon further scaling up.
- The expected technical and legal bottlenecks regarding variable capacity agreements to resolve to a point where a follow-up with a larger-scale demonstration project is possible be deployed with one or more network operators.
- Support a Go / No Go decision to invest in the development and commercialization of a smart charging platform at medium voltage level and thus the implementation of the business model for one or more network operators and the project partners and stakeholders involved.

Flexibility of the energy system is understood to mean the capacity of network operators to increase or reduce such that congestion in energy networks is prevented.

If the results of this pilot project are positive and the added value of clustering is demonstrated, then the results will be widely shared with stakeholders, partners, customers and investors (including RVO), ACM, as well as via online channels and publications.

3. Approach

1. Description of Work Packages

In this project technologies are developed to test the intended smart charging platform on pilot scale. Activities take place in the following work packages:

1. WP1. Extension of OSCP and OCPI for smart charging
2. WP2. Development of smart charging services
3. WP3. Building test setup and conduct pilot tests
4. WP4. Project management and dissemination

The content of each work package is described in the sections below.

1. WP1: Extension of OSCP and OCPI for smart charging

Within this work package, the protocols are developed, or extended, that are required for the proposed form of demand management. On the one hand it includes the extension of Open Smart Charging Protocol (OSCP) for sending capacity signals. On the other hand, it includes the development of the Open Charge Point Interface protocol (OCPI).

2. WP2: Development of smart charging services

In WP2 the digital services are developed that make smart charging possible for the CPO and EV driver. More specifically, this is about communicating charge point related information to EV drivers via a mobile app, predicting the availability of charge points based on historical data and developing smart charging dashboards.

3. WP3: Building test setup and conduct pilot tests

If the required technology has been developed, a pilot will be set up in WP3. In this pilot, 50 charging stations will be *virtually* linked to the capacity of a transformer. The results will be analysed to determine what is needed for any further scale up. Research is also conducted on the technical and legal implications of this new type of grid connections.

4. WP4: Project management and dissemination

WP4 is mainly about the dissemination of knowledge gained within this project, the management of the project itself and the contact with the RVO. The goal is to disseminate results to the industrial community and to a broad stakeholder audience to encourage the use and acceptance of project outputs.

4. Results from WP1: Extension of OSCP and OCPI for smart charging

This chapter describes the results of the activities carried out under WP1.

4.1. Control signals for aggregated charging stations.

An MV/LV transformer has a maximum amperage that it is able to handle. The grid operator continuously measures the load on the transformer and forwards the available capacity in real time to the CPO. Predictions are not necessary because the delay between measuring and receiving the CPO is at most one minute. In addition a fallback profile is sent to the CPO: this is the capacity that a CPO is allowed to use in case of a connection loss with the grid operator.

4.2. Smart Charging Algorithm

This section describes the event-based smart charging algorithm that was developed within this project.

Inputs and Outputs

In general, there are three 'external inputs' that matter on a group level with regard to smart charging. Group level meaning that these inputs influence the behavior of the group of aggregated charge stations as a whole: all charging stations are or can be influenced by a change in any of these inputs:

1. Local renewable energy production within the microgrid
2. Inflexible loads in the microgrid
3. Energy prices

Inputs 1 and 2 have an effect on both the available power and the power quality. However, power quality control cannot be done by smart charging electric vehicles and is therefore out of scope for this part of the algorithm. Power quality optimization can be handled within the algorithms for the convertor and the stationary battery.

Further there are inputs to the algorithm that come from the interaction with charging stations and EV-drivers. These inputs do not affect the group as a whole but do have an effect on one or several charging stations that are part of the group as a whole

1. User requirements
2. MeterValues from charging stations
3. The arrival of an electric vehicle
4. The departure of an electric vehicle

Events

The algorithm developed for this project is event-based. Instead of allocating capacity to EVSEs at fixed time intervals, the algorithm reallocates when an event takes place. This way the algorithm can respond faster to changes such as available transformer capacity. Within this project, the following events are relevant:

1. EVSE status changed
2. EVSE Priority requests
3. EVSE MeterValue received
4. Group capacity changed

Charge control

The charging of an electric vehicle cannot be controlled by a third party platform directly. To control the charge rate of an electric vehicle, one needs to control the charging station. The great news about this is that over 97% of all charging stations in the world support communication via the Open Charge

Point Protocol. Version 1.6 and 2.0 of this protocol support smart charging[1]. This means that one platform can connect to a wide range of charging stations and still be able to provide smart charging services to all of them.
The charging station then in turn communicates with the charging station via the IEC 61851 protocol (for high speed DC charging other standards are used, but these are usually not used for smart charging).
There are a few important observations to be made here:

- Via OCPP, the maximum charge rate for a charge point/socket can be set for a specific period
- The charge point imposes this maximum on the EV
- The EV can choose its own charge rate, as long as it is below the maximum

It is therefore not possible to set a specific charge rate for an electric vehicle, only the maximum charge rate can be set

Of course this makes sense, it would be very dangerous if a third party could override the battery management system of an electric vehicle, but it is very important to take this fact into account when developing algorithms.

Algorithm approach

The Smart Charging Algorithm works on two levels:

1. Group capacity resolving with the Dynamic Capacity Engine
2. EVSE charge power allocation with any allocation algorithm

The group capacity can either be a static or dynamic value. Within this project the group capacity is equal to the predicted transformer capacity.

EVSE Charge Power Allocation

The GreenFlux smart charging algorithm allocates power to individual EVSEs, in such a way that charging for each connected EV is optimized while adhering to capacity constraints. The algorithm is indifferent to how these capacity constraints are set and only concerns itself with the allocation to EVSEs. This allocation is always in Amperes and is communicated via the OCPP 1.6 *SetChargingProfile* message.
Allocation is based on how fast the EV can charge (for efficiency reasons) and the behavior of the EV so far during an ongoing charge session. This results in the following life cycle of a typical charge session.

Charge session life cycle

During a charge session, the EV will (typically) go down in priority towards the end. There are exceptions to this.

1. A new charge session starts. We give it maximum power, which is the minimum of the max EVSE power or the group capacity, for 10 minutes. This serves two purposes: the user will confirm its EV is charging and GreenFlux can profile the unrestricted charge behavior.
2. During the largest part of the charge session, after 10 minutes, we allocate whatever the EV has shown to be able to consume. If more EVs need power, we shift them on the priority list every 15 minutes (default value).

[1] https://www.openchargealliance.org/protocols/ocpp/ocpp-16/

3. After a while, the battery will approach 80/90% SoC and the charge current will go down. The EVs priority will go down and EVs still charging at their maximum charge rates will be handled first.

An EV can go a step back - from low priority to normal priority - in this cycle, if their current suddenly goes up. This can happen if the EV has an internal charging schedule, which is not communicated with the charger.

Charge Assist
Through the Charge Assist app, users can request priority. This will put them higher on the priority list, just below EVs that have recently started their charge session.

Chargepoint constraints
Because of cost savings, often a charge point has its own capacity limit because of the cable supplied to it. That means we end up with three capacity constraints in a group:

1. TransformerGroupCapacity
2. ChargePointMaxAmperage
3. EvseMaxAmperage

As an example, we can have a group with 20 charge points on one transformer, each with two EVSEs (thus 40 EVSEs in total). We can then have:

1. TransformerGroupCapacity = 400 A
2. ChargePointMaxAmperage = 32 A (for each charger)
3. EvseMaxAmperage = 32 A (for each EVSE)

Assuming every charge point in this example has two EVSEs, we cannot supply them both 32 A without exceeding the ChargePointMaxAmperage. The smart charging algorithm can handle this by taking this extra constraint into account: SamePhasesUsed, which indicates if the EVSEs on the same charge point charge on the same phases of the charge point.

Lessons learned
Most important lessons are:

- Real life limitations matter
- Smart charging is very well possible, even when taking these limitations into account
- User interaction should be there, but extremely simple

With respect to the last point, there are two important observations.

1. Users want the option to indicate they need a high priority (are in a hurry). They do not use this often, but they need it for peace of mind. No other inputs are requested from users!
2. Users need insight in what smart charging is doing. If not, smart charging is always to blame: they didn’t plug in their cable correctly? Smart charging did it. They used an invalid charge card? Smart charging did it. The charging cable won’t unlock? Smart charging did it. Once you provide users with insight on the effects of smart charging on their charge rate, they can tell fact from fiction again and smart charging becomes very acceptable.

4.3. Simulation model
An error in the fairly complex smart charging algorithm can have major consequences for an EV user, for example if he/she cannot leave due to an empty battery. For this reason, an extensive smart charging simulation model is developed in which all kinds of everyday scenarios are modeled.

This environment includes user behavior, EV battery behavior, the Electric Vehicle Supply Equipment (EVSE) and GreenFlux Services and Operations Platform (GSOP).

Parts that have to be modelled are:

1. User behavior
2. Battery behavior
3. ChargePoint/EVSE
4. GSOP (GreenFlux Service and Operations Platform)

Together, these components form the simulation environment that is capable of simulating the interaction of EVs with the charging infrastructure and the Smart Charging Algorithm running in the cloud.

Model Structure

The simulation environment consists of multiple components that interact with each other. Interaction between the different models are shown in Figure 1.

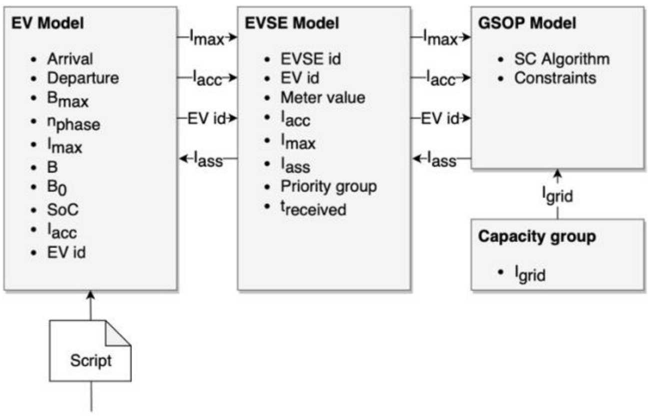


Figure 1: Simulation Environment Architecture with internal states, parameters, data flows and control variables

EV Model

The EV model holds static user-specific parameters such as arrival and departure time but also EV specific parameters such as battery size and charging capabilities. Further EV charging is simulated on single EV level. This section describes how the charging process is modelled.
Li-ion batteries have high energy densities, generally a long lifetime, a low self-discharge and the ability to deliver high power. This makes that Li-ion batteries are commonly used in modern EVs. This section describes the method that is used to model EV batteries.
The SoC is the EV-equivalent of a fuel gage: it indicates the energy content of the battery. Generally the SoC is expressed as a percentage: 0 % meaning empty and 100% meaning a full battery. In numerical simulations it makes sense to use the amount of energy stored in a battery divided by the nominal capacity of a battery, such that:

$$x_{soc}(t) = \frac{B(t)}{B_{max}}$$

With *B(t)* the energy context of the battery at time *t* and B_{max} the maximum energy capacity of the battery.

When constant current and constant battery voltage is assumed, the energy content of a battery at time step $\mathrm{k}+1$, (with $\mathrm{B_k} = \mathrm{Q_k} * \mathrm{V_{batt}}$) , can be rewritten as:

$$B_{k+1} = B_k + \Delta B$$

with ΔB the amount of energy that is added to the battery at time step k. ΔB depends on the charging power P_{in}, State of Charge x_{soc}, charge time dt and charging efficiency η:

$$\Delta B = P_{in} \cdot f_{cccv}(x_{soc}) \cdot dt \cdot \eta$$

here $P_{in} = 230 \cdot n_{phase} \cdot I_k$. In practice, charging always is subject to losses that occur in charger hardware and in the battery itself. These losses depend on, among other things, the temperature but also on the charging current. For modelling purposes, it can be assumed that the overall efficiency is constant at around 92 %. The SoC dependent function f_{cccv} mimics the SoC dependent current acceptance from EVs.

Other assumptions made in modelling the charging process are:

- The battery cell voltage is constant
- The capacity of the battery is not dependent on charge current (no Peukert effect)
- Temperature and humidity do not affect the battery behavior
- No self-discharge is present in the model
- Battery sizes are constant (not dependent on number of cycles)
- Charging curve is the same for all EVs

ChargePoint Model

Chargepoint behavior is also simulated. Communication takes place between the Chargepoint and GSOP (and not between the EV and GSOP). GSOP sends via OCPP how much A the Chargepoint is allowed to allocate per EVSE. A chargepoint holds two EVSEs. An EV can interact with one EVSE.

GSOP Model

A simplified version of GSOP has been developed for simulation purposes. Operational functions that directly influence the charging process are included in the GSOP model. Issues that are not directly related to EV (think of billing and roaming functionalities) are not included in the simulation model.

Validation & Testing

Since the model is an approximation of reality, the results cannot be 100% accurate. Despite the inaccuracies in the model, results can still be used depending on the purpose. In the model, the charging curve and charging efficiency are assumed equal for all EVs, regardless of brand, battery size and other external influences. Both however have their influence on how much energy can be delivered and how long it takes to fully charge an EV.

The accuracy of the simulation model is tested as follows: for a certain period, the corresponding data for a number of charge points are retrieved from the database. That is: the start time, end time, volume demand and charging characteristics (1 or 3 phase, 16 or 32 A). This data is used as parameters to describe EV charging sessions the simulation environment.

The simulation model is validated by comparing real life charging session data with simulation outputs. More specifically the delivered energy (in kWh) and charging time are compared. The average error found is on average less than 0.25 kWh. Additionally, the difference in time to fully charge an EV is 9 minutes, which is less than the interval at which measurements are received from the chargepoint. This makes the simulation environment accurate enough for analysis of various smart charging approaches.

4.4. Prediction module for availability and power available

Setting the scene

Different spots are connected to different transformers. If an e-MSP (e-Mobility Service Provider) wants to communicate at time t_1 the predicted charging speed (for a spot that is connected to a specific transformer) at t_2 , the e-MSP needs to predict the total supply and total demand of current (of all spots connected to that transformer) at time $t_{2,}$ where t_1 is now and $t_1 < t_2$.

The total supply at a certain time t is defined by the current (A) that is allocated by the DSO to all spots connected to a specific transformer at time t.

The total demand of current at time t is defined by the sum of the maximum accepted current of each car that is connected to a spot connected to a specific transformer at time t. Thus, to predict the demand of current (A), it is crucial to define a transformer group for spots.

We could say that a car is likely to charge at high speed at a future time t if its own maximum accepted current at time t is fully supplied by the charger at time t_2. Currently, cars do not communicate explicitly maximum accepted current. Yet, the maximum accepted current can be derived by the CPO and this derived maximum will be used by the CPO to allocate current (A) to the spot. Two cases can be distinguished:

1. Demand of current is smaller than the supply of current for a transformer group: EVs will charge at maximum accepted current; i.e. high speed charging.
2. Demand of current is greater than supply of current for a transformer group: EVs will charge at maximum accepted currents, but the algorithm will alternate the current allocations across spots with connected cars. The net effect over time will be lower average current allocation over charging period (i.e. lower charging speed). The greater the exceed of current demand, the lower the average charging speed will be.

Necessary data for predicting charging speed

For an e-MSP to predict charging speed at some future time t_2, we need to have information that is not yet provided completely by OCPI.

Firstly, we need to know what spots are connected to what transformer by defining:

- Transformer group, defined as the group to which a charging spot belongs; charging spots that are connected to the same transformer belong to the same transformer group;
- Transformer subgroup, is defined as the subgroup to which a charging spot belongs; charging spots of different CPOs (charge point operators) can be connected to one transformer. Within a transformer group charging spots of the different CPOs are divided accordingly into different transformer subgroups;

Secondly, we need historical timestamped data of the following parameters:

- Total capacity (defined as capacity in OCPI 1.0) is defined as the current of a transformer allocated to charging spots of the corresponding transformer group; this is information that flows from the grid operator (DSO) to the CPOs;

- Sub-capacity, is defined as the capacity (current / power) that the DSO assigns to a transformer subgroup. The sum of the sub-capacities of all transformer subgroups equals the total capacity;
- Sum of maximum accepted current of each car connected to a specific transformer group (influenced by car type, battery charge status, AC-1 phase or AC-3 phase, etc).

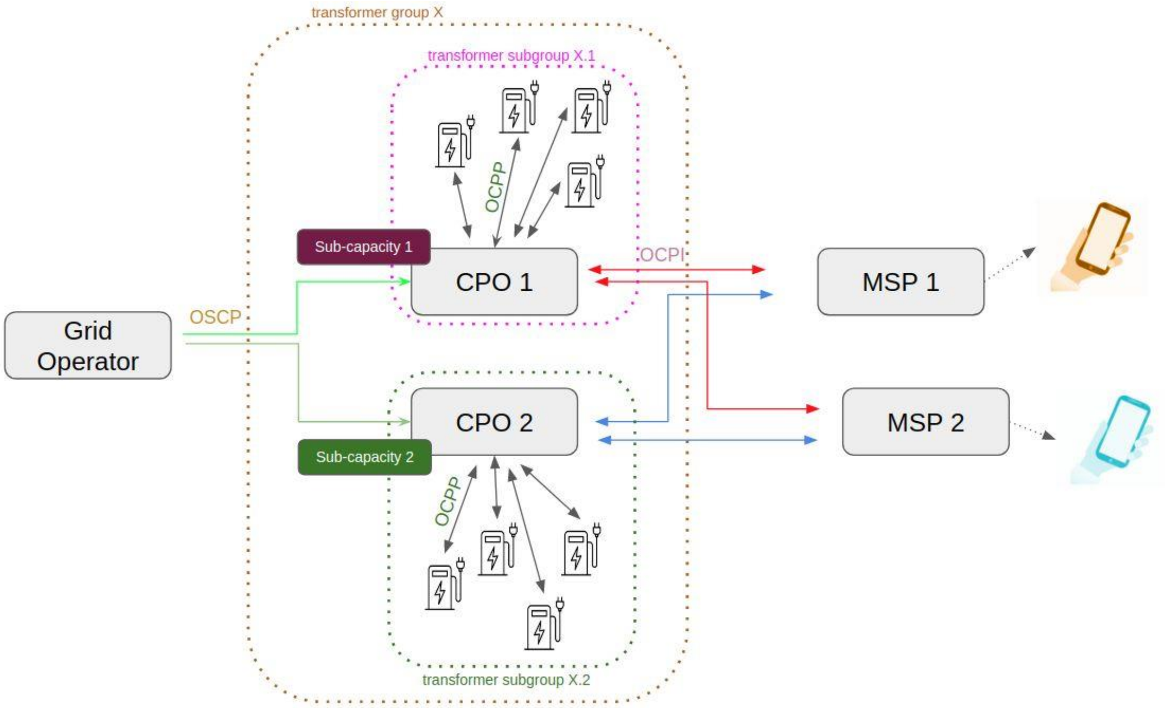


Figure 2: Transformer group and subgroup definitions

In case spots of more than one CPO are inside the transformer group, there will be a transformer subgroup for each CPO. The DSO divides the total capacity across the transformer subgroups (i.e across CPOs). The CPOs will subsequently distribute the allocated current (A) across connected cars. Important to note in this context: for each spot in a smart charging context, either the transformer group with its total capacity, or the transformer subgroup with the corresponding sub-capacity is necessary for predicting charging speed. In the text below we will use *transformer group* and *total capacity* to define the group to which the spot belongs and the current that is allocated to this group of spots. Nevertheless, you could read *transformer subgroup* and *sub-capacity* here as well.
Thirdly, information about the allocation algorithm, defined as the method by which the CPO distributes total capacity across charge points in a specific transformer group would improve predictions.

Necessary adaptations in OCPI for prediction of charging speed

To enable e-MSPs, or other third parties like Eco-Movement, to communicate the actual charge speed to EV drivers, CPOs should communicate:

1. Transformer group information, such as information indicating what transformer group every spot belongs to. We suggest that this information should be a new field in the existing *location module* in OCPI;
2. Total capacities and/or sub-capacities that have been allocated to transformer groups and/or transformer subgroups by the DSOs. We suggest that this should be provided by a field in a *new module* in OCPI;

3. Spot current allocations. We suggest that the existing field *limit* in chargingProfile module OCPI *chargingProfiles module* in OCPI provides the necessary information.

Spot_id's to be stitched when renamed

Building occupancy calculations from update status data requires precise measurements and dependable historical records. As a result, we propose two adaptations to the current OCPI protocol in order to ensure a more accurate and reliable availability metric.

Firstly, we propose a permanent and unalterable identification field be added to each spot. During our development of the occupancy metrics, we noticed that, at certain locations, spots would register a "Removed" status, while simultaneously new spots emerged at that specific location. Below is a timeline showing one such example.

Figure 3: Timeline with removed spot

In the highlighted section, two spots register the status "Removed", with two additional spots appearing shortly afterwards. It is our suspicion that this case was caused by a renaming of the spot id by the CPO. If our assumption is correct, (that the two spots were only internally renamed, and therefore the four timelines above fundamentally represent only two spots), then it could be beneficial to stitch these timelines together.

In a broader context, as the charging infrastructure develops and matures, renamings, deletions, removals, hardware updates and other changes can be expected to occur more frequently. Due to our reliance on historical data to predict availability, it would be beneficial to ensure protocols remain robust to these changes. The recommendation would provide the functionality to stitch multiple histories together, and therefore prevent any loss of historical data.

4.5. Protocol additions & changes

OCPI

We would encourage clearer definitions of the OCPI status updates, as well as more rigorous adherence to their implementation. The current protocol lists 9 categories (see table below), yet their distinctions are not immediately clear (e.g. the differences between "Out of order" and "Inoperative", or "Removed" and "Inoperative"). Clearer definitions would allow for greater interpretability of the statuses, and more accurate predictions.

8.4.21 Status *enum*

The status of an EVSE.

Value	Description
AVAILABLE	The EVSE/Connector is able to start a new charging session.
BLOCKED	The EVSE/Connector is not accessible because of a physical barrier, i.e. a car.
CHARGING	The EVSE/Connector is in use.
INOPERATIVE	The EVSE/Connector is not yet active or it is no longer available (deleted).
OUTOFORDER	The EVSE/Connector is currently out of order.
PLANNED	The EVSE/Connector is planned, will be operating soon
REMOVED	The EVSE/Connector/charge point is discontinued/removed.
RESERVED	The EVSE/Connector is reserved for a particular EV driver and is unavailable for other drivers.
UNKNOWN	No status information available. (Also used when offline)

Additionally, during our calculations we often came across spots which were recorded as having multiple statuses with the same timestamp (e.g. a spot is recorded as having the statuses “Out of order” and “Charging” at identical timestamps). This inconsistency makes:

a) Constructing an accurate historical timeline difficult (we cannot confirm the order of statuses and therefore the historical sequence of the status updates is ambiguous) and therefore,
b) Limits to accuracy of our predictions.

Greater attention to providing status updates would improve our occupancy calculations.

OSCP

Activities within this project related to OSCP are the implementation of a number of use cases from the OSCP 2.0 draft (which can be found as an appendix to this document). Use cases that have been implemented for this project are:

- 3.1.1. Capacity Provider distributes Capacities to Flexibility Provider(s)
- 3.1.3. Flexibility Provider request additional Capacity
- 3.3.2. Capacity Provider handshakes with Flexibility Provider
- 3.4.2. Detect an offline situation
- 3.4.3. Flexibility Provider adapts to a situation where the Capacity Provider is offline

5. Results from WP2: Development of smart charging services

5.1 Expansion of the GreenFlux Service & Operations Platform

Smart Charging Portal Prototype

The GreenFlux portal has been expanded such that it is now possible to manage smart charging functionalities from here. The portal allows to create and manage smart charging groups. Adding or removing chargers to / from existing groups and it is possible to choose between different smart charging algorithms.

Smart Charging Dashboard Prototype

The Smart Charging Dashboard that was developed provides insight into the operation of the smart charging algorithm. It shows how capacity is distributed between different EVSEs as a function of time.

An example is shown in Figure 4. Time is shown on the x axis. Each plane represents a different EVSE. The height of the plane corresponds to the number of amperes that have been allocated to the respective charger. The figure shows the progression of capacity allocation between 5 different EVSEs over a 12 hour period.

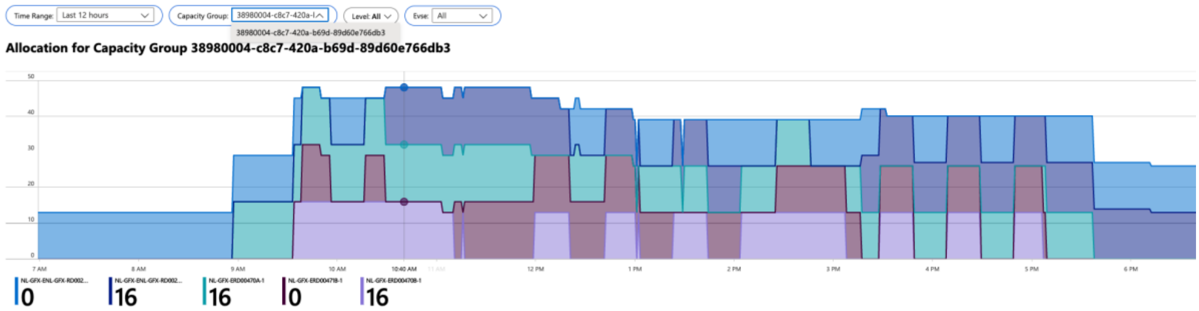


Figure 4: Smart Charging Dashboard Prototype

5.2 Improving POI quality through data aggregations and real-time predictions

Correcting, completing and cleaning

Raw P.O.I. data is imported via various automatic links from more than 70 sources. Some of these links implement the OCPI standard, which also enables real-time data exchange. Others are imported via custom links. The majority of these links are not real-time, but are run in batches at night on configurable frequency. The exchange format of the custom links varies per link. and is usually json or xml with a specific structure (different from OCPI). The custom links transform the incoming data to an OCPI structure.

The raw data is often incomplete or incorrect. The raw data is validated in a batch process and corrected if necessary. Validations and corrections are logged and stored as a new source layer and consolidated together with the raw delivered data from other source layers into one layer, which represents the data that can be accessed. In addition to automatic validations and corrections, manual corrections can also be made in a data management system. These changes are also logged and included in the consolidation.

Validation includes checks for combination of amperage, voltage, power and connector type. Missing information is supplemented based on available information. In addition, address data is validated and supplemented using external reverse-geo services and public geographic data (e.g. PDOK). Locations from different sources are matched on location to avoid duplications of the same locations from different sources.

Relay-time changes (mainly in EVSE status) are immediately processed and forwarded by means of outgoing OCPI links to customer parties. The system is hosted in the cloud and is multiple and scalable. Peaks in delivery and extradition are handled through horizontal scaling.

Occupancy predictions

As electric vehicles become more common, and the charging infrastructure continues to expand, predicting charging spot availability, and communicating this occupancy to EV drivers will become increasingly important.

Beyond the aforementioned EV drivers, occupancy predictions can also be insightful to DSOs, CPOs, and e-MSPs for a wide variety of reasons. With such broad interest, it becomes important to understand each party’s underlying interest in occupancy, and define specific criteria for each stakeholder.

For the purposes of this research, we concentrated on predicting occupancy and charger availability from the perspective of an EV driver. From this framework, we were able to clearly identify EV driver stakes, and approached occupancy through three main criteria:

1. We define the goal of an occupancy predictions as: providing drivers with a reliable estimation that a specific spot, on a specific week day and hour, will be available to a driver to charge their vehicle;
2. Since drivers are primarily interested in whether or not a spot is available for charging, we label all statuses as either Available or Not Available. All statuses other than Available, defined in OCPI (such as: “Blocked”, “Out of order”, “Inoperative”, “Unknown”, “Reserved”, “Removed” or “Planned”), are categorized as Not Available;
3. Additionally, this probability should be interpreted through accessible categories (e.g. High availability, Medium availability, Low availability) in order to effectively and most intelligibly be communicated to drivers.

At our disposal was update status data, in which, for each spot, a status was provided, along with the timestamp indicating when that status was registered.

From this historical status data, we were able to construct an hourly timeline (rounded to the nearest minute), detailing a spot’s status at every hour. This timeline began from our earliest record of the spot, until the most recent query of our database.

With this timeline, we could calculate how many minutes per hourly interval a spot was labeled as Not Available. After that, we aggregated these calculations by week day and hour, and averaged the time occupied. The results provided the average amount of minutes that a spot, on a specific week day and hour, was occupied, and therefore inaccessible to a new driver.

This numeric value was then categorized, in order to provide drivers with a more accessible metric to suit their needs.

Average amount of minutes occupied per week day/hour	**Labeled availability ranking**
0m ≤ to ≥ 12m	*Very High*
12m < to ≥ 24m	*High*
24m < to ≥ 36m	*Medium*
36m < to ≥ 48m	*Low*
48m < to ≥ 60m	*Very Low*

In other words, if a spot on Tuesdays between 10am and 11:00am averaged 22 minutes of occupancy, we labeled that spot’s respective availability as “High’’. The resulting data table provided 168 rankings for every spot (one for each hour of each week day). The data table can be updated whenever decided necessary.

Power predictions

Once a spot becomes available, the charging speed a driver can expect might vary significantly, and this variability necessitates additional metrics that can further inform an EV driver’s understanding of their battery charging experience.

Complementing occupancy predictions, available power predictions would provide additional insights to drivers, and help drivers understand the expected charging potential of various spots.

However, predicting the available power a driver can expect to charge at is highly dependent on several factors, such as:

1. The allocated current/power distributed from the local transformer;
2. The amount of electric vehicles presently charging from that transformer;
3. The ratio of high vs. low amperage cars;
4. The effects of priority ranking, which might divert power to higher priority vehicles;
5. Battery charge status (e.g 10%, 40% or 90% charged).

These factors complicate the ability to accurately provide EV drivers with reliable estimates of how much power will be available for their vehicle. However, we can make certain assumptions in order to provide a broad estimation of what drivers can expect.

Similar to occupancy predictions, we calculated the average amount of allocated power per week day and 15 minute intervals. Afterwards, we calculated the average amount of vehicles for this same interval. Using the allocated power threshold and the average vehicle activity, we calculated a theoretical amount of power required to charge all cars at their maximum capacity during that interval.

This theoretical power, or ideal power requirement was found by:

1. Calculating the average amount of vehicles per session,
2. Calculating an average ratio between high and low amperage cars,
3. And then summing these figures to determine the amount of power needed to ensure all cars charged at their maximum capacity.

With this metric we can compare the *ideal power equirement* with the *actual allocated power*, and determine whether the allocated power is sufficient. Below is a table detailing how we categorized these comparisons.

Differences between ideal power demand and allocated power	**Labeled power ranking**
*Ideal demand < 0.85 * allocated_power*	*High power predicted*
(0.85)(allocated power) < I deal demand < (1.15)(allocated power)	*Medium power predicted*
Ideal demand > (1.15)(allocated power)	*Low power predicted*

Reservations in OCPI

Currently, the OCPI protocol has implementations regarding reservations. However, Dutch CPOs do not presently utilize this functionality. With the addition of a prediction module, it is possible that the desire for spot reservation becomes more salient, and therefore, the reservation implementation would be utilized. With the proposed prediction module, the mentioned adoption (reservations based on availability predictions) could be developed by CPOs.

How 3rd parties like e-MSPs could make use of extended OCPI

The proposed prediction module would offer availability predictions per spot for each week day and hour. The resulting data table (number of spots x 168 values), would be accessible through an API.

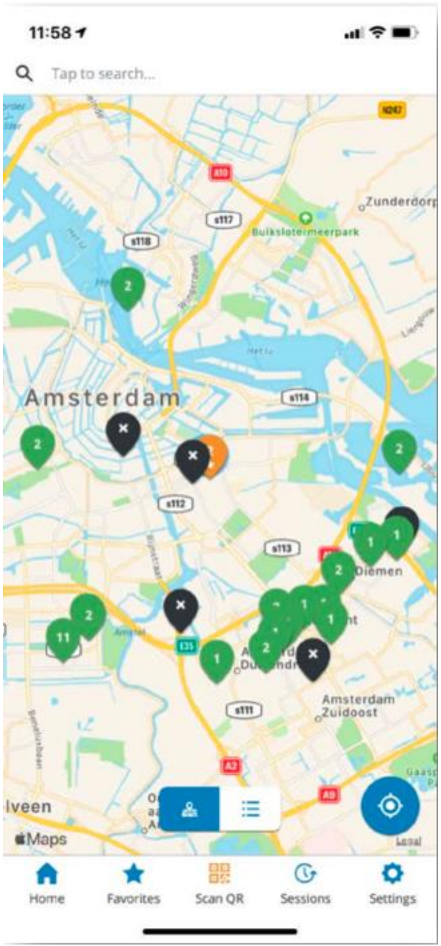
With this data, simple visualizations, such as histograms showing daily activity per spot, could be easily integrated into mobile or web applications, and offer valuable insights to EV drivers.

5.3 (Smart) Charging App Prototype

A mobile app was developed to assist EV drivers in interacting with charging infrastructure. This app is called *Charge Assist* and is available for both iOS and Android. An overview of the main functionalities is given below.

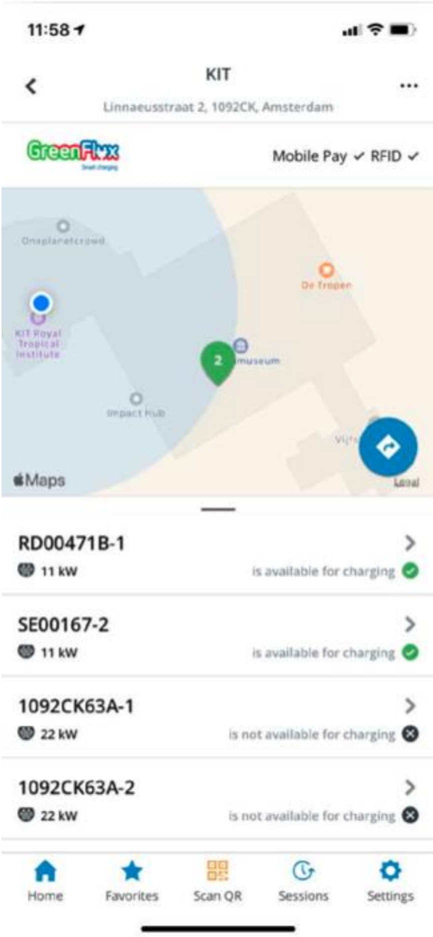
Show nearby locations to charge

When a user opens the app, nearby locations will show.



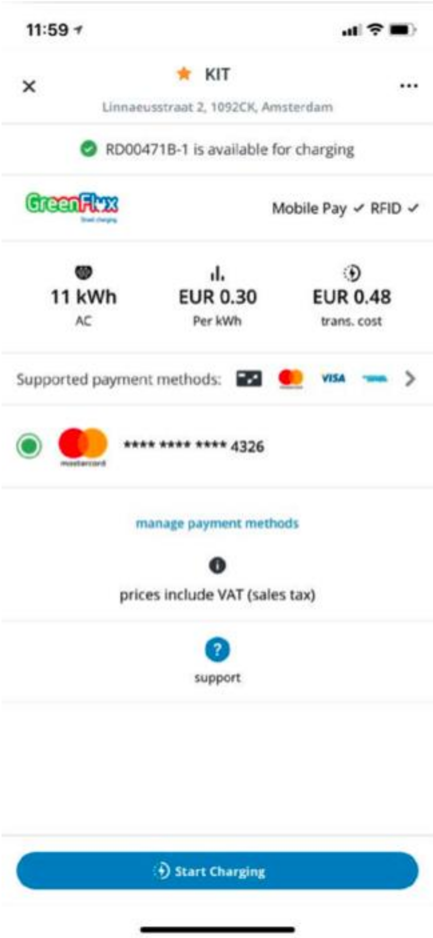
Show individual EVSEs per location and check details

By selecting a location the individual EVSEs and their status will show.



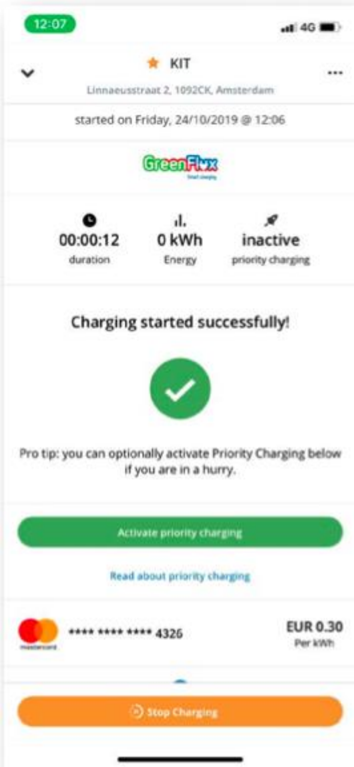
View EVSE details and start charging

By selecting an EVSE, details on maximum charging power and tariff are shown. It is also possible to start a charging sessions from here.



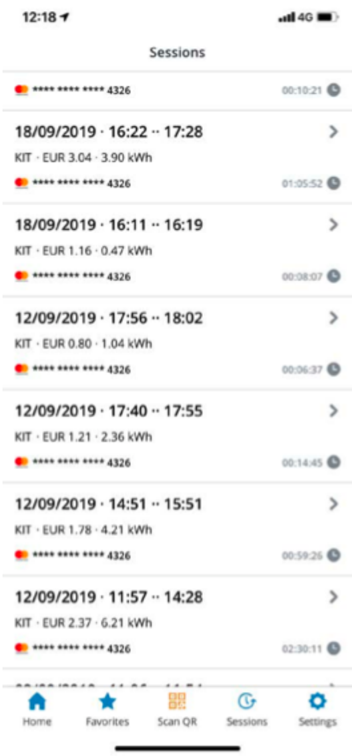
View charging progress

When in a charging session the charging progress is shown. It is also possible to request priority and stop the charging session.



View historical charging sessions

Users can find historical charging session from all chargers that are directly connected to the GreenFlux platform



6. Results from WP3: Building test setup and conduct pilot tests

6.1 Pilot Experiments

A number of experiments have been conducted to verify the theory from previous chapters. The experimental setup and results will be discussed in this chapter.

Experimental setup

First, a total of 50 chargepoints (a total of 100 EVSEs) have been selected that are used frequently. To minimize local impact, the locations of the chargepoints are spread throughout the Netherlands. Smart charging will be applied to these chargers *as if* they were all connected to the same transformer station. Since in practice several CPOs may be active on a single transformer, the chargepoints are assigned to one of in total three virtual CPOs. Smart charging is applied at the level of chargepoints with the same CPO group. The available capacity (in A) is the same for all CPOs and for all phases.

The EVSEs for the pilot are divided into two groups.

25A Uncontrolled

Smart charging is not applied to the first group. The purpose of this experiment is to see how many sessions are taking place. How much energy is supplied and whether the transformer capacity is violated (if the posts were physically connected to the same transformer). Chargepoints in this group are connected to the grid through a 3x25A grid connection. Hence the name of this scenario.

25A Controlled

In the second group smart charging is applied. The CPOs have an equal part of the available transformer capacity available. Further, each CPO may allocate capacity to its connected chargers as long as the total allocated capacity does not exceed the available capacity. Finally, chargers in this scenario have a grid connection of 3x25A, which means that if two EVs are connected to the same charger, a maximum of 12.5 A can be used per EV.

63A Controlled

Within the pilot it was not possible to physically provide 50 chargers with a 3x63A grid connection. For this reason, the sessions that took place at 50 chargers from the *25A controlled* scenario were used in simulations where the capacity was set to 63A per connection.

Metrics

There are a few things that we are interested in. On the one hand, the transformer capacity must not be exceeded as this can lead to a power failure. On the other hand, it must still be possible to supply energy and users should not be without power too often. Finally we want to describe the *flexibility* that is added to the energy system by each of the smart charging approaches. Since there is no standardized method to describe flexibility, one way is suggested below.

Quantifying flexibility

The proposed smart charging technique attempts to create more flexibility in the energy system by spreading out the actual charging time over the time EVs are connected to a chargepoint. We want to quantify the extent to which more flexibility is created to allow better comparisons of the different smart charging approaches. For this a new parameter, φ, is introduced.

Since flexibility is created by spreading the actual charge time over the connection time, the flexibility can be measured. First, we determine the total energy (in kWh) that is delivered in a charging session: E_{del}. Next the nominal charging power of the EV at the socket is determined: P_{nom}. These parameters are divided to determine what the nominal charging time would be:

$$t_{nom} = \frac{E_{del}}{P_{nom}}$$

Note that P_{nom} is *not* the nominal charging power of the EV but the nominal charging power of the EV at the given chargepoint. This way, EVs whose charging power is *physically* limited by the charger are not considered flexible. After all, they still use the charger's full capacity.

Next, we determine the total time that was used to charge: t_{char}. This is the time between the start of a charging session and either:

1) the moment when a car is fully charged (i.e. it stops taking energy from the chargepoint)
2) the last moment that the car is still charging in a session

Short example: a charging session with an EV that would be full after 2 hours of nominal charging but is full after 6 hours of smart charging has a flexibility of 6/2 = 3.

The flexibility per charging session is defined as the total time actually charged divided by the nominal charge time:

$$\phi = \frac{t_{char}}{t_{nom}}$$

Finally, for each scenario the average flexibility is taken over all charging sessions. This value describes the extent to which the charge is *spread* over the time the car is at the charge point.

1. How often is the transformer capacity exceeded
2. How many hot unplugs are there
3. How much flexibility is realized

Results

Results are shown in the table below:

Scenario	**Transformer overload**	**# sessions**	**Hot unplugs**	$\bar{\phi}$
25A Uncontrolled	55.2 %	1777	425 [24%]	1.64
25A Controlled	0 %	2663	832 [31%]	2.09
63A Controlled	0 %	2663	917 [34%]	2.24

A few things stand out from this table. First, in the case of the 25A uncontrolled, there is a transformer overload 55.2% of the time. This is considerable and indicates that large-scale uncoordinated charging of cars not only can but will lead to a power outage. The maximum uncontrolled demand was 581 A with a maximum capacity exceedance of 343 A.

Then regarding the hot unplugs, it can be seen from the table that the percentage of hot unplugs is higher for both controlled scenarios as compared to the uncontrolled scenario. This is to be expected since in the second case the charging speed of the chargers is limited. However, the difference is only 7 and 10 percentage points for 25A and 63A scenarios, respectively.

Finally regarding flexibility, though no smart charging is applied, the average flexibility for the uncontrolled 25A scenario is still at 1.64. This can be explained by the fact that chargers that have two EVs connected simultaneously have to divide the capacity between the two EVs. This way, albeit very locally, smart charging is still applied. The *controlled* scenarios have an even higher flexibility score, both above 2. In other words, the time it takes to charge an EV is more than doubled.

Capacity-demand alignment

In the figure below the available transformer capacity (for five days) is plotted as function of time as well as the uncontrolled demand by EVs. This figure shows that the moments when the demand of the EVs is high, the available transformer capacity is low. On the other hand, the extra transformer capacity falls precisely at times when there is little demand from the EVs.

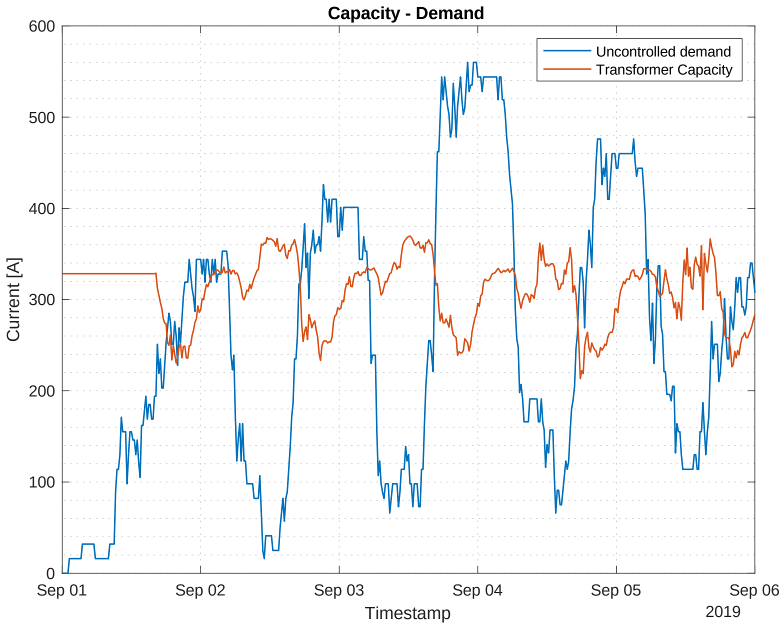


Figure 5: Capacity & demand

This means that, for the controlled scenarios, the extra capacity can hardly be used and therefore no additional benefit can be gained for EV drivers.

User mix

Typically, charging station users can be classified into one of the following user groups:

- Home users: arrivals in the evening with sessions longer than 8 hours
- Work users: arrivals in the morning with durations of approximately 9 hours
- Other / short stay users: arrival throughout the day and durations up to 5 hours

We are interested in the distributions between each user group within this pilot.

Assigning a session to a group is done through clustering, based on the start time and duration or a session. Since the number of clusters is known a priori, *k-means* clustering is used to identify which sessions belong to which cluster. The performance of k-means clustering strongly depends on the initial guess. For that reason we use values based on as initial guess, these are shown in the table below:

	Start	Duration
Home	18:30	14:00
Work	9:00	9:00
Other	13:00	2:30

A total of 4440 sessions were analysed. The share of sessions belonging to each group is shown in the table below:

Group	Share
Home	2124
Work	79
Other	2237

As to be expected from the 'uncontrolled demand' profile from Figure 5, the sessions in this pilot mainly consist of home and short stay.

Additional experiment

We are interested in the effects if there would be a larger share of work users. For example in cases where an office building is located in or near a residential area, so that these chargers follow a different user pattern. We want to study the effect of this based on a simulation. For this new experiment, a number of charging stations have been selected, but this time with mostly work users. In Figure 6 the uncontrolled demand and transformer capacity are shown. It shows the influence of the user mix on the energy demand of EVs during the day. First, the peak is much narrower, and second, the peak better matches the extra transformer capacity.

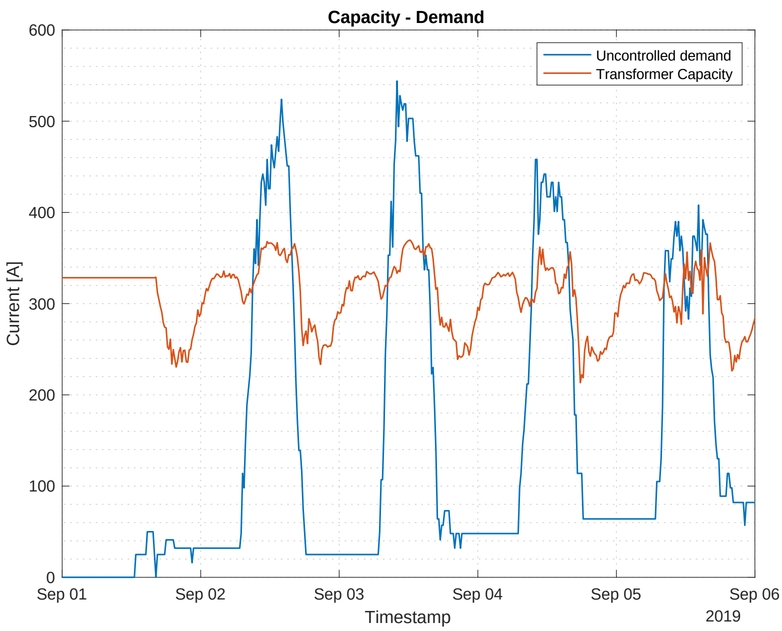


Figure 6: Capacity & demand (other user mix)

A total of 1941 sessions took place on these chargers from September – November 2019. The corresponding Charge Detail Records were collected from the GreenFlux database and used as basis for a simulation. Now all three scenarios were simulated: 25 A connections (uncontrolled), 25 A connections (controlled) and 63 A connections (controlled).

Results are shown in table below. The maximum uncontrolled demand was 681 A and the maximum capacity exceedance 350A.

Scenario	Transformer overload	# sessions	Hot unplugs	$\bar{\phi}$
25A Uncontrolled	17.4 %	1941	247 [13%]	1.86
25A Controlled	0 %	1941	517 [27%]	2.44
63A Controlled	0 %	1941	472 [24%]	2.42

From the results we see that again without any smart charging, a considerable amount of time there is an overload on the transformer. Further the flexibility for the uncontrolled scenario is already quite high. This is again due to the simultaneous charging of 2 EVs on a single charger. Since more charging sessions are taking place simultaneously for this user mix, capacity is distributed more on the charger level as well. The most striking is that flexibility is more or less the same for both controlled scenarios, but that the number of hot unplugs is lower at 63A. This is due to the better overlap of additional capacity and demand.

6.2 Technical impact

In conclusion, the uncontrolled charging of EVs *will* lead to an overload of MV/LV transformers. This can be prevented by applying smart charging at transformer level. Although EV charging is slowed down considerably (on average by more than factor 2), the increase in the number of hot unplugs remains limited. This means that the adverse effects for EV drivers remain limited as well. But more important: the current grid can still be used to supply the EVs with their energy demand without need for expensive grid expansions. All it takes is a coordinated approach to distribute available transformer capacity.

While allocating capacities, it is quite common for an EV to leave while it is not yet full (hot unplug), while another EV is already full but remains connected to the charging station for some time. This means that there is still room for improvement in allocating capacity to different EVs in the time domain. If we would be able to better which users are in a hurry and which ones are not, the number of hot unplugs could be further reduced, thereby improving the experience for all users.

6.3 Validation of prediction accuracy

The accuracy of availability predictions

Regarding the veracity of availability predictions, the described methodology relies heavily on the accuracy of timestamps, as well as the dependable delivery of status data. As a result, discrepancies between realized occupancy and predicted occupancy would be contingent on how precisely actual status changes, and their associated timestamps, were reported by the respective CPOs.
Additionally, the proposed methodology does distinguish between weekdays, but averages occupancy evenly across all week days (i.e. every Tuesday is weighted identically). The accuracy of predictions could be improved if contextual factors (time of year, urban activity, etc.) would be taken into account.

The accuracy of power predictions

With regards to power predictions, the accuracy is largely depended on the idealized power demand we calculated, and its foundation on our calculated ratio between high and low amperage cars.

The amount of power available to drivers depends mostly on: (1) the allocated power from the transformers, and (2) the current demands of cars charging. Due to Greenflux's smart charging allocation algorithm, when the demanded power from cars exceeds the allocated power, Greenflux alternates which cars charge in 15 minute intervals.

In other words, this means that if 10 cars are presently changing, but the power allocated permits only 7 to charge, the first 7 cars to arrive will charge, and the remaining 3 cars will wait until the next 15 minute interval. After 15 minutes, the 3 cars in waiting will charge, and replace 3 of the 7 cars that were charging previously.

The challenge this smart charging allocation presents is that, while charging, we can identify a cars' amperage. However, as described, not all cars charge simultaneously, and therefore, the amperage of certain cars, at specific intervals, remains unknowable. To overcome this, we assumed the ratio of low (i.e. 16A) to high amperage (i.e. 32A) cars in the sample, which are randomly chosen, would represent the actual ratio of the population (i.e. all the cars presently plugged in). With this assumption, we found that, on average, for every 1 high amperage car (e.g. 32A), there is 1.2 low amperage cars (e.g. 16A).

With this ratio, we could calculate the ideal power demand for every interval, and therefore move closer towards providing power predictions for drivers.

The charger selection for experiment

For the experiment we have quasi-randomly selected 50 publicly available charge stations managed by Greenflux. A condition of the selection of stations was the availability of a historical track record of at least two months of charge sessions, since we want to only include charge stations that are actively used by consumers.
In Figure 7 a visualisation of the timelines of the usage of 11 charge stations. Every timeline represents a spot/socket. Blue means the socket is available, and yellow means the station is charging a car.

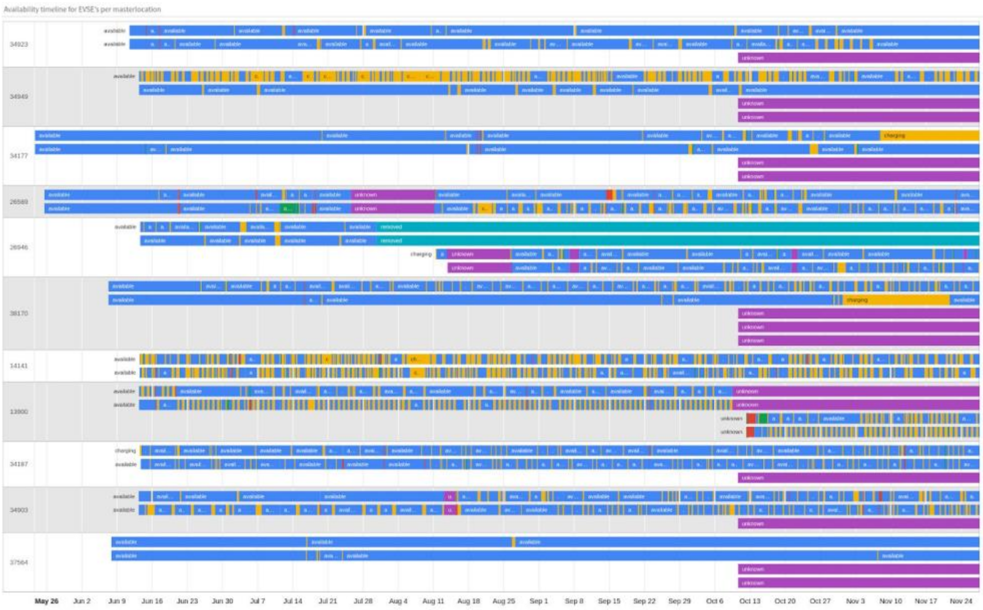


Figure 7: Visualisation of Charge Station Usage

6.4 Proposal for OSCP and OCPI modifications

The proposed changes for OSCP and OCPI are described in the sections 4.4 Prediction module for availability and power available and 4.5 4.4Protocol additions & changes.

6.5 Technical possibilities and legal framework

IT

Electric charging is controlled via various protocols, whereby OCPP and 61851/15118 form the link that takes care of the communication between the charging point and the car. A limitation on the power level to be supplied can be entered in these protocols. The loading session will automatically obey this. There are therefore no IT technical restrictions on the introduction of variable capacity.

Hardware

Assuming that electric cars and charging stations meet the applicable standards, there are no restrictions on the implementation of a variable capacity.
In various current practical tests, however, it appears that not all cars and / or charging stations meet the applicable standards (yet). On the one hand this is the result of the still developing technology. On the other hand, checking standards is not yet legally guaranteed. The National Agenda for Loading Infrastructure (NAL) states that manufacturers can voluntarily have the hardware tested by the ElaadNL test center[2].

Legal framework

Flexible capacity does not currently exist in the tariff code or network code. As already stated in the introduction, the purchase of a connection currently gives the user the full right to make full use of the connection. A change in the tariff structure requires changes to the underlying regulations as included in the Electricity Act 1998.
The first option concerns the Electricity Act 1998 with regard to the rights of affiliates. Section 10, Article 86d[3], provides an opening for this in the form of a General Administrative Order to be drawn up. It is plausible and reasonable that in the event of a change in the service provided with regard to transport capacity, the rate also changes. This requires a change to the underlying codes in the Electricity Act 1998. There are no inconsistencies with European legislation.

A second option concerns a change to the Electricity Tariff Code. Articles 32 to 37 of the 1998 Electricity Act describe how a change to the electricity tariff code can be implemented.

A third option concerns applying for an exemption, as described in Article 37A of the Electricity Act 1998.

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[2] Page 32 NAL: Agreements | To prevent complications between EVs and charging stations, ElaadNL can advise on the charging behavior of an EV independently of charging station suppliers and OEMs. On the one hand, it is important to prevent issues from occurring. Dutch importers and charging station manufacturers voluntarily bring the new type of EVs and charging stations to the ElaadNL test center to test functionality, interoperability, compatibility, Smart Charging, Power Quality and the chain. On the other hand, a process is organized through which disputes are followed up and independently assessed.

[3] Electricity Act: § 10. Transparency and liquidity, Article 86d
If that is necessary in the interest of a sufficiently transparent and liquid market for the supply and demand of electricity, transmission capacity or production capacity or in the interest of the related security of supply, rules will be laid down by or pursuant to a general administrative order concerning:

a) the manner in which or the conditions under which producers, traders, suppliers or network operators offer electricity, transmission capacity or production capacity that they have;
b) the information provided by producers, traders, suppliers or network operators with regard to the supply and demand of electricity, transmission capacity or production capacity.

7. Effects on Top Sector Energy

Realised flexibility in the electricity grid

The realised flexibility is described in section Results.

Replication potential

In this pilot, the new smart charging technology has been applied (virtually) to 50 charging points. Here it has been shown that the approach is technically feasible: the algorithms can handle it and it is clear how the existing communication protocols should be extended to make this possible.

At the time of writing, there are approximately 55,000 (semi-)public charging points in the Netherlands. This is expected to grow to about 1.8 million in by 2030[4] . In theory, all public chargepoints can be controlled based on the available capacity at transformer level. This is a significant growth potential for this technology.

The growth potential is not limited to the Netherlands alone. It is expected that the technology can also be applied abroad, since the protocols used between the various parties are open and can therefore be used anywhere in the world.

However, the possibilities for upscaling depend on whether the grid operator is legally allowed to implement variable connection tariffs. This may depend on the region where the technology is applied. In addition, the charge point operators and network operators active locally must actively apply this new method.

8. Economic perspectives

Economic opportunities and earning model

Based on the activities that have been carried out for this project, it is expected that savings can be made on grid reinforcements that would otherwise be necessary. The Dutch electricity grid is over dimensioned in such a way that it can handle peaks in high energy demand, for example at the beginning of the evening. For most of the day there is more than enough capacity to charge EVs.

In the case of uncontrolled charging, an additional grid capacity is needed to accommodate for everyone who charges their EV at the beginning of the evening. In any case, this will lead to large costs for grid reinforcement. Smart charging ensures that the excess capacity during the rest of the day can be used to charge cars. The entire electricity grid is used more efficiently this way. Fewer grid reinforcements are needed on the short term and, moreover, existing transformers and cables will last longer since they operate less often at (or above) their nominal limit. Existing charging stations are smart charging ready, eliminating the need to convert existing infrastructure (which normally entails significant costs).

Non-technological risk factors

Successful implementation is highly dependent on legislation. The flexibility that can be achieved through smart charging is greater if it can be applied to *flexible* grid connections. In addition, it depends

[4] https://www.klimaatakkoord.nl/mobiliteit/vraag-en-antwoord/voldoende-laadpunten

on how grid operators will deal with the legislation. If there are no smart incentives coming from the grid operator, the technology may be less likely to be adopted by charge point operators.

9. Conclusions and Recommendations

This project investigated the feasibility, both technical and legal, of applying smart charging at the transformer level. In this chapter the conclusions are summarized and a few recommendations are made for further research.

Conclusions

The overall goal of this project was to validate a new technology of smart charging using practical data, at which the energy demand of charge points is merged at transformer level in order to be able to use the available capacity in a more efficient way. To this purpose a new smart charging algorithm was developed which was then tested in practice on a group of chargers. The results of this were compared to a group of chargers that did not have smart charging. At the same time, a simulation environment was developed that allows to simulate scenarios from the field under different circumstances (different capacities, smart charging algorithms). In addition to the development of new technologies, research has been carried out into what is needed to implement this. The main conclusions are given below.

- *Applying smart charging at transformer level is technically feasible*
  In this project, technology has been developed that allows to perform smart charging at a higher level.

- *Adverse side effects for end users are only limited*
  Though the average charging time for an EV due to smart charging doubles, there is only a small increase in number of sessions that end before the EV is fully charged.

- *Entering flexible connection capacities can be done legally in three different ways*
  This is possible by adjusting the electricity act, by adjusting tariff codes or by requesting exemption.

Recommendations

Recommendations for protocol amendments and future research are given below.

- *Clearer definitions in OCPI beneficial for predictions*
  From a prediction perspective, it would be beneficial if OCPI applied more unambiguous definitions for the status levels of chargepoints

- User tests should be performed
  In this project the effects of a smart charing algorithm were determined on the basis of the number of hot unplugs. The effects of predictions on users have not yet been investigated. The influence of this on loading behavior should be investigated in a follow-up project.

- *Investigate the influence of priority users*
  The benefits for end users are expected to be greater if some of the users are in hurry. For this reason, it is recommended to investigate the effects of:
    1. More end users requesting priority
    2. Better predictability of end users