Towards Grid-Friendly Electric Vehicle Charging: Architectural Concept and Field Trials

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Abstract—**Electric mobility leads to an increasing challenge for power grid operators, particularly due to its high peak power demand in low voltage grids in the scenario of home charging. Power grid enhancements are considered either as cost-intensive or as environmentally unfriendly and, hence, more intelligent ICT-based solutions are needed for economic and ecological reasons. Therefore, our intention is to develop a practical approach of grid-friendly smart electric vehicle charging methods. The approach entails two methods, namely: (i) Proactive electric vehicle charging control via prediction of available charging capacity and a corresponding intelligent scheduling of charging processes; (ii) Reactive, decentralized charging process control as a response to critical grid situations. Proactive forecasting of available power capacity and energy from (distributed) renewable sources can lead to a better utilization of the power grid in place and extend the usage of renewable energy, which is required for a successful turnaround in energy policy. A reactive control of ongoing charging processes guarantees that the power grid infrastructure can run at its limits, while not overshooting power quality limits. This bipartite concept exploits the flexible potential of the power supply network and at the same time optimizes the ongoing charging processes to meet the requirements of the grid.**

I. Introduction

High penetration of *Electric Vehicles* (EVs) in the future will put new challenges to residential low voltage power distribution grids, especially when EVs are connected to long feeder lines with spatial unevenly distributed loads. Massive EV integration into the low voltage grid can cause asset overloading and power quality problems such as critical voltage drops if the grid is not appropriately enhanced or an intelligent management is not established. However, EVs can partially contribute to solve many existing issues in the grid due to their hidden flexibility in terms of consumed charging power and charging times. They can improve the power quality, act as distributed storage units and support the integration of distributed renewable energy sources.

The different emerging requirements of EV charging infrastructures such as high availability of fast chargers and the possibility of performing multiple charging operations simultaneously without causing shortages or power quality issues, lead to the following (additional) roles of the power *Distribution System Operator* (DSO):

- Monitor the consequences of additional charging points for grid reliability, power quality regarding EN 50160 and the need for additional network capacity like with normal grid connections.
- Provide proactive information on potential network constraints for EV charging points to multiple market stakeholders. In this way, good planning of charging operations can eliminate most of the predictable grid issues. Nevertheless, there is a certain overhead for synchronization of grid data and the requirement for a reliable ICT infrastructure.

Typically, the DSO while planning their grid considers two criteria: (1) expected peak power at each grid connection considering a simultaneous peak load factor and (2) voltage drop/rise on the feeder line. Let us assume the following scenario in a low voltage grid where a new charging station/wallbox needs to be installed. Besides the peak power of the residential units, an additional peak power for the connection request is used in the calculation of the grid enhancement. Typically, a peak power of 7.4 kW (balanced on three phases) is assumed for one residential unit, 10.7 kW for two residential units due to the simultaneous factor, 13.3 kW for three residential units and so on. An additional wallbox with peak charging rate of 11 or 22 kW highly increases the peak power of a grid connection point. First analysis show a simultaneous factor of 0.4 with 11 kW charging power in low voltage grids, still resulting in an additional peak load of 4.4 kW. To handle the added peak load in a 100% battery electric mobility scenario, there are basically two options: traditional grid enhancement and bottleneck management.

a) Grid enhancement: In Germany and most European countries, the feeder lines in the low voltage grid are built underground, which is highly costly and requires longer installation time compared to overhead lines. Furthermore, in case of very fast increasing peak demand (very fast adoption of EVs), the required construction work is not manageable for whole Europe. With overhead lines, grid enhancement is faster and cheaper, but still consumes similar amount of resources (aluminium, copper, etc.). Transformer stations in urban areas are often hard to replace due to space limitation, resulting in high costs. In any case, the grid enhancement only is required for short peak loads in the distribution grids during the day.

b) Bottleneck management: Limited resource (power grid) can be managed in an intelligent way in order to avoid bottlenecks, such as transformer overloading or voltage problems. It can further be distinguished between proactive and reactive control of feed-in and loads. The focus in this paper is on intelligent charging process control.

Proactive scheduling of charging processes is based on grid status forecasts and its goal is to avoid predictable line voltage drops or asset overloading in advance by shifting EV charging processes to non-critical times and locations. The grid forecast precision and the predictability of extraordinary situations, e.g. traffic jams, which can impede or delay planned charging operations, appear as a very challenging point.

Reactive control of charging processes uses real-time data, which is collected in the power distribution grid, for estimating the current and future (very-short term) state of the grid in order to control the charging stations behaviour, e.g. by changing the charging power or other parameters of the charging station. On one hand, this approach is not always technically feasible due to missing support of charging station control functionalities. However, recent proposed communication protocols/standards such as *Open Charge Point Protocol* (OCPP) 2.0 for communication between the *Charging Station Management System* (CSMS) and the *Charging Stations* (CSs) and ISO 15118 for communication between the CS and the EV propose standardized communication channels to overcome the technical limitations. On the other hand, reactive control is not always economical, especially for fast chargers, since the DSO must compensate the EV user or the CSP for power curtailment similar like it is defined for example in the German law *EnWG* §14*a*.

II. Proposed Architecture

We propose a grid-friendly smart charging solution based on proactive and reactive bottleneck management. The solution is implemented using a multi-agent architecture, in which the different agents, extracted from the electromobility eco-system, communicate with each other to introduce a grid-friendly smart charging service. The architecture of two involved agents, representing the *Charging Service Provider* (CSP) and the DSO, is depicted in Figure 1. These two agents also provide interfaces to other stakeholders in the eco-system, namely the *Electric Fleet Operator* (EFO) for optimally scheduling fleets of EVs [1] and the *Advanced Driver Assistance Service* (ADAS) representing the interface to the user. Furthermore, they incorporate the two involved physical systems, namely the power distribution grid to gather measurements and the charging infrastructure to control the CSs.

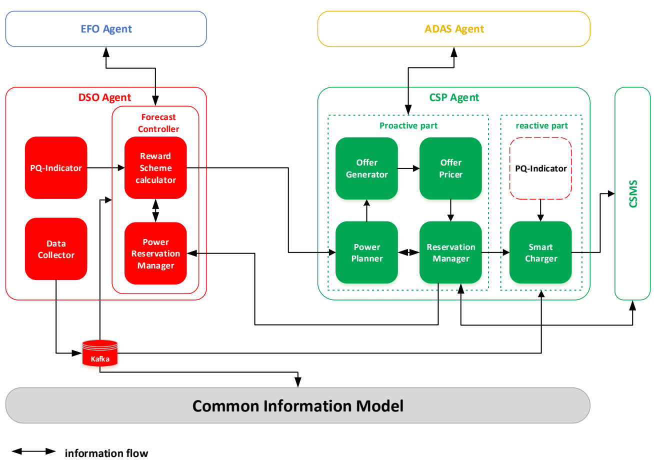


Fig. 1: Internal architectures of CSP agent and DSO agent.

A. CSP Agent

The CSP agent is split into a proactive and a reactive part, which can be mapped to the smart charging solution of ELECTRIFIC presented above.

- The proactive part includes four components: (1) The *Power Planner* requests the available power capacity from different energy sources from the DSO agent and prepares a time series of available power capacity at the CS that considers the CSPs objectives to maximize the renewable intake but also takes the grid constraints into account. (2) The *Reservation Manager* coordinates reservations, charging profiles and availability of the different connectors with the CSMS. (3) The *Offer Generator* and (4) the *Offer Pricer* [2], [3] create and price suitable charging offers.
- The reactive part includes the *Smart Charger* (SC) and the *PQ-Indicator* - a micro service of the DSO agent - which estimates the grid status by a PQ-Indic value $\in [-1, 1]$ based on measurements from the power grid. The control signals of the SC are send to the charging station via the CSMS using OCPP. More details on the proposed smart charging algorithms can also be found in [4] and [5].

B. DSO Agent

The DSO agent introduces two kinds of services, one for data gathering and one for forecasting.

- The first service of the DSO agent gathers measurements from the low voltage grid in real time and passes the recorded data to an event engine, which is implemented using Apache Kafka[1]. The reactive part of the CSP agent consumes the data from Apache Kafka and processes the data in its algorithms. The same data stream is used as input to the forecasting models in the DSO agent.
- The second DSO service provides forecasts on the available power capacity by considering historical data and the physical properties of the distribution lines and assets in the grid. The forecast calculation focuses on predictable grid properties like asset overloading and line voltages, which might occur during charging processes. The *Reward Scheme Calculator* compresses the predicted grid state information into a time series of grid-friendliness options, where each option is tagged with a Grid-Friendliness factor $G \in [-1, +1]$. The computation of this factor uses similar logic like the PQ-Indicator and is explained in [6].

The DSO agent contains a *Power Reservation Manager*, which similarly to the Reservation Manager in the CSP agent coordinates the reservation of power at grid connection points. The power reservation implements a *first-come-first-serve* strategy and the reserved power is considered during the calculation of the Reward Scheme.

The remainder of the paper is structured as follows: For each, proactive and reactive part of the system, we first introduce the main ideas and second provide initial evaluation of the approach. Finally, we conclude the paper with a short summary and outlook to future work.

[1] kafka.apache.org/

III. Proactive Part

In the proactive solution of the proposed architecture, it is important to have a good forecast of the grid situation in order to plan future charging processes. Afterwards, the grid-friendliness of a certain charging process can be calculated using optimal power flow calculation. The result is then communicated from the DSO agent to the CSP agent via the Reward Scheme [6]. Via a reservation manager, the charging power can be booked with a first-come first-serve strategy. The focus in this paper is limited to the performance of the prediction models for the power grid.

A. Concept

For the grid prediction part, we considered three different models, namely *simulation-driven*, *data-driven* and a *hybrid* model, which combines the strengths of the first two.

1) Simulation-Driven Model: The simulation-driven model is built on a Newton-Raphson power flow solver using the grid topology (transformer station, feeder lines and grid connection points), recorded measurement data and standard load profiles for each grid connection point. The load profiles are connected to the grid connection points and are adjusted to fit the measured data at the transformer station. The training process for these profiles was done manually using BDEW[2] standard load profiles as basis and parameterizing the type of profile (household, different type of business), the power factor and the amplitude of the peak load.

The advantage of the simulation-driven model is that the current flow and the voltage drop can be calculated for every point in the grid. Thus, these values can be used to calculate and evaluate the impact of an additional charging operation at any point in the grid. After evaluation, the most grid-friendliest charging slots can be extracted and communicated to the CSP agent with certain rewards.

2) Data-Driven Model: The data-driven model uses different data sources, including historical weather (temperature, rain index, sunshine hours and wind) from the German weather service[3], temporal classifications (day time, weekday and working day), historical data of the charging stations (P, Q, S and U), and measured data at the transformer (P, Q, S and U). From the different machine learning methods, the random forest regression showed the best results and was thus used further for model tweaking.

The advantage of the data-driven model is that less knowledge of the grid is required (no topology, no consumption profiles). It purely operates on historical data and thus could be used in a self-improving way by adapting to a changed behaviour of grid users (e.g. adoption of the grid usage prediction if a new PV system is installed in the grid).

3) Hybrid Model: To improve the accuracy of a purely simulation-driven power grid model, we used predicted data from the data-driven model to build a hybrid model. A major improvement is required especially for voltage prediction. The transformer loading (P, Q, S) is already quite accurately estimated with the profiles. The power flow values are only very slightly influenced by the voltage values from the data-driven model. This is due to the fact, that we use PQ load profiles given, where the total power is not depending on voltage values as it is with impedance or current load profiles.

The advantage of the hybrid model is that the current flow and voltage drop can be calculated and the voltage values are much more accurate because they now also include the data-driven predicted voltage oscillations from the medium voltage level.

[2]The German Federation of Energy and Water created standard load profiles for different German consumers [7]

[3]dwd.de

	MAE	MAPE	RMSE	Median Error	Correl
P	11.87 kW	16 %	15.53 kW	9.34 kW	0.732
Q	15.48 kVAr	21.2 %	20.38 kVAr	11.9 kVAr	0.594
S	16.59 kVA	16 %	21.92 kVA	12.95 kVA	0.723

TABLE I: Accuracy metrics of the simulation-driven model.

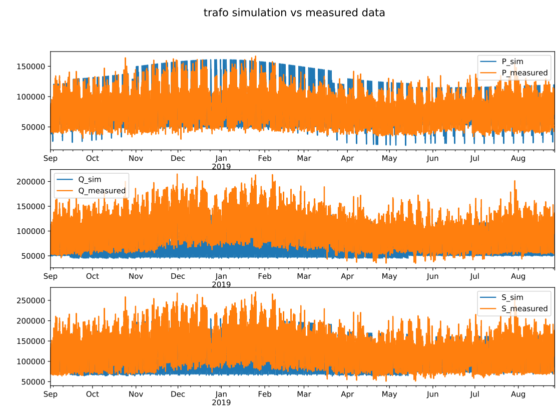


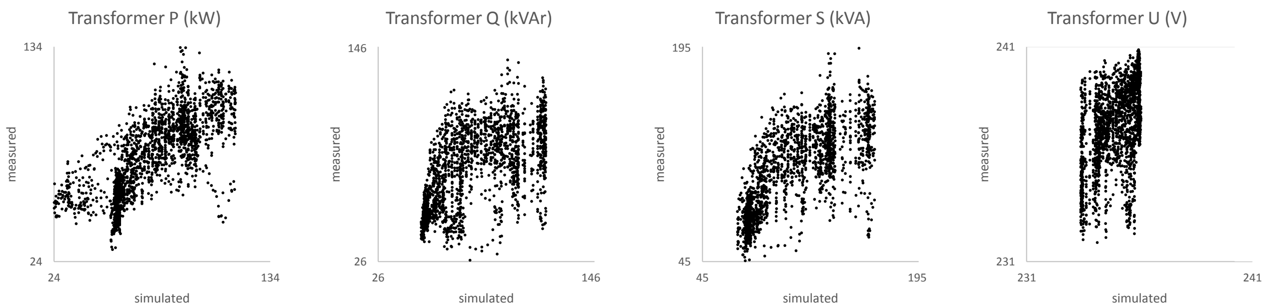
Fig. 2: Long-term simulation accuracy from September 2018 until August 2019.

B. Evaluation

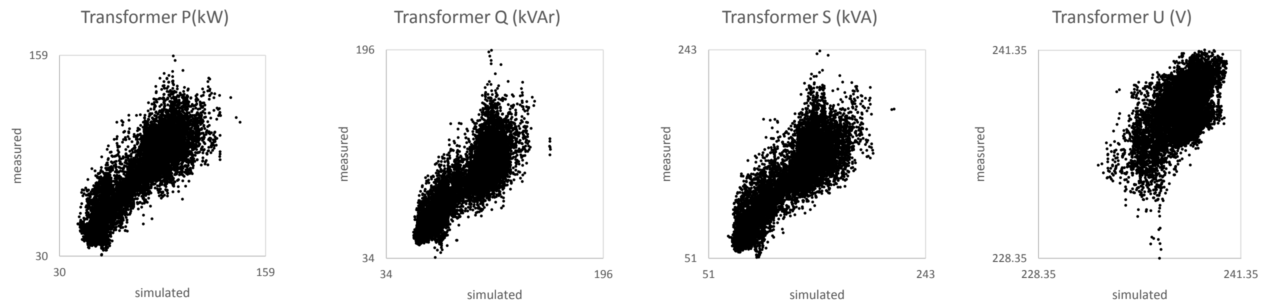
In the following, the testing periods and the accuracy of the three different models are presented.

1) Simulation-Driven Model: The training period for the simulation-driven model is from 23rd April, 2018 until 21st May, 2018. The testing period is from 22nd May, 2018 until 4th June, 2018. In Figure 3 (a), the correlation of the measured loading (y-axis) and the simulated loading (x-axis) of the transformer for *real power* (P), *reactive power* (Q) and *apparent power* (S) are represented. The figure clearly shows the rigidity of the profiles in the stepwise changes of the simulation (multiple measured values on y-axis are simulated with the same value on x-axis). The MAE, MAPE, RMSE, Median Error and Pearson correlation factor of the simulation-driven model within this short testing period are listed in Table I. A MAE of 16 kVA already provides enough accuracy to schedule multiple slow charging operations or fast charging operations by adding an additional safety margin bigger than the expected model error.

In a long-term testing run from 1st September, 2018 until 27th August, 2019 (shown in Figure 2), the Pearson correlation for P improves to 0.815 and the MAE get worse to 13.79 kW (compared to short term test-run in Table I). Similar observation can be seen for Q (correlation improved to 0.682, MAE increased to 28.79 kVAr) and S (correlation improved to 0.79, MAE increased to 26.59 kVA). Only the



(a) Pearson correlation analysis of the simulation-driven model.



(b) Pearson correlation analysis of the data-driven model.

Fig. 3: Comparison of simulation-driven and data-driven model.

	MAE	MAPE	RMSE	Median Error	Correl
P	9.21 kW	12.5 %	11.86 kW	7.68 kW	0.882
Q	12.12 kVAr	13.0 %	15.46 kVAr	10.16 kVAr	0.866
S	14.68 kVA	12.4 %	18.96 kVA	11.36 kVA	0.875
U	1.11 V	0.5 %	1.39 V	0.96 V	0.583

TABLE II: Accuracy metrics of the data-driven model.

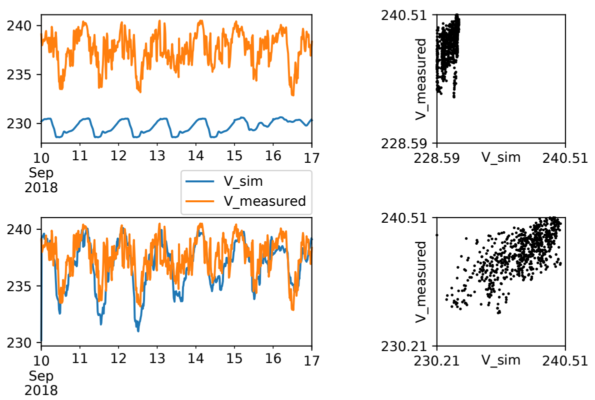


Fig. 4: Voltage prediction of the simulation-driven model (top) and the data-driven/hybrid model (bottom).

real power shows dynamic change in the profiles over the seasons, reactive power and therefore apparent power are have a fixed power factor. An improvement possibility of the simulation-driven model is to use profiles that also add seasonal effects on reactive power.

2) Data-Driven Model: The data set for the random regression tree contains 15-minute resolution power grid data and spans more than one year between 22nd April, 2018 until 20th May, 2019. For training the first 66% of the data set are used, whereas the remaining data serves as test set. The Pearson correlation is shown in Figure 3 (b) and accuracy metrics to evaluate the usability of the model are listed in Table II.

3) Hybrid Model: The data-driven model part for voltage prediction was created the same way as the data-driven model for transformer loading, described before. Figure 4 visualizes the comparison of the purely simulation-driven (top) and the data-driven/hybrid model (bottom) concerning their accuracy in voltage estimation. In the specific period (10th September, 2018 until 17th September, 2018), the MAE improved from 7.87 V to 1.3 V and the Pearson correlation improved from 0.525 to 0.691.

IV. Reactive Part

We propose a decentralized architecture in order to support high scalability, in particular, the controller logic is located at the actuator side, which in our case is the CS, and has no direct communication with other CSs. It is based on high-resolution data collected through *Measurement Points* (MP) in real time. The DSO determines the locations in the power distribution grid and the data resolution of each MP. The data is delivered to an event-driven data collector (e.g. Apache Kafka) via network connection, e.g., using power line communication or dedicated Internet access. In order to keep the transferred data over the communication channel as small as possible and at the same time stable, we apply the messaging pattern of publish/subscribe. Furthermore, OCPP 1.6^+ is used to establish the communication between the smart controlling algorithm and the CSs.

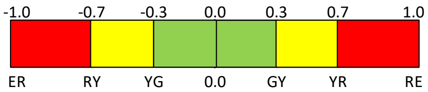


Fig. 5: Traffic light concept of the PQ-Indicator [5].

A. Concept

As described in [4] and [5], the internal architecture of the smart charging algorithm consists of two main components, the *PQ-Indicator* and the *Smart Charger*.

1) PQ-Indicator: The task of the PQ-Indicator is to estimate the grid state using measurement values from the power distribution grid and to indicate the capability of the grid for further charging operations. Each single power quality parameter, such as voltage magnitude, and congestion measurement, such as loading of the transformer, are normalized to the range of $[-1, 1]$. The value -1 corresponds to a drastic decrease of charging power and 1 indicates that a higher charging power can be accepted by the low voltage grid in terms of power quality and congestion. These single *PQ-Indic* values of the different parameters are aggregated in a hierarchical manner such that the output of the PQ-Indicator is a value in the same range of $[-1, 1]$. Within this range, the DSO defines sub-ranges, which can be visualized using the traffic light model similar like in Figure 5. The colour corresponds to the level, how critical the situation is. Within the colour red, a very fast and strong reaction is required, within yellow a smooth reaction is enough and within green the grid is stable and the SC can control the CS based on the users' requirements, e.g. following the reserved charging profile from the proactive part.

2) FSM-based Smart Charger: The SC component internally implements a *Finite State Machine* (FSM). Since the PQ-Indicator differentiates between two different kinds of required reactions, namely, *increase* and *decrease*, two kinds of red (*Red+*, *Red-*) and yellow states (*Yellow+*, *Yellow-*) states exist, one for increase and one for decrease, respectively. However, the current state of the algorithm corresponds to the last determined traffic light colour as depicted in Figure 6. The transition between states depends on the colour of the new PQ-Indic input value, which has a significant role in defining the required reaction. For example, a transition to the red state, independent of the previous state, results in a polynomial increase/decrease of the charging power and transitions to yellow result in a linear adaption of the charging power. Within the green range where the grid is in a stable state, the SC can follow the requirements of the EV user.

Alternatively to the FSM-based solution, a TCP-like SC that incorporates the PQ-Indicator as a notification mechanism about the grid state can be used as well [8]. It considers the previous states of the grid in order to react smoothly and efficiently to the diverse sequence of events in the grid.

B. Evaluation

The aforementioned FSM-based SC is evaluated in a field trial. The location of the field trial is in a small town in Bavaria. The selected grid section connects 22 households, 21 shops and small commercials, three PV systems (with

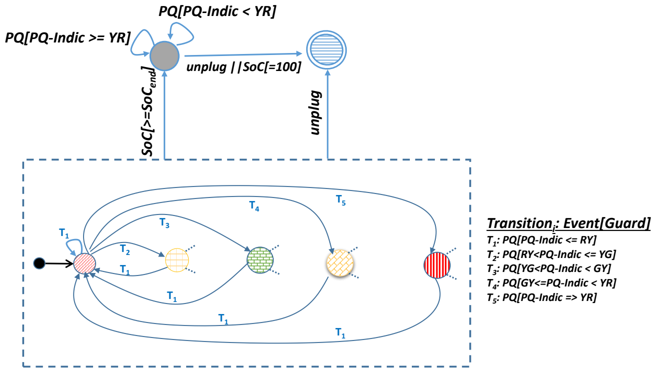


Fig. 6: FSM of the Smart Charger based on the traffic light model [5].

50 kWp) and four charging stations (together 7 AC connectors and one DC connector with total power of 204 kW) to a transformer using 64 cables. A cable with the length of 485 meters gives the maximum distance to the transformer.

From the field trial, we want to gain two main information, first, how EVs are reacting to control signals send from the SC to test the controllability and, second, how well the SC performs in real world scenarios to evaluate its impact on the power grid.

1) Controllability: Figure 7 depicts three important behaviours discovered during a ramp up of the charging power by the SC. As can be seen in the first red circle, the initial charging power is set to 18 kW (9 kW for each of the two connectors), but the connected EV drains only 6.1 kW real power instead of expected 9 kW from the grid. Instead, 9 kVA apparent power is measured during this period. The reason is the bad power factor of the rectifier at that power level. After the SC changed the power limitation to 26.76 kW (13.38 kW per connector) in the second red circle, the EV first stops the charging process for a short moment, but finally reaches the desired level after restart of the charging operation. This re-initialization of the charging process happened only once out of five tests with the same power level and takes approximately 26 seconds. In continuing tests, four other EVs of the same manufacturer did not show this behaviour at all. Finally, highlighted in the third red circle, the charging signal change to 35.52 kW (17.76 kW per connector) resulted in an only very small increase of the drained power of the EV and even further increase did not have any effect. As against to the specification of the used EV (maximum of 22 kW), the maximum power level reached only 12.70 kW (13.36 kW) with power factor of 0.95 lagging for unknown reasons.

Except from some outliers in Figure 8, the power factor continuously increased with the attached charging power. We can conclude that reducing the power level at charging stations does not linearly reduce the used real power, as reactive power consumption increases. It is important to note, that the power factor is lagging, hence the load is inductive, which is also typical for households. A leading power factor would be more beneficial with regard to voltage level stabilization at wallboxes, because it could compensate the reactive power at households.

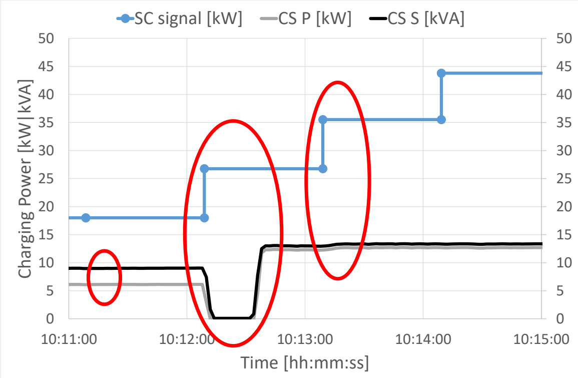


Fig. 7: Controllability of the EVs.

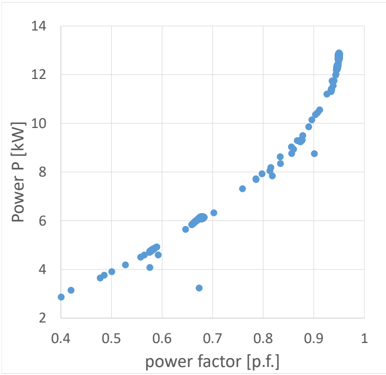


Fig. 8: Reactive Power behaviour of the EVs.

2) Impact: During a longer charging operation, depicted in Figure 9, we analysed the impact of the SC on the transformer loading. This scenario was created with very close transformer loading thresholds in order to see the reaction of the four connected EVs with a total controllable power between 36 and 88 kVA. The impact on the voltage is negligible, because all charging stations are placed near to the transformer.

The background colouring of Figure 9 shows the PQ-Indicator configuration with regard to transformer loading. The yellow area at the bottom corresponds to *Yellow+* (linear increase) and the green area above corresponds to the stable values green (increase is up to the SC, but as the charging profile is defined to be the maximum charging power of the EV, also linear increase). The yellow and red area above correspond to *Yellow-* and *Red-* and result in a linear and polynomial decrease, respectively. In the area above red, the SC decreases the charging power with the maximum configured value in order to avoid voltage swells. The three curves show the behaviour of the SC (blue) and the estimated baseline scenarios with uncontrolled charging (green) and no charging at all (red). During this charging period, the SC was able to reduce the peak loading by 13.5 %, while increasing the power consumption in the valleys, such that the standard deviation of the transformer loading reduces by 44 %. In that specific scenario, the SC reactions reduced the overall delivered energy to 61% compared to the uncontrolled baseline scenario.

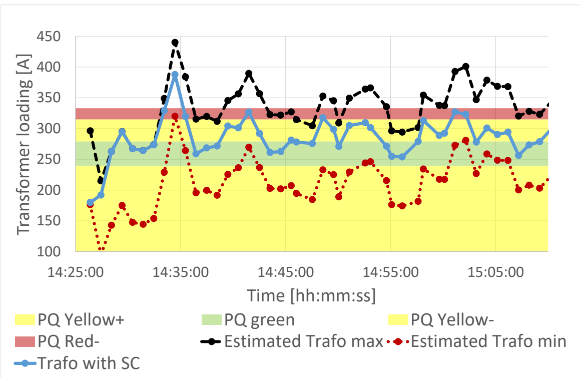


Fig. 9: Impact of the Smart Charger.

V. Conclusion and Future Work

This paper proposed a complete architectural concept towards grid-friendly electric vehicle integration by separating the proactive planning part and the reactive control part. The forecasted grid data - obtained using different forecasting models - is made available to the charging service provider via the *Reward Scheme*. After selecting a suitable charging profile, the smart charger avoids congestion and voltage problems, while following the users' demand. Furthermore, both concepts are evaluated using field trials, which underlines the applicability to real world scenarios.

In the future, the interoperability of both concepts will be investigated deeper, more particular, how both, proactive and reactive, interact in real life scenarios.

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