European Research Infrastructure supporting Smart Grid Systems Technology Development, Validation and Roll Out

User Project Technical Report

USER PROJECT	
Acronym	**AQUA**
Title	**A**nalysis of power **QUA**lity through smart EV charging processes
ERIGrid Reference	**01.013-2016**
TA Call No.	**Call 1**

HOST RESEARCH INFRASTRUCTURE			
Name	**AIT SmartEST**		
Country	**Austria**		
Start date	**30.10.2017**	**Nº of Access days**	**14**
End date	**01.12.2017**	**Nº of Stay days**	**15**

USER GROUP	
Name (Leader)	**Prof. Hermann de Meer**
Organization (Leader)	**University of Passau**
Country (Leader)	**Germany**
Name	Ammar Alyousef
Organization	University of Passau
Country	Germany
Name	Dominik Danner
Organization	University of Passau
Country	Germany

1. Research Motivation (objectives, Scope)

The electrification of the mobility sector is seen as an opportunity to act as a compensatory element for volatile generation. This electrification comes with multiple challenges such as the lack of information on when, where, how long and how fast charging processes of electric vehicles, which poses the major challenges, especially for a *Distribution System operators (DSO)*. Furthermore, the unknown grid perturbations of electric cars in single or parallel operation must also be sufficiently well understood. Similar to the volatile feed-in structure, peak loads must be avoided but sufficient capacities for the charging processes must still be provided. To this regard, a good power planning is required to minimize the cost of upgrading the power grid to hold on the increased demand caused by charging processes. In addition, a mechanism for supporting the stability of the grid in terms of overloading the grid elements or other power quality issues can help DSOs in many cases, this mechanism should be decentralized to meet the scalability requirements.

In this project, we propose to analyze the stability of the grid by studying its power quality through the setting up of an ecosystem consisting of DSO, Charging Station Operator (CSO) and EVs. For this analysis, the utmost priority is the provision of such an ecosystem through the combination of both real physical and simulated environments. The main objective of this project is developing a decentralized load management controller that takes the power quality of the grid into account.

2. State of the Art

Potential impacts of introducing a large number of EVs to the power distribution network have been studied extensively in the literature and many ideas have been introduced to use the EV penetration for supporting the grid stability and power quality.

2.1 Approaches for Charging Management

We can classify these solutions in the following categories:

• Challenges in terms of power quality are tackled by the design of a new charging connector or a complete new design of a charging station with a power-quality compensation for electric vehicles as in [14, 18, 19, 21, 22]. This class of solutions is not relevant to our study since we solve the problem using the legacy hardware and software and validate our proposed architecture with real hardware in the loop simulation.

• Scheduling algorithms have been proposed to shift the EV charging load to off-peak hours, thereby avoiding branch congestion and voltage drop in the distribution network. Most existing work suggest a centralized controller for the load of EV charging. For example, [4] propose master-slave control scheme for the PEV smart charging in purpose of increasing the number of PEVs that can be plugged into a single circuit avoiding grid bottlenecks. Other centralized solutions are investigated by [6, 13, and 16]. However, as discussed in a white paper [17], coordinating control at different levels becomes infeasible with such centralized control.

• Instead of using a centralized approach, some authors propose a decentralized or hierarchical charging schedule [1, 5, 9, 15]. Most of them are off-line algorithms that decide based collecting data about the grid 24 hours ahead. Furthermore, they consider real-time load balancing as the only grid stability constraint and completely ignore the voltage control.

• Ardakanian et al. [3] propose a distributed control algorithm that adopts the charging rate of EVs to the available capacity of the network ensuring that network resources are used efficiently and each EV charger receives a fair share of these resources. Their algorithm requires a heavy and synchronous communication overhead and considers the stability of the grid in terms of load balancing ignoring the voltage control completely.

2.2 Approaches for Charge Control

Other way to increase the penetration of EV into the grid is to have a controlled charging process reacting in real time to the changes of the different local or global parameters of the grid. Authors in [10] discuss three different types of charge control approaches, local voltage driven, central-power driven and a combination of these two. The decentralized approach is like the proposed approach in this paper but ours is more sophisticated and consider a dynamic change of the charging capacity regarding to the different situations of the grid. Foster et al. [8] propose a PEV charging policy that considers transmission and distribution integration issues and reacts to market signals across time scales and systems. Furthermore, voltage support for the distribution network is introduced in terms of allowing increased penetrations of distributed photovoltaic (PV) solar arrays. The authors considered only the local voltage near to the CS and ignore considering the situation at the transformer or other critical points in the low voltage grid or the fairness between the running charging process, which are the main concerns of our proposed architecture. Other solutions propose a local smart charging algorithm based on a droop controller [2, 12] and is able, without relying on any vehicle-to-grid capability, to mitigate line voltage drops and voltage unbalances. These solutions are based on estimating the voltage locally without considering the situation at the other critical points in the grid which can need different reactions at some times.

2.3 Contribution

The large majority of related works have studied scheduling for peak power reduction. However, besides line and transformer loading, voltage constraints play also a significant role in restricting the hosting capacity of European distribution grids [20]. Therefore, our work differs from the aforementioned categories in the following points: We propose a completely decentralized smart charging approach considering the real-time conditions of the grid by an event-driven architecture that collects data from different points in the grid. Our approach also considers a smooth changing of the used charging capacity to avoid drastic changes of the states of the grid. We consider as input parameter of our smart charging solution both, the overloading of the grid elements (specifically the transformer and feeder lines) and the voltage magnitude at the CS and critical points in the grid.

3. Architecture

The objective of the proposed architecture in Figure 1 is to stabilize the grid and its power quality. In order to monitor the power quality, it’s essential to measure voltage, current, frequency, harmonic distortion and waveform at different points of the grid (measurement point **MP**). In this architecture, the power quality is indicated by some Key Performance Indicator (KPIs), e.g. voltage level at certain points of the grid or overloading of some grid elements such as the transformers. These KPIs are measured directly at some points by some measurement devices in real time or computed based on the measured values. Since the proposed architecture should response in real time to the different PQ-issues in purpose of supporting the grid stability, a real-time data stream in high resolution is required (e.g. 3 seconds of resolution). On one hand, a real-time handling of big data streams requires a data processing architecture which should be generic, scalable and fault tolerance. On the other hand, the measured KPIs are important only if it is beyond a certain threshold in terms of PQ (For instance, beyond ± 10% of nominal voltage). Hence, an event driven architecture (KAFKA in our case) is proposed for triggering about some events in the grid (for example, high/low voltage) which need a special reaction from the consumers of the variable load (e.g. charging stations CS). A component called PQ-Indicator runs on the level of the charging station responds to the triggered events (Key, Value) and estimates the grid status based on different KPI values of these events. For example, it monitors the voltage of the part of the grid its charging stations are connected to. In case of voltage fluctuations (e.g. degradation of the power quality), it gradually asks the Smart Charger (SC) to decreases/increases the charging rate with the hope that this can lead to flatten the voltage fluctuation and hence improve the power quality. The indication is defined as a scale value within [−1, 1], called ’PQ-Indic’. Whereas (-1) means stop charging completely, (+1) means using the maximum capacity of the CS. The output of the PQ-indicator is used by a component called Smart Charger (SC) whose responsibility is to apply a smooth or drastic change in the used charging capacity regarding the value of "PQ-Indic". Hence, SC considers the concerns of the grid as a highest priority without ignoring fully the requirements of the charging process when the grid is stable.

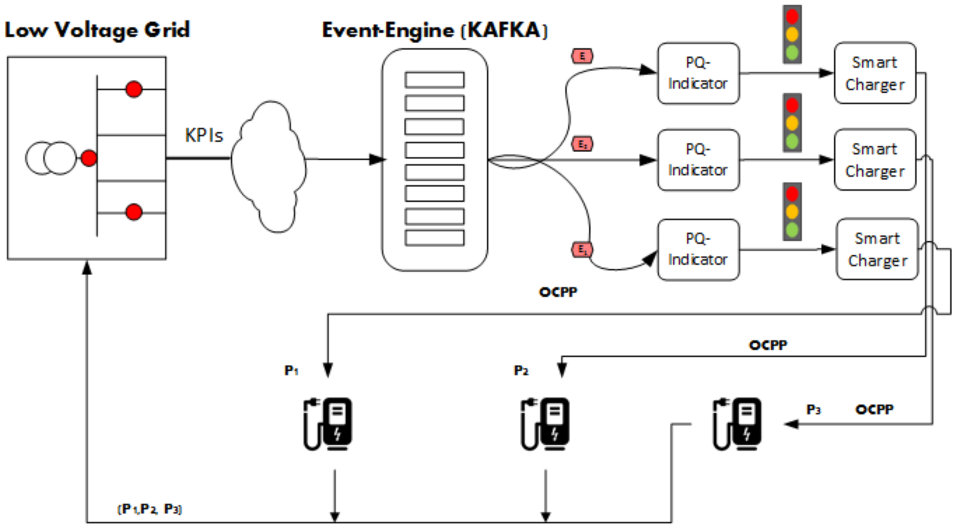


Figure 1: Schematic of Smart Charging Architecture

To enable this kind of capacity limitation, an already developed generic protocol is used for communicating between the SC and the CS. This protocol is called OCPP ("Open Charge Point Protocol") and last version is 1.6 and the next version 2.0 will be released at the end of 2017. OCPP 2.0 allows Central Systems and Charge Points (connector), that both support the Smart Charging Profile, to cooperate with smart charging of electric vehicles. Where a charge connector or a central system or both can set constraints to the amount of power that is delivered during the course of a charge transaction. Enable smart charging profiles to the infrastructure will enable charge point operators to provide dynamic charging profiles to the charging station installed. This will allow the definition of charging profiles related to a location or even a charging process itself. Within these profiles, charging stations will now be enabled to react to specific behaviors directly without further control. Furthermore, reserving the CS with a certain charging profiles considering both the power requirements of the car and the available capacity in the grid will allow for a better power planning of the charging processes in the future

4. Tests and Experiments

The test targets to investigate the reaction of the smart charging algorithm in the different situations of the grid. It starts by using very small grid (in terms of nodes number) containing a transformer of relative small capacity and four households. The goal of using this grid is to simplify the tuning of the algorithm and testing the proposed functionality of the Smart Charger. The experiments in this Phase targets to test:

1. Termination of the algorithm.
2. The algorithm in real environment in term of load profiles with (out) integrating of renewable system.
3. The Behaviors of the SC with fixed load profiles but the charging profiles start with different values (2.6, 3.9, 5.2, 6.5 kW).
4. The Convergence of multiple SCs.
5. The controllability of the car depending on the SoC.
6. Different reaction rates of the SC (20, 30, 40, … Seconds)

Later we repeated similar tests using a larger model of a municipal area (around 60 nodes), where the supply lines are rather short (a few hundred meters). The different positions of the SC are tested in terms of the distance to the transformer, PV system, and position at the line.

Table 1: Characteristic of real low voltage grid in "Vilshofen-Germany

Grid element	Amount	Characteristics
Transformer	1	400kVA
household	19	
industry/Business	20	
PV-plant	3	2x20kW und 1x10kW
Cable	64	150mm², 95mm², 50mm², 35mm², 25mm2, 16mm²

During the setup all measureable parameters at the charging station, including active power, reactive power of each phase, power factor, frequency, current and voltage, are measured from the hardware-in-the-loop (HIL) equipment using DEWESoft measurement device and a resolution of 10 kHz. The voltage and current are stored in synchronous way and asynchronous data with a resolution of 200 ms is available. Software parameters from the simulation environment, including algorithm input, output and data from the power grid simulation, are stored in an influxDB in a 5 second resolution.
In the AIT Lab we measured several types of EVs that are listed in Table 2. The charging station in the Lab supports one Type 2 connector that can deliver up to 22 kW power. This charging station can be controlled either by OCPP 1.5 or via dedicated Modbus.

Table 2: List of all tested EVs

Car type	Emulated	Real	Number of phases	Maximum charging power
Renault Zoe	x		3	22 kW
Tesla P90D	x		3	11 kW
Nissan iMiev	x	x	1	3.7 kW
BMW i3	x		1	7.2 kW

The details of all performed tests are depicted in Annex A

5. Results and conclusions

In order to develop an effective charging algorithm in term of PQ, multiple experiments in the Smart Lab are performed with different goals. The results of these experiments should reflect a deep understanding of the grid, e-cars and perturbation of the charging processes on the grid. This knowledge should help to make the change of the used capacity smooth and considers the real needs of the grid and the actual consumption of the car during the charging. Hence, we classified the results in four categories:

I. Real/Emulated EV behavior on control commands

Nowadays charging stations communicate rarely with electric vehicles. The only possibility to control the EV emulation model and the real EV in the Lab is to change the current (I) that is provided by the charging station and the cables. This value is forwarded to the EV via a PWM signal on the Type 2 connector and is valid for each phase of the connection, hence phase balancing is not possible with the hardware at the Lab. Since the design of this protocol only considers integer current values, the maximum charging capacity can only be controlled in discrete steps. The charging station in the Lab supports 3 phase charging from 6 to 32 A. Hence, the maximum charging power is 22 kW. For example, the BMW i3 charges only on one phase and the control steps are given by 1.3 kW, 1.6 kW, etc. We run tests with different EVs and different State of Charge (SoC) in order to understand under which conditions the EVs are controllable. With the available equipment. For this purpose we investigate two points using different cars models: Renault Zoe, Nissan iMiev, BMW i3, and Tesla P90D.

- Constant Current – Constant Voltage behavior of EVs

  Charging a battery is done normally in two phases. First the battery chargers with a constant current phase, at which the cell voltage of the battery increases. After reaching a certain threshold, the cell voltage stays constant, while the charging current decreases. In EVs a battery management system (BMS) is placed between the charging station and the battery cells. This management system regulates the charging current from the charging station to charge the battery most efficient, e.g. it can balance the charge between the single battery cells. The BMS also can hide the constant voltage phase of the battery by simply charge only until the end of the constant current phase. In order to see the reaction of the car, when reaching a high value of SoC (where normally the constant voltage phase of the battery starts) we tested to charge different emulated cars with a starting SoC of 80 %.

  - **Renault Zoe (3 phase up to 22 kW):** As depicted in Figure 2, from SoC around 90% the Zoe limits the charging current to 2.43 A per phase, which result in 7.3 kW. The end of the charging process is an abrupt stop.

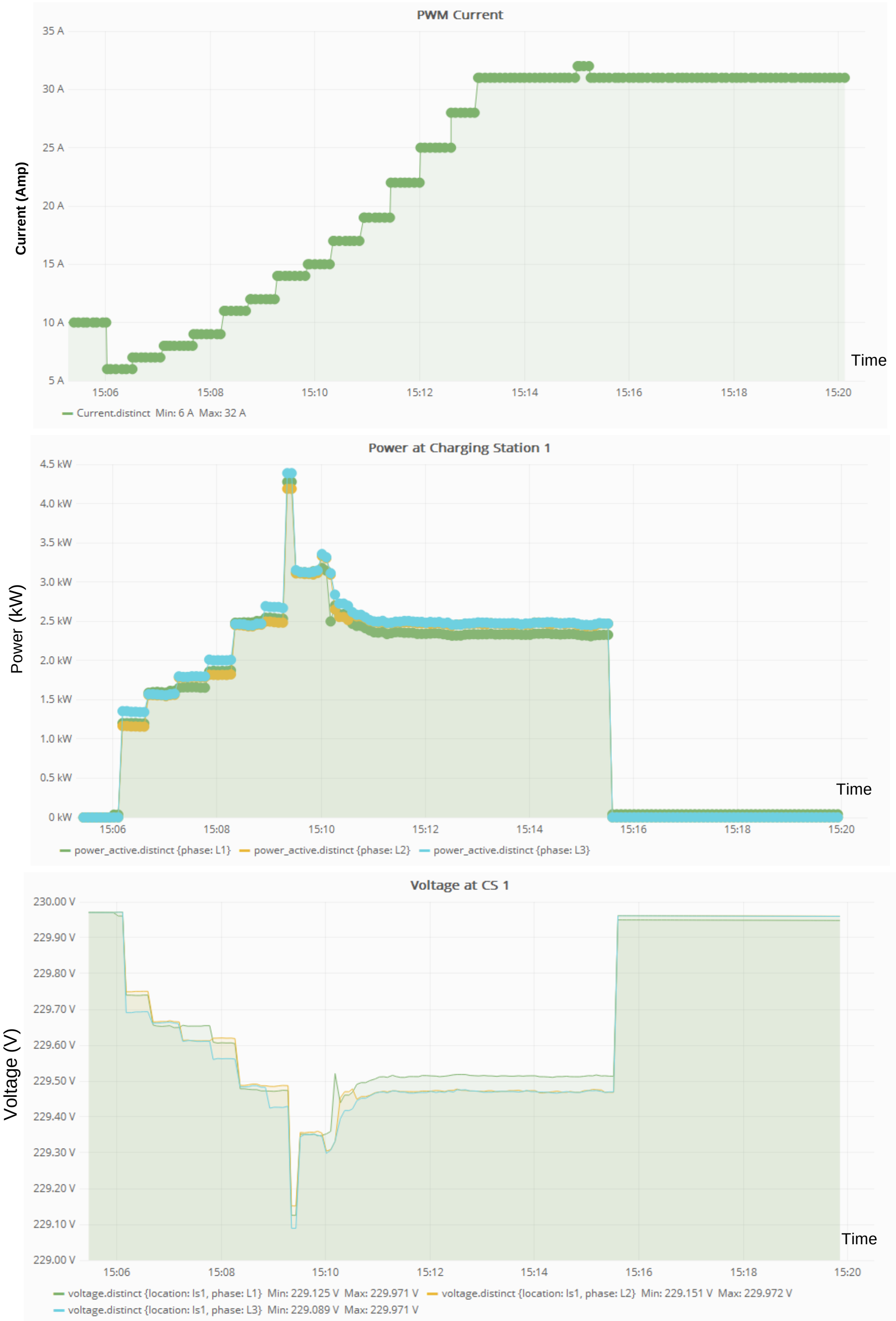
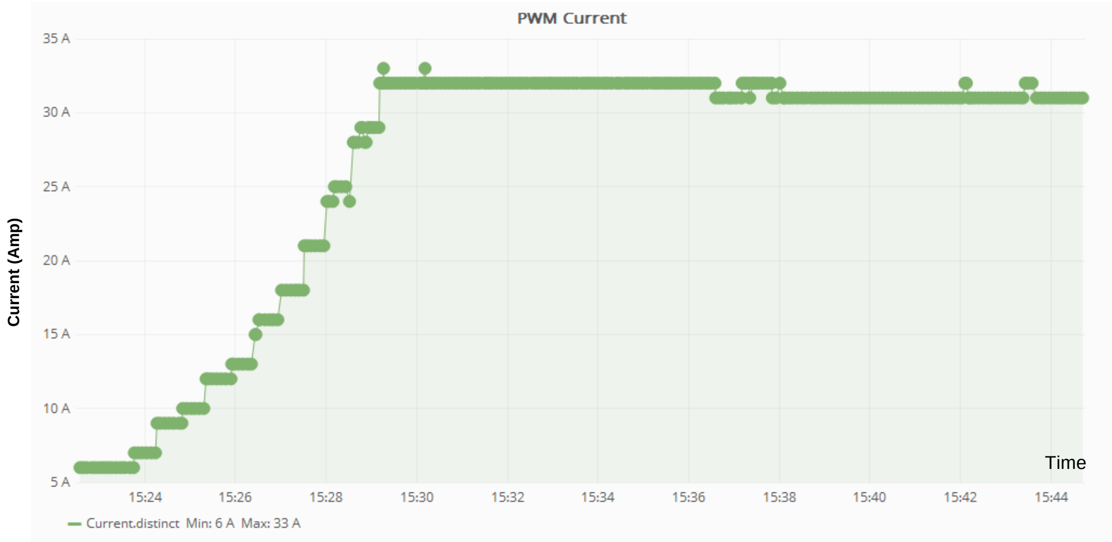
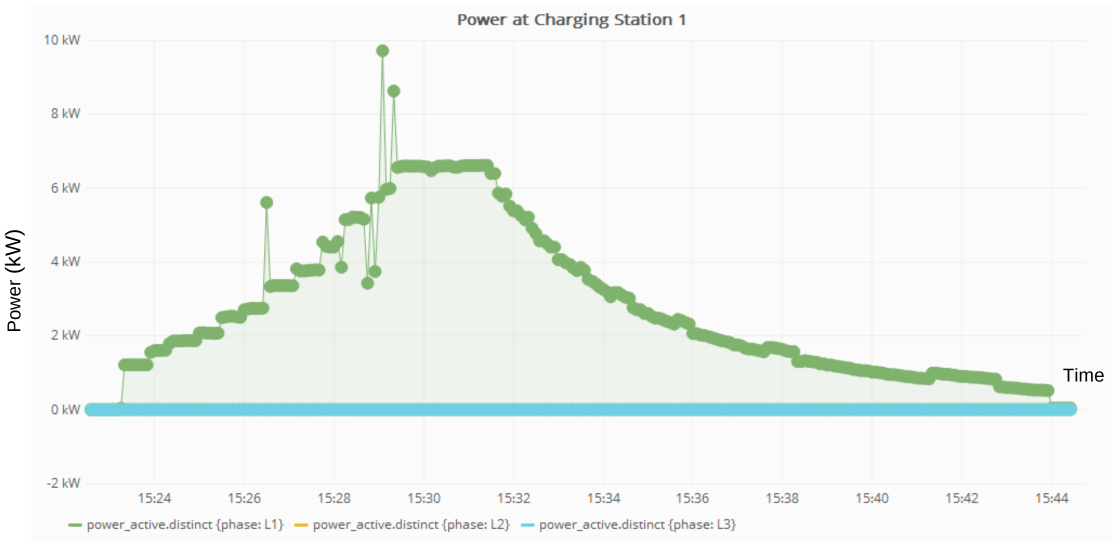


Figure 2: Charging Process of Renault Zoe starting with SoC 80%. This car limits the charging power to 7.3 kW until it reaches 100% SoC.

- **BMW i3 (1 phase up to 7.2 kW –measured with 6.5 kW):** As depicted in Figure 3, from SoC around 90 % the i3 slowly reduces its charging power with a logarithmic curve. The charging process stops with the lowest value of 515 W.





a

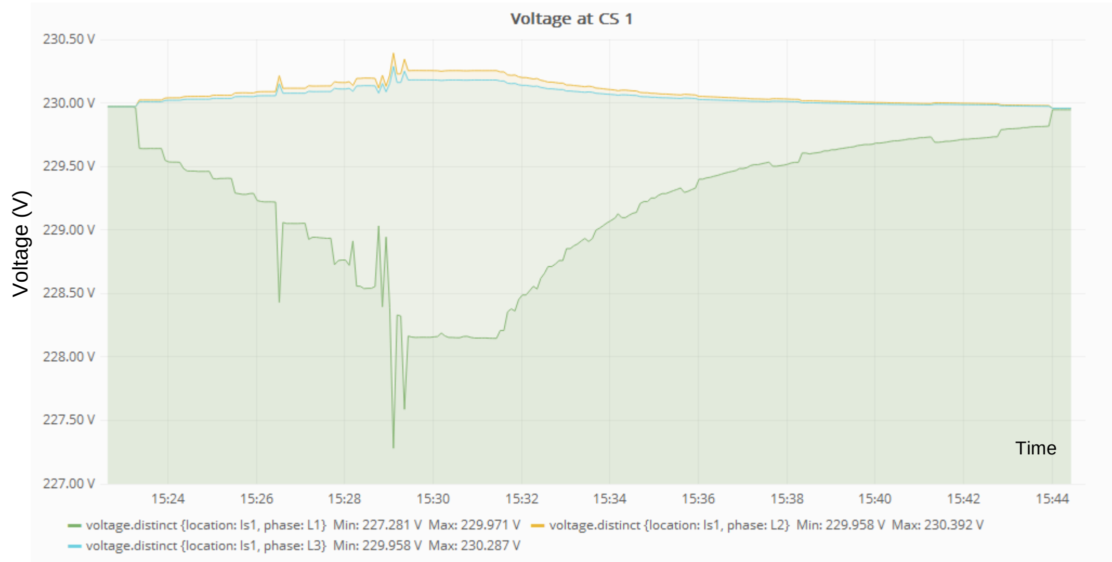
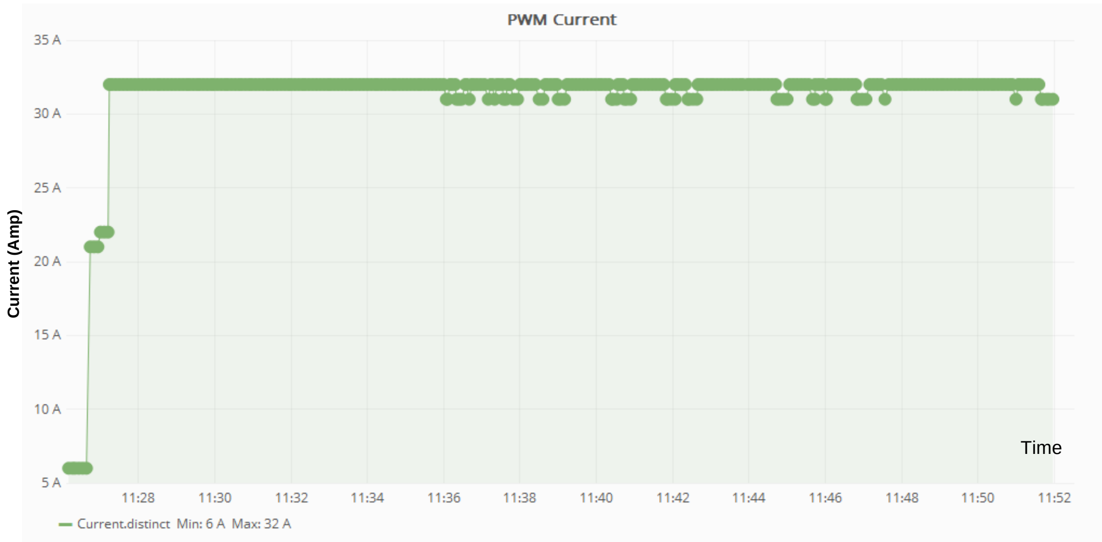


Figure 3: Charging process of BMW i3 starting with SoC 80 %. This car slows down the charging rate

- **Tesla P90D (3 phase up to 11 kW):** as depicted in Figure 4, the Tesla charges with the maximum charging speed until the SoC of 100%.



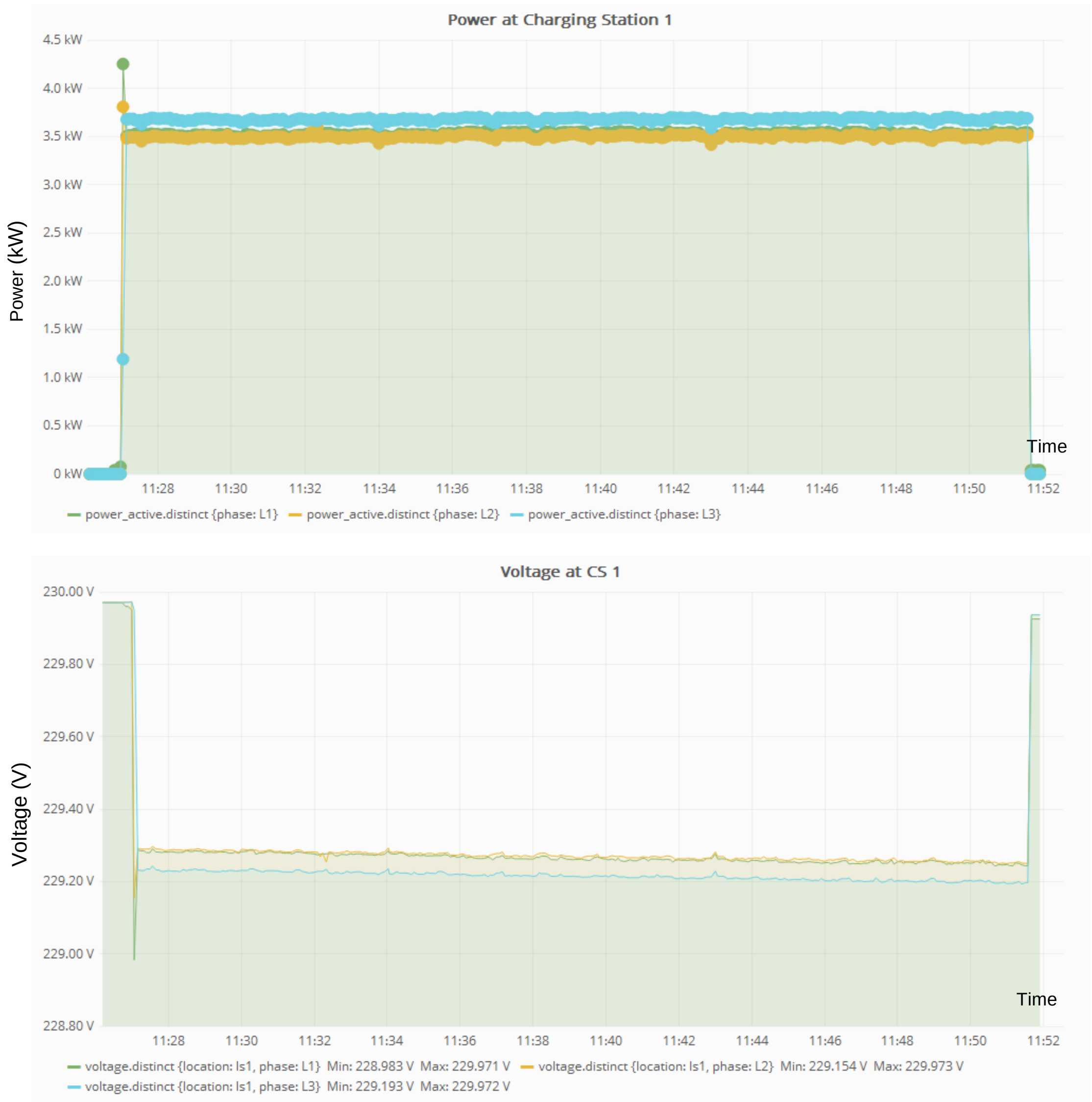


Figure 4: Charging process of Tesla P90D starting with SoC 80%. This car charges until 100% with the maximum available power.

In the previous 3 Figures (2, 3, and 4), we can see some spikes when the charging power changes. These are not reactions from the car, but are due to switching at the RLC load that emulates the different car types.

- ### Reaction on control commands

Aside the different charging phases of the EVs, we wanted to know the EVs react on control commands that are sent to the charging station. From the previous Figures we can see that during the constant current phase, the car changes the used power according to the input current PWM value that constantly increases in the beginning of the charging process. In the following we tested the reaction of the real and emulated car with different levels of PWM changes. The SoC of the cars always is equal to 0% (except the real car with SoC of 80%).

- **Renault Zoe (3 phase up to 22 kW):** we set several start values for charging with a SoC of 0 %. The car accepted all proposed current values directly (with a certain short delay). One thing that can be seen, is that the charging station consumes energy unbalanced from the grid. This is because of the construction of the charging station itself. The whole charging station electronics are connected to phase 1 and consume a standby power of 36 W. In the following figures the direct reactions on control signals of the Renault are shown (see Figure 5).

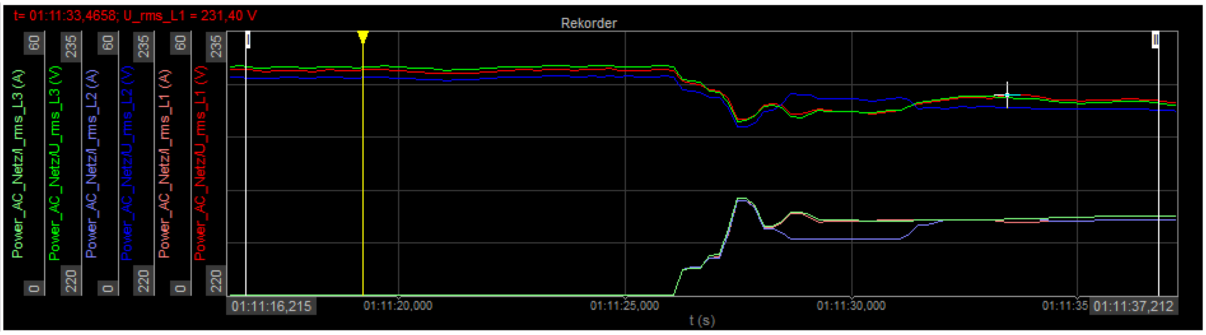


Figure 5: Renault Zoe starting with 11.7 kW.

- **Tesla P90D (3 phase up to 11 kW):** In contrast to the Renault Zoe, a Tesla P90D starts its charging process totally different. The figure 6 shows the starting phase of the Tesla using the charging power of 11.7 kW. The Tesla activates the charging processes phase by phase.

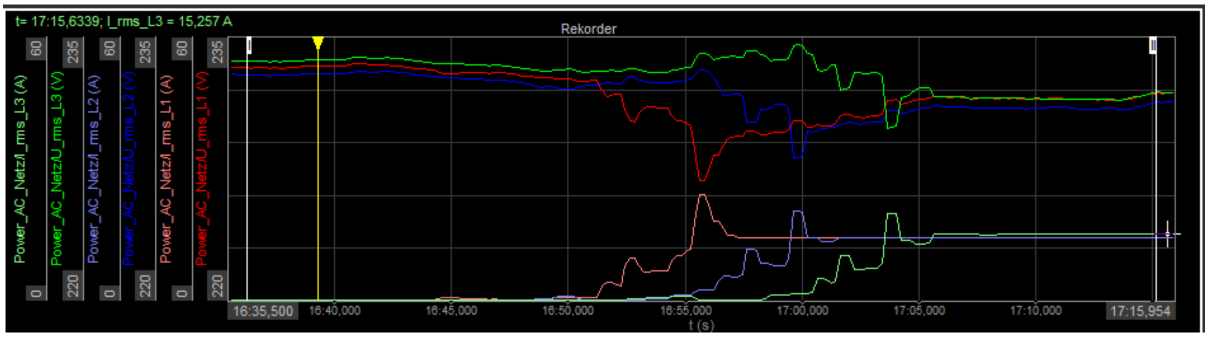


Figure 6: Tesla P90D starting with 11.7 kW (charging station alows 19.5kW, but the car only uses 11.7 kW). The three phases are activated one after each other. The last part of this figure shows the detailed change of current and voltage during the starting phase in 200 ms resolution. The spikes after each small change are due to switching operations of the RLC load.

- **Nissan iMiev (1 Phase 3.7 kW):** also implement a “slow starting phase”, this car simply increases the charging power linearly until it reaches the desired maximum (see Figure 7).

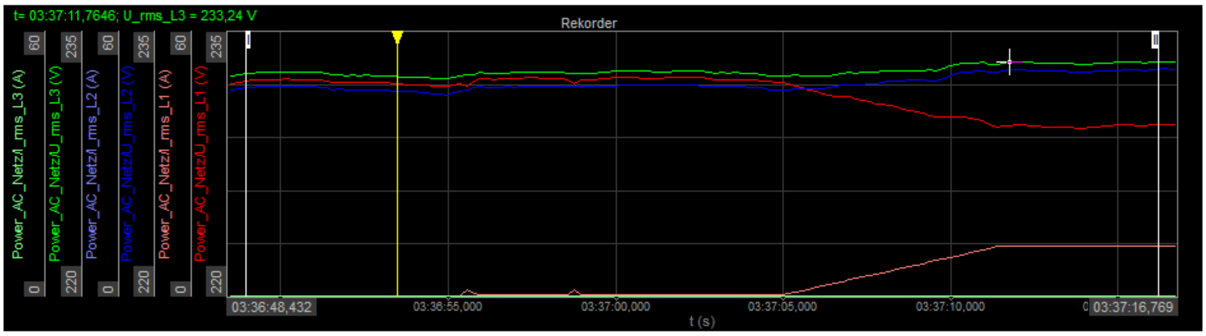


Figure 7: Real Nissan iMiev starting with 3.7 kW. The power is linearly increasing until it reaches the desired maximum.

<u>Conclusion</u>: Apart from the before tested cars, we assume that many other cars, but not all, have implemented some "slow start phase". In order to guarantee a smooth start for the grid, we should implement a grid friendly starting phase that can be applied to each car.

II. Which effect can we expect from EV Charging on the Grid in terms of power quality?

In order to design an appropriate smart charging algorithm, we first need to investigate what grid effects we can expect, when a real or emulated electric vehicle changes its charging behavior (either on its own or via a charging control signal). For this reason, we set up and carried out several experiments as follows.

- Charging EVs with different SoC during the constant current and the constant voltage charging phase.
- Testing different emulated vehicles (Renault Zoe, BMW i3, Tesla P90D, Nissan iMiev)

As can be seen in Figure [5, 6, 7], the voltage level at the charging station directly depends on the increasing charging power. The depth of the voltage change is given by the line length between the transformer and the charging station.

Furthermore, we measured power factor of the real car, Nissan iMiev, during different charging currents and the power factor is always better than 0.9863 during all test with that car. The nature of the power factor is capacitive. As depicted in Figure 8, the power factor of this car changes with the applied PWM current. The higher the charging current, the better the power factor. Note, that the Nissan iMiev can charge with only 3.7 kW on one phase.

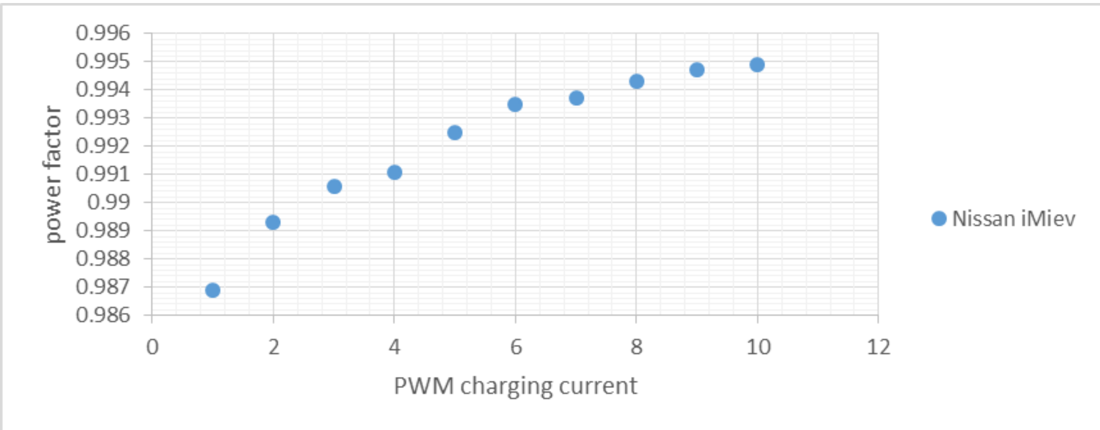


Figure 8: Power factor of the Nissan iMiev with different PWM currents

Since the DEWESoft measurement device record data in 10 kHz resolution, we can extract up to the 40 harmonic order of the real Nissan iMiev car charging at different levels. From Figure 9, we can see that the highest harmonics are in the order 3, 5, 7 and 11. Over the range of charging current from 0A until 14A.

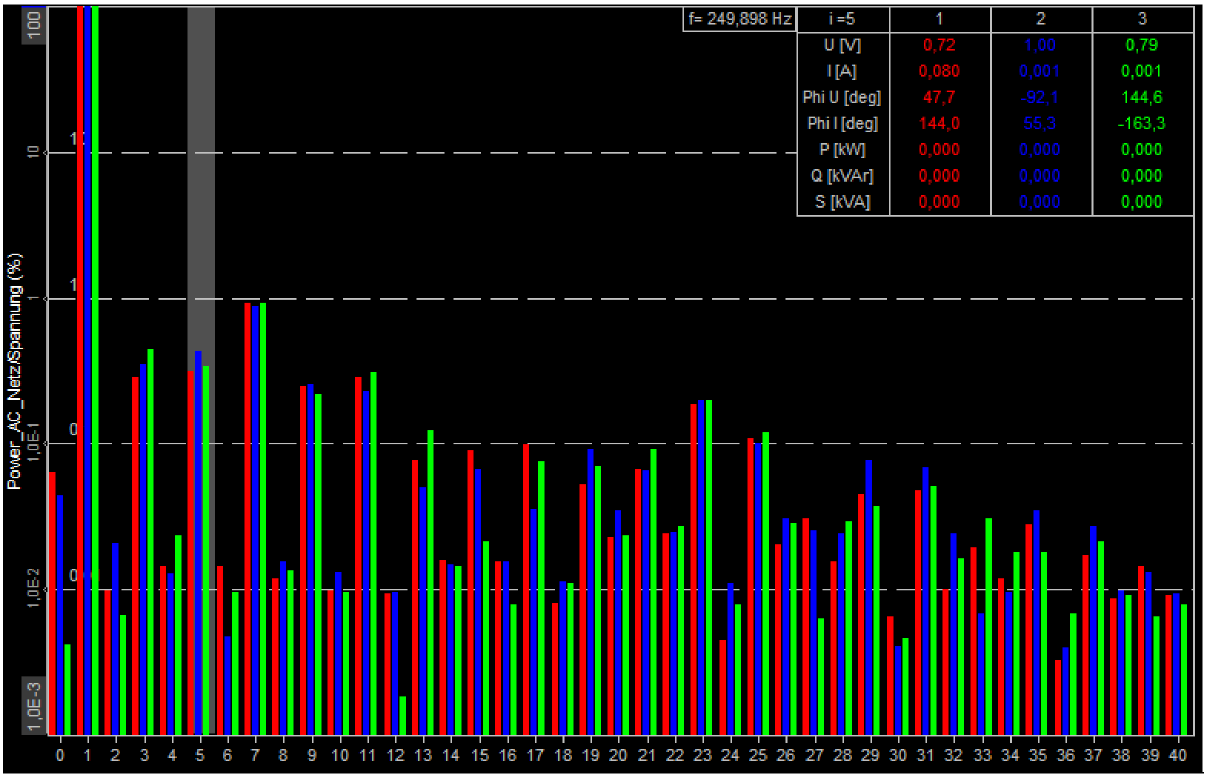
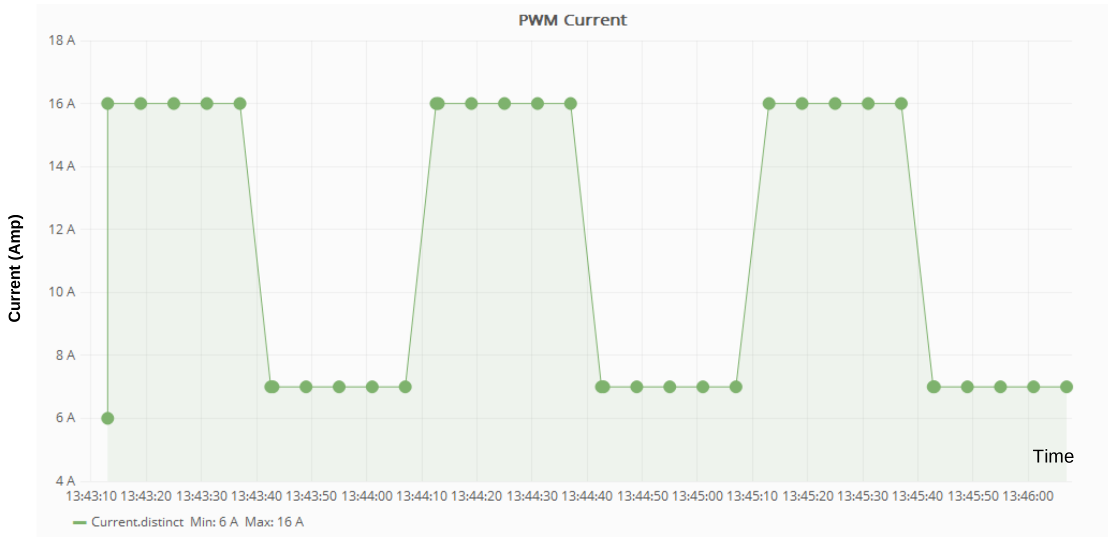


Figure 9: Harmonics of the Nissan iMiev charging with 14A

Unfortunately, it was not possible to measure the power factor nor the harmonic effects of different cars, especially at higher power values around 11 kW or 22 kW, since the EV emulation model does not support this feature.

A simple experiment with alternating charging power of 3.7 kW and the maximum power of 22 kW is depicted in Figure 10.



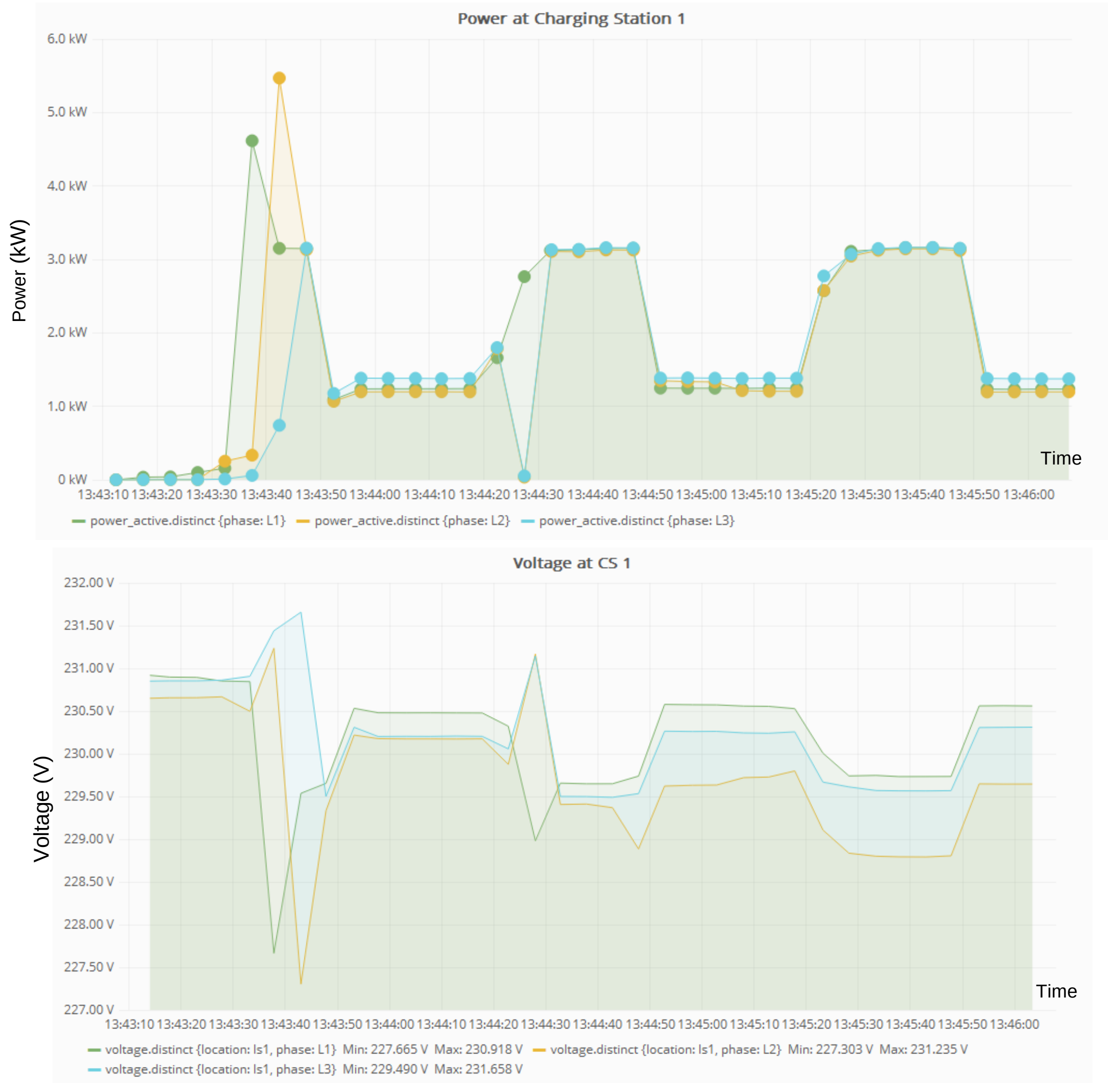


Figure 10: Renault Zoe reaction on alternating charging currents.

III. Evaluation of Smart Charging Algorithms

We evaluated the Smart Charging algorithm defined in ELECTRIFIC on several different grid situations, e.g. with high renewables, high voltage drops at the charging stations and using different types of cars. In the following we present two of these scenarios.

➢ Impact of the reaction of the Smart Charger on the grid

The first evaluation is carried out on a small grid with only 4 household loads and up to 3 charging stations that can operate in parallel. During the evaluation we configured the PQ Indicator and added some fine tunings to the smart charger for better performance and appropriate reactions.

The Figure 11 shows the reaction of the Smart Charger on the small grid with only one active charging station. The top part shows the voltage fluctuations on the grid that are due to one second based load profiles attached to the 4 household loads. The second subgraph shows the initial version of the PQ Indicator that simply looks at a certain moment of the gird and calculates the PQ-Indic value. The next three subgraphs refer to the Smart Charger output, the hardware current that is set to the HIL charging station and the measured consumed power from the attached car. As can be seen, the Smart charger reacts according to the PQ Indicator output and can control the voltage in a way that it stays in given boundaries. The result of this experiment is that a very short voltage drop (11 seconds like in the red circle) can trigger the Smart Charger (which operates in 30 second turns) to reduce the charging power, even so the reaction of the Smart Charger and the car is to slow to compensate this problem.

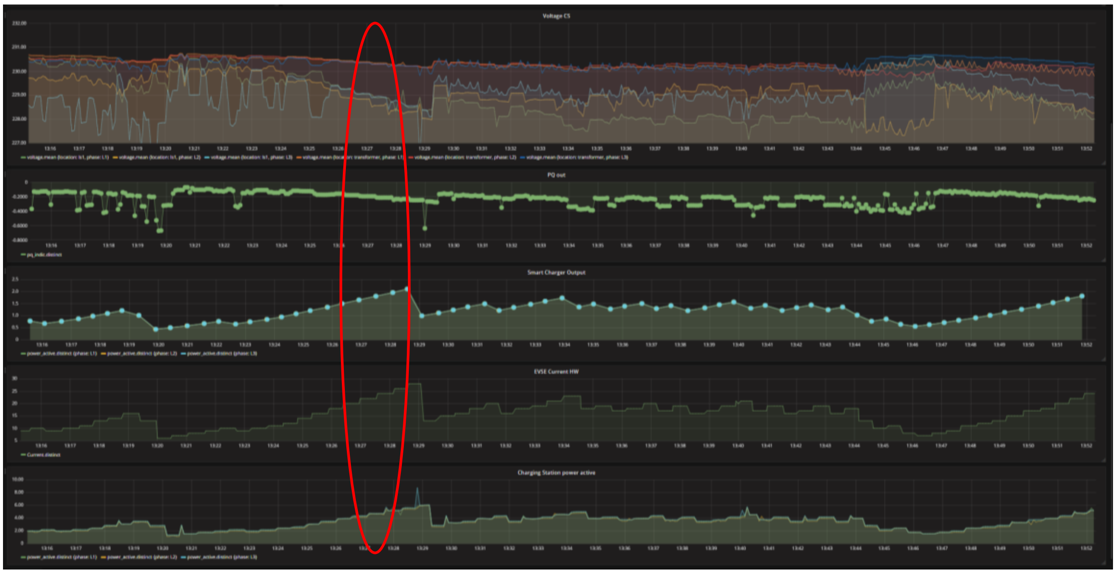
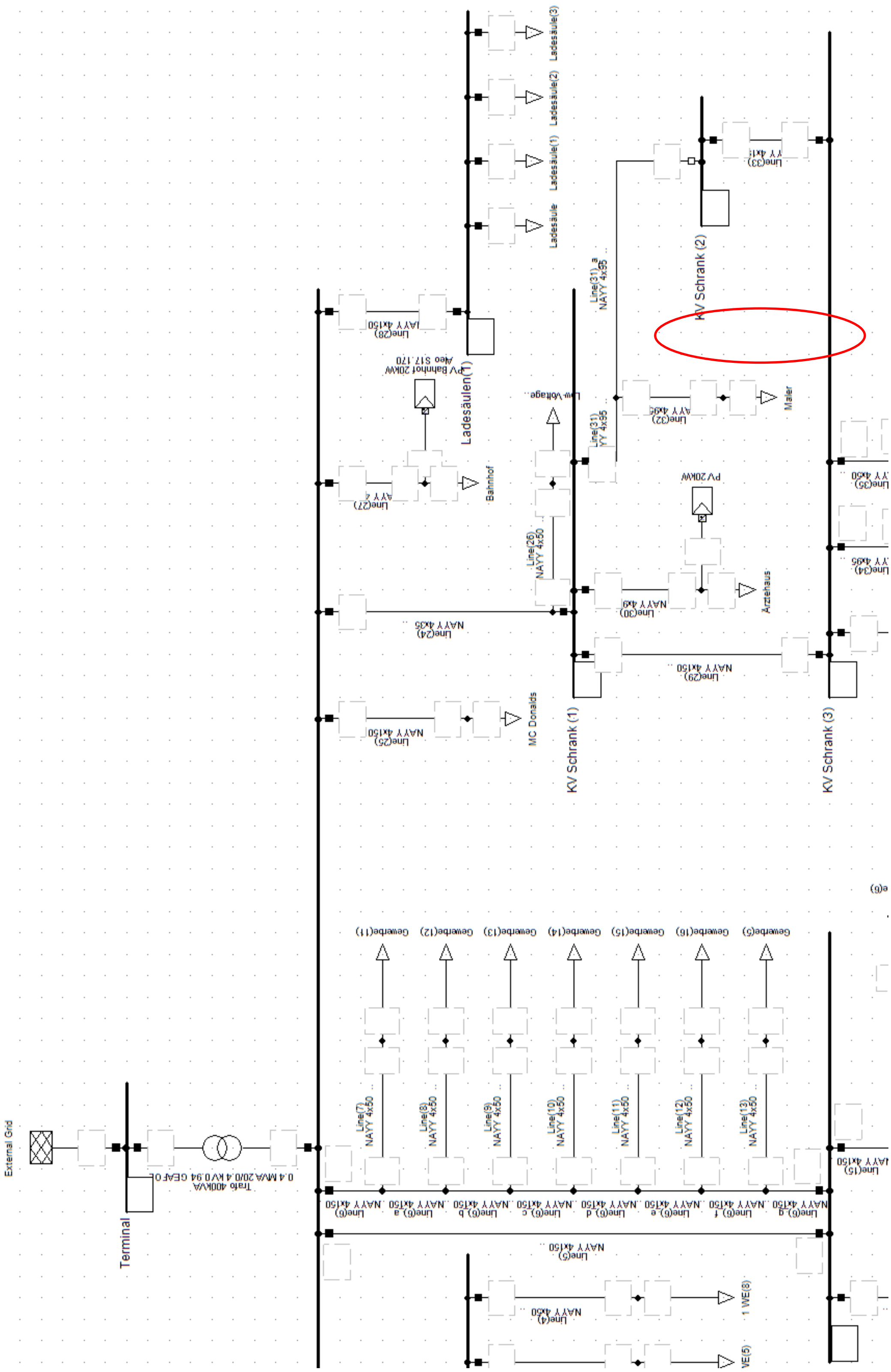


Figure 11: Smart Charger attached to the EVsmallGrid. Only one CS is activated.

After that result, we modified the PQ Indicator to smooth such short spikes by applying an aggregation function over the last PQ values using weights, e.g. last 5 values and exponential weights. As a result, the Smart Charger only reacts on longer time voltage swells and sags.

The second evaluation is carried out on the real Vilshofen Grid. As in the real grid, all charging stations are connected to nearly the same connection point to the grid. In this simulation we activated 4 smart chargers at 4 charging stations. The Figure 12 shows the voltage values at the charging station and the voltage values at the critical point in the grid. Since the voltage levels at the charging stations is in a valid range, the smart charger reacts on changes of the voltage at the critical point in the grid in order to maintain the power quality in the grid. In this experiment, we used the real Nissan iMiev and scaled the measured values by the factor of two and mapped the single-phase values to all 3 phases, such that the car charges with up to 22 kW and an impact can be seen in the power grid simulation.


External Grid
Terminal
Trafo 400kVA
KV Schrank (1)
KV Schrank (2)
KV Schrank (3)
Ladesäulen(1)
Ladesäule
Ladesäule(1)
Ladesäule(2)
Ladesäule(3)
Bahnhof
MC Donalds
Arztehaus
Maler
PV 20kW
PV Bahnhof 20kW
Line(26) NAYY 4x50
Line(31)_a NAYY 4x95
Line(7) NAYY 4x50
Line(8) NAYY 4x50
Line(9) NAYY 4x50
Line(10) NAYY 4x50
Line(11) NAYY 4x50
Line(12) NAYY 4x50
Line(13) NAYY 4x50

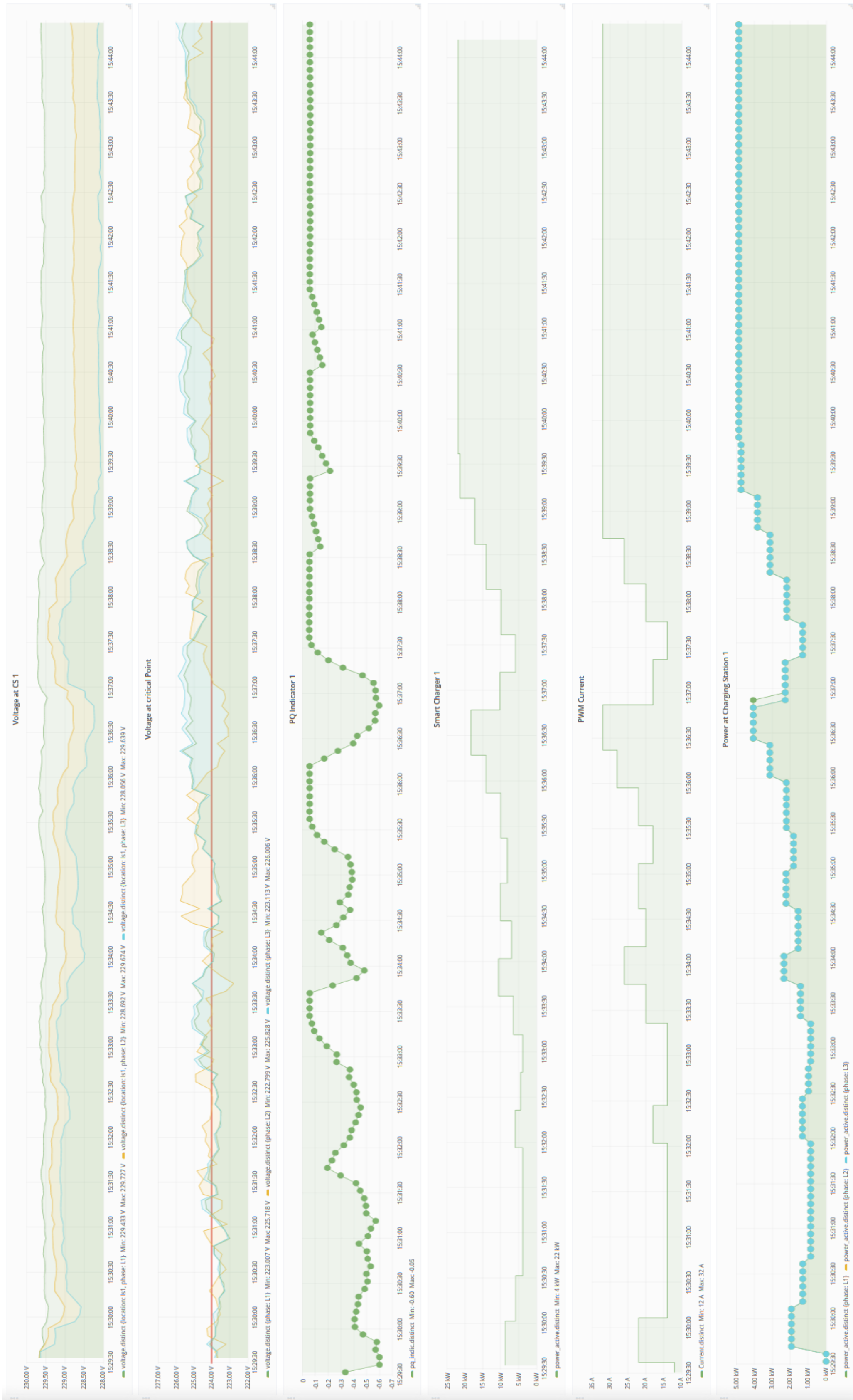


Figure 12: At the real Vilshofen grid we attached 4 charging station with Smart Charging to the real CS location (first part), in order to simulate the time period between 20:00 and 23:00, we additionally changed the reaction time of the smart charger to 5 minutes and the ,easur,emt interval to 1 minute

- **Reaction Interval of the Smart Charger Time**

  We tested different reaction times of the Smart Charger with the result, that a 30 second interval sometimes is to fine granular and it would be enough to react all 5 minutes on the voltage level changes that are the result of load and PV injection, since the long term voltage change over day is much slower than 30 seconds. In some other cases, e.g. starting of the charging process or directly after critical events, a fast reaction time, e.g. in 30 seconds, makes sense.

  In this context also the smoothing function of the PQ Indicator can be used to remove unnecessary reactions of the Smart Charger. We believe that the configuration of both, the smoothing and the Smart Charger reaction time, need to be configured based on the fluctuations of the real grid

IV. Fairness between several Charging operations

With only one enabled charging operation in the same low voltage grid, the smart charger reacts according to the measured input values (voltage level at the charging station and the transformer, apparent power at the bottleneck elements of the grid, it is the transformer in our case). Joining additional charging processes to the same low voltage grid result in locally optimal behavior of the single smart chargers, such that the one that is nearer to the transformer, hence has a higher voltage level, is still charging, while other charging processes with a higher voltage drop are regulated down.

In order to overcome this issue, we integrated a “global view” into the distributed smart chargers. In case the local situation needs a control of the charging process this is done immediately. In case the local power quality indication is green, first the critical point in the gird is investigated, whether the grid requires control of the charging process. In simply low voltage networks, the critical point can easily be defined using load flow calculation. A more sophisticated approach to determine the critical point is by self-learning, which is not implemented yet and not reasonable for small test grids. The effect of all changes of one charging station could be recorded at different points of interest in the low voltage grid. Based on the impact, we can priories the points and determine the most critical point for the specific charging station. This can be done either during a calibration period or as an ongoing process.

6. Open issues and suggestions for improvements

In the future, including the PV inverter and a battery storage into HIL simulation can be interesting in terms of power quality and smart charging. In this way, we can investigate more on the reactive power control. Furthermore, enabling more functionalities of Power factories controlled by LabLink such as state estimation or harmonics analyze can help so much to enhance the functionality of the Smart Charger, even testing some power planning strategies.

7. Dissemination Planning

The main goal of our research period is to write a scientific work based on the results and insights gained and submit it to a proper workshop or conference. Currently the plan includes writing one publication and submit it to e-Energy 2018 conference (Karlsruhe, Germany), one of the top conferences regarding to the topics of energy informatics. The title of this paper is “Smart Charging Algorithm for Power Quality Control in the Electrical Distribution System”.

In addition, The knowledge obtained through this project about controlling the voltage and enhancing the power quality should be used to enhance the content of the lectures in purpose of teaching at the Chair of Prof. de Meer, for example. Computer Networking and Energy Systems, where the basic principles of energy supply and distribution are explained, but also the topic safe network operation is discussed.

Finally, many master and bachelor thesis can be proposed as an extension or follow up mini project for this project including reactive power control in the grid or considering other power quality parameters such harmonics.

8. References

[1] Monica Alonso, Hortensia Amaris, Jean Gardy Germain, and Juan Manuel Galan. 2014. Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms. Energies 7, 4 (2014), 2449–2475. https://doi.org/10.3390/en7042449

[2] Jorge Nájera Álvarez, Katarina Knezović, and Mattia Marinelli. 2016. Analysis and Comparison of Voltage Dependent Charging Strategies for Single-Phase Electric Vehicles in an Unbalanced Danish Distribution Grid. In 51st International Universities Power Engineering Conference. IEEE.

[3] Omid Ardakanian, Catherine Rosenberg, and S. Keshav. 2013. Distributed control of electric vehicle charging. Proceedings of the the fourth international conference on Future energy systems - e-Energy '13 (2013), 101. https://doi.org/10.1145/2487166. 2487178

[4] Ching-Yen Chung, Joshua Chynoweth, Chi-Cheng Chu, and Rajit Gadh. 2014. Master-Slave control scheme in electric vehicle smart charging infrastructure. The Scientific World Journal 2014 (2014).

[5] Andres Cortés and Sonia Martínez. 2016. A Hierarchical Algorithm for Optimal Plug-in Electric Vehicle Charging with Usage Constraints. Automatica 68, C (June

2016), 119–131. https://doi.org/10.1016/j.automatica.2016.01.060

[6] Sara Deilami, Senior Student Member, Amir S. Masoum, Senior Student Member, Paul S. Moses, Senior Student Member, Mohammad A. S. Masoum, Senior Student

Member, Amir S. Masoum, Senior Student Member, Paul S. Moses, Senior Student

Member, Mohammad A. S. Masoum, and Senior Student Member. 2011. Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize

Power Losses and Improve Voltage Profile. IEEE Transactions on Smart Grid 2, 3

(2011), 456–467. https://doi.org/10.1109/TSG.2011.2159816

[7] Mario Faschang, Friederich Kupzog, Ralf Mosshammer, and Alfred Einfalt. 2013.

Rapid control prototyping platform for networked smart grid systems. In Industrial Electronics Society, IECON 2013-39th Annual Conference of the IEEE. IEEE, 8172– 8176.

[8] J. M. Foster, G. Trevino, M. Kuss, and M. C. Caramanis. 2013. Plug-In Electric Vehicle and Voltage Support for Distributed Solar: Theory and Application. IEEE Systems Journal 7, 4 (Dec 2013), 881–888. https://doi.org/10.1109/JSYST.2012.

2223534

[9] Fanxin Kong, Xue Liu, Zhonghao Sun, and Qinglong Wang. 2016. Smart Rate Control and Demand Balancing for Electric Vehicle Charging. In 2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS). IEEE, 1–10. https: //doi.org/10.1109/ICCPS.2016.7479118

[10] Felix Lehfuss. 2017. Evaluation of different control algorithm with low-level communication

requirements to increase the maximum electric vehicle penetration. CIRED - Open Access Proceedings Journal 2017 (October 2017), 1750–1754(4). Issue

1. http://digital-library.theiet.org/content/journals/10.1049/oap-cired.2017.0265

[11] M. Longo, D. Zaninelli, F. Viola, P. Romano, R. Miceli, M. Caruso, and F. Pellitteri. 2016. Recharge stations: A review. In 2016 Eleventh International Conference on

Ecological Vehicles and Renewable Energies (EVER). 1–8. https://doi.org/10.1109/EVER.2016.7476390

[12] Sergejus Martinenas, Katarina Knezović, and Mattia Marinelli. 2017. Management of power quality issues in low voltage networks using electric vehicles: Experimental validation. IEEE Transactions on Power Delivery 32, 2 (2017), 971–979.

[13] J. A. Peças Lopes, F. J. Soares, and P. M. Rocha Almeida. 2009. Identifying management procedures to deal with connection of electric vehicles in the grid. 2009 IEEE Bucharest PowerTech: Innovative Ideas Toward the Electrical Grid of the Future (2009), 1–8. https://doi.org/10.1109/PTC.2009.5282155

[14] M. Restrepo, J. Morris, M. Kazerani, and C. Canizares. 2016. Modeling and Testing of a Bidirectional Smart Charger for Distribution System EV Integration. IEEE Transactions on Smart Grid PP, 99 (2016), 1–1. https://doi.org/10.1109/TSG.2016.

2547178

[15] Jose Rivera, Christoph Goebel, and Hans-arno Jacobsen. 2015. A Distributed Anytime Algorithm for Real-Time EV Charging Congestion Control. In Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems - e-Energy

’15. ACM Press, New York, New York, USA, 67–76. https://doi.org/10.1145/2768510.

2768544

[16] Nusrat Sharmin and HyungJune Lee. 2016. Adaptive Optimal Charging Schedule in Electric Vehicular Networks. Proceedings of the Korean Institute of Communication Sciences Conference (2016), 1057–1058.

[17] J. Taft and P. De Martini. 2013. Ultra-large scale control architecture. In 2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT). 1–6. https://doi.org/10.

1109/ISGT.2013.6497906

[18] Toshihiko Tanaka, Tsukasa Sekiya, Hidenori Tanaka, Masayuki Okamoto, and Eiji Hiraki. 2013. Smart charger for electric vehicles with power-quality compensator on single-phase three-wire distribution feeders. IEEE Transactions on Industry Applications 49, 6 (2013), 2628–2635. https://doi.org/10.1109/TIA.2013.2262915

[19] H. Vahedi and K. Al-Haddad. 2016. A Novel Multilevel Multioutput Bidirectional Active Buck PFC Rectifier. IEEE Transactions on Industrial Electronics 63, 9 (Sept 2016), 5442–5450. https://doi.org/10.1109/TIE.2016.2555279

[20] J. Varela, N. Hatziargyriou, L. J. Puglisi, M. Rossi, A. Abart, and B. Bletterie. 2017. The

IGREENGrid Project: Increasing Hosting Capacity in Distribution Grids. IEEE Power and Energy Magazine 15, 3 (May 2017), 30–40. https://doi.org/10.1109/MPE. 2017.2662338

[21] Jia Ying Yong, Vigna K Ramachandaramurthy, Kang Miao Tan, and N Mithulananthan. 2015. Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation. International Journal of Electrical Power & Energy Systems 64 (2015), 300–310.

[22] Yajiao Zhong, Mingchao Xia, and Hsiao-Dong Chiang. 2017. Electric vehicle charging station microgrid providing unified power quality conditioner support to local power distribution networks. International Transactions on Electrical Energy Systems 27, 3 (2017), e2262–n/a. https://doi.org/10.1002/etep.2262 e2262 ETEP-15-0870.R4.

9. Annex A

Detailed documentation of all tests can be found here:

		Grid			Charging Station				Car			SoC		Time	
Experiment ID	**Input**	**Name**	**Line 1 (m)**	**Line 2 (m)**	**LS 1**	**LS 2**	**LS 3**	**LS 4**	**Model**	**Type**	**Max Power**	**start**	**end**	**start**	**end**
E1_GA_S	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%	11%	0	900
E3_GA_S	HTB load profiles	E3_GA	80	50	x				Zoe	3 phase	7.3	0%	28%	07:19	08:19
E3_GA_S	HTB load profiles	E3_GA	80	50	x				Tesla P90d	3 phase	7.3	0%		07:19	07:34
E3_GA_S	HTB load profiles	E3_GA	80	50	x				Tesla P90d	3 phase	3.7	0%		07:19	07:34
E1_GA_S	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	80%		0	900
E1_GA_S	static load at LD1 - LD4	E1_GA	20	100	x				Zoe	3 phase	7.3	80%	99,90%	0	900
E1_GA_S	static load at LD1 - LD4	E1_GA	100	100	x				i3	1 phase	7.3	80%		0	
E1_GA_S	static load at LD1 - LD4	E1_GA	20	100	x				i3	1 phase	7.3	80%	99,90%	0	900
E1_GA_S	static load at LD1 - LD4	E1_GA	20	100	x				Tesla P90d	3 phase	3.7	80%	99,90%	0	900
E1_GA_S	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%	99,90%	0	900

E4_GA_S	HTB load profiles + REN	E4_GA	80	50	x				iMiev	3 phase	7,3	85%	95%	12:14	12:24
E1_GA_M	three CS static load at LD1-LD4	E1_GA	100	100	x	x	x		Zoe	3 phase	7.3				
E3_GA_M	HTB load profiles	E3_GA	80	50	x	x	x		Zoe	3 phase	7.3				
E4_GA_M	HTB load profiles + REN	E4_GA	80	50	x	x	x		i3	1 phase	7.3			12:08	13:08
W1_0	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_20	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_40	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_60	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_80	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_100	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3	0%		0	120
W1_0	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120
W1_20	static load at	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120

	LD1 - LD4														
W1_40	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120
W1_0	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120
W1_20	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120
W1_40	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7	80%		0	120
W1_0	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W1_20	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W1_40	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W1_60	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W1_80	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W1_100	static load at LD1 - LD4	E1_GA	100	100	x				Tesla P90d	3 phase	3.7	0%		0	120
W2	static load at LD1 - LD4	E1_GA	100	100	x				Zoe	3 phase	7.3			0	180

W2	static load at LD1 - LD4	E1_GA	20	100	x				iMiev	1 phase	3.7			0	180
W2	static load at LD1 - LD4	E1_GA	20	100	x				Tesla P90d	3 phase	3.7			0	180
W3_20	HTB load profiles	E3_GA	100	100	x				Zoe	3 phase	7.3			07:24	07:34
W3_40	HTB load profiles	E3_GA	100	100	x				Zoe	3 phase	7.3			07:24	07:34
W3_60	HTB load profiles	E3_GA	100	100	x				Zoe	3 phase	7.3			07:24	07:34
E7_GC_M	HTB load profiles radnom	E3_GC			x	x	x	x	i3	1 phase	7.3	0%		05:00	08:00
E7_GC_M	HTB load profiles random	E3_GC			x	x	x	x	i3	1 phase	7.3	0%		12:00	15:00
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	i3	1 phase	7.3	90%		20:00	23:00
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	iMiev	3 phase	7.3	80%	96%	20:00	23:00
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	iMiev	3 phase	7.3	80%	ca 85%	20:00	23:00
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	Tesla P90d	3 phase	3.7	80%		20:00	23:00
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	Zoe	3 phase	7.3	0%		12:00	15:00
E7_GC_M	HTB	E3_GC			x	x	x	x	Zoe	3	7.3	0%		14:00	16:00

	load profiles average									phase					
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	Zoe	3 phase	7.3	0%	99,90%	06:00	07:45
E7_GC_M	HTB load profiles average	E3_GC			x	x	x	x	Zoe	3 phase	7.3	0%	54,97%	08:00	11:00