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Real-World Implementation of Smart Charging : Challenges and Lessons Learned

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Executive Summary

Smart charging is an effective solution to mitigate the impact (such as peak powers, high energy demand, high energy cost) of electric vehicles (EV) charging in a local energy system (LES). This study presents the real-world implementation of an advanced predictive smart charging scheduler in a living lab. This paper will report on the challenges and lessons learned for the set-up of a smart charging scheduler on both technical and driver related aspects. Moreover, demonstrations of the capabilities of the smart charging scheduler will be illustrated.

Keywords: Demonstration, Load & Power management, Prediction, Smart charging, Solar energy

1 Introduction

Governments are announcing new regulations to push the electrification of the transport sector to reduce the human-related CO_2 emissions. For instance, the European Parliament announced that new passenger cars shall be 100% free-emissions by 2035 [1]. Such climate-focused policy pledges and announcements will increase the number of electric vehicles on the market since they are zero tailpipe emission cars. It is well-known from literature that mass adoption of electric vehicles can have strong impacts on the grid, in particular on increasing peak powers [2]. To act on this, smart charging shows great results to mitigate negative impacts of electric vehicles on the grid [3].

There is a consequent number of scientific papers on the development of smart charging schedulers assessed in simulation environments, as shown in this review [4]. Only very few include the practical real-world implementation such as [5]. In this study, the authors detailed an experiment with smart and fast chargers in California. The results show that smart charging can be beneficial if at least a portion of the EV charging demand has a high charging flexibility. Authors in [6] and [7] developed a software based EV monitoring, control and management system in California in 2014. Thanks to their system, they are able to charge more EVs with the same grid capacity compared to uncoordinated charging. The report in [8] shows the results of a project in Denmark where they tested smart charging and vehicle-to-grid (V2G). The report focuses on charging methodology for grid services (such as FCR). The full report details the grid applications, the testing, the replicability and scalability of their method.

The papers cited previously are strongly limited in number, addressing only part of the topic scope. In addition, they are particular to certain sites/countries with specific conditions. Most of the existing literature is also predecessing the more recent technological advances in EV charging technology.

The key contributions of this paper are:

- Realisation of a state-of-the-art model predictive control (MPC) smart charging algorithm with real forecast running continuously in a real-world environment,
- Analysis on the EV driver's needs and impact on the scheduling,
- Lessons learned from the implementation of a smart charging scheduler.

The paper is organized as follows. The living lab physical set-up and the smart charging scheduler set-up are introduced in section **Error! Reference source not found.**. The lessons learned from deploying the smart charging scheduler are detailed in section 3. The performances of the smart charging scheduler are presented with an example in section 4.

2 Living lab setting & smart charging set-up

2.1 Living lab set-up

The living lab is located in the Green Energy Park [9] near Brussels, Belgium and consists of multiple controllable chargers, multiple photovoltaic solar systems, multiple loads and multiple batteries. Figure 1 shows an aerial view of the site and **Error! Reference source not found.** shows a scheme of the electrical layout of the experiments. The experiment makes use of three different solar panels systems (named PV1, PV2 and PV3), two different AC smart chargers (named CP1 and CP2), one building electrical load demand and one grid connection. The site and the experiment are open to employees of the surrounding companies but is mostly used by university staff and staff of the Green Energy Park.

Figure 1: Areal picture of full set-up of charging

2.2 Smart charging scheduler algorithm & commissioning

In order to bring smart charging to a real-world environment in comparison to a simulation environment, additional elements needed to be placed into the system. The elements consist of a local controller, a cloud environment where the smart charging scheduler is running, a driver interface to get information from the EV drivers and a manager interface to show the performances of the scheduler. Each device is detailed in the following paragraphs. The set-up of the scheduler is detailed in Figure 3.

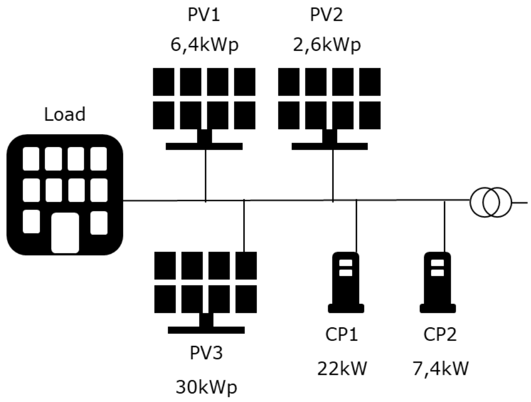

Figure 2: Scheme of full set-up of charging site

2.2.1 Cloud environment hosting the smart charging algorithm

The advanced smart charging scheduler algorithm applied in this use case is a model predictive control algorithm available and demonstrated in simulations in [10]. The objectives are to minimize electricity costs and peak powers (peak shaving and valley filling principle) based on the forecast of electricity generation and electricity demand. In the experimental set-up, the electrical demand is forecasted using a recurrent neural network (RNN) and the PV generation is forecasted using an existing forecast available from ELIA [11]. The algorithm is running in a cloud environment and is sending setpoints to the local controller at a timestep of 15 minutes. The algorithm is also triggered when a new EV plugs in or plugs out. The full detailed smart charging algorithm is available in [10].

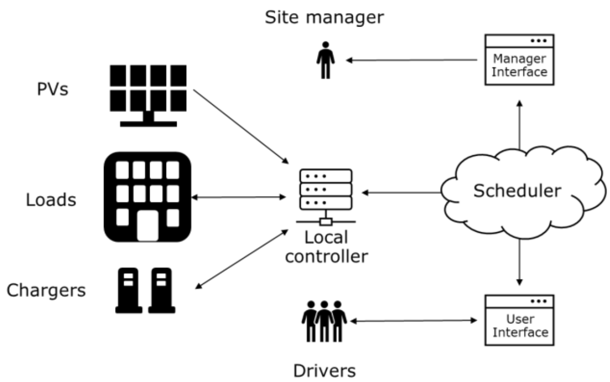

Figure 3: Scheduler commissioning set-up

2.2.2 Roles of the local controller

The assets shown in Figure 2**Error! Reference source not found.** are all locally connected to a central controller. The first role of the local controller is to ensure a continuous and safe communication with the assets in case of loss of cloud connection or in case of sudden change in energy balance of the local energy system (LES). The cloud connection loss can happen in case of a problem with internet or if the cloud environment is down. The sudden change in the energy balance can happen, for instance, when the PV production drops due to a cloud, which induces a change in the energy balance in a very short time (seconds) and requires a fast response to ensure the stability of the LES.

The second role of the local controller is to gather all the data points of the assets and transfer them to the cloud environment. Such data points are stored in a database and also used by the smart charging scheduler to execute its tasks. For instance, the stored data points of the load demand of the building are used to train the neural network in order to better forecast its demand.

The third role of the local controller is to transfer the decisions setpoints of the smart charging scheduler running in the cloud to the assets.

2.2.3 Driver and manager interfaces

The smart charging algorithm requires two data points from the EV drivers in order to build the constraints and boundaries over the charging session. These two data points are:

1. The expected departure time of the driver,
2. The desired energy demand to be charged during the parking time.

To get these two points from the EV driver, a web interface has been build that can be reached using a QR-code on the charger. The web interface also contains a dashboard which shows to the driver how its EV will be charged on the parking time entered. Similarly, a manager web interface has been build in order for the site manager to understand what happened, what is happening, and what will happen on his charging site.

3 Challenges & Lessons learned

The implementation of a smart charging scheduler is not a full straightforward process and was faced with some major and minor challenges. The major challenges identified during the implementation are related to communication protocol issues and to the driver's input. Such major challenges are detailed in section 3.1 and section 3.2. The minor challenges, which are mostly technical, are summarized in section 3.3.

3.1 Communications challenges

The first communication challenge relates to the use of multiple different existing communication protocols. Each asset in the set-up has its own communication protocol (e.g. Modbus TCP/IP, OPCUA, MQTT, OCPP, etc.). Consequently, an important engineering effort was required to implement these multiple communication protocols. This could be an important threat in the future for small businesses that want to start smart charging activities.

In addition, some assets use the same type of communication protocol but not the same variables. For instance, some assets use MODBUS TCP/IP but do not use the same registers, nor the same naming of the variables, nor the same units, etc.

Moreover, most of the assets update their internal firmware, inducing, in some cases, an update of the communication protocol. It can be an update on the name of certain variable, or sometimes the whole list of variables. Consequently, this requires new engineer efforts to update the local controller with the firmware updates.

Finally, some set-ups require the charger to have two communications; a control communication (e.g. Modbus TC/IP) with the local controller and an authentication communication (e.g. OCPP) with the charge point operator (CPO) backend. In the experimental set-up, some communications issues rose because of conflicts between the two communications protocols.

These communications issues are a major challenge to the implementation of smart charging. One of the main solutions is the use of communication standards. Further development of these standards, taking the EMS / Smart charging into account, and applying the latest versions to the assets is needed.

3.2 Driver's requirements challenges

The smart charging scheduler makes use of explicit data points from the driver regarding his energy needs. While a web interface has been developed to capture these drivers needs, the process of engaging drivers to input their needs in accurate manner is a real challenge.

The first obstacle encountered when starting the experiment was that most of the drivers did not entered their preferences at all. Since most of the drivers are not used to give in their preferences, they assume that the charger will automatically start charging, as usual. To counter this issue, extra explanations were given as well as stickers were added on the chargers with extra information on how to start the smart charging process.

It helped to engage drivers into smart charging but it is not yet sufficient since still today some sessions did not get drivers input.

The seconds obstacle encountered is that most of the driver's inputs were not accurate. An example of driver engagement analysis is presented in **Error! Reference source not found.** and Figure 4 where twelve drivers that came more than once are presented, as well as 'one artificial' driver representing all drivers that came only one time (represented with an 'X' on the figure and usually corresponding to visitors). It is important to note that the results are based on a small sample. Since the experiment is still going on, up-to-date figures will be presented at the conference.

Figure 4 shows the difference between the driver parking times entered in the web interface and the real parking times, in absolute values, relative values and a zoom-in on relative values between -100% and 100%. Positive values mean that the driver overestimate its parking time (the input parking time is higher than the real parking time).

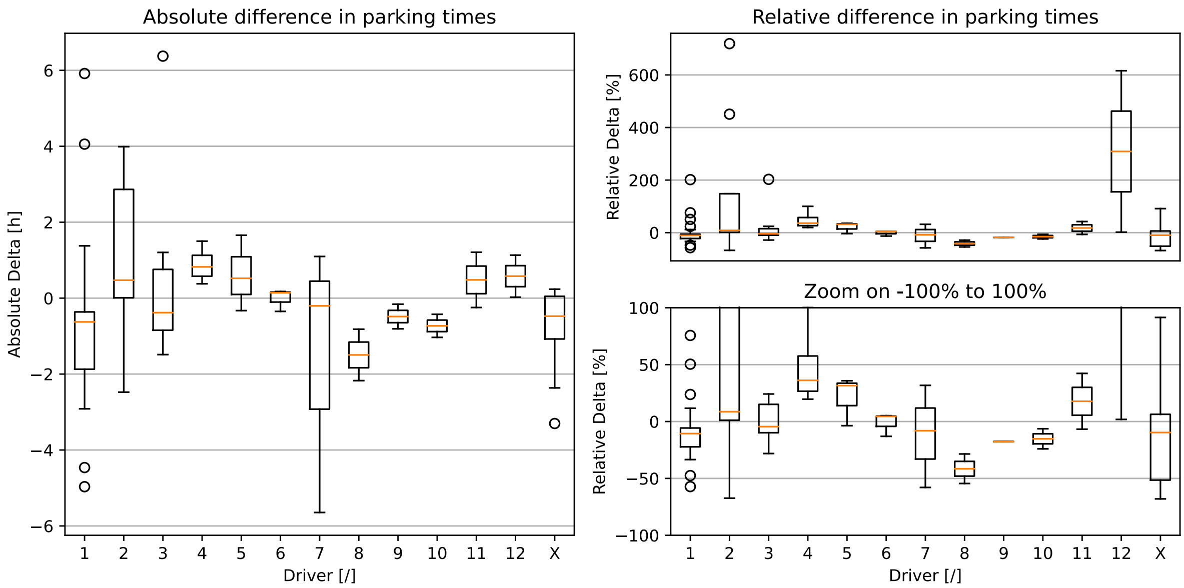

Figure 4: Box plot showing difference between parking time input and real parking time

The first observation shows that the ranges are strongly different for each driver. Only one driver (Driver 6) presents accurate parking time input with an absolute and relative value close to null. Then, six drivers (Driver 1, 3, 7, 8, 9, 10) tend to underestimate their parking time (shown with negative values). Among them, one driver (Driver 8) has a median difference in parking time of -1.5h, which represents a 41.7% error. Driver 7 has an important interquartile range with a maximum error of -5.68h. Such underestimation tends to reduce the charging flexibility, hence lower performances on the scheduling but higher probability of satisfying the drivers needs.

Regarding the other drivers who tend to overestimate their parking time (Drivers 2, 4, 5, 11, 12), the differences are less important. Most of them have a median absolute parking time lower or equal to 1h. They also tend to have shorter interquartile ranges compared to underestimation drivers. The reason behind these lower values is that overestimation is a risk for the driver since there is a higher probability of not satisifying drivers needs, because the algorithm expects the driver to stay longer.

While the parking times are relatively accurate, the energy needs are not. **Error! Reference source not found.Error! Reference source not found.** shows the difference between the driver's energy inputs and the real energy charged. Note that 0 kWh values mean the driver's energy needs are satsified after which the smart charging scheduler stops charging. Positive values mean charging has stopped prior to reaching the user required energy. This means the schedule by the smart charging algorithm was not executed completely. This can either be because of the vehicle departed prematurely, or the battery was recharged

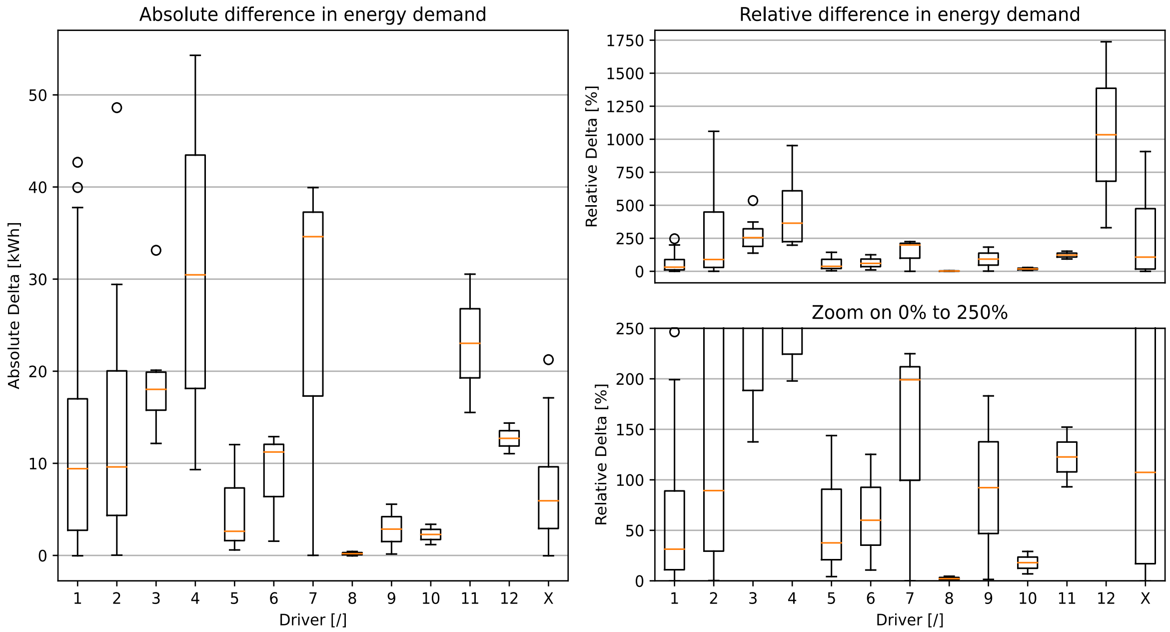

Figure 5: Box plot showing difference between energy input and real energy charged

before reaching the user indicted required energy.

A first observation shows that all drivers tend to ask more energy than can be charged. This is can be seen with positive values in kWh. Among all of them, some are asking up to a median of 30 kWh more than what can be charged. On a relative basis, some drivers ask up to 17.5 time more energy that can be charged. Other drivers enters more accurate values such as Driver 8. Such non-accurate driver's energy inputs lead to reduction in performances of the smart charging scheduler. This will be shown in the next paragraph with a charging flexibility analysis and a concrete scheduling example.

3.2.1 Charging flexibility analysis and impact on scheduling

Previous figures and paragraphs are interesting to have an understanding on user inputs. However, it does not help understand what could be the impact on scheduling. This is the reason why a new parameters is defined called the charging flexibility. The charging flexibility is defined in equation (1)

$$charging\ flexibility = 1 - \frac{energy}{power \times time} \tag{1}$$

From equation (1), three different charging flexibility can be defined:

- The theoretical charging flexibility based on the driver's input. The energy and time values corresponds to the energy and parking time entered by the driver. The higher the value is, the higher the charging flexibility is.
- The real charging flexibility based on the measurements. The energy and time values corresponds to the measured energy and parking time at the end of the session. The higher the value is, the higher the charging flexibility is.

- The loss charging flexibility which is the difference between the real and theoretical charging flexibility. The higher the negative value is, the higher the loss in charging flexibility is.

The three different charging flexibilities are shown in Figure 6 for each driver.

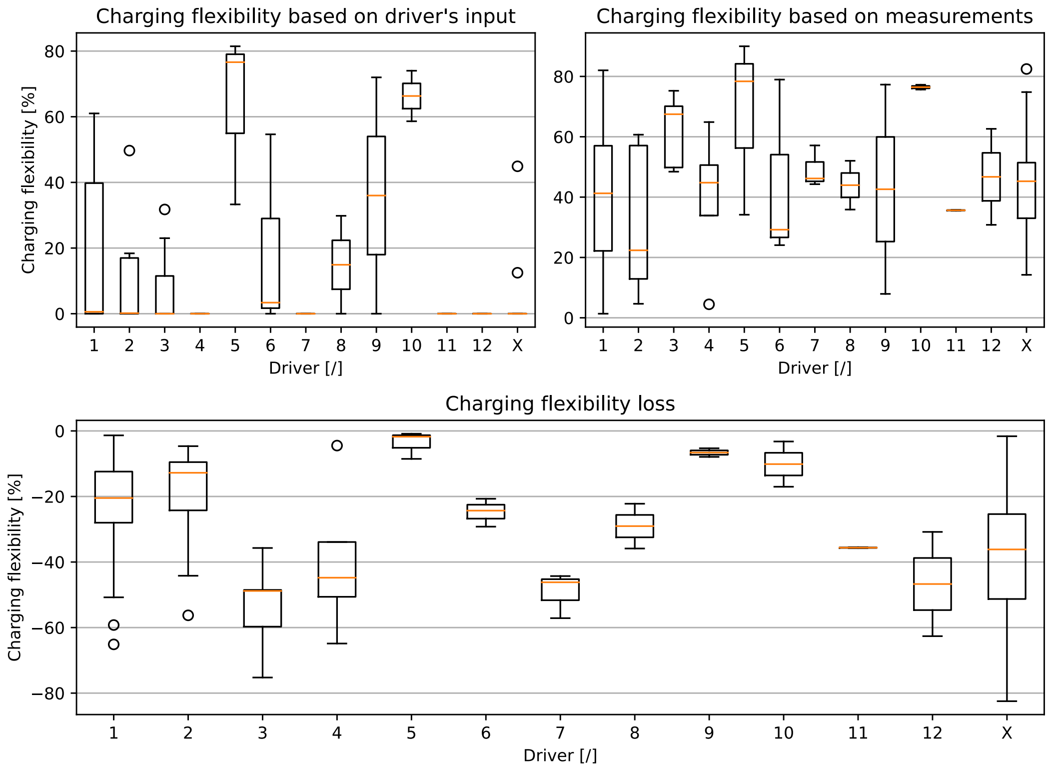

Figure 6: Charging flexibility analysis. On the upper left is the theoretical charging flexibility, on the upper right is the real charging flexibility and below is the loss charging flexibility

Regarding the theoretical charging flexibility, most of the driver's input give no charging flexibility (median value of 0%) at all. It is important to note that in reality, the charging flexibility is negative since these drivers ask more energy that can be charged. However, negative flexibility means by-default no flexibility, hence a value of 0%. Only Drivers 5, 8, 9 and 10 are giving some charging flexibility with values up to 80%.

While most of the median theoretical charging flexibility are 0%, in reality, the real charging flexibility is almost never 0% as shown on the upper right of the figure. In reality, most of the charging sessions have a median value between 20% and 90%. Such difference between theoretical and real charging flexibility is the reason why the charging flexibility loss is also shown. From this boxplot, an important drop in charging flexibility can be observed. For instance, Drivers 3, 4 and 7 present a median loss in charging flexibility of -30%. In some cases, the loss in charging flexibility can go up to -80%.

To clarify the importance of loss in charging flexibility and the impact of it on the scheduling, an exemple is shown in Figure 7. In this exemple, a driver asked an energy of 28 kWh on a parking time of 2h30. The maximum charging power is 7.14 kW measured directly on the charger.

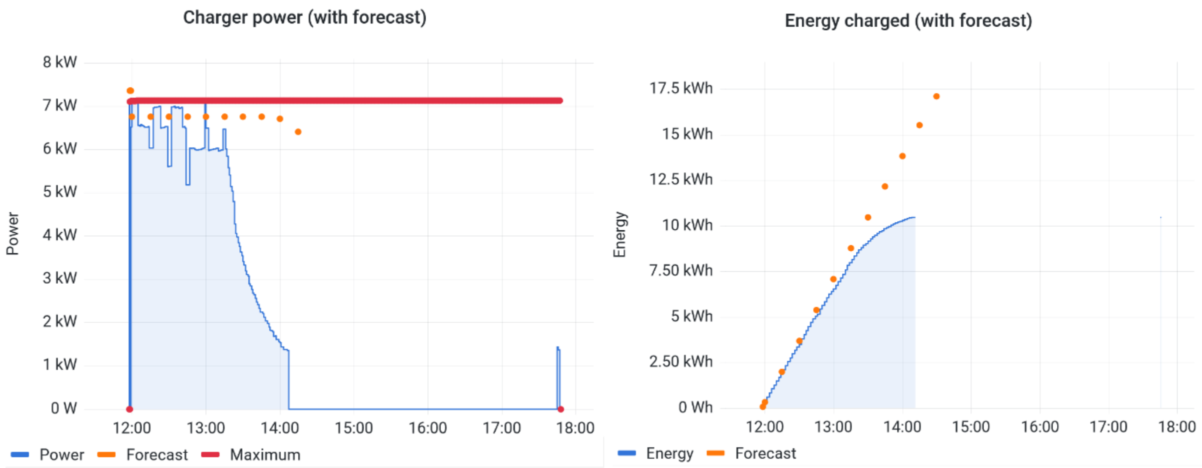

Figure 7: Charging power (left) and energy (right) profils with inaccurate driver's inputs

From the driver input, it can observed that the charging flexibility is negative (null) because the driver is asking more energy that can be theoretically charged (in this case 17.85 kWh). Still, this is automatically corrected by the scheduler when optimizing the problem. Nevertheless, the charging flexibility is null, leading no choice to the scheduler to charge at maximum power (uncoordinated charging), as shown in Figure 7, with an almost constant maximum charging power (in orange). Moreover, for this particular use case, the charging ends earlier because of a fully charged battery (decreasing exponential charging power). In other words, the driver asked 28 kWh, which has been corrected to 17.85 kWh, but at the end only 10.5 kWh could be charged. Moreover, the real parking time was 5h45 which is 3h15 more than what has been entered by the driver. Such example shows that smart charging cannot work correctly if drivers do not participate adequately.

3.3 Other minor challenges

The implementation of a smart charging scheduler has also many minor challenges. A non-exhaustive list of minor issues is presented hereunder.

- Lack of vehicle data available at charger: With today's AC chargers, the standard communication protocol does not allow to exchange data between the charger and the electric vehicle. Consequently, at the beginning of a charging session, the state-of-charge (SOC), the capacity and the maximum charging power are unknown. The lack of information reduces the possibility to have optimal scheduling. To know the maximum power, the local controller has to let the EV charge at maximum power during a certain period of time. Moreover, knowing the capacity and SOC of the EV, the scheduler could avoid wrong drivers inputs, since it knows the charging boundaries. Such challenges should be solved with the introduction of the new standard protocol ISO15118.

- Minimum charging power to be applied: Today's AC chargers do not allow to charge below a current of 6A. With a three-phase charging session on 230V, this represents a minimum charging power of 4kW. Most of the smart charging schedulers in literature do not include such constraint. This could lead to serious issues when dealing with a significant number of chargers. This has been solved in the experimental set-up using semi-continous variables and by using a specific solver.

- Intolerance of (some) vehicles to session interruptions: Another challenge is that the smart charging scheduler decides to stop a charging session for different reasons (e.g. give priority to another EV or to wait until PV production starts). The issue is that some EVs or some chargers do not allow to restart the session. Specific artefacts have been developed to still be able to restart the session.

- Non-feasible solution in the smart charging scheduler: The smart charging scheduler presented earlier had to be modified in order to accept non-feasible solutions. Typical non-feasible solution raise when a driver inputs non-feasible charging preferences. Non-feasible solutions can also happen when there is not enough grid supply to satisfy all drivers energy demand. Such nonfeasibile solutions where not an issue on the simulation environment since the driver's input where based on the real energy demand logged by the Charge Detail Record from OCPP.

- Phase imbalances on the LES level: The smart charging scheduler works with power values since the production and consumption forecasts are power-based forecasts. However, in reality, the chargers work with current setpoints and are either single-phase or three-phase. Phases imbalances must be taken into account in the optimization to avoid overload of a phase (due to chargers combined with building current demand on a single phase). Such issue had to be included with extra constraints in the smart charging algorithm.

4 Results example of smart charging

Most of the technical challenges have been solved in the experimental set-up, except for the driver's requirements. Nevertheless, some drivers still allow for charging flexibility which allows for better scheduling performances. To illustrate this, an example has been taken and is shown in Figure 8 and Figure 9 for respectively charger 1 and charger 2, where the orange dots show the forecasted optimized power setpoints and the blue the actual charging powers.

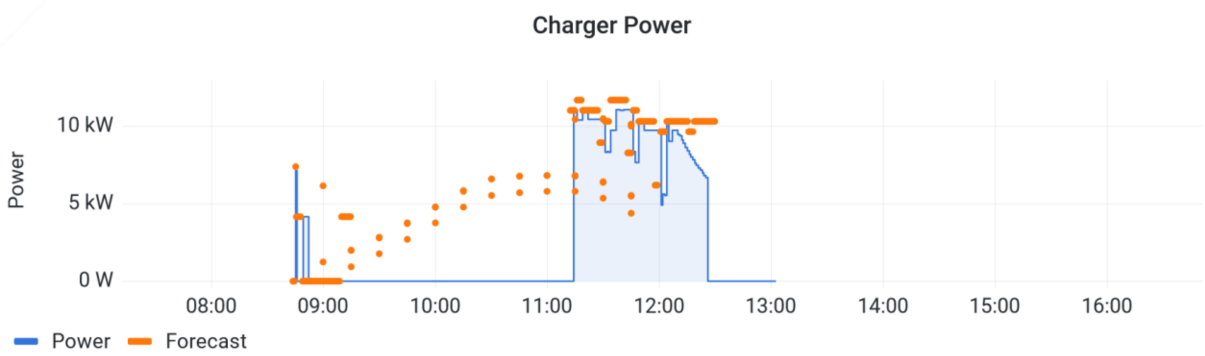

Figure 8: Smart charging scheduling on charger 1

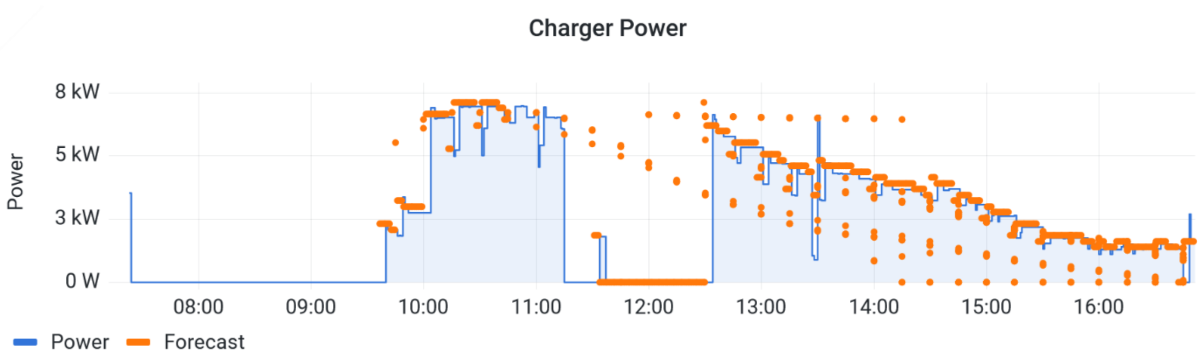

Figure 9: Smart charging scheduling on charger 2

In this particular case, three different behaviours can be observed:

1. The scheduler does not activate the charging session when the drivers plug in. The reason is that it is waiting for the PV production to kick-in. (plug-in at 7:23 am for charger 1, plug-in at 8:45 am for charger 2).
2. Charging is stopped on one charger (between 11h13 and 12h26 on charger 2) in order to allow the other charger to charge and to satisfy the energy demand of the driver while minimizing the power peak.
3. Power is following the reduction in production power of the solar panels (power is decreasing between 12h26 until the end on charger 2).

Thanks to the smart charging scheduler, a peak in the morning has been avoided and the self-consumption of the solar panels increases, lowering the charging costs, while satisfying driver's needs.

5 Conclusion

In this paper, the implementation of a smart charging scheduler in real-work set-up is presented. The paper explains the full set-up, the devices which are used and the extra services implemented to run the scheduler. Following this, an in-depth explanation is given on the challenges faced during the implementation, from minor to major challenges. The impact of certain challenges is shown in the scheduling of the charging session.

Among the major challenges, the communication issues faced during the implementation require further development of the communication standards taking EMS / Smart charging into account. These latest standard protocols should be implemented in order to avoid unnecessary manpower for small business. The other major challenge due to non-accurate driver's inputs are a real thread to smart charging. Wrong driver's inputs leads to bad scheduling, hence poor performances of smart charging. Finally, once most of the issues are solved, the results of smart charging show great performances by reducing peak power demand and by increasing the self-consumption, lowering the charging costs, while satisfying driver's needs.

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Presenter Biography

Gilles Van Kriekinge obtained his Master's Degree in Electromechanical engineering at the Université Libre de Bruxelles (ULB) in 2019, with a specialization in energy. His master thesis is about a techno-economic assessment of the integration of solar energy, storage system and vehicle-to-grid technology in a microgrid. He is currently a PhD candidate at the Vrije Universiteit Brussel (VUB) and is working on the project “Optimized bi-directional & smart vehicle charging in local energy systems (OPTIBIDS)".