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Real-life demonstration of Vehicle-to-Grid in Sweden

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Executive Summary

The automotive industry is shifting toward sustainable transportation, with electric vehicles (EVs) at the forefront. EVs not only offer a solution to climate change while enabling innovative approaches to energy management, including smart charging. This paper presents the main finding from a real-life demonstration of smart bidirectional charging using a 20kW bidirectional DC-charger. The study explores bidirectional charging in realistic scenarios, demonstrating its potential for peak shaving, CO2 reduction, and spot price arbitrage. A key outcome of this research is the detailed description of a smart charging test environment. The initial tests on bidirectional charging show that the bidirectional charging system is functioning satisfactory and follows the desired setpoint. Furthermore, key parameters such as, charger efficiency and ramp up/down response time have been evaluated and are presented within this study.

Keywords: Electric Vehicles (EVs), Smart Charging, Bidirectional Charging, Vehicle-to-Grid (V2G).

1 Introduction

In recent years, the automotive industry has undergone a transformative shift toward sustainable transportation. Electric vehicles (EVs) have become a central driver of this change, presenting a compelling alternative to traditional internal combustion engines [1]. The rise of EVs not only tackles urgent climate change issues but also paves the way for innovation in energy systems, urban planning, and grid infrastructure [2]. As highlighted in previous studies [3-5], the impact of EV charging on the power system is expected to be significant, particularly in terms of increased load demand. Therefore, it is essential to investigate various alternative charging strategies to mitigate potential issues. Among the various charging approaches, strategies focused on minimizing charging costs from a socio-economic perspective are generally considered the most favorable [6]. These can range from simple cost minimization—primarily targeting lower electricity prices—to more comprehensive strategies aimed at minimizing the total cost of ownership. The latter includes not only electricity costs but also costs associated with power losses, grid capacity limitations, and charging infrastructure [7].

In light of recent advances within the energy management of EV charging, it is today possible to use bidirectional smart charging strategies for EVs not only to meet the mobility needs of users but also support the power grid through services such as load balancing [8], peak shaving [9], and frequency regulation [10].. Likewise, research indicates that bidirectional charging can substantially reduce the total cost of ownership for EVs and support integration of renewables[11]. Although the theoretical potential of bidirectional charging is well-documented, most charging algorithms in practical applications are still designed for unidirectional charging. This gap between research and real-world implementation highlights the need for further development, demonstration, and standardization of bidirectional charging strategies to ensure their widespread adoption and effectiveness.

The aim of this paper is to implement and evaluate smart bidirectional charging strategies using a real-life pilot system equipped with a DC charger that supports bidirectional capabilities. The development of such pilot systems is crucial for testing and validating smart bidirectional charging control strategies. These systems not only enable technical verification but also generate valuable user experience data—an essential component, as effective smart charging solutions often require input from users. Using real-life demonstrations, the study will explore the practical application of bidirectional charging and highlight its potential benefits, such as peak shaving, providing ancillary services to the grid, and interacting with the local energy system. By conducting actual charging cycles rather than relying solely on simulations, the study allows for accurate quantification of key parameters such as charger efficiency and response times. Furthermore, it addresses the potential challenges encountered when transitioning from simulation-based models to real-world implementation, offering insights into both the opportunities and limitations of smart bidirectional charging in practice.

The rest of the paper is organized as follows: Section 2 presents the structure of the developed energy management system. Section 3 describes the demonstration setup. Section 4 discusses the results. Finally, Section 5 concludes the paper.

.2 Energy management system

The EMS developed in this study is designed to control and optimize bidirectional EV charging in alignment with user requirements. Operating as the central intelligence of the system, the EMS facilitates decision-making and manages charging and discharging actions based on a set of inputs and predefined strategies. Figure 1 illustrates the architecture of the developed EMS. As depicted, the system comprises hardware components, control algorithms, data services, and a user-friendly web application, all structured in a modular and scalable manner.

At the core of the EMS is a Ferroamp bidirectional charger, which enables both charging an EV from the grid in unidirectional mode and feeding energy back to the grid or building during peak demand periods in bidirectional mode (Vehicle-to-Grid, or V2G). The following modules comprise the developed EMS:

- **Web App User Interface**: This interface allows users to interact with the EMS by selecting the charging method (Unidirectional or Bidirectional), configuring charging parameters such as target state-of-charge (SoC), maximum SoC, minimum SoC, maximum power, and chrging/discharging duration.
- **Data Visualization**: Graphs and plots embedded in the web app provide insights into spot market prices, desired charging/discharging set points, DC charger power levels, EV battery power levels, PV generation, and load demand of HSB over time. This transparency helps users make informed decisions.
- **InfluxDB Data Exchange**: All system data, including user inputs, system states, sensor readings, and charging profiles, are logged in a time-series database (InfluxDB). This central datahub enables efficient communication and coordination among all modules.
- **Data Service Provider**: This module acts as a middleware that ensures data integrity and formatting. It retrieves data from InfluxDB, processes it as needed, and delivers it to the relevant control modules.
- **Charging/Discharging Controller**: Responsible for executing commands by interfacing with the hardware. It sends control signals to the charger based on optimized strategies and ensures compliance with the user's selected parameters.
- **Charging/Discharging Optimizer**: The optimizer module forms the intelligence of the EMS. It processes available data—such as energy prices, CO_2 equivalents, end-user requirements, battery status, and grid conditions—to determine an optimal charging/discharging strategies that minimize cost or minimize CO_2 emission.

The algorithm starts with user input, which is stored in InfluxDB and accessed by the optimizer. The optimized profile is then translated into actionable control commands by the controller. Real-time performance data from the charger and EV are continuously recorded, visualized, and fed back into the system.

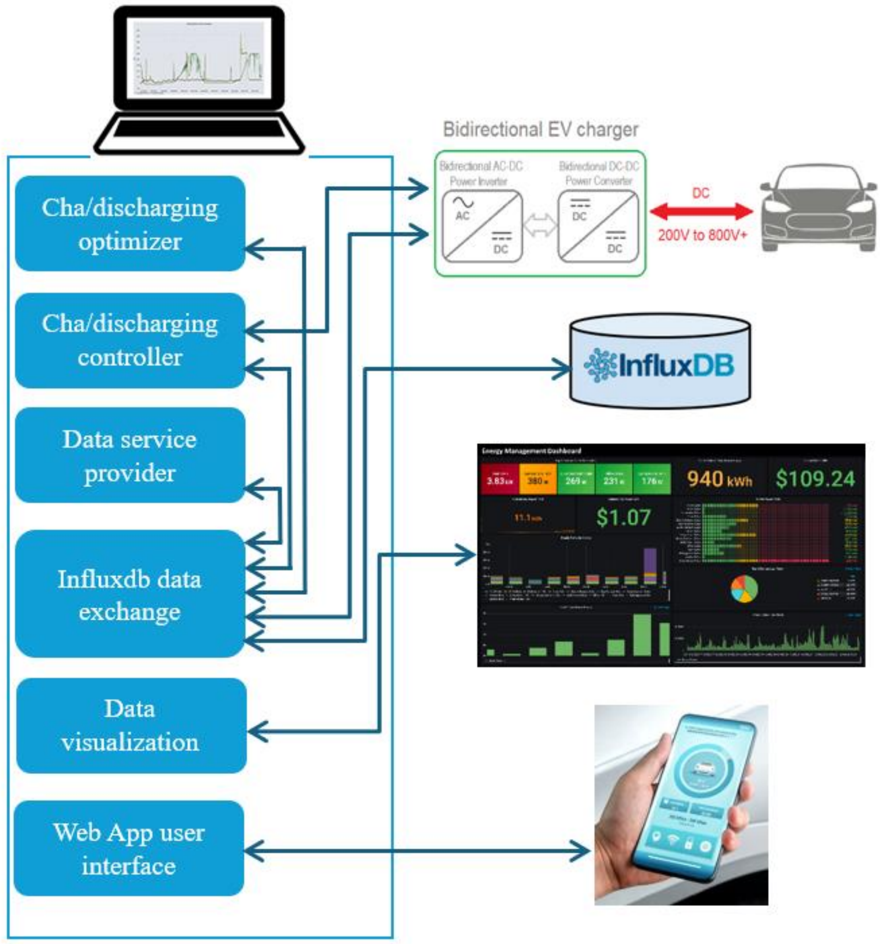

Figure 1 Schematic of energy management system

The objective functions for cost minimization and CO_2 emission minimization optimization problems are formulated as follows [12]:

$$Minimize: \sum_{t=1}^{N_T} \{ (\pi_t^{spot} + \pi^{tax} + \pi^{grid}) \times P_t^{G2V} \times \Delta t + \pi_t^{Peak} \times P^{Peak} - (\pi_t^{spot} + \pi^{incentive}) \times P_t^{V2G} \times \Delta t \} \tag{1}$$

$$Minimize: \sum_{t=1}^{N_T} E_t^{\mathrm{CO2}} \times P_t^{G2V} \times \Delta t \tag{2}$$

In equations (1) and (2), π^{spot} represents the hourly spot price, π^{tax} denotes the energy tax, π^{grid} is the grid usage charge, and π^{peak} corresponds to the daily peak price. Similarly, $\pi^{incentive}$ is the incentive fee for exporting power to the grid. The charging and discharging power of EV are indicated by P^{G2V} and P^{V2G}, respectively. The maximum charging power is denoted by P^{Peak}, while the charging and discharging duration is represented by Δt. The CO_2 equivalents is denoted by E^{CO2}.

The charging/discharging intervals are assumed to be 1 hour. Therefore, N_T denotes the number of hours within parking duration.

The constraints of the optimization problems are as follows:

$$SoC_t = SoC_{init} + {(\eta^{G2V} \times P_t^{G2V} \times \Delta t)}\Big/{E^{cap}} - {(P_t^{V2G} \times \Delta t)}\Big/{(\eta^{V2G} \times E^{cap})}, t = t_0 \tag{3}$$

$$SoC_t = SoC_{t-1} + {(P_t^{G2V} \times \Delta t)}\Big/{(\eta^{G2V} \times E^{cap})} - {(P_t^{V2G} \times \Delta t)}\Big/{(\eta^{V2G} \times E^{cap})}, t > t_0 \tag{4}$$

$$P_t^{G2V} \leq P^{max} u_t^{G2V} \tag{5}$$

$$P_t^{V2G} \leq P^{max} u_t^{V2G} \tag{6}$$

$$u_t^{G2V} + u_t^{V2G} \leq 1 \tag{7}$$

$$SoC^{min} \leq SoC_t \leq SoC^{max} \tag{8}$$

$$SoC_t = SoC_{final}, t = t_N \tag{9}$$

$$P^{Peak} \geq P_t^{G2V} \tag{10}$$

Equations (3) and (4) describe the dynamic of the EV battery's SoC over time. Equations (5) and (6) impose upper bounds on the charging and discharging power based on the maximum allowable power. The binary variables indicate whether the EV is in charging or discharging mode, respectively. Equation (7) ensures that charging and discharging cannot occur simultaneously by limiting the sum of the binary variables to a maximum of one at any given time step. Equation (8) constrains the SoC within predefined operational limits, ensuring that the battery operates within a safe and efficient range. Equation (9) enforces that the SoC at the end of the scheduling horizon must reach a target value. Finally, equation (10) determines the peak charging power.

3 Demonstration setup

The physical setup of the demonstration setup has been shown by the real-world images in Figure 2 which indicate the connection between the EV and the bidirectional charger, along with the deployment of the EMS at the lab. The DC charger is compliant with the latest ISO 15118-20 standard allowing bidirectional charging through the OCPP 2.01 protocol, it also includes a local MQTT server that can handle the charge and discharge commands. Although the OCPP2.01 protocol has been released it was not possible to run the initial demonstration using that protocol. Instead, the communication with the EMS was done through a local MQTT server, where power set points are handled and the meter readings from the charge session are being reported. The EMS has been implemented in python and GLPK solver has been used to solve the optimization problems.

Figure 2: Physical setup of the bidirectional charging demonstration

The required end-user preferences—such as parking duration, battery capacity, maximum charging/discharging power, maximum and minimum SoC, and desired final SoC—are provided through a web interface developed using Streamlit [13], as illustrated in Figure 3. The initial SoC is retrieved automatically from the EV when it is connected to the charger. During discharging mode, the battery's SoC is continuously monitored, and discharging is halted if the SoC drops below the defined minimum threshold to keep safety constraint of the EV battery.

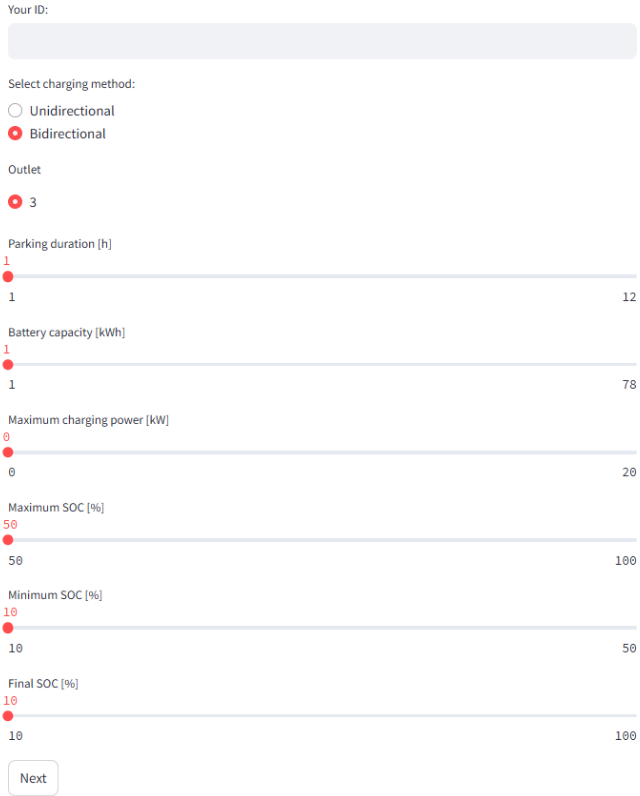

Figure 3: Streamlit-based user interface for end-user preferences

As shown in Figure 4, the user selects the API model, e.g. which charger and standard to be used to communicate with the charger and initiating a preferred charging strategy. Once an API model is selected, the user is prompted to select one of three available charging plans:

Cost Minimization – This option prioritizes charging the EV when electricity prices are lowest, aiming to reduce the overall charging cost. In the example shown, a potential 34.27% cost reduction is achievable with respect to immediate charging.

CO_2 Minimization – This strategy schedules charging during periods of low carbon intensity in the grid mix, thereby minimizing the environmental impact. A 4.50% CO_2 reduction is shown as achievable in this scenario with respect to immediate charging.

Immediate Charging – This option starts charging the EV instantly, without considering cost or environmental optimization.

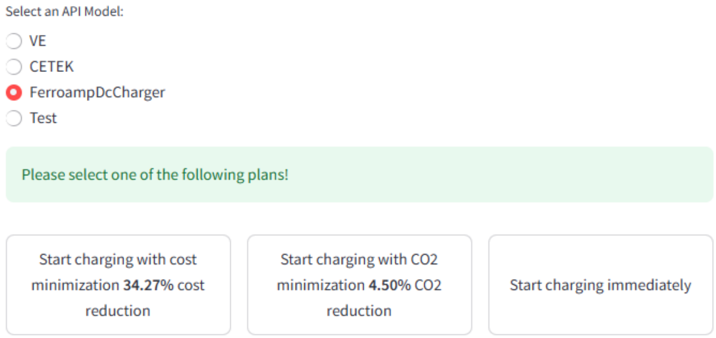

Figure 4: Streamlit-based user interface for selecting API model and smart charging strategy

4 Demonstrations results

The grid tariffs used in this study are sourced from Göteborg Energi [14]. Hourly spot prices are derived from the Nordic electricity market, as referenced in [15]. Additionally, the hourly average CO_2 emission rate associated with electricity generation for the corresponding month is obtained from [16].

An initial functional test was conducted where charge and discharge commands were sent to the charger to assess the efficiency of the charger at different charge/discharge power and to validate the functionality. The charge power was reduced stepwise with 2 kW every 30 seconds from 20 kW The power drawn from the grid, the DC power and the battery power was measured and collected with a 1 second resolution. The results from the demonstration are presented in Figure 5 and 6. As can be seen the charge power follows the commands quickly for the small change in power, for the large step in the end, e.g. from -20kW to 20 kW it takes approximately 105 seconds to reach the final value due to the internal controller of the charger. Since the charging/discharging interval is 1 hour, this 105-second delay does not introduce a significant error in the overall results.

The efficiency was found to be above 90% for charging power over 4 kW but reduced rapidly as the power fell below 4 kW to -4 kW. However, the efficiency increased again to above 90% for discharge powers exceeding 4 kW. Therefore, the optimal efficiency is achieved when the charging power exceeds 4 kW, and the discharging power is below -4 kW.

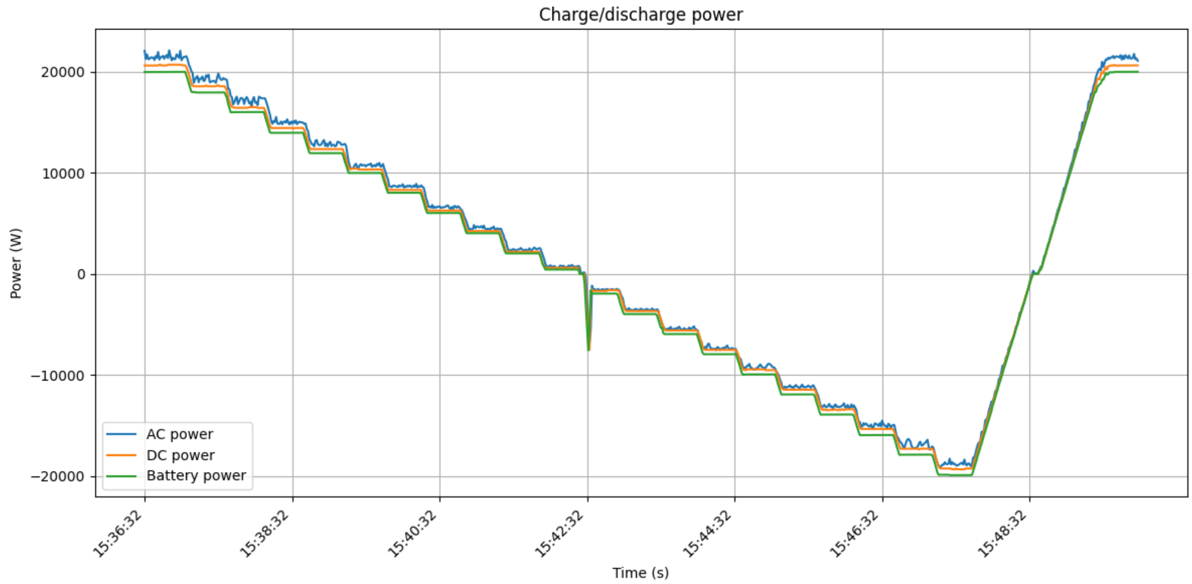

Figure 5: Charge and discharge power for the efficiency calculation

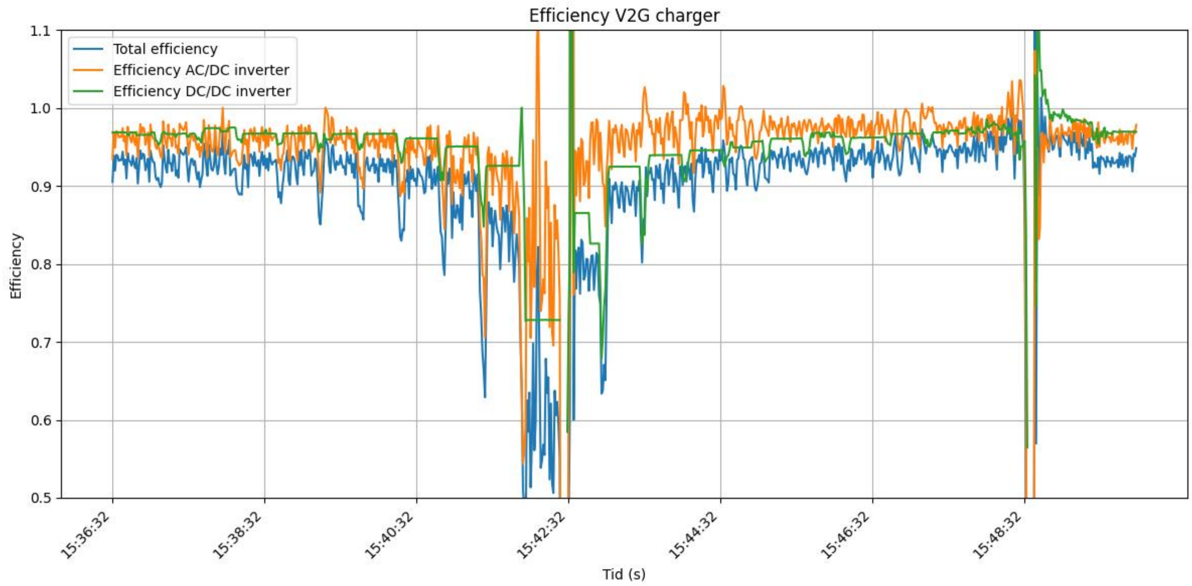

Figure 6: AC/DC, DC/DC and overall efficiency of the charger for the different operating points.

The demonstration results of the full optimization test are illustrated in Figure 7. The EV connected to the charge point at 10:00 and selected to leave after 5 hours, e.g. at 15.00. A minimum and maximum SoC of 50% and 90% were selected together with a desired SOC at departure of 85%. The optimization model calculated the possible cost reduction to 23% and sent the charging command to the charge point. Figure 8 presents the set points sent to the EV, together with the actual charge/discharge power from the EV. As can be seen, the actual power follows the setpoints by adjusting the charge/discharge power. Likewise, the EMS discharges the EV until 11:00 when the electricity price is relatively high and then charges the EV to reach the desired SOC of 85% by the departure time. The main reason for charging evenly during the remaining hours, although the spot price varies is due to the peak power tariff that penalize high charge power.

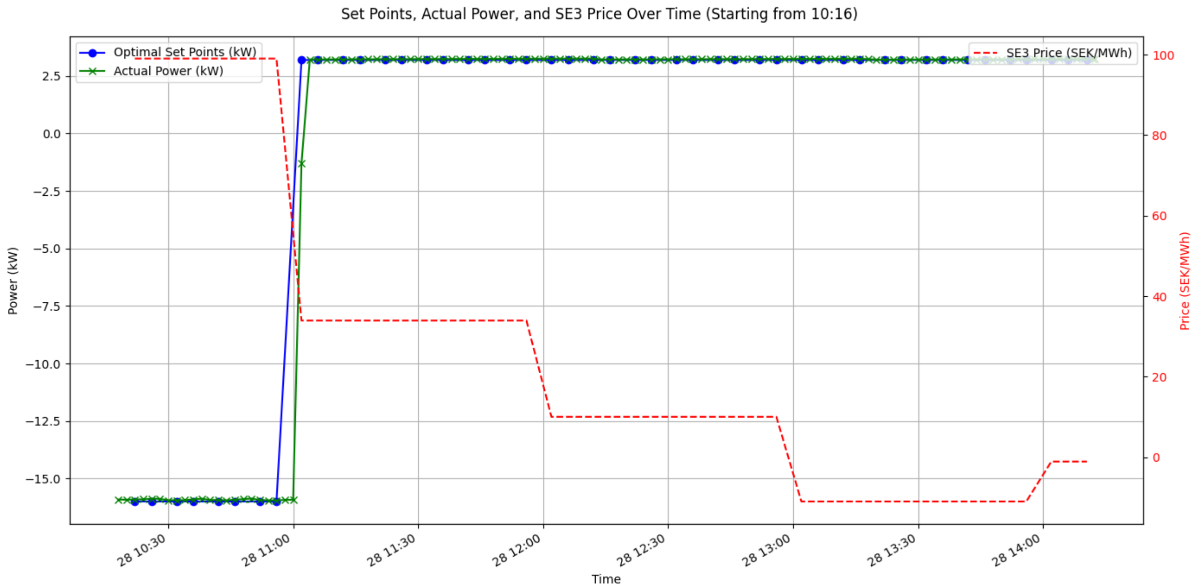

Figure 7: Setpoints calculated from the optimization model together with the actual charge and discharge power drawn from the grid/EV.

5 Conclusions

Real-world demonstrations are essential for validating theoretical charging strategies and ensuring their practical feasibility and user acceptance. This study aimed to apply the latest bidirectional charging technologies and methods to realistic case studies. The demonstration architecture presented in the paper handles both the communication and monitoring of the charging session as well as the optimization of the set point. The results demonstrate that the bidirectional charging system operates satisfactorily and maintains the desired setpoint. Additionally, charger efficiency remains around 90% when the charging power exceeds 4 kW and the discharging power is below -4 kW. The architecture opens up for more demonstration activities including advanced modelling of battery aging and energy efficiencies. It also enables us to demonstrate the use of different communication protocols such as OCPP and MQTT.

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Presenter Biography

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