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Optimal integration of electric vehicles fast charging stations into medium voltage power distribution grids

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Subsidy recipients:
EPFL/STI/I EL/DESL
Station 11
1015 Lausanne

GridSteer Sàrl
c/o EPFL STI IEM DESL
ELL 038 (Bâtiment ELL)
Station 11
CH-1015 Lausanne

Romande Energie SA
Rue de Lausanne 53
1110 Morges

GOFAST AG,
Wiesenstrasse 10a,
8952 Schlieren

Authors:
Max Chevron, GridSteer, max.chevron@gridsteer.ch
Rahul Gupta, EPFL, rahul.gupta@epfl.ch
Sherif Fahmy, EPFL, sherif.fahmy@epfl.ch
Enea Figini, GridSteer, enea.figini@gridsteer.ch
Mario Paolone, EPFL, mario.paolone@epfl.ch
Georgios Sarantakos, EPFL, georgios.sarantakos@epfl.ch

SFOE project coordinators:
Karin Soderstrom, karin.soederstroem@bfe.admin.ch
Michael Moser, michael.moser@bfe.admin.ch
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1. Introduction

1.1. Background information and current situation

The worldwide **utilisation of fossil fuels'** as primary source of energy accounts for most global greenhouse gas emissions (GHGs). International efforts, such as the **Paris agreement** [1], aim to address this issue, requiring countries to develop national GHGs emissions targets and associated actions for their achievement. Switzerland has already undertaken several steps in this direction. On January 1st, 2018, the **Swiss Energy Strategy 2050** came into force, and on 27 January 2021, the Federal Council adopted the climate strategy for Switzerland, aiming for a net zero emissions target by 2050 [2]. Since **energy usage represents 75%** of the national GHG emissions [3], fossil fuels need to be replaced by renewable energy resources for the achievement of this strategy. This would require the electrification of several sectors (e.g., private heating and mobility along with several industry processes) and the massive integration of distributed renewable energy resources into the power grid.

The **road transport** account for 30% of Swiss CO_2 emissions [4]. In recent years, significant progress has been achieved in the electrification of this sector, via the massive rollout of low-emission vehicles, including electric vehicles (EVs)[1] [5]. It is indicative that since the beginning of the MESH4U project, in 2019, the EVs' share in new sales has increased from 20% to over 50%.

The transport sector electrification entails several challenges for the power grid. Indeed, this transition should be paired with the massive integration of renewable energy resources to positively affect the GHGs of the sector. However, the stochasticity of both EV's charging and renewables generation both have an impact on the power grid equilibrium. In this respect, proactive EV integration in renewable-based power systems can serve as grid-connected small-scale distributed battery systems capable to enhance the overall system's operation. As a matter of fact, EVs can adapt their charging patterns to provide ancillary services to both transmission and distribution grid operators such as: dispatchability of the aggregated local resources,

[1] By EVs, we refer to vehicles with a full electric power train and an on-board battery energy storage system (BESS).

frequency containment, and restoration reserves, as well as voltage control and line congestion management. They can further facilitate the integration of renewable energy resources, especially if coupled with stationary battery energy storage systems (BESSs).

1.2. Purpose of the project

The synergy between EVs and renewables allows for a reduction of fossil-fuel dependency in both the electricity generation and transportation sectors. The deployment of smart grid solutions, including EV charging strategies, along with the optimal coordination of distributed energy resources, requires a multi-disciplinary approach and the solution of complex control problems of stochastic nature. Furthermore, a suitable validation in realistic scale pilot and demonstration sites can be made possible via close collaboration between academia and industry.

The MESH4U project capitalizes on the existing infrastructure in two demo sites, one in Aigle developed in the frame of the SFOE P&D REeL project, and another one on the Lausanne campus of the EPFL. For the purpose of the project, these sites have been expanded by including at the EPFL a high-power EV fast charging station and establishing in Aigle links with various energy actors, notably the local distribution system operator (DSO), Romande Energie, and the local municipality of the city of Aigle. The configuration of these two sites is ideal to develop control frameworks aiming at: (i) optimizing the EV integration in renewable-supplied power grids, (ii) analysing the performance of the developed tools in a real environment, while (iii) considering insights and feedback from the DSO's and the society's perspectives. In view of the above, the ***aim of this project is to enhance the operation of a power distribution grid hosting stochastic MW-class renewable resources, MW-class BESSs, and EV fast chargers, in order to maximize multiple grid operational objectives***.

For the achievement of the above-mentioned project aim, a list of research questions was defined, namely:

A) **How much flexibility** is available and how much of this is accessible for the provision of grid ancillary services? This can be split into sub-questions that are related to the behavioural flexibility of the EV users (a and b) and the technical flexibility of each car (c):
   a. What are the objectives of users charging at public fast charging stations and how inclined are they to provide flexibility to the grid?
   b. How can we statistically model the stochasticity of EV charging sessions to forecast future sessions?
   c. How precise and how responsive is the control of such charging stations?

B) How the above-mentioned **flexibility can be optimally integrated into the operation** of a power distribution grid hosting stochastic resources?
   a. Are there any measurable benefits, in terms of battery size and dispatching cumulative energy uncertainty, in considering EVCSs as controllable resources?
   b. What is the impact on these benefits of: (i) the BESS's energy and apparent power capacity, (ii) the number of EV charging stations, and (iii) the type of EVs, i.e., public EVs vs industrial fleet?

C) Is the above-mentioned **flexibility marketable**? This can be split into the following sub-questions:
   a. What are the available services that stationary batteries can provide and how profitable are they?
   b. What is the impact on the batteries' profitability of the battery size and grid topology?

2. Activities

To respond to these research questions, specific activities have been defined. These activities and associated results are described below for each question.

Question A.a: What are the objectives of users charging at public fast charging stations and how inclined are they to provide flexibility to the grid?

Methodology

A web-based system and a QR code were placed on the parking spots of the EV fast-charging station installed at EPFL at the end of January 2022. Once scanned, the customer is brought to an online survey (Figure 1). Although no reward scheme has been set, over 131 valid submissions were recorded until April 2023. This survey aims to: (a) understand the willingness of the customers to participate in providing flexibility in their EV charge, and (b) quantify the accuracy of the user to estimate their EV charge duration and energy needs. The questions of the survey were defined to be easy and fast to answer yet yield as much interesting information as possible. To this date, the average time spent on the survey is less than 3 minutes. An example of questions (from a mobile device) is reported in the screenshots here below.

With the submitted responses, the actual charging profile of each user was compared to the (user) predicted one. The set of questions and post-process analysis allowed to yield results on the behavioural features such as (a) deviation of energy delivered vs expected, (b) deviation of stay duration vs expected, (c) end of session decision factor, (d) tolerance for a flexible charge, and (e) gamification readiness.

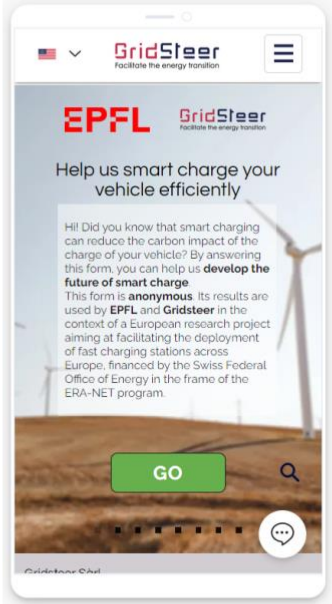

Figure 1: Example of a question as presented in the application interface of the online survey.

Results

The energy **delivered to the customer vs his prediction** has been computed based on the following customer's inputs: (a) the EV starting state-of-charge (SoC), (b) the EV target SoC at the end of the session, and (c) the vehicle model (for retrieving the battery capacity). It turns out that customers tend to charge about 4% more energy than the targeted value. Although not statistically significant, the answers to this question show that most users could receive slightly less energy and still meet their target (and therefore be satisfied by their charging session). Hence, some (limited) controllability could be applied with minimized customer dissatisfaction.

Comparing the **expected vs realized charge duration**, users tend to stay 10% longer than anticipated. This is the average response and the tendency to stay less or longer than anticipated cannot be drawn with statistical significance as answers vary in both directions and with rather a good accuracy with respect to the actual stay duration. The overall answers are quite precise between planned and actual stay duration probably because of the accurate prediction of the EV on-board computer to reach a target SoC).

More than half of the participants **decide to stop their session** based on a target SoC. About a third leaves at the desired stay duration and less than 5% with the reach of a specific cost.

In order to assess the **customers' readiness to allow for a slower charge** if this helps the electrical grid, we pay attention to the phrasing of the question since it can significantly affect the response. The selected question was: *"Would you agree to increase your charging time (a few minutes) to help the electric grid? "*. More than two-thirds of participants would accept to provide flexibility (for which half of them would do it even without a discount). This shows a rejoicing number of customers ready to participate in grid flexibility. It is however possible that these participants could be considered as early movers in the EV sector and as electric cars will gradually hit the common mass market, these results may change over time.

Asking users to provide some **information on their upcoming charge profile** might be crucial to control their charge without significantly impacting the user's satisfaction. However, the user does not have any incentive to answer honestly. A competition between users for the most accurate answers could be such an incentive. In this respect, the following question was formulated. *"Would you participate in a competition where the 3 users of this charging station that have responded the most accurately to the questions of this survey win free charges (you would be required to provide your email address)?"*. It appears that the reluctance to share one's email is still significant. 40% of users would rather not participate and an additional 27% are unsure.

Question A.b: How can we statistically model the stochasticity of EV charging sessions to forecast future sessions? [2]

Since EVCSs are considered controllable entities, i.e., the active (and reactive) power of EVCSs are decision variables of the control problem, there is the need to forecast EV users' charging profiles. More specifically, for a given EVCS, we refer to: (i) the number of EV charging sessions per day, (ii) the EVs' arrival and departure times, (iii) the initial and final, i.e., target, SoCs of EVs' batteries, (iv) the EVs' battery capacities, and (v) the minimum and maximum active power injections (defined as, respectively, the maximum and minimum imposed by either the EVCSs' converters limits or by the EV on-board controller).

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[2] This section is adapted from the work presented in [6].

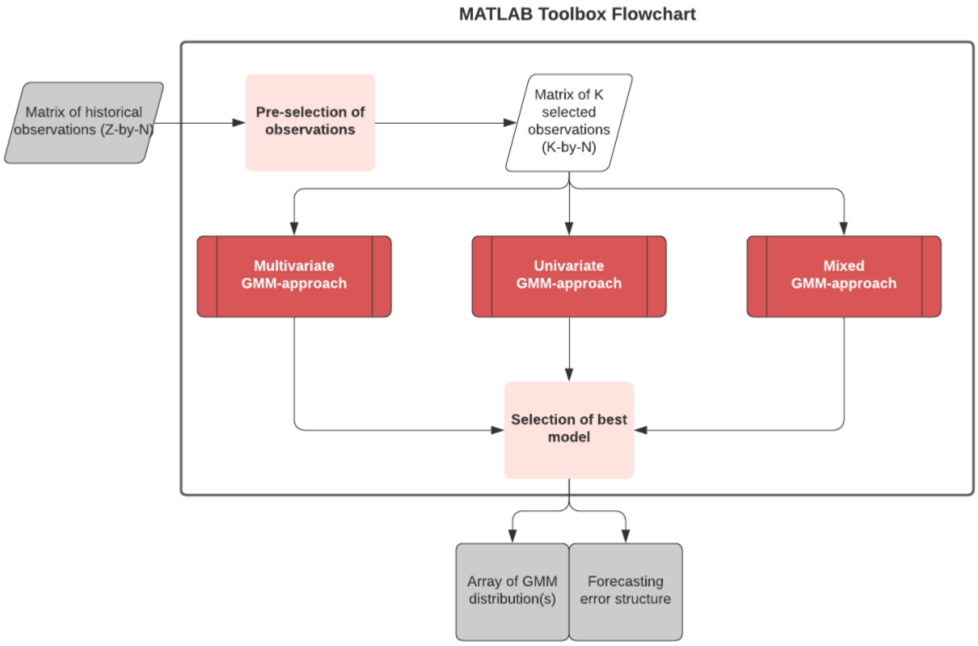

Figure 2: Flowchart of the data-agnostic EV user statistical modelling toolbox

In view of the large number of quantities that define EV user behaviour, a data-agnostic tool has been developed. It uses generic amount of EV session data and features (e.g., initial and final SoC, temperature, charging session time etc.) as inputs and outputs the best Probability Density Functions (PDFs) that would model the data. As the input data is multi-variate, the output PDFs can be anything from several univariate distributions to a full Gaussian mixture model (GMM) that models all input variables (or features) simultaneously. The algorithm's idea is to fit the data with different functions and then output the best-performing-probabilistic-model. The flowchart of the developed toolbox is depicted in Figure 2. The input data is first filtered and then fitted to: (i) one multi-variate GMM (Multivariate GMM- approach), (ii) *N*-univariate GMMs (Univariate GMM-approach), with *N* being the number of input features, and (iii) a mix of multi- and uni-variate GMMs (Mixed GMM-approach). Once all three fittings converge, they are compared using accuracy, bias, and correlation metrics. Finally, the fitting with the overall best metrics is selected as the best-performing-probabilistic- model, where from the latter, EV user behaviors can be inferred based on the features – i.e., location, season and day-type – of the day we wish to forecast.
This method has been integrated in the control algorithm (see the following questions) and the accuracy of the whole methodology evaluated.

Question A.c: How precise and how responsive is the control of such charging stations?

Methodology

Since different EV manufacturers produce vehicles with different components, EVCSs' controllability becomes dependent on both: (i) the EVCS internal control mechanisms, different available plug types, and front-end communication protocol, and (ii) the EV management system, converter ramping time for on-board chargers and charging limitations that are a function of the EV battery SoC and its state (i.e., mainly cells' temperature and balancing).
This activity aims at experimentally testing the controllability of the GOFAST charger installed at the EPFL. For this, the manufacturers of the charging station, i.e., EVTec, gave access to the specifications of their proprietary communication protocol called DCMS. The DCMS protocol aims to exchange data packets containing: (i) monitoring information (packet sent from charger to our controller) and (ii) active power setpoints (packet sent from our controller to the charger). The protocol is based on a communication framework where setpoints can

only be sent when a monitoring packet is issued/sent[3]. The protocol was integrated into a dedicated LabView code. This code streams the collected data to a dedicated database installed in a local server for logging purposes. A GUI of the logged data has been developed on the Grafana web-based platform.

Results

Figure 3 illustrates an example of recorded data of an *uncontrolled* EV charge.

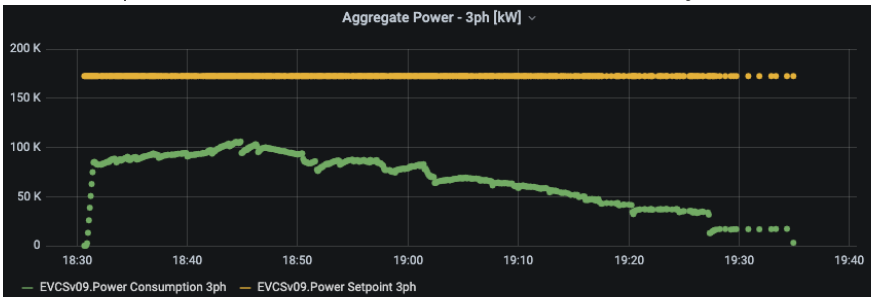

Figure 3: GUI for the DCMS logged data from the EVTec EVCS at the EPFL - Three-phase (Green) measured power and (Yellow) power setpoint

A controllability assessment was experimentally performed on the EVTec GOFAST EVCS at EPFL using a Tesla Model S90D. Subsequent step-like power setpoints were sent to the car to measure its response (i.e., ramp-up and ramp-down times) and the accuracy (i.e., the error between the requested setpoint and implementation in steady state). The duration of the steps is long enough for the implementation to stably reach a steady state. Before and after the step-like setpoints requests, the requested power has been kept to 20kW. The results are shown in Figure 4. The measured ramp-up and ramp-down times are in the order of several seconds and are linearly increasing with the setpoint amplitude, meaning that the power ramping is constant (values in the range of 3 – 5 kW/s have been measured). The implementation error is characterised by a quadratic trend where for low and high setpoints, the errors are the largest.

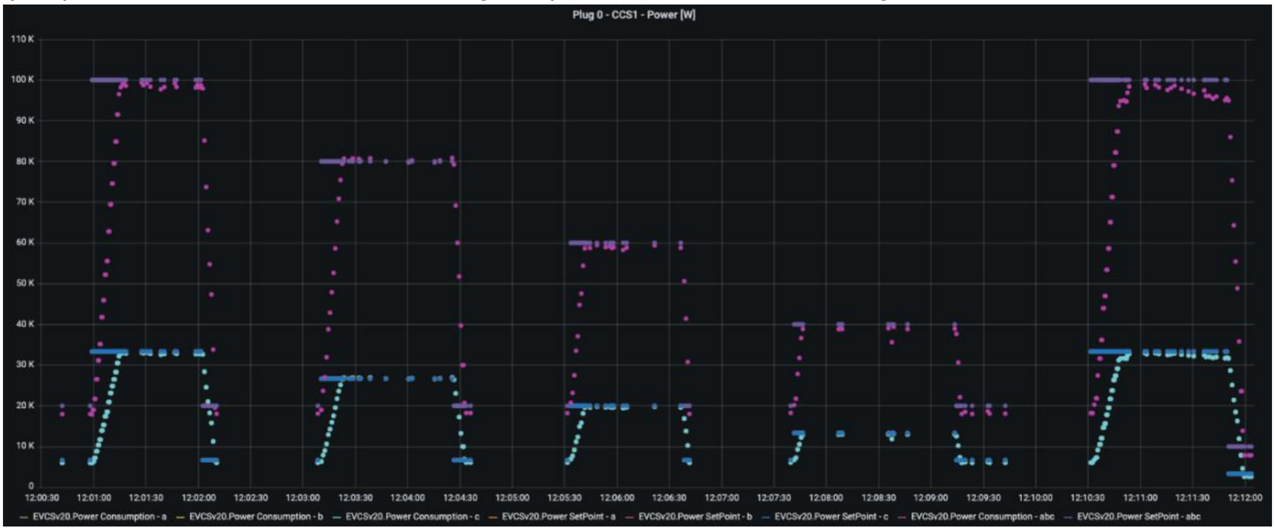

Figure 4: Results of GOFAST station controllability experiment: Active power setpoint vs. implementation

Question B.a: Are there any measurable benefits, in terms of battery size and dispatching cumulative energy uncertainty, in considering EVCSs as controllable resources?

Methodology

In [7], EPFL-DESL proposed a control framework of Active Distribution Networks (ADNs), based on a day-ahead and intra-day scheduling of heterogeneous DERs. This framework consists of two-stages as shown in Figure 5.

[3] In practice, we observed that monitoring packets are issued by the charger in an event-based fashion.

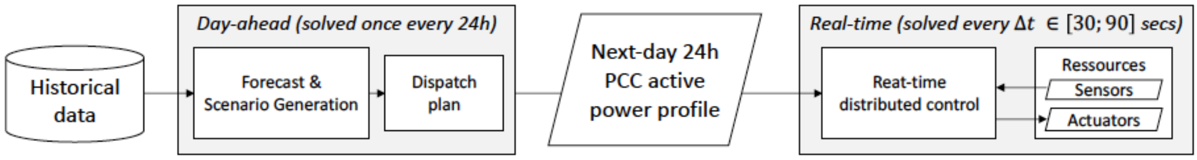

Figure 5: Schematic overview of the proposed two-stage ADN dispatching framework.

At the **day-ahead stage**, the operator computes a dispatch plan (DP) in the form of an active power profile to be followed at the Point of Common Coupling (PCC) during the next-day operation. This stage is split into two processes, called forecasting and DP in Figure 5. During the forecasting process, historical data is used as input into statistical engines that output parametric probabilistic models. During the DP process, a security-constrained scenario-based Optimization Problem (OP), leveraging the models created in the last process, is solved to generate a 24h active power DP. Compared to [7], the OP (i) further accounts for next day-stochasticity of EV user behaviour through scenarios (as described in the responses of the previous questions), and (ii) is solved iteratively to alleviate the inaccuracies introduced by the linearizations of the power-flow equations.

For non-EV injections, active and reactive nodal injection profiles were created for every resource connected to a given ADN's node, based on historical data. These profiles were clustered by season, by day-type or sky clearness, and by the fixed time resolution of the control algorithm. Then, each EVCS has one associated EV user scenario based on the model described under *question Ab*. An EV user scenario is the set of all charging sessions for a specific day, where each charging session is described by: (i) the EV's arrival and departure times, (ii) initial and desired EV battery SoCs, (iii) the EV's battery capacity and (iv) minimum and maximum active power injection limits. The total number of scenarios would be the total combinations of all generated scenarios for all uncontrollable resources and EVCSs. To reduce the complexity of the method, the number of scenarios was reduced by k-means clustering ensuring statistically meaningful results.

The second process of the day-ahead stage is to solve a stochastic scenario-based security-constrained OP that outputs an optimal DP. The OP objective is to minimize (a) the deviation between the active power flow at the PCC for all scenarios and the optimally computed DP, (b) the absolute reactive power flow at the PCC for all scenarios and timesteps, and (c) all resource-specific cost functions that reflect the controllable resources' willingness to provide regulating power (including customer satisfaction for EVCS control). The OP constraints are related to the operation of the ADN and the controllable resources, mainly the BESS and the EVCS.

At the **real-time stage**, the ADN resources are controlled in real-time to compensate for power mismatches at the PCC between the optimal DP and actual realization. Unlike the day-ahead stage, the resources' states are assumed to be known through proper sensing. The problem is expressed by leveraging a distributed MPC formulation to (i) render the problem resolution efficient and scalable, and (ii) account for potential uncertainties along the optimization horizon. The distributed formulation leverages the Alternating Directing Methods of Multipliers (ADMM) to decouple the ADN and resources operational problems. Compared to [7], since we consider EVCSs as controllable entities, extra objectives and constraints are added to the centralised OPF based on those presented in [8].

Once developed this control framework was validated in simulations and experimental setup at the EPFL-DESL microgrid and extended building of DESL, namely the ELL building at the EPFL Lausanne campus. The microgrid contains energy storage systems, generation and loads, as well as a PMU-based situational awareness system and a dedicated communication network. Equipment used for this project included (a) 45kW (peak) photovoltaic (PV) system, divided into three separated power plants; (b) a 25 kW – 25 kWh BESS based on the Lithium Titanate Oxide electrochemistry; (c) fast dynamic AC electronic load emulators capable of consuming active and reactive power up to an overall rated power of 30 kVA; and (d) a level-2 charging station. The ELL building includes (a) a commercial GOFAST EV fast CS (EVCS1) and (b) a 720kVA / 500 kWh Lithium Titanate Oxide BESS (Figure 6), along with the previously mentioned (c) level-2 CS (EVCS2), and (d) the 45kW PV system. The schematic of the experimental infrastructure is illustrated in Figure 7.

Figure 6: The 720kVA / 500 kWh Lithium Titanate Oxide BESS and the GOFAST EV fast-charger used for the simulations and experimental validation

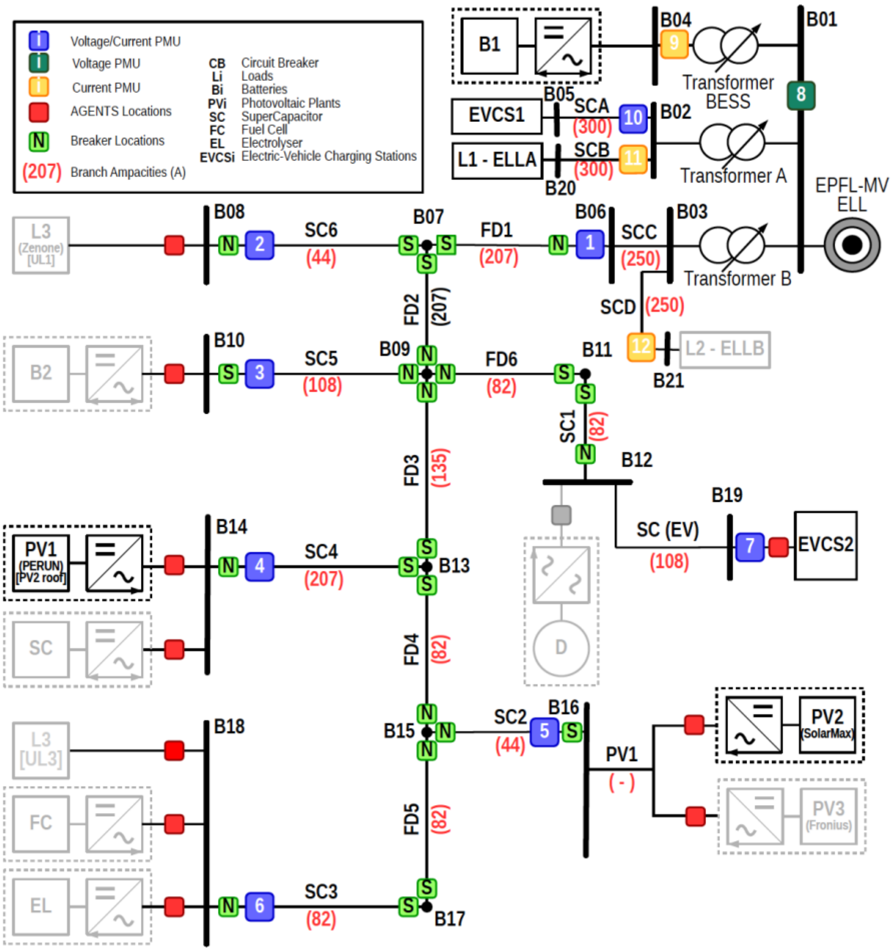

Figure 7: Low-Voltage ADN of the ELL building at the EPFL Lausanne campus

All simulations were performed using a virtual twin (single-phase equivalent) of the low-voltage electrical-grid of the ELL building at the EPFL Lausanne campus. These simulations were followed by experimental validation, first at the EPFL microgrid and then at the ELL building. The goal of the experiment is twofold. First, we show that the integration of EVCSs in both the day-ahead and real-time stages improves the tracking of an optimally computed DP. Second, we experimentally prove the aptness of the proposed real-time EVCS controller to best satisfy EV user demands.

In order to evaluate the impact of the EVCSs use as controllable resources, the DP obtained when EVCSs are controllable was compared to the DP when EVCSs are not controlled (plugged EVs simply charge at their maximum rated power). For the comparison, a set of metrics was defined including (a) the Uncovered Energy Error (UEE) representing the cumulative *worst-case*, upper- and lower- bound of the energy discrepancy needed to merge all PCC nodal active power into the unique DP [9], (b). the maximum absolute error (MAE), in terms of power, between the DP and the PCC active power injection realizations, and (c) the Maximum PCC Power (MPP) equal to the maximum absolute PCC active power injection realizations.

During the experiments, all resources were used at full-capacity and the ADN operational limits were set to the values in the EN-50160 standard. Furthermore, power-to-current lookup tables were precomputed for every available Type-2-EV at the DESL, namely a Renault Zoe and a Tesla Model S, to enable explicit active power control of the plug [10]. Also, the controllability of the EVs (see *Question Ac*) and the EV user behaviour model to compute next-day realisation for the EVCS (see *Questions Ab)* were taken into consideration. Furthermore, the control time-step is set to 1min with an MPC-horizon the real-time controller of 5mins.

Results

The results of the simulations are depicted in Figure 8, and Figure 9. Figure 8 *a* and *b* show, respectively, the active and reactive nodal power injections at the PCC. Figure 9 shows the time evolution of the UEE. All results lead to the same conclusion: controlling EVCSs in the day-ahead stage (i) improves the merger of all PCC active power scenario realizations into a unique DP (with and without control respective: UEE^{+}[kWh]: 860 vs 1281, and UEE^{-}[kWh]: -284 vs -316), (ii) reduces the untracked energy error (MAE[kW]: 189 vs 214) and (iii) shaves the peak PCC injections, without penalizing EV users' satisfaction (MPP[kW]: 209 vs 240). However, in practice, having *only* EVCSs as controllable entities in the day-ahead stage is not enough to fully merge the PCC active power realizations into the DP. Indeed, when no cars are plugged, there would be no flexibility to merge the PCC into the DP and bidirectional energy exchange with EVs is not widely available yet[4].

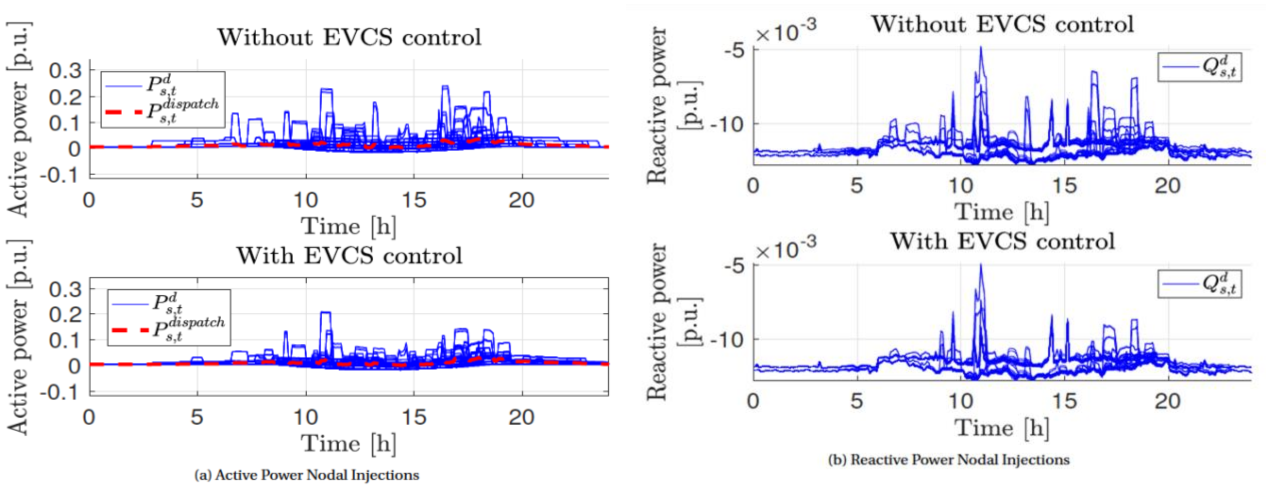

Figure 8: PCC nodal power injections.

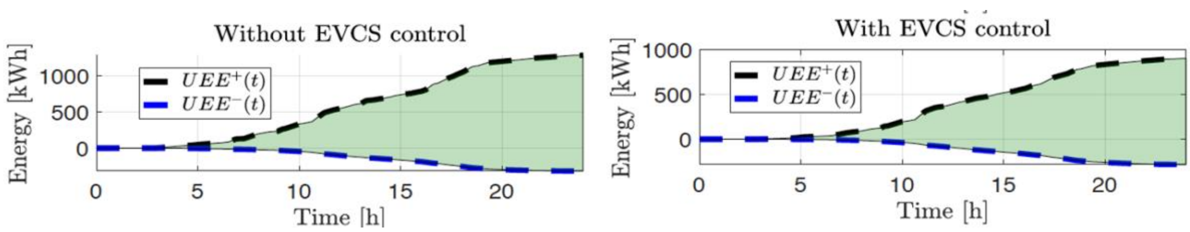

Figure 9: UEE time evolution

[4] Indeed, this could change in the future with the potential penetration of large quantities of bidirectional public chargers which would render the aggregate usable storage of plugged EVs comparable to BESSs used in grid-applications.

The experimental validation was performed for several days, exhibiting different day types and irradiance conditions. For the sake of brevity, the results for two distinct days are presented in this report. Day 1 (17 April 2023) is a weekday and a cloudy day, whereas day 2 (15 April 2023) is a weekend day and rainy. Results for multiday experiments (14-18 Apr 2023) are presented, demonstrating the ability of the dispatching framework to run successfully for multiple contiguous days.

Day 1 (17 April 2023)

Figure 10 shows the dispatch plan in shaded green and realized power at the GCP with and without control is shown in black and red color, respectively. Since each experiment day is unique with respect to the solar irradiance, number, and energy demand of EV charging sessions, it is impossible to redo the same experiments in “without control” mode. Therefore, we obtain the plot “without control” by removing the contribution of the BESS and re-running the AC load flow with the rest of the injections. As can be observed from the figure, the dispatch plan is tracked with high fidelity, thanks to the power injected from the controllable BESS and curtailments actions from EVCS(s).

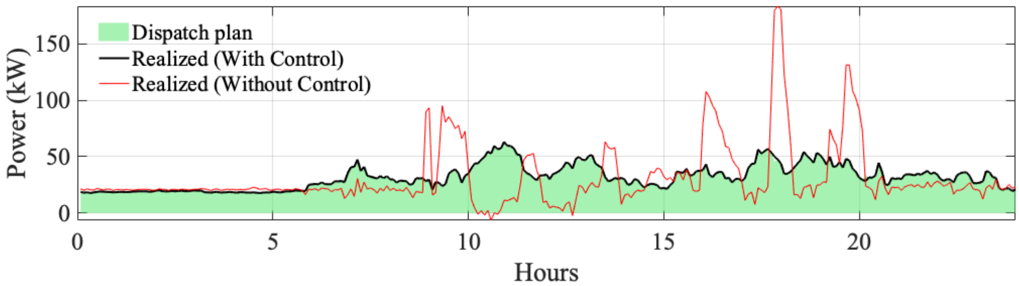

Figure 10: Dispatch plan, and power at the GCP with and without control.

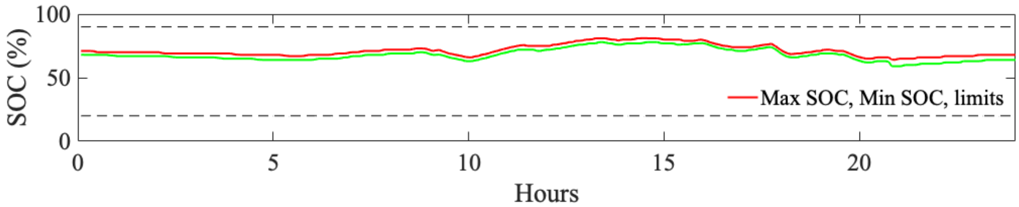

Figure 11: Minimum and maximum state-of-charge (SoC) of the BESS1(i.e., the 720kVA / 500 kWh Lithium Titanate Oxide BESS).

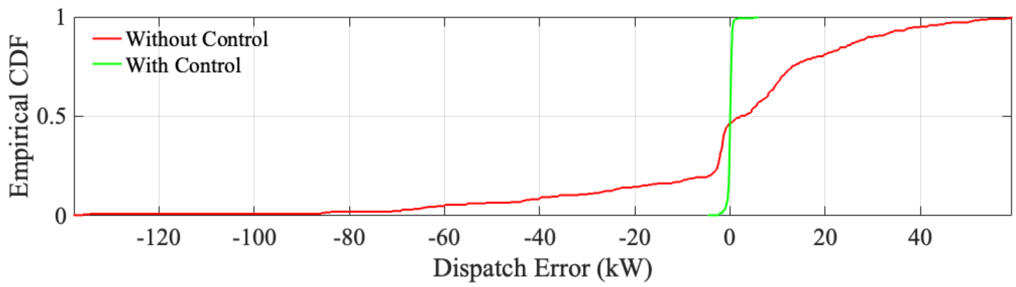

Figure 12: Cumulative distribution function (CDF) of Dispatch error with and without control.

Figure 11 shows the power injections and the SoC from the controllable battery BESS1 (i.e., the 720kVA / 500 kWh Lithium Titanate Oxide BESS). The BESS SoC is kept within the imposed constraint of 20 to 90 %. Figure 12 shows the histogram of the error in power (averaged over the dispatch period of 5 minutes) with and without real-time control while Table 1 shows different metrics to quantify the dispatch error with and without control. It shows the RMSE error, max absolute error (MAE), and Absolute Energy Error (AEE) of the dispatch over the day. From the comparison, it is clear that the RT control manages to track with high accuracy exhibiting low RMSE and MAE. The real-time control manages to reduce error metrics by more than tenfold.

Table 1: Performance Metrics for Real-time Operation

Metrics	Day 1		Day 2	
	Without Control	**With Control**	**Without Control**	**With Control**
RMSE (kW)	28.7	0.7	19.1	0.5
MAE (kW)	137.9	5.9	91.9	2.9
Absolute Energy Error (kWh)	441.7	8.5	327.4	1.5

Day 2 (15-April-2023)

Figure 13 saws that the dispatch plan is again tracked well, thanks to the power regulation provided by the controllable batteries, as shown in Figure 14 and curtailment action of EVCS1. As this day corresponds to a rainy day, the peak power of the dispatch plan is higher than in the case of day 1. On this day, there are no sessions on the EVCS2, as it belongs to the office's private space, which is turned off during the weekend. There are many sessions on the EV charging station, of which all of them met their targets. Thanks to the good quality forecasting of the EV charging profiles accounted in the day-ahead stage, there are not any curtailments in EV demand leading to 100% satisfaction of the EV consumers. Also, the batteries' SoC is within the designated range of 20 to 90% SoC (Figure 14). Figure 15 shows the histogram of the dispatch error with and without control and it can be concluded that the real-time control achieves a very good accuracy in the dispatch tracking, as depicted also in Table 1.

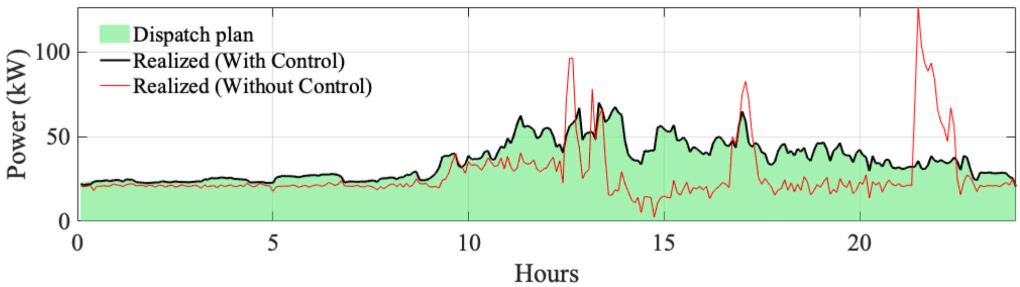

Figure 13: Dispatch plan, and power at the GCP with and without control.

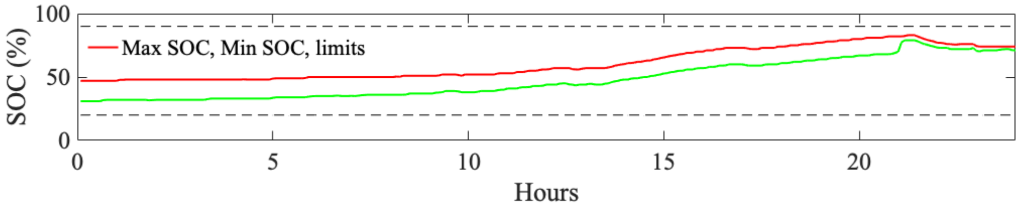

Figure 14: Minimum and maximum state-of-charge (SoC) of BESS1.

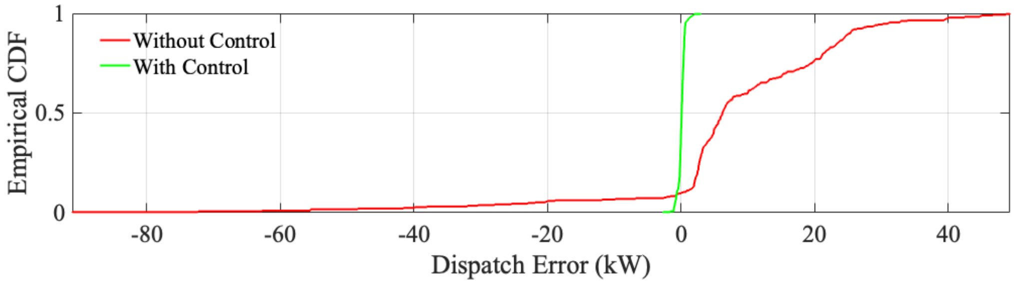

Figure 15: Cumulative distribution function (CDF) of Dispatch error with and without control.

Multiday (14-18 Apr 2023)

To demonstrate the effectiveness of the dispatching scheme, we ran the control of the BESS for four contiguous days. Figure 16 shows the dispatch plan and the measured GCP power with and without the control scheme. In Figure 17, we show the SoC evolution of BESS1 during the 4-days. The power at the GCP follows the dispatch plan and keeps the BESS SoC within a comfortable SoC so that dispatching is continued the next day.

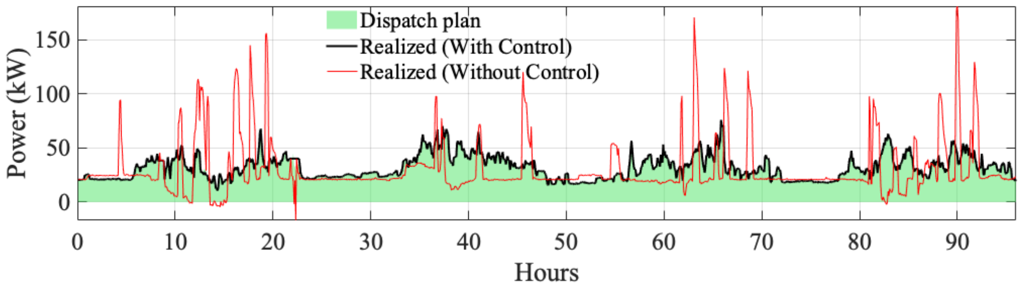

Figure 16: Dispatch plan, and power at the GCP with and without control.

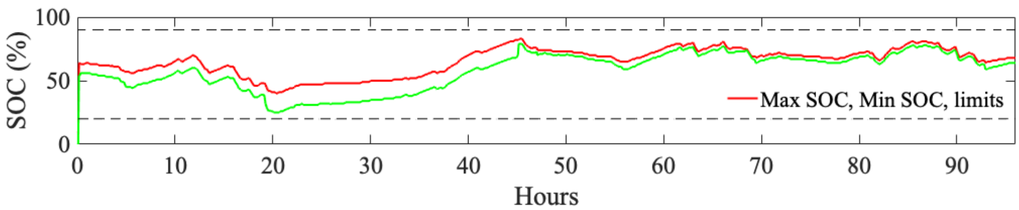

Figure 17: Minimum and maximum state-of-charge (SoC) of BESS1

Question B.b.i: What is the impact of the BESS's energy and apparent power capacity on the dispatching cumulative energy uncertainty?

Methodology

A second set of simulations was undertaken at the ELL building. In this case, the controllable entities in the day-ahead stage are the BESS, and the two EV CSs. As in the previous simulations, the same scenarios are used and the idea is to compare the obtained DPs when (i) neither EVCSs nor the BESS are controlled, (ii) only the EVCSs are controlled, (iii) only the BESSs are controlled and (iv) both EVCSs and the BESS are controlled. The comparison is done for different sizes – in terms of maximum apparent power *and* energy capacity – of the BESS. All simulations assume that for all scenarios the BESS's beginning of day SoC is 0.5. Since the BESS is considered, two extra metrics are introduced: the *maximum BESS usage (MBU)* and the *Maximum absolute BESS injections (MABI)*. The MBU is defined as the ratio of the largest energy usage of the BESS over all scenarios and, the total usable capacity of the BESS. The MABI represents the absolute maximum BESS active power injections over all scenarios and timesteps.

Results

The results of all simulations are summarized in Table 2. In terms of merging the PCC active power realizations into a unique DP, Table 2 confirm that (i) the BESS decreases the UEE more than EVCSs, (ii) increasing the BESS size decreases the UEE, (iii) controlling EVCSs always further decreases the UEE, and (iv) the PCC active power realizations are only *perfectly* merged when the BESS is sufficiently large *and* the EVCSs are controlled. As in the previous simulation, there were no grid operational constraints' violations. Table 2 shows the BESS's MBU for different BESS sizes and simulation configurations. Increasing the BESS's apparent power limit had little-to-no influence as the maximum active power injections were practically all equal. This behavior is due to: (i) the scenarios used for the simulations that did not require extra BESS injections and (ii) the lack of ADN operational constraints violations. Finally, Table 2 proves again the advantages of controlling EVCSs as it always led to less utilization of the BESS for the same EV user satisfaction.

Table 2: Simulation 2 – results.

	Controllable Entities	BESS power [kVA] & capacity [kWh]			
		200 & 200	300 & 300	500 & 500	1000 & 1000
$UEE^-(t{=}T)$ kWh	None	-316.1	-316.1	-316.1	-316.1
	EVCSs	-284.26	-284.26	-284.26	-284.26
	BESS	-178.93	-145.35	-74.37	-5.73
	EVCSs+BESS	-136.48	-97.51	-20.95	-0.02
$UEE^+(t{=}T)$ kWh	None	1280.93	1280.93	1280.93	1280.93
	EVCSs	860.32	860.32	860.32	860.32
	BESS	222.46	154	66.88	13.92
	EVCSs+BESS	165.45	110.77	14.12	0.03
MAE kW	None	214.09	214.09	214.09	214.09
	EVCSs	188.59	188.59	188.59	188.59
	BESS	58.13	48.19	38.71	38.62
	EVCSs+BESS	8.39	5.09	0.93	0.02
MPP kW	None	240.64	240.64	240.64	240.64
	EVCSs	208.94	208.94	208.94	208.94
	BESS	117.27	119.12	115.55	109.64
	EVCSs+BESS	57.24	50.83	48.59	50.26
MBU %	None	N/A	N/A	N/A	N/A
	EVCSs	N/A	N/A	N/A	N/A
	BESS	100	99.6	92.71	67.57
	EVCSs+BESS	98.73	76.22	84.06	43.69
MABI kW	None	N/A	N/A	N/A	N/A
	EVCSs	N/A	N/A	N/A	N/A
	BESS	178.72	178.07	172.45	164.05
	EVCSs+BESS	198.88	206.42	197.5	198.14

Question B.b.ii: What is the impact of the number of EV charging stations on the battery size and dispatching cumulative energy uncertainty?

Methodology

For the evaluation of the impact of the number of EV charging stations on the battery size and dispatching cumulative energy uncertainty, another demo site was chosen with higher installed renewables and storage capacity than EPFL, namely the Aigle demo site. This demo site was developed in the frame of the SFOE P&D REeL project and maintained as a permanent research infrastructure. It represents a unique field test site to carry-out research in the domain of control and coordination of renewables-fed medium-voltage grids. It is also considered a scale-up of the EPFL-ELL setup. Indeed, the grid topology features a similar number of nodes to the EPFL-ELL setup. However, the complexity and global prosumption of the network is significantly larger. At the PCC, the power fluctuates between -2MW and +1MW whereas on EPFL-ELL setup, it fluctuates between 0 and 200kW. The Aigle demo site thus has a PCC overall amplitude variation fifteen times greater than EPFL-ELL. The battery has a rated apparent power of 1.6MVA and a rated capacity of 2.5MWh. It is planned to install four charging stations like the one installed on EPFL campus, however with 300kW peak power each instead of 150kW. Since these CS will be installed after the end of the project, the simulation of a DP with the existing infrastructure with the anticipated stations was performed. This considered all the specifications of the existing infrastructure and those of the EV fast CS due to be deployed. For accessing the impact of the EVCS on the battery size and dispatching cumulative energy uncertainty, two simulations were undertaken, one with 4 CS and another one with 40.

Results

For simulation 1 (4 EVCS), 20 scenarios of prosumption on every node were generated based on historical data. For each scenario, an additional anticipated scenario for the four EVCS was added. The PCC power for each scenario is shown in blue in Figure 18. We notice how the dispatching squeezes the profiles thanks to the control of both the battery and four charging stations. The profiles don't overlap perfectly because the variance is too high with respect to the size of the battery and charging stations. The uncovered energy error reduced from 16.39MWh without control down to 6.88MWh with BESS+EVCS control as shown in Table 3.

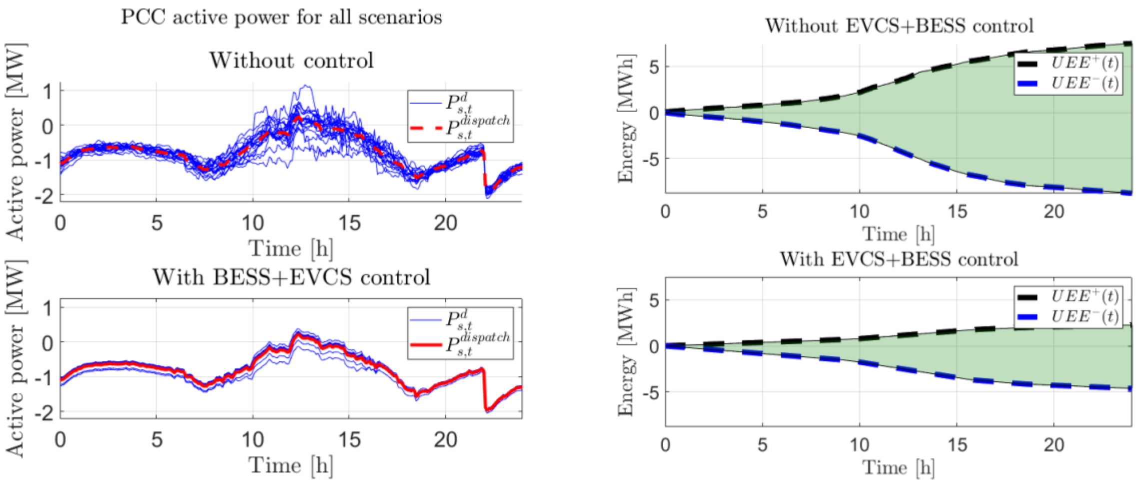

Figure 18: PCC active power for all scenarios (4 EVCS) and Uncovered energy error (4 EVCS).

Using the metrics presented in *Question Ba*, we notice the strong contribution of controlling the battery. Adding the four charging stations control does improve the metrics yet only in a small manner as the flexibility provided is very small with respect to the PCC volatility.

Table 3: Aigle simulation metrics (4 EVCS)

Metric	no control	BESS control	BESS + EVCS control
UEE^{+} [MWh]	7.52	2.39	2.26
UEE^{-} [MWh]	-8.87	-4.61	-4.62
MAE [MW]	1.05	0.37	0.34
MPP [MW]	2.12	2.06	2.06
MEVUS [%]	100	100	100

For simulation 2, 40 EVCS were considered instead of 4 to match t long-term growth of electric mobility. In this case, the total UEE without control rises from 16.39MWh up to 17.5MWh brought by the additional stochasticity of the stations (Table 4). However, as they are controllable, they bring additional flexibility to the whole system reducing the uncovered energy error with control from 6.88MWh down to 4.81MWh. This shows that adding new highly stochastic charging stations can in fact have a positive impact on the overall consumption predictability if they are adequately controlled. And this without significantly impacting the customer satisfaction as seen in the MEVUS metric.

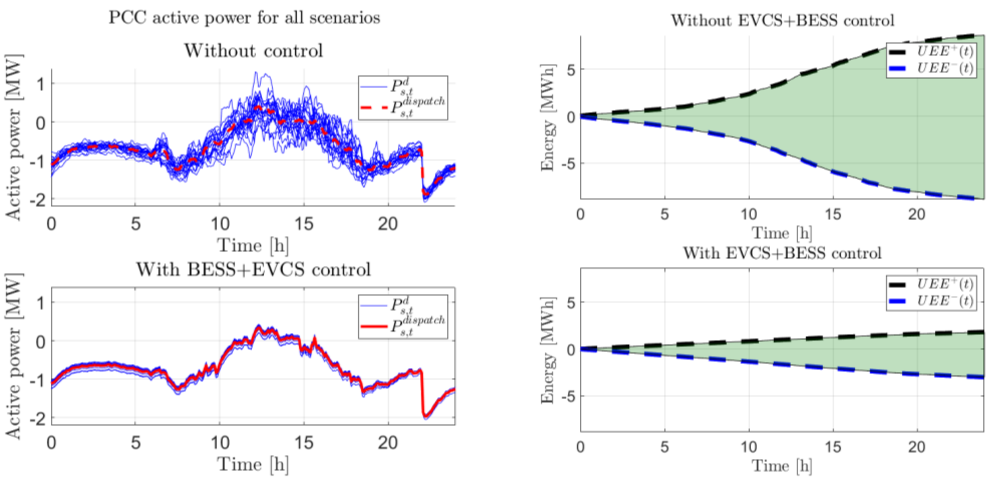

Figure 19: PCC active power for all scenarios (40 EVCS) and Uncovered energy error (40 EVCS)

Table 4: Aigle simulation metrics (40 EVCS)

Metric	no control	BESS control	BESS + EVCS control
UEE^+ [MWh]	8.65	2.39	1.8
UEE^- [MWh]	-8.85	-3.71	-3.01
MAE [MW]	1.04	0.18	0.14
MPP [MW]	2.09	2.03	2.05
MEVUS [%]	100	100	98.9

Question B.b.iii: What is the impact of the type of EVs, i.e., public EVs vs industrial fleet, and associated charging scenarios and charging stations, on the battery size and dispatching cumulative energy uncertainty?

Methodology

In order to address this question, the Swiss research partners collaborated with the Italian project partners. Particularly, MESH4U project partners from the University of Rome Tor Vergata undertake activities on optimal sizing and scheduling of commercial fleet charging stations specifically for grid support [11]. These commercial fleet charging stations were incorporated in the EPFL-DESL's control framework to compare its dispatchability performance between public fast charging stations (PFCS) and commercial fleet charging stations (CFCS). Special focus was put on the assessment of the battery size difference in both cases.

The considered grid topology is the same as EPFL-ELL presented in *Question B.a*. For the case of CFCS, the GOFAST station was replaced by a station with ten 22kW slots, one per vehicle. The shift schedule and energy demand per vehicle for each day of the week were provided by the University of Rome Tor Vergata. The optimization problem was readjusted in order to add in the cost function objectives related to the achieved SoC at the start of the shift. Constraints added include (a) the SoC dynamics accounting for the energy consumption during the shift, (b) the limit of the overall active power consumption to 150kW ensuring the ampacity limit of the line following the charging station node, and (c) power limits only to active power since reactive power cannot be controlled on type 2 AC chargers. For PFCSs, several scenarios are generated including session start and end time as well as the energy demand.

Results

The physical battery on EPFL campus is large enough to remove all the uncovered energy errors in both CFCS and PFCS. However, even if the daily energy throughput is the same for both CFCS and PFCS, the BESS energy throughput and maximum active power are approximately ten times larger to remove the UEE for the latter than the former (see last three rows of Table 5). This significant difference is due to:

1. The battery compensates for the high uncertainty of arrival, departure, and energy demand of PFCS customers. For CFSC, there is only one scheduled scenario, so the arrival/departure times have no uncertainty. Figure 20(a) shows the PCC power volatility between scenarios. In Figure 20 (b) the differences between scenarios are only due to the load and PV uncertainties that with a good forecast, can be small.
2. Fleet EVs are plugged in much longer and have no rush to differ their charge whereas public fast charging stations have similar energy demands yet for very short stay duration and limited flexibility. The last point can also be grasped by focusing on the contribution of EVCS control. The BESS throughput is reduced by about 20% for the PFCS and 60% for the CFCS when EVCS control is applied.

Table 5: Dispatching public and fleet charging stations

Metric	no control		BESS control		BESS + EVCS control	
	Public	Fleet	Public	Fleet	Public	Fleet
UEE+ [MWh]	1762.4	105	1.8	0.1	1.2	0.1
UEE- [MWh]	-587.5	-105	-1.3	-0.1	-0.9	-0.1

MAE [MW]	219.5	11.3	0.3	0.01	0.3	0.03
MPP [MW]	264	224.9	98	218.3	95.7	210.6
MEVUS [%]	100	100	100	100	100	100
CS throughput [kWh]	454.9	554.2	454.9	554.2	391	403.4
BESS throughput [kWh]	-	-	561.9	83.3	450.2	42.4
BESS Pmax [kW]	-	-	219.5	11.4	173.8	11.4

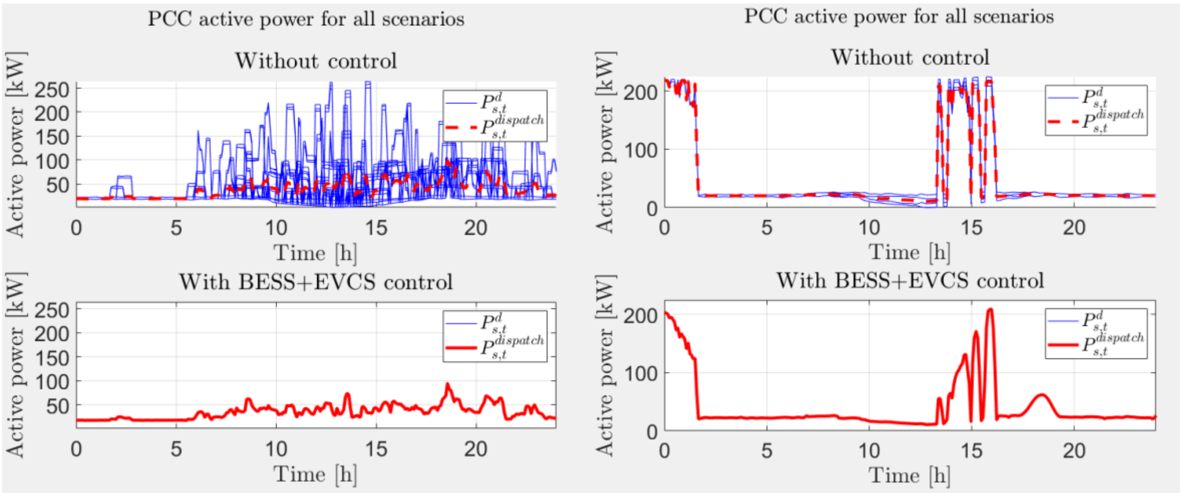

Figure 20: PCC active power for all scenarios with and without control for (a) a public fast charging station and (b) an industrial fleet charging station

Question C.a: What are the market available services that stationary batteries can provide and how profitable are they?

Methodology

Although guaranteeing dispatchability at the PCC seems to be interesting for grid operators, it is a value proposition which is currently not marketable. In that sense, other market opportunities of the Aigle setup were assessed via interviews with numerous companies and researchers as well as online market research. Indeed, the ancillary services are expected to represent a cost of around CHF1B in 2024 [12]. With respect to assets integrating BESSs and EV fast charging stations, services were identified for different clients, notably:

- TSO and Battery owner: Frequency Containment Reserve (FCR) and automatic Frequency Restoration Reserve (a.k.a secondary reserve) (aFRR)
- DSO: Peak power shaving, Balancing errors reduction, Voltage control and Congestion management.
- Industrial consumer: Peak power shaving (PPS), self-consumption, energy backup reserve, and postponement of electrical infrastructure enhancement

Results

The services which are the most interesting economically and compatible with each other are described below.

Peak power shaving (PPS) (for DSO or Industrial consumers)

Swissgrid bills the DSOs and big customers connected to the transmission grid based on their 15 min peak power consumption of each month. In 2023, this price is 48 660 CHF/MW [13], DSOs pass a part of this cost directly to their own big final customers (equivalent to all consumers with over 100 MWh/year) based on the monthly or yearly (this depends on the DSO) 15 min peak power consumption. In that sense, to perform PPS with a limited energy reservoir such as a BESS, the controller must anticipate its peak shaving objective month/year-ahead. To set this peak power limit, the controller must be able to forecast the load with sufficiently low uncertainty to not deplete the battery before the highest consumption. This is a very difficult and risky task and even more so when the power is billed yearly.

Frequency containment reserve (FCR) (for TSO and Battery owners/operators)

FCR (or primary frequency regulation reserve) is a fast response (~10 seconds) mechanism of the power grid to match supply and demand. Any resource with enough flexibility can apply for a Swissgrid prequalification and participate in the FCR market. This is a dynamic market with bids advertised day-ahead in steps of 1 MW and must be made available for slots of 4 hours (i.e., 6 slots a day). From the beginning of the year until today (March 30th, 2023), the price has fluctuated from 1 to 95 CHF/MWh as shown in the figure below. This figure also displays the secondary (aFRR) market prices. A strong price increase since October 2022 is noticeable. aFRR can be bid separately in both negative and positive directions (reduce/increase prosumption respectively). This service was not considered here as it is much more constraining than FCR for ~1MW/1MWh scale limited energy reservoirs (the bids are for a full week duration and in steps of 5MW).

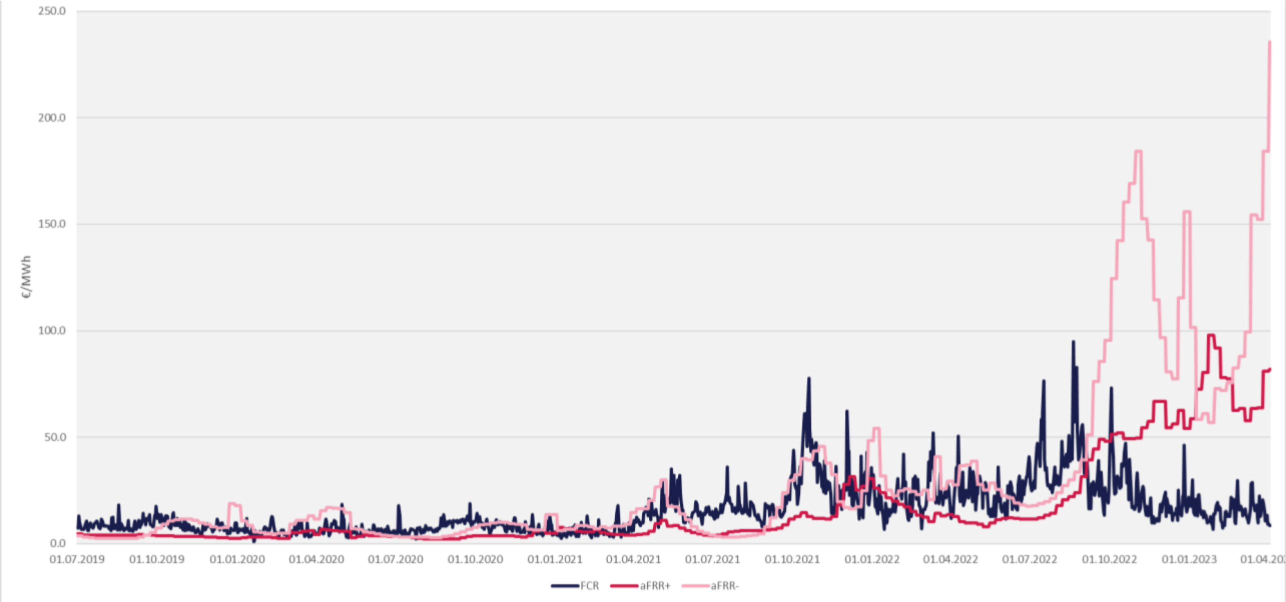

Figure 21: FCR and aFRR bid prices in euros/MWh

For flexible entities below 1MW, they can be activated by a pooling strategy. One can thus consider smaller granularity per unit if the aggregated resources in the pool allow for it.

Backup energy reserve (For industrial consumers)

The concerns regarding energy shortages in Switzerland are rising. More and more companies are looking into backup energy solutions such as diesel generators or BESSs. Since this service may not be linked to a direct revenue stream, e.g., by ensuring the satisfaction of the BESS operator's clients, it is not possible to attribute a generic economical value. By establishing beforehand the amount of energy needed for backup, one can guarantee that amount to always be stored in the BESS and perform other services on top of it. As load shedding is most of the time planned and communicated in advance, a company can also reserve the battery for backup only for a specific scheduled moment while performing other services the rest of the time. This turns the backup energy resource into a revenue generating asset contributing to the energy transition.

Other services:

Balancing errors reduction for DSOs:

DSOs may pay a penalty fee if their real-time prosumption is different from their day-ahead announcement. As the over 500 Swiss DSOs group in about 18 balance groups, it is only the per group aggregated mismatch between planned and realisation which is fined. Hence, if a DSO has a poor prediction in a direction opposite of the other participants of a given balance group, they will not be penalised. Considering the current penalties and regulatory framework, limited energy reservoirs are more profitable executing a combination of FCR and PPS.

Voltage control:

Swissgrid penalises the DSOs who deteriorate the voltage levels at their interconnections with the transmission lines. The rules [14] and prices [13] show little economical interest for providing reactive power control with battery energy storage systems (even though it is a highly compatible side service with the other services controlling active power).

Congestion management:

In Switzerland, medium and high-voltage lines are not under threat of congestion yet. Installing battery energy storage systems can therefore be interesting only for specific low-voltage lines where changing the infrastructure would be more costly than installing a BESS (to support the occasional peak demands). This scenario has not been studied further here.

Self-consumption:

For industrial consumers, the energy consumption price can widely vary according to the DSO supplier and either the contract is on the free market or not. The same goes for the feed-in price (net production of electricity). The feed-in price is in most cases significantly lower than the purchase price (often around 10 cts/kWh lower) which provides an incentive to self-consume (for example a mid-day excess PV production stored in the battery and consumed later in the night). The battery investment cost can be boiled down to a usage cost (in chf/kWh) by accounting a lifetime fixed number of cycles (can widely vary on many parameters yet typically ~5000 cycles). For a 1 MW/1MWh battery at 500 kCHF, the usage cost would be about 10 cts/kWh to store and consume energy later. Including the deployment and maintenance cost as well as depleting capacity over time, at this rate, it would not be economical to self-consume.

Additionally, within the MESH4U project, the focus is on grid topologies with charging stations (which don't imply net exports for the moment). Hence this service is not included in the following simulations.

Question C.b: For a given set of services, what is the impact of the battery size and grid topology on the batteries' profitability?

Methodology

For the assessment of the BESS profitability for different battery sizes and grid topologies, a dedicated EMS for the BESS was developed: the multi-service battery controller (MSBC). Its objectives are to plan the services that the BESS performs every day and to ensure a safe operation of the BESS according to the plan. The software can run in a physical system or in simulation mode, in which an equivalent series resistance (ESR) model of the battery and historical data of the load to simulate are used to assess the performance of the software on a given site.

The MSBC consists of a communication interface and a controller. The communication interface handles all communication aspects of the system: it reads the state of the BESS, the state of the managed grid (i.e., PCC measurements, load consumption, etc), transfers them to the controller, then reads and sends the setpoints computed by the controller to the battery. It also sends data to a database to be stored and visualised. The controller's tasks are to safely operate the BESS and maximise the revenues it generates. To do so, the controller is divided into two elements: the planner and the real-time controller.

The planning process includes (a) a monthly/yearly (depending on the DSO's policy) computation of a peak-shaving objective for the coming period, considering estimated FCR and PPS revenues, and (b) a daily forecast of the load for the coming day based on which the slots of the coming day that the BESS is going to perform PPS or FCR are determined. Figure 22 illustrates this concept.

At every control cycle, the real-time controller computes the setpoints to send to the battery according to what is feasible and what was planned by the planner. This computation is based on measurements such as BESS state, (P, Q) load consumption and (P, Q) at the PCC. For the provision of peak shaving, a proportional-integral (PI) control is applied while for the provision of FCR services, the frequency deviation, as well as the SoC of the battery are considered. The frequency deviation is used to compute the frequency regulation component of the setpoint (according to Swissgrid's regulation), while the SoC of the battery and an autoregressive integrated moving average (ARIMA) forecast of the frequency are used to compute the charge management power (which is subject to Swissgrid regulation and ensures that the state of charge of the battery stays within given bounds). In particular, for limited energy reservoirs (LER) to participate to FCR, the asset operator must ensure that the asset can always provide the bid power for 15 min (consumption and production).

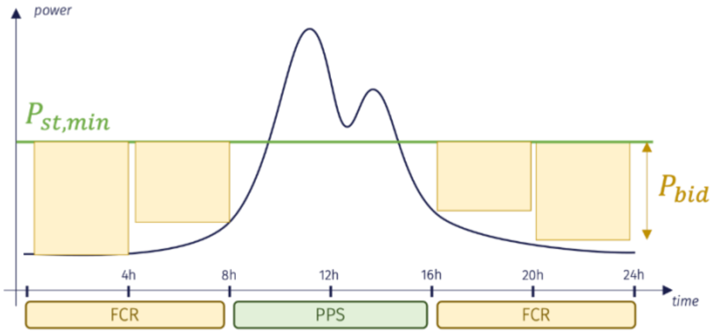

Figure 22: Illustration of FCR and PPS service planning

The MSBC performance is validated through simulations of the Aigle setup and an experimental setup at EPFL. A first simulation considers the BESS deployed in Aigle, 4 EVCS (soon to be deployed as discussed in *Question Bbii*) as well as real grid tariffs [15] and average primary control bid price. To accurately model the EVCS profile, GOFAST shared the data of another existing station with similar frequentation. A second simulation including 40 EVCS instead of 4 was conducted to evaluate the impact of future enhancement of the charging infrastructure in Aigle. Finally, a third simulation in which the peak power price was increased from 5.63chf/kW/month to 13 CHF/kW/month (which is in fact the tariffs already applied by several operators in Switzerland) was performed to increase the importance of the PPS service. Since the Aigle setup is not ready for the experimental validation of the framework, the setup was replicated at EPFL by scaling down the ratings of the hardware in Aigle by a factor of 62.5. This limitation is due to the rated power of the controllable load (that is used to mimic the load of the Aigle setup) being 30kVA. Additionally, 1 string out of 9 of a 740 kVA/560 kWh BESS was used, resulting in an 80 kVA/62 kWh battery virtually capped in order to effectively have a 25.6 kVA/40kWh battery (i.e., a battery 62.5 times smaller than the battery in Aigle).
The multi-service battery controller runs its planning algorithms with the following services:

1. Primary control regulation, assuming a granularity in the primary bids that the battery can advertise to the pool aggregator set to 10 kW, while this aggregator ensures that the pool bids have the 1 MW market granularity.
2. Peak-power shaving (PPS).
3. 750 kWh back-up energy reserve guarantee, ensuring at least 10 EV charges.

Results

Simulation 1:

With 4 EVCS, the MSBC decides to perform the FCR service only. The bid power is sometimes lowered to never exceed the PPS target (which changes monthly). To allow a limited energy reservoir to participate in FCR, BESS' SoC must stay within the bounds specified by the transmission system operator (orange band in the left part of Figure 23). In the simulation, the battery never went below 53 % SoC (i.e., 1.325MWh of usable energy is always available in case of black-out). To ensure that the SoC stays in such bounds, the LER performs charge management: every hour, it can change its steady state operating power (i.e., the power it draws or outputs when there is no frequency deviation). Focusing on a single day (Figure 23- right), the BESS power profile is illustrated as it performs FCR vs the hourly charge management requests. For the sake of simplicity, the figure illustrating the repartition of PPS and FCR is not shown since, as mentioned here above, only FCR is performed.

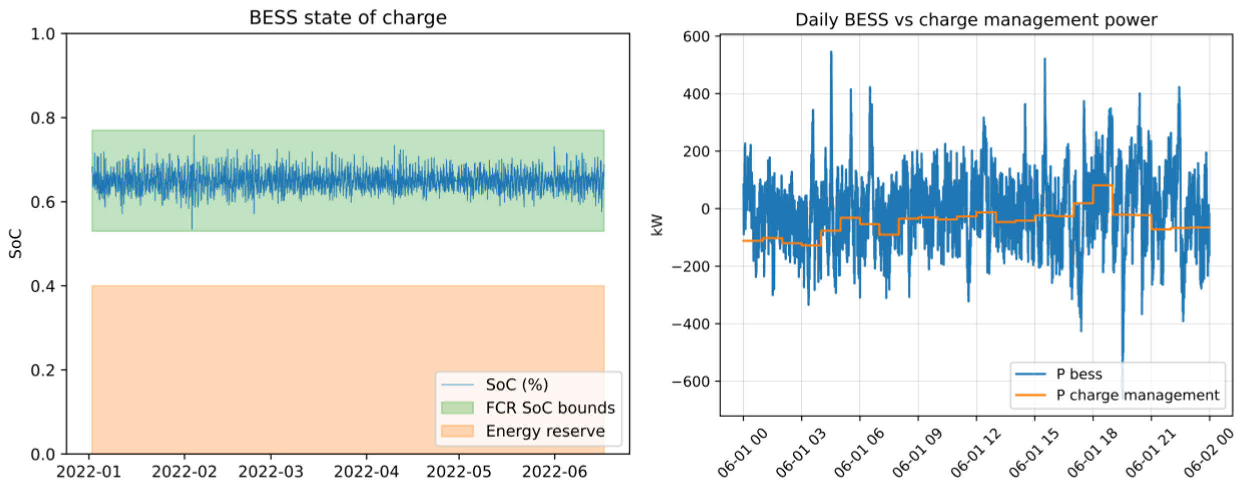

Figure 23: Simulation 1 BESS SoC.(left) and BESS charge management (right)

Simulation 2:

With 40 EVCS, the MSBC sets the shave target around the transformer limit (1.6 MW) (Figure 24(left)). The controller is able to shave the power at the point of coupling. The FCR service is performed most of the time, with bids that change to ensure that the shave target and transformer limit are always respected. Figure 24(right) shows the power profiles of the resources on the 9th of July 2022. Between midnight and 4 p.m., the MSBC decides to perform FCR with different bids. Between 4 and 8 p.m., PPS is performed, which can be seen by the bid power set to zero and comparing the load (red line) and PCC consumption. Between 8 p.m. and midnight, the planner chooses FCR again. Also, the battery never goes below 58.7% of SoC (1.467 MWh of energy is always available). For the sake of simplicity, the SoC evolution is not shown here.

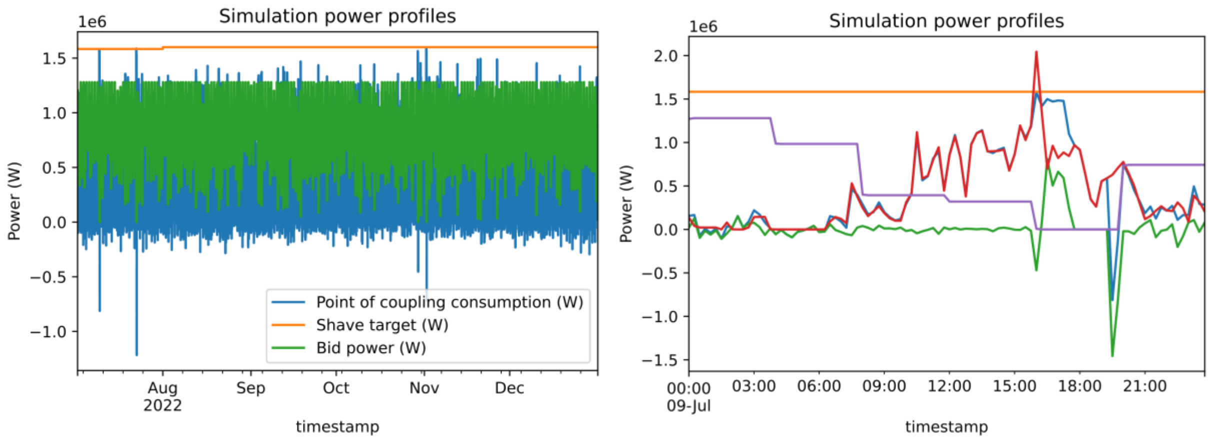

Figure 24: Simulation 2 power profiles during the full simulation (left) and in a single day (right).

Simulation 3:

With higher tariffs and 40 EVCS, more occurrences of PPS were applied in order to remain within transformer limits (i.e., to prepare PPS, the battery charges resulting in peaks in the SoC dynamic, see Figure 25 - left). Zooming on the 22nd of July better shows the PPS service being performed, with a PPS target of less than 1.5 MW (Figure 25- right).

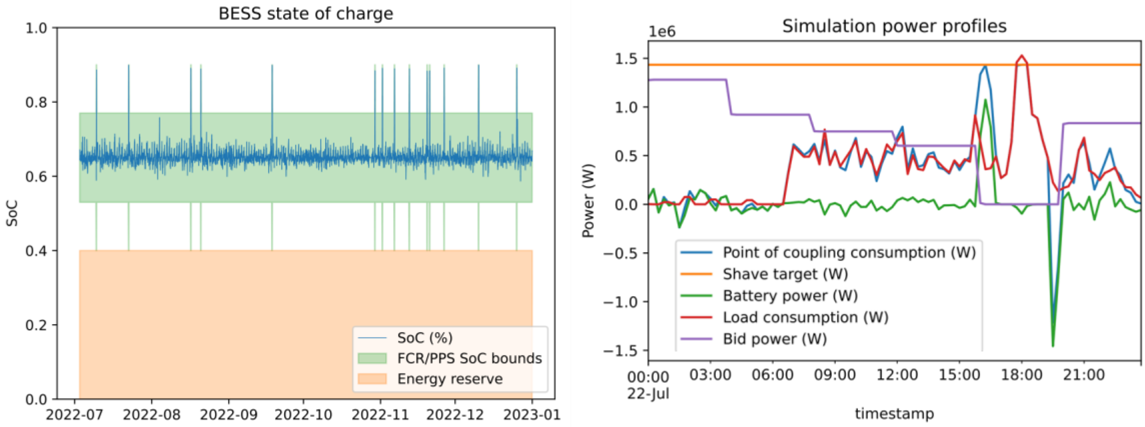

Figure 25: Simulation 3 BESS SoC (left) and a single day (right)

The experimental validation was done using the load of simulation 3 (on the 22nd of July 2022) scaled down. This simulation is the one that better shows the MSBC in action. During the validation, the BESS performed FCR at all times except from 4 pm to 8 pm for PPS as planned. This respects the scheduled services, and the profile curves match the simulation well as shown in Figure 26. The results show that the scaled-down battery is operated in the same way as in the simulation, therefore displaying the physical feasibility of the MSBC control framework.

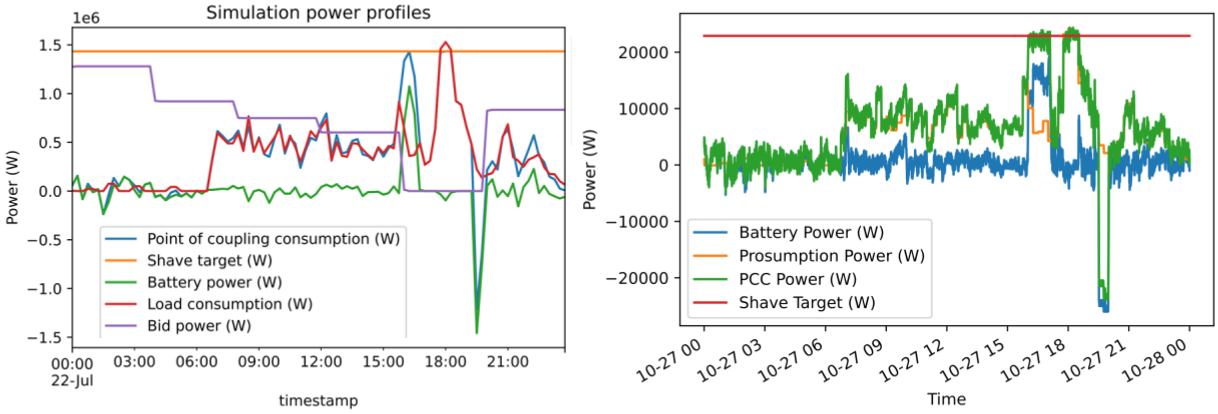

Figure 26: Simulation (left) vs experiment (right) power profiles.

In terms of economics, in simulation 1, the owner of the battery can expect a return on investment (RoI) in 15.7 years. In simulation 2, the annual revenues from primary regulation (136.6kCHF) and electricity bill decrease (2.3kCHF) lead to a RoI of 23 years. The profitability is lower than simulation 1 due to the increased load to the transformer limits reducing the possibilities of FCR participation from the BESS. With higher tariffs and 40 EVCS (i.e., simulation 3), the RoI is 18.6 years mainly due to the higher PPS occurrences resulting in higher savings in the electricity bill (21kCHF vs 2.3kCHF) while the FCR was slightly affected (136.4kCHF vs 136.6kCHF).
These estimations do not consider the economic advantages provided by the 750-kWh backup energy reserve that aims at increasing the system's resilience to shortages. Indeed, this value needs to be estimated by GOFAST and corresponds to the value of having the charging stations available in case of shortage. Nonetheless, the value of the energy reserve can also be estimated as cost avoidance (i.e., it avoids paying for a diesel generator). Considering this as well as the grid upgrade cost avoidance, the RoI in simulation 3 is approximately 16 years.

3. Conclusions

The key takeaway messages of this project are the given here below.

A. EVs charging profiles can be (slightly) controlled for the benefit of the grid without significantly changing users satisfaction. The control framework should consider that: (i) customers tend to receive more energy than targeted (4% more); (ii) customers leave later than anticipated (10% later); (iii) customers are ready to extend their charge duration (by a few minutes) to help the grid (32% against a discount and 35% even without a monetary discount), and (iv) most users (65%) plan their EV charge based on SoC rather than a target stay duration or cost.

B. Controlling EV fast charging stations is not suitable for sub-second control frameworks and their dynamic needs to be accounted for in sub-minute control frameworks. By testing the GOFAST EVTEC charging station with a Tesla Model S90D, one can observe response times varying between the second to minute range depending on the setpoint power jump. Moreover, one can observe that the implementation error follows a quadratic trend, where the error is largest for low and high setpoints. However, the car model might contribute to these characteristics, thus implying that other car models might lead to significantly different results.

C. Combining a controllable EVCS and a BESS has measurable benefits for grid management and control. The control of EVCS alone in the day-ahead stage already provides several measurable benefits in terms of reduction of the untracked energy error, and shaving the peak PCC injections, without penalizing EV users' satisfaction. However, it does not guarantee that the flexibility will be available when it is needed since it is uncertain when the EV(s) will be present at the charger. Therefore, the installation of a BESS is required. Even more, when EVCS and BESS are controlled in real-time, notably by the control framework developed in the MESH4U project, all error metrics are reduced by more than tenfold compared to a without-control scenario.

D. The control of EVCS can reduce the need for BESS investment without affecting EVCS user's satisfaction. At the same time, the increase of the BESS's energy and apparent power capacity has a limited impact on the dispatching cumulative energy uncertainty (at least in our case study).

E. The expansion of EVCS deployment that is adequately controlled can lower their perturbation into the grid. It is ubiquitous that adding fast EVCS is inevitable to promote the transition towards electric mobility. It is also known that their deployments are viewed as a risk for the grid from the added stochasticity and peak power demands. However, with adequate control of the stations, one can not only lower their perturbations into the grid but also provide grid support by increasing the overall day-ahead predictability. Public fast charging stations can therefore not only help the electric mobility transition but also provide grid flexibility to the condition that they are both controllable and controlled. It is thus important to consider this aspect in the selection process of future charging station providers.

F. Commercial fleet charging stations (CFCS) can support the electrification of the mobility sector in a more cost-efficient way than the public fleet charging stations (PFCS). For the same CS energy demand, the required battery size to track the dispatch plan is ten times smaller for a CFCS. In terms of required infrastructure and investments, one can achieve more grid predictability and flexibility with lower investments by implementing dispatch plans on nodes encapsulating schedulable and controllable commercial fleet charging stations. Due to the significantly higher stationary battery investment costs, when truly necessary for the grid, tracking a PCC node encapsulating highly stochastic PFCSs can be achieved. Figure 27 qualitatively shows the grid support versus cost analysis between different levels of prediction/scheduling and control for both PFCS and CFCS:

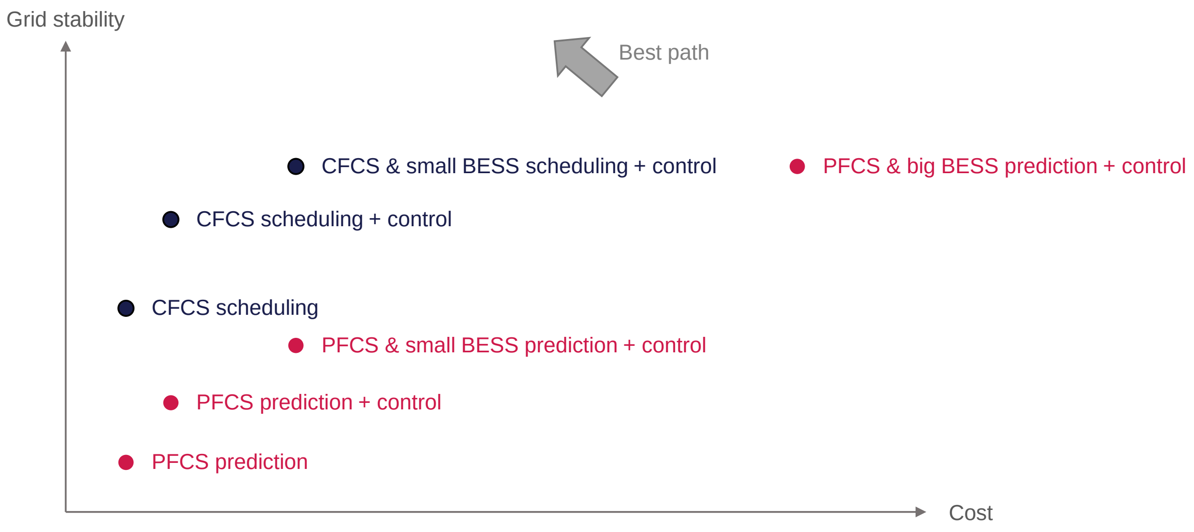

Figure 27: CFCS vs PFCS measures analysis in grid stability and cost.

G. The profitability of an investment in BESS coupled with EVCS is case specific. To make BESS coupled with EVCS economically worth performing peak power shaving (PPS), the distribution grid operator should increase the price of the power component. Note that the energy component can be reduced so that the overall bill of a charging station operator (without the use of batteries) does not change. While, in Aigle, using the battery to perform PPS is not economical, in some specific cases, BESSs can be economical even with the current prices. For example, in remote places, where upgrading the infrastructure to supply the rated power of the charging stations would lead to huge investment costs, batteries can be deployed to take care of the consumption peaks. Other locations with significant PV production and low feed-in tariffs can also make BESS profitable as self-consumption would be added to the panel of services. To reach an attractive break-even cost, a careful dimensioning of the BESS must consider numerous parameters which vary during its lifetime. These parameters include market prices, number of EVCs, transformer size, the load evolution and others.

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