Refer To Power Monitoring For Ac Electric Vehicle Charging

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Abstract: **Electric vehicle (EV) charging is commonly viewed as a major enabling technology that may maintain system stability and provide ancillary services to the grid. The present work aims to advance the state of the art in dynamic charging of individual EVs within existing AC-charging facilities. The study suggests two different control strategies based on adaptive feedforward and feedback linear controllers, respectively, for tracking EV power setpoints Extensive real-world tests conducted on the workplace charging facility operated on the JRC Ispra campus validate the effectiveness of the proposed control methods in tracking two different current profiles for flexibility scheme qualification. The control design, which does not require any higher-level communication or ad-hoc hardware adjustment of the standard EV charging infrastructure, is supported by the experimental results.**

I.INTRODUCTION

Concerns have been raised about how electric cars (EVs) might affect the electrical grid as their use grows particularly in view of anticipated market shares. If not planned for and maintained appropriately, EV parking facilities which are power-intensive assets can cause grid instability. On the other hand, they can offer a useful source of flexibility that can help with grid operation and balancing.

As a result, grid operators have begun implementing market-based compensation plans to reward resources with better power-flexibility performance. In order to compensate distributed energy resources (DER) that can modify their consumption in response to automated power set-points broadcast at particular times, the American grid operator PJM, for example, established a so-called "Regulation Market" [5]. PJM uses a performance score that evaluates accuracy and latency to evaluate the effectiveness of load-regulation resources and precision the capability to track a power reference signal. To receive certification from PJM, a resource must achieve three consecutive performance scores of 0.75 or higher, indicating its reliability and effectiveness in providing demand side response and thus contributing to grid stability [6]. Ancillary services markets are also evolving in Europe, following the objectives introduced in [7]. An example in such regard is the Frequency Containment Reserve Cooperation [8], which currently involves twelve Transmission System Operators (TSOs) from nine countries in the EU that interact with national Balancing Service Providers (BSPs) with the aim of procuring fast regulation resources. Provided sufficient availability, a faster service to the grid (e.g., with response time of about 1 second) can decrease the amount of alternative regulation resources required to guarantee system stability. To participate in these markets, slow to medium-fast EV charging facilities can be designed with load-flexibility in mind, especially if the users have typical dwell (i.e., park & charge) times from below 30 minutes up to an entire working day. This has led to research on the design and operation of so called "smart charging" facilities that can better respond to the needs of the grid [9].

Among the various factors influencing AC grid stability, frequency is a key indicator of grid health, as any deviation from the nominal frequency indicates imbalances between power supply and demand, potentially culminating in system instability and disruptions [10]. The primary challenge underlying frequency regulation pertains to the inherent dynamic nature of power systems, characterized by constantly fluctuating loads, with EV charging being no exception. The growing share of intermittent renewable electricity further increases such fluctuations on the generation side. Consequently, increasing regulation resources are required to maintain the grid frequency within the prescribed bounds and the intrinsic flexibility of EV harging can provide an important support in this regard. In our experimental setup, we analyze the European Commission's Joint Research Centre (JRC) EV charging field located at the Ispra campus as a dynamic resource capable of modulating its power absorption in accordance with given reference signals. Our objective is to design and test novel control methods for dynamic regulation of EV charging, assessing their improvements in terms of accuracy and robustness with respect to standard power regulation approaches.

RELEVANT WORK

One of the bottlenecks in AC charging, the most diffused and low cost technology to date, remains the lack of a digital communication between the EV and the charging infrastructure's grid-side requirements [11]. This issue has prompted the Open Charge Alliance, a consortium of global EV charging station manufacturers, operators, and service providers to develop the Open Charge Point Protocol (OCPP), an open communication standard for EV charging stations. OCPP facilitates interoperability between different EV charging stations and management systems, ensuring effective communication and management of the charging infrastructure. Although the protocol is publicly available and an increasing number of manufacturers embed it in their systems, its adoption remains optional, and often relegated to local development (see [12] for constantly updated statistics about the adoption of the OCPP protocol).

Possible approaches to overcome such limitation include machine learning techniques to predict charging patterns and anticipate station availability and thus peak power demand [13], [14] (also relying on control variables such as weather, mobility, and near by events[15]),or the introduction of demand response programs to incentivise EV owners to adjust their charging behaviour and concentrate charging in periods of low energy prices [16], [17], [18] possibly accounting for overloading constraints [19]. The comprehensive review of smart EV charging methods presented in [9] identifies several solutions that can reduce the impact of EVs on the electricity grid and its operational costs.

Another interesting research area focuses on the prediction and estimation of EVs features on the basis of their charging data. EVScout2.0 is a tool that analyzes the current and pilot signals exchanged during charging, and extracts relevant features of the tested EVs, showing how vehicles can be successfully identified or classified for cyber-security issues [20].
Numerous strategies have been put forward in the literature to effectively integrate EV charging facilities into the grid. However, these approaches often necessitate the implementation of ad-hoc management systems and extensive data integration. On the one hand, EV parking operators frequently face challenges due to constraints such as time, knowledge, and resources (and, at times, even interest) required for autonomous implementation. On the other hand, commercial service providers, as well as EV and chargers' manufacturers may not always prioritize energy flexibility, particularly as in the European Union they are not yet mandated to adhere to specific flexibility standards.

A fundamental aspect in enabling the intrinsic flexibility of EV charging assets is the capability of tracking a specified set-point of power consumption (or, alternatively, of drawn current) in order to full-fill certain requirements or provide specific ancillary services. To the best of the authors' knowledge, this aspect has not been fully investigated in the literature. As a matter of fact, several works have tackled the EV charging regulation problem from a low-level hardware perspective. For example, [21] takes explicitly into account the specific power electronic features of an EV charging station and proposes an adaptive control method to ensure disturbance rejection. A similar problem is tackled by [22], [23], and [24], which rely on model predictive control to achieve a robust regulation with dynamic set-point of the charging process. It is worth emphasizing that the afore mentioned papers do not analyse real EV charging assets but they either consider a fully simulative setup [21], [23] or Hardware-in-the-Loop simulations [24]. When real-world tests are conducted, like in the case of [25], the tracking of power/current references is not explicitly analysed and addressed.

II. EV FLEXIBILITY WITH REFERENCE POWER TRACKING

From an operational perspective, the flexibility of an EV parking facility can be characterized as the capability of following a prescribed profile P_r for its aggregate power consumption, which can be determined on the basis of the contingent system conditions and of the fleet of vehicles that is currently connected to the charging points. For the purposes of the present analysis, which is focused on AC charging at constant voltage levels (for a comprehensive review of EV charging standards refer to [26]), a current reference i_r can be considered instead, with no loss of generality.

The main operational challenge that needs to be tackled in this regard is the discrepancy that is often experienced in real-world conditions between the current set-point i_r that is utilised by the EV charging points and the actual current i_{out} that is drawn by the EVs (see top plot in Fig. 2. As discussed in [26], the charging station can only impose a maximum current limit, whereas the EV's internal control systems determine the actual current it draws. Due to differences in how various BMS implementations control power delivery during charging—particularly as the battery approaches different states of charge—as well as effects from operating temperature and other vehicle-specific factors, this frequently leads to a discrepancy, usually a negative one. Our goal is to make it possible for the EV charging infrastructure to provide power regulation services, even if this is not a problem in typical operating settings. It is crucial in this situation to minimize tracking mistakes for a certain reference setpoint. In order to solve this, we suggest two different controllers that enhance the EV's tracking performance by dynamically altering its response during charging. The control systems discussed in this part are specifically designed to minimize the aforementioned disparity and track an equal current reference that is piloted in parallel to each linked EV.

The two alternative control strategies that are taken into consideration are a feed-back controller (FBC) with a PID regulator and a feedforward controller (FFC) that uses ex-ante linear regression tuning to account for the unique characteristics of each vehicle. Next, a thorough explanation of the methods is given.

A. FEEDFORWARD CONTROL WITH LINEAR-REGRESSION TUNING (FFC)

The first method, shown in Fig. 1, controls the single EV's charging process feed forwardly without taking any feedback action to take into account model inconsistencies and outside disturbances. Since the usage of a feedback loop, which is assessed in the following paragraph, is susceptible to time-varying delays in the current configuration, which might significantly impact a feedback controller's performance, this alternative has been deemed viable.

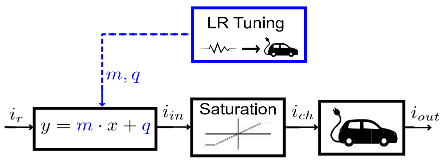

FIGURE 1Diagram of FFC approach.

To improve the suggested feedforward approach's performance and resilience, an ad-hoc reference signal tuning has been applied to take into consideration the unique characteristics of the various automobile types and the charging control logic that goes along with them. Specifically, the affine function of the initial reference ir is used to represent the control signal iin that is broadcast to each individual EV: iin = m∗ · ir + q∗.(1)

Before the EV's charging session begins, and when it is first connected to the charging station, a linear regression tuning procedure is used to determine the parameters m∗ and q∗. A two-minute test signal consisting of sinusoidal components with varying frequencies

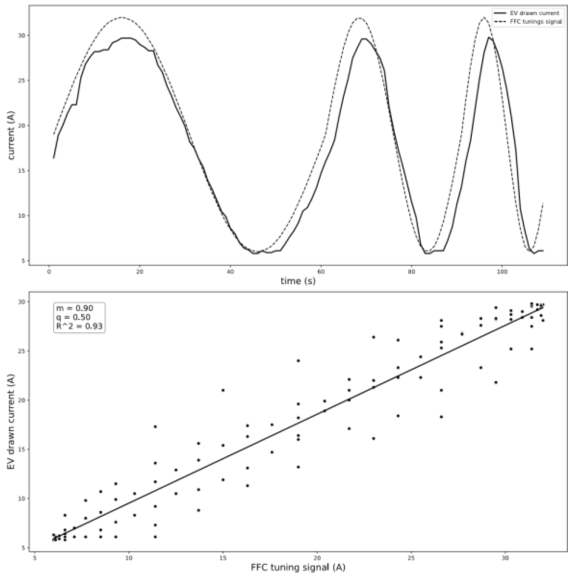

FIGURE 2. A scatter-plot representation of the FFB testing signal with an approximated regression line at the bottom, and an example of an EV response at the top is sent to the charging EV, measuring the absorbed current that results (see top plot in Fig. 2). This is how the parameters m∗ and q∗ are computed: ˜i (m∗,q∗) = argmin eq − r − ʜiout.(2) m,q m Stated differently, m∗ and q∗ characterize the affine static transformation that more closely resembles the inverse of the EV's charging dynamics (between iin and iout). As a result, they can be utilized in (1) to reduce the total tracking error between the current iout and the reference ir. In contrast to the average length of a charging session, we would like to highlight that the 2-minute FFC tuning method is quite brief, suggesting that the FFC does not significantly slow down the EV charging process. An example of the tuning process used on a Renault Zoe 2022 model with a 52 kWh usable battery capacity is shown in Fig. 2. The top plot shows how the tuning

reference profile selection accurately depicts the charging dynamics, even at higher frequencies, a need that not all EV models are able to meet. It is noteworthy that the upsurging section of the third wave has a little higher response latency. The decision to use a linear model for tuning is supported by the plot at the bottom, which displays the value of each current output sample ˜iout (y-axis) in relation to the corresponding input ̧ir (x-axis).

B. FEED-BACK CONTROL WITH PID REGULATOR (FBC)

Fig. shows the overall layout of the feedback controller that was designed.

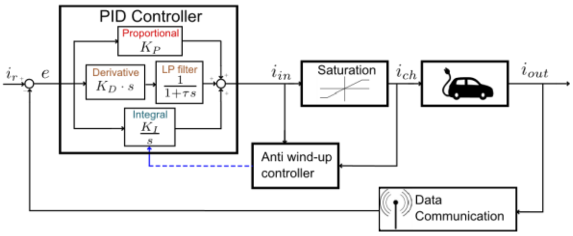

FIGURE 3. Diagram of FBC approach.

The purpose of the proposed FBC is to test a different strategy that uses proven feedback regulation techniques to reduce the tracking error on the setpoint ir for all vehicle types, as opposed to depending on ad hoc tuning and adjustments for every vehicle type (as in the FFC case). The ideal controller for this is a standard PID controller with two modifications: i) an extra low-pass filter added to the derivative component to lessen the high-frequency noise brought about by the numerical implementation of the signal derivative, and ii) an anti-wind-up controller that acts on the integral term of the PID controller to lessen dynamical transients on the EV charger after input saturation.

III. EXPERIMENTAL VALIDATION PLATFORM

The JRC Ispra site's EV charging field has been used to test and validate the regulatory strategies described in Section II. The facility, shown in Fig. 4, has a 60 kW peak production capacity and is situated beneath a solar canopy. It features nine single-phase AC wall-box chargers that were supplied for testing by the Italian business Silla. Python, Influx DB, and MQTT were the only open-source technologies used in the bespoke design of the facility's whole backend system.

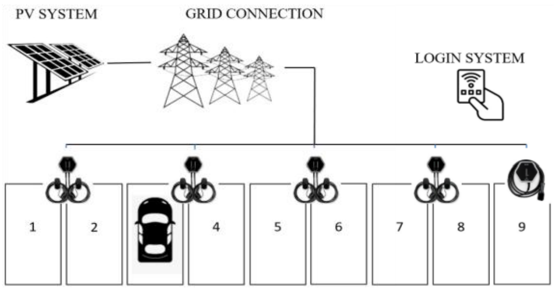

FIGURE 4. The EV charging infrastructure.

In exchange for research data, the EV charging field offers free EV charging to all JRC employees. In order to identify EV users and appropriately categorize their charging behavior within the available historical data, a badge system and a Radio Frequency Identification (RFID) totem are utilized. The back-end system includes an experimental layer that allows for the execution of different experiments in real-world settings in addition to offering a practical charging infrastructure. The facility, which employs 166 people, has offered a variety of test conditions for various experiments since its opening in May 2022. These include credit penalty testing schemes, PV production instant power matching, smart scheduling, and, most importantly for this work, power tracking [27].

Fig. 5 shows the major structural elements of the IT system together with the pertinent relationships between them. The nine charging boxes are set up to use Message Queuing Telemetry Transport (MQTT) topics for both publishing and receiving control commands.

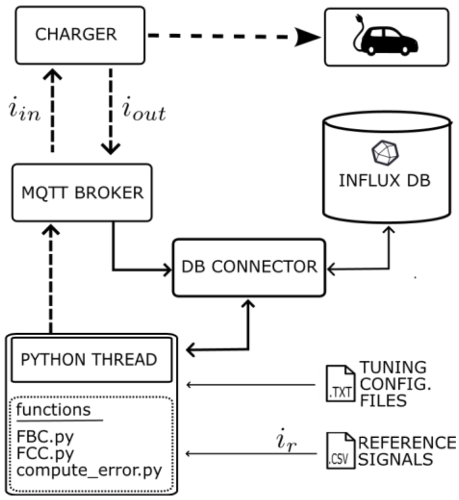

FIGURE 5. elements of the IT infrastructure and their pertinent linkages.

A popular lightweight messaging protocol for Internet of Things applications is MQTT [28]. The protocol's asynchronous communication and publish-subscribe structure make it especially useful for controlling EV charging. The charging box broadcasts I out values (with a precision of 0.1 A) as MQTT messages, which are timestamped by the application as it receives them, usually with very little delay. Other items, including charging status, voltage, total session duration, etc., are defined to indicate various aspects of the charging process. For every connected EV, a Python client application initializes a MQTT broker and subscribes to these topics while operating concurrently. Messages are automatically saved in an Influx database system as soon as they are received. Updated values for I r (sampled from the reference signal under test) and I out are sent to the program at runtime. It calculates the error e and feedback delay Td based on this data, which are then transmitted to the selected controller (FFC or FBC) to determine the controlled setpoint I in, which is ultimately supplied to the charging box. A number of libraries are employed by these functions, including Numpy, Pandas, and Paho .Mqtt. These routines use several libraries, including as Numpy, Pandas, and Paho.Mqtt. To guarantee a perfectly discretized time domain of 1s, the code's execution time is carefully taken into account at each iteration. When compared to the system's normal operating condition, the test's execution had no discernible effect on the use of it resources. During the test, monitoring of CPU and memory utilization showed very little change from typical system activity.

V. CONCLUSION

A innovative approach to smart power tracking in EV AC charging is presented in this research. The suggested method greatly increases EV charging stations' capacity to adhere to specified aggregate power consumption profiles, which strengthens their capacity to provide ancillary services and actively participate in power system control. In order to improve the charging facility's tracking performance and reduce the inherent power tracking errors associated with EVs under charge—which depend on a number of variables like battery condition, current state of charge, and vehicle design—two different control strategies, based on feedforward tuning and feedback control, respectively, have been developed and tested. It is important to emphasize that the suggested solutions can be implemented with little software change and no additional hardware, greatly easing the possibility of a large-scale deployment. Real-world testing of the provided control methods has yielded a variety of experimental results that evaluate and illustrate the enhanced performance of the suggested strategies.

The design and testing of more intricate and alternative control strategies will be the focus of future research in this field. By dynamically altering the controller parameters in real time, adaptive control strategies will be assessed in order to increase tracking accuracy. Additionally, an algorithmic End-of-Charge detector will be employed to predict how EV charging dynamics will alter as the battery gets closer to full capacity. Additionally, in order to minimize the effect of external disturbances on tracking performance, the tuning process for the FFC regulation approach will take into account alternative non-linear models and determine whether quadratic or discontinuous functions might be more appropriate to characterize the differences between the specified tracking signal and the open-loop response of the EV under charge. To gain a better understanding of the grid-EV interaction, these disruptions may be caused by a number of circumstances, such as: (i) EVs reaching the terminal stage of charging, where reduced current may affect data accuracy; (ii) unexpected voltage and frequency oscillations in the grid, which can disrupt charging stability and alter control dynamics; (iii) extreme weather conditions, such as high or low temperatures, which impact the EV charging efficiency and the overall system robustness. Future experiments will also aim to include a broader range of EV models. Moreover, the EV charging platform will be equipped with an EV classification mechanism. This additional feature (currently under development by the authors) will rely on an ad-hoc neural network to estimate and classify the models of the EVs connected at the parking facility, thus avoiding the necessity of initial control tuning and speeding up the charging and regulation processes.

A framework for assessing the financial aspects of this service will also be created, given the possible financial advantages connected to an EV charging asset with power tracking capabilities. The performance of the suggested control mechanism will be evaluated, and future improvements and changes to the control strategy will be compared, using this framework, which will build upon current schemes and mechanisms that quantify and price the power tracking service for charging EVs. Lastly, our research highlights an issue that remains unaddressed in the current framework for EV regulations. The varied reaction patterns of the evaluated EVs indicate an underlying problem with load flexibility. The presented experimental results show that the suggested control mechanisms can significantly aid in lowering such heterogeneity and unpredictability. To standardize the charging practices of EVs of various brands and models, regulatory action will probably be necessary if EV charging facilities are to provide power regulation services on a wide scale.

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