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Reference Power Tracking for AC Charging of Electric Vehicles

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ABSTRACT Electric vehicle (EV) charging is widely considered as a key enabling technology that can support 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 paper proposes two alternative control solutions for tracking of power setpoints in EVs, based on adaptive feedforward and feedback linear controllers, respectively. The control design, which does not require any ad-hoc hardware adjustment of the standard EV charging infrastructure, nor higher-level communication, is supported by extensive real-world tests that have been performed on the workplace charging facility operated in the JRC Ispra campus. The experimental results validate the effectiveness of the proposed control methods in tracking two different current setpoints for flexibility scheme qualification.

INDEX TERMS Battery chargers, E- mobility, Power control, Power demand, Energy management

I. INTRODUCTION

The increasing adoption of electric vehicles (EVs) has been accompanied by concerns regarding their potential impact on the electricity grid [1], [2], specifically in light of future market shares [3]. As power-intensive assets, EV parking facilities can contribute to grid instability if not properly designed and managed. Conversely, they can also provide a relevant source of flexibility that can support grid balancing and operation [4].

Grid operators have thus started the introduction of market-based compensation schemes to incentivize resources that have a higher power-flexibility performance. For instance, the American grid operator PJM launched a so-called "Regulation Market" providing financial compensation for distributed energy resources (DER) that can adjust their consumption in response to automated power set-points broadcast at specific moments [5]. PJM assesses the performance of load-regulation resources through a performance score that quantifies in terms of accuracy, delay, 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 charging 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.

A. RELEVANT WORK

One of the bottlenecks in AC charging, the most diffused and low cost technology to date, remains the lack of a standardized communication between the EV and the charging infrastructure [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 nearby 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]–[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 fulfill 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]–[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 aforementioned papers do not analyze 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.

B. CONTRIBUTIONS

From the analysis provided above, it appears that there is a substantial gap in the existing literature regarding the dynamic regulation of EV charging for the purpose of flexibility and ancillary services provision. In particular, the cited papers do not assess the capability by single or multiple EVs to follow a prescribed profile of power consumption in real-world charging facilities, nor they consider or mitigate the impact that some components and features of the EVs can have on their power tracking performance.

The present paper aims at tackling this research gap and advancing the state of the art with the following contributions:

- Development of a realistic experimental platform that is capable of accurately quantifying the power tracking performance of several brands and models of EVs.
- Design and testing of two adaptive control approaches that account for the specific properties of the different EVs under exam and rely on linear regression tuning and feedback regulation, respectively, to increase the tracking accuracy of dynamic EV charging.
- Extensive assessment in a realistic simulation framework of the two proposed methods, in order to highlight their substantial improvements in power tracking performance.

In particular, the proposed approach introduces a flexible and straightforward mechanism that enhances the flexibility

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and efficiency of EV charging operations and is designed to operate using only standard current measurements, thus eliminating the need for additional data streams within the control mechanism. This not only simplifies the implementation but also ensures robust performance with minimal infrastructure changes, addressing both operational efficiency and scalability. This becomes particularly relevant in the context of large-scale EV integration in decarbonized power systems, where an effective use of the EVs' flexibility can play an important role in supporting efficient and robust system operation.

C. PAPER STRUCTURE

The structure of the paper is organized as follows: Section II provides an overview of our modeling system and the control theory employed in our experiments. Section III details the infrastructure established at the JRC Ispra campus, highlighting communication infrastructure and IT implementation. In Section IV, we delve into the case studies, presenting the two adopted reference signals and comparing results obtained with both feedforward and feedback control systems. Additionally, we present an evaluation of overall performance and statistical errors. Finally, conclusive remarks and research directions for future work are discussed in Section V.

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, while the actual current drawn by the EV depends on its internal control mechanisms. This often results in a discrepancy, typically negative, due to variations in how different BMS implementations manage power delivery during charging—especially as the battery approaches various states of charge—along with influences from operating temperature and other vehicle-specific characteristics. While this is not an issue under normal operating conditions, our objective is to enable the provision of power regulation services by the EV charging infrastructure. In this scenario, the minimization of tracking errors for a prescribed reference setpoint is critical. To address this, we propose two distinct controllers that dynamically modify the EV's response during charging to improve its tracking performance.

The control schemes presented in this section have been specifically designed with the objective of tracking an equal current reference i_r piloted in parallel to each connected EV, and limit as much as possible the above mentioned discrepancy.

The two alternative control approaches considered are: a feedforward controller (FFC) that relies on ex-ante linear regression tuning to account for the specific characteristics of each vehicle, and a feed-back controller (FBC) with PID regulator. A detailed description of the approaches is provided next.

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

In this first approach, represented in Fig. 1, the charging process of the single EV is controlled in feedforward, with no feedback action to account for external disturbances and model discrepancies. This choice has been considered as a feasible option since the use of a feedback loop, evaluated in the next subsection, is subject in the present setup to time-varying delays that may affect considerably the performance of a feedback controller.

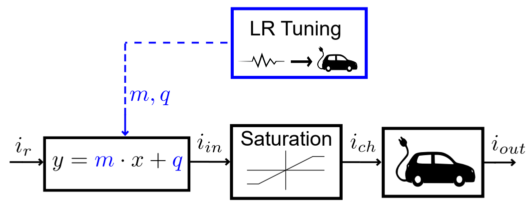

FIGURE 1. Diagram of FFC approach

In order to enhance the performance and robustness of the proposed feedforward approach, an ad-hoc tuning of the reference signal has been implemented to account for the specific features of the different car models and their associated charging control logic. In particular, the control signal i_{in} that is broadcast to each single EV is expressed as an affine function of the initial reference i_r:

$$i_{in} = m^* \cdot i_r + q^*. \tag{1}$$

The parameters m^* and q^* are obtained through a linear regression tuning process that is conducted when the EV is initially connected to the charging station, and before the start of its charging session. A 2-minute testing signal $\tilde{i}_r$, composed by sinusoidal components of different frequency (see top plot in Fig. 2), is broadcast to the charging EV, measuring the resulting absorbed current $\tilde{i}_{out}$. The parameters m^* and q^* are calculated as follows:

$$(m^*, q^*) = \arg\min_{m,q} \left\| \frac{\tilde{i}_r - q}{m} - \tilde{i}_{out} \right\|. \tag{2}$$

In other words, m^* and q^* describe the affine static transformation that better approximates the inverse of the charging dynamics of the EV (between i_{in} and i_{out}) and can therefore be used in (1) to minimize the overall tracking error between the

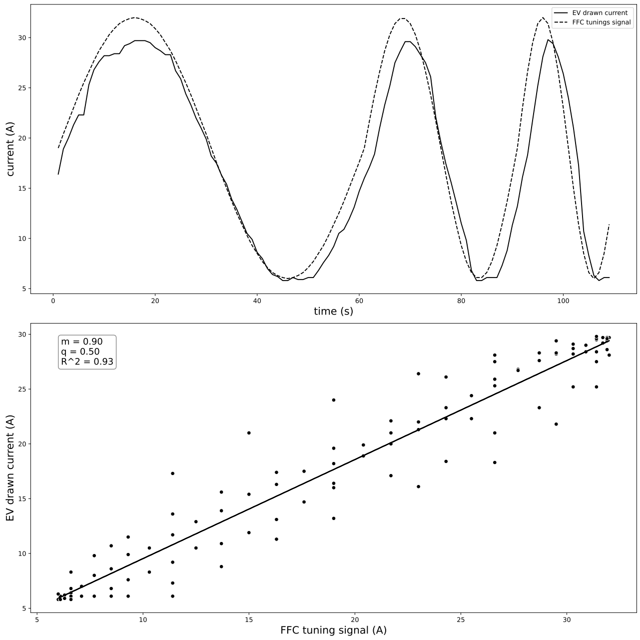

FIGURE 2. FFB testing signal with example of EV response (top), and associated scatter-plot representation with approximated regression line (bottom)

reference i_r and the current i_{out}. We wish to emphasize that the 2-minute duration of the FFC tuning procedure is relatively short when compared to the typical duration of a charging session, implying that the FFC does not introduce significant delays in the EV charging process. Fig. 2 illustrates an example of the tuning procedure applied to a Renault Zoe 2022 model featuring a 52 kWh usable battery capacity. The top plot demonstrates how the choice of the tuning reference profile effectively captures the charging dynamics even at higher frequencies, condition not effectively met by all EV models. It is worth noting a slightly greater response delay in the upsurging portion of the third wave. The plot at the bottom shows instead the value of each current output sample $\tilde{i}_{out}$ (y-axis) in correspondence with the associated input $\tilde{i}_r$ (x-axis), and supports the decision of performing the tuning with a linear model.

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

The general scheme of the designed feedback controller is represented in Fig. 3.

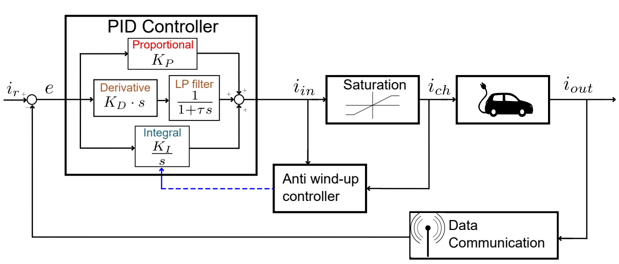

FIGURE 3. Diagram of FBC approach

The idea behind the proposed FBC is to test an alternative approach that, rather than relying on an ad-hoc tuning and adjustments for each vehicle type (as in the FFC case), applies well-established feedback regulation methods to minimize the tracking error on the setpoint i_r for all types of vehicles. For this purpose, the desired controller is a standard PID controller with two modifications: i) an additional low-pass filter added to the derivative component to reduce the high-frequency noise introduced by the numerical implementation of the signal derivative and ii) an anti wind-up controller that reduces dynamical transients following input saturation on the EV charger by acting on the integral term of the PID controller.

III. EXPERIMENTAL VALIDATION PLATFORM

The testing and validation of the regulation approaches presented in Section II have been conducted on the EV charging field of the JRC Ispra site. The facility, represented in Fig. 4, is located beneath a solar canopy with a peak production capacity of 60 kW and it is equipped with nine single-phase AC wall-box chargers, provided by the Italian company Silla[1] for experimental purposes. The entire backend system of the facility was custom-designed utilizing open-source technologies exclusively, specifically Python, InfluxDB, and MQTT.

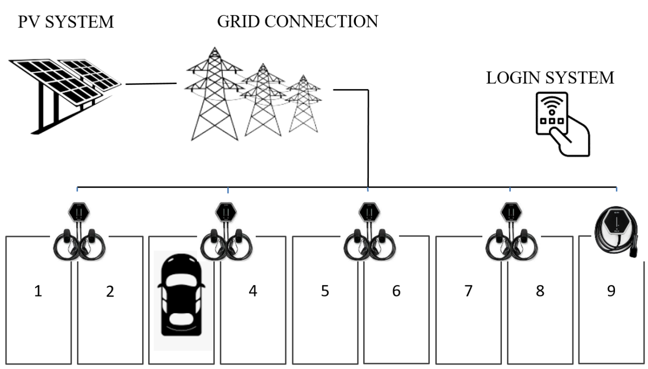

FIGURE 4. The EV charging infrastructure

The EV charging field provides free EV charging to all JRC staff members in return for research data. A badge system and a Radio Frequency Identification (RFID) totem are used to identify the EV users and properly classify their charging behaviour within the existing historical data. Beyond providing a convenient charging infrastructure, the back-end system incorporates an experimental layer that enables the execution of various experiments under real-world conditions. Since its launch in May 2022, the facility has been used by a user population of 166 individuals, which have provided a wide range of different test conditions for several experiments, including credit penalty testing schemes, PV production instant power matching, smart scheduling, and, notably for this work, power tracking [27].

[1] See: https://silla.industries/en/prism-solar-single-phase/

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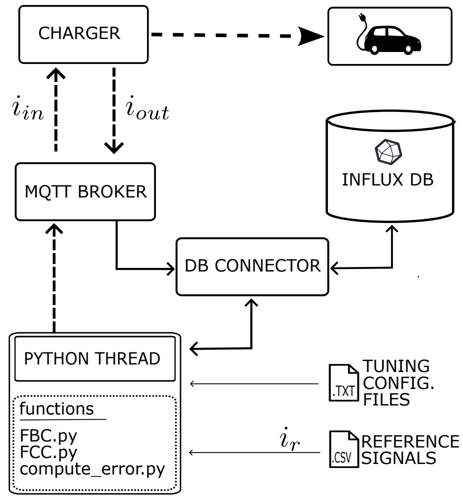

FIGURE 5. Components and relevant connections of the IT infrastructure

The main structure components of the IT system and their relevant connections are illustrated in Fig. 5. Each of the nine charging boxes is configured to publish and receive control commands via Message Queuing Telemetry Transport (MQTT) topics. MQTT is a lightweight messaging protocol extensively used for IoT applications [28]. The protocol features a publish-subscribe mechanism with asynchronous communication, particularly effective for managing EV charging. The charging box samples i_{out} values (with a 0.1 A precision) and broadcast them as MQTT messages, that get timestamped by the application upon receipt, normally within negligible delay. Other topics are defined to represent different aspects of the charging process, such as charging status, voltage, total session time, etc. A python client application, running in parallel for each connected EV, initializes a MQTT broker and subscribes to these topics. When messages are received they are automatically stored in an Influx database system. At runtime, the applications receives updated values for i_{r} (sampled from the reference signal currently in test) and i_{out}. On the basis of this data, it computes the error e and the feedback delay T_{d}, which are then passed to the chosen controller (either FFC and FBC) for computing the controlled setpoint i_{in} which is eventually sent to the charging box (which in turns applies saturation if i_{c} is outside the range 6 to 32 A). A number of libraries are employed by these functions, including Numpy, Pandas, and Paho.Mqtt. The execution time of the code is carefully considered during each iteration to ensure a perfectly discretized time domain of 1s. The execution of the test had no significant impact on IT resource utilization compared to the system's regular operational state. Monitoring of CPU and memory usage during the test revealed negligible variation in comparison to normal system activity.

IV. CASE STUDIES

The proposed approaches for reference power tracking introduced in Section II have been tested experimentally in the EV charging field. The tests have been conducted on a total of 10 different EV models (see Table 1 for more details), starting from 5th February 2024 and ending on 4th March 2024. The considered EV models have been selected in order to achieve an accurate representation of the heterogeneous EV fleet currently circulating in the EU [29][2]. Users were informed about the ongoing test and asked for written consent beforehand. The testing process occurred in a supervised fashion, considering the absence of a standardized method for screening the State of Charge (SoC) of the connected vehicle during charging. The potential interference that could arise upon reaching full SoC was taken into account, as it may disrupt the normal charging process. Two distinct setpoint signals, with a sampling step of 1 second, have been employed in the tests. The first current reference signal, consists of two step variations and takes the values of 16 A, 11 A, and 21 A over a time span of 9 minutes. This step reference has been selected in order to assess the behaviour of the controllers over the full frequency spectrum, evaluating their dynamical response and the steady state error that they introduce. The second signal, in Fig. 6, represents an example of the 'Regulation D' signal, i.e. the dynamic reference used by the PJM TSO for real-time frequency regulation with flexible resources, and is employed in our work as a well recognized performance benchmark to test charging flexibility.

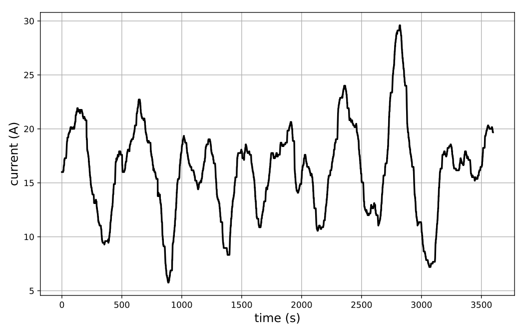

FIGURE 6. PJM's Regulation D signal

TABLE 1. Electric Vehicle List

Car Brand	Car Model	Car Year	Battery Capacity (kWh)
Fiat	500e	2021	45
Hyundai	Kona	2021	64
Link&co	01	2022	14
MG	4	2022	62
Peugeot	e-208	2022	45
Renault	Megane	2023	45
Renault	Zoe	2022	52
Skoda	Enyaq	2023	77
Tesla	Model 3	2022	57
Tesla	Model Y	2022	75

[2]See also independent statistics published by companies and organizations such as https://evplugchargers.com/the-50-best-selling-ev-in-europe/. The conducted experiments include seven of the top ten selling models.

The signal has been retrieved from PJM's Ancillary Services resource webpage [30], interpolated over a 1s time step and rescaled from its original proportional values between -1 and 1 to meet a feasible range of current values comprised between 6 A and 32 A (as the majority of EVs do not react to current values below 6 A), in order to ensure its feasibility within the current framework. Such reference has been considered in order to evaluate the performance of the controller in a real-life scenario, where the EVs are utilised as flexible resources that support the secure operation of the power grid.

A. TUNING OF THE POWER TRACKING CONTROLLERS

The tuning of the FFC controller is conducted for each EV once this is connected for charging. Prior to testing, the linear regression model is built from each EV's response to the signal shown in Fig. 2. The model parameters (m^*, q^*) are then estimated for the calculation of the control setpoint i_{in} in order to minimize the objective function indicated in (2).

The trend illustrated in Fig. 2 shows a typical EV response, exhibiting a delay in time (usually below 10 seconds) and a negative tracking error during the ramping up phases. Rarely, the EV response to the FFC tuning may display distinctive characteristics due to external factors such as SoC, external temperature, or unpredictable EV settings. Fig.7 shows an example of an EV with considerable delay in the ramp up phases. For uniformity, we ensure that the coefficient R^2 value exceeds 0.75, else the tuning is repeated, and the EV excluded from test if such condition is not eventually met.

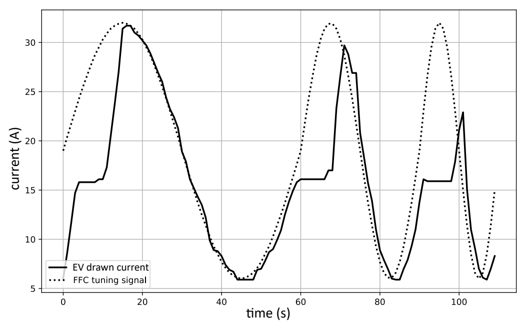

FIGURE 7. EV reacting to FFC tuning with distinctive character

Regarding the choice of the PID parameters for the FBC controller, a range of standard methodologies proposed in the literature have been tested [31], [32]. However, given the particular features of the system under exam (sampling time step of 1 s, variable delays in the feedback communication channel, different dynamic behaviour by each EV model) an ad-hoc heuristic procedure has been utilised for the PID tuning. The resulting PID parameters utilised in the simulations are the following:

$$K_P = 0.5 \qquad K_I = 0.1\ \mathrm{s}^{-1} \qquad K_D = 1\ \mathrm{s}. \tag{3}$$

B. NUMERICAL RESULTS AND PERFORMANCE

The first presented experiment focuses on two different EV models (MG 4 and Renault Zoe) and has been conducted with the step current reference signal described in the previous subsection. The obtained results are shown in Fig. 8.

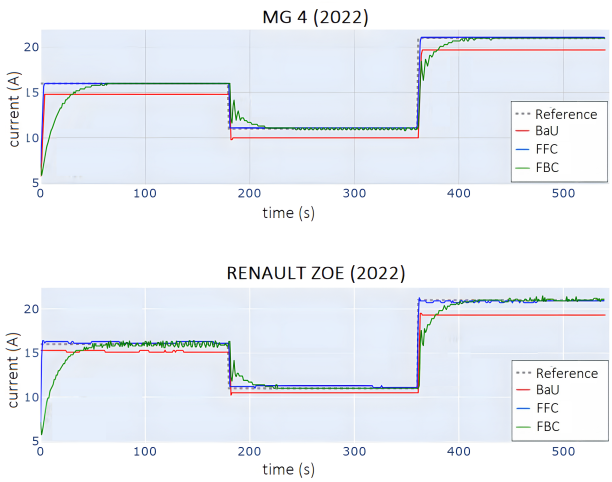

FIGURE 8. Experimental tracking results with step current reference.

The dashed black line in the figure indicates the reference setpoint signal i_r that is being provided to the EV under test whereas the red line indicates the current drawn by the EV when no specific control action is implemented (Business-as-Usual, or BaU) and i_r is simply passed as reference to the charging box of the EV. It can be seen that such approach introduces relevant steady-state tracking error in both cases, probably due to the internal control logic of the charging box and of the EV. The results obtained with the introduction of the proposed FFC and FBC controllers are indicated in blue and green trace, respectively. It can be seen that, in the FFC case, a very good tracking of the reference signal is achieved for both types of EVs. This indicates that the BaU approach typically introduces linear error dynamics that can be almost completely cancelled by estimating appropriate parameters $(m^*,\ q^*)$ of the feedforward controller. Note that the results of the FFC controller have been obtained with a different choice of the tuning parameters for the two vehicles, with $(m^*,\ q^*)$ =(1.14,-4.24) for the MG 4 and $(m^*,\ q^*)$ = (0.94,-0.31) for the Renault Zoe. On the other hand, the performance of the FBC is obtained with a unique set of parameters and is impacted by practical limitations of the feedback data communication channel in Fig. 3, which is subject to noise and time-variable delays. Within this challenging operating framework, the FBC is still capable of providing a noticeable improvement in the tracking of the i_r set-point which is comparable with the FFC performance. The low-pass filter introduced in the derivative term of the PID controller is able to maintain the numerical derivative error within acceptable limits and the only significant difference with respect to the FFC case is a slightly higher rise time in response to step variations of the reference.

The performance of the FFC and FBC controllers when the PJM regulation D signal is used as reference are shown in Fig. 9, where they are compared again with the BaU case (red trace) in which no specific control action is undertaken. In general, both FFC and FBC are able to achieve a good tracking of the reference and provide better performance than the BaU case. Moreover, the results in Fig. 8 and 9 show that, in all the considered experimental tests, the initial tuning procedure of the FFC approach does not seem to induce any unexpected behavior during the actual charging process.

A more detailed comparison is available in Fig. 10, where a zoomed-in representation of the EV charging pattern is shown for the MG4 and for the Renault Zoe. It can be seen that the FFC approach achieves a very precise tracking, as the associated current signal is almost indistinguishable from the chosen reference. As in the previous test, the FBC controller shows slightly worse performance than the FFC but it is still capable of providing a significant improvement with respect to the BaU case.

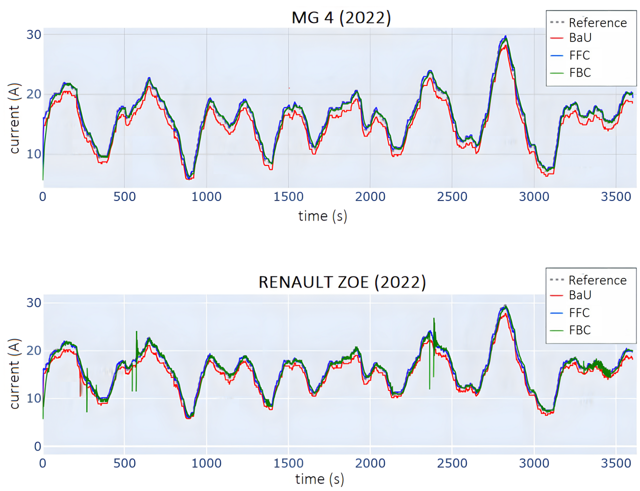

FIGURE 9. Measured EV drawn current with PJM regulation D signal as reference.

Fig. 11 displays the cumulative result of all the 10 EVs under test over a time span of 30 minutes. It is observable that the overall trend is comparable to the one seen in Fig. 9 and Fig. 8 for individual EVs. Over 1 h of charging, the absolute integral tracking error in the BaU scenario is approximately 16 kWh. When the FFC and FBC approaches are applied the error is equal to 2 kWh and 5 kWh, respectively, corresponding to a significant error reduction of 87.5% and 68.7% in the two cases. Since we may assume that at least part of the measured error is random rather than systematic, it is reasonable to expect a similar (or better) tracking performance when larger groups of charging EVs are considered.

In order to assess the performance of the proposed tracking approaches from an energy perspective, Fig. 12 shows the percentage error in cumulative energy tracking for the FFC and FBC controllers, i.e., the integral over time of the difference between the reference signal in Fig. 11 and the resulting FFC/FBC current responses. It can be seen that,

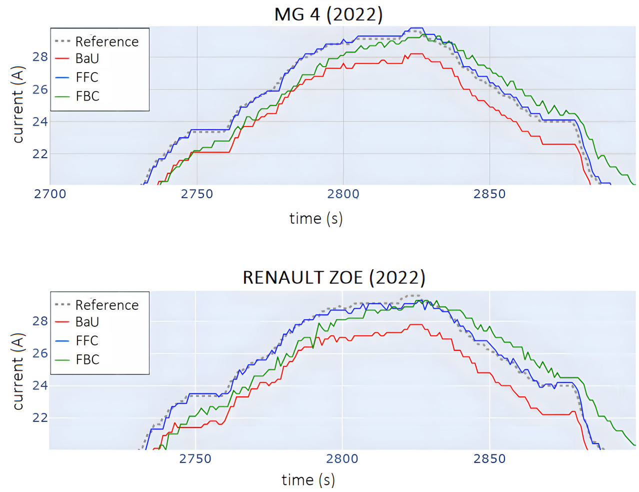

FIGURE 10. Measured EV drawn current with PJM regulation D signal as reference (zoomed-in details).

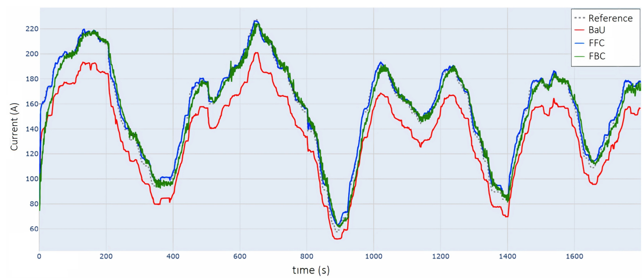

FIGURE 11. Total charging current drawn by the 10 tested EVs

in both the FFC and FBC cases, the integral tracking error ranges between 0.2% and 1.8%. This is much smaller than in the BaU case, where the error is between 8% and 12% (not shown in the new figure for scale), confirming the substantial tracking improvements achieved by the proposed controller. There are noticeable differences between the FFC and FBC results. In the latter case, the integral error exhibits more significant variations over time, possibly due to delays in the communication of the current readings (i.e., in the "Data communication" block in Fig 3). Conversely, it can be seen that the energy error tends to decrease over time, likely due to the integral action of the controller. A more detailed breakdown of the tracking performance according to different error metrics and for each tested vehicle is provided in Table 2. The "2-norm" columns indicate the normalized Euclidean norm of the error signal in the conducted experiments. On the basis of the diagrams in Fig. 1 and Fig. 3 and denoting by T the duration of the experiment, this can be defined in continuous time as follows:

$$||e||_2 = \frac{1}{T}\left(\int_0^T \left(i_{out}(t) - i_r(t)\right)^2 \, dt\right)^{\frac{1}{2}} \quad (4)$$

Similarly, the "Mean Abs Error" in Table 2 corresponds to

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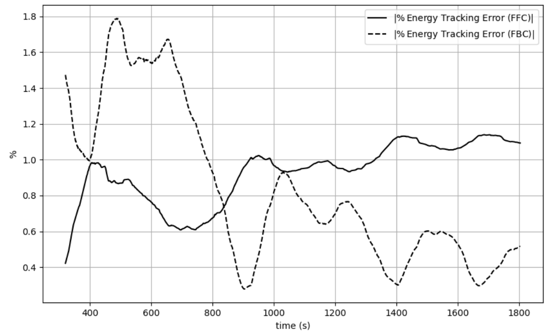

FIGURE 12. Percentage error in cumulative energy tracking for 10 tested EVs

TABLE 2. Error metrics of the performed tests using FBC and FFC controller and in the Business-as-Usual (BaU) case.

Car Model	2-Norm (FBC)	2-Norm (FFC)	2-Norm (BaU)	Variance of Error (FBC)	Variance of Error (FFC)	Variance of Error (BaU)	Mean Abs Error (FBC)	Mean Abs Error (FFC)	Mean Abs Error (BaU)
Skoda-Eniaq	39.68	20.34	20.67	0.87	0.2	0.15	0.09	0.18	0.29
Link&co-01	41.41	15.68	33.38	0.94	0.13	0.1	0.09	0.07	0.72
MG-4	40.08	14.47	53.3	0.89	0.1	0.17	0.07	0.12	1.19
Tesla-model Y	41.63	16.79	15.69	0.96	0.19	0.13	0.08	0.14	0.1
Peugeot-208	43.24	11.65	31.15	1.03	0.07	0.29	0.09	0.04	0.49
Renault-Zoe	45.22	18.73	48.42	1.13	0.19	0.22	0.08	0.07	1.04
Hyundai-Kona	39.48	22.44	46.1	0.86	0.28	0.23	0.07	0.04	0.98
Tesla-model 3	58.21	25.59	21.39	1.87	0.31	0.24	0.12	0.2	0.1
Renault-	48.69	27.42	21.77	1.31	0.27	0.26	0.08	0.39	0.05
Fiat-500e	52.77	33.94	22.97	1.54	0.39	0.28	0.1	0.5	0.1

the normalized absolute-value norm of the error signal:

$$||e||_1 = \frac{1}{T} \int_0^T |i_{out}(t) - i_r(t)|\, dt. \tag{5}$$

Finally, the ''Variance of Error'' columns indicate the experimental variance exhibited by the current tracking error $i_{out(k)} - i_{r(k)}$, evaluated over the discrete time samples of the considered experiments.

The evaluations on the mean absolute error confirm previous comments on Fig. 9-11, indicating a decreased accuracy of the BaU case with respect to the FBC and FFC approaches. It is interesting to note that the variance of the error across the different sampled time instants is higher with the FBC approach. This can be explained by the substantial delay in the feedback loop. Such phenomenon is particularly relevant in the considered experimental framework, where the delay is not constant, as EV chargers typically are programmed ''on trigger'', i.e., they communicate an updated current measurement only when a certain variation threshold is registered by the internal ammeter. Delay inconsistencies are therefore even more probable when using highly dynamic signals as input.

V. CONCLUSIONS

The paper presents a novel methodology for smart power tracking in EV AC charging. The proposed approach significantly improves the capability of EV charging stations to follow prescribed profiles of aggregate power consumption, thereby enhancing their ability to support ancillary services and actively contribute to the regulation of the power system. Two distinct control methods, based respectively on feedforward tuning and feedback control, have been designed and tested, showing improvements in the tracking performance of the charging facility and alleviating the inherent power tracking errors associated with EVs under charge, which depend on various factors such as battery condition, current state of charge, and vehicle design. It is worth underlining that the proposed solutions require minimal software modifications and no additional hardware components for their implementation, significantly facilitating their potential large-scale rollout. The developed control solutions have been tested in real-world conditions, producing a wide range of experimental results to assess and demonstrate the improved performance of the proposed approaches.

Future work in this area will consider the design and testing of alternative and more complex control approaches. Adaptive control techniques will be evaluated to improve the tracking accuracy by dynamically modifying the controller parameters in real time. Moreover, an algorithmic End-of-Charge detector will be used to forecast changes in the charging dynamics of EVs as they approach full battery capacity. Also, the tuning process carried out for the FFC regulation approach will consider alternative non-linear models, assessing whether quadratic or discontinuous functions might be more suitable to characterize the differences between the specified tracking signal and the open-loop response of the EV under charge, minimizing at the same time the impact of external disturbances on the tracking performance. These disturbances can arise from various factors that warrant further investigation to better understand the grid-EV interaction, including: (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.

Given the potential economic benefits associated with an EV charging asset with power tracking capabilities, a framework for evaluating the economic aspects of this service will also be developed. This framework will build upon existing schemes and mechanisms that quantify and price the power tracking service for charging EVs, and will be used not only to assess the performance of the proposed control mechanism but also to evaluate and compare future enhancements and modifications to the control strategy.

Finally, our study also underscores an unresolved concern within the existing EV regulatory framework. The tested EVs exhibit heterogeneous response patterns, revealing an inherent challenge in load flexibility. The proposed control mechanisms can provide significant support in reducing such heterogeneity and unpredictability, as demonstrated by the provided experimental results. At the same time, a large-scale provision of power regulation services from EV charging facilities will most likely require regulatory intervention to standardize the charging behavior of EVs of different brands and models.

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