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Harmonics-aware Smart Charging of Electric Vehicles

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***Abstract*—Smart charging of electric vehicles (EVs) is emerging as a critical tool to ease grid congestion, defer costly network upgrades, and leverage off-peak electricity rates. While most research highlights voltage management and peak load reduction, harmonic emissions associated with varying smart charging currents demand closer attention. This paper presents harmonic emission profile of different EV models and simplifies harmonic modeling for multiple EVs. Then, a non-linear optimization framework is introduced to enable harmonics-aware EV charging, accommodating random arrival, departure, and energy (kWh) demands. The framework prioritizes maintaining total harmonic distortion (THD) within set limits while ensuring a minimum fulfillment rate (e.g., 90% of requested demand). Results indicate that THD can be managed effectively by marginally curtailing demand. The model integrates seamlessly with existing smart charging systems, requiring minimal investment for deployment.**

***Index Terms*—Electric vehicles, harmonics, smart charging, total harmonic distortion**

I. INTRODUCTION

Governments worldwide are setting ambitious climate neutrality targets, with the transportation sector under transformation for its substantial greenhouse gas emissions [1]. The shift to electric vehicles (EVs) is essential for reducing road transport emissions. The AC charging, whether public or domestic, is the dominant EV charging option due to the following reasons [2]. Firstly, AC charging is significantly cheaper to deploy when compared to DC charging. Secondly, most early EV adopters have access to garage (or night time) charging, making it easier to use. Finally, the all electric range of EVs which typically exceeds 300 miles, is more than sufficient to meet two to three days of charging needs [3].

However, scaling EV adoption hinges on integrating aging power grids with expanding EV charging infrastructure. Smart charging emerges as a key solution to mitigate the negative effects of uncontrolled EV charging on power systems [4], [5]. On the other hand, our previous research shows that smart charging at lower rates can produce harmonic emissions two to three times greater than those observed at rated charging levels. This finding emphasizes the need to factor harmonic emissions into smart charging frameworks to meet industry standards and regulatory requirements [6]–[8]. Note that increasing harmonic content from smart EV charging leads to higher harmonic distortion across power networks, deteriorating power quality. Uncontrolled harmonic distortion can degrade EV power cables, overheat transformers, destabilize voltage, and amplify electromagnetic interference, affecting nearby equipment [9], [10].

The smart charging of EVs has been extensively studied, with numerous survey papers providing comprehensive overviews [11]–[13]. The focus of most smart charging studies is to optimally schedule multiple EV demand which is characterised by random EV arrival, departure, and demand requests to reduce infrastructure requirements or minimize overloading of transformers while keeping voltage levels within operational limits. Previous works, such as [14], address harmonics at rated power by optimizing the rescheduling of switched shunt capacitors through an online maximum sensitivity selection-based EV coordination algorithm. Similarly, [15] introduces an adaptive smart charging approach leveraging convex optimization to mitigate unbalanced EV charging, demonstrating notable increases in operator profit.

However, these methods largely overlook the complexities introduced by dynamic charging rates, which reflect real-world scenarios where EVs charge at varying levels depending on grid conditions, user preferences, or pricing incentives. This oversight creates a critical knowledge gap, as lower charging rates are known to exacerbate harmonic distortion, potentially doubling or tripling emissions compared to rated power operations [8]. Therefore, there is a trade-off between reducing the peak demand and controlling harmonic emission levels. Ref. [15] illustrates a real-world smart charging implementation at a university campus equipped with various charger types. Here, smart charging dynamically allocates charging schedules based on vehicle arrival, departure, and energy demand, effectively leveraging user flexibility. However, a key practical issue

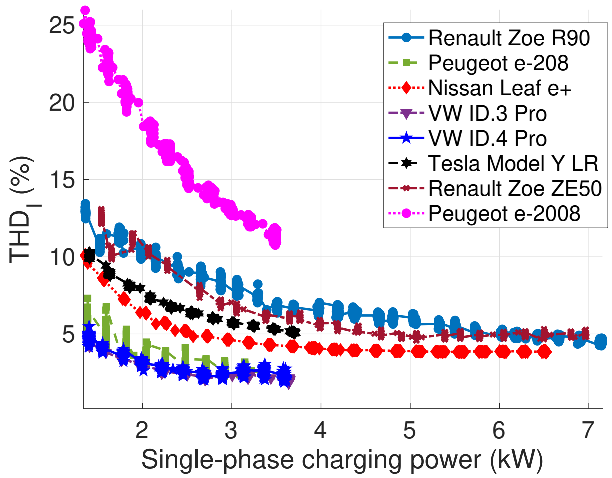

Fig. 1: Correlation between EV charging power and THD.

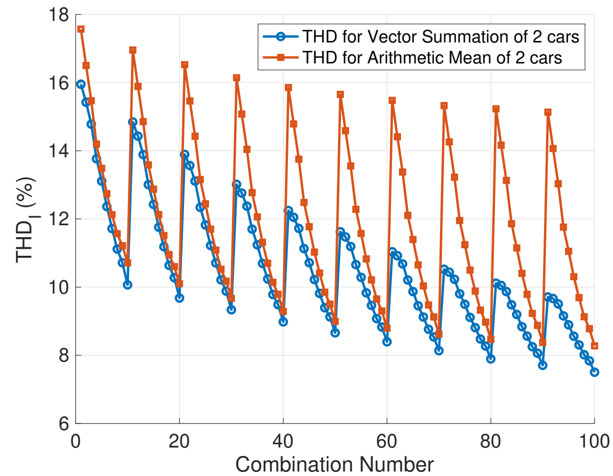

Fig. 2: Comparison of vector summation and arithmetic mean.

arises: in AC chargers, charging rates below 6 A (1.38 kW in EU/UK) are typically infeasible, creating a discontinuity in possible charging rates. In [15], this issue is addressed by allocating a minimum of 6 A to each connected EV, prioritized by user flexibility and deadline constraints until infrastructure capacity is reached.

This paper bridges this gap through two key contributions. First, it presents a simplified method to model harmonic emissions using a closed-form expression using actual datasets collected from field trials. Second, it introduces a non-linear optimization framework that guarantees a minimum charge for each EV (e.g., 90% of the requested amount) while ensuring the station's aggregate profile remains within predefined total harmonic distortion (THD) limits. Both contributions are based on actual EV smart charging data collected from eight different vehicles which is presented in the next section.

II. Problem Formulation

A. Harmonics Modelling

The harmonic modeling framework in this paper builds upon the analysis presented in [6] and [8]. In these studies, eight different EV models were analyzed and their harmonics emissions were assessed for varying charging rates. As shown in Fig. 1, harmonic emissions increase significantly as charging power decreases. For the vehicles considered (Peugeot e-208, VW ID.3 Pro and Pro 4, Tesla Model Y, and Peugeot e-2008), the maximum single-phase charging power is 3.68 kW $= 230$ V $\times$ 16 A. For other vehicles, the maximum power reaches 7.36 kW with charging currents up to 32 A. The minimum charging current is 6 A for all vehicles. Harmonic emissions are modeled by fitting the data for each vehicle type to a quadratic polynomial:

$$THD(x) = p_1 x^2 + p_2 x + p_3,$$

where x represents the charging power in kW. This model provides a closed-form representation of harmonic behavior as

TABLE I: Polynomial fitting for total harmonic distortion.

EV Model	p_1	p_2	p_3	R^2
Renault Zoe R90	0.26	-3.41	16.14	0.9675
Peugeot e-208	0.82	-5.39	11.42	0.8634
Nissan Leaf e+	0.41	-4.16	13.98	0.9235
VW ID.3 Pro	0.73	-4.63	9.36	0.9734
Renault Zoe ZE50	0.48	-5.26	18.92	0.9681
VW ID.4 Pro	0.86	-5.26	10.28	0.9167
Tesla Model Y Long Range	1.00	-7.17	18.07	0.9920
Peugeot e-2008	1.94	-15.76	42.74	0.9928

a function of charging power, supporting further optimization and analysis. The corresponding polynomial fitting parameters and associated R^2 are provided in Table I. It can be seen that charging power dependent THD values can be well-represented by second order polynomials which are convex. Moreover, in our experimental work ([6] and [8]) due to limitations of the EV supply equipment, the resolution of the charging power is a function of charging current which took integer values starting from 6 A. Therefore, the proposed convex function can represents non-integer values and make the problem more realistic.

While modeling the harmonic emissions of a single electric vehicle (EV) is straightforward, with the equations provided in Table I being sufficient, the harmonic emissions from multiple EVs—whether of the same model operating at different charging powers or of various models charging at arbitrary rates—introduce greater complexity due to the absence of a closed-form expression. The precise harmonic emissions from multiple EVs can be determined through vector algebra, wherein the summation of individual harmonics accounts for the cosine and sine components of their respective phase angles.

For instance, an individual harmonic can be expressed as the phasor $A \cdot e^{j\theta}$, which, in rectangular form, is given by $A \cdot (\cos(\theta) + j\sin(\theta))$, where A denotes the magnitude and θ represents the phase angle. The harmonics of multiple sources are summed, and the resulting vector is used to compute the overall total harmonic distortion (THD) through the expression

$$THD = \frac{\sqrt{\sum_{h=2}^{H} I_h^2}}{I_1} \times 100\%,$$

where h corresponds to the harmonic order and I_h denotes the magnitude of the h^{th} harmonic component.

Incorporating vector summation into classical optimization frameworks introduces significant challenges. To address this, we propose a simplified approach that yields an upper bound for THD levels. As demonstrated in [8], a clear trend emerges: as the number of simultaneously charging EVs increases, THD levels decrease due to harmonic cancellation and the new THD levels are always less than the arithmetic mean of multiple sources. This effect arises from the reduction in aggregate amplitude caused by the multiplication of harmonic amplitudes with $\cos(\theta)$ and $\sin(\theta)$. Such behavior ensures that the overall amplitude stabilizes when harmonics from EVs of identical models and charging states are summed.

Fig. 2 compares the arithmetic and vector summation of two EVs (Tesla Model Y and Peugeot e-2008), illustrating that the arithmetic mean consistently exceeds the result obtained via vector summation. In this plot, y-axis shows the charging combination number which starts from (6A, 6A) charging and the last combination shows (15A, 15A) charging combination. Nevertheless, in all cases, arithmetic mean is always greater than the vector summation. Consequently, assuming the arithmetic mean for the harmonic emissions of multiple EVs offers a reasonable approximation.

Additional examples are provided with different vehicles. At 6A charging, the THD of Renault Zoe, Peugeot e-208, and Nissan Leaf are 12.76%, 5.4%, and 10.06 %, respectively. When the Zoe and e-208 charge at the same time, the corresponding THD level is 6.46% which is lower than the arithmetic mean of $\frac{12.76+5.4}{2} = 9.08\%$. Similarly, when Zoe and Leaf charge at the same time, the corresponding THD level is 7.97%, which is less than the arithmetic mean of 11.41%. Finally, when all three vehicles charge at the same time, the actual THD is 5.43% and the arithmetic mean is 9.4%. A detailed Monte Carlo simulation of multiple vehicle charging is presented in [6] and [8].

B. Smart Charging Framework

Next, we present the mathematical model for the smart charging framework which is modelled as a non-linear optimization problem with the following parameters. Let $i = \{1, 2, ..., N\}$ represent the index of EVs arriving at a charging station operating over discrete time slots $t = \{1, ..., T\}$. Each EV arrives at time $A_i \in T$ and departs at time $D_i \in T$, with the minimum charging duration $D_i - A_i$ assumed to be a positive value M, $\forall i$. Each vehicle's charging demand (in kWh) is denoted by C_i, while the $1 \times T$ smart charging vector (in kW), $\boldsymbol{c_i}$, $\forall i$, serves as the decision variable. The vector $\boldsymbol{c^t}$ represents the charging rates across all chargers at time t. The objective function of the smart charging system aims

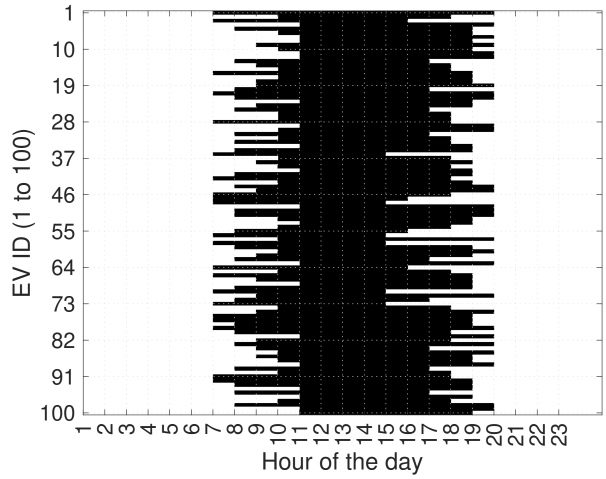

Fig. 3: Arrival and departure schedule of 100 EVs charged at the station.

to minimize the deviation between the requested demand and actual charging, formulated as

$$\sum_i \left(\frac{\sum \boldsymbol{c_i}}{C_i} - 1 \right)^2. \tag{1}$$

When the time slot is one hour, $\sum \boldsymbol{c_i}$ corresponds to the total energy transferred. The optimization problem is subject to the following constraints. The first constraint ensures that the actual charging meets a minimum percentage of the requested demand:

$$rC_i \leq \sum \boldsymbol{c_i} \leq C_i, \quad \forall i \tag{2}$$

where $r \in [0, 1]$ is a constant. The second constraint restricts the charging power vector $\boldsymbol{c_i}$ to values between 1.38 kW and 3.68 kW (reflecting minimum and maximum per-phase charging rates in Mode 3 charging) or to 0 (standby mode):

$$\boldsymbol{c_i} \in \{0 \cup [1.38, 3.68]\}, \forall i. \tag{3}$$

The minimum parking duration constraint is expressed as

$$D_i - A_i \leq M, \quad \forall i. \tag{4}$$

Finally, the optimization problem incorporates a harmonic constraint, which will be examined in subsequent sections. This constraint is defined as

$$THD(\boldsymbol{c^t}) \leq H_{\text{lim}}, \tag{5}$$

where H_{lim} represents the THD limit specified by the station operator. The THD function follows a quadratic form, as presented in Table I.

THD constraints can be effectively enforced by dynamically adjusting the charging power levels of individual electric vehicles. Fig.1 reveals that harmonic emissions are minimized when vehicles operate near their rated charging capacity. Alternatively, coordinated deactivation of selected charging sessions provides an additional layer of control to ensure that aggregate THD levels remain within regulatory thresholds.

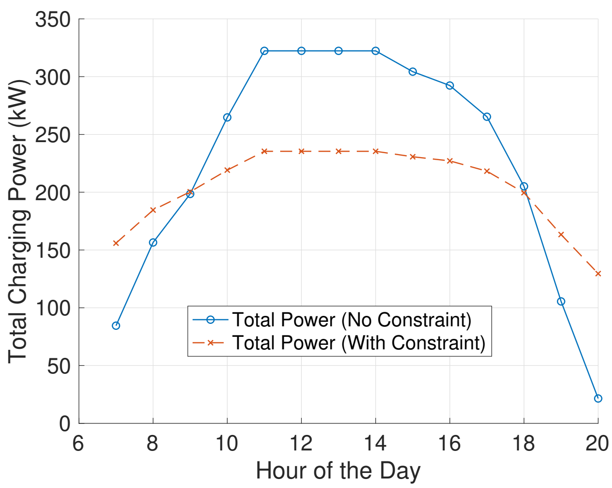

Fig. 4: Total hourly station demand profile in kW.

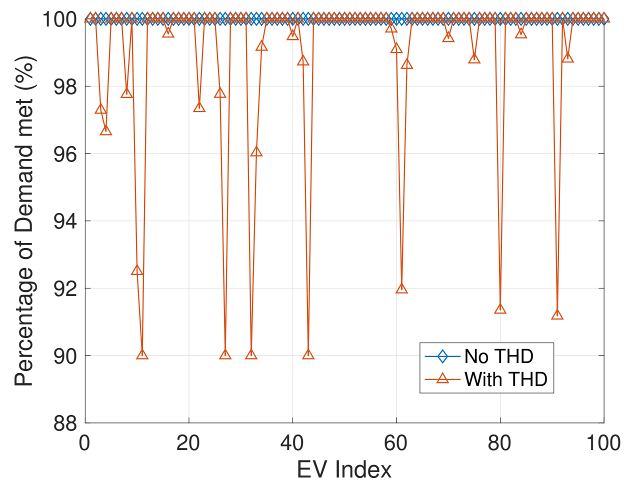

Fig. 5: Demand completion rates in %.

III. Case Study

As a case study, we consider a charging station operating between 7 am and 8 pm. It is assumed that 100 EVs visit the station with random arrival, departure, and demand patterns. Arrivals and departures occur uniformly throughout the day, with a minimum parking duration of 8 hours. The arrival and departure times of each EV are depicted in Fig. 3. It can be seen that the peak demand occurs between 11 am and 3 pm. Each vehicle's charging demand is randomly distributed between 60 kWh and 90 kWh (or 20 kWh to 30 kWh per phase). The chargers are assumed to be identical, operating as three-phase 11 kW AC chargers. For simplicity, all EVs are assumed to be Tesla Model Y as a representative of a mainstream EV.

The THD limit is set at 6%, and the station operator guarantees that at least 90% of the requested demand is met for each EV. The charging power per phase ranges between 6A and 16A, or 0A, corresponding to 1.38 kW to 3.68 kW at 230V. The THD model for Tesla Model Y is expressed as the following quadratic polynomial:

$$THD(c) = 1.00 \times c^2 - 7.17 \times c + 18.07, \tag{6}$$

where c represents the charge rate, as described in the previous section. This model is implemented and solved using MATLAB's $fmincon$ function.

The per-phase results are presented in Figs. 4, 5, and 6. As presenting the charging schedules for 100 EVs individually is impractical, Fig. 4 illustrates the total charging power for two scenarios. The results demonstrate that demand shifts towards off-peak hours and total power is spreaded across longer durations. To satisfy the THD constraints, the smart charger sacrifices a small percentage of customer demand. As shown in Fig. 5, 75% of EV demands are fully met, while 25% of demands achieve 96.03% fulfilment, resulting in an overall demand satisfaction of 99%.

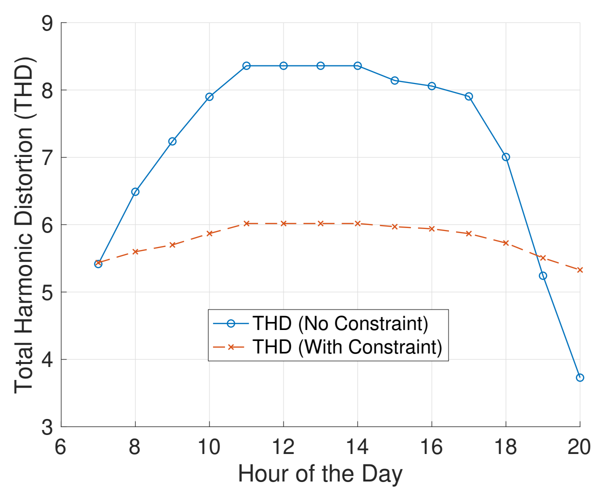

Fig. 6: Hourly current THD (%) with a THD limit of 6%.

Lastly, Fig. 6 compares the THD performance across different charging strategies. The results indicate that THD remains consistently below the 6% target, whereas this limit is frequently exceeded when harmonics are disregarded. This flexibility is achieved by curtailing EV charging during periods of high harmonic emissions. An alternative approach would be to overcharge the vehicles beyond requested demand, if there is unused battery capacity below 80% state of charge levels. This is because, the harmonic content is at its lowest levels at peak charging rate as given in Fig 1.

The success of the proposed control method fundamentally depends on the alignment of individual EV harmonic emission profiles with the system-wide THD compliance targets. To illustrate, replacing the Tesla vehicle model with a Peugeot e-2008, which has inherently higher harmonic emissions, would potentially alter the feasibility of adhering to the 6% THD limit under a stringent 90% demand satisfaction constraint. Despite such considerations, the proposed methodology remains a practical and readily implementable solution, substantially mitigating aggregate THD levels without necessitating additional infrastructure investments or technological modifications.

IV. Conclusions and Future Work

This paper presented a harmonics-aware smart charging framework that optimizes EV charging schedules to manage THD levels while maintaining grid stability. The model dynamically adjusts charging based on harmonic emissions, ensuring at least 90% of energy demands are met. The proposed approach balances performance and power quality, making it suitable for real-world applications. Future work will extend the model to include additional EV types, three-phase networks, and harmonic imbalance management. Moreover, we will investigate how good the arithmetic mean assumption as an upper limit approximation is and will improve this approximation by meta modeling of the two approaches (vector summation versus arithmetic mean) and the gap between them.

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