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ORIGINAL RESEARCH

Assessing the influence of electric vehicle charging profile modelling methods

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Abstract

In the scientific literature, it has been a common assumption that electric vehicles (EVs) draw a constant current during the whole charging session. In reality, EV charging profiles are not linear, and the non-linearities have recently gained more attention. However, a thorough analysis of the influences of different charging profile modelling methods is not yet carried out. This paper aims to fill this gap by comparing experimental measurements of four commercial EVs and results of a developed simulation model that considers different charging profile modelling methods. According to the results, the use of linear charging profiles may lead to notable modelling inaccuracies (error > 30%) whereas the use of measurement-based non-linear charging profile models yields relatively accurate results (error mostly ≤ 3.5%). The results also demonstrate that the use of a simple, but justified, bilinear charging profile model is likely to be sufficiently accurate in most scenarios.

1 | INTRODUCTION

Over the past few years, a lot of work has been done to improve the electric vehicle (EV) charging load modelling methods. This work is necessary in order to accurately predict EV charging loads which further enables safe and efficient operation of the power grid [1]. However, at the present, there remains a gap in the scientific literature regarding the modelling accuracies.

1.1 | Literature review

To give an outlook of the EV charging load modelling related research found in the scientific literature, 25 recent studies are listed in Table 1. For each study, the modelling method of the EV charging profiles is presented. In this paper, a charging profile refers to the charging current behaviour over the charging session.

As seen in the Table 1, most of these recent studies consider a linear charging profile (i.e. the simplest method where the current stays constant over the whole charging session) to model the EV charging. In [24– 26], it is acknowledged that the charging power is non-linearly dependent on the state of charge (SoC). To overcome the issue, only SoCs between 5% and 95% are considered in [24]. In [25] and [26], bilinear charging profiles are used. However, very little effort is made to justify the modelling method or to assess its influence on the modelling accuracy.

To classify different charging profiles, an iterative clustering framework is developed in [27]. The results show that even though the number of different charging profiles is significant, they can be classified into a small number of types (in the study, 304 different charging profiles are successfully classified into six types). These types can then be used to model charging behaviour with a reasonable accuracy. In [28], machine learning is used to form charging profile models and predict charging currents. The simulation results show that the XGBoost machine learning model yields the most accurate results with a mean absolute error of 126 W. Additionally, an ablation study is conducted to demonstrate that the exact EV model is not necessary to attribute to accurately model charging profiles. Instead, the necessary information includes charging features such as the number of phases and the maximum current used for charging.

TABLE 1 Recent studies

Ref.	Charging profile modelling method
[1–24]	Linear
[25]	Bilinear: charging power decrease linearly to zero after 60% SoC
[26]	Bilinear: charging power decrease linearly to zero after 80% SoC

Based on [27] and [28], it seems that there is no need to have a separate charging profile model for each different EV model. However, these studies do not assess the influence of the use of simplified charging profiles on the modelling accuracy. Therefore, the need to consider more accurate charging profile models remains currently unknown.

1.2 | Contribution and structure

Based on the literature review, it seems necessary to assess the influence of the EV charging profile modelling methods on the charging load modelling. To fill the gap in the literature, experimental measurements of a small charging site are compared with simulation results obtained by using different charging profile models. Similar simulations are also carried out for a large charging site using real charging data. The goal is to analyze the impact of different charging profile modelling methods on the charging load modelling accuracy in different situations. The results provide guidance and strengthen the scientific background for future studies related to EV charging load modelling. It is worth emphasizing that this paper focuses on the charging loads seen from the charging site point-of-view. The contributions of this paper are listed below.

- Assessing the accuracy of the linear charging profile modelling method that is widely used in the scientific literature.
- Assessing the accuracy of a measurement-based non-linear charging profile modelling method, in which the charging profiles are formulated based on experimental measurements of the considered EVs.
- Formulating bilinear charging profiles based on the experimental measurements and assessing the modelling accuracies of these charging profile models. Two bilinear charging profile modelling methods are considered. The first utilizes a separate charging profile for each EV and for each current limit, and the second utilizes a single bilinear charging profile that is applied for all EVs and for all current limits.
- Evaluating the influence of using charging control together with different charging profile modelling methods on the modelling accuracy.

The rest of the paper is as follows. Section 2 describes the assessment method including the simulation model and the experimental hardware-in-the-loop (HIL) measurements. Section 3 presents and analyses the results. The paper is finalized with conclusions in Section 4.

2 | ASSESSMENT METHOD

This section describes the key values of interest, the different charging profile modelling methods, the used charging data, the two examined scenarios, the used control method, the experimental HIL laboratory setup, and the used simulation model. Each topic forms its own subsection.

2.1 | Key values of interest

This paper assesses the influence of different charging profile modelling methods on the modelling accuracy in two different scenarios. To achieve this, three key values are examined: the highest peak power (P), the highest hourly peak power (Ph), and the charged energy (E). These values are often needed to determine, for example, the charging costs of an EV user, the costs and profits of a charging site operator, and the EV user satisfaction. Consequently, if these values are incorrect, the economical assessment of the charging site will also be unreliable. These values can also be used to estimate the optimal sizing of the charging infrastructure, and thus, inaccurately modelling the values could lead to over sizing or under sizing. Therefore, these values should be modelled accurately, and thus, they are considered as the key values in the assessment.

The highest peak power simply refers to the highest peak power measurement value of a single time step (10 s) in a day, whereas the highest hourly peak power refers to the highest average loading during a 1-h-long period in a day. The highest hourly peak power is an interesting value because it can be the basis for a power-based distribution tariff component as in [29]. The charged energy refers to the energy that is charged during each 1-h time slot (i.e. 0:00–1:00, 1:00–2:00 etc.). This definition is made because the temporal resolution in electricity pricing is often 1 h, and thus, a modelling error in the hourly level may affect certain cost or benefit analysis.

For each key value, a percentual root mean square error (RMSE) is calculated by comparing the simulation results to the results of the selected baseline (described in Section 2.4). The percentual RMSE for the highest peak power and the highest hourly peak power is calculated using (1), where $Value$ is either P or Ph, N_d is the number of cases or days (25 cases for Scenario 1 and 89 days for Scenario 2, described in Section 2.4), subscript b represents baseline, and subscript c represents the compared value. Since an hourly charged energy can be zero, the percentual RMSE for the charged energy is calculated using (2) and (3), where $E_{\mathrm{RMSE,abs}}$ is the absolute RMSE (in kWh) and E_{avg} is the average hourly charging load (in kWh).

$$Value_{\mathrm{RMSE},\%} = \sqrt{\frac{1}{N_\mathrm{d}} \times \sum_{n=1}^{N_\mathrm{d}} \left(\frac{Value_{\mathrm{b},n} - Value_{\mathrm{c},n}}{Value_\mathrm{b}} \right)^2} \times 100\%. \tag{1}$$

$$E_{\mathrm{RMSE,\,abs}} = \sqrt{\frac{1}{N_\mathrm{d} \times 24} \times \sum_{h=1}^{N_\mathrm{d}\times 24} \left(E_{\mathrm{b},h} - E_{\mathrm{c},h}\right)^2}. \tag{2}$$

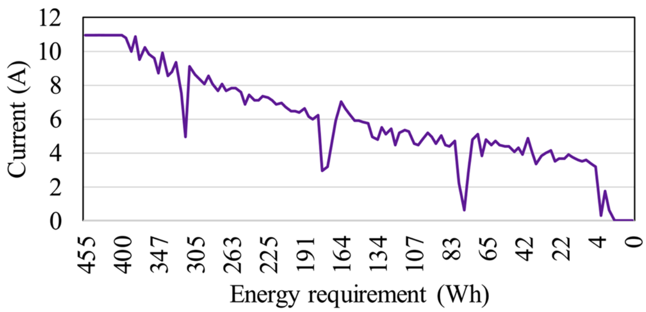

FIGURE 1 Charging profile lookup table for Nissan Leaf 2012 with 11 A current limit

$$E_{\mathrm{RMSE},\%} = \frac{E_{\mathrm{RMSE,\,abs}}}{EE}. \tag{3}$$

2.2 | Different charging profile models

In this study, five different charging profiles are compared: real HIL measurement, measurement-based non-linear (NL) model, bilinear (BL) model made separately for each EV and for each current limit set by the EV supply equipment (EVSE), unified bilinear (UBL) model which is used for each EV and for each current limit set by the EVSE, and linear (L) model.

The NL charging profiles are obtained by measuring the current drawn from the grid of each EV with all possible current limits (integers) set by the EVSE in 10-s resolution. Only current limit integers are considered as the used charging points (described in Section 2.6) do not support floating point current limits. The measurements are used to calculate the missing energy from the batteries in each time step. The calculation begins from the end of the charging session where the missing energy, referred to as energy requirement, is zero (i.e. the EV is fully charged). The process is illustrated in Figure 1 for the charging of Nissan Leaf 2012 with a current limit of 11 A set by the EVSE. In this case (Figure 1), the energy requirement (E_R) of 400 Wh separates the constant power (CP) and the constant voltage (CV) stages. After calculating the energies, a lookup table is formed to link the calculated energy requirements to the measured charging currents.

The lookup table is formed only for the CV stage of the charging profile. The charging current is assumed to be constant over the whole CP stage in the modelling methods. This is seen reasonably accurate because the charging current is shown to be very steady (variation of less than 0.5 A) during the CP stage [30]. After forming the lookup tables for all current limits, a three-dimensional lookup table is formed which links the current limit set by the EVSE (in amperes) and the missing energy of the EV (in Wh) to the charging currents (each phase current in amperes). A separate three-dimensional lookup table is formed for each EV. The process and the received charging profile models are similar than the ones mentioned in [30] and [31]. However, in this paper, other charging profile modelling methods (BL, UBL, and L) are also considered and compared.

TABLE 2 The used electric vehicles

EV	Charging power
Nissan Leaf 2012	3.7 kW (1 × 16 A)
Nissan Leaf 2019	7.4 kW (1 × 32 A)
BMW i3 2016	11.0 kW (3 × 16 A)
Smart EQ for four 2020	22.1 kW (3 × 32 A)

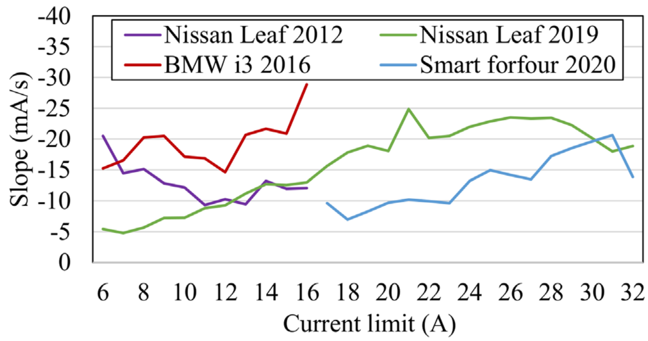

FIGURE 2 Slope of charging current in CV stage

The BL charging profile model utilizes the previously mentioned measurements to determine the energy requirement (E_R in Wh) at which point the charging currents begin to decrease (i.e. the point separating CP and CV stages). Then, Equation (4) is used to calculate the slope α that leads to the same energy (E_R) being charged in the CV stage, where L denotes current limit set by the EVSE, M denotes EV model, I_{CP} denotes the current in the CP stage, U denotes phase voltage (230 V). For the three-phase EVs (namely BMW and smart, as shown later in Table 2), separate slope for each phase is calculated. In the BL charging profile model, the slope is calculated separately for each EV and for each current limit set by the EVSE. The slopes are illustrated in Figure 2. For current limits 6–16 A, the charging of smart stop without a clear CV stage. This results in a very small E_R and thus a very high α. These slopes are considered to be outliers, and thus, they are excluded from the consideration and from the figure. Additionally, only the average slope of the three phases is presented for BMW and smart in the figure.

$$\alpha\,(L, M) \;=\; -\frac{\left(I_{CP}\,(L, M)\right)^2 \times U}{2 \times E_R\,(L, M)}. \tag{4}$$

The UBL charging profiles are formed using the same average slope for all EVs and all current limits set by the EVSE. The slope is the result of first calculating an average slope of each EV (Nissan Leaf 2012—12.8 mA/s, Nissan Leaf 2019—15.9 mA/s, BMW i3 2016—19.4 mA/s, Smart for four 2020—13.1 mA/s), and then calculating the average of all EVs which is −15.3 mA/s. The same average slope is assumed to affect each phase current, and thus, the charging powers of the three-phase EVs are decreasing three times as fast as the powers of the single-phase EVs.

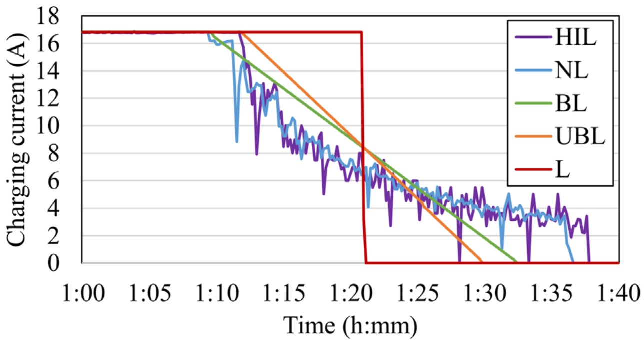

FIGURE 3 Illustration of Nissan Leaf 2012 charging profile

The L charging profile model assumes that the charging currents do not decrease when the EV is becoming fully charged. The charging profiles are illustrated in Figure 3 for Nissan Leaf 2012. In the figure, the charging is uncontrolled (i.e. current limit is ≥16 A) and the initial energy requirement is 5.2 kWh. Regardless of the modelling method, the EV draws 5.2 kWh from the grid. However, it can be clearly seen that different modelling methods result in different currents in the CV stage.

It is worth noting that some deviations between the HIL measurements and the simulation results are expected because the simulation model does not consider battery temperatures in the modelling. It is commonly known that a battery temperature plays an important role in the charging management of an EV, and thus, it should be considered the battery management system of the EV. However, due to the increased complexity of the modelling and the data requirements to form the model, the temperature factor is excluded from the charging load simulation model.

Additionally, this paper does not consider either percentual SoCs or charging efficiencies. Since the HIL charging current measurements were not able to record the SoCs of the EVs during the charging and the considered charging session data (described in Section 2.3) also measured charged energies in kWh, it is more convenient to consider energy requirements in kWh instead of utilizing SoC in this paper. Because this paper only deals with charging energies and currents seen from the grid point-of-view, the charging losses are being included. Therefore, the impact of not considering charging efficiencies explicitly is not expected to have a notable influence on the results.

2.3 | Used data

To evaluate a large charging site in a realistic manner, charging session data of REDI is used. REDI is a shopping centre located in Helsinki, Finland, which has over 200 charging points that support 22-kW charging [32]. The data is gathered over 89 days in 2020 (January–March) and contains 3801 charging sessions which results in 42.7 charging sessions per day. The data includes arrival and departure time, active charging time, charged energy, and charging peak power. All charging sessions are uncontrolled.

TABLE 3 Examined scenarios

	Site	N_{max} [a]	Control method	N_d [b]
1.	A small charging site	4	PLM	25
2.	A large charging site	21	Unc. / PLM	89

[a] N_{max} is the highest number of EVs simultaneously charging.
[b] N_d is the number of investigated cases or days.

According to the data, the EVs have an average stay duration of 236 min, an average active charging time of 101 min, and an average charged energy of 7.4 kWh. It is also seen that in 59.3% of the charging sessions the stay duration is less than 5 min longer than the active charging time. This indicates that the stay duration often acts as a bottleneck, and consequently, most EVs are not fully charged before departure. It is worth noting that a further analysis of the EV usage-related behaviour (parking time and driving requirements) is excluded from the paper. Instead, the focus is on the charging profiles (i.e. charging current drawn over the charging session) and the modelling accuracies of the different charging profile models.

2.4 | Examined scenarios

The simulations focus on two scenarios: a small charging station with four charging points and a large charging site with up to 21 simultaneous charging sessions. Scenario 1 is carried out in 25 different cases. In each case, three or four of the EVs shown in Table 2 are charged which results in 89 HIL charging sessions in total. For each event, the arrival times, the departure times, and the driving distances are randomly selected. In this scenario, the average driving distance is 19.1 km (min 4.3 km and max 65.0 km). This leads to an average energy requirement of 3.8 kWh (min 0.8 kWh and max 11.6 kWh) from the grid point-of-view (i.e. the charging losses are included). The arrival times of the EVs vary between 16 and 22 h and thus create circumstances where 1–4 EVs are simultaneously requesting charging. Sojourn times are assumed to be long enough so that the EVs can be fully charged. In each event, a peak load management (PLM) with a total charging current limit of 3 × 32 A is used. The used PLM is described in Section 2.5.

Scenario 2 is formed using the charging session data of the 89 days of REDI. For the modelling purposes, the recorded charging peak powers are used to determine the type of the EV according to (5), where P_p is the charging peak power. The second scenario is divided into three subscenarios based on the used control method: an uncontrolled charging (Unc.), PLM with a total charging current limit of 3 × 160 A, or PLM with a total charging current limit of 3 × 126 A. These limits are chosen based on preliminary simulation results that show that the highest peak current is 191 A in case of uncontrolled charging. The subscenarios are used to determine the impact of the modelling method together with the use of charging control to the modelling accuracy in a large charging site. The EVs and the key parameters of the scenarios are presented in Tables 2 and 3, respectively. The control method is presented in the next subsection.

$$\begin{cases} EV_{\text{type}} = \text{ Nissan Leaf 2012, if } 0 \text{ kW} < P_{\text{p}} \leq 4.5 \text{ kW} \\ EV_{\text{type}} = \text{ Nissan Leaf 2019, if } 4.5 \text{ kW} < P_{\text{p}} \leq 10 \text{ kW} \\ EV_{\text{type}} = \text{ BMW } i3 \text{ 2016, if } 10 \text{ kW } < P_{\text{p}} \leq 15 \text{ kW} \\ EV_{\text{type}} = \text{ Smart EQ fourfour 2020, if } 15 \text{ kW } < P_{\text{p}} \leq 25 \text{ kW} \end{cases} \tag{5}$$

In Scenario 1, HIL measurements are used to set realistic baselines for the comparisons. Due to the limited number of available EVs, Scenario 2 with up to 21 simultaneous charging sessions can only be simulated. In that scenario, the measurement-based NL charging profile models are used to form the baselines because they are the most accurate in Scenario 1 according to the results seen in Section 3.1.

2.5 | Charging control method

In this paper, a benchmark control algorithm, fair sharing, presented in [33] is used. The algorithm divides the available charging capacity evenly among the EVs. The capacity allocation is illustrated in (6), where I_{EV} is the allocated current for each EV, I_{total} is the available total charging capacity, and N is the number of active EVs requesting to be charged. The current limit is then sent to the EV through the corresponding EVSE according to IEC 61,851 charging mode 3.

$$I_{\text{EV}}\ (t) = \frac{I_{\text{total}}}{N\ (t)} \tag{6}$$

It should be noted that the following control method in itself is not the focus of this paper. Instead, the goal is to create a situation that is the opposite of uncontrolled charging: the charging capacity is very limited and the state of a single EV (charging or not charging) influences on the available charging capacity of all EVs that are charging at the moment. In Scenario 1, the maximum total loading of the charging station (3 × 32 A) allows all four charging sessions to be simultaneously active. However, a dynamic PLM is required if more than one EV is simultaneously charging. The subscenarios of Scenario 2 are effectively the same than Scenario 1 except that the total loading is either not limited, limited to 3 × 160 A, or limited to 3 × 126 A.

2.6 | Experimental setup

The idea of the experimental setup is to form the baselines for Scenario 1 by measuring the real charging events. The experiments are carried out as HIL simulations at TU Dortmund University [34]. The hardware components include the four EVs mentioned in Table 2 and two charging stations (Wirelane Doppelstele and RWE eStation). Both charging stations include two 22 kW (230 V, 3 × 32 A) sockets. The charging currents at the

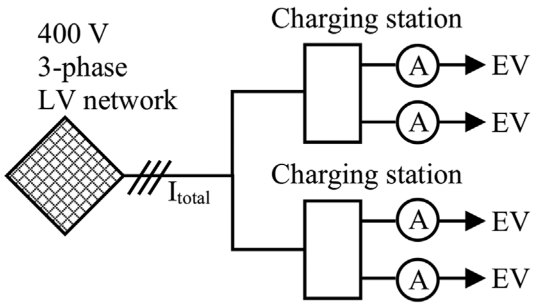

FIGURE 4 The experimental setup for Scenario 1

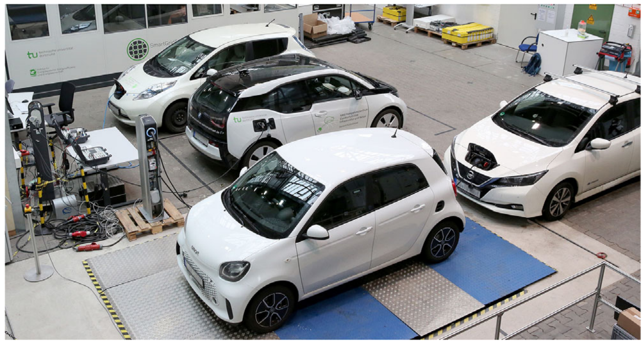

FIGURE 5 The laboratory setup

RWE charging station are measured by using KoCoS EPPE PX power quality analysers, whereas Wirelane charging station includes built-in current measurement devices for both sockets.

PLM is implemented using Python programming language. The algorithm is run on a computer that is connected to the same local network with the charging points so that the system is able to adjust the charging current limits of the EVSE and read the measurements of the realized charging currents in real time. The experimental setup for Scenario 1 is shown in Figure 4. The simulated setup for Scenario 2 is similar than the setup shown in Figure 4, but there are 21 virtual charging points instead of the four physical charging points. A picture of the laboratory setup is shown in Figure 5.

2.7 | Simulation model

The idea of the simulation model is to allow the real charging sessions to be replicated with different charging profile modelling methods. These must be done as pure simulations without any HIL components. A similar simulation model is used previously in [30] and [31]. However, in these studies, only a single charging profile modelling method (NL) was considered, and thus, the influence of different modelling methods could not be assessed.

The operation of the simulation model is illustrated in Figure 6. At the beginning, the model reads general input data and EV related input data. After the initialization, the model simulates the EV charging until all EVs have either been fully charged or been departed. In each time step, the model

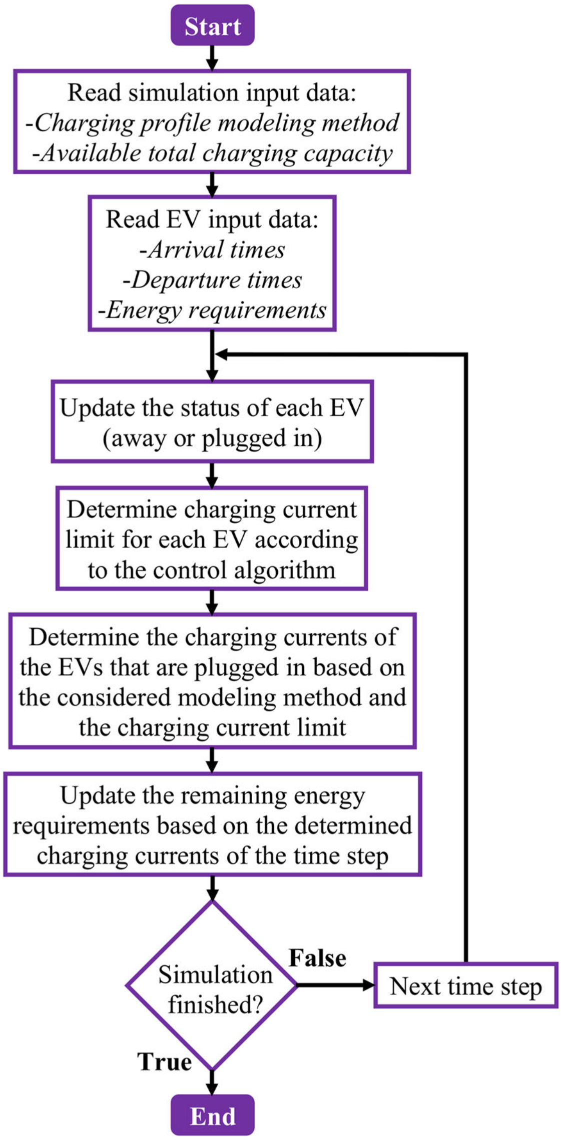

FIGURE 6 Block diagram of the simulation model

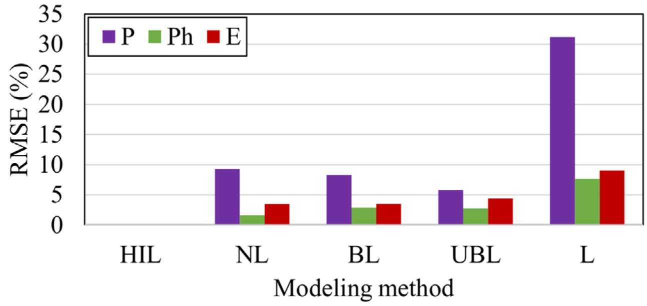

FIGURE 7 Results of scenario 1

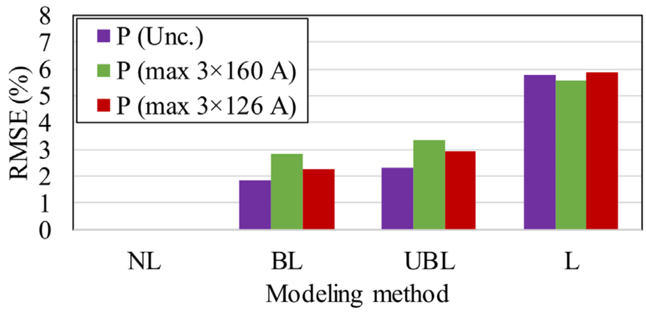

FIGURE 8 RMSE of the highest peak powers in Scenario 2

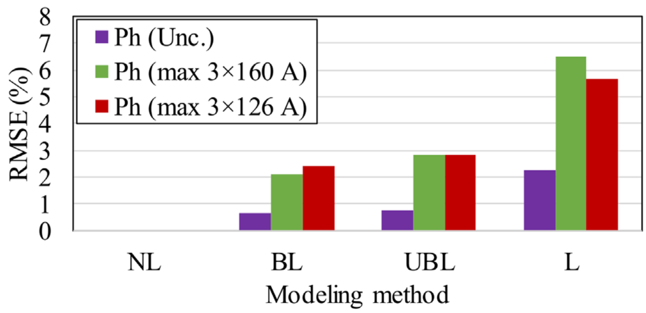

FIGURE 9 RMSE of the highest hourly peak powers in Scenario 2

determines the status of each EV (away or plugged in). For the EVs that are plugged in, the charging control algorithm determines the charging current limits according to (6). After that, the charging currents are determined according to the considered charging profile models and the determined current limits. Finally, at the end of each time step, the remaining energy requirements of the EVs are updated based on the determined charging currents. The simulation model uses a temporal resolution of 10 s.

3 | RESULTS

3.1 | Scenario 1: A small charging site

The results of Scenario 1 are presented in Figure 7. It can be seen that the highest hourly peak power and the charged energy can be modelled most accurately using the NL charging profiles (RMSE of 1.62% and 3.45%, respectively). The use of separate BL charging profiles or the UBL charging profile yields smaller RMSEs in terms of the highest peak power (8.30% and 5.80%, respectively) and slightly higher RMSEs in terms of the highest hourly peak power (2.88% and 2.72%, respectively) and the charged energy (3.49% and 4.39%, respectively). Most significantly, the results show that the use of L charging profile leads to notable modelling errors (31.21% for the highest peak load, 7.62% for the highest hourly peak power, and 9.05% for the charged energy).

3.2 | Scenario 2: A large charging site

The modelling RMSEs of each key value of Scenario 2 are presented separately in Figures 8–10. Again, the results clearly indicate that the use of L charging profiles yields the highest RMSEs (5.59%–5.86% for the highest peak power, 2.29%–6.52% for

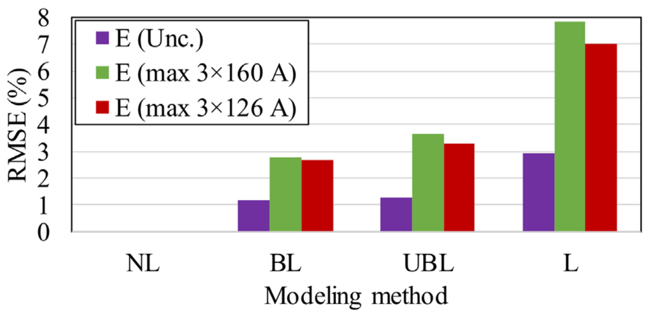

FIGURE 10 RMSE of the charged energy in Scenario 2

the highest hourly peak power, and 2.95%–7.84% for the charge energy). Compared to each other, the use of BL or UBL charging profiles yields similar results (1.87%–3.37% for the highest peak power, 0.64%–2.83% for the highest hourly peak power, and 1.19%–3.65% for the charged energy) even though the BL charging profile is slightly more accurate in each scenario.

4 | DISCUSSION

The results of Scenario 1 demonstrate that the use of NL charging profiles can be made to enable a high modelling accuracy for the EV charging load simulations even though the battery temperatures are not taken into account. However, some modelling inaccuracies were expected and seen due to this simplification. According to the results, the highest hourly peak power and the charged energy can be modelled accurately (RMSE of ≤ 3.45%), whereas the highest peak power is more susceptible to modelling errors (RMSE of 9.29%).

In general, the results show that the use of L charging profiles is likely to lead to significant modelling errors (RMSE of 2.29%–31.21%). Conversely, the use of BL or UBL charging profiles seems to be reasonably accurate compared to the HIL measurements and to the results obtained using NL charging profiles (RMSE of 0.64%–4.39% when excluding the highest peak power in Scenario 1). These results indicate that the use of a simple BL charging profile is likely to be sufficiently accurate in most cases as long as the slope of the CV stage is justified. This kind of result was expected because the studies [27] and [28] indicated that an EV model-specific charging profile model (such as the non-linear profile model considered in this paper) may not be needed in order to model charging loads relatively accurately.

The comparison of the three subscenarios of Scenario 2 shows that the uncontrolled charging can be modelled more accurately in terms of the highest hourly peak power (seen in Figure 9) and the charged energy (seen in Figure 10) than the controlled charging. This is assumed to be due to two reasons. Firstly, in case of controlled charging, the capacity allocation is influenced by the number of EVs actively requesting energy. Secondly, compared to the usage of the other modelling methods, the EVs become fully charging faster when using linear charging profile model (seen in Figure 3). This means that the use of linear charging profiles is inaccurate to model the charging states of the EVs (requesting to be charged or not) which further influences the control algorithm. In general, these results indicate that the more complex the considered control algorithm is, the more complex charging profile modelling methods should be used. In terms of the highest peak power, there does not seem to be a similar correlation to the use of charging control (seen in Figure 8) even though the loads are affected in case of controlled charging by the two reasons just mentioned. This is expected to be due to the fact that the highest peak load only takes into account the single highest value. So, despite the loads being modelled more inaccurately over the course of the simulated periods in case of controlled charging, it seems that the highest momentary power is often achieved with a similar accuracy regardless of the use of charging control. It is also worth noting that the highest peak load seems to be less susceptible to modelling inaccuracies when the number of EVs increases. This can be seen by comparing the results of Scenarios 1 and 2.

5 | CONCLUSIONS

In this paper, the influence of the charging profile modelling method on the EV charging load is assessed. Laboratory experiments with up to four commercial EVs are carried out to form realistic baselines for the comparisons. In addition, to evaluate charging at a large charging site, charging session data of REDI shopping centre is used.

The results show that the use of linear charging profile can lead to significant modelling errors, and thus, it is not recommended to be used especially in case of controlled charging. It is shown that the use of measurement-based non-linear charging profiles is likely to lead to the most accurate modelling. However, the results also demonstrate that the use of a simple, but justified, bilinear charging profile model can also lead to reasonably accurate results.

According to the measurements and calculations of this paper, the charging currents of commercial EVs decrease around 15.3 mA/s per phase on average in the constant voltage stage. Also, the results shown in this paper demonstrate that using this value to model charging profiles leads to reasonable low modelling errors of 0.64%–4.39% for the highest hourly peak power and the charged energy. Therefore, it can be used in future studies, which relates to EV charging load modelling from the charging site point-of-view, to ensure reasonable modelling accuracy with reduced computational requirements. Additionally, the results of this paper show that the battery temperatures do not have a notable influence on the charging loads seen from the charging site point-of-view, and thus, it may not be necessary to consider them in the related studies.

The results of this paper indicate that uncontrolled charging can be modelled more accurately than controlled charging. To investigate the accuracies of different charging profile modelling methods in case of different control algorithms, more work is required. However, this can be a challenging task because the commercially available EVs may have some limitations. For example, some EVs may not support vehicle-to-grid, or they may not be able to communicate certain information, such as SoC, to the control system. And, if real measurements are not used as a baseline for the comparisons, it may be difficult to assess the accuracies of different modelling methods in different scenarios.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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