Received: 9 June 2021 | Revised: 20 August 2021 | Accepted: 29 August 2021

IET Generation, Transmission & Distribution

DOI: 10.1049/gtd2.12301

ORIGINAL RESEARCH PAPER

Network-adaptive and capacity-efficient electric vehicle charging site

Kalle Rauma[1] | **Toni Simolin**[2] | **Pertti Järventausta**[2] | **Antti Rautiainen**[2] | **Christian Rehtanz**[1]

[1] Institute of Energy Systems, Energy Efficiency and Energy Economics, TU Dortmund University, Emil-Figge-Str. 76, Dortmund 44227, Germany

[2] Unit of Electrical Engineering, Tampere University, Korkeakoulunkatu 7, Tampere, Finland

Correspondence
Kalle Rauma, Institute of Energy Systems, Energy Efficiency and Energy Economics, TU Dortmund University, Emil-Figge-Str. 76, 44227 Dortmund, Germany.
Email: kalle.rauma@tu-dortmund.de

Funding information
Bundesministerium für Verkehr und digitale Infrastruktur Parken und Laden in der Stadt, Grant/Award Number: 03EMF0203; Business Finland: Prosumer Centric Energy Communities – Towards Energy Ecosystem (ProCemPlus); European Commission: LIFE-IP CANEMURE-FINLAND: Towards Carbon Neutral Municipalities and Regions in Finland, Grant/Award Number: LIFE17 IPC/FI/000002

Abstract
The adaptive charging algorithms of today divide the available charging capacity of a charging site between the electric vehicles without knowing how much current each vehicle draws in reality. Thus, they are not able to detect deviations between the current set point at the charging station and the real charging current. This leads to a situation where the charging capacity of the charging site is not used optimally. This paper presents an algorithm including a novel feature, Expected Characteristic Expectation and tested under realistic circumstances. It is demonstrated that the proposed algorithm enhances the adaptability of the charging site, increasing the efficiency of the used network capacity up to about 2 kWh per charging point per day in comparison with the previous benchmark algorithm. The algorithm is able to increase the average monetary benefits of the charging operators by up to around 5.8%, that is 0.6 € per charging point per day. No input, such as departure time, is required from the user. The proposed algorithm has been tested with real electric vehicles and charging stations and is compatible with the IEC 61851 charging standard. The charging algorithm is applicable in practice as it is described in this paper.

1 | INTRODUCTION

With an increasing need to build new charging sites for electric vehicles (EVs), a remarkable consideration is that most of the new charging sites must be retrofitted to an already existing network infrastructure [1]. This is likely to pose challenges with the current capacity, particularly during the daily peak hours. In most cases, a reinforcement of the network results in high costs and is not economically feasible [2]. Regardless of the limited network capacity, the charging time is a critical constraint in order to provide a charging service of high quality. Another issue is that each EV possesses different charging characteristics, or non-idealities [3]. Ignoring this aspect will reduce the charging efficiency when it comes to the use of network capacity and increase charging times [4–6]. It is shown that about 76% of the users of public charging stations find a high-quality charging service more important than the price of charging [7]. With such restrictions from the side of the network and from the side of the customers, a highly efficient and adaptive charging algorithm is a key element to improve the quality of the charging service.

In the literature review of this paper, six requirements to develop a practical charging algorithm are considered. These requirements are used to highlight the differences between already published research works and this paper. The requirements are as follows:

1. Is the algorithm tested by applying real charging data? Commercial EVs have a wide range of charging characteristics and the charging habits of the users are strongly dependent on the type of the charging site.
2. Are the non-ideal charging characteristics considered? In practice, this means the use of charging curves that are measured on real EVs with sufficient accuracy. If the goal is to develop an algorithm to manage charging in a time frame of seconds or a few minutes, real, session-based charging data does not reveal the dynamic charging characteristics of each

TABLE 1 Comparison of related research works

Reference	1) Tested using real charging data	2) Non-ideal charging considered	3) Compliancy with charging standards tested	4) Tested with real EVs	5) Control time-step ≤ 1 min	6) Utilizes measured current of EVs as feedback for the real-time charging management algorithm
[9]	yes	no	yes (J1772)	yes	no (15 min)	no
[10]	yes	no	yes (J1772)	yes	not mentioned	no
[11]	no	no	yes (IEC 61851)	yes	yes (30 s)	no
[5]	yes	yes	no	no	yes (1 min)	no
[12]	no	no	no	no	yes (1 min)	no
[13]	yes	no	no	no	no (15 min)	no
[14]	no	no	no	no	no (30 min)	no
[15]	no	no	no	no	no (60 min)	no
[16–20]	no	no	no	no	no (15 min)	no
[21–23]	no	no	no	no	not mentioned	no

vehicle that could cause undesirable decisions of the algorithm in practice.

3. Is the compliancy of the algorithm with the charging standards verified? It is important to ensure that the algorithm is able to work with commercial charging stations and electric vehicles as well as to rule out any unrealistic features of the algorithm.
4. Is the algorithm tested with real EVs and charging stations, either directly or via hardware-in-the-loop simulations?
5. Is the time step applied by the algorithm short enough so that no meaningful dynamic phenomena, such as sudden power peaks, remain unnoticed? The results in [8] suggest that a time step longer than one minute may not be accurate enough to observe the load peaks when operating charging stations with nominal powers up to 22 kW.
6. Does the algorithm utilize measured charging currents of the EVs in its operation? In order to make the algorithm agile and adaptive, it should use as accurate values of currents as possible.

In the best case, all six abovementioned requirements are included when developing a practical algorithm for charging management that works with the commercial hardware of today. Table 1 summarizes related works found in the literature where real-time charging management algorithms are developed and evaluates their matching with the abovementioned six requirements. Then, the contribution of our work is stated against the papers that the authors consider the most relevant for this work.

In [5], a real-time charging management algorithm with a focus on non-ideal charging characteristics is presented. The algorithm is based on neural network models, which means that the neural network must be trained with the charging characteristics of each EV model before the algorithm works in an optimal manner. The study overlooks the fact that the charging curve is different at each current set point [4], but the same charging curve is used for all current set points, which will result in a reduced accuracy to predict charging profiles in a practical application. Also, the simulation or the algorithm, does not take into account that the charging curve depends on the temperature and the lifetime of the battery, which will further reduce the performance of the algorithm. In order to reach the optimal operation, all EV models should be measured at all possible set points in different temperatures. This would be extremely laborious and unpractical. Because of the fact that the operation of the algorithm is based on predefined charging curves, all abnormalities in the charging curve are automatically ignored. The algorithm in [5] requires a certain computation time between the connection of the EV to the charging point and the start of the charging session to schedule the charging sessions. If this computation time becomes too long, customer experience may be reduced. The scheduling algorithm in [5] works in time slots of 15 min, which means that if an unexpected charging behaviour occurs, the scheduler must wait until the end of the time slot to consider the behaviour, which can be too long time for some applications.

In [10] it is mentioned that the individual charging characteristics of each EV complicate priority sharing. This is due to the fact that the EVs do not always charge according to the indicated maximum power. However, no solution for the issue is offered. In [9], an adaptive charging algorithm is presented, where the charging current is used to measure the energy consumption of each vehicle, but is not used as an input to the charging algorithm. The algorithm is tested with single-phase AC chargers and a fast charger, not with three-phase AC chargers. In [17], constant-current and constant-voltage charging stages are included in the mathematical modelling of the EVs. This makes the scheduling algorithm more efficient than considering only a constant charging curve. However, only one generic load curve is used, which makes it inaccurate in a real application.

The work in [21], presents a real-time adaptive charging algorithm. The algorithm uses discrete charging powers: 0 kW, 20 kW, 40 kW and 62.5 kW, for every EV, which can be inefficient from the network-capacity viewpoint. In [24], the capacity utilization rates of the charging stations are increased by changing their physical locations in the network, but these are rather fixed solutions than algorithms, as the solution presented in this paper.

The second study with a focus on non-ideal charging behaviour of EVs is presented in [6]. In the work, an offline method for clustering charging curves is presented. Even if the work does not present a real-time method to deal with non-idealities, it underlines the importance of considering non-idealities in charging management.

The literature review in Table 1 shows that non-ideal charging characteristics are taken into account only in one study developing a real-time algorithm for charging management. In addition, no algorithm uses the measured charging current as an input to the charging management algorithm. Three works are identified where the algorithm is proven to be functional with real electric vehicles and charging stations or is otherwise proven to be compatible with the charging standards. What is also noticeable in Table 1 is that most real-time algorithms have a fixed operating time-step of 15 min or more. This is rather long for many applications of demand response [8].

In this paper, the term 'network adaptivity' means that the charging current that is available for a charging site changes over time and, consequently, the current drawn by the charging site adapts to these changes. The term 'capacity efficiency' describes how many percent of the charging current that is available for the charging site is used by the charging site (consisting of one or more charging points). To the best of the authors' knowledge, no other paper has considered the capacity efficiency related to EV charging as it is done in this work.

To fill the identified gaps in research, the contribution of this paper is as follows:

1. Propose a novel adaptive charging algorithm, called CCE (charging characteristic expectation) algorithm that employs actual charging currents and has a capacity to learn the charging characteristics of the charging EV. The CCE algorithm would enhance the operation of the charging algorithms, for example the ones presented in [9, 10, 17] and [21], by reducing idle network capacity and charging times. The charging algorithm is extended to function with a prioritized fast-charging station or under varying load in the network.
2. Test the functionality of the algorithm with four real electric vehicles, charging stations and a fast-charging station emulator via hardware-in-the-loop simulations. The hardware testing guarantees that the algorithm is compatible with the IEC 61851 charging standard. All data used in the hardware-in-the-loop simulations are real, measured data.
3. Compare the proposed charging algorithm with a commonly used reference algorithm.
4. Demonstrates that the CCE algorithm outperforms the reference algorithm in terms of efficient use of the charging capacity.

Non-idealities of EV charging and their impacts on charging management, supported by detailed laboratory measurements, are studied in [3], where an initial version of such adaptive algorithm is also presented. The benefits of an adaptive charging algorithm on a larger simulation case are further explored in [4]. In comparison with [3] and [4], in this paper, the algorithm is further developed by a complete reorganization and including a load prioritization. Also, new features, such as metrics on the performance of the algorithm are added. In addition, new EV models are added to the simulation model as well as used in the experiments as hardware. Further, an extent comparison between the CCE algorithm and the reference algorithm is carried out.

The remainder of the paper is structured as follows. Section 2 presents the complete algorithm step-by-step. CCE, which is a remarkable feature of the algorithm, is explained in its own sub-section. Also, the reference algorithm is separated as a subsection. Section 3 describes the used data and the modelling in the hardware-in-the-loop simulations as well as the laboratory setup. Section 4 provides the results of the experiments and Section 5 discusses the results and their implications. Section 6 concludes the paper and gives directions to the future work.

2 | PROPOSED CHARGING ALGORITHM

This section explains the functioning of the proposed charging algorithm. Henceforth, the algorithm is referred to as the CCE algorithm according to its distinctive feature called CCE. The reference algorithm that is used for comparison purposes, is briefly explained in Section 2.1. A flowchart of the CCE algorithm is presented in Figure 1. The main idea of the algorithm is to find the most suitable current set points for each charging station so that the current capacity available for the charging site is used as efficiently as possible without causing an overload. The time step of the algorithm is 10 s. The algorithm does not require any input from the user. The maximum current that is shared between the prioritized load(s) and the charging points can be a fixed value, for example an ampacity of the feeder where the charging stations are connected, or non-fixed, such as the free current capacity at the feeding secondary substation. In order to enhance the readability of Figure 1, the steps of the algorithm are numbered and explained separately in the text.

Step 1–2: The currents of the prioritized load(s) are read. In the experiments of this study, the prioritized load is a DC fast charging station, but it could be any other network load, such as a current measurement from a building that is connected to the same feeder. The fast-charging station is selected as a prioritized load in order to maintain the quality of service as high as possible for the fast-charging customers. This selection is done because the use of fast charging stations has usually a higher price than charging stations with lower nominal charging power. Thus, the fast-charging station is not controlled by the CCE algorithm. In this step, also the actual 3-phase charging currents of each charging station are read.

Step 3: A set of performance metrics is calculated. The metrics include, for example, the error between the predicted and the actual charging current of each vehicle as well as the total error consisting of the sums of the errors for each time step. Also, the charged energies and the capacity usage rates of each charging station are calculated. Finally, the metrics are saved for

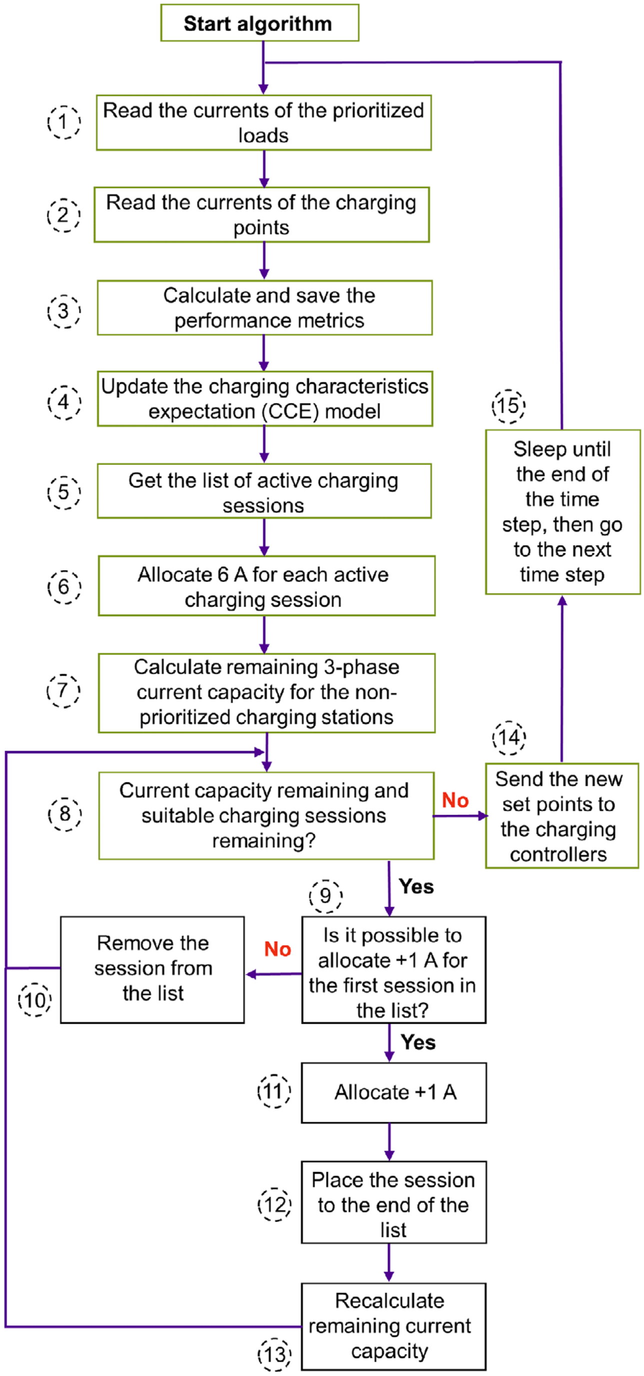

FIGURE 1 A flowchart of the proposed charging algorithm

later analysis. In operational use, such detailed data for each time step may not be necessary and the number of metrics can be reduced.

Step 4: The CCE model is updated for each charging session based on current measurements in Step 2. In short, the CCE model enables the algorithm to estimate the upcoming charging currents before applying the current set point. A CCE model is a matrix where the charging current of each phase at each current set point is memorized. The details of the CCE model are described in Section 2.1.

Step 5: A list of active charging sessions is formed. An active charging session refers to a charging session where an EV is connected to the charging station and is ready to be charged (status B in IEC 61851) or charging (status C or D).

Step 6: 6 A for each active charging session is allocated. This is the minimum non-zero charging current according to IEC 61851. The idea is that each EV can always be charged with at least 6 A, which is important from the user experience point-of-view.

Step 7–8: Once 6 A for each active charging session is allocated, the remaining current capacity is calculated for each phase. The remaining charging capacities are calculated based on the CCE models. If there is still available charging capacity in the network to be allocated, the algorithm continues the inner loop to Step 9. Otherwise, it moves to Step 14.

Step 9: From Step 8, a secondary loop is started. The idea of this loop is to increase the charging current of each EV by 1 A until the whole charging capacity is used or there are no more EVs that can increase their charging current without causing an overload. It is important to notice that the current set points are not sent to the charging stations yet, but only in Step 14. In this step, the possibility to allocate +1 A without causing overloading is estimated using the CCE model. Additionally, the algorithm considers the maximum current limit of the charging point. If it is not possible to allocate +1 A for the first EV in the list, the algorithm moves to Step 10. Otherwise, the algorithm moves to Step 11.

Step 10: If the charging session is unsuitable for further capacity allocation, it is removed from the list of active charging sessions and the algorithm returns to Step 8.

Step 11–13: If possible, +1 A is allocated to the EV and the EV is placed at the end of the list. This ensures even capacity allocation among the active charging sessions. Afterwards, the remaining current capacity is recalculated.

Step 14–15: A physical signal of the current set point is sent from the computer that runs the algorithm to each charging station with an active charging session (including the ones removed from the list). Once the set points are sent, the algorithm waits until the end of the 10 s time step before starting a new time step.

It is important to point out that always, when the remaining current capacity is calculated, it is done so that the current capacity is not exceeded in any of the three phases. So, the current in phases A, B and C must stay below the maximum current limit. The algorithm is developed in Python.

2.1 | Charging characteristics expectation

The CCE model is a way to memorize the charging currents of each EV. The CCE is a crucial component to improve the performance of the algorithm. It is computationally light, which enables fast computation and high scalability.

A CCE model is essentially a matrix that includes the phase currents of an EV at all current set points. The use of CCE allows an accurate prediction of the charging currents of an EV, before the current set point is sent to the charging station (Step

14 in Figure 1). Each CCE model is updated in every iteration of the algorithm with new measurements values of the phase currents of the corresponding charging session. Thus, each CCE model corrects itself during a charging session, which is a way to include non-ideal or non-linear characteristics in the charging algorithm.

When an EV arrives at the charging station, the CCE model supposes that the EV charges exactly according to the current set point and is able to use the maximum current of the charging station. Thus, the initial CCE matrix is

$$\left[\begin{array}{cc} & \begin{array}{ccccc} I_{sp} & I_A & I_B & I_C & Meas \end{array} \\ \begin{array}{c} I_{cs,max} \\ 32.0, \end{array} & \begin{bmatrix} 6 & 6.0 & 6.0 & 6.0 & False \\ 7 & 7.0 & 7.0 & 7.0 & False \\ 8 & 8.0 & 8.0 & 8.0 & False \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 32 & 32.0 & 32.0 & 32.0 & False \end{bmatrix} \end{array}\right], \tag{1}$$

where $I_{cs,max}$ is the maximum current of the charging session. This is typically either 3 × 16 A or 3 × 32 A (11 kW or 22 kW) in Europe. I_{sp} is the current set point at the charging station controller. I_A, I_B and I_C are the measured phase currents at the given current set point I_{sp}. The matrix is updated at each iteration loop. At the beginning, the values are set according to the set point values (as in (1)). This is an initial assumption as there is no preliminary knowledge of the charging sessions. *Meas* is a Boolean variable to indicate whether the values of I_A, I_B and I_C are measured values (*True*) or initial values (*False*). For example, after the first loop, if the CCE of a charging station receives measurement at current set point 6 A: $I_A = 6.2\ A$,$I_B = 5.7\ A$ and $I_C = 5.4\ A$, the CCE is updated as

$$\left[\begin{array}{cc} & \begin{array}{ccccc} I_{sp} & I_A & I_B & I_C & Meas \end{array} \\ \begin{array}{c} I_{cs,max} \\ 32.0, \end{array} & \begin{bmatrix} 6 & 6.2 & 5.7 & 5.4 & True \\ 7 & 7.0 & 7.0 & 7.0 & False \\ 8 & 8.0 & 8.0 & 8.0 & False \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 32 & 32.0 & 32.0 & 32.0 & False \end{bmatrix} \end{array}\right]. \tag{2}$$

As seen in (2), the updated values are bolded in purple. In this way, the CCE model learns a part of the charging characteristics of the EV, and thus, the accuracy of the CCE model to estimate the upcoming charging currents increases. In order to accelerate the operation of the charging algorithm, CCE includes three auxiliary functions.

The first function detects the charging phases of an EV. When the EV has charged during few seconds and if current at one or two phases are obviously above 0 A and one or two phases are close to 0 A, the corresponding columns (I_A, I_B and I_C) of the latter one(s) will be set to 0.0 A.

The second function verifies the highest charging current of an EV. The function calculates the difference between the current set point and the realized charging current. If the difference is more than a couple of amperes, the realized current is set as the maximum charging current of the charging session ($I_{cs,max}$).

The third function interpolates values of I_A, I_B and I_C that are not yet measured (*Meas* = *False*), but lay between two measured values (*Meas* = *True*). The measured values provide the upper and the lower boundary for the estimation. The interpolated value is placed linearly between the measured values.

When measuring the charging currents to update the CCE model, it is important to consider that each EV has a different reaction time to the input signals. When a new current set point is set, it may take up to even 10 s before the EV starts reacting to the new current set point. Another point is the noise in the measurement devices that should not be confused with charging current.

2.2 | Reference algorithm

The same hardware-in-the-loop simulations are carried out with the CCE algorithm as well as with a reference algorithm. The reference algorithm is a fair sharing algorithm that divides the available charging capacity equally among the charging vehicles as

$$P_{cs,t} = \frac{P_{available,\ t}}{n_{active,\ t}}\ , \tag{3}$$

where $P_{cs,t}$ is the energy that each vehicle receives [10] at a given time step t. $P_{available,\ t}$ is the available charging capacity to be divided between all vehicles at time step t. $n_{active,t}$ is the number of active charging sessions. In addition to [10], the algorithm is used in [9] as well as by several commercial charging operators and charging point manufacturers [25–27]. In [5], the fair sharing algorithm is used as a reference algorithm, like in this paper. Thus, the algorithm can be considered as a benchmark and is referred to as the 'reference' algorithm throughout this paper.

3 | USED DATA, MODELLING AND LABORATORY SETUP

In this section, the used data and how it is used in hardware-in-the-loop simulations are described. Also, general descriptions of the studied cases are provided.

3.1 | Case description

The charging site modelled in the hardware-in-the-loop simulations is located in the district of Kreuzviertel, in the city of Dortmund, Germany. There are plans to install 40 new charging stations in Kreuzviertel in 2021. The charging stations are manufactured by Wirelane and provide three-phase AC charging up to 22 kW via a Type 2 connector. The charging stations are operated by a local energy company. High and irregular variations in load make the EV charging loads at different sites very difficult, or nearly impossible [18], to be predicted with sufficient accuracy. In addition, a significant rotation of short-time customers will intensify the use of the charging stations. In spite of the demanding charging environment and limited network capacity, a high quality of charging service will be offered. This makes Kreuzviertel a feasible location for an adaptive and capacity-efficient charging algorithm. Furthermore, more AC charging points or DC charging stations might be installed in the area in the future.

3.2 | Used charging data and modelling

As suggested in [28] and in [29], creating synthetic load curves from mobility data involves several possibilities for pitfalls. That is why real charging data is used in this work. The data is measured at a commercial charging site at Dortmund city centre, located close to the planned charging site, and is expected to possess similar user behaviour as the charging site under this case study. The power of these two charging stations is limited to 22 kW and any further smart charging strategies are not employed, so the EVs are charged with their respective maximum charging powers. They are in commercial use and equipped with Type 2 sockets.

The measured average parking time at the site where the charging data is measured is 3 h 53 min and the average charged energy is 11.3 kWh, which is much higher in comparison with other studies, such as [30–34]. From the data set, it is not possible to see when the charging is finished, which means that exact average charging powers cannot be directly concluded.

In this study, four different EV models consisting of six different charging characteristics are used. The EV models are Nissan Leaf ZE0 2012 (1 × 16 A), Nissan Leaf 2019 (1 × 32 A), BMW i3 1Z61 2016 (3 × 16 A) and Smart EQ forfour 2020 (3 × 32 A). The reason behind the selection of these EV models in the study is that they cover the most of the common combinations of phases and maximum AC charging currents on the market:

- 3.7 kW (1 × 16 A),
- 6.6 kW (1 × 32 A),
- 11 kW (3 × 16 A) and
- 22 kW (3 × 32 A).

These EV models are also common in the European market. More details of the EVs used in this study are included in Section 3.3.

From the measured charging data, the used energy is divided by the parking time of the charging session in order to have an estimated average charging power. Then, the EV model of each charging session is concluded as follows:

1. all charging sessions with an estimated average power of > 15 kW are modelled as Smart forfour,
2. all charging sessions with parking time < 2 h and estimated average charging power between 8 kW and 15 kW are modelled as BMW i3,
3. all charging sessions with parking time < 2 h and estimated average charging power between 4 kW and 8 kW are modelled as Nissan Leaf 2019,
4. all charging sessions with parking time < 2 h and estimated average charging power between 0 kW and 4 kW are modelled as Nissan Leaf 2012 and,
5. the EV model for the rest of the charging sessions is selected arbitrarily.

The idea is that each charging session is linked to one of the abovementioned EV models. By far, most charging sessions fall in categories (1) to (4), so the estimate is relatively accurate. The reason why 2 h is selected in categories (2) to (4) is that the shorter the charging session, the more likely it is that the estimated average charging power is close to the real maximum charging power. In other words, the shorter the charging session, the more likely it is to be inflexible [30]. The mode of the BMW i3 ('low', 'reduced' or 'maximum' mode) is selected randomly. More information about the charging modes of BMW i3 can be found in [35] and related measurements are presented in [3].

The charging data from the two charging points are combined to cover eight charging points. This is done so that the different days of the week are not mixed. Three weekdays are selected for this study: Tuesday, Wednesday and Friday. For example, data from several Tuesdays at two charging stations are assembled so that representative data for a Tuesday of eight charging points are obtained. The same is repeated to gather charging sessions for Wednesday and Friday. As a result, the charging schedules of one typical Tuesday, one typical Wednesday and one typical Saturday consisting of real charging sessions are formed. The charging behaviour at a charging site varies typically according to the weekday. In order to form as realistic charging schedules as possible, it is important that charging sessions from different weekdays are not mixed with each other.

The charging data for the fast-charging station is obtained from the same dataset as used in [32]. The charging data is from the urban area of Oslo, which is expected to have similar charging behaviour as a fast-charging site in Dortmund would have. Also, the same weekdays, Tuesday, Wednesday and Friday, are respected when selecting the data from the fast-charging station. The currents of the fast-charging station used in the study for each day are illustrated in Figure 2.

The main intention of the work is to assess the performance of the proposed charging algorithm during a typical day, not in a worst-case scenario. That is why any special circumstances are avoided when selecting the days for the simulations. In this way, it is proven that the algorithm brings benefits to daily operation, instead of only during extreme cases.

In reality, more than four different EV models are used at the real charging site, however, using four categories (e.g. EV models) allows us to construct a rather comprehensive and realistic simulation model for virtual EVs. The load curves of the EVs are modelled very accurately based on real measurements carried out on the same EVs models presented previously. Every possible charging curve within the possibilities of the IEC 61851 charging standard and commercial charging controllers is

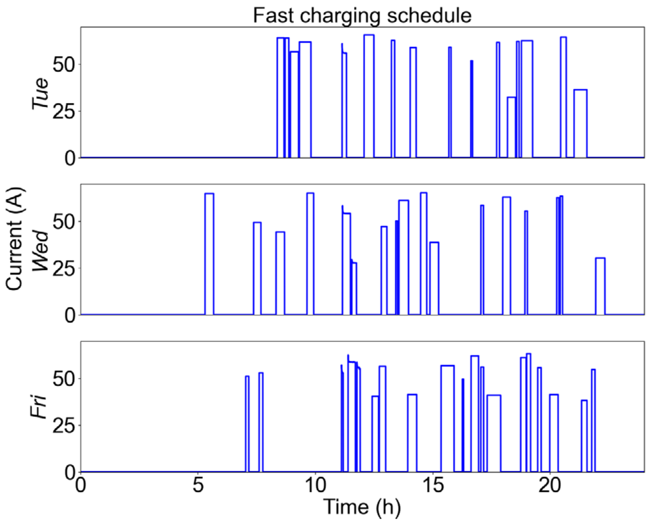

FIGURE 2 The currents of the fast charging for the experiments in different days

considered. This means that the load curves are measured at every current set point with a resolution of 1 second:

- Nissan Leaf 2012 and BMW i3: 6, 7, 8, 9, 10, 11, 12, 13, 14, 15 and 16A, and
- Nissan Leaf 2019 and Smart forfour: 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31 and 32 A.

These measurements are used as a model to simulate virtual EVs. More information about the modelling of the virtual EVs used in the HIL-simulation is found in [4].

3.3 | Laboratory setup

The algorithms are tested through hardware-in-the-loop simulations carried out at TU Dortmund University [36]. The laboratory setup resembles a public parking and charging site with eight AC charging stations (22 kW, 32 A each) and one fast charging station (45 kW, 65 A), that are connected to the same 400 V 3-phase feeder. Figure 3 illustrates a simplified scheme of the laboratory setup.

It is important to notice that according to IEC 61851 charging standard, the minimum possible charging current set point is 6 A. Any set points between 6 A and 0 A are not allowed according to the standard. In this case, the total current limit is set high enough that the power of the fast-charging station does not need to be reduced. This is to guarantee a maximum quality of service to the fast-charging station, which is typically more costly to the users than an AC charging station.

A limit of 115 A per phase is set as the maximum current of the whole charging site (I_{max}). The idea behind setting I_{max} to 115 A is that all AC charging stations are able to operate at least with the minimum charging current and the fast-charging station with the nominal one, simultaneously. The

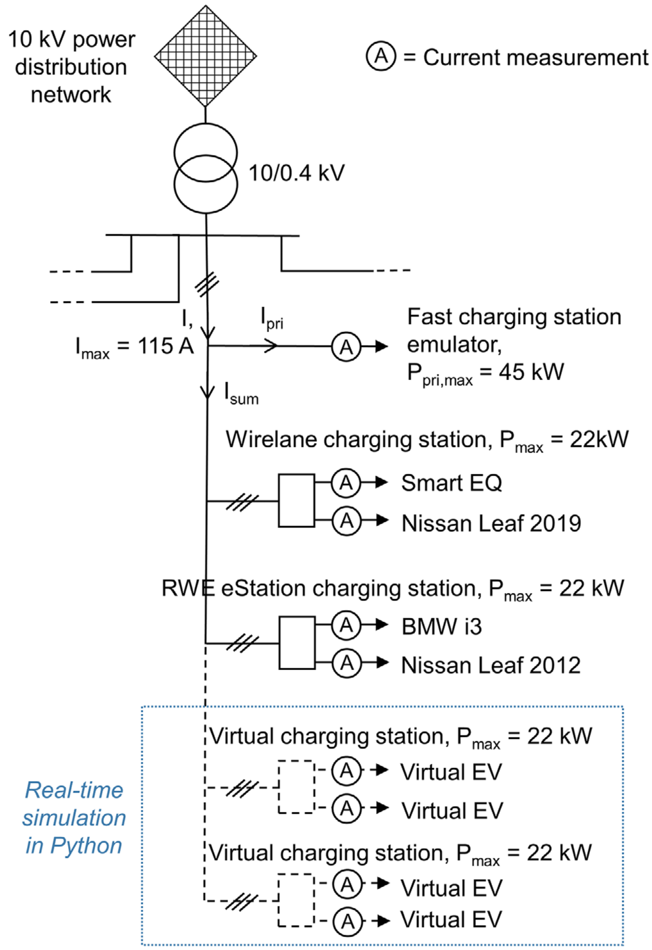

FIGURE 3 Laboratory setup for the Hardware-in-the-Loop simulations to evaluate the algorithms

fast-charging station draws a maximum power of 45 kW that is about 64.95 A per phase. If, at the same moment, all AC charging stations operate at the minimum capacity, that is 6 A, then $64.95\ A + 6 \times 8\ A \approx 113\ A$. Thus 115 A is slightly above 113 A and guarantees the intended operation. This is a trade-off between the flexibility of the charging site, quality of the charging service and customer experience.

The hardware-in-the-loop simulation consists of a hardware and a real-time simulation that are linked to each other via Modbus TCP communication. Four commercial electric vehicles; Nissan Leaf 2012, Nissan Leaf 2019, BMW i3 and Smart forfour EQ, are used. The EVs are connected to two commercial charging stations (each charging station has two charging sockets): Wirelane Doppelstele and RWE eStation. At the RWE charging station, currents from phases A, B and C are measured by using a KoCoS EPPE PX power quality analyser. Wirelane charging station already includes a current measurement off the shelf. The charging stations are connected to the 400 V 3-phase power network of the laboratory. In parallel with the charging stations, a programmable load is connected and used as a fast charging station emulator. The load is controlled according to the fast-charging schedules illustrated in Figure 2. Thus, it has the same electrical characteristics as a fast charging station.

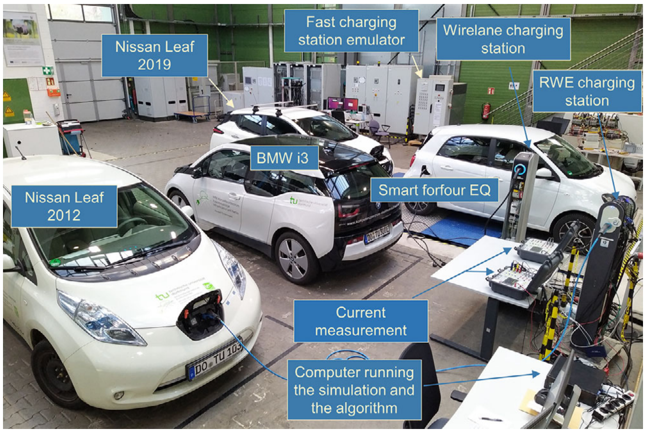

FIGURE 4 Laboratory setup

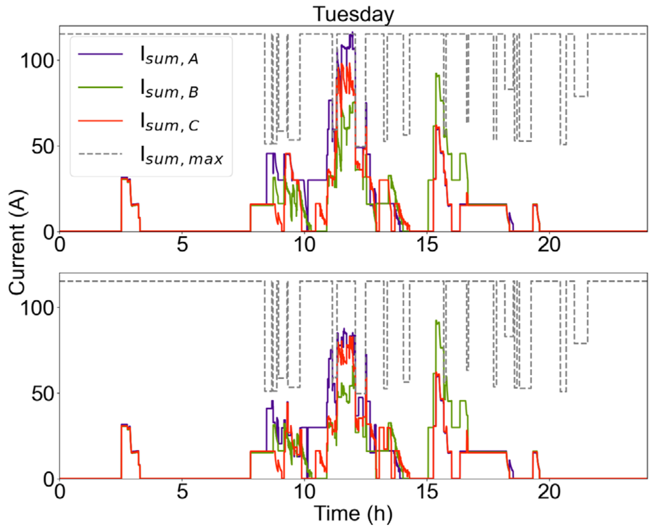

FIGURE 5 The phase currents and the available capacity limit on Tuesday: the CCE algorithm (above) and the reference algorithm (below)

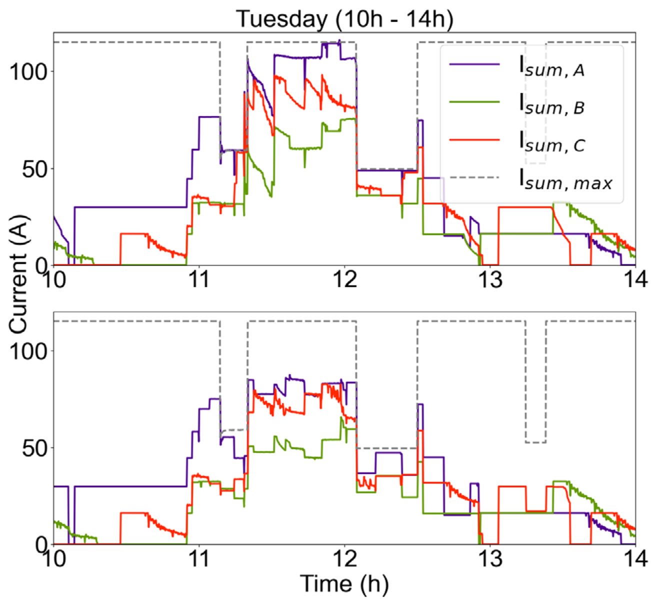

FIGURE 6 The currents of Tuesday from 10 h to 14 h: the CCE algorithm (above) and the reference algorithm (below)

With the real EVs, the driven distances are calculated based on the energy consumption in the real charging data for each simulated day. When assessing the different algorithms, exactly the same routes are driven, and the same SoCs are obtained, in each case. In this way, the results can be compared with high accuracy.

The real-time simulation is written in Python and runs on a computer in the laboratory. The simulation includes four virtual charging points that are virtually connected to the same feeder as the real charging points. The virtual EV models are selected according to the procedure clarified in Section 3.2. During one day, one charging station can host several virtual charging sessions. In addition, the charging curves of the virtual EVs are based on measurements with an accuracy of 1 s, as explained in Section 3.2. Figure 4 shows a photo of the laboratory during the experiments.

4 | RESULTS

In this section, the results of the hardware-in-the-loop simulations are presented. Each illustration from Figure 5 to Figure 10, shows the results of the CCE algorithm in the upper half and the results of the reference algorithm are in the lower half. The summed charging currents of phases A, B and C as well as the current limit $I_{sum,max}$ are presented from Figure 5 to Figure 10. The current limit $I_{sum,max}$ is the maximum available current capacity that can be shared between all non-prioritized EVs, which means all charging stations, except the fast charging station. Each phase has an own maximum current limit. But since the fast-charging load causes very balanced three-phase loading from the grid point-of-view, the current limit of each phase is almost the same. Thus, only one current limit is shown in the results. The current limits are calculated according to

$$\begin{cases} I_{sum,max,a} = I_{max} - I_{pri,a} \\ I_{sum,max,b} = I_{max} - I_{pri,b} \ , \\ I_{sum,max,c} = I_{max} - I_{pri,c} \end{cases} \tag{7}$$

where I_{pri} is the current of the prioritized fast charging point and a–c denotes each phase. When the fast charging station is idle ($I_{pri} = 0$), the current limit I_{max} is 115 A, as presented in (7). When the fast charging station operates, the current limit (I_{sum}) for the AC charging stations is decreased. For the sake of clarity, the results are shown during the whole period (24 h) as well as during the peak hours (10–14 h). The results of Tuesday are presented in Figure 5 and in Figure 6.

In both, Figure 5 and in Figure 6, it can be seen that the charging stations operate closer to their limits when the CCE algorithm is used (upper halves of the figures) as opposed to the reference algorithm (lower halves). This is evident, especially between 11 h 20 min and 12 h 5 min, where the average value

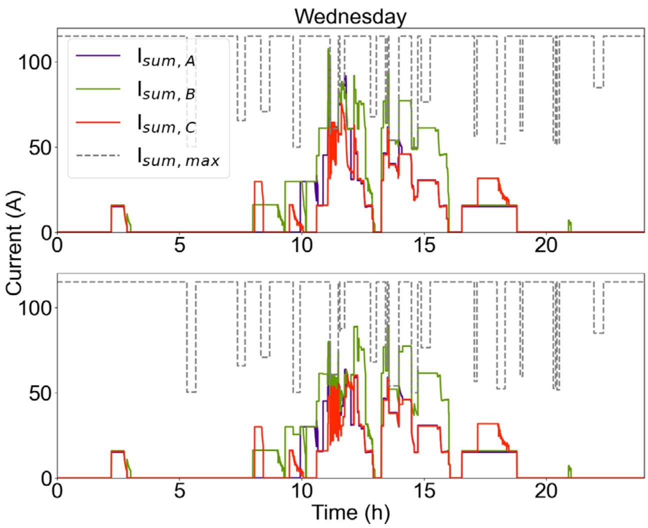

FIGURE 7 The phase currents and the available capacity limit on Wednesday: the CCE algorithm (above) and the reference algorithm (below)

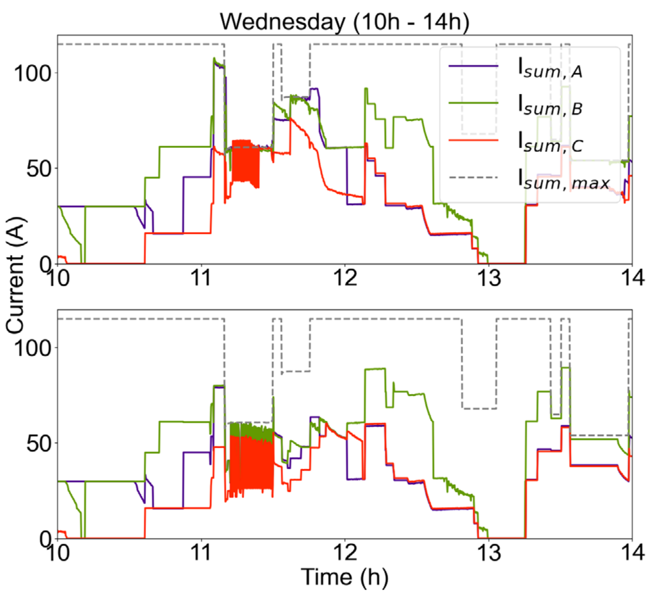

FIGURE 8 The currents of Wednesday from 10 h to 14 h: the CCE algorithm (above) and the reference algorithm (below)

of current on phase A is 104.3 A with the CCE algorithm and 72.9 A with the reference algorithm. This means that during the time the reference algorithm operates at 69.9% of the capacity of the CCE algorithm. This means that at least some of the EVs are able to charge faster with the CCE algorithm than with the reference algorithm. The results of Wednesday are presented in Figure 7 and in Figure 8.

The results of Wednesday are similar to the results of Tuesday; the summed charging currents are often higher, or at least not lower, with the CCE algorithm than with the reference algorithm. A major difference is between 11 h 30 min and 12 h 30 min, when the average current on phase B is 72.2 A with the CCE algorithm and 53.4 A with the reference algorithm. During this time period, the reference algorithm charges 73.9%

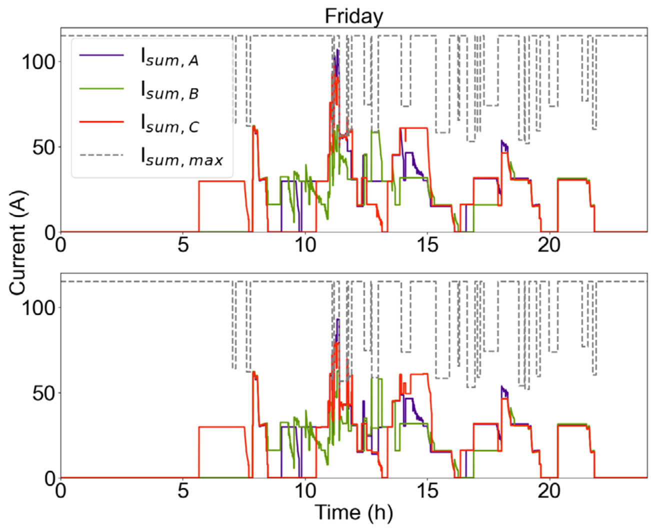

FIGURE 9 The phase currents and the available capacity limit on Friday: the CCE algorithm (above) and the compared algorithm (below)

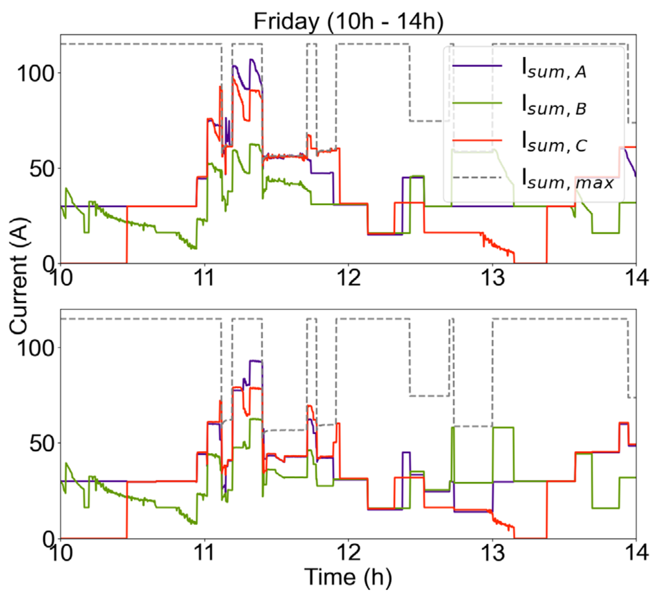

FIGURE 10 The currents of Wednesday from 10 h to 14 h: the CCE algorithm (above) and the compared algorithm (below)

of the current on phase B compared with the CCE algorithm. The results of Friday are illustrated in Figure 9 and in Figure 10. Again it is seen that, especially between 11 h and 12 h, the charging current with the CCE algorithm are closer to the current limit ($I_{sum,max}$) when using the CCE algorithm than with the reference algorithm.

Due to the fact that not all EVs are charged fully during the charging sessions, higher charging current means that they charge more energy during the same amount of time when the CCE algorithm is used. If a charging operator charges its customer based on the amount of charged energy, the operator achieves higher earnings with the CCE than with the reference algorithm. Because of the higher charging currents on average, the CCE algorithm causes a slightly higher

TABLE 2 Summarized results when comparing the reference algorithm with the CCE algorithm

	Tuesday (reference)	Tuesday (proposed)	Wednesday (reference)	Wednesday (proposed)	Friday (reference)	Friday (proposed)
Charged energy (kWh)	178.33	194.01	202.19	212.44	261.02	270.69
Gross profit (€)	53.50	58.20	60.66	63.73	78.31	81.21
Capacity utilization rate (%)	18.03	18.84	18.74	19.29	22.20	22.71
Prediction error (A)	48.79	0.42	47.85	0.42	68.80	0.39
Prediction error (%)	130.49	0.85	108.80	0.82	130.34	0.61

TABLE 3 Changes in the performance of the charging site when comparing the reference and the CCE algorithm

	Tuesday	Wednesday	Friday
Charged energy	+15.65 kWh (8.79%)	+10.25 kWh (5.07%)	+9.67 kWh (3.71%)
Gross profit	+4.7 € (8.79%)	+3.07 € (5.07%)	+2.9 € (3.63%)
Capacity utilization rate	+4.30%	+2.85%	+2.25%
Prediction error	−99.14%	−99.12%	−99.43%

capacity utilization rate than the reference algorithm. As the result of the learning mechanism in the CCE algorithm, it can predict the charging currents more accurately than the reference algorithm, which increases the adaptability of the algorithm in general. Table 2 presents the charged energies, gross profits, capacity utilization rates and prediction errors each day with the proposed as well as with the reference algorithm. The gross profit is calculated based on the energy price of 0.3 €/kWh that is a common rate of commercial charging operators at public AC charging sites across Germany [37]. In Table 3, the performance of the CCE algorithm is compared with the reference algorithm.

Table 3 shows the CCE algorithm improves the performance of the charging site in all analysed aspects. On average, daily charged energy increases by 11.86 kWh. The average gross profit increases by 3.56 € per day that is 5.8%. The capacity utilization rate increases by 3.13% and the prediction error decreases by 99.23% per day on average. In the worst day, that is on Friday, the CCE algorithm increases the charged energy of the site by nearly 10 kWh, resulting in almost 3 € higher gross profits than the reference algorithm, which is 8.8%. Consequently, the capacity utilization rate increases by more than 2% and the prediction error decreases by more than 99%. It should be taken into account that the studied charging site is small, consists of only eight charging stations. The benefits of the CCE algorithm are much higher at larger sites, for example, shopping centres, with tens, or even hundreds, of charging stations.

Since the number of EVs increases rapidly and the charging powers are increasing, the EV charging sites are expected to operate closer to their limits in the near future. That is why it is valuable to analyse the difference between the CCE algorithm and the reference algorithm during a peak hour with many simultaneous charging sessions. Table 4 shows the differences in charged energies and gross profit in the time frame from 11 h to 12 h.

Table 4 shows even more drastic differences between the two algorithms. A remarkable difference is that on average, about 24.5% more energy is charged during the peak hour with the CCE algorithm. When comparing Table 3 with Table 4 it can be seen that most of the advantages of the CCE algorithm are gained during the peak time.

5 | DISCUSSION

It is demonstrated that the current state-of-the-art adaptive charging algorithm does not provide as high utilization of available charging capacity as possible. An alternative adaptive charging algorithm is presented and compared against the previous benchmark algorithm. The key factor why the CCE algorithm performs better than the compared benchmark algorithm is that it uses real charging currents as an input to the algorithm. In other words, the algorithm efficiently divides the available charging capacity amongst the active charging sessions while considering their real charging currents. Simply, without current measurements, it is not possible to know how much current the EVs draw and the real-time charging management cannot be organized that accurately. The accuracy of the charging algorithm is further enhanced with a simple learning mechanism, CCE that makes the algorithm capable of memorizing and forecasting the real charging current of each connected EV with a given current set point. It is demonstrated that the CCE algorithm gives a great advantage over the reference algorithm especially during the hours when the charging site operates close to its capacity limits.

For many demand response applications, it is crucial that the charging algorithm recognizes the charging currents of the EVs.

TABLE 4 Changes in the performance of the charging site when comparing the reference and the CCE algorithm between 11 h and 12 h

	Tuesday	Wednesday	Friday
Charged energy	+8.45 kWh (20.56%)	+11.54 kWh (34.43%)	+6.12 kWh (18.42%)
Gross profit	+2.54 €	+3.46 €	+1.84 €

As an example, if a BMW i3 charges at a 22 kW charging point that allows the maximum charging capacity (22 kW, 3 × 32 A, 230 V), consequently the BMW charges at its maximum capacity (11 kW, 3 × 16 A, 230 V). The energy management system of the charging site wishes to set a new current set point to the BMW so that the charging power of the BMW is reduced by 5.5 kW. By using the reference algorithm. The energy management system would reduce the charging power from 22 kW to 16.5 kW (22 kW – 5.5 kW = 16.5 kW). This means that the BMW would still continue charging with its maximum capacity (11 kW, 3 × 16 A, 230 V) and finally, the real charging current is not reduced at all. Without a reasonable measurement and anticipation of charging currents, it may be difficult to obtain the expected load value for a given charging site in a short amount of time. That is why the applicability of the reference algorithm in demand response applications, such as in peak shaving or frequency regulation, is questionable. On the contrary, the CCE algorithm enables an accurate way to set the power consumption of the charging site to a wished value, as demonstrated by the results.

The benefits to be obtained from the use of the CCE algorithm are highly dependent on the number and the type of the charging stations, the maximum allowed charging current and the charging behaviour of the customers (charging durations and simultaneity). The results show meaningful benefits over the reference algorithm even on average days and circumstances. On one hand, the algorithm can be guaranteed that the available charging capacity is used efficiently, which decreases the charging times, improves the customer experience and increases the economic gains of the charging operator. On the other hand, the algorithm can be used to prevent overloads in the feeding distribution network. After all, the algorithm leads to increased utilization of network capacity, which can lead to savings in the network investment costs.

From the power system-viewpoint, the constant-voltage phase of the charging curve is where a notable share of the charging capacity may be lost, if the decreasing charging current is not recognized by the algorithm Due to the fact that the EVs with 32 A charging current may have a longer constant-voltage phase, the difference between the charging current and the current set point is significant during longer time than with 16 A EVs. For example, for Nissan Leaf 2012, the constant-voltage phase takes about 25 minutes, and for Nissan Leaf 2019, it takes about 1 h 28 min, under the nominal charging currents, 16 A and 32 A, respectively. An example of the lost network capacity and the effectiveness of the CCE algorithm is illustrated in Figure 11.

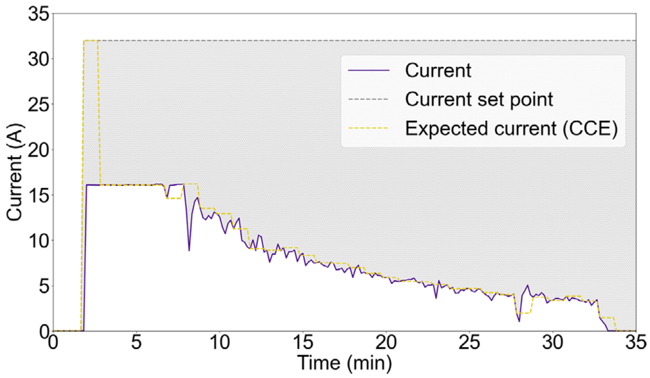

FIGURE 11 Idle charging capacity that can be allocated to other electric vehicles (grey area) during the constant-voltage charging phase. The purple line is the measured charging current (Phase A) of Nissan Leaf 2012. The grey dotted line is the current set point. The yellow line is the expected charging current of the CCE algorithm

In Figure 11, the grey dotted line shows the current set point. When the reference algorithm is used, the control system practically assumes that the realized loading follows the set point. On the contrary, the yellow dotted line illustrates the expected charging current, when the CCE algorithm is applied. When the reference algorithm is used and the current drawn by the EV is supposed to be the same as the nominal current of the charging station, the unused capacity in the network is the difference between the realized charging current and the current set point (the grey area in Figure 11). When the algorithm is used, this capacity is estimated and allocated to other vehicles if there are no additional network constraints. Due to small and sudden fluctuations of the charging currents in practice, sometimes the CCE algorithm forecasts the expected charging current marginally lower than it is. In such a situation, the algorithm can allocate more charging capacity to the charging site than it has. In reality, such errors are relatively rare and are likely to be evened with the simultaneous charging of several vehicles.

Some commercial EVs turn to a 'waiting' mode, when the charging cable is connected to the EV if the charging station does not instantly allow charging. The EV remains in this mode until the charging starts. However, some EV models stay in the 'waiting' mode for some minutes. If the charging process does not start, let's say, within 1–2 min, the EV goes to a "stand by" mode. During the 'stand by' mode, the charging process cannot be started without disconnecting and connecting the charging cable physically from the EV. Such behaviour is observed for BMW i3, for example [35].

In the future, peak-power based electricity tariffs are likely to become more common as they improve the cost-reflectivity of the electricity pricing [38]. As a consequence. there may be situations where it is economically feasible to limit the peak loading at the charging site below the capacity that would normally be available. This further emphasizes the need to effectively utilize the available charging capacity.

Although the algorithm presented in this paper is intended for a charging site where all charging stations are connected in a star-configuration, the CCE feature of the algorithm is topology-independent and can be applied to more complex network configurations, including several series and parallel connections. In this case, the rest of the algorithm, excluding CCE, should be adapted to such network configuration.

5.1 | Deployment of the proposed charging algorithm in practice

When a charging point operator plans to use the CCE algorithm in the daily operation of its charging sites, it does not entail significant additional equipment of operational costs compared with the already existing solution. Most importantly, each charging station must be equipped with a controller that is able to control the charging current according to the local standard, such as IEC 61851, in Europe. In addition, the charging station should have a current measurement, this can be embedded in the energy meter or can be a separate device. Generally, energy meters with the capability to deliver a current measurement are common in modern charging stations. A usual industrial solution is that an energy meter is physically connected to the charging controller, via a master-slave structure, where the charging controller is the master and the energy meter is the slave. When a current measurement is asked by, for example, the server where the CCE algorithm is running, the server sends a message to the controller that further reads the measurement value from the energy meter and sends the measurement value to the server.

The crucial technical requirements to be able to operate the CCE algorithm in a real case are:

- a charging controller,
- a current measurement device,
- communication media, such as LTE, 4G or Ethernet, and
- a backend server, where the algorithm is running.

In practice, all requirements are already fulfilled by a typical European charging point operator. Thus, it can be said that deploying the CCE algorithm does not entail significant additional equipment or operational costs compared with most solutions of today. There may be regulations considering data privacy and communication media that vary from country to country, which must be taken into account.

6 | CONCLUSION AND FUTURE WORK

The adaptive charging algorithms of today overlook the non-ideal charging characteristics of EVs. As a consequence, they are likely to operate in a non-optimal way, leading to wasted charging capacity and increased charging times. To contribute to this problem, a new charging algorithm that shows an evident advantage over the benchmark charging algorithm is proposed. The performance of the charging algorithm is proved under realistic circumstances and tested with real EVs. In a site of eight charging stations, the proposed CCE algorithm increases the capacity utilization rate by 3.13% and the charging capacity by 11.9 kWh per day on average. This means that the algorithm brings an additional gross profit of about 3.6 € per day for eight charging points, so about 0.6 € per charging point, to the charging operator. This means an increment of 5.8% in the average gross profit. During the peak hour, the CCE algorithm can deliver 24.4% more energy to the EVs than the reference algorithm, which shows that the benefits of the algorithm are likely to increase in the near future when charging sites will be used more than they are used today.

The algorithm is compatible with the IEC 61851 charging standard and can be applied as presented in this paper. Besides, no information, such as the state-of-charge of the battery or leaving time, from the user is necessary. The algorithm can be applied to modern charging stations without the need for specialized additional hardware.

Future work focuses on testing the algorithm in commercial operation, altogether in about 40 charging stations in Dortmund, Germany. To gain more insights from the pilot test, additional metrics that help to design following versions of the algorithm are developed. Additionally, it will be studied, how much CCE can improve the performance of other charging algorithms found in the research literature. Also, the use of the proposed algorithm in the case of complex configurations (several parallel and series connections) of the power network within a charging site will be studied.

ACKNOWLEDGEMENT

Kalle Rauma would like to thank the support of the German Federal Ministry of Transport and Digital Infrastructure through the project Parken und Laden in der Stadt (03EMF0203). Kalle Rauma would also like to thank the project partners supporting this work. The work of Toni Simolin and Pertti Järventausta was supported by the European Commission through LIFE-IP CANEMURE-FINLAND project (Towards Carbon Neutral Municipalities andRegions in Finland, LIFE17 IPC/FI/000002) and by Business Finland through Prosumer Centric Energy Communities–Towards Energy Ecosystem (ProC emPlus). The authors would also like to thank Laura Spies from TU Dortmund University for her help during the experiments (Parken und Laden in der Stadt) .

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

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

ORCID

Kalle Rauma https://orcid.org/0000-0002-5553-8751
Toni Simolin https://orcid.org/0000-0002-0254-1113

REFERENCES

1. Melliger, A., van Vliet, O., Liimatainen, H.: Anxiety vs reality sufficiency of battery electric vehicle range in Switzerland and Finland. Transp. Res. Part D 65, 101–115 (2018)
2. Brinkel, N., Schram, W., AlSkaif, T., Lampropoulos, I., van Sark, W.: Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits. Appl. Energy 276 (2020)
3. Rauma, K., Simolin, A., Rautiainen, A., Järventausta, P. & Rehtanz, C.: Overcoming non-idealities in electric vehicle charging management. IET Electrical Systems in Transportation. (2021). http://doi.org/10.1049/els2.12025
4. Simolin, T., Rauma, K., Rautiainen, A., Järventausta, P. & Rehtanz, C.: Foundation for adaptive charging solutions: Optimised use of electric vehicle charging capacity. IET Smart Grid. (2021). http://doi.org/10.1049/stg2.12043
5. Frendo, O., Graf, J., Gaertner, N., Stuckenschmidt, H.: Data-driven smart charging for heterogeneous electric vehicle fleets. Energy and AI 1, (2020)
6. Sun, C., Li, T., Low, S., Li, V.: Classification of electric vehicle charging time series with selective clustering. Electr. Power Syst. Res. 189, (2020)
7. Wang, Y., Yao, E., Pan, L.: Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. J. Cleaner Prod. 286, (2020)
8. Shepero, M., Munkhammar, J.: Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data. Appl. Energy 231, 1089–1099 (2018)
9. Heredia, W.B., Chaudhari, K., Meintz, A., Jun, M., Pless, S.: Evaluation of smart charging for electric vehicle-to-building integration: A case study. Appl. Energy 266, (2020)
10. Zhang, T., Pota, H., Chu, C., Gadh, R.: Real-time renewable energy incentive system for electric vehicles using prioritization and cryptocurrency. Appl. Energy 226, 582–594 (2018)
11. García Veloso, C., Rauma, K., Fernández Orjuela, J., Rehtanz, C.: Real-time agent-based control of plug-in electric vehicles for voltage and thermal management of LV networks: Formulation and HIL validation. IET Gener. Transm. Distrib. 14(11), 2169–2180 (2020),
12. Boglou, V., Karavas, C., Arvanitis, K., Karlis, A.: A fuzzy energy management strategy for the coordination of electric vehicle charging in low voltage distribution grids. Energies 13, 3709 (2020)
13. Da Silva, F.L., Nishida, C.E.H., Roijers, D.M., Reali Costa, A.H.: Coordination of electric vehicle charging through multiagent reinforcement learning. IEEE Trans. Smart Grid 11(3), 2347–2356 (2020)
14. Khaki, B., Chu, C., Gadh, R.: Hierarchical distributed framework for EV charging scheduling using exchange problem. Appl. Energy 241, 461–471 (2019)
15. Liu, J., Lin, G., Huang, S., Zhou, Y., Li, Y., Rehtanz, C.: Optimal logistics EV charging scheduling by considering the limited number of chargers. IEEE Trans. Transp. Electrif. 7(3), 1112–1122 (2020)
16. Godina, R., Rodrigues, E., Matias, J., Catalão, J.: Smart electric vehicle charging scheduler for overloading prevention of an industry client power distribution transformer. Appl. Energy 178, 29–42 (2016)
17. Graber, G., Calderaro, V., Mancarella, P., Galdi, V.: Two-stage stochastic sizing and packetized energy scheduling of BEV charging stations with quality of service constraints. Appl. Energy 260, (2020)
18. Zheng, Y., Shang, Y., Shao, Z., Jian, L.: A novel real-time scheduling strategy with near-linear complexity for integrating large-scale electric vehicles into smart grid. Appl. Energy 217, 1–13 (2018)
19. Seddig, K., Jochem, P., Fichtner, W.: Two-stage stochastic optimization for cost-minimal charging of electric vehicles at public charging stations with photovoltaics. Appl. Energy 242, 769–781 (2019)
20. Shang, Y., Liu, M., Shao, Z., Jian, L.: Internet of smart charging points with photovoltaic Integration: A high-efficiency scheme enabling optimal dispatching between electric vehicles and power grids. Appl. Energy 278, (2020)
21. Wang, R., Wang, P., Xiao, G.: Two-Stage Mechanism for Massive Electric Vehicle Charging Involving Renewable Energy. IEEE Trans. Veh. Technol. 65(6), 4159–4171 (2016)
22. Xydas, E., Marmaras, C., Cipcigan, L.: A multi-agent based scheduling algorithm for adaptive electric vehicles charging. Appl. Energy 177, 354–365 (2016)
23. Mobarak, M.H., Bauman, J.: Vehicle-Directed Smart Charging Strategiesto Mitigate the Effect of Long-Range EV Charging on Distribution Transformer Aging. IEEE Trans. Transp. Electrif. 5(4), 1097–1111 (2019)
24. Yang, Y., Zhang, Y., Meng, X.: A Data-Driven Approach for Optimizing the EV Charging Stations Network. IEEE Access 118592–118592 (2020)
25. Liikennevirta Oy: Virta Platform Overview. www.virta.global, accessed on the 8th January 2021
26. EVling Charging Stations Commissioning Guide. www.schneider-electric.com (2019), accessed on the 8th January 2021
27. The Mobility House GmbH: ChargePilot–The Charging and Energy Management by The Mobility Houser. www.mobilityhouse.com/int_en/charging-and-energy-management, accessed on the 8th January 2021
28. Pareschi, G., Küng, L., Georges, G., Boulouchos, K.: Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. Appl. Energy 275, (2020)
29. Zhang, J., Yan, J., Liu, Y., Zhang, H., Lv, G.: Daily electric vehicle charging load profiles considering demographics of vehicle users. Appl. Energy 274, (2020)
30. Fenner, P., Rauma, K., Rautiainen, A., Supponen, A., Rehtanz, C., Järventausta, P.: Quantification of peak shaving capacity in electric vehicle charging–Findings from case studies in Helsinki Region. IET Smart Grid 3(6), 777–785 (2020)
31. Fernández, J., Herrera, O., Mérida, W.: Impact of an electrified parkade on the built environment: An unsupervised learning approach. Transp. Res. Part D 78, (2020)
32. Rautiainen, A., Rauma, K., Rohde, L., Supponen, A., Raulf, F., Rehtanz, C., Järventausta, P.: Anatomy of electric vehicle fast charging: Peak shaving through a battery energy storage–A case study from Oslo. IET Electr. Syst. Transp. 1–12 (2020)
33. Pareschi, G., Küng, L., Georges, G., Boulouchos, K.: Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. Appl. Energy 275 (2020)
34. Flammini, M., Prettico, G., Julea, A., Fulli, G., Mazza, A., Chicco, G.: Statistical characterisation of the real transaction data gathered from electric vehicle charging stations. Electr. Power Syst. Res. 166, 136–150 (2019)
35. Bayerische Motoren Werke AG: The BMW i3. Owners Manual. BMW AG, München, pp. 183 (2016)
36. Spina, A., Rauma, K., Aldejohann, C., Holt, M., Maasmann, J., Berg, P., Häger, U., Rettberg, F., Rehtanz, C.: Smart Grid Technology Lab–A full-scale low voltage research facility at TU Dortmund University. AEIT International Annual Conference, Bari, Italy, 3–5 October (2018)
37. A.llgemeiner Deutscher Automobil-Club e.V. (ADAC), 'Ladestationen für Elektroautos: Das kostet der Strom', 6.10.2020. https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/laden/elektroauto-ladesaeulen-strompreise/
38. Öhrlund, I., Schultzberg, M., Bartusch, C.: Identifying and estimating the effects of a mandatory billing demand charge. Appl. Energy 237, 885–895 (2019)

How to cite this article: Rauma, K., Simolin, T., Järventausta, P., Rautiainen, A., Rehtanz, C.: Network-adaptive and capacity-efficient electric vehicle charging site. IET Gener. Transm. Distrib. 2021; 1–13. https://doi.org/10.1049/gtd2.12301.