Received: 17 November 2020 | Revised: 17 March 2021 | Accepted: 28 March 2021

DOI: 10.1049/els2.12025

IET Electrical Systems in Transportation

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH PAPER

Overcoming non-idealities in electric vehicle charging management

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Funding information

Bundesministerium für Verkehr und Digitale Infrastruktur
Open access funding enabled and organized by Projekt DEAL.

Abstract

The inconvenient nature of non-ideal charging characteristics is demonstrated from a power system point of view. A new adaptive charging algorithm that accounts for non-ideal charging characteristics is introduced. The proposed algorithm increases the local network capacity utilization rate and reduces charging times. The first unique element of the charging algorithm is exploitation of the measured charging currents instead of ideal or predefined values. The second novelty is the introduction of a short-term memory called expected charging currents. This makes the algorithm capable of adapting to the unique charging characteristics of each vehicle individually without the necessity to obtain any information from the vehicle or the user. The proposed algorithm caters to various non-idealities, such as phase unbalances or the offset between the current set point and the real charging current but is still relatively simple and computationally light. The algorithm is compatible with charging standard IEC 61851 and is validated under different test cases with commercial electric vehicles.

1 | INTRODUCTION

Because of the increasing popularity of electric vehicles (EVs), charging them is expected to have a notable impact on the power distribution network [1, 2]. To avoid overinvestment in network components, charging management will become a necessity in the future [3]. Insufficient charging infrastructure and long charging times are regarded as obstacles for EVs [4–6]. That is why capacity-efficiency and reduced charging times should be relevant considerations when designing a charging algorithm. With a more efficient algorithm, the charging system operator can minimize the idle capacity of the power network, which leads to shorter charging times and a higher-quality charging service. To the authors' knowledge, this efficiency is not considered under realistic conditions in the charging algorithms that have been presented in the research literature.

By network capacity, we refer to the capacity of the power network at the charging site. Usually, this is part of the electricity network at the real estate (parking hall etc.). Several algorithms for EV charging management are offered in the scientific literature. However, the shortage of most is that they do not focus on the efficient use of network capacity, with the result that many of these proposed solutions may lead to low usage rates in real life. In addition, most available algorithms are tested only through computer simulations, which may not guarantee that they work as efficiently in reality as in the simulation. In reality, there are significant differences in the behaviour of EVs that in the worst case could jeopardize the correct functioning of a charging algorithm or reduce its efficiency.

The work presented in [7] focuses on developing an online charging algorithm and testing it with a fleet of 55 real charging stations. A time step of 5 min is used for the operation of the algorithm. A distinguishing aspect of the work is that it considers real-life constraints such as a non-ideal charging curve, unbalanced phase conductors, and unknown state-of-charge (SoC) of the EV battery. The charging current is measured at the charging station, but it is not used for control purposes. The batteries are charged according to a predefined two-stage model. First, a constant current is allowed up to 80% of the SoC followed by a decreasing current model. A benefit of this approach is that it is closer to the real load curve of most EVs than a completely constant load curve. However, each EV model has a different load curve, which means that applying the same load model for all EVs will inevitably decrease the efficiency of the charging algorithm. The great advantage of this paper in comparison with [7] is that it handles each EV separately in real time without relying on predefined models, which makes it more adaptive and reliable.

In [8], an adaptive charging algorithm is presented. The work also considers unbalanced charging and is able to carry out phase balancing. The algorithm is run every 10 min. Unlike this paper, the studies in [8] are based on simulations and the compatibility with the standards is not discussed. It is not clearly explained, how the currents are measured and how they are applied in the charging management. In [9], an adaptive charging algorithm with the objective of peak-load management is introduced. The major lacks in [9] are that unbalanced charging is not considered and the actual charging currents are not used as an input to the algorithm. The operation of the algorithm is validated through simulations and no dynamic charging characteristics of the EVs are mentioned, which makes the work much less detailed than this paper.

In [10, 11], a charging management algorithm to cope with fluctuating available power is presented. It also considers various user groups through prioritization. The algorithm does not consider different phases or the fact that EVs may not charge according to the current value used as a set point. The algorithm is tested in a hardware-in-the-loop simulation using three electronic loads that mimic EVs but not with real EVs or charging hardware. Neither does the work discuss its suitability on practical applications or compatibility with current charging standards.

The article [12] tackles a similar problem of EV charging under changing power capacity. The algorithm is tested through simulations with a time step of 10 min. Herein, the different phases are not taken into account. The charging stations used have a maximum charging power of 50 kW, which means the algorithm is oriented towards DC charging stations.

Another algorithm that uses predefined load curves to control the charging algorithm is presented in [13]. A neural network–based algorithm is trained with a dataset that consists of data from more than 10,000 charging session and includes 18 different EV models. The algorithm performs well, but the drawbacks are the large amount of data and computationally heavy data processing. Data from all EV models has to be available so that the neural network model can be trained to accommodate all EVs, which may not be realistic in a practical setting. The SoC is used in the algorithm and is estimated based on the dataset. The algorithm does not account for different phases separately as the work done here. In contrast to our work, the algorithm presented in [13] can be computationally burdensome and prone to errors in real life.

Different phases and the problem of phase unbalance is considered in [14]. The problem is solved by using a phase switcher at each charging station. The approach is verified through simulations with a time step of 15 min. The work does not include tests on real EVs. The results lack the real measured charging curves that would likely impact the results significantly. The work in [15] introduces a new EV charging algorithm with the main objective to reduce losses in the low voltage distribution network and considers phase balancing for domestic single-phase chargers. In addition, the impact of loss minimization, load flattening, and phase balancing on the increased charging times is not included in the work. Likewise, compatibility with common charging standards is not mentioned.

As seen in the state of the art, there are no algorithms that use the actual measured current as feedback to the algorithm and are compatible with the commercial charging standards as well as validated with real EVs. The non-idealities considered by the algorithm presented include the following:

- At three-phase charging stations, a customer can charge by using one, two, or three phases.
- The charging phase(s) can be any, or any combination, of the three phases.
- Charging can be unbalanced—different currents drawn from different phases.
- The charging system operator does not know beforehand which phases the EV uses for charging.
- The current drawn by the EV is altered during a charging session.
- The EV can use any current for charging below the maximum current limit, or set point, at the charging station.
- There is always an offset (positive or negative) between the current set point and the real charging current.
- There is always a time delay from the moment the current set point is changed to the moment that the desired charging current is reached.

Accounting for the above non-idealities will improve the efficiency of any adaptive charging algorithm. To the knowledge of the authors, no paper considering all of the above non-idealities in charging management can be found in the literature. This is the major difference between this work and the previous works. The aim of this work is to provide a strategy for how the non-idealities of EV charging can be accounted for to make each charging process more capacity efficient. The algorithm presented can be used with a fixed maximum current for the charging site. In addition, the algorithm can be used with any other strategy that determines the maximum current of the charging site according to an external signal, such as the price of electricity. That is to say, the algorithm of this work does not replace, but complements, other charging algorithms. Thus, this paper addresses this previously unstudied topic, and the proposed algorithm answers different questions from those of most other research on EV charging algorithms. The main contributions of this paper are the following:

- Demonstrate that non-idealities exist in EV charging that have not been considered in previous research.
- Identify the impact of these non-idealities on EV charging management.
- Provide a novel strategy how the non-idealities can be handled in a commercial EV charging application.
- The strategy considers the above-mentioned factors and improves the use rate of network capacity at the charging

site significantly in comparison with the previously suggested algorithms.
- The strategy is tested using commercial EVs and charging infrastructure.

The remaining parts of this paper are organized as follows. Section 2 describes the experimental setup used. Section 3 introduces the proposed charging algorithm. Section 4 presents the experimental results. Section 5 discusses the obtained results. Finally, Section 6 presents the conclusion and suggests ideas for future work.

2 | EXPERIMENTAL SETUP

This section covers the descriptions of the experimental laboratory setups. The first subsection describes the organization of the current set point response test. The second subsection describes the experimental setup of the algorithm validation by using two real EVs. The third subsection covers the experimental testing of the proposed algorithm under a real test case. All laboratory tests are carried out at TU Dortmund University [16].

2.1 | Current set point response test

The purpose of the current set point response test is to measure how quickly popular commercial EV models react when the current set point is changed at a charging station. In addition to the time delays, the offsets between different current set points and the real charging currents are observed. The measurements are coordinated by a Python script that sends the current set points to the charging station and reads the current measurement. The communication is carried out by using Modbus TCP/IP protocol. The used charging station is an RWE eStation equipped with a Phoenix Contact Advanced EV Charge Controller. The controller supports the standard IEC 61851-1. The currents are measured at the charging station once per second with a KoCoS EPPE PX power quality analyzer and KoCoS ACP 300 current probes.

During the first 10 s of the test, the charging is disabled. At the beginning of the 11th second, the charging process is enabled, and the current set point is set to 6 A. At the beginning of the 21st second, the current is set to 7 A. The current set point is increased every 10 s until it reaches 16 A. After that, it is again reduced by 1 A every 10 s until it reaches 6 A and finally the charging is disabled. The used charging controller supports integer values with a minimum resolution of 1 A when controlling the charging current. Thus, steps smaller than 1 A are not possible. That is why a current step of 1 A is used thorough in all experiments and in the presented charging algorithm. For additional clarification, the idea of current set point response test is to assess the behaviour of the EVs at all possible current set points that a commercial charging controller can have between 0 and 16 A.

A Modbus signal is registered and sent to the charging station once it is executed by the Python programme. However, there are communication delays before the signal reaches the EV, such as the mechanical movement of the contactor at the charging station, when enabling and disabling the charging, causes an additional time delay. Thus, these delays are in the range of 2–4 s and are included in the delays seen in the measurement results. The used EV models are shown in Table 1.

TABLE 1 Characteristics of the used electric vehicles

Vehicle model	Charging phase	Max. charging current	Connector
Nissan Leaf	Phase A	16 A	Type 1
BMW i3	3-phase	16 A ('max.')	Type 2
BMW i3	3-phase	16 A ('reduced')	Type 2
BMW i3	3-phase	16 A ('low')	Type 2

A charging controller at a charging station sets the current set point, but an EV can charge with any current below that set point. It should be noticed that an EV can have charging modes or settings. The purpose of the different charging modes may be to increase the energy efficiency or safety. For example, the BMW i3 has three charging modes for AC charging: 'low', 'reduced' and 'maximum' mode [17]. These modes cannot be changed from the charging station. The current is measured only at the charging phases: for the Nissan Leaf phase A and BMW i3 phases A, B, and C.

Table 2 shows the differences between the different charging modes of the BMW i3 [17]. The settings are country-specific and vary between different areas [17].

TABLE 2 The differences between the different charging modes of BMW i3 according to the manufacturer [17]

Current set point	'Maximum' mode	'Reduced' mode	'Low' mode
8 A	8 A	6 A	6 A
10 A	10 A	7.5 A	6 A
12 A	12 A	9 A	6 A
15 A	15 A	11.25 A	7.5 A

2.2 | Validation of the charging algorithm

Here the experimental setup of the second test is explained. The objective is to validate the algorithm in a laboratory environment by using two real EVs so that the behaviour of the EVs is easy to observe. Moreover, this test proves that the algorithm is compatible with the standard IEC 61851.

The laboratory setting is similar to the one of the current set point response test with the exception that now both charging sockets are measured with KoCoS EPPE PX power quality analyzers that communicate with the controlling computer via Modbus TCP/IP. The control algorithm is written in Python and runs on a computer in the laboratory. In the algorithm, measured current less than 1 A is considered as noise and set to 0. This is to prevent a noise-originated malfunction of the algorithm. Even if the algorithm runs in the time steps of 1 min, the current measurements are taken every 20 s. The

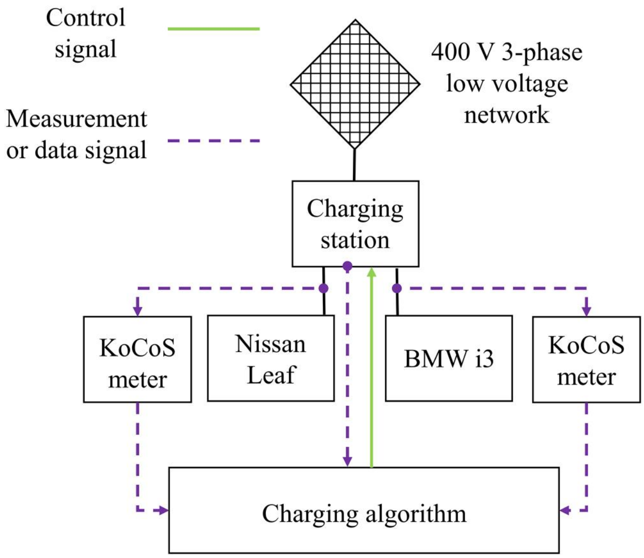

FIGURE 1 Experimental setup of the charging algorithm validation

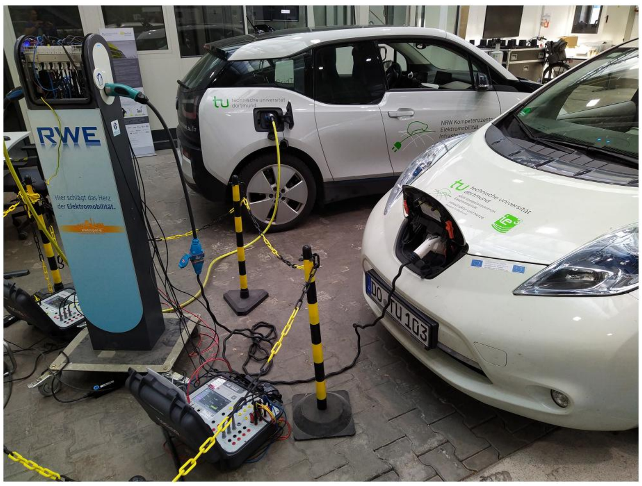

FIGURE 2 Laboratory setting in the algorithm validation

scheme of the experimental setup is illustrated in Figure 1. The setup with the charging station, the measurement equipment and the used EVs can be seen in Figure 2.

To understand the details of the following Tests 1, 2, and 3, the uncontrolled charging curves of the Nissan Leaf and BMW i3 are presented in Figures 3 and 4.

In Figures 3 and 4, not the complete charging curve, but the part of decreasing current is presented. The starting SoC of the Nissan Leaf is 92% and the SoC of the BMW i3 is 87%. The current measurement is taken every 10 s. The BMW i3 is in 'maximum' mode. It is important to point out that by using two EVs, the details of the functioning of the proposed algorithm are distinguishable. The common purpose of the tests is to demonstrate in a detailed manner that the algorithm works with real hardware.

In continuation, the used three test cases are presented. The tests are selected so that the performance of the proposed charging algorithm can be observed in detail under challenging

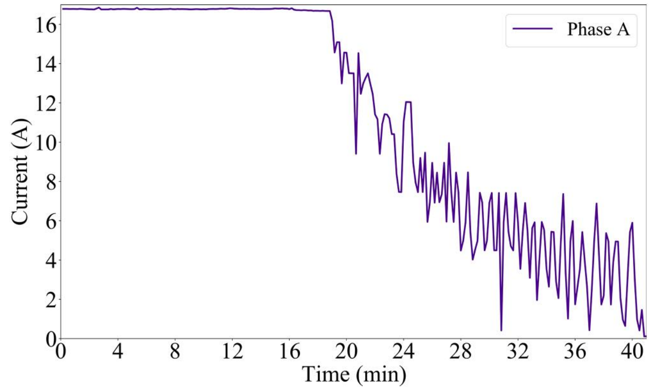

FIGURE 3 Decreasing-current part of the uncontrolled charging curve of Nissan Leaf

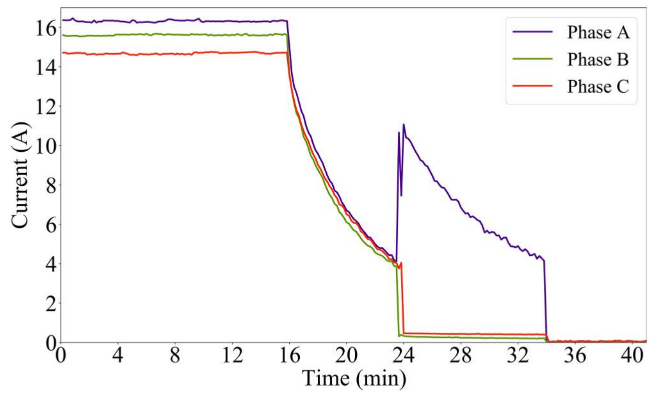

FIGURE 4 Decreasing-current part of the uncontrolled charging curve of BMW i3

circumstances. In each test case, a limit for the total current (current drawn by the Nissan Leaf summed by current drawn by the BMW i3) is set. This is the total current that the charging site uses to supply EVs. In Tests 1 and 3, the limit is 20 A, and in Test 2, it is 15 A. In reality, this limit would be defined by a selected electro-technical limit, such as the rating of the fuses, cables or a transformer. In the following tests, two EVs are used, so the limit is set lower than it would be in a reality to increase the complexity of the test cases and to verify the operation of the algorithm.

2.2.1 | Test 1

The purpose of this test is to demonstrate the dynamic performance of the charging algorithm. In this test, the BMW i3 is set to 'low' mode to see the functioning of the algorithm as evidently as possible. This is because in this mode, the BMW i3 has fewer current steps than in other modes, and as a consequence, the offset between the current set point at a charging station and the real charging current is larger and thus better observable. Before the start of the test, the initial SoC of the Nissan Leaf is 50% and the SoC of the BMW i3 is 85%. In this test, the maximum limit for both EVs is selected as 20 A, which means that both EVs cannot charge at full current simultaneously and the algorithm has to limit the charging.

2.2.2 | Test 2

This test shows the performance of the algorithm in another situation with a lower current limit and with different starting SoCs of the EVs than in Test 1. In addition, the BMW i3 is in a different charging mode. The total limit of the current is set to 15 A, which means that any of the two EVs is not able to charge with maximum current. The BMW i3 is set to 'maximum' mode. The starting SoC of the BMW i3 is 73% and of the Nissan Leaf is 90%.

2.2.3 | Test 3

The objective of this test is to show how the algorithm detects that two EVs charge at different phases, so charging current does not need to be limited. The total current limit is 20 A. On the side of the BMW i3, phase A and phase C are disconnected at the charging station, so the BMW i3 can only charge using phase B. The Nissan Leaf is charged at phase A as in all tests. The BMW i3 is set to 'maximum' mode. The initial SoC of Nissan Leaf is 85%, while the BMW i3 has 70%.

3 | CHARGING ALGORITHM

Before the description of the algorithm, it is important to underline that the objective is to form a set of practices that create a basis for other charging management algorithms. The proposed algorithm is illustrated in Figure 5. The algorithm is executed in 1 min time steps.

The algorithm is divided into two parts. Firstly, the 3-phase capacity is divided evenly between all EVs in state C or D, meaning that they are ready to receive energy (see Table 3). An even division of the 3-phase charging capacity means that total charging capacity (in amperes) is divided by the number of active charging sessions. The decimals of the division are eliminated, and the remaining natural number is given as a set point to all active charging sessions. Secondly, the remaining capacity is divided between 1-phase EVs, repeating phases A, B, and C (phase p). This means that the 1-phase charging sessions may receive higher allowed current. However, 3-phase charging sessions are still likely to receive higher charging powers.

When an EV is connected, the algorithm supposes that the EV charges at three phases. The algorithm gives one-time step to the EV to react. During this time, the algorithm memorizes which phase(s) the EV uses for charging. Because some EVs react slowly, one time step is required to avoid a malfunction.

A core feature of the algorithm is that it learns the behaviour of the EV that is currently charging through the use of expected charging currents. For clarity, this is described in an own subsection. Simplified explanations of the charging states according to the standard IEC 61851 are explained in Table 3. It is important to notice that even though each EV is modelled separately by means of expected charging currents, the algorithm is computationally light, which makes it easily scalable to cover large charging sites.

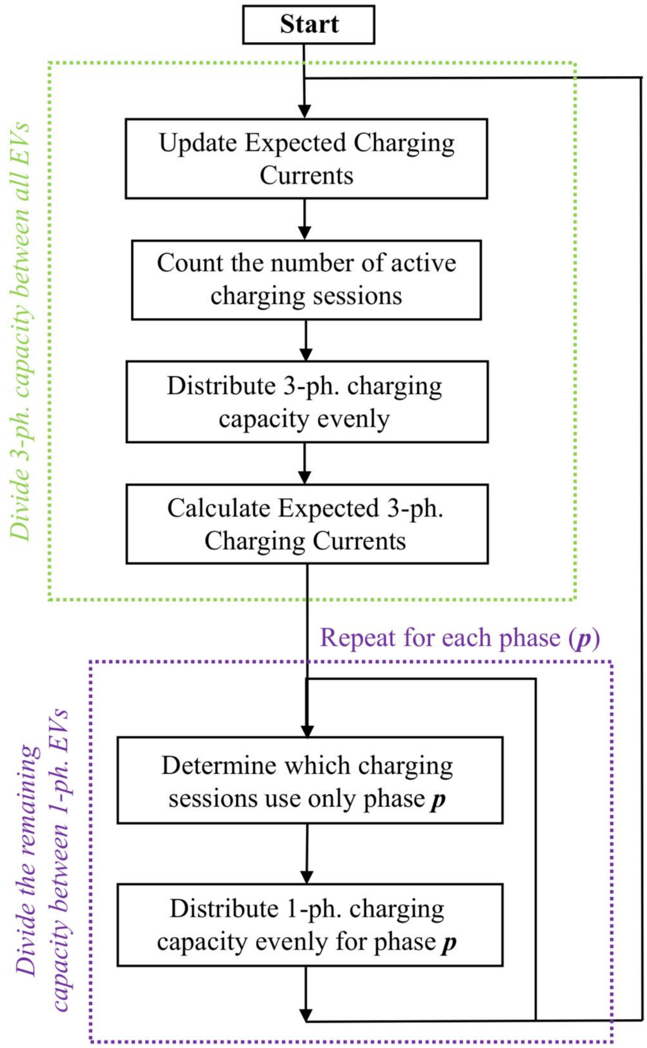

FIGURE 5 Flowchart of proposed charging algorithm

TABLE 3 Simplified charging states according to IEC 61851

State	Message
A	EV not connected
B	EV or Electric Vehicle Supply Equipment not ready to receive energy
C	EV is charging
D	Charging is possible. EV requires charging area ventilation.
E	Error
F	Fault

Abbreviation: EV, electric vehicle.

TABLE 4 Expected charging currents during the first time step of the algorithm for every charging station. All values in amperes

Set point	Phase A	Phase B	Phase C
6	6.0	6.0	6.0
7	7.0	7.0	7.0
8	8.0	8.0	8.0
9	9.0	9.0	9.0
⋮	⋮	⋮	⋮
32	32.0	32.0	32.0

TABLE 5 Expected charging currents during second time step of the algorithm for BMW i3 after updating first-row values. All values in amperes

Set point	Phase A	Phase B	Phase C
6	6.3	5.8	5.7
7	7.0	7.0	7.0
8	8.0	8.0	8.0
9	9.0	9.0	9.0
⋮	⋮	⋮	⋮
32	32.0	32.0	32.0

3.1 | Expected charging currents

The idea of expected charging currents is to make the algorithm capable of memorizing the unique charging characteristics of a charging session without the need for obtaining any information from the vehicle. Expected charging currents keeps track on each EV of which phases are being used and how much current is drawn from each phase. It is important to underline that expected charging currents are not calculated, but they are direct measurements of phases A, B, and C at the charging station.

When an EV is connected to a charging station and changes from state A to state B, the behaviour of the EV is expected to be 'ideal' and three-phase connected. This means that the EV draws exactly the current indicated by the current set point at each phase. Expected charging currents of each charging session are updated every time the algorithm is executed. An update means that the three-phase currents at the given current set point are added to expected charging currents. An illustration of how expected charging currents are structured and updated as illustrated in Tables 4 and 5. During the very first time step of the algorithm, the EV is expected to be 'ideal'. In this case, expected charging currents for any charging station are as presented in Table 4.

During the second execution of the algorithm, expected charging currents is updated according to the measured current. The measured current values are stored in the columns labelled according to the phases as A, B, and C. In the case of the BMW i3, for example, the expected charging currents after the first update are presented in Table 5.

The BMW i3 charges at 3 × 6 A, but in reality, offsets in the phase currents exist. This procedure is continued through the whole charging process. If the algorithm detects that current flows only during one phase (a single-phase EV), the values of the other phases are set to 0. Allowing each EV to start charging with 6 A means that the algorithm allows temporary overload of maximum 6 A per EV. However, this overload will last 1 min as maximum. In case of a failure when reading a current measurement, the algorithm uses the previously measured value. This alleviates the impacts of short communication failures while still allowing the algorithm to operate on each control cycle.

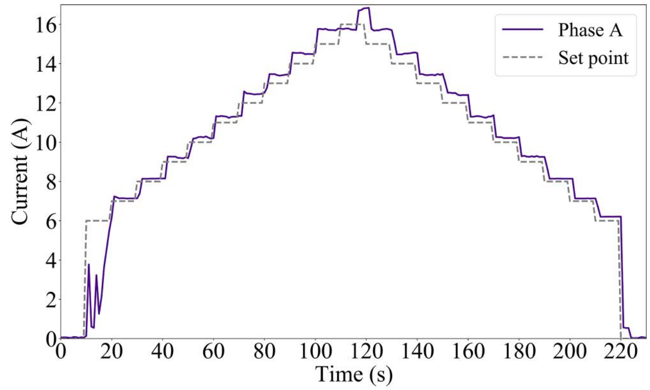

FIGURE 6 Measured current of Nissan Leaf and current set point

4 | RESULTS

This section first presents the results of the current set point response test. Subsequently, the results of the algorithm validation are introduced.

4.1 | Current set point response test

The results of the current set point response test of the EVs in Table 1 are presented in Figures 6–9. The current of phase A of the Nissan Leaf and the current set point are illustrated in Figure 2.

In Figure 6, it is observed that the Nissan Leaf starts to react within 2 s after the charging is enabled. It takes 10 s to reach 6 A charging current from the disabled position. Once the charging is enabled, the next charging current is reached within the maximum time of 2 s. Similar time delays are seen thorough the increasing part (0 to 110 s) as well as the decreasing part (110 to 220 s) of the test.

The current offset is higher with a higher charging current. When the current set point is 7 A, the maximum measured current is 7.24 A. The largest offset is measured when the current set point is at 16 A, in this case the current is 16.84 A. According to the standard IEC 61851, the maximum current drawn by the EV does not include inrush or leakage currents. The currents of phases A, B, and C of the BMW i3 under different charging modes and the current set point are shown in Figures 7 ('low' mode), 8 ('reduced' mode), and 9 ('maximum' mode).

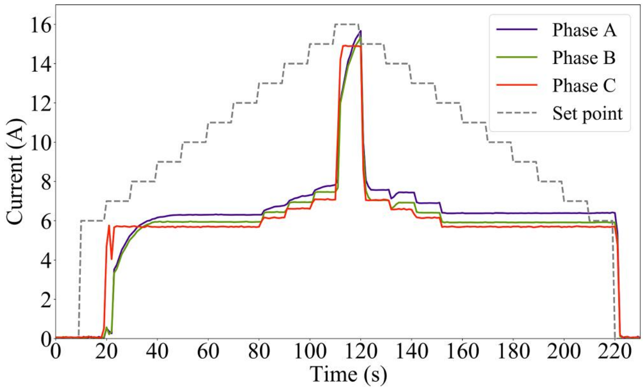

FIGURE 7 Measured current of BMW i3 ('low' mode) and current set point

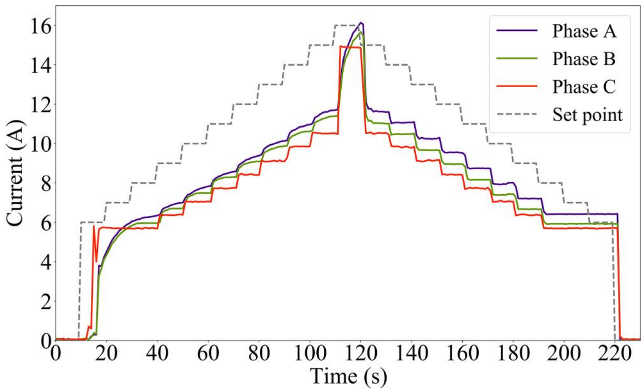

FIGURE 8 Measured current of BMW i3 ('reduced' mode) and current set point

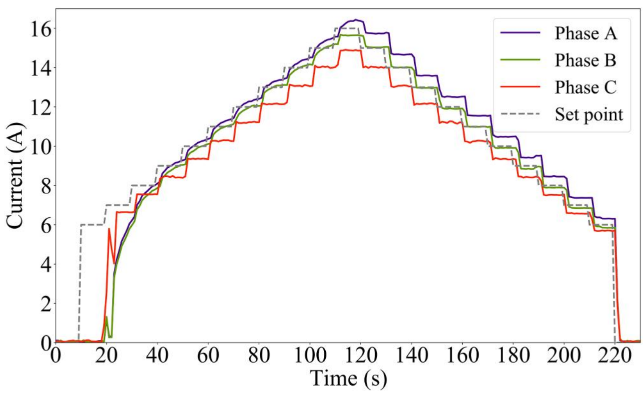

FIGURE 9 Measured current of BMW i3 ('maximum' mode) and current set point

Through all three charging modes, phase C has the shortest response time. When the BMW i3 is on the 'low' mode, five levels of charging currents are measured at phase C with the following set points: 6, 7, 8, 9 and 16 A. In 'reduced' mode, different current levels are measured with the set points 6, 7, 8, 9, 10, 11, 12, 13 and 16 A.

Most of the time, current at phase A has the most elevated values. In 'low' mode, the largest measured difference of the

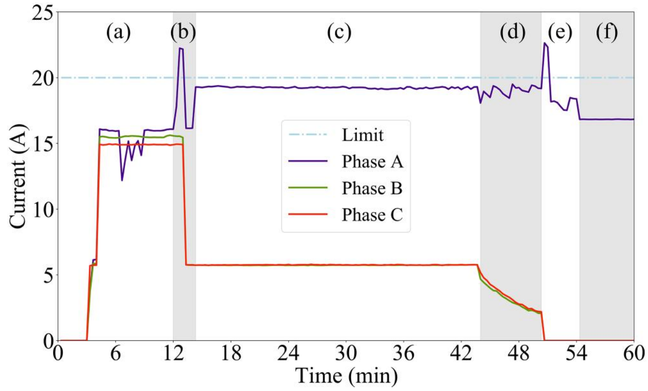

FIGURE 10 Sum of the measured phase currents of both electric vehicles and the limit in Test 1

current between phase A and phase C is 2.3 A. In 'reduced' mode it is 3.3 A and in 'maximum' mode, it is 2.3 A. However, these values are measured during the transient times when the current is changing from one set point to another one. Most of the time, the current difference between phase A and phase C is around 1 A.

In 'low' mode, the differences between the measured phase currents and the current set point is the largest. At steady state, the largest measured offset between phase C and the set point is 7.96 A at the time step 124 s (in Figure 7). In 'reduced' mode, the measured currents are closer to the set point (Figure 8) and in 'maximum' mode, even more (Figure 9). However, it is crucial to consider that at 'low' and 'reduced' modes, the EV is not designed to charge at the set point current but has its internal limitations [17]. These limitations cannot be changed by the charging controller at the charging station.

When the Nissan Leaf mostly draws current that is higher than the set point, in the case of the BMW i3, it depends on the phase. On the 'maximum' mode, during the time when the charging is enabled, phase A has an average bias of 0.93 A, phase B 0.73 A and phase C 1.03 A from the set point. Therefore, once the current has reached the desired level, phase B follows the set point most accurately.

4.2 | Validation of charging algorithm

The results of Tests 1, 2, and 3 are presented in the following three subsections to validate the correct functioning of the algorithm with real EVs. The results from Figure 10 onwards are shown in corresponding order. Only the phase currents where the EVs draw energy are illustrated. The solid lines present currents and the non-solid lines present the limit (light blue) or the corresponding current set point (grey).

To increase the readability, each test is divided into steps (a), (b), (c) etc. and highlighted by a grey or white background colour, all of which is clarified in detail following the figures.

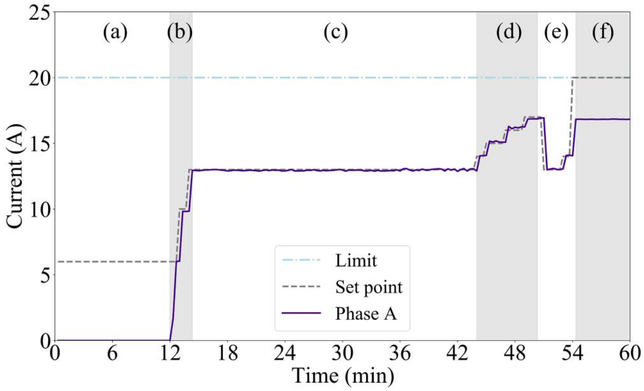

FIGURE 11 Measurements of Nissan Leaf in Test 1

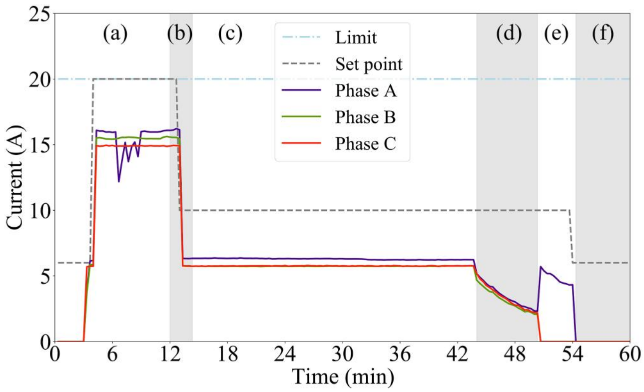

FIGURE 12 Measurements of BMW i3 in Test 1

4.2.1 | Test 1

Results of Test 1 are observed in Figures 10 (the sum of the currents), 11 (Nissan Leaf), and 12 (BMW i3).

(a) At the beginning, no EV is connected. At about 3.5 min, the BMW is connected. The algorithm allows the BMW to charge with 6 A using all three phases. During this minute, the algorithm verifies how much free charging capacity the charging site has. Because no other vehicles are connected, the algorithm gives 20 A to the BMW. Thus, BWM increases the charging current to full capacity (∼16 A). The measured ripple at phase A between 6 and 9 min (Figures 10 and 12) is characteristic behaviour of the BMW i3 and is not caused by the algorithm.

(b) At minute 12, the Nissan Leaf is connected to the charging station. Since the algorithm allows the Nissan to start charging at ∼6 A, and the BMW is using ∼16 A at phase A, the total current of the charging site at phase A increases to ∼22 A. In the next control cycle, the algorithm notices that the current limit is exceeded and calculates new current set points to both EVs. By design, the algorithm aims at dividing the charging current as evenly as possible between the EVs. Thus, it establishes a set point of 10 A to both EVs. However, in 'low' mode, BMW charges at ∼6.3 A (measured in Figure 7) with the set point of 10 A. Hence, ∼3.7 A of the charging capacity allocated to BMW is not used. The algorithm allocates 3 A more to the Nissan, and it starts charging at ∼13 A. This is the maximum capacity that can be allocated to the Nissan without exceeding the total limit of the charging site (20 A).

It is important to notice that in (b), the efficiency of the algorithm is easily observable. If the algorithm did not have an adaptive nature, the real charging current of the BMW (∼6.3 A) could not be detected, and as a consequence, additional current (3 A) could not be allocated to the Nissan. Thus, the Nissan would have continued to charge at ∼10 A instead of ∼13 A, representing a longer charging time.

(c) The Nissan is charging at ∼13 A and the BMW at ∼6.3 A. Due to the used charging controller, current is regulated in the steps of 1 A, the total current is slightly less than 20 A (Figure 10).

(d) At minute 44, BWM starts the decreasing-current phase of charging since the battery is close to be full. This characteristic can be also clearly seen in Figure 4. Decreasing charging current of the BMW means that more capacity can be allocated to the Nissan. As the BMW frees the charging capacity, the algorithm allocates more charging capacity to the Nissan. This is seen as stepwise increase of the set point and the charging current in Figure 11.

(e) The Nissan charges at ∼16.9 A. At minute 51, phase A current of the BMW increases to ∼5.7 A. This is characteristic of the BMW i3, and the same phenomenon is visible also in Figure 4. The increasing current of the BMW can be seen as a peak of ∼22.7 A in Figure 10. The algorithm reacts to this by decreasing the set point of the Nissan to 13 A. When the BMW naturally decreases the charging current, more charging capacity is allocated to the Nissan by increasing the set point of the Nissan to 14 A. When the BMW stops charging as a result of its fully charged battery at minute 53, the whole charging capacity of the charging site (20 A) is allocated to the Nissan. However, the Nissan can charge at ∼16.8 A, as measured also in Figure 3.

4.2.2 | Test 2

Results of Test 2 are presented in Figures 13, 14, and 15.

(a) At minute 0, no EV is connected. During minute 1, the Nissan Leaf is connected to the charging station. Directly when the Nissan is connected, 6 A is allocated to it. During this minute, the algorithm calculates the capacity that can be allocated to the Nissan. Since the limit of the charging site is 15 A and there are no other EVs connected, the algorithm allocates 15 A to the Nissan. Consequently, the charging current of the Nissan increases. However, with the set point of 15 A, the Nissan Leaf actually charges at ∼15.2 A, which would mean

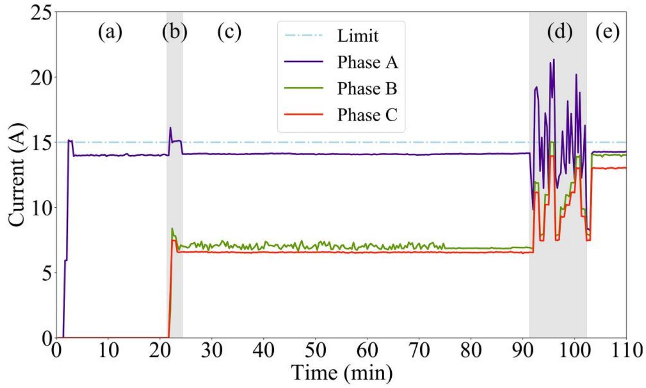

FIGURE 13 Sum of the phase currents of both electric vehicles in Test 2

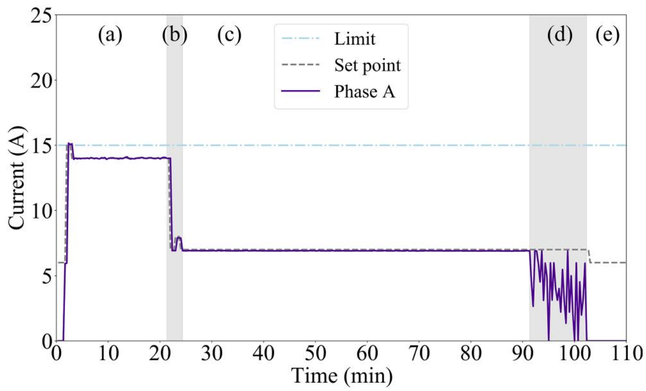

FIGURE 14 Measurements of Nissan Leaf in Test 2

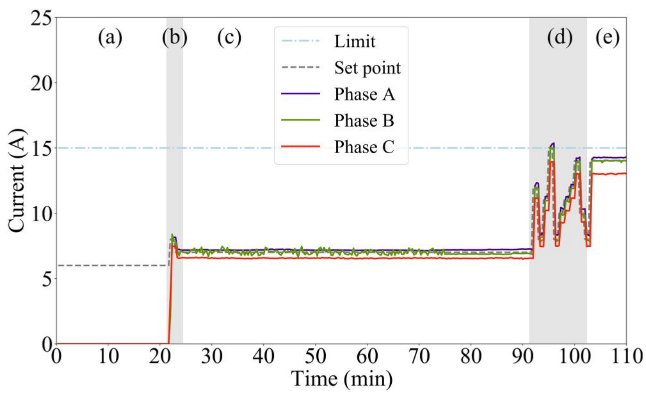

FIGURE 15 Measurements of BMW i3 in Test 2

~0.2 A overload. This behaviour is also measured in Figure 6. As a consequence, the algorithm reduces the set point of the Nissan to 14 A, and the Nissan actually charges at ~13.9 A. This is an inherent characteristic of the algorithm to guarantee that the total current limit of the charging site is not exceeded over several minutes.

(b) At minute 22, the BMW i3 is connected to the charging station. Since the Nissan is already charging at ~14 A and 6 A is allocated to the BMW when connected, and the BMW slowly increases its charging current, a maximum peak of ~16.1 A is experienced at phase A. Other phases are not overloaded. The algorithm corrects the overload situation by dividing the charging capacity between both EVs as evenly as possible. Thus, it allocates 7 A to the Nissan and 8 A to BWM. However, it notices that with the set point of 8 A, the BMW actually draws ~8.2 A and the Nissan ~6.9 A, so the algorithm reduces the set point of the BMW to 7 A and increases the set point of the Nissan to 8 A. Then, the algorithm learns that the Nissan charges ~7.9 A with the set point of 8 A and that the BMW charges ~7.2 with the set point of 7 A, so it reduces the set point of the Nissan to 7 A, resulting in a charging current of ~6.9 A. Thus, the set point of both EVs is set to 7 A with the total resulting charging current of ~14.1 A.

(c) Both EVs are charging with a constant charging current.

(d) During minute 91, the Nissan Leaf starts to reduce its charging current because of the high SoC of the battery. Throughout this time, the current oscillates. This is a characteristic of the Nissan Leaf, which is seen also in Figure 3. This causes stepwise increments and reductions of the current set point of the BMW i3. During this time, short overloading occur (Figure 13), with the highest peak of ~21.1 A. At minute 102, the battery of the Nissan Leaf is full and it stops charging.

(e) Since the Nissan Leaf does not charge anymore, the total capacity (15 A) could be allocated to the BMW i3. However, during (d), the algorithm has memorized that with the set point of 15 A, the BMW i3 charges slightly more than 15 A at phase A. This has been registered in expected charging currents of the BMW i3. Thus, the algorithm fixes the set point of the BMW i3 to 14 A instead of 15 A with the aim at avoiding a long-term overload. The BMW i3 continues to charge with the set point at 14 A.

4.2.3 | Test 3

Lastly, the results of Test 3 are presented in Figures 16, 17, and 18. It should be noticed that in this test, the BMW i3 uses only phase B to charge because of the physical disconnection of phase A and phase C. That is why only the measurements at phase B of the BMW i3 are presented. The current limit of the charging site is set to 20 A.

(a) At the beginning, no EV is connected to the charging station. Before minute 2, the Nissan Leaf is connected. During the first minute of connection, the algorithm has set the set point of the Nissan Leaf to 6 A.

(b) Approximately at 2 min 20 s, the set point of the Nissan is set to maximum of 20 A, since no other EVs are connected to phase A. The Nissan continues charging with the maximum current, which is measured at ~16.7 A. In the moment of 5 min 20 s, the BMW i3 is connected to the charging station. In this case, the BMW i3 is charging only at phase B, but the algorithm does not have such

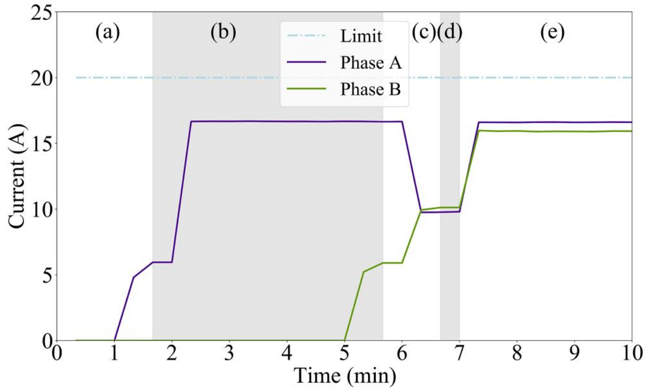

FIGURE 16 Sum of the phase currents of both electric vehicles in Test 3

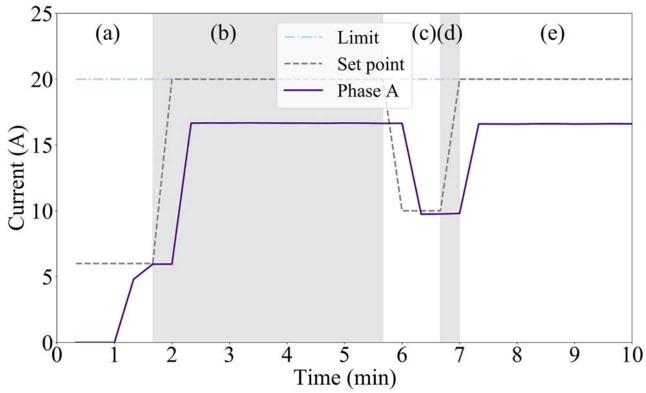

FIGURE 17 Measurements of Nissan Leaf in Test 3

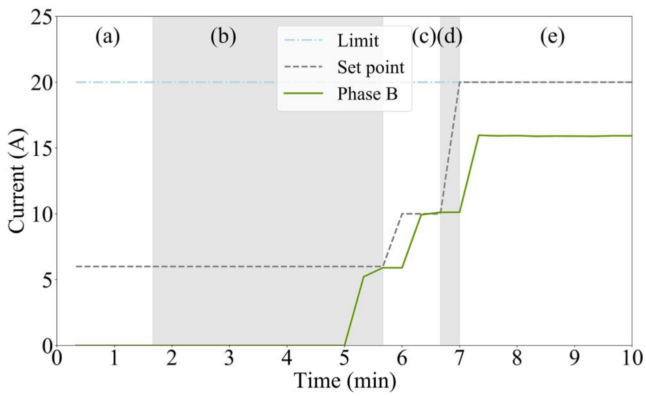

FIGURE 18 Measurements of BMW i3 in Test 3

information, so it supposes that the BMW will charge in 3-phase manner as explained in Section 4.1.

(c) The algorithm expects that the BMW i3 charges 3-phase and divides the charging capacity evenly to both EVs. Thus, it increases the set point of the BMW i3 from 6 to 10 A and reduces the set point of the Nissan Leaf from 20 to 10 A.

(d) The algorithm learns that the BMW i3 charges only at phase B. In addition it knows that the Nissan Leaf uses only phase A. In addition, from expected charging currents of the Nissan Leaf it knows that with the set point at 20 A, the Nissan Leaf does not exceed 20 A. As a consequence, it increases the set points of both vehicles to the maximum of 20 A.

(e) Both EVs continue charging with the full capacity because they are connected to different phases.

5 | DISCUSSION

The measurements demonstrate that the delays from a change in the current set point to a steady state are mostly a matter of a few seconds. Standard IEC 61851 defines 5 s as the time an EV has to react to a new current limit, and during this time, the charging controller shall not change the current limit. This sets the absolute minimum limit for the time step that can be used to execute the algorithm. To guarantee the correct functioning of the charging algorithm, a time step shorter than 5 s should not be used. Otherwise, not all EVs may have time to reach a new current set point. The used communication technology, the charging controller, and the charging station can have an impact on delays.

In the current set point response test, the current set points are changed in 1 A steps. The charging dynamics may be different if, for instance, the set point is set from 6 to 16 A. This should be verified in further development work. The current set point test illustrates that there is always a difference between the current set point and the real charging current. With the measured EV models and charging modes, there is a great variety of offset. The largest measured offset at a steady state with the BMW i3 is 7.96 A, which was measured in the ‘low’ mode at the time step 124 s (in Figure 7) in phase C. From the point of view of the EV, this is really not an offset, because the EV is not even meant to be charged at the current indicated by the set point. In this case, the EV is designed to charge at 7.5 A [17] and in reality, it charges at 7.04 A in phase C, while the algorithm would like it to charge at 15 A. The issue is that the charging algorithm is not aware of the internal limitations of the EV and does not know that by changing the charging mode, a higher charging current can be used. Thus, from the viewpoint of the EV, the offset is 0.46 A, and from the viewpoint of the charging algorithm, the offset is 7.96 A.

Such an extreme offset can have a fundamental reducing impact on the efficiency of a charging algorithm, especially, when controlling several EVs at the same charging site. Otherwise, when the difference between the current offset and the measured current is, say, less than 1 A, it probably will not have much impact small charging sites. Another story is in the case of large sites with tens of simultaneous charging sessions. In that case, even offsets of 1 A may accumulate up to tens of amperes. If the charging current was not measured at all but expected that the EVs charge exactly the current defined by the set point, it could lead to overloading cables or a distribution transformer.

In reality, the EV fleet consists of different models with different load curves and offsets. This leads to a balancing effect at a large charging site and reduces the risk of malfunction of the algorithm due to the accumulation of the offsets at the same phase. For better general knowledge, the current set point response test covering more EV models should be repeated to see the variations between different EV models in this regard. However, the proposed charging algorithm takes the offsets into account.

The validation of the proposed algorithm through three tests show that the algorithm works as intended with commercial EVs, under various circumstances. The algorithm adapts well in situations, where current drawn by EV or EVs increases or decreases suddenly. The proposed algorithm complies well with the charging standard IEC 61851.

EV models possess different characteristics with regard to charging [18]. Even the same EV can behave in different ways depending on its charging settings. The charging system operator does not know what kind of charging curve the EV connected to a charging station has. It is also possible that even the EV driver is not aware of the charging settings. This poses a potential reduction in efficiency of the charging management algorithm applied by the charging operator. If the charging management algorithm is unable to regulate the charging current as intended or if the gap between the current set point and the real charging current is overlooked, it is likely that there is network capacity allocated to an EV that in reality is not used completely. Perhaps this unused capacity could be allocated to another EV. For instance, if 10 A is allocated to an EV, but it charges with only 6 A, the resting 4 A could be used by another vehicle.

While in the case of most EVs, the load curve starts to decrease during the last 1%–3% of the SoC. Keeping in mind the average daily distances, a large part of the time, the EVs are charged during this decreasing phase [19]. As one EV releases network capacity because of the decreasing current phase of the charging process, this free capacity is reallocated to other EVs. This is an inherent and efficient characteristic of using measured currents in the charging algorithm. In this regard, the efficiency of the proposed algorithm is assessed in Tests 1 and 2.

In essence, the less accurately the charging operator can regulate the charging current of the charging EVs, the higher is the inefficiency of the charging system as a whole because the charging management algorithm does not perform as it was designed to. The problem of phase imbalance can be mitigated through phase swapping [20] at difference charging stations. This helps to alleviate the problem but does not guarantee that it will be eliminated. The algorithm handles well sudden unbalances as seen in Test 1. In addition, it operates even under a case of long-term unbalance as seen in Test 3.

Even if the algorithm allows a temporal overload of maximum 6 A per vehicle, in a real case, it is very unlikely that it would pose a problem because of two reasons. Firstly, the fuses of a charging site do not react immediately to small overloads. For example, a widely used gG fuse must withstand 25% overcurrent at least 1 h, according to the standard IEC 60269. In addition, such short-term overcurrent does not have time to overheat the network components. Secondly, it is unlikely that many EVs are connected to the charging station exactly within the same minute at the same charging site. The performance of the algorithm under overloads is seen in Tests 1 and 2.

It can be argued that from the customer point of view, it might be important that the charging process starts as soon as possible when the EV is connected to the charging station. In this way, a customer notices immediately that the EV starts charging and does not worry that the EV will not charge because of a malfunction, for example. This may improve the user experience.

The proposed algorithm is especially suitable for large charging sites with tens or hundreds of charging stations. This is because it may not be economically feasible to size the network of such site to be able to cover the peak demand. Apart from that, many large charging sites, such as shopping centres, have a high percentage of short charging sessions [19]. Thus, an efficient charging management is likely to be reflected as higher SoCs of the batteries and improved customer experience.

Even if the algorithm focuses on the network capacity at the charging site, more efficient use of this capacity may be also indirectly beneficial for the distribution network upstream. With a view to practical applications, an advantage of the proposed algorithm is that it is mathematically easy to understand and computationally lightweight. It does not include computationally demanding algorithms, such as neural networks.

6 | CONCLUSION AND FUTURE WORK

An original algorithm for EV charging management is presented. The proposed algorithm creates a basis for further charging algorithms to become more efficient in real charging solutions. The novelty of the algorithm is twofold.

Firstly, the proposed algorithm considers several non-ideal charging behaviours of EVs in which no comprehensive solutions have previously been proposed. These non-idealities are the unknown charging phase or phases, the offset between the real charging current and the current set point at the charging station, unbalanced charging, and the otherwise unknown charging curve. The key to the algorithm is that it is based on measurements of the actual charging current and does not rely on predefined load curves. Thus, no modelling or data about the EVs is necessary.

Secondly, the algorithm focusses on maximizing the charging current within the capacity limits of the power network or otherwise set limit. This leads to a high use rate for the power network and a reduction in charging times.

According to the test with commercial EVs, the algorithm is robust, straightforward, and computationally light. These are positive aspects with a view towards practical applications. In addition, the algorithm does not need any additional information from the vehicle or user. The only requirement is that the vehicle must fulfil charging standard IEC 61851. The algorithm is tested experimentally by using commercial EVs and charging infrastructure. Consequently, the algorithm is suitable for real applications and compatible with charging standard IEC 61851. For communication amongst the algorithm, charging controllers, and measurements devices, Modbus TCP/IP is used, which is a well-established and robust communication protocol.

To the best knowledge of the authors, no other algorithm in the published research literature uses measured phase currents in the operation of charging management. Neither has any other algorithm had the main objective to maximize used network capacity to overcome the non-ideal behaviour of EVs. Therefore, the presented work fills a gap in research knowledge.

In the future, new strategies to improve expected charging currents will be studied, and the algorithm will be improved against oscillations. The performance of the algorithm will also be compared with other charging management algorithms. Additionally, the algorithm will be tested using a larger number of real EVs and charging stations to prove its scale capabilities. Lastly, the algorithm will be validated by a commercial charging system operator in a field test.

ACKNOWLEDGEMENTS

Kalle Rauma would like to thank the support of the German Federal Ministry of Transport and Digital Infrastructure through the project PuLS–Parken und Laden in der Stadt (03EMF0203 B).

Toni Simolin and Pertti Järventausta would like to thank the support by the projects LIFE Programme of the European Union (LIFE17 IPC/FI/000002 LIFE-IP CANEMURE-FINLAND) and the project ProCemPlus (Prosumer Centric Energy Communities – towards Energy Ecosystem). The work reflects only the author's view and the EASME/Commission is not responsible for any use that may be made of the information it contains. Open Access funding enabled and organized by Projekt DEAL.

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How to cite this article: Rauma K, Simolin T, Rautiainen A, Järventausta P, Rehtanz C. Overcoming non-idealities in electric vehicle charging management. *IET Electr. Syst. Transp.* 2021;1–12. https://doi.org/10.1049/els2.12025