REALISTIC QOS OPTIMIZATION POTENTIAL AT COMMERCIAL EV CHARGING SITES THROUGH PRICING-BASED PRIORITIZATION

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Abstract

At present, EVs are emerging at a fast pace. This may cause pressure for commercial buildings to offer electric vehicle (EV) charging services for their customers. In a cost-efficient charging site, it is necessary to find a balance between the costs and the offered quality of charging service (QoCS). This may be a difficult task as the charging requirements of the customers are unpredictable and vary daily. In this paper, an algorithm using a charging price–based prioritization is proposed and discussed. This can be used to take unpredictable charging requirements into account and to improve the QoCS while requiring a minimal effort from the EV users. To ensure an improvement in the QoCS and the practicality of its implementation, the algorithm is tested using hardware-in-the-loop simulations with two commercial EVs and real charging data. The results verify that the QoCS can be improved by 2% on average and by up to 16% for a single EV user. This leads to a more attractive and more cost-efficient charging site.

1 Introduction

Due to their environmentally friendly nature, electric vehicles (EVs) are emerging at a fast pace. Since the range anxiety is common among the EV users [1], commercial buildings, e.g. shopping centres, may want to offer charging services to attract customers. However, it can be a challenging task to design a cost-efficient charging site that provides a high quality of charging service (QoCS) with minimum investment costs.

In this paper, the charged energy of an uncontrolled case is chosen to represent the level of 100% QoCS. Since the uncontrolled charging represents the maximum charged energy under the limitations set by, e.g., the on-board charger (OBC) of the EV, the maximum charging power of the EV supply equipment (EVSE), and the available charging time, it is a reasonable reference value to evaluate the negative impacts of a charging control algorithms.

The QoCS could be optimized using the driving schedules and the charging demands. However, requesting such information from the EV users could be burdensome and requires a suitable interface [2]. Additionally, it may be difficult for an EV user to predict an accurate duration of their stay at commercial locations, such as shopping centres. And, if the users are requested to report their parking time and charging demand, they may be tempted to exaggerate their needs to improve their own convenience. Therefore, a price-based prioritization could be used to allocate charging capacity to those with more urgent demand. This can also increase the utilization rate of the total charging capacity, and thus, lead to a more cost-efficient charging site.

In the scientific literature, several algorithms to improve QoCS are presented [3]–[6]. However, these studies [3]–[6] share common deficiencies: the limitations of the OBCs of the EVs or the compatibility with commercial EVs are not considered. Therefore, the practicalities of the proposed solutions are not thoroughly assessed. As mentioned in [7], there are several non-ideal charging characteristics, such as the EV's on-board charger reducing the charging current to protect the battery from overheating or the vehicle's maximum charging rate being lower than the current limit indicated by the charging controller. These factors may impact the QoCS. According to [8], more than 76% of the EV users see a high QoCS as more important factor than the price of the charged energy. Thus, these factors should be considered in order to accurately evaluate the operation of the proposed charging solution in a real-life implementation.

This paper proposes a charging control algorithm that considers prioritization levels to distribute the available charging capacity between the EVs. The proposed solution is partly similar to the mechanism presented in [6]. However, the proposed algorithm offers more flexible prioritization options, ensures high capacity usage rate while considering non-ideal charging characteristics, and operates in real-time. The algorithm is tested using

hardware-in-the-loop (HIL) simulations with two commercial EVs and real charging data to ensure practicality and compatibility with the IEC 61851 charging standard. The algorithm does not require any user inputs other than the request of whether to prioritize or not.

The remainder of the paper is organized as follows. The proposed control method is presented in Section 2. The details of the experiment are presented in Section 3. The results are presented and discussed in Section 4. Finally, the conclusions are provided in Section 5.

2 EV charging control method

To know whether the OBC of the EV limits the realized charging current, the control method uses a charging current measurement feedback of all EVSEs. The measurements are used to detect the number of used phases and memorize the correlation between the current limit set by the EVSE and the realized charging currents. This function is referred to as charging characteristics expectation (CCE) algorithm that enables the control algorithm to adapt to the charging profile of each EV without any preliminary knowledge.

The algorithm utilizes prioritization levels to distribute the total charging capacity between all EVs. The prioritization levels could be linked to charging prices so that a higher charging price equals a higher prioritization level. This leaves the decision to the customers and guides them to choose a higher priority only when it is necessary. The proposed control method could be applied into charging algorithm that focuses on determining the available charging capacity to improve its capacity utilization rate and enable prioritization-based capacity distribution.

The charging capacity allocation algorithm is illustrated in Algorithm 1. It begins by gathering a list of charging points with an active charging session (list_ACP). After that, the current limit of each charging session is initialized to 6 A which is the minimum current limit (IEC 61851). The available charging capacity (ACC) to be allocated in the main loop can then be calculated based on the total charging current limit (TCCL) and the minimum value returned by total_CCE function. This total_CCE function returns the expected charging currents of each phase (A, B, and C) of all EVs which can then be used to calculate remaining available charging capacity.

To allocate the remaining charging capacity, the algorithm considers a priority index (p_i) that is determined based on the prioritization level (p_l) and the currently allocated capacity (p_c) according to Eq. 1. The charging current limit of the charging session with the lowest p_i will be increased by one ampere in each cycle of the loop until the total capacity is allocated or until there are no more suitable charging sessions remaining. A charging session becomes unsuitable if the allocated charging current limit reaches the maximum current of the charging point (row 7) or if at least one of the phase currents would rise above the total charging current limit when the current limit of the charging session increases (row 12).

$$p_i(n) = \frac{p_c(n)}{p_l(n)}. \quad (1)$$

Algorithm 1 prioritization-based capacity allocation

```
def distribute_capacity_based_on_priority():
1. list_ACP = check_CPs_with_active_charging_session()
2. for i in range(length(list_ACP)):
3.     list_ACP[i].current_limit = 6
4. ACC = TCCL - min(total_CCE())
5. while ACC > 0 and length(list_ACP) > 0:
6.     list_ACP.sort(key = priority_index, order = ascending)
7.     if list_ACP[0].max_current <= list_ACP[0].current_limit:
8.         delete list_ACP[0]
9.     else:
10.        list_ACP[0].current_limit = list_ACP[0].current_limit + 1
11.        list_ACP[0].priority_index = list_ACP[0].current_limit /
           list_ACP[0].prioritization_level
12.        if max(total_CCE()) > TCCL:
13.            list_ACP[0].current_limit = list_ACP[0].current_limit - 1
14.            delete list_ACP[0]
15.    ACC = TCCL - min(total_CCE())
16.    return
```

3 Experiment

In the following subsections, the used charging data, the simulation model, the scenarios, and the laboratory setup are described. The use of commercial EVs and real charging data ensures compliancy with the charging standard IEC 61851 and that the scenarios are realistic.

3.1 Data

The experiment utilizes real charging data measured at Mall of Tripla [9] located in Helsinki, Finland. At the charging site, there are almost 300 charging points suitable for 22 kW charging power. The data was measured between 10/2019–3/2020 and consists of nearly 5,000 uncontrolled charging sessions. The data include information such as arrival and departure times, active charging times, energies charged, and charging peak powers.

3.2 HIL simulation model

The HIL simulation model includes two real charging points and a necessary amount of fully simulated charging points. The simulation model utilizes preliminary measured EV charging profiles in the modelling. The charging profiles of both EVs (Nissan Leaf and BMW i3) are measured for all possible charging current limits (integers) set by the EVSE to build a simulation model for the charging profiles where the charging current depends on the current limit set by the EVSE and the energy that is missing from the battery of the EV. This ensures that the non-ideal charging characteristics (e.g. on-board charger starts limiting the charging current

when the battery becomes nearly fully charged) are taken fully into account. The algorithm uses a time step of 10 seconds. At each time step, all values of the simulated EVs are calculated and the charging currents of the HIL charging points are measured. The control algorithm is run every 60 seconds or in the next time step after a new EV is plugged into a charging point.

3.3 Laboratory setup

Besides the EVs (Nissan Leaf and BMW i3), the laboratory equipment includes a charging station (a modified RWE eSTATION) with two charging sockets (22kW, 3×32 A, 400 V) and charge controllers (Phoenix Contact Advanced EV charge Controllers, type EM-CP-PP-ETH). The charging currents are measured with KoCoS EPPE PX power quality analysers with KoCoS ACP 300 current probes. The algorithm is implemented by using Python programming language, and a Modbus library (PyModbus [10]) is used to enable communication with the charging controllers and the metering devices. The experiment is carried out at the Smart Grid Technology Lab at TU Dortmund University [11]. The laboratory setup is shown in Fig. 1.

Fig. 1. Laboratory setup

3.4 Scenarios

According to the charging data, the charging point utilization rates are currently very low at the Mall of Tripla. Therefore, to investigate realistic scenarios with higher EV penetrations, charging sessions of two consecutive days are grouped into one day. Three scenarios are considered which represents the days with the highest energy consumption. The scenarios are illustrated in Table 1. To increase the need for peak load management that may also reduce the QoCS, the charging capacity of each three phase is limited to (n_{max}×6 A), where the n_{max} is the highest number of simultaneously present EVs.

The data does not contain information whether a charging session is a single-phase or a three-phase. However, if the peak power of a charging session is higher than 10 kW, it is likely to be a three-phase one. Two-phase charging sessions are also possible but, for the simplicity's sake, all charging sessions are assumed to be single-phase or three-phase depending on whether their peak power is under or over 10 kW. This information is then used to couple each charging sessions with the modelled charging profile of either the Nissan (single-phase) or the BMW (three-phase).

Since the priority preference of the EV users and the willingness to pay for it are unknown, the priority levels have to be assumed. For demonstration purposes, two prioritization levels are assumed: either 1 or 5. This means that the algorithm tries to allocate 5 times more capacity for the more prioritized charging sessions. In each scenario, the higher prioritization level is given to 0%, 20%, 40%, 60%, or 80% of the EVs. The higher prioritization levels are given to the EVs with the highest energy requirement indexes ($E_{r,i}$), which are calculated according to Eq. 2, where E_c is the energy consumption, t_p is the parking time, and P_{max} is the maximum charging power (3.68 kW for a single-phase and 11.04 kW for a three-phase charging session).

$$E_{r,i}(n) = E_c(n) - t_p(n) \times P_{max}(n). \quad (2)$$

It is worth mentioning that all charging sessions will receive at least the minimum capacity (3×6 A) and the algorithm always tries to allocate the whole available charging capacity. This means that both prioritized and non-prioritized sessions receive the same minimum capacity during peak congestion hours or the same maximum capacity if there are only a few EVs present.

Table 1 Scenario data

Scenario	1.	2.	3.
Charging sessions (3-p / 1-p)	96 (16 / 80)	106 (21 / 85)	101 (12 / 89)
Total charged energy	760 kWh	707 kWh	692 kWh
n_{max}	37	22	31
Date	14–15th Dec. 2019	18–19th Oct. 2019	18–19th Jan. 2020

4 Results

As mentioned earlier, the uncontrolled charging is used as a reference to represent 100% QoCS level. The average QoCS of all EVs in each scenario and case are presented in Fig. 2. The results show that by offering an option for a prioritized charging, the charging system operator can improve the average QoCS. According to Fig. 2, the QoCS is the highest when the prioritization is requested by around 20% of the customers. This information can be used to design optimal pricing levels for commercial charging sites. Determination of the actual pricing levels (€/kWh) is excluded from this paper. In Fig. 2, it can be seen that when comparing the cases with 0% and 20% prioritization in Scenario 1, the prioritization increases the QoCS up to 1.9% which results in 14.9 kWh higher charged energy.

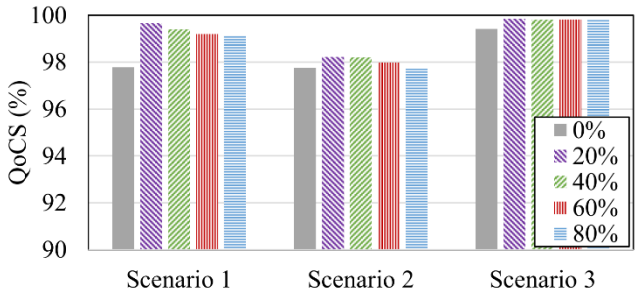

Fig. 2. QoCS in each scenario and case

In Fig. 3, the total charging currents in Scenario 1 between 13:50–15:50 are presented for the cases where none of the EV users request prioritization and where 20% of the users request prioritization. During the congestion hour between 14:00–15:00, the currents in Phase 2 and 3 are higher for the case with 20% of users requesting prioritization (Fig. 3 b) which explains the higher QoCS. The prioritization has more notable impacts on the individual EVs than the average of all EVs. This is illustrated in Fig. 4, where the charging currents of a BMW i3 in Scenario 1 are presented. In Fig. 4 a and Fig. 4 b, none of the EVs and 20% of the EVs (including the BMW i3) are prioritized, respectively. The QoCS for the BMW in these cases are 83.9% and 100.0%, respectively. The request of the prioritization results in 3.5 kWh higher charged energy for the BMW.

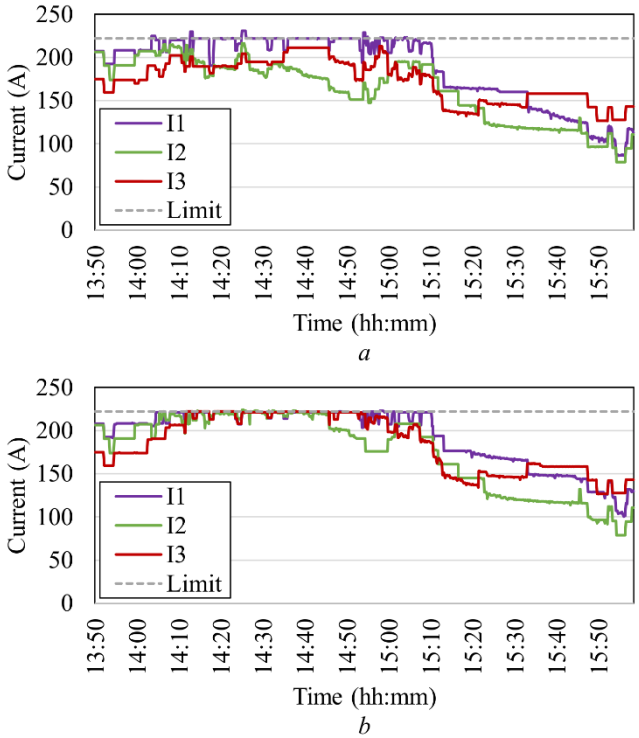

Fig. 3. Charging currents in Scenario 1 when (a) none of the EV users and (b) 20% of the EV users request prioritization

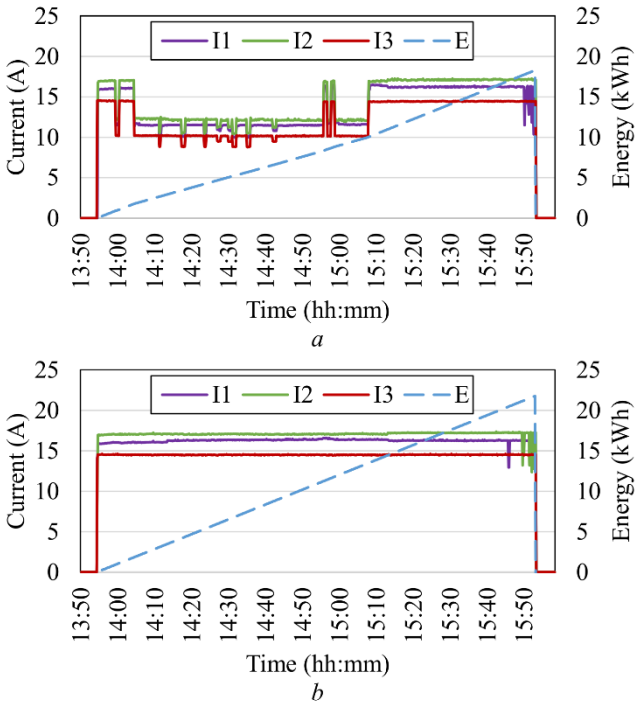

Fig. 4. Charging currents of a BMW i3 in Scenario 1 (a) without prioritization and (b) with prioritization

As mentioned earlier, prioritized and non-prioritized charging sessions receive the same capacity during peak congestion hours or if there are only a few EVs present. Therefore, it might be reasonable to increase the price of the charged energy of a prioritized charging session only when the prioritization increases the charging power compared to the non-prioritized sessions. This could simplify the situation from the EV user perspective as a customer would not have to pay extra in case of the prioritization is not possible.

5 Conclusion

This paper proposes a price–based prioritization algorithm for EV charging. The algorithm is tested by using HIL simulations with two commercial EVs and real charging data. The strengths of the proposed algorithm include the ease of implementation and its convenience from the user perspective as the only required information is whether to prioritize or not.

The results show that the highest QoCS is achieved when around 20% of the EVs users with the highest charging requirement are requesting prioritization. This increases the average QoCS up to 1.9% which means 14.9 kWh increase in the daily total charged energy. More notably, the QoCS of an individual EV user increases up to 16.1%.

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