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Quantification of peak shaving capacity in electric vehicle charging – findings from case studies in Helsinki Region

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Abstract: An increasing share of electric vehicles can mean excessive peak loads in low-voltage power distribution networks. Introducing peak shaving mechanisms to the charging systems, such overloads can be mitigated significantly. The first contribution of this study is to quantify the amount of flexibility that electric vehicles can contribute to peak load reduction so that the drivers can still fully charge the batteries of their vehicles. The second contribution is that the study presents and compares two optimisation strategies for peak load reduction. The work is based on real charging data covering about 25,000 charging sessions at various charging sites in the metropolitan area of the Finnish capital city. The main finding is that the peak loads at charging sites can be reduced by up to 55%. Another important result is that load reduction through low-power charging is achievable only if the average parking time at the charging site is >3 h, without affecting the user experience negatively. It is also found out that the average parking time is over 2 h longer than the average charging time, which indicates the enormous potential of electric vehicles in peak shaving.

1 Introduction

The undesirable impacts of uncontrolled charging of electric vehicles (EV), such as network congestions and the resulting network reinforcement costs, affect mostly low-voltage distribution networks [1–3]. In power networks, the primary components, such as transformers and cables, must be sized to withstand the peak load. Thus, reducing this peak load can lead to lower investment costs and significant savings.

On the other hand, a high percentage of vehicles remain parked most of the time [4], and the parking time often exceeding the charging time. This implies that the charging process does not necessarily have to be started immediately when the charging cable is plugged in. It also entails that the nominal (the highest possible) charging power may not be needed and that the charging power can be varied along the charging process. Simply, the more time the vehicle is parked, the more flexibility the charging process has. Knowing the flexibility capacity of EVs is essential when considering the use of EVs for network services, for example by a sub-aggregator.

In order to achieve climate targets [5] and improve air quality [6], the European Union (EU) defines the basic requirements for the renovation of existing buildings. Electric mobility, which helps to reduce CO_2 and air quality-related emissions through the electric power train of the EVs and an increasing share of renewable energies, plays an important role in this context. To ensure that the integration of EVs is as efficient as possible, certain requirements must be fulfilled when renovating buildings. EU directive (EU) 2018/844 of 30 May 2018 amending directive 2010/31/EU on the energy performance of buildings will come into force on the 10 March 2020 [7]. The directive makes a difference between non-residential buildings and residential buildings. Article 1, point 5, paragraph 2 of the directive (EU) 2018/844 specifies the requirements for the non-residential buildings. If there are >10 parking places in or in the immediate vicinity of the building, at least one charging point for EVs must be installed as a part of the renovation. In addition, 20% of all parking places must already have an infrastructure that enables a quick retrofitting of a charging point. In addition, by January 2025, a minimum number of charging points will be specified for car parks with >20 parking places. Once again, all buildings with ten or more parking places are affected. As a part of a renovation, all parking places must be equipped with an infrastructure that enables quick retrofitting of charging points. This means that they would be charging ready. However, a minimum number of charging points are not specified. If the costs of charging readiness (for example laying cable pipes) exceed the total costs of renovation by >7%, or if a possible charging system could endanger the stability of the power network, it is possible to deviate from this requirement. An example of a charging ready parking place that is being made to a functional charging point is illustrated in Fig. 1.

The possibility to control the charging processes of EVs is strongly dictated by three major factors. The first factor is the required energy in the charging process [9] that is related to the driving and charging patterns. The second important point is the plug-in time to the charging point [10]. The third limiting factor is the maximum available charging power. The maximum power can be limited by the individual charging point or the point of connection to the charging site.

Two of the three above-mentioned factors are strongly dependent on the behaviour of the customer. It is also important to consider that different charging sites may have very different charging behaviour.

The charging behaviour being strongly influenced by human factors, studies based on real charging data are requisite to quantify the realistic possibilities and limitations of smart charging [2]. Studies based on actual charging data, rather than on estimations, are scarce in the scientific literature.

1.1 Objective of the paper

With the benefits of peak load reduction in mind, the principal objective of this paper is to quantify the real capacity limits of flexibility that EVs can provide to the power system in terms of peak shaving. In other words, to discover the realistic boundaries of EV charging without decreasing the level of service for the final customers. The major contribution of this paper is to answer the following fundamental questions:

- How much peak load can be reduced with peak shaving at charging sites under realistic conditions?
- What kind of charging sites is the most prominent for peak shaving?
- What is the minimum average parking time that permits the use of peak shaving without decreasing user comfort?

The second objective of the paper is to present and to compare two different optimisation algorithms: individual optimisation and field optimisation.

The two previously mentioned objectives are tied together by the fact that the available flexibility of the charging processes is determined by using the optimisation algorithms.

The use of real-world data helps to identify the most feasible locations and the types of parking sites for the implementation of smart charging strategies.

The subsequent parts of this paper are structured as follows. Section 2 presents the state-of-the-art found in the literature in this field. Section 3 explains the methodology used in this work. This section also describes the used data and clarifies how it has been processed for the study as well as describes the two optimisation strategies. Section 4 presents the case study results of this paper that are further discussed in Section 5. Lastly, the conclusion and suggestions for future research are provided in Section 6.

Fig. 1 *Example of a charging-ready parking place. It can be converted to a functional charging station by installing the actual charging point through the quick connector [8]*

2 Related research works

Due to concerns and possibilities related to the charging of EVs, peak shaving has gained attention in academic research during the last years. In this section, a comparison with this paper and the most related latest research works is carried out.

The study in [11] proposes a real-time algorithm for peak shaving at non-residential charging sites. This study is based on real data from charging sites of various sizes. The percentage of flexible sessions is similar than in this paper; ranging from 43 to 61%, depending on the type of the charging site. Unlike this paper, Zhang *et al*. [11] have focused on the development of a functional real-time algorithm, rather than finding the maximum possible peak shaving capacity of EVs. The study in [11] does not have the constraint of not reducing the quality of charging service as this paper, which leads to up to 80% peak reductions. The same 15 min time step is used in the computation process of [11] and in this paper. Despite the objective of this work being slightly different, it can be stated that the results point in the same direction and this paper complementing the findings in [11].

The study in [12] aspires minimising both, the peak power at a charging site as well as the costs of the battery deterioration. Such an approach has undoubtable benefits to the power utility and the customers. The work does not rely on real charging data, but on three synthetic scenarios with the number of EVs ranging from 30 to 50 at one charging site, similar numbers as presented in this paper. The peak power can be reduced by about 50% in comparison with the original case. A major drawback is that the requirement of knowing the exact vehicle and the battery model could make the practical implementation troublesome.

The study in [13] presents a distributed charging algorithm with the goal of decreasing the power peak at the charging site. The work relies strongly on previously known parameters, such as the models of the vehicles, the mobility data (daily travelled distance, arrival and departure time) and the load profile of the network. The result shows that the algorithm is able to reduce peak power by nearly 60%. In all cases, the state of charge (SoC) of the battery does not reach 100%. However, SoCs over 95% are obtained in every case. The results presented in [13] are very well in line with the results presented in this paper, even if Kisacikoglu *et al*. [13] do not include real charging data.

The work in [14] does not focus only on peak shaving, with an EV, but also with a battery energy storage and a photovoltaic power plant at one household. The data of the household over 15 days is used. The study does not use real EV charging data, but artificial data based on 30 km driving per day. The maximum peak load reduction by only using an EV is 55%. The major difference to this work is that in [14], only one household with one EV is considered and the study is restricted to a relatively narrow period of time.

The study in [15] is a continuation of [14], but instead of a household, algorithms are applied in a commercial building with six EVs, a battery energy storage and a photovoltaic generator. The study does not use real EV charging data. The time period of data from the building covers 16 days and the computation is carried out in 10 min time steps. The peak load reduction by using only EVs in not studied, but through the combination of EVs together with a photovoltaic power generator, the maximum peak reduction of 31% is reached.

The work in [16] also successfully minimises the charging costs and the peak load. Additionally, it expands its concept to vehicle-to-grid strategies. The study does not rely on real charging data, but on scenarios that are modelled based on average daily driving distances in Singapore. The study uses a rather complex 37-bus network with industrial, commercial, residential and combined branches. The work compares the peak load increment with an increasing share of EVs, with the result that peak load increases during the coming years much slower than the share of EVs. The maximum rates of EVs that the studied network can accommodate ranges from 60 to 80%, depending on the case. Due to the fact that the study in [16] is not focused on individual charging sites, but on a larger distribution network, and the results are not directly comparable with this paper.

It is important to notice that many studies in the literature include peak shaving as a secondary feature among others in their charging management approach. Such features can be, for example, minimisation of the charging cost [17, 18], minimisation of the battery degradation cost [12] or the minimisation of losses in the distribution feeder [19]. In practice, it can be difficult to implement a charging management system with such many features due to the complexity, the need for a large amount of information and possible contradictory objectives.

As stated earlier, in order to achieve realistic research outcomes, there is a need for research based on real charging data. That is where this paper stands out from the most other research works. Additionally, even less research works compare results between different types of charging sites. Finally, similar optimisations in the same context are not presented previously.

3 Methodology: analysis and optimisation of real parking and charging data

In this section, the analysis of low-power charging data used in this study is described. The charging behaviour of EV drivers thereby represents a central element. By comparing the deviation between the charging time and the parking time, the flexibility potential of each charging process will be determined. Further on, two optimisation methods are presented in order to reduce the overall peak load by load shifting mechanisms. The two optimisation methods are called individual optimisation and field optimisation. If a general reduction of the peak load is possible, the installation of further charging points can be considered without exceeding the limits of the building infrastructure. The aim of the analysis is to show the potential of smart scheduling to reduce the peak loads. Both algorithms are meant to be used to reduce the power peaks at a single charging site by the charging operator.

3.1 Description of the data

The study is based on roughly 25,000 charging sessions that have been measured at various charging sites in the Helsinki metropolitan area in Finland between September 2017 and July 2019. The charging sites under the study can be divided into two categories. The first category includes public charging sites that can be used by all EV drivers. The second category includes commercial charging sites that can only be used by the employees of the companies located in the proximity. Not all charging sites have the same pricing for the end user. An overview of the charging data is presented in Table 1.

From the data sets, it is possible to read the plug-in as well as the plug-out times. It is assumed that a customer does not remove the charging cable until driving away from the parking area. The time between the aforementioned time stamps can therefore be assumed as the total parking time. Although it is possible that the real parking time exceeds the time between the plug-in and plug-out time stamps, it appears rather unlikely and is therefore not taken into account. In order to determine the pure charging time, the current flow is analysed more closely. If the battery of the vehicle is fully charged, the current flow of zero is assumed. This moment can also be taken from the data set. The charging time is therefore defined by the time between the plug-in and the end of the current flow time stamps.

The respective charging power is derived from the total amount of energy charged. It can be assumed that the maximum charging power decreases with an increasing SoC. Due to the fact that low-power charging does not charge with the maximum charging power of the battery, an approximately constant charging power, with only a minor error, can be assumed [20]. To determine the charging power, the amount of energy charged is divided by the charging duration. Information on the current SoC of the battery cannot be seen from the data set. However, if the parking time exceeds the charging time, it is assumed that the battery is fully charged.

In order to reduce the complexity of the analysis, a compromise must be made regarding the choice of the analysis interval. With an interval length of 15 min, the expected deviation of the results from a shorter analysis interval is small. This means that the analysis and the optimisations are carried out in time blocks of 15 min. In the further work, this interval length will be used. Before the data analysis, the data set is adjusted to the time interval. The amount of energy charged is not changed and is kept constant even if the time intervals of the charging are changed. Since the parking and charging times can change due to an analysis interval of 15 min, the charging capacity must be corrected accordingly. The calculation of the new parking and charging intervals ($\text{time}_{\text{new},i}$) is shown in (1). If an original interval ($\text{time}_{\text{orig},i}$) is <15 min, it will be rounded up to full 15 min. For all other cases, the remainder of an integer division of 15 is considered as follows. If this value is <7.5 min, it is subtracted from the interval. Otherwise, the difference between 15 and the corresponding value is added to the interval:

$$\text{time}_{\text{new},i} = \begin{cases} 15 & \text{time}_{\text{orig},i} < 15 \\ \text{time}_{\text{orig},i} - \text{mod}(\text{time}_{\text{orig},i}) & \text{mod}(\text{time}_{\text{orig},i}) < 7.5\,. \\ \text{time}_{\text{orig},i} + 15 - \text{mod}(\text{time}_{\text{orig},i}) & \text{else} \end{cases} \quad (1)$$

The modified charging power ($\text{power}_{\text{new}}$) is calculated from the original charging power ($\text{power}_{\text{orig}}$) as

$$\text{power}_{\text{new}} = \text{power}_{\text{orig}} \times \frac{\text{time}_{\text{orig},i}}{\text{time}_{\text{new},i}} \quad (2)$$

Table 1 Overview of the charging data

	Public charging	Commercial charging
charging sites	5	3
charging points per site	8–80	10–36
charging sessions	20,382	4664

3.2 General data analysis

This section describes more closely the data analysis that is carried out separately for the public and commercial charging data. The real charging data from the measurements is referred to as the base scenario. In further step two optimisation approaches to reduce the peak loads will be presented.

In the first step, the average parking and charging times are calculated. These indicators provide initial awareness about the feasibility of possible smart charging algorithms. The third valuable indicator is the percentage of the flexible charging sessions from the total number of sessions.

The classification of charging sessions to fixed and flexible ones together with average parking and charging times helps to identify quickly the realistic possibilities of smart charging at a charging site.

It is assumed that a charging process can be stated as flexible if the parking time is at least 7.5 min longer than the charging time. The reason for this is the fact that the analysis is carried out in the time steps of 15 min, making it necessary to round up and round down the time series accordingly. Finally, the average consumed energy is calculated.

3.3 Load profile – real charging data

The objective of analysing the base scenarios is to obtain an overview of the average load profiles for the two categories. In order to use the capacity of the given infrastructure as efficiently as possible, peak loads are of particular importance.

In order to create the average load profile, all charging sessions of the considered days are superimposed first. In a second step, they are normalised to the value of the peak load.

The processing of the data is carried out in a Java-tool developed for this purpose. A timer is used to check at intervals of 15 min which vehicles are plugged in at each time step. By adding the charging power of all vehicles that are plugged in, the total load profile is determined and temporarily stored. Finally, in another loop, the individual load time series of each day are combined and added together.

3.4 Individual optimisation

The objective of the individual optimisation is to minimise the peak load of each individual charging process in order to reduce the total load of the charging site. If in the base scenario, the charging time is equal to the parking time (fixed session), the power consumption is already the minimum and cannot be further minimised. In contrast, the situation is different with flexible sessions. The peak load can be reduced by using the entire parking time as the charging time. The optimal case is a constant charging power over the entire parking time. The aggregation of parallel charging processes finally provides the optimised load curve.

For the optimisation, the average charging power ($\text{power}_{\text{ind.opt.}}$) over the entire parking time must be determined as well. For the analysis of the base scenario, the charging power is assumed to be constant and it is calculated according to (3). In comparison with the original case, the amount of energy obtained is not divided by the original charging time but by the parking time as

$$\text{power}_{\text{ind.opt.}} = \frac{\text{Charged energy}}{\text{Parking time}}. \tag{3}$$

Finally, a timer is used to verify how many vehicles are present at each time step, analogous to the analysis of the base scenario. The sum of the optimised charging capacities of all present vehicles results in the optimised load at the respective time step. The summary and evaluation of the results are performed in the same way as in the base scenario.

The individual optimisation method represents a simple approach to reduce peak load curves. If it is possible to obtain information from the customers about their expected parking times and the amounts of energy to be charged, the optimisation can be carried out within a single charging point. Data exchange between individual charging points and a higher-level control mechanism is not necessary. For this reason, however, there is also a weakness in the optimisation. Due to the fact that all charging events are optimised independently, the optimum of the aggregated charging processes can be different.

3.5 Field optimisation

In contrast to the individual optimisation of all charging processes, the objective of the field optimisation is to minimise the peak load of the resulting aggregated load curve at a charging site. On the one hand, the weaknesses of the individual optimisation are removed. Moreover, it is possible to further reduce the peak loads of the entire system by a load shift. On the other hand, due to the fact that all parallel charging processes are highly related to each other, the complexity of the optimisation increases significantly. An optimisation over the entire period of up to 20 months is computationally heavy with the available resources, so the optimum is determined separately for each day. Anyway, a daily optimisation would be sufficient for most practical applications.

Due to the defined analysis interval of 15 min, a charging process can therefore take place at a maximum of 96 different charging intervals. For the optimisation, a matrix $\boldsymbol{X}$ must therefore be defined first, which assigns an individual time profile of the charging process to each vehicle

$$\boldsymbol{X} = \begin{matrix} x_{1,1} & \dots & x_{1,n} \\ \dots & \dots & \dots \\ x_{m,1} & \dots & x_{m,n} \end{matrix}, \tag{4}$$

where n is the number of cars, m is the time of day (15 min interval) and x_{ij} is the charging power.

Next, the boundary conditions of the optimisation are defined. Firstly, each vehicle must have received the required amount of energy (reqEnergy) at the end of the charging session as

$$\text{reqEnergy}_j \le \sum_{i=1}^{m} \left(x_{i,j} \times 0,25h\right). \tag{5}$$

Secondly, the power is only allowed to be drawn from the grid when a vehicle (Car_j) is plugged in. Additionally, it must be ensured that the maximum power consumption cannot be exceeded and that it can never become negative:

$$x_{i,j} = \begin{cases} 0, & \text{Car}_j \text{ not connected} \\ \text{power}_{\text{new}} \ge x_{i,j} \ge 0 & \text{else} \end{cases}. \tag{6}$$

In the next step, the total load Z of the parallel charging processes must be determined. For this purpose, the elements of matrix $\boldsymbol{X}$ are to be summed up line by line as follows:

$$Z = (z_1, \dots, z_m) = \begin{matrix} \sum_{j=1}^{n} x_{1,j} \\ \vdots \\ \sum_{j=1}^{n} x_{m,j} \end{matrix}. \tag{7}$$

The objective of the optimisation is to maintain the elements of Z as close to each other as possible so that the total load is approximately constant. A load distribution that would be on the same level over the entire day represents the absolute optimum. Due to the fact that the flexibility of the individual charging processes is limited, the absolute optimum can only be achieved theoretically.

Finally, to optimise the total load curve, the elements of Z are squared and multiplied with the interval duration of 15 min. The addition of all values finally results in the squared area A below the total load curve as

$$A = \sum_{i=1}^{m} (z_i^2 \times 0,25\ h). \tag{8}$$

If the minimum of area A is found, the total load curve is constant. The objective function Y is therefore formed by minimising A:

$$Y = \min \{A\}. \tag{9}$$

The 'fmincon' optimiser of MATLAB [21] is used for the technical implementation of the optimisation. Even though the absolute minimum is only theoretically achievable, the optimisation ensures that peaks are flattened as much as possible.

The optimised total load curves ($Z_{\text{opt.},k}$) of all days (d) considered are finally summarised again so that an average load profile can be obtained:

$$\overline{Z_{\text{opt}}} = \frac{\sum_{k=i}^{d} (Z_{\text{opt},k})}{d}. \tag{10}$$

The peak load of each individual day ($P_{\text{peak},k}$) is also of great interest:

$$P_{\text{peak},k} = \max \left\{z_{\text{opt.},i}\right\}. \tag{11}$$

In the final step, the sum of all peak loads from the field optimisation is compared with the peak load sum of the base scenario and with those of the individual optimisation.

It should be mentioned that the results are based on historical data. In this case it is therefore comparatively easy to determine an optimal charging strategy. A much greater challenge, on the other hand, is the implementation of the optimisation on a real system. In addition to the information of the customers about their parking time, the user behaviour must also be analysed as well. In order to achieve an optimal result, the arrival times and the required energy amounts must be predicted as accurately as possible. The results of this work therefore represent the potential of a perfect prediction. That is the largest theoretical flexibility that the EVs can provide for peak shaving without reducing the quality of service of the charging processes. The boundary condition of maintaining the highest quality of service possible is selected, because network services should not compromise the main use of EVs i.e. the driving.

4 Results

4.1 General data analysis

A general data analysis shows that the average charging time is far below the parking time. This can be seen in Table 2. Noticeably, many charging processes exhibit a certain degree of flexibility.

As illustrated in Fig. 2, the share of flexible charging processes for public charging is almost 50%. In the area of commercial

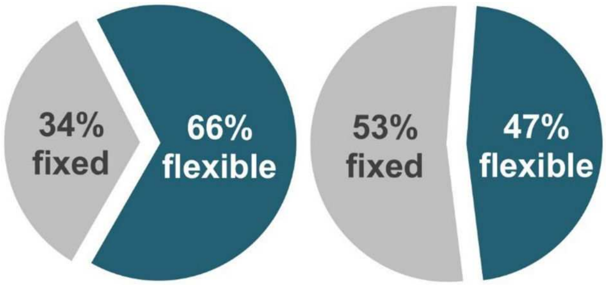

Fig. 2 *Share of fixed and flexible charging sessions in commercial (left) and public (right) charging sites*

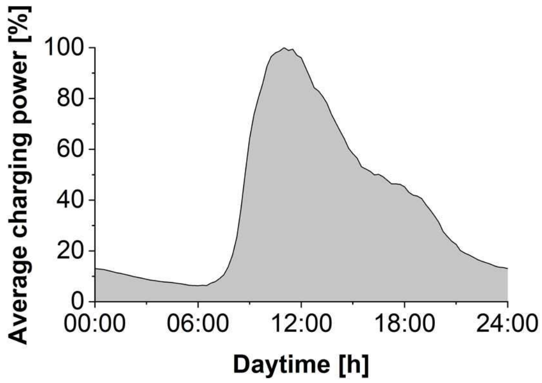

Fig. 3 *Aggregated normalised load curve of the public charging sites*

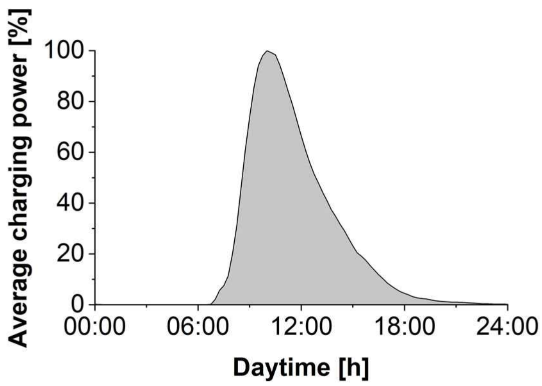

Fig. 4 *Aggregated normalised load curve of the commercial charging sites*

charging, even 2/3 of all charging processes can be stated as flexible.

4.2 Load profile – real charging data

By adding all daily load profiles together, an average profile can be formed. The load profiles of both categories, public and commercial charging sites, are presented in Figs. 3 and 4, respectively.

For the analysis, especially the peak loads are of great interest. While the energy consumption of public charging is more evenly spread over the entire day, the progression of commercial charging shows a sharp peak around 10 am.

4.3 Optimisation: public charging

The average peak load reduction of two public charging sites is shown in Figs. 5 and 6, respectively. All three cases: the base scenario, the individual optimisation and the field optimisation, are visible. It is discovered that the charging behaviour varies greatly between different sites. Therefore, the average load curves of different charging sites do not provide essential information about the potential of flexibility. That is why the result of two charging sites (Sites R and C) are shown. These two sites are selected because Site R is the one with the least peak shaving potential and Site C is the one with the largest peak shaving potential among the

Table 2 Details of the charging sessions

	Public charging	Commercial charging
no. of charging sessions	20,382	4664
ø parking duration, h	5:05	6:14
ø charging duration, h	3:03	3:42
ø consumed energy, kWh	6.4	5.9

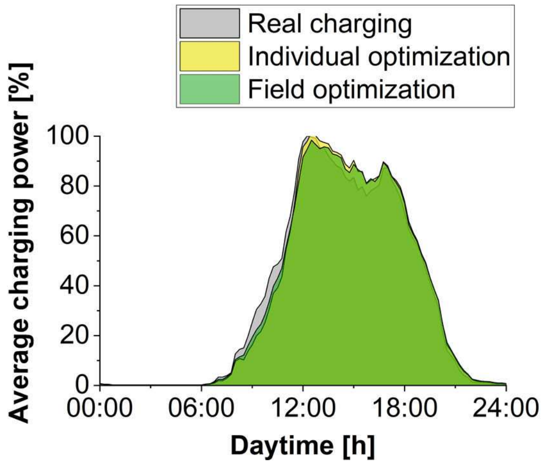

Fig. 5 *Base scenario (real charging) and the optimised results at Site R*

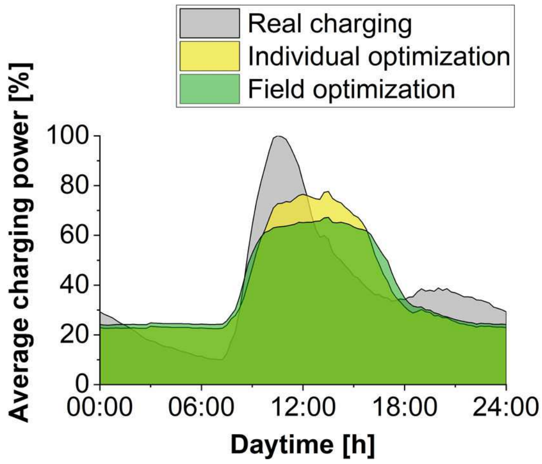

Fig. 6 *Base scenario (real charging) and the optimised results at Site C*

public charging sites analysed in this study. Choosing the two extreme cases, the range of flexibility is conceivable. At Site R, where the average parking time is <2 h, only minor improvements are visible. The individual optimisation decreases the peak load by 4% and the field optimisation by 12% (in Fig. 5). Site C, with an average parking time of around 7 h, on the other hand, shows a completely different situation. Through the individual optimisation, a more even load curve, with a reduction of 21%, can be achieved (in Fig. 6). These effects are further improved through the field optimisation by 42% from the base scenario (Fig. 6).

Fig. 7 examines the peak load values of five different public charging facilities in more detail. The real values are compared with the optimised time series. It turns out that the level of the optimisation potential depends strongly on the average parking duration. The lines show that there is approximately a linear correlation between the parking time and the potential for peak reduction.

4.4 Optimisation: commercial charging

Analogous to public charging, the load profiles of two charging sites are illustrated in Figs. 8 and 9, respectively, showing the average load profiles of two charging sites (Sites S and I). Fig. 8 shows the result from Site S that offers the least load reduction potential among the commercial charging sites. On average, a peak

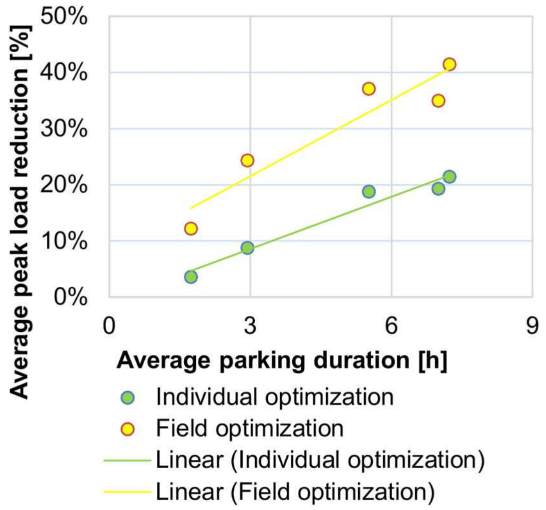

Fig. 7 *Reduction of peak load at five of the public charging sites used in the study. The average peak load reduction is calculated from the base case (real data)*

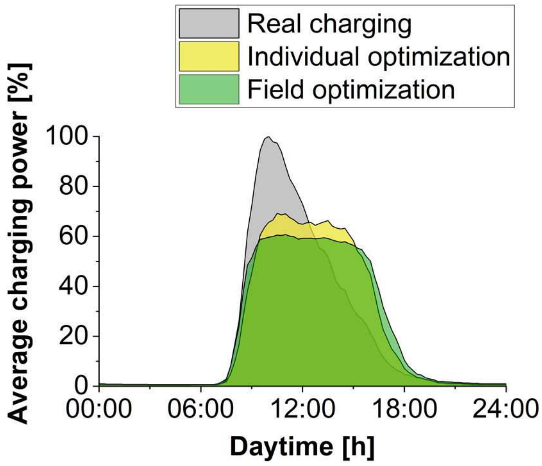

Fig. 8 *Base scenario (real charging) and the results of the optimisation algorithms at Site S that is a commercial charging site*

load reduction of 26% is obtained by the individual optimisation strategy (Fig. 8) in comparison with the base scenario. The field optimisation reduces the peak load by 44% (Fig. 8). Correspondingly, Fig. 9 shows the results of Site I that offers the largest potential for peak shaving. The individual optimisation achieves an average peak reduction of 39% and the field optimisation reaches 55% (in Fig. 9). The grey graphs show the real load profile. The load profiles resulting from the optimisation procedures are shown in yellow and green. It can be seen that a large part of the energy consumption can be shifted to the afternoon by the optimisations.

The average peak load reduction which results from the three analysed larger commercial locations are visible in Fig. 10. It can be seen that the potential for peak reduction between the commercial locations are more similar to each other than at public charging sites, where the average parking times are also at a similar level. Overall, peak loads can be reduced by up to 55% through the field optimisation.

4.5 Summarised results of peak load reduction

Table 3 illustrates the reduction of peak load at all charging sites. The average parking times, charging times and average charged energies are visible. In addition, the average peak reduction for both optimisation algorithms is shown.

5 Discussion

In this section, the results are discussed more in detail.

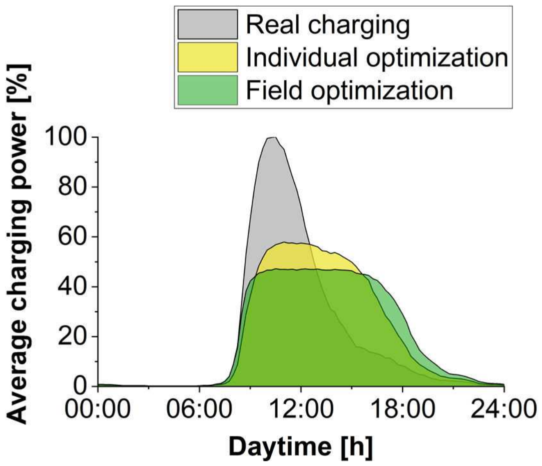

Fig. 9 *Base scenario (real charging) and the results of the optimisation algorithms at Site I that is a commercial charging site*

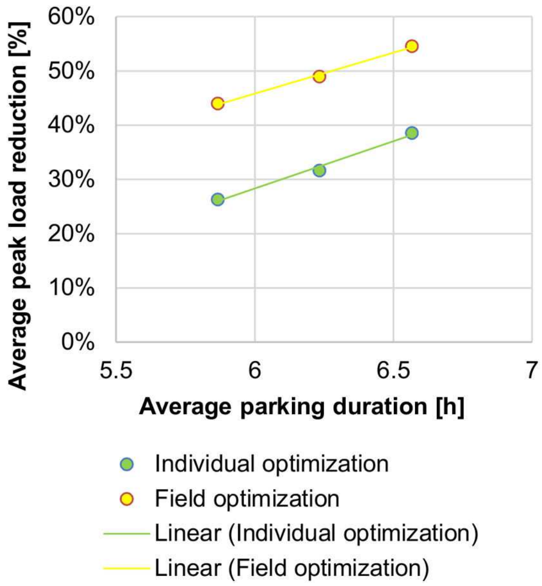

Fig. 10 *Reduction of peak load at three of the commercial charging sites used in the study. The average peak load reduction is calculated from the base case (real data)*

5.1 General data analysis

For both categories (public and commercial charging) the high degree of flexible charging processes shows significant potential for optimisation and peak shaving. Comparing the average parking times with average charging times, the public and commercial data are at a similar level. The average parking times are 2–2.5 h longer than the average charging times. The fact that the parking times are usually much longer than the charging times reduces the need for extremely accurate load forecasting if the load reduction capacity is used, for example in sub-aggregation.

Expecting that the EV owners charge their vehicles overnight at home and also during the day at work or at other public charging sites, the average energy consumption is about 11.3 kWh [22]. Considering that the charging losses are about 11% [22] and the average consumption is about 19.6 kWh/100 km [22], the average driving distance is about 51.3 km/day. A comparison of these values with the average daily distance travelled by all vehicles in Finland of 50 km/day [23] shows that the data used are representative for the whole country. It should be noted that the statistic does not take into account any days on which no charging has taken place, therefore the actual values are slightly lower. It should also be considered that the average distances travelled in urban areas are lower than in rural areas [22]. Due to the fact that the used data comes from the metropolitan region of Helsinki, a range below the national average is not surprising.

Table 3 Summarised results from all charging sites

Site	Ø parking time, h:min	Ø charging time, h:min	Ø energy, kWh	Peak reduction, %	
X	02:56	01:25	6.9	*9*	***24***
C	07:14	04:20	6.8	*21*	***42***
K	07:00	04:30	8.7	*19*	***35***
E	05:31	03:27	5.9	*19*	***37***
R	01:44	01:22	2.7	*4*	***12***
H	06:14	03:42	6.3	*32*	***49***
I	06:34	03:37	5.5	*39*	***55***
S	05:52	03:52	5.7	*26*	***44***

The public charging sites are the sites in bold type.

Peak reduction [%]: the individual optimisation is italic and the field optimisation is bold italic.

5.2 Load profile – real charging data

The charging profiles of public and commercial charging have different characteristics. The commercial charging reaches its peak late in the morning. It can be assumed that most of the company's employees arrive between 9 and 11 am, which explains a significant load increase during this time. Already before midday a significant drop in the consumption of energy can be observed. However, it seems unlikely that many employees will leave work at this time of day. It seems much more realistic, however, that the cars are still parked but the batteries are already fully charged. This means that the peak loads could be reduced by a more evenly charging of the batteries throughout the entire working day.

Likewise, the profile of public charging has a significant load increase during the general office hours. In contrast to the commercial charging curve, the power consumption in the afternoon does not drop much. After 7 pm a further drop in power consumption is noticeable. As a result, it can be assumed that users of public parking facilities therefore use the charging stations for both private and business reasons.

5.3 Optimisation: public charging

The results show that an optimisation does not always bring significant benefits. For the Site R only slight load shifting is noticeable, which brings up the question of whether the additional effort of an intelligent charging system exceeds the benefit of a lower peak load. At Site C, on the other hand, both optimisation approaches show a great shift potential.

While the individual optimisation is able to reduce the average peak load by 20%, the field optimisation results in an improvement potential of 40%. For all locations, the results of the field optimisation are therefore significantly better than those of the individual optimisation. As Fig. 7 shows, there is a strong correlation between the optimisation potential for improvement and the average parking time of the vehicles. If it can be expected that users park their vehicles only for a short period of time, for example in front of a supermarket, the installation of an intelligent charging system seems questionable. For a parking garage, for example at a trade fair site, where vehicles are parked for a longer period of time a great optimisation potential can be expected. Due to the fact that the system is more complex, a cost–benefit analysis should be carried out for every charging site.

One of the boundary conditions in the optimisation is that the customers can charge the same amount of energy that they would charge without the optimisation. With this approach, the charging operator is on the 'safe side', because the quality of service does not suffer. On the other hand, the accurate use of such optimisation requires the knowledge of each plug-out time before the charging starts. On the other side, in reality, if some customers received slightly less energy than they expected, it probably would not lead to remarkable discomfort. It is likely that most affected customers would not even notice a modestly lower SoC during their daily trips.

5.4 Optimisation: commercial charging

A similar result can be obtained for all analysed locations of commercial charging. Due to the fact that many vehicles arrive within a short period of time, the peak of the real charging data is comparatively high. With the help of individual optimisation, the charging can be distributed more evenly over the entire working day. Compared to the results of the public parking sites, the reduction of the peak load for commercial charging is considerably higher. Due to the field optimisation a further reduction is possible. A comparison of the average peak loads shows that field optimisation can reduce these by around 55% (see Fig. 9). The additional potential which can be used compared to the potential of the individual optimisation is relatively small. It should therefore be discussed whether the individual optimisation for commercial parking lots already achieves a satisfying result. Overall, however, there is a very high optimisation potential for both optimisation methods.

5.5 Strengths and weaknesses of the different approaches

All optimisation alternatives represent a trade-off between the resulting benefits and the resulting additional efforts. In the case of individual optimisation, it is necessary that all users provide information about their parking time and the desired amount of energy. It is hard to imagine that this would simply happen without a certain benefit for the customer. Consequently, an incentive system must be developed that motivates users to disclose their behaviour. Furthermore, it should be considered that the individual optimisation can under certain circumstances cause a worse solution compared to the uncoordinated charging process [22]. The field optimisation can prevent this effect, but at the same time causes a much more complex calculation. Unlike the field optimisation, the individual optimisation does not require communication between a central computation unit and the charging stations.

Bearing the above-mentioned benefits of the individual optimisation in mind, this seems more likely to be implemented in a practical charging management application, at least as the first solution. If the charging site possesses the communication capacity is operating close to the limits of power capacity, the charging site can be updated with the field optimisation. As a more complex approach, the field optimisation gives more freedom to include additional parameters in the optimisation.

In this paper, the algorithms are used to compute the best possible scenario (the lowest power peak) within the boundary conditions. In reality, these results can be achieved if

- the arrival and the leaving times of every EV are known and
- if the expected energy to be charged is known.

Since this information is usually not available before a charging process starts, these results are reachable with great difficultly. However, these algorithms can be applied in real life with adjustments including error margins.

In case that only one vehicle has to be charged, a constant charging power over the entire day is the optimum. If, by contrast, it is known that other vehicles will arrive in the afternoon, the charging process for the first car should be completed in the morning. It should also be taken into account that drivers may deviate from their predicted parking times. For example, if a user indicates to park the car for 8 h, the optimal solution might be that the vehicle is not charged until the second half of the parking period. In the event that the driver returns to the car after 4 h to drive to a spontaneous appointment, the battery may still be completely empty. It is likely that the user experience will suffer greatly from this example. For improvement, it should therefore be considered to implement an additional minimum charging power for each vehicle in the system. Emergency rides could thus be covered, but the complexity of the charging system would continue to increase at the same time.

The results of the analysed charging sites clearly show that the respective optimisation should be evaluated for each location. If parking times are relatively short, the benefits of optimisation are relatively small. If, in contrast, the parking times are very long, the individual optimisation provides a large optimisation potential, so that a more complex optimisation can be dispensed with.

The technical requirements of the installed charging points must also be taken into account when deciding for or against field optimisation. If all charging points are connected to the main connection as a star, an optimisation is possible across all charging points. In the event that several bus topologies branch off from the main connection point, a sub-optimisation must take place separately each bus.

6 Conclusion and future work

The main conclusions of this paper and the directions for future work are presented hereunder.

6.1 Conclusion

The paper reveals several insights into the realistic possibilities of smart charging based on real data from Finland. It shows that there is a significant potential for peak load reduction. In addition, this potential has been quantified under realistic boundary conditions at several charging sites.

In this study, it is found out that the average parking time is >2 h longer than the average charging time. This simple finding shows that the power peaks at charging sites can be reduced significantly. Another indicator discovering the potential of EVs in peak shaving is that at commercial charging sites 66% and at public charging sites 47% of the charging sessions are flexible. This means that they are able to provide peak load reduction without a decline in the quality of the charging service.

A relevant finding is that if the parking time is roughly <3 h, there is no margin for peak shaving without decreasing the quality of service. In other words, applying smart charging in such locations does not bring much benefit.

Contrarily, if the average parking time exceeds a duration of $\simeq$3 h, a large optimisation potential can be identified for both presented optimisation approaches. However, this is also dependent on the available charging power.

Through a load shift, the average peak load of a charging site can be reduced by up to 55%. A comparison of location-dependent charging data shows that charging sites at commercial locations have particularly great potential. On the other hand, public charging sites show a strong dependency on the average parking time.

Furthermore, the paper presents two strategies for peak load reduction at charging sites: an individual optimisation and a field optimisation. Generally, the field optimisation achieves better results, but also entails more complexity.

The average driving distances can be derived from the average amount of charged energy. Due to the fact that these values correspond to the general national average driving distances in Finland, the results are very valuable.

6.2 Future work

The used data set consists of about 25,000 charging sessions. In the future, more detailed statistical studies by using hundreds of thousands or more charging sessions will be carried out.

The future work will focus on how the algorithms presented in this work can be used to control charging sessions in real time. In addition, the impact of non-optimised peak shaving on the quality of service will be studied.

In the future, a more detailed analysis of realistic possibilities of the flexibility of EVs in sub-aggregation will also be studied. Additionally, forecasting of EV charging loads and the available flexibility will be considered. Economic aspects of the possible savings related to peak load reduction will also be taken into account.

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8 References

[1] Zahedmanesh, A., Muttaqi, K.M., Sutanto, D.: 'Direct control of plug-In electric vehicle charging load using an In-house developed intermediate control unit', *IEEE Trans. Ind. Appl.*, 2019, **55**, (3), pp. 2208–2218

[2] Daina, N., Sivakumar, A., Polak, J.W.: 'Modelling electric vehicles use: a survey on the methods', *Renew. Sustain. Energy Rev.*, 2017, **68**, pp. 447–460

[3] Pirouzi, S., Aghaei, J., Niknam, T., *et al.*: 'Proactive operation of electric vehicles in harmonic polluted smart distribution networks', *IET Gener. Transm. Distrib.*, 2018, **12**, (4), pp. 967–975

[4] De Gennaro, M., Paffumi, E., Martini, G., *et al.*: 'A pilot study to address the travel behaviour and the usability of electric vehicles in two Italian provinces', *Case Stud. Transp. Policy*, 2014, **2**, (3), pp. 116–141

[5] Union, E.: 'A clean planet for all a European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy', 2018

[6] Lelieveld, J., Evans, J.S., Fnais, M., *et al.*: 'The contribution of outdoor air pollution sources to premature mortality on a global scale', *Nature*, 2015, **525**, (7569), pp. 367–371

[7] European Union: 'Directive (EU) 2018/844 of the European parliament and of the council of 30 May 2018 amending directive 2010/31/EU on the energy performance of buildings and directive 2012/27/EU on energy efficiency', 2018

[8] 'The photo courtesy of Parking Energy Ltd.', 2019

[9] Neaimeh, M., Salisbury, S.D., Hill, G.A., *et al.*: 'Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles', *Energy. Policy.*, 2017, **108**, pp. 474–486

[10] Daina, N., Sivakumar, A., Polak, J.W.: 'Electric vehicle charging choices: modelling and implications for smart charging services', *Transp. Res. C, Emerg. Technol.*, 2017, **81**, pp. 36–56

[11] Zhang, G., Tan, S.T., Wang, G.G.: 'Real-time smart charging of electric vehicles for demand charge reduction at non-residential sites', *IEEE Trans. Smart Grid*, 2018, **9**, (5), pp. 4027–4037

[12] Wei, Z., Li, Y., Cai, L.: 'Electric vehicle charging scheme for a park-and-charge system considering battery degradation costs', *IEEE Trans. Intell. Veh.*, 2018, **3**, (3), pp. 361–373

[13] Kisacikoglu, M.C., Erden, F., Erdogan, N.: 'Distributed control of PEV charging based on energy demand forecast', *IEEE Trans. Ind. Inf.*, 2018, **14**, (1), pp. 332–341

[14] Mahmud, K., Hossain, M.J., Town, G.E.: 'Peak-load reduction by coordinated response of photovoltaics, battery storage, and electric vehicles', *IEEE Access*, 2018, **6**, pp. 29353–29365

[15] Mahmud, K., Hossain, M.J., Ravishankar, J.: 'Peak-load management in commercial systems with electric vehicles', *IEEE Syst. J.*, 2019, **13**, (2), pp. 1872–1882

[16] Mehta, R., Srinivasan, D., Khambadkone, A.M., *et al.*: 'Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure', *IEEE Trans. Smart Grid*, 2018, **9**, (1), pp. 299–312

[17] López, K.L., Gagné, C., Gardner, M.: 'Demand-side management using deep learning for smart charging of electric vehicles', *IEEE Trans. Smart Grid*, 2019, **10**, (3), pp. 2683–2691

[18] Yao, L., Lim, W.H., Tsai, T.S.: 'A real-time charging scheme for demand response in electric vehicle parking station', *IEEE Trans. Smart Grid*, 2017, **8**, (1), pp. 52–62

[19] Hafez, O., Bhattacharya, K.: 'Integrating EV charging stations as smart loads for demand response provisions in distribution systems', *IEEE Trans. Smart Grid*, 2018, **9**, (2), pp. 1096–1106

[20] Rautiainen, A., Repo, S., Jarventausta, P., *et al.*: 'Statistical charging load modeling of PHEVs in electricity distribution networks using national travel survey data', *IEEE Trans. Smart Grid*, 2012, **3**, (4), pp. 1650–1659

[21] MathWorks: 'Mathworks documentation – fmincon', 2019

[22] Fenner, P.: '*Efficient use of the existing real estate infrastructure for electric vehicle charging*' (TU Dortmund University, Germany, 2019)
[23] Rautiainen, A., Markkula, J., Repo, S.*, et al.*: 'Plug-in vehicle ancillary services for a distribution network'. 2013 Eighth Int. Conf. and Exhibition on Ecological Vehicles and Renewable Energies (EVER), Monte Carlo, Monaco, 2013, pp. 1–8