CONTROL OF EV CHARGING TO REDUCE PEAK POWERS IN DOMESTIC REAL ESTATE

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ABSTRACT
The paper discusses electric vehicle (EV) charging control in apartment buildings in cases of high EV penetration. The introduced control method for EV charging utilizes real-time measurements and memorized peak power consumptions to determine a suitable charging power. The aim of the control method is to avoid an unnecessary increase to the peak powers of the whole property, while still allowing EVs to be charged sufficiently. This kind of control method could lead to cost savings if the power-based distribution tariff of distribution system operators (DSO) included a price component based on monthly peak power. Some Finnish DSOs have launched this kind of power-based distribution tariff for small-scale customers also. Simulations indicate that PHEVs can likely be sufficiently charged without increasing the monthly peak powers or controlling other loads of the property when EV penetration is around 40% or less.

INTRODUCTION
The Finnish government has set a target for Finland to have 250,000 EVs by 2030 [1], which is equivalent to an EV penetration of around 10%. However, with the relative growth of EV penetration during the last five years according to [2], this target could be achieved by 2023. It is well known that uncontrolled EV charging can cause problems for power distribution networks [3–5]. Smart EV charging can be optimized from different perspectives, such as minimizing peak loads or electrical energy costs. Depending on the control method, various issues might occur. According to [6], use of real-time energy market pricing for the benefit of EV charging would likely increase the peak loads for the distribution networks. As the pricing information would be available to all customers at once, they would all receive the incentive for turning on loads at the same time. In [5] and [7] the smart charging method to reduce peak loads is based on an assumption where the state of charge (SOC) and departure of every EV is known, which is not typically the case.

In recent years, there has been ongoing discussion in Europe on shifting DSOs’ distribution tariffs in a power-based direction. This means that in addition to or instead of traditional basic (€/month) and volumetric charges (€/kWh), there would be a tariff component (€/kW) based on peak power of some time period, i.e., the latest year or month. Power-based distribution tariffs are enabled by a rollout of smart meters. In Finland, the electricity consumption of over 99% of network customers including households is measured by smart meters [8]. As some distribution system operators in Finland have already started using power-based distribution tariffs for small-scale customers, suboptimal control of EV charging could cause an unnecessary increase in operational costs. Therefore, it is reasonable to investigate options to charge EVs with a minimal increase in the peak powers.

EV charging peak load management in an apartment building could result in cost savings for each apartment owner if the energy community model is used; the apartments form an energy community, which makes one contract with the energy retailer and another with the DSO. Each apartment should have its own electricity meter so the customers can divide the cost of all electricity purchased by the whole building from the grid. The law requires that every customer should have the possibility to tender out energy retailers, so the energy community model is possible only if all the apartment owners accept the energy community model.

This paper investigates the EV charging control method introduced in [9], which aims to keep total peak loads at minimum while charging EVs alongside an apartment building. Different scenarios are examined to evaluate the effects of various parameters and the general accuracy of the results. The paper includes discussion and simulation results.

THE CONTROL METHOD
The monthly peak power will likely be a popular basis for the power-based fee charged by DSOs in the future. By using fuse or cable capacity as the only limiting factor for EV charging, the peak powers of the whole property might increase significantly and thus the operational costs of EV charging might also increase.

The introduced control method is based on memorizing the peak power consumption of the month, measuring the present power consumption of the building, and then calculating the available power capacity. EV charging power should then be adjusted according to the available capacity. The main principle of the system structure is illustrated in Fig. 1 and the operation of the control method is illustrated in Fig. 2. This kind of control method is possible in mode 3 EV charging according to the standard IEC 61851-1, where the charging station can restrict and adjust the maximum AC charging current (per phase) between 6 A and 80 A. In Fig 2., the feeder limit is there to ensure that the charging power would not exceed the
limits of the cable or fuse of the EV charging feeder. To prevent the previous month from affecting the peak power of the new month, the highest memorized peak power should be reset at the beginning of each month. However, the resetting method has a clear impact on the energy that can be charged to EVs. By setting the starting value of the memorized peak power too low, there might not be enough free capacity to charge EVs. And by setting the starting value too high, the peak powers of the month might increase more than is necessary. In the subsection “Resetting methods of the memorized monthly peak power,” four simple resetting methods are investigated.

![Figure 1. The basic setup of the control method.](image1)

![Figure 2. Simplified block diagram of the control method.](image2)

**SIMULATION DATA AND MODELING**

**Case description**

The investigated case is called “Tammela,” which is an apartment building built in 1980 in Finland. Between 2013 and 2015, various renovations were made, which resulted in a 67% reduction in purchased energy. However, the share of electrical energy increased, resulting in electrical energy consumption increasing by around 30%. This was caused by the installation of exhaust air heat pumps, where produced heat energy replaces the purchase of energy from district heating.

Simulations were carried out based on long-term electricity consumption measurements made in the apartment building. This consumption data was measured from 2013–2016 at one-hour intervals. The apartment building has 53 parking spots. The property does not include any EV charging points at present in real practice, so all 53 charging points, one for each parking spot, are modeled for simulations done in this study. Simulations focus on a charging power of 3.7 kW per charging point, which should be roughly suitable for almost every commercial EV.

**EV load modeling**

According to [2], the number of plug-in hybrid electric vehicles (PHEVs) is increasing much more rapidly than full electric vehicles (FEVs). With the average relative increase of PHEVs and FEVs during the last five years, there would be only around 4%–5% FEVs in Finland when the EV penetration reaches 100%. Therefore, simulations focus on PHEVs in this paper.

The average travel distance per passenger car was 14,000 km/a in Finland in 2017, according to Statistics Finland [10]. This equals around 38.4 km/day. To simplify the simulations, it is assumed that all PHEVs have the same maximum energy storage capacity of 8.0 kWh and energy consumption of 280 Wh/km. These are based on the most common PHEVs in Finland in [11] and data tables found in [12]. However, the real battery capacities and energy consumptions depend on the car and the operation conditions, so the simulations are repeated with slightly different parameters to improve the reliability of the results.

The case is an apartment building and, therefore, the EVs are assumed to depart in the morning and return later in the evening. Two different schedule types are investigated. The first assumes every EV departs at the same time and returns at the same time, e.g., depart at 0600 and return at 1900. This represents the worst-case scenario from the peak power point-of-view. The other schedule type includes random variations in the arrival and departure times. This random variation is normally distributed, where the median is 0 and the standard deviation is 2.0 hours. The same variation is added to both arrival and departure time so that the available charging time of each EV remains the same. The highest delay and advancement was 5 hours. Four other time variations were made based on this, but the variation is divided accordingly to get maximum delays or advancements of 1, 2, 3, or 4 hours. The effect of available charging time is investigated separately.

There are also three different driving schemes investigated in the simulations. The same driving scheme is assumed to occur daily through the whole year. The first driving scheme assumes every EV drives exactly 38.4 km/day. The second and the third driving schemes assume the average travel distance of EVs stays 38.4 km/day, but the travel distances varies between 0 km and 100 km with a standard deviation of 10 or 20 km, respectively. The needed charging energy of EVs can then be calculated using the energy consumption and the limitation set by the maximum usable battery capacity.

**System modeling**

Simulations use a time step of 15 minutes, which allows a whole year to be simulated within a reasonable amount of
time. In order to use the measured consumption data of the apartment building in the simulations, an interpolation was necessary to change the time step of 1 hour to 15 min. This was done by simply dividing each of the 1-hour energy consumptions evenly into four parts. Power loss in EV charging is assumed to be 10%, which is reasonable according to [13]. Acceptable charging speed for the EV is assumed to remain at the maximum during the whole charging time, which is relatively accurate for the slow charging of lithium-ion batteries [3].

In the simulations, for simplicity’s sake the total available power capacity for EV charging is distributed for every EV that is connected to a charging point at the time. As there are often multiple EVs charging simultaneously and only a limited amount of available charging capacity, some of the EV charging currents fall below 6 A, which is not generally supported by the EVs. One solution to this would be to suspend some of the EV charging sessions so that there would be enough power for all active EV charging sessions. The suspended EV charging sessions could be rotated to achieve even distribution of charging energy. If the EVs would support all charging powers between e.g. 1.8 – 3.7 kW, roughly all available EV charging power capacity could be used as long as it is more than the said minimum charging power of 1.8 kW. The further investigation of this issue is, however, left out of this paper.

SIMULATION RESULTS

Resetting methods of the memorized monthly peak power

Four simple resetting methods are investigated, where the starting value of memorized peak power is

1. 0,
2. the apartment building power consumption of the final hour of the previous month,
3. a fraction of the previous month peak power of the apartment building, or
4. based on the previous month peak power and the relative monthly peak power difference of the previous years.

The resetting method could also use statistics from previous years more sophisticatedly to determine the new memorized peak power for each month. However, this was left out from this paper as there have been multiple renovations in this apartment building, which have affected the electrical energy consumption, as mentioned before.

According to the apartment building consumption data from 2013–2016, the highest decrease in monthly peak powers of two consecutive months was 27.4%. Therefore, the multiplier for the third resetting method was chosen to be 0.7. The fourth resetting method is similar to the third except that there is an individual multiplier for each month. Therefore, a maximum relative difference in monthly peak powers for each month was calculated. These were then rounded down to one decimal place resulting in 0.8, 0.8, 0.7, 0.7, 0.7, 0.8, 0.9, 1.0, 1.1, 0.9, 1.1, and 0.8 for January to December, respectively. More accurate multipliers would likely give better results but also increase the risk of unnecessary increase in monthly peak powers. The ideal situation was also simulated, where the upcoming peak power of the apartment building of the new month is assumed to be perfectly forecasted and set as the starting value for the memorized peak power.

The impacts of these resetting methods were simulated in different EV penetrations using the 2016 consumption data of the apartment building. In these simulations the available charging time was 1900–0600 and the needed charging energy of each EV was 8.0 kWh. Results are shown in Fig. 4 and Table I. The uncharged energy shown in the following figures describes the proportion of the total charging energy need of the EVs that were not charged. The maximum EV penetration, where over 99% of the total energy need of all EVs were charged without increasing the peak powers of the apartment building, is referred to as “maximum EV penetration without peak power increase” for the rest of the paper.

![Figure 4. Simulation results with different starting values of the memorized peak power.](image)

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>The maximum EV penetrations without peak power increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting value for the memorized peak power</td>
<td>EV penetration</td>
</tr>
<tr>
<td>Zero</td>
<td>28.3%</td>
</tr>
<tr>
<td>The power of the latest hour of the previous month</td>
<td>28.3%</td>
</tr>
<tr>
<td>0.7 x the peak power of the previous month</td>
<td>35.8%</td>
</tr>
<tr>
<td>Varying percent of the peak power of the previous month</td>
<td>39.6%</td>
</tr>
<tr>
<td>Perfect forecast of the upcoming peak power of the current month</td>
<td>43.4%</td>
</tr>
</tbody>
</table>

Simulations indicate that excluding the perfect forecast, the fourth resetting method, where the starting value of memorized peak power is based on a fraction of the memorized peak power from previous years, clearly gives the best results. This resetting method was selected to be used in the simulations of the following subsections. The ideal situation, where the upcoming peak power of the month is perfectly forecasted, is notably better, but the selected resetting method reaches close to the same maximum EV penetration without peak power increase.
The effect of available EV charging time

To evaluate effects of the available charging time on charged energy, simulations were carried out using 14, 12.5, 11, 9.5, and 8 hours as the time that EVs can be charged per day. The daily charging energy need were 8.0 kWh for each EV. These results are shown in Fig. 5. The maximum EV penetrations without peak power increase were 47.2%, 43.4%, 39.6%, 35.8%, and 30.2% for the scenarios that had available EV charging time 14, 12.5, 11, 9.5, and 8 hours, respectively.

Simulations were also conducted on scenarios where the EV arrival and departure times included some variations, as mentioned in “EV load modeling.” The available EV charging time for these scenarios was chosen to be 11 hours and the average arrival and departure time to be 1900 and 0600, respectively. These results have been illustrated in Fig. 6. The maximum EV penetrations without peak power increase were 39.6%, 43.4%, 45.3%, 49.1%, 50.9%, and 54.7% for the scenarios that had charging time variations of 0, 1, 2, 3, 4 and 5 hours, respectively. It can be seen that increased variation in EV charging schedule gives similar results to longer available charging time, which was expected.

The effect of the energy need of the EVs

To evaluate effects of the charging energy need of the EVs, simulations were carried out using the energy need based on the randomized daily travel distances of PHEVs mentioned in “EV load modeling” section and different fixed charging energy needs of PHEVs. The arrival and departure times were chosen to be 1900 and 0600, respectively. When the average daily travel distance is divided evenly for every PHEV, the usable battery capacity of PHEVs will be the limiting factor of the charging energy need. Therefore, longer driving distances will not increase the energy need of a PHEV, but a shorter driving distance may decrease the energy need of the PHEV. Therefore, more randomized travel distances results in lower total energy need of the PHEVs and thus more PHEVs can be charged without peak power increase. This can be seen from Fig. 7, where the scheme with more randomized travel distances will result in lower uncharged energies. The maximum EV penetrations without peak power increase were 39.6%, 41.5%, and 43.4% for the scenarios that had randomized driving distances with a standard deviation of 0, 10, and 20 km, respectively.

The effect of the actual charging energy need of PHEVs is illustrated in Fig. 8. The maximum EV penetrations without peak power increase were 39.6%, 32.1%, 26.4%, 22.6%, and 18.9% for the scenarios that had required EV charging energy 8.0, 10.0, 12.0, 14.0, and 16.0 kWh, respectively.

EV charging using different consumption data of the apartment building

To investigate the reliability of the results, simulations were also carried out using the consumption data of the apartment building from 2013–2016. The simulation used the slightly randomized EV driving scheme mentioned earlier: average arrival time 1900, average departure time 0600, and ±2 as the maximum variation in arrival and departure times. The results have been illustrated in Fig. 9. The maximum EV penetrations without peak power increase were 39.6%, 41.5%, and 43.4% for the scenarios that had randomized driving distances with a standard deviation of 0, 10, and 20 km, respectively.
increase were 47.2%, 41.5%, 39.6%, and 35.8% for the years 2016, 2015, 2014, and 2013, respectively.

The annual growth in electricity consumption of the apartment building during 2013–2016 was around 10%. The average monthly peak power also increased each year about 6%. The increase in electricity consumption and the increase in monthly peak powers seems to correlate with the maximum EV penetration without peak power increase. The higher the electricity consumption and monthly peak powers an apartment building has, the more EVs can be charged, when the EV charging power is limited with this kind of control method.

Figure 9. Simulation results using building consumption data from years 2013–2016.

CONCLUSION AND FUTURE WORK

According to the simulation results presented in this paper, EVs could be charged alongside an apartment building relatively well without notably increasing the peak powers, when using the introduced control method. The maximum EV penetration, where PHEVs can be charged at least 99% on average without peak power increase, would be up to around 30 – 50%. It can be seen that in case of 100% PHEV penetration, only around 25 – 35% of the energy need of PHEVs were left uncharged.

There are multiple assumptions and simplifications, which might affect the results one way or another. Also, the electricity consumption of apartment buildings, which is a key factor in this study, varies from case to case and year to year and thus has an impact on the results. The impacts of FEVs are also left out of this study. However, these simulations are somewhat pessimistic, because EV charging is assumed to occur only at the apartment building. The more EV charging occurs at the workplace and the more EVs are charged at fast charging stations, the less charging needs to be done at the residential area.

Future work could investigate smart options to increase peak power only when necessary to allow more EVs to be charged sufficiently. The EV charging outside of residential areas should also be assessed so that the required EV charging energy demand could be estimated more accurately. Future work should also confirm that the FEVs would have always enough energy to carry on after a night of charging when using this kind of control method. Modeling could also be improved in future studies by using, for example, the results of the national travel survey data, where real departure and arrival times are recorded, or by taking into account that charging powers under 1.8 kW are not accepted.

REFERENCES