Smart Electric Vehicle Charging Scheduling at Capacity Limited Charging Sites

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Abstract

Simultaneous charging of electric vehicles (EV) may lead to problems in distribution grids and in the electric infrastructure at charging sites. An alternative to investing in new capacity is to control the charging power to each EV, so called *Smart Charging*. In this paper, we propose two different smart charging scheduling methods aiming at reducing maximum power at a charging site and thereby avoiding violation of the capacity limit: A rule-based algorithm, which is easy to implement, and an optimization-based model, which requires information about the EV drivers' preferences. The latter can utilize flexibility by prolonging the charging session. We assume that information is revealed gradually, allowing us to perform iterative planning in a rolling horizon. In a case study, we analyze how the two smart charging methods are able to reduce the maximum power needed and how they perform in delivering the charging demand in situations where the capacity is limited. We find that both Smart Charging methods reduce maximum power considerably, but that the optimization-based method outperforms the rule-based in all datasets. Further, by including storage and local solar generation, both methods lead to improvements, and the difference between the methods decreases. We also analyze how well the two methods can deliver the charging demand in cases where the maximum power is given. They perform equally good when the power limit is high or very low, otherwise the optimization-based method outperforms the rule-based. Finally, as a benchmark, we calculate optimal solutions under perfect foresight. The findings indicate that our optimization-based method delivers solutions close to the ones with perfect foresight.

Keywords: Electric vehicles, Optimization, Smart charging, Smart Grids

1. Introduction

According to statistics by the International Energy Agency (IEA) [1], the transport sector currently accounts for about 23 % of total energy-related CO2 emissions. This is expected to increase by nearly 50% within 2030 and more than 80 % by 2050 in absence of new policies. In Norway, the authorities have introduced strong incentives to promote EVs. The incentives include exemption from import tax and VAT, free toll roads and parking and access to bus lanes to mention a few [2],[3]. Because of these policies, Norway has the largest number of EVs per capita in the world. In 2015 more than 20% of all new vehicles sold were 100 % electric, and by the end of September 2015, Norway had more than 74,000 EVs out of a total of 2,500,000 (battery EVs and plug-in hybrid EVs) [4], [5], [6].

It is well documented that large scale integration of EVs in the power system may lead to challenges at different levels of the power system [7]–[10]. In Norway, we are already starting to experience such situations [11]. Uncontrolled simultaneous charging can give voltage deviations or grid congestions, which coincides with morning peak and afternoon peak, respectively. This happens especially when charging at work and at home and in any case increases the need for capacity reinforcements both in the distribution grid (e.g. transformers and lines/cables) and in the electricity system related to buildings and charging sites (cables and fuses). These enforcements are expensive and will probably have small utilization factors. An alternative to investments in new capacity is to implement separate battery storages, potentially in combination with local generation like solar photo voltaic panels (PV) [12]. Another alternative is to control the charging processes like we suggest in this paper. It is documented in [13] that up to 70 % of the incremental investment costs can be avoided. However, a crucial question is how to design optimal charging strategies [9].

An extensive number of recent articles focus on this issue. They have different actor perspectives which briefly can be divided into system operators ([8], [10], [14]–[18]), aggregators and fleet operators ([19]–[24]) and EV users ([25], [26]). Furthermore, the different articles have different objectives, like cost minimization ([19], [22], [26]–[28]), maximization of renewable generation utilization ([29]–[31]), power loss minimization ([10], [14], [32]) and load variation minimization ([33]–[35]).

The control methods can basically be divided into direct and indirect control ([36], [37]), also denoted centralized and decentralized control. Indirect control is when a third party sends a signal, for example a price, and a customer, like an EV owner, responds to this signal ([38], [39]). In this case the EV owner makes the decision on how to respond. A review of indirect control methods is given in [22].

With direct control a centralized party remotely controls the charging power to an EV. Contrary to indirect control, direct control means centralized decision making. A recent review of direct control scheduling methods for integrating plug-in electric vehicles in power systems is given in paper [40]. They divide the literature based on mathematical optimization methods: Conventional methods like linear and non-linear programming, quadratic programming, mixed integer programming and dynamic programming, and meta-heuristic approaches like genetic algorithms and particle swarm optimization.

In this paper, we focus on direct control methods applied on a charging site with capacity limits. Our goal is to develop and evaluate models that can work in a real life setting. For that reason, we do not assume perfect foresight, in contrast to many of the articles referenced above, but make decisions based on available information. Since the information is revealed gradually, we plan iteratively according to a rolling horizon. We propose two different models, both providing solutions where the capacity limit is not violated. The first is a simple rule-based algorithm, while the second is based on optimization, where the objective is to maximize the delivered EV charging demand and also to distribute potential deviations between the EVs.

Our main contribution is three-fold:

- We propose two different smart charging scheduling methods for charging sites with capacity limits
- Our charging decisions do not anticipate perfect information, but are based on information that is available at the decision time
- We perform a case study and analyse the properties of the two methods in different situations, alone and in combination with battery storage and local solar PV generation

Since our objective is to propose models that can support operational decisions, we do not analyze how a charging site should be optimally designed. Moreover, we do not perform economic analyses, although the models may be used for such purposes.

The remainder of the paper is organized as follows: Section 2 outlines the charging site model and the smart charging methods. The mathematical formulations are presented in Section 3, while Section 4 contains the case study.

2. The charging site model and the scheduling methods

Our focal entity is a charging point manager (CPM) [41], who controls the charging process at a charging site. We define a charging site as a location where one or multiple EVs can charge their batteries. This broad definition covers home charging, parking lots and commercial charging sites. The charging site is equipped with one or multiple charging points, where EVs can connect. A charging point is characterized with a maximum charging power (kW), and we assume that the charging power can be scheduled to any level between 0 and the maximum. The charging site has a total capacity limit (maximum power) for the electricity imported from the grid. Such a limit can be a technical limit (fuse, substation transformer capacity, voltage level or congestion in overlying grid) or economic (tariff constraint).

We introduce the concept of prioritized charging, meaning that in cases with limited total capacity, some charging points are prioritized above others [42]. An EV will arrive, connect to a charging point, charge, disconnect and finally depart. We do not anticipate that this information is available in advance - it will be revealed gradually during the day.

In events of charging site capacity limitation, the problem is to schedule the charging, i.e. decide the power to each charging point, in such a way that the limitation is not violated.

In addition to the charging points, the charging site can have one or multiple renewable generation units, producing electricity from sun or wind. Such generation is modelled as uncontrollable, and will influence the charging decisions. Finally, we assume that the charging site can have one or multiple separate storage units, like battery banks. Their main purpose is to increase the probability that the EV drivers' charging demands are fulfilled, to avoid investments in higher total capacity and to utilize the renewable electricity generation.

Fig. 1 illustrates the total charging site model, including the charging points (CPs), storage units (SUs) and generating units (GUs). The storage and generating units are within a dashed rectangle to illustrate that these are optional in the model. The fuse symbol illustrates the capacity limit for the charging site.

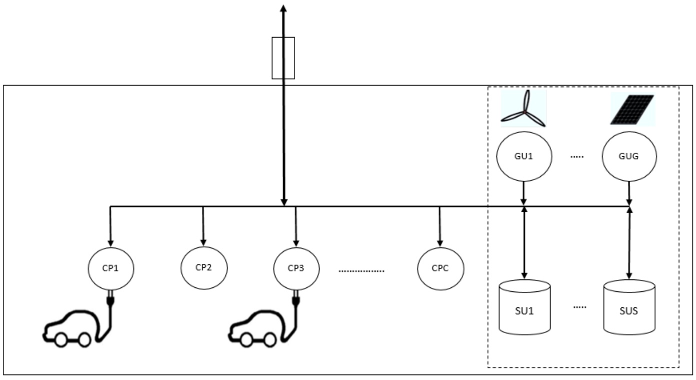

Fig. 1. A general representation of the charging site

The starting point for this paper is that uncontrolled EV charging will break the capacity limit and hence lead to an infeasible situation. We propose and analyze two different scheduling methods: a rule-based method and an optimization-based method. The term scheduling covers both control of the EV charging process, which we denote *Smart charging*, and control of the charging and discharging of the storage.

3. The charging site model and the scheduling methods

3.1 Rule-based method

The rule-based scheduling method is myopic, meaning that it only cares about the "here-and-now" situation without looking backwards in history or forward into the future. It does not require additional information from the EV driver, and hence is easy to implement.

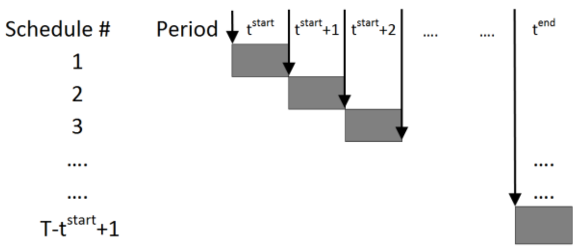

Fig. 2. Scheduling process for the rule-based method

Fig. 2 illustrates the planning process for the rule-based method. When the first period (t^{start}) is entered, we receive information about connections and generation in this period, illustrated by the left arrow. We make schedule number 1, valid for period t^{start}, and implement this.

Next, when period $t^{start}+1$ is entered, we receive new information (disconnections of EVs, connected EVs that are fully charged, new connections for period $t^{start}+1$ and generation in $t^{start}+1$). Based on this information, we make schedule number 2 valid for period $t^{start}+1$, and implement this. The process is repeated through all the periods until period t^{end}. Note that when a connection is allocated to a period, we use the next period after the connection time. By for example having periods with the time resolution of one minute and a new EV is connected at 08.01.32, the connection period will be the period from 08.01 to 08.02. Likewise, the disconnection is allocated to the period prior to the disconnection time. Consequently, we have full information about current period.

In cases where a capacity problem exists, the rule-based method will first try to discharge storage units if possible. If the capacity problem still exists, it will regulate down the charging power for the normal mode charging points. Each charging point will be regulated evenly (with equal fractions of reduction), until the capacity problem is relieved. If there still is a problem when the normal mode charging points are regulated down to 0 power, the same procedure will be repeated for the priority mode charging points. A flow chart for the method is shown in Fig. 3.

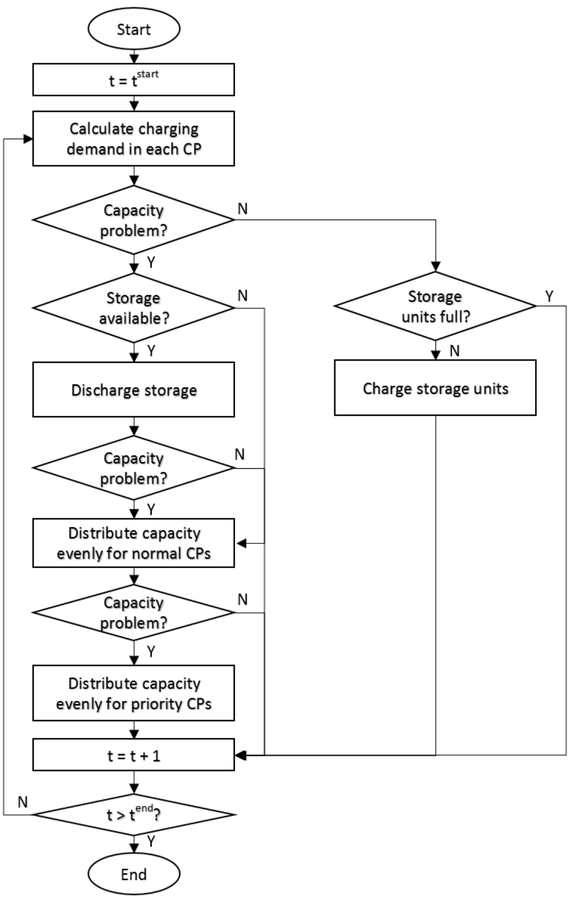

Fig. 3. Flow chart for the rule-based scheduling method

3.2 Optimization-based method

In a typical charging session, an EV starts charging when it is plugged in, and often the charging is completed before the vehicle departs [28]. Such cases represent flexibility, since the vehicle could have been charged in later periods, and the EV owner would still be satisfied. In the optimization-based method, this flexibility is utilized by moving some of the charging to later periods. Then the target is to increase the total delivered charging demand, compared to the rule-based method. To get information about available flexibility, we assume that the EV driver submits his preferences regarding departure time and charging volume in kWh, alternatively km or % of battery capacity ([19], [43]). Technically this may be done through an app. For simplicity reasons we assume that the EV drivers reveal their true preferences. This might be obtained through a price model where the driver is compensated for being connected more than the minimum needed periods, but this is outside the scope of this article. Compared to the rule-based method we are now able to look into the future for the already connected EVs and to use the additional information to make smarter decisions. The mathematical formulation of the optimization-based method is presented in section 4.

The planning process for the optimization-based method is similar to the process for the rule-based method, see Fig. 2. Unlike the rule-based method, we now in addition receive information about preferred disconnection period and charging demand. Schedule number 1 will now be valid for all the periods between t^{start} and t^{end}, but we implement this schedule only for period t^{start}. Similarly, we step through all the periods. Each time a new period is entered, we receive new information and make a schedule for all periods between current period and t^{end}. The schedule is implemented only for the current period.

4. Mathematical formulation of the optimization-based method

This section defines the mathematic model for the optimization-based method. We first list all sets, subsets, indices, parameters and variables. Then, we formulate the model, starting with the objective function, followed by the constraints.

4.1 Sets, subsets and indices

C	Set of charging points, indexed by c
$C^{pri} \subset C$	Subset of charging points in priority mode
$C^{norm} \subset C$	Subset of charging points in normal mode
T	Set of time periods, indexed by t
L	Set of storage units, indexed by l
G	Set of generating units, indexed by g
Y	Set of charging sessions, indexed by y
$T^{y} \subset T$	Subset of time periods from start time to end time in charging session y

4.2 Parameters

α	Weight for expected state of charge deviation in objective function
β	Weight for smoothing term to distribute charge deviations between charging poi
γ	Weight for minimizing export (sale of surplus electricity) in the objective functi
η	Weight for minimizing discharging of storage units in the objective function
θ	Weight for maximizing EV charging in the objective function
φ	Weight for maximizing storage charging in the objective function
P^{pri}	Penalty for not meeting charging demand for charging points and charging sessi
P^{norm}	Penalty for not meeting charging demand for charging points and charging sessi

N	Number of periods in one hour
X^{cap}	Capacity limit for electricity to (and from) charging site [kW]
X_c^{max}	Maximum charging power in charging point c [kW]
$T_{c,y}^{start}$	Start time for charging in charging point c in charging session y [period number
$T_{c,y}^{end}$	End time for charging in charging point c in charging session y [period number]
$E_{c,y}$	Demanded charging energy in normal mode for charging in charging point c in c
$M_{c,y}$	Charging mode for charging point c in charging session y (“Priority” or “Norma
$O_l^{\min}$	Minimum storage state of charge for storage unit l [kWh]
$O_l^{\max}$	Maximum storage state of charge for storage unit l [kWh]
Q_l^{in}	Maximum charging capacity for storage unit l [kW]
Q_l^{out}	Maximum discharging capacity for storage unit l [kW]
A_l^{in}	Efficiency factor for charging storage unit l
A_l^{out}	Efficiency factor for discharging storage unit l
$I_{g,t}$	Intermittent electricity generation from generating unit g in period t [kWh/perio
t_{curr}	Current period

4.3 Variables

$\chi_{c,t}$	Charging power in charging point c in period t [kWh/period]
$\varepsilon_{c,t}^{sod}$	State of delivered charging energy to charging point c in the end of period t [kWh]
$\sigma_{l,t}^{in}$	Charging power to storage unit l in period t [kWh/period]
$\sigma_{l,t}^{out}$	Discharging power from storage unit l in period t [kWh/period]
$\sigma_{l,t}^{soe}$	State of energy for storage unit l in the end of period t [kWh]
$\Delta_{c,y}^{pri}$	Deviation between delivered and demanded charging in priority mode for charging point c and charging session y [kWh]
$\Delta_{c,y}^{norm}$	Deviation between delivered and demanded energy in normal mode for charging point c and charging session y [kWh]
χ_t^{import}	Electricity amount purchased from the grid in period t [kWh/period]
χ_t^{export}	Electricity amount sold back to the grid in period t [kWh/period]
δ_t^{import}	Binary variable equal to 1 if the system is importing in period t, else 0
δ_t^{export}	Binary variable equal to 1 if the system is exporting in period t, else 0
$\delta_{l,t}^{in}$	Binary variable equal to 1 if storage unit s is importing in period t, else 0
$\delta_{l,t}^{out}$	Binary variable equal to 1 if storage unit s is exporting in period t, else 0

4.4 Objective function

The objective function contains six terms: 1) a penalization of expected deviation from meeting the EV drivers’ charging demand over the planning horizon, 2) a distribution of the deviations between the EVs, 3) a minimization of the surplus electricity sales back to the grid in the next period, 4) a minimization of the storage unit discharging power in the current period, 5) a maximization of the charging power to the EVs in current period and 6) a maximization of the storage unit charging power in current period.

$$\begin{aligned} \min z = {} & \alpha \sum_{c\in C} \sum_{y\in Y} \left(P^{pri} \Delta_{c,y}^{pri} + P^{norm} \Delta_{c,y}^{norm} \right) + \beta \sum_{y\in Y} \left[\sum_{c\in C^P} \left(\frac{\Delta_{c,y}^{pri}}{E_{c,y}} \right)^2 + \sum_{c\in C^N} \left(\frac{\Delta_{c,y}^{norm}}{E_{c,y}} \right)^2 \right] \\ & + \gamma \chi_{t^{curr}}^{export} + \eta \sum_{l\in L} \sigma_{l,t^{curr}}^{out} - \theta \sum_{c\in C} \chi_{c,t^{curr}} - \varphi \sum_{l\in L} \sigma_{l,t^{curr}}^{in} \end{aligned} \tag{1}$$

The first term sums the deviations $\Delta_{c,y}^{pri}$ and $\Delta_{c,y}^{norm}$ for all charging points *c* and charging sessions *y*, multiplies with the respective penalty factor P^{pri} and P^{norm} and finally multiplies with the deviation weight α.

The second term is a smoothing term which sums the squared relative charging demand deviations $\left(\frac{\Delta_{c,y}^{pri}}{E_{c,y}} \right)^2$ and $\left(\frac{\Delta_{c,y}^{norm}}{E_{c,y}} \right)^2$ over all charging points and charging sessions multiplied with the smoothing weight β. This element aims at distributing the deviations between EVs. Without this element, the model would be indifferent to how to distribute the deviation. Hence, in a situation with two equal EVs (i.e. with equal charging demand, maximum power and disconnection period) the model might allocate all the deviation to one of the EVs. By including the smoothing term, the model will distribute the deviation evenly between the two EVs.

In situations where the model is able to deliver all charging demand, the two first elements will equal zero.

The third term multiplies the sales of electricity back to the grid $\chi_{t^{curr}}^{export}$ for current period with the weight for sales γ. This element will only be active in cases that include storage units or generation. Since we have a rolling planning horizon, current period will always mean the first period in the remaining horizon, i.e. the period for which we are going to implement the decisions.

The fourth term sums the discharging power $\sigma_{l,t^{curr}}^{out}$ from storage unit l in current period over all storage units and multiplies with the weight η.

The fifth term sums the charging power $\chi_{c,t^{curr}}$ in all charging points in current period. This term is needed to force the model to utilize as much as possible of the available charging capacity in the current period. Without this term, the model could choose to delay charging when making a plan early in the planning horizon. Then, when new EVs connect, the capacity might be limited and a deviation could be unavoidable.

The last term sums the discharging power $\sigma^{in}_{l,t^{curr}}$ from storage unit l in current period over all storage units and multiplies with the weight φ.

Since the main target with the model is to minimize charging demand deviations, the α should be the largest of the weight parameters.

4.5 Constraints

Charging site constraints - In each period t total electricity imported to χ_t^{import} or exported from χ_t^{export} charging site, must balance sum charging power to each charging point $\chi_{c,t}$ and storage unit $\sigma^{in}_{s,t}$, minus discharging of storage units $\sigma^{out}_{s,t}$ and generation for generation units $I_{g,t}$:

$$\chi_t^{import} - \chi_t^{export} = \sum_{c \in C} \chi_{c,t} + \sum_{s \in S} \sigma^{in}_{s,t} - \sum_{s \in S} \sigma^{out}_{s,t} - \sum_{g \in G} I_{g,t}, \ \ t \in T \tag{2}$$

In each period the charging site will either import or export:

$$\delta_t^{import} + \delta_t^{export} \leq 1, \quad t \in T \tag{3}$$

Total electricity to or from charging site must be below capacity limit:

$$\chi_t^{import} \leq \delta_t^{import} X^{cap}, \quad t \in T \tag{4}$$

$$\chi_t^{export} \leq \delta_t^{export} X^{cap}, \quad t \in T \tag{5}$$

Charging point constraints - We define periods according to Fig. 4: An EV connects to a charging point c in the start of period $T^{start}_{c,y}$ and disconnects in the end of period $T^{end}_{c,y}$ (period 2 and 7 in the example), where y is the charging session. Charging is possible in all periods from (and including) $T^{start}_{c,y}$ to (including) $T^{end}_{c,y}$. In the figure, these periods are marked in grey. A possible schedule is illustrated with dark grey.

Fig. 4 Illustration of the connection and disconnection process

Charging to each charging point must be below maximum power X_c^{max} for each charging point:

$$\chi_{c,t} \leq X_c^{max}, \quad c \in C, t \in T \tag{6}$$

State of delivery ε_c^{sod} to an EV in the end of current period is equal to state of delivery in the previous period plus charging during current period divided by the number of periods in one hour N.

$$\varepsilon_{c,t}^{sod} = \varepsilon_{c,t-1}^{sod} + \chi_{c,t} / N, \quad c \in C, t \in T(y) \tag{7}$$

State of delivery deviation $\Delta_{c,y}$ for charging point c and charging session y is defined as the difference between demanded $E_{c,y}$ and real state of delivery for priority and normal mode charging points, respectively:

$$\Delta_{c,y}^{pri} = E_{c,y} - \varepsilon_{c,t}^{sod}, \quad c \in C^{pri}, t = T_{c,y}^{end}, \tag{8}$$

$$\Delta_{c,y}^{norm} = E_{c,y} - \varepsilon_{c,t}^{sod}, \quad c \in C^{norm}, t = T_{c,y}^{end}. \tag{9}$$

Storage unit constraints - For storage unit l we define efficiency factors for charging and discharging, A_l^{in} and A_l^{out}, respectively. The state of energy, i.e. the storage content, $\sigma_{l,t}^{soe}$, is dependent on the state of energy in previous period $\sigma_{l,t-1}^{soe}$, charging in current period $\sigma_{l,t}^{in}$ and discharging $\sigma_{l,t}^{out}$ in current period.

$$\sigma_{l,t}^{soe} = \sigma_{l,t-1}^{soe} + \sigma_{l,t}^{in} \cdot \frac{A_l^{in}}{N} - \frac{\sigma_{l,t}^{out}}{A_l^{out} N}, \quad l \in L, t \in T. \tag{10}$$

For each storage unit and period, charging and discharging must be below limits, Q_l^{in} and Q_l^{out}, respectively:

$$\sigma_{l,t}^{in} \leq \delta_{l,t}^{in} Q_l^{in}, \quad l \in L, t \in T \tag{11}$$

$$\sigma_{l,t}^{out} \leq \delta_{l,t}^{out} Q_l^{out}, \quad l \in L, t \in T \tag{12}$$

A storage unit cannot charge and discharge in the same period:

$$\delta_{l,t}^{in} + \delta_{l,t}^{out} \leq 1, \quad l \in L, t \in T. \tag{13}$$

The storage state of energy for storage unit *l* must be within minimum $O_l^{\min}$ and maximum $O_l^{\max}$ limits:

$$O_l^{\min} \leq \sigma_{l,t}^{soe} \leq O_l^{\max}, \quad l \in L, t \in T. \tag{14}$$

5. Case study

5.1 Charging site and input data

We illustrate the properties of the models and analyze their performances in a case study based on a projected charging site outside a Norwegian office building. The reason for choosing an office building is that many of the cars are parked over a long time. The charging site consists of 14 charging points – 6 points with 3.7 kW maximum charging power, 5 with 7.4 kW and finally 3 with 11 kW. The last 3 charging points are intended for visitors and hence given priority in cases with capacity limitations.

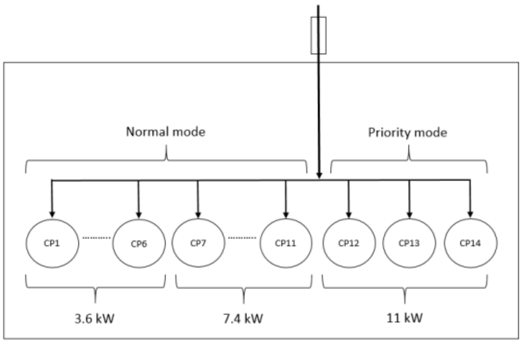

Fig. 5. Case study charging site

Data about charging sessions is received from Fortum Charge & Drive[4] for a charging site at a similar type of building. This dataset contains information about time for connection (to the level of one second), connection duration (number of minutes) and charging volume (kWh with two decimals). We have split our planning horizon into 15 minutes time intervals (periods from 1 to 96 for a day) and then allocated each charging session to a start period (the first after connection time) and an end period (the last one prior to the disconnection time). We have removed charging sessions that start and end outside the time interval from 0600 to 1759. Our total dataset consists of 303 charging sessions with an average charging volume equal to 12.2 kWh and an average connection duration equal to 18.6 quarters (4 hours and 40 minutes). Based on these data we have generated four different datasets with charging

[4] https://chargedrive.com/

sessions for one day: Dataset 1: *Average day*. This dataset has statistical properties similar to the full dataset, meaning that the average charging demand and connection duration for the sampled dataset is close to those for the full dataset. Total charging demand is 173 kWh for dataset 1. Then we have generated three *High demand*-datasets, each with a demand approximately twice the demand in dataset 1. Dataset 2, denoted *High demand, no peak*, has evenly distributed charging sessions, dataset 3, denoted *High demand, mid-day peak* has peak (simultaneous charging) in the middle of the day, while dataset 4, denoted *High demand, morning and afternoon peak*, has peaks in the morning and in the afternoon, but not so high in the middle of the day.

5.2 Analytical approaches

In the analysis, we compare four different EV scheduling methods:

- Uncontrolled method, meaning that the EVs start charging as they connect and stop charging as they disconnect or are fully charged (denoted Uncontrolled)
- Rule-based method (denoted Rule)
- Optimization-based method, where decisions are made based on available information (denoted Optim avail)
- Optimization-based method, where we assume perfect foresight (denoted Optim perf)

Since we will never have perfect foresight in real life, the last method is included just to analyze how well *Rule* and *Optim avail* delivers compared to the theoretical best solution. We denote method 2 – 4 *Smart Charging*.

Furthermore, since an alternative to introducing smart charging is to invest in a separate storage unit, we also include this. Parameters are decided in a straightforward way: Storage energy content is set equal to ¼ of average charging demand for one day (43 kWh), while maximum charging and discharging capacity is set equal to ¼ of sum installed charging point capacity (23 kW in and out).

Finally, we include a solar PV panel. We have chosen a solar panel similar to the ones that have been installed in 2015 at Hvaler[5], located Southeast in Norway. We assume a 50 m^2 panel area, which gives 7.75 kWp. Further, we use metered solar generation for a typical day in September as input to our analyses. For an overview of input-parameters, see Appendix A.

We analyze nine different combinations of smart charging, storage and generation (denoted *Technology options*) according to Table 1. Analyzed combinations of smart charging and technology options:

[5] http://www.smartenergihvaler.no/sol/

Table 1. Analyzed combinations of smart charging and technology options

Technology option	Smart Charging	Storage	Generation
Base case	No	No	No
Storage	No	Yes	No
Storage + generation	No	Yes	Yes
Rule	Yes (R)	No	No
Rule + storage	Yes (R)	Yes	No
Rule + storage + gen.	Yes (R)	Yes	Yes
Optim avail	Yes (O)	No	No
Optim avail + storage	Yes (O)	Yes	No
Optim avail + storage + generation	Yes (O)	Yes	Yes

Note that for all the combinations that include a storage unit, we perform scheduling of the storage, also if we do not perform smart charging. Further, for smart charging, we analyze both *Rule* and *Optim avail*, in addition to the benchmark *Optim perf*. We use the six technology combinations and 3 smart charging methods to answer two main research questions:

- What is the lowest maximum imported power needed (in kW) to deliver all EV charging demand?
- How well will the different methods deliver the EV charging demand if the maximum imported power is given?

An alternative interpretation of question 1 would be the minimum grid capacity needed. We iterate with different capacities and calculate demand not delivered until it turns to 0 kWh. Our target is to find how the different technology combinations and Smart Charging methods perform in terms of lowest maximum power.

The answer to research question 2 is the percentage of charging demand that is met. We have chosen the following approach: We start out by finding the lowest maximum power where *Optim perf* is able exactly to deliver 100 %, according to the same approach as for research question 1. Then we calculate delivered charging demand for each technology combination and Smart Charging method. To simulate an extremely limited situation, we next reduce the capacity by 50 % and repeat the calculations. Finally, we increase the capacity to 150 % and repeat the calculations to simulate a not so limited situation.

By performing these analyses, our goal is to obtain knowledge about capabilities of each method, to find structural differences between the methods and to quantify the value of each method in our datasets.

5.3 Results

We start out with research question 1. For each of the four datasets, we analyze all combinations of technology and smart charging method. The analyses are repeated for each of the three different smart charging methods, each time calculating the lowest maximum power that makes it possible to deliver all charging demand. Detailed results are given in Appendix

B. Fig. 6 shows an overview of the results, where each bar shows the average value over all datasets.

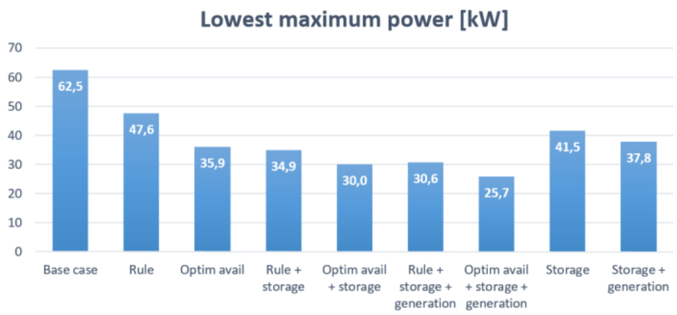

Fig. 6. Lowest maximum power to deliver all charging demand for each combinations of technology options and Smart Charging method

First, we see that in *Base case*, the lowest maximum power is 62.5 kW on average. Next, we see that by introducing *Smart Charging* method *Rule*, the maximum power is 47.6 kW, which represents 14.9 kW or 23.8 % reduction. By introducing *Optim avail*, the respective numbers are 35.9 kW total, 26.6 kW and 42.6 %. By combining *Smart Charging* with storage, the values are further reduced to 34.9 and 30.0 kW, which represents 44.2 and 52.0 % reduction compared to base case. Finally, by adding the solar panel, the lowest maximum power is 30.6 and 25.7 kW, respectively.

Next, we analyze the technology options without smart charging. By including a storage unit, the lowest maximum power is reduced by 21.0 kW to 41.5 kW. Further, by adding solar PV unit, it is additionally reduced by 3.7 kW to 37.8 kW. It must be commented that these figures are valid for the specified storage and solar panel parameters: A larger storage volume or larger solar panel would provide smaller maximum power values.

By including only smart charging or only a storage unit, we obtain a large reduction in the lowest maximum power. On the other hand, the combination of the two does not provide a large further reduction. The reason is that when we go from base case and introduce either *Smart Charging* or a storage unit, we flatten the power profile, by large reductions in some periods and smaller reductions in other. Going to the next step, means to reduce a flat power profile, which will require reductions in many of the periods. Hence, this action will require a larger energy volume [kWh] for each power unit [kW] that is reduced. This means that it is the storage unit **volume** that limits the added reduction by going from *Smart Charging* to *Smart Charging + storage*.

While *Optim avail* reduces the maximum power with 26.6 kW, *Rule* only reduces with 14.9. Likewise, we see the same pattern when we first include storage and next include storage and generation: *Optim avail* yields a reduction 70 – 80 % higher than *Rule*.

Fig. 6 presents average values over all datasets. The results vary between the datasets, see Table 5 to Table 7 in Appendix B for details.

We observe that *Optim avail* delivers a larger reduction compared to *Rule* in all datasets. However, how much better varies between the datasets. Particularly in dataset *High demand, mid-day peak*, *Rule* delivers a small reduction, compared to *Optim avail*. The reason is that the more complex the case is (in terms of many simultaneous EVs connected and little flexibility available in some of the EVs), the better *Optim avail* performs compared to *Rule*. An interesting observation is that *Optim avail* delivers results close to *Optim perf* in all datasets, which means that the value of perfect information is close to 0. Remember that we have not included any forecast information for the future, only information regarding departures for the connected vehicles.

Next, we want to analyze how the technology options perform in delivering the charging demand when the capacity limit is given (research question 2). We first calculate the lowest maximum power for *Optim perf* to be able to deliver 100 % of the demand for each combination.

Table 8 in Appendix B presents the results, which can be interpreted as the lowest capacity limit where the charging site theoretically is able to deliver all demand. We use this limit and calculate how much the other methods deliver. Note that the *Base case* is not relevant here, since it will give congestion and hence infeasible solutions. Fig. 7 shows average values over all datasets, while details for each dataset is presented in Table 9 to Table 11 in Appendix B.

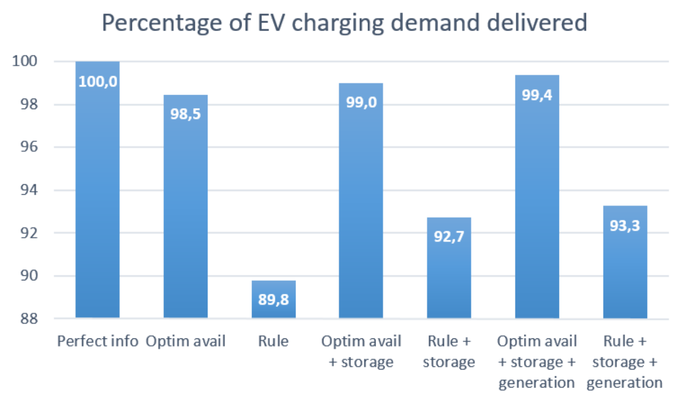

Fig. 7. EV charging demand delivered when Optim perf delivers 100 %

Observe that *Optim avail* delivers close to 100 % in all combinations, while *Rule* delivers between 10.2 and 6.7 % lower. We also see that the delivery increases with storage and generation, due to more available flexibility, and that the difference between the methods decreases with storage and even more with generation. The reason is that *Optim avail* is better at utilizing small amounts of flexibility.

Table 9 also shows that in very limited situations (50 %) or only slightly limited (150 %), *Rule* performs equally with *Optim avail* and in line with *Optim perf*.

All the analyses show that *Optim avail* delivers better than *Rule*. However, in the very limited situations, *Rule* delivers more prioritized demand than *Optim avail* for some of the datasets in some of the techonolgy combinations. An example is if all charging points are not yet connected and charging power must be reduced. *Optim avail* may then see that it is possible to deliver all prioritized in later periods and decide not to deliver to the prioritized charging point in current period. Later, when more vehicles connect, it may be impossible to deliver all prioritized demand. Since *Rule* always decides a pro rata reduction, it may be better off. This problem, that only happens in very constrained situations and only in some datasets, can be avoided by introducing forecasts, but we leave this topic to future research.

6. Conclusion and future research

In this paper we propose decision-support models for scheduling the charging processes for EVs at charging sites with capacity limits. In addition to the EV charging processes, we look at *Smart Charging* in combination with storage and generation units. We propose two different *Smart Charging* methods: A rule-based algorithm, which is easy to implement, and an optimization-based method, which in addition requires information about the EV drivers' expected departures.

To test the models and illustrate their properties, a case study is performed based on a charging site outside an office building. First, we analyze how different combinations of smart charging strategies and technology options reduce the lowest maximum imported power, when the objective is to deliver all the charging demand. We find that *Smart Charging* reduces the maximum power considerably. By combining with storage and generation, the maximum power needed is further reduced, but not in line with the power of the storage or generation units. We also find that the *Optim avail*-method outperforms the *Rule*-based method in all datasets, but that the difference between the methods decreases when including storage and generation units.

Further, we analyse how the *Optim avail* and *Rule* methods deliver in cases where the maximum imported power is given. In situations where the capacity is very limited or only slightly limited, both methods deliver equal results. However, if the limitation is in between, *Optim avail* outperforms *Rule*. We also find that *Optim avail* delivers results close to *Optim perf*, which indicates that the value of perfect information is negligible and that forecasting or stochastic programming will not add value.

In this paper, we have focused on the *Smart Charging* methods by analyzing four different datasets. Further research should include a pilot study of a real charging site run on real data over a long period of time. Shorter periods than 15 minutes should be considered. We have assumed a given set of storage and solar panel parameters, and further, that solar generation is known with certainty. Different setups of storage units and solar parameters should be evaluated, as well as how uncertain solar generation will influence the results. Integration with demand response possibilities in buildings close by the charging site, is also an issue that requires more research, in addition to vehicle-to-grid (V2G) capabilities.

We have assumed that the EV drivers reveal their true preferences regarding charging demand and expected departure time, but we have not looked into how business models should be designed to achieve this. Nor have we investigated different price models for the charging. Finally, since we in this article have focused on direct control, we propose further research also for indirect control methods.

7. Acknowledgements

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Appendix A: Input data to case study

Table 2. Charging data

			Average day			*High demand, no peak*			*High demand, mid-day peak*			*High demand, morning and afternoon peak*		
Ch point	Max power	Mode	Con. period	Disc. period	Dem. [kW]	Con. period	Disc. period	Dem. [kW]	Con. period	Disc. period	Dem. [kW]	Con. period	Disc. period	Dem. [kW]
1	3.7	N	33	61	7.5	35	63	16.2	32	64	16.2	35	63	21.0
2	3.7	N	29	60	15.7	35	70	9.8	31	63	19.8	35	70	9.8
3	3.7	N	35	70	9.8	56	71	6.6	33	63	20.0	56	71	6.6
4	3.7	N	30	56	13.5	54	66	6.7	34	60	24.0	54	66	6.7
5	3.7	N	32	57	11.5	43	61	9.9	35	64	9.9	43	61	13.6
6	3.7	N	42	53	2.7	32	63	8.9	31	48	14.9	35	63	8.9
7	7.4	N	51	52	1.1	36	62	36.0	31	62	36.0	29	47	29.7
8	7.4	N	29	44	13.6	33	58	32.1	33	52	32.1	51	70	32.1
9	7.4	N	29	48	14.8	34	64	49.7	48	64	25.7	34	64	49.7
10	7.4	N	35	64	7.5	34	64	41.5	34	60	41.5	29	47	31.5
11	7.4	N	27	38	6.6	31	61	34.4	31	61	34.4	52	70	30.4
12	11	Pri.	39	48	6.9	34	59	57.4	45	59	37.4	29	47	47.4
13	11	Pri.	34	66	42.7	50	59	22.2	46	57	22.2	53	65	22.2
14	11	Pri.	44	53	19.0	59	66	18.0	47	58	28.0	53	68	28.0

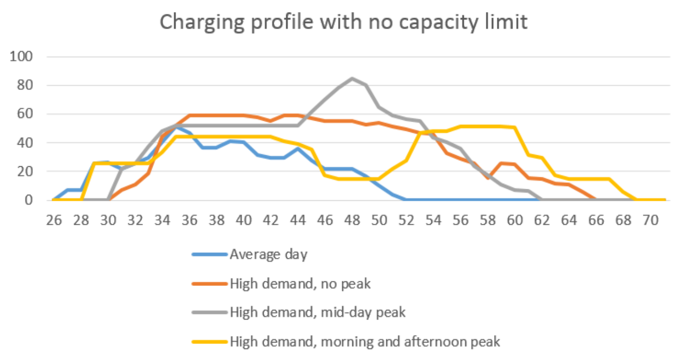

Fig. 8. Charging profile for each dataset in case of no capacity limit

Table 3. Objective function parameters

Parameter name	Value
α	10
β	2
γ	1
η	1
θ	2
φ	1
P^{norm}	1
P^{pri}	5

Table 4. Storage parameters

Parameter name	Value
$O_l^{\max}$	43 kWh
$O_l^{\min}$	0 kWh
Q_l^{in}	23 kW
Q_l^{out}	23 kW

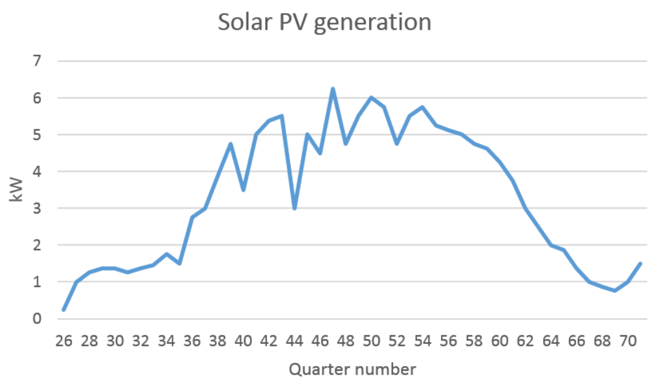

Fig. 9. Generation from solar panel

Appendix B. Case study detailed results

Table 5. Lowest maximum power for the different methods and Base case

	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and afternoon	Mean values all datasets
Uncontrld	51.7	59.1	80	59.0	62.5
Rule	25.9	50	69.1	45.3	47.6
Optim avail	18.2	42.1	47.0	36.3	35.9
Optim perf	17.6	41.7	46.7	34.9	35.2

Table 6. Lowest maximum power for the different methods and Storage

	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and aftern. peak	Mean values all datasets
Uncontrld	28.3	47.1	59.0	31.7	41.5
Rule	18.6	41.7	49.5	29.9	34.9
Optim avail	13.2	36.7	41.1	28.9	30.0
Optim perf	12.9	35.9	40.3	28.6	29.4

Table 7. Lowest maximum power for the different methods and Storage + generation

	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and aftern. peak	Mean values all datasets
Uncontrld	26.8	42.8	54.3	27.1	37.8
Rule	14.3	37.1	45.5	25.4	30.6
Optim avail	9.1	32.0	36.7	24.9	25.7
Optim perf	9.1	31.6	35.8	24.7	25.3

Table 8. Overview of grid capacities [kW]

	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and afternoon peak	Mean values all datasets
Uncontrolled	51.7	59.1	80.0	59.0	62.5
150 %	26.4	62.6	70.1	52.4	52.8
100 %	17.6	41.7	46.7	34.9	35.2
50 %	8.8	20.9	23.4	17.5	17.6

Table 9. Percentage of demand delivered with the different methods in Base case

Method	Grid Cap	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and aftern. peak	Mean values all datasets
Optim perf	100 %	100.0	100.0	100.0	100.0	100.0
Optim avail		96.7	100.0	98.8	98.3	98.5
Rule		81.6	93.9	92.3	91.2	89.8
Optim perf	50 %	52.7	54.4	54.0	54.6	53.9
Optim avail		52.7	54.4	54.0	54.6	53.9
Rule		51.2	52.7	54.0	54.5	53.1
Optim perf	150 %	100.0	100.0	100.0	100.0	100.0
Optim avail		100.0	100.0	100.0	100.0	100.0
Rule		100.0	100.0	100.0	100.0	100.0

Table 10. Percentage of demand delivered with the different methods with storage

Method	Grid Cap	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and afternoon peak	Mean values all datasets
Optim perf	100 %	100.0	100.0	100.0	100.0	100.0
Optim avail		99.9	98.2	98.4	99.5	99.0
Rule		87.6	94.7	93.0	95.6	92.7
Optim perf	50 %	64.4	59.7	58.8	57.5	60.1
Optim avail		64.4	59.7	58.8	57.5	60.1
Rule		64.1	58.3	58.8	57.5	59.7
Optim perf	150 %	100.0	100.0	100.0	100.0	100.0
Optim avail		100.0	100.0	100.0	100.0	100.0
Rule		100.0	100.0	100.0	100.0	100.0

Table 11. Percentage of demand delivered with the different methods with storage and generation

Method	Grid Cap	Average day	High demand, no peak	High demand, mid-day peak	High demand, morning and afternoon peak	Mean values all datasets
Optim perf	100 %	100.0	100.0	100.0	100.0	100.0
Optim avail		100.0	99.1	98.7	99.7	99.4
Rule		88.4	95.0	93.1	96.6	93.3
Optim perf	50 %	74.6	64.4	63.1	62.4	66.1
Optim avail		74.6	64.4	63.1	62.4	66.1
Rule		73.9	62.5	63.1	62.4	65.5
Optim perf	150 %	100.0	100.0	100.0	100.0	100.0
Optim avail		100.0	100.0	100.0	100.0	100.0
Rule		99.3	100.0	100.0	100.0	99.8