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Planning Electric-Drive Vehicle Charging under Constrained Grid Conditions

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***Abstract*—This paper presents a novel method of planning the charging of electric-drive vehicles that takes electricity grid constraints into account. The method computes an individual charging plan for each vehicle while minimizing the cost of electricity, avoiding distribution grid congestion, and satisfying the individual vehicle owner's requirements. The underlying algorithm is explained through a simple example and tested on a simulated electricity grid. The method is shown to significantly reduce the overloading in the electricity grid compared to charging schemes that do not consider grid constraints.**

***Index Terms*—Balancing Power, Demand Management, Distribution Networks, Electric Vehicles, , Electricity Grid, Intermittent Energy Sources, Netflow Algorithms, Smart Charging**

I. Introduction

For reasons of CO_2 reduction, independence from fossil fuels, and potential provision of balancing energy in grids with high proportions of intermittent power generation, plug-in hybrid and fully electrical vehicle technology has attracted renewed attention. It is clear that electric vehicles (EVs) will be available on the market because most manufacturers are developing EVs. The impact of the EV fleet on the power grid is therefore inevitable. The impact of EVs on the grid was studied as early as 1983 [1]. However, the time and extent of this impact are largely dependent on the success of EVs. Ungar et al. [2] argue that the impact will in fact be a major concern to the power grid operators, in particular the distribution grid operator.

Several new concepts have been proposed on how to use the grid-connected EVs for grid services, also known as vehicle-to-grid (V2G). These concepts usually involve both discharging and charging of EVs to help the grid to level out peaks in overall consumption. A literature overview of the V2G field is given in Jenkins et al. [3]. Jenkins et al. focus on the United States power grid and argue that several challenges such as managing and dispatching power remain to be solved. Additional V2G concepts have been studied in [4], [5], [6], [7], [8]. However, there are challenges with V2G services because it is not clear how much EV battery ageing, and therefore also the associated warranty, are affected during V2G operation.

It is clear that there are several entities interested in managing the charging of the electric vehicles. The vehicle owner has of course an interest in minimizing the cost of charging. The recent trend to move to hourly electricity pricing can help the owner to shift EV charging request from high-price hours to hours with less demand. This management of the charging should of course be automated, and could essentially be performed by the vehicle's system if the price information is available. Several concepts have been proposed for charging management using price-based methods. In [9], the charging and discharging of eight plug-in vehicles is optimized based on the day-ahead electricity price. The optimization scheme used is based on particle swarm optimization, i.e., a variation of a randomized search algorithm. The study also investigates the impact of grid faults on smart charging parking lots. The price-based charging scheme is also described in [10], where time-based or price-threshold charging is suggested. A time-shifted charging, in which different geographical regions have different charging hours, is proposed in [11]. In general, price-based charging schemes depend on that the resulting reduction in charging cost is a sufficiently strong incentive for the EV owner to choose price-based charging. Additional studies on forecasting and managing EV charging can be found in [12], [13].

More interestingly, distribution grid operators also have an interest to manage the charging because for them it is important to incorporate a large number of EVs without massivly reinforcing the distribution grid. The impact of EVs on the electricity grid is studied by Letendre et al. [14], where the focus is on the Vermont power grid. They assume a dual-tariff, nightly charging scheme, and conclude that enough transport capacities are available in the power grid. Grid constraints are only considered for the transport and high-voltage distribution grid, whereas the low-voltage distribution grid is not considered.

More details on potential impact on a low-voltage distribution grid are given in [15]. Smart charging behavior is considered to maximize the density of EV deployment into the grid, i.e., to reach the maximally tolerable number of EVs while maintaining grid constraints. The charging goals were set to achieve full charge for all plugged-in EVs. Hence this approach does not consider flexible charging schemes with variable charging goals. In [16], the impact of a large fleet of plug-in hybrid electric vehicles on the Virginia-Carolinas electric grid is studied. The focus is on the supply of electricity and not on the transmission and distribution capabilities. However, it is concluded that a large fleets of plug-in vehicles will impact the electricity grid.

This paper considers the power grid on the Danish island of Bornholm, similarly as in [17], where the isolated main island of the Azores is used to study the impact of EVs and the potential profit to be made on grid services. The focus of this paper is not on estimating the impact of the EVs, but rather

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on proposing a method of planning the individual charging schedules of a large EV fleet while respecting the constraints in the low-voltage distribution grid. The method has been tested in a simulation environment in which the movement and charging of individual EVs are simulated simultaneously. A load-flow simulation of the electric grid is performed to assess the impact of the large fleet of EVs.

The paper is structured as follows: the basic functions of the fleet operator are described in Section II. The simulator is described in Section III with the focus on the electric vehicle model and the topology of the simulated grid. The optimization of the charging schedules for an unconstrained grid is described in Section IV and the proposed method of optimizing the schedules for a constrained grid is shown in Section V. The results of using the method on a simulated large-scale distribution grid are given in Section VI. Finally Section VII discusses and concludes the paper.

II. Fleet Operator

There are several ideas on how electric vehicles will be integrated into society. Waraich et al. [18] envision two charging schemes: a per-EV, decentralized, decision process and a centrally controlled charging scheme. Each method has benefits and drawbacks. The decentralized approach assumed that the EV itself optimizes its charging behavior based on, for example, a price signal. The drawback with this approach is that the EV needs to collect and store trip history and, if the EVs need to coordinate their charging, for example to include grid constraints, the need for communication is high. The centralized approach on the other hand assumes that the centralized unit optimizes the charging and that the resulting charging schedules are communicated to the EVs.

In this study, it is assumed that there is a centralized EV aggregator that can act on the power market and use the available electricity products and financial instruments to, for example, minimize the cost of charging the EVs. In the remainder of this paper, the EV aggregator is referred to as the fleet operator (FO). It has the following basic modules:

- *Data storage*: The FO needs to gather considerable amounts of data to perform its EV-fleet management tasks. In particular, historical trip data is needed to predict future EV usage. In addition, end customer information may need to be stored, as well as billing information.
- *Trip forecasting*: The forecasting of the anticipated energy requirements for EV usage is essential to minimize the driver interactions. The FO has to estimate how much energy has to be fed into an EV while it is connected to the power grid. The connection location also plays a role when handling potential grid congestions. This module evidently depends on the data storage subsystems.
- *Optimization*: This module computes an optimal EV charging plan, taking into account estimated energy production, required energy needs, expected durations of charging periods and potential grid constraints.
- *Customer relationship and billing information*: This is traditional IT infrastructure for maintaining information on customers, their billing information, as well as the metering of the EV-specific power consumption and feedbacks into the grid. A user-facing client GUI needs to be provided to enable users to manage their data and to let the VPP operator interact with customer data.
- *Communication*: To gather data from the various entities (EVs, transport and distribution grid, power generation, markets) an appropriate communication infrastructure must be deployed.

As the goal of this paper is to propose and evaluate a novel algorithm for performing grid-aware charging of large EV fleets, the focus is on the *Optimization* block. It is assumed that the EV trips for the next day are perfectly predictable, i.e., the location and time of connection and disconnection, as well as the required energy are known. This assumption is further emphasized in the discussion and conclusions in Section VII.

III. Simulator

To evaluate the proposed algorithm of coordinating the charging of EVs, a simulator is used. The simulator is a hybrid simulator including both discrete and continuous state variables. It simulates a large fleet of EVs and the electricity grid to which the EVs connect for charging. In this section, the electric vehicle model and the electricity grid simulation methods are explained.

A. Electric vehicle fleet overview

For the fleet operator that optimizes the charging schedules the electric vehicles are mobile energy buffers. The energy buffers in this study are batteries, which are simulated using a non-linear model. Each battery is modeled as an equivalent electric circuit containing a voltage source in series with a resistor. Both the voltage source and the internal resistance depend on the state-of-energy $\zeta \in [0,\ 1]$ of the battery. The battery model also depends on the specific cell charateristics and the size of each battery pack. The dynamic state variable for a single electric vehicle is the state-of-energy

$$\dot{\zeta} = f(\zeta, P_b) = \frac{P_{\text{int}}(\zeta, P_b)}{E_{\text{int0}}}. \tag{1}$$

where E_{int0} is the maximum stored energy in the battery and $P_{\text{int}}(\zeta, P_b)$ is the internal power of the battery. The detailed battery model is described in [19]. Because of battery limitations, the charging power is limited to

$$P_b \in [P_{b,\min}(\zeta),\ P_{b,\max}(\zeta)] \tag{2}$$

and the state-of-energy is constrained to

$$\zeta \in [0.2,\ 0.8] \tag{3}$$

to avoid premature aging.

B. Electricity grid overview

The electricity grid is simulated using a conventional load-flow simulation. In the load-flow simulation, each component is modeled as a two-port element. The electricity grid model, i.e., the admittance matrix, is based on the grid on the Danish island of Bornholm. The parameters for the grid model are constructed using both real-world and synthetic data, where no real-world data is available.

The grid contains three voltage levels 60 kV, 10 kV, and 400 V. The 60 kV network is meshed whereas the 10 kV and the 400 V networks are radial trees extending from the 60/10 kV substations. In total, the grid contains roughly 12000 400 V end nodes. The ratio of cables to end nodes is roughly 1:1. There are several types of consumers in the grid, such as households, farms, and bakeries. These consumers vary in size and are spread out through the grid. The load curves are based on German VDEW consumption profiles. On the generation side, the grid simulator includes a single power plant and several wind turbines spread out across the island. The wind speed, which is an input to the turbines, is based on historical measurements of actual wind speeds in Denmark. The grid is artificially dimensioned to handle twice the peak load of the base consumption. After the grid has been dimensioned, each 400 V end node is equipped with a charging spot with a maximum power of 16 kW. Each charging spot can handle two EVs simultanously.

Thus, for an outlet node, u, in the electricity grid, the base load, $p_f(u)$, and the EV load, $p_v(u)$, give the total load at each end node:

$$p(u) = p_f(u) + p_v(u) \tag{4}$$

at each time instance. The grid is simulated using a load-flow simulation and is evaluated every 15 minutes.

IV. Optimization in an Unconstrained Grid

The goal of the optimization in an unconstrained grid is to derive a charging schedule for each vehicle that ensures sufficient energy for the predicted trips, while, for example, minimizing the total cost of the electricity used for the fleet. The charging schedules are divided into time slots for the given planning period. In this paper the planning period, which is the next day, is divided into 96 slots of 15 minutes each. An EV charging schedule therefore contains a charging power level for each of the 15-minute slots during the day of operation. Establishing charging schedules for an EV fleet can be done by solving an optimization problem [19], which can be formulated as the linear program

$$\min_{\mathbf{p}_b} \; t_s \mathbf{c}^T \mathbf{p}_b \tag{5a}$$

$$\text{subject to}$$

$$\mathbf{A}_s \mathbf{p}_b \;\geq\; \mathbf{b}_s \tag{5b}$$

$$\mathbf{A}_g \mathbf{p}_b \;\leq\; \mathbf{b}_g \tag{5c}$$

$$\mathbf{A}_b \mathbf{p}_b \;\leq\; \mathbf{b}_b \tag{5d}$$

$$\mathbf{b}_l \;\leq\; \mathbf{p}_b \;\leq\; \mathbf{b}_u, \tag{5e}$$

with the cost vector $\mathbf{c}$, the charging power vector $\mathbf{p}_b$, the stop-over inequality constraints ($\mathbf{A}_s$, $\mathbf{b}_s$), the generation inequality constraints ($\mathbf{A}_g$, $\mathbf{b}_g$), the battery inequality constraints ($\mathbf{A}_b$, $\mathbf{b}_b$), and the upper and lower bounds ($\mathbf{b}_u$, $\mathbf{b}_l$). Assume $i = 1, 2..., m$ is the index of the vehicle, $j = 1, 2, ..., n$ the index for the time slot contained in one plan duration. The decision variable $\mathbf{p}_b$ then has $m \cdot n$ elements. The cost vector $\mathbf{c}$ comprises of the cost associated for each vehicle in each time slot $c_{i,j}$. The charging power vector $\mathbf{p}_b$ comprises the charging power for each vehicle and time slot $p_{b,i,j}$.

$$\mathbf{c} = [c_{1,1},\ c_{1,2},\ \ldots,\ c_{1,n},\ \ldots,\ c_{m,1},\ c_{m,2},\ \ldots,\ c_{m,n}]^T \tag{6}$$

$$\mathbf{p}_b = [p_{b,1,1},\ p_{b,1,2},\ \ldots,\ p_{b,1,n},\ \ldots,\ p_{b,m,1},\ p_{b,m,2},\ \ldots,\ p_{b,m,n}]^T. \tag{7}$$

Because of battery or charging spot limitations, the charging power is limited to $\bar{p}_{b,i,j}$. The charging power is then limited to $\mathbf{p}_b \in [0,\ \bar{\mathbf{p}}_b]$, i.e., $\mathbf{b}_l = 0$ and $\mathbf{b}_u = \bar{\mathbf{p}}_b$ in (5). Note that all those slots in which vehicles are not connected can be eliminated prior to solving the optimization problem.

V. Optimization in a Constrained Grid

The goal of the optimization in this section is to derive a charging schedule for each vehicle that ensures sufficient energy for the predicted trips while respecting the grid capacity and minimizing the total cost of electricity for the fleet. The grid can be considered by including each edge, i.e., line and transformer load, as an additional variable. The additional constraints are then the load balance in each node in the network. The upper bound of each network-load variable is the actual maximum tolerable load. The new linear optmziation problem can be formulated using a single large linear program. The number of variables in this problem is

$$n_{\text{variables}} \approx n_{\text{slots}} \cdot n_{\text{vehicles}} + n_{\text{slots}} \cdot n_{\text{edges}} \tag{8}$$

and the number of constraints is

$$n_{\text{constraints}} \approx 2 \cdot n_{\text{stopovers/vehicle}} \cdot n_{\text{vehicles}} + n_{\text{slots}} + n_{\text{slots}} \cdot n_{\text{nodes}}. \tag{9}$$

If assuming 15-minute slots, 50'000 managed electric vehicles, and a small city with a distribution grid that contains 200'000 edges and 100'000 nodes, the total number of variables is on the order of $25 \cdot 10^6$ and the number of constraints is $15 \cdot 10^6$. However, even though this problem could be solved using appropriate hardware and software, the size of the problem is even larger for a larger city.

Also, it is not clear whether the information regarding the grid topology and capacity is available to the EV fleet operator that optimizes the charging schedules. For example, if the distribution system operator is separated from the FO, there must be an exchange of information with the districution system operator to be able to consider grid constraints. The method proposed in this paper uses a clear separation between evaluating the grid congestion and optimizing the charging schedules. This separation can be used when the grid information is not available to the FO.

In the unconstrained case, the planning can be done by solving the optimziation problem in (5). In the constrained, case the same optimization problem is solved and iteratively

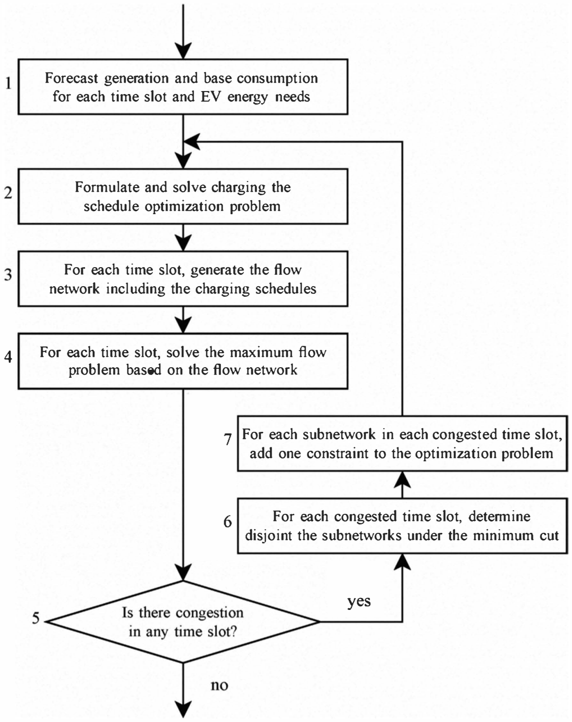

Figure 1. Flowchart of the algorithm of optimizing the charging schedules under constrained grid conditions.

updated to include the constraints in the electricity grid. A flow chart of the proposed algorithm is shown in Fig. 1. The details of each element are presented in the following list:

1) **Forecast generation and base consumption for each time slot and EV energy needs:** The available power for the EV fleet can, for example, be the predicted available wind power. The base load is determined using generalized consumption profiles for a variety of consumer types, e.g. farms, households, etc. The EV energy needs are predicted using the trip history of each vehicle. The EV trip prediction contains the location and duration of the connection events and the minimum required state-of-energy after each charging interval.
2) **Formulate and solve the charging schedule optimization problem:** Formulate the optimization problem in (5) based on the given generation, consumption, and EV charging need forcasts. If this is not the first iteration, include the grid constraints calculated in the preceding iterations. The optimization problem (5) is solved using IBM ILOG CPLEX[1] library [20].
3) **For each time slot, generate the flow network including the charging schedules:** To determine whether there is a congestion in the electricity grid, a flow network is constructed for each time slot j based on the electricity grid model, which in this paper is a network of two ports. A flow network is defined as follows.

   Definition Let a flow network be $F = \{(V,\ E),\ s,t \in V,\ c : V \times V \to \mathbb{R}^+\}$, where $(V,\ E)$ is a directed graph with edges E and nodes V containing a source $s \in V$, a target $t \in V$, and a capacity $c(u,v) \in \mathbb{R}^+\ \forall\ (u,\ v) \in E$ and $c(u,\ v) = 0\ \forall\ (u,\ v) \notin E$. Let the flow in a flow network be a function $f : V \times V \to \mathbb{R}$ where

$$f(u,\ v) \leq c(u,\ v)\ \forall\ (u,\ v) \in V \times V \tag{10a}$$

$$f(u,\ v) = -f(v,\ u)\ \forall\ (u,\ v) \in V \times V \tag{10b}$$

$$\sum_{u\in V} f(u,\ v) = 0\ \forall\ v \in V \setminus \{s,\ t\}. \tag{10c}$$

   The capacitites of the interior edges in the flow network

$$\{c(u,\ v) \mid u,v \in V \setminus \{s,\ t\}\} \tag{11}$$

   are the maximum power that can be transmitted though the two ports. The flow network includes additional edges from a virtual source node s to all nodes representing generation units. The capacities of these edges are the generated power $g(u)$ for each generation unit u. Similarly, the flow network also includes additional egdes from all nodes representing outlets to a virtual target node t. The capacities of these edges are the total power demand of each outlet $p(u)$ in (4).
4) **For each time slot, solve the maximum flow problem based on the flow network:** The problem of maximizing the flow from the source to the target can be formulated as a linear program

$$\max \sum_{u\in V} f(s,u) \tag{12}$$
$$\text{subject to (10a), (10b), (10c),}$$

   which in this paper is solved using IBM ILOG CPLEX. The maximum flow problem can, of course, also be solved using other techniques such as the Edmond-Karp algorithm or the Goldberg-Tarjan algorithm. The choice of using an LP solver was made because of the straightforward formulation and the simple possibility of warm starting the solver.
5) **Is there congestion in any time slot?** If the capacities of the flows to the target are equal to the actual flows, the requested power levels at the outlets are feasible and can be delivered through the network. The criteria can be checked as follows:

$$f(u,\ t) = c(u,\ t)\ \forall\ u \in V. \tag{13}$$

   If (13) is not true, there is a congestion in the grid and the optimization problem needs to be updated and solved again in the next iteration. If (13) is true the flow is not congested and the algorithm terminates.
6) **For each congested time slot, determine the disjoint subnetworks under the maximal source minimum cut:** This step starts by determining the maximal source minimum cut. This cut is calculated after the maximum flow by finding the nodes in the residual graph that

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can reach the target node. After the cut with partition $(S,\ T)$ has been determined, the disjoint subnetworks are determined by finding the reachable nodes in T from each edge in the cut. In this paper a subnetwork is defined as follows.

Definition Let a subnetwork N_T of a constrained flow network F, i.e., with partition $(S,\ T)$ from the maximal source minimum cut C, be

$$N_T = (V',\ E'), \tag{14a}$$

$$V' \subseteq T \setminus \{t\} \tag{14b}$$

$$E' = \{(u,\ v) \mid u, v \in V' \ \cap \ (u,v) \in E\}\,. \tag{14c}$$

The subnetworks N' and N'' are disjoint if $V' \cap V'' = \emptyset$ and $E' \ \cap \ E'' = \emptyset$.

7) **For each subnetwork in each congested time slot, add one constraint to the optimization problem:** For each disjoint subnetwork $N_T = (V',\ E')$ in the constraint flow network F with the maximal source minimum cut C,

$$\sum_{(u,t)\in E'} p_v(u) \leq \sum_{\substack{(u,v)\in C \\ v\in V'}} f(u,v) - \sum_{(u,t)\in E'} p_f(u), \tag{15}$$

where $p_f(u)$ is the base load used to set up the flow network in step 3) of the algorithm. Constraint (15) limits the sum of the EV loads $p_v(u)$ of all EVs in the disjoint subnetwork to the difference between the maximum inflow to the subnetwork given by the cut and the total base load of the outlets in the subnetwork.

VI. Simulation Results

This section shows the results when applying the proposed algorithm to plan the charging of an EV fleet with 3'500 commuter vehicles driving over the simulated grid. To evaluate the proposed algorithm, three different charging schemes have been tested:

- *Eager charging*: All EVs charge their battery fully when connecting to the charging spot.
- *Price-based charging*: The charging schedules are determined by solving the unconstrained optimization problem in (5).
- *Grid-aware price-based charging*: The charging is done using the algorithm proposed in Section V.

For both the price-based and grid-aware charging, the information of the price of electricity is needed. Figure 2 shows the artificial price curve that has been used in the optimization. It is assumed that the price is not influenced by the charging of the electric vehicles.

The resulting total load in the system is shown in Fig. 3 for the three charging schemes. Because the fleet only contains commuter vehicles, the eager charging is done when the vehicles arrive at work in the morning and also after returning home in the afternoon. The charging peaks therefore overlap with the existing peaks in the base load. This effect should be avoided as much as possible. For the pure price-based

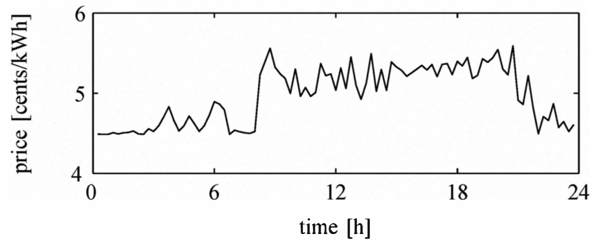

Figure 2. Artificial day-ahead price of electricity used for optimzing the charging schedules.

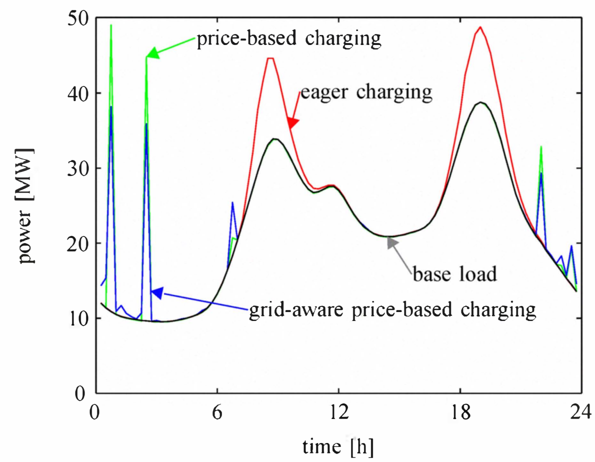

Figure 3. The base load excluding EV charging and the total load including EV charging during the day of operation. The total load is shown for the three different levels of charging management.

charging, all vehicles charge at the low-priced slots during the day. In Fig. 3 these peaks in charging, can be seen at 00:45 and 02:30 in the morning. When using our approach of grid-aware price-based charging these peaks are reduced and charging is moved to more expensive slots to avoid grid congestion.

To assess the benefits of using the proposed method, the actual loading of the grid must be further analyzed. Figure 4 shows the distribution of the average loading during the day of each two-port element in the grid. The differences between the three charging schemes are not significant. The majority of the loading is in fact below 50%, which is the effect of having our grid dimensioned to handle twice the base load peak.

More interestingly is the loading during the EV charging peaks. Figure 5 shows the average loading distribution, similarly to Fig. 4, for the four slots with the highest EV charging power. This means that for eager charging the average is taken during the morning and the afternoon peaks. For price-based and grid-aware charging, the average is taken during the nightly charging peaks. Figure 5 shows that both for eager and pure price-based charging, the grid is significantly overloaded. In fact, for the four considered slots eager charging overloads 1.8% of the grid by more than 10%. For pure price-based charging, 4.1% of the grid is overloaded by more than 10%. Using the proposed method of including the grid constraints in the optimization actually reduces the overload. This can be seen in Fig. 5 by the peak in loading at 100% of the grid capacity and the reduced loading above 100%. Using the

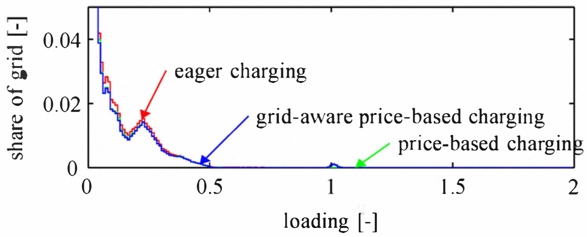

Figure 4. The grid loading distribution at the peak charging slots during the day for the three different levels of charging management.

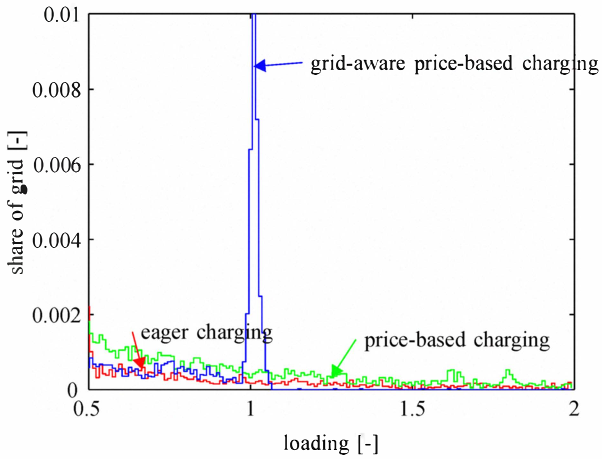

Figure 5. The grid loading distribution at the four peak charging slots during the day for the three different levels of charging management.

proposed method, only 0.04% of the grid is overloaded by more than 10%.

As the grid-aware charging shifts some charging to more expensive slots during the day, the total cost of charging the fleet is increased. However, based on the assumed price curve the actual cost per kWh charged to the fleet is only increased by 0.2%.

VII. Conclusions and Future Work

The proposed method of considering the electricity grid when planning the charging of large EV fleets has been tested in a simulation environment. The simulation results show clearly that using the proposed algorithm the overloading in the grid is significantly reduced. The simulated grid is dimensioned to handle twice the peak in base load. If the grid is more constrained, the overloading will be even more significant for all types of charging. Also, this paper considers only one type of EV and charging spots rated to 16kW. It is therefore interesting to consider a mix of vehicle types and a mix of charging spot ratings, such as low-power home charging and fast charging spots in central locations.

In this paper perfect EV trip prediction is assumed. Future work will, therfore, involve studies on the impact of trip prediction errors on the results. If the EV charging does not impact the price of electricity price-based charging will actually syncronize the charging of the vehicles at the low price hours during the day. As shown in this paper, the peaks are still present even if grid constraints are included in the optimization. There is therefore a need to study other objectives and business models for the FO that will enable smooth integration of large EV fleets.

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