Evaluation of Multiple Design Options for Smart Charging Algorithms

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***Abstract*—We evaluate the impact of limitations that may exist in actual implementations of plugin electrical vehicle chargers (e.g. no controllable charging current) on smart charging algorithms. We use quadratic programming to control and coordinate the charging of multiple vehicles in order to reduce the peak load and load profile variability observed by a distribution grid transformer. Simulation results are presented for a section of a residential distribution grid comprising 150 households.**

***Index Terms*—Smart Grid, Electric Vehicles, Demand Side Management, Smart Charging, Communication.**

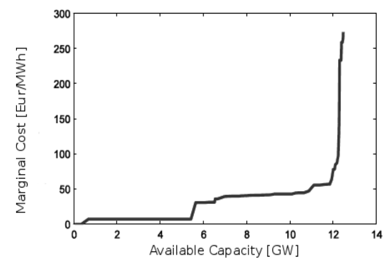


Fig. 1. Merit order of the electricity production park in Belgium [3].

I. Introduction

The electrification of the vehicle fleet is ongoing (e.g. the share of plug-in (hybrid) electric vehicles (P(H)EV) is predicted to reach 30% of the vehicle fleet in Belgium by 2030 [1]). An essential component in this evolution is the charging infrastructure. Since it has to be interoperable with vehicles from different manufacturers, standards are being developed for both vehicles and the associated infrastructure, e.g. by the International Electrotechnical Commission (IEC) and the Society of Automotive Engineers (SAE): e.g. IEC 61851 and SAE J1772 specify a conductive charging system.

Charging these electrical vehicles will significantly impact the daily load profile of the power grid: adding a single PEV to a residential home approximately doubles that household's average total power consumption. Hence, additional energy will have to be generated to support EVs (e.g., estimates show that 5% of the total energy production in Belgium is required to support EVs for a penetration degree of 30% in 2030 [2]). Another concern is the peak load, because charging of EVs can coincide with existing (e.g. evening) peaks and hence increase them. This would require additional and often more expensive power to be generated: Fig. 1 shows a representative relation between the load and cost of power [3]. As marginal energy costs are low for base load capacity, but high for peak load capacity, there is a need to manage the peak load to reduce energy costs. The peak load is also an important factor when dimensioning the infrastructure of the power grid. Voltage deviations, power losses [4], transformer and feeder overloads, reduced operating efficiency [5], etc. could occur as a result of higher peak loads. Smart charging algorithms can be used to avoid these problems by controlling and coordinating the charger loads (e.g. load shifting).

Different approaches have already been taken to develop smart charging algorithms. Quadratic programming [4], [6], dynamic programming [4], multi-agent systems [7], [8], etc. have shown promising results in supporting the integration of electric vehicles. However, these methods make certain assumptions regarding the charging infrastructure, i.e. support for variable charging rates. The need to manage the charging process more intelligently is not only illustrated by academic research, but also by the standardization bodies: e.g. SAE J2847 specifies the communication between plug-in vehicles and the utility grid, which could be the foundation to support smart charging services.

The topic of this paper is the design of smart charging algorithms. Specifically, we study the impact of different charging infrastructure assumptions and evaluate their impact on the peak load and variability of the load profile of a distribution grid. We start with the ideal case where the charger would be fully controllable in terms of current (and hence power drawn from the grid) and timing (i.e. charging intervals with arbitrary duration). Next, we also study the case of a more simple charging control interface that can only turn it on or off (no controllable current). Subsequently we consider the impact of minimum charging interval durations: once we start the charger, it will remain on for a minimum period. Last, we impose that the charging happens in a single contiguous time interval. To optimize the scheduling of the charging process over a set of homes under aforementioned constraints, we extended the smart charging algorithm based on quadratic programming we developed during earlier research [6], and implemented in our smart grid simulator [9]. The original algorithm assumed support for variable charging rates, however it has been extended with additional constraints to support fixed charging rates and/or minimum charging interval durations.

This paper is structured as follows: Section II defines our problem statement and the different charger design options. Section III discusses the charger scheduling algorithms. To evaluate them, we performed a case study: its parameters are discussed in Section IV, and results are presented in Section V. Our conclusions are summarized in Section VI.

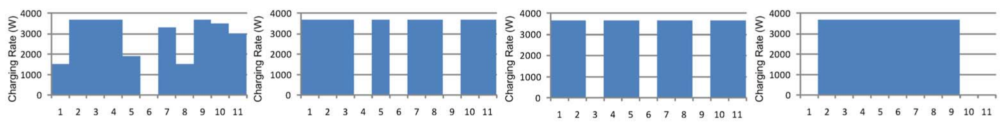


Fig. 2. Example of the different charging schedules: (1) variable charging rate + interruptions, (2) fixed charging rate + interruptions, (3) fixed charging rate + interruptions + minimum runtime of 2 time slots, (4) fixed charging rate + no interruptions

II. Problem Statement

The simplest charging scenario, uncontrolled charging, can be summarized as follows: vehicles are plugged in to the power grid upon arrival at home and charging starts immediately at a constant charging rate until the batteries of the vehicle are fully charged, i.e. no control or coordination is performed. Given e.g. the unacceptable peak loads this causes, smart charging algorithms have been proposed. They adapt the charging process in function of a certain objective, e.g. reducing the peak load or energy costs [6], [8]. Several actions can be taken to adapt the charging process: shifting in time, interruptions or adjusting the charging rate. In this paper we determine the influence that certain design decisions have on the results of the smart charging algorithms. We do this by posing three research questions:

1) What are the potential advantages of having a fully controllable charger which allows to adjust the rate of charging?
2) What is the effect of requiring a minimum runtime before the charging process can be interrupted?
3) What is the influence of not allowing the charging process to be interruped?

These decisions in the first place influence the complexity and cost of the charger hardware (in terms of control interfaces that need to be addressable by e.g. a electricity provider): e.g. a simple on/off interface or rather controllable current drawn from the grid. Clearly, this also influences the load profile that results from the charging process. We assume that the individual residential load profiles will be impacted the most, however it is not clear how this will impact the aggregated load profile as seen by the distribution transformer. We will therefore quantitatively evaluate the influence of these design decisions in terms of *peak load* and *variability* of the resulting aggregated load profile. The following section will discuss these design options in more detail.

A. Smart charger design options

The goal of our smart charging algorithms is to reduce the peak load and variability of the aggregated load profile. Fig. 2 illustrates the differences between the charging schedules that are the result of the different smart charger algorithm extensions. We assume that an adjustable charging rate will result in a better solution because of the finer grained control that is possible. This is especially true when considering individual load profiles. However, at an aggregated level, it is possible that this fine grained control does not offer a significant improvement (in terms of load peak/variability reduction). This could significantly reduce the complexity and cost of the charger hardware.

The minimum charging time constraint defines how long the charger should be turned on before it can be turned off again. This results in coarser grained control, therefore we expect this to have a negative impact on the load peak/variability.

Allowing the charging process to be interrupted adds more flexibility to the coordination and control of the charging processes, but the battery charger has to support this functionality. When we do not allow interruptions, we lose a certain degree of flexibility, because the charging process has to be scheduled as a whole. This is an extreme case of the constraint discussed in the previous paragraph, i.e. the value of the minimum charging time constraint equals the required time to fully charge the vehicle.

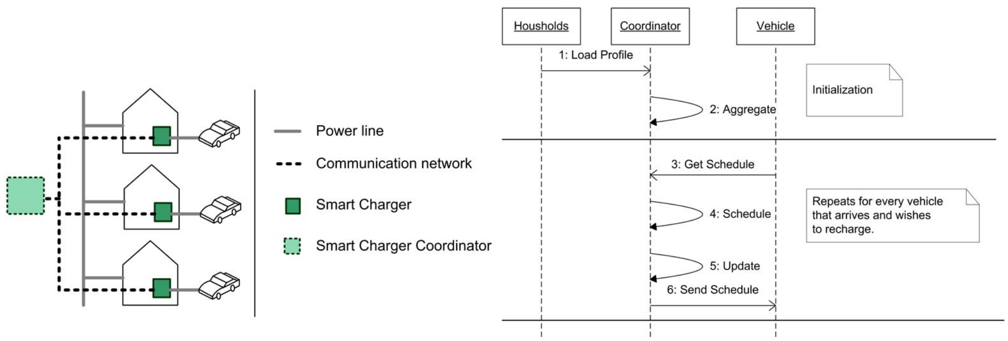
III. Smart charging algorithms

The smart charging algorithms discussed in this paper are extensions of the iterative global algorithm developed as part of earlier research [6]. The original algorithm approaches the problem of reducing the peak load and load profile variability by solving a quadratic programming model. Quadratic programming is a specific type of optimization problem in which a quadratic objective function of several variables subject to linear constraints on these variables is optimized. The result of this optimization is a charging schedule that indicates the times during which the vehicle will be charged and the corresponding charging rates. Fig. 3 illustrates how the algorithm (and its extensions) works and how it could be implemented.

The algorithm is initialized by the smart charger coordinator which gathers all the individual load profiles of the households (step 1) and calculates the aggregated load profile (step 2). The load profiles, and therefore also the aggregated load profile, consist of demand predictions for the simulated time period (24 hours in our case). We assume there is no prediction error (but further research will address the influence of imperfect predictions).

After the initialization procedure, the algorithm waits until the smart charger of a vehicle requests a charging schedule (step 3). The algorithm then calculates a charging schedule based on the aggregated load profile (step 4). The objective of the charging schedule is to minimize the peak load and variability of the load profile. This is achieved by minimizing the squared Euclidean distance between the aggregated load (including the charger load), and the ideal aggregated load profile, which would be a horizontal line. The result is a charging schedule with varying charging rates and interruptions. The algorithm updates the aggregated load profile (step 5) and sends the schedule to the requester (step 6).

To investigate the first research question we adapted the algorithm discussed in the previous paragraphs to only support



(a) Architecture (b) Operation

Fig. 3. Smart Charger

on or off states, resulting in an Integer Quadratic Programming model. The original algorithm [6] resulted in charging rates (continues values) in each time slot that lie between 0 and the maximum rate during each time slot. The adapted algorithm results in a charging schedule with only 2 possible values during each time slot: on or off.

Additional constraints were added to this integer quadratic programming model to investigate the second and third research questions. The constraints specify that a charger should stay turned on for a predefined period before it can be turned off again. The third research question, which considers uninterrupted charging, is an extreme case (of the second research question) in which the constraint equals the time required to fully charge the vehicle.

IV. Case Study

The algorithms are evaluated using three scenarios of which each scenario simulates a distribution network consisting of 150 households with a certain penetration degree of plug-in hybrid electric vehicles. The light scenario consists of 10% electric vehicles, the medium scenario 30% and the heavy sceario 50%. Each scenario simulates a 24 hours and starts at noon and continues until noon the following day. The 24 hours are divided in time slots of 5 minutes.

A. Power Grid

The simulated distribution network consists of 150 households (of which x % owns a electric vehicle, with $x \in \{10\%, 30\%, 50\%\}$). The load profiles that model the power drawn by each household are based on real life measurements performed on 5 representative Belgian households during different winter days (the highest seasonal load in Belgium). Each household is randomly assigned one of the measured load profiles which is randomly shifted in time (max. 1 hour) using a uniform distribution (to avoid identical profiles for multiple houses, and hence artificial coincidence of peak load loads in a single profile with those of the aggregated load of the neighbourhood).

B. Electric Vehicles

We assume a plug-in hybrid electric vehicle to have a battery capacity of 15 kWh. The households are assumed to be provided with a single-phase connection that supports a standard charger of 3.6 kW, using 16A and 230V. These assumptions are based on the IEC 62196 standard which describes conductive charging of electric vehicles.

C. User Behaviour

It is assumed that most of the times, vehicles will be recharged at home or at work. In this paper we focus on charging at home. The plug-in times of the vehicles are modeled using a normal distribution with mean 17:00 and a standard deviation of 45 minutes. The vehicles have to be recharged by around 06:00 (again with a stdev of 45 minutes). The state of charge of the car battery upon arrival is assumed to be uniformly random distributed between 20% and 60%.

V. Results

We modeled several simulation parameters as random distributions, and therefore we simulated each scenario 100 times (with different random generator seeds). The result of each simulation is the load profile that would be observed by the distribution transformer of the simulated distribution grid. We evaluate the different extensions of the algorithm based on two metrics that we calculate for each load profile:

1) *The peak load*: maximum value of the load profile over all the 5 min interval values.
2) *Load variability*: standard deviation over the 5 min interval values of the load profile, which is a measure for the flatness of the load profile.

Next we calculate the average of these metrics over the 100 instances per scenario, and use these to evaluate the various design options and corresponding algorithms.

A. Reference scenario: uncontrolled charging

As a reference we simulated uncontrolled charging for each scenario. We evaluate the impact on the peak load and variability of the load profile. The results shown in Table I and Fig. 4a indicate that the peak load becomes higher as a result of the uncontrolled charging of multiple vehicles. The peak load is approximately 191 kW if a penetration degree of 0% is assumed, but if 10% of the households own a PHEV, the peak load rises to approximately 233 kW. Similarly in the medium and heavy scenario, the peak load rises to respectively 318 kW and 408 kW. These results indicate that uncontrolled charging has a significant impact on the peak load for the considered scenarios. We evaluate the impact on the variability of the load profile by calculating the average standard deviation between the values of the load profiles: 49 kW in the light scenario, 72 kW in the medium scenario and 97 kW in the heavy scenario.

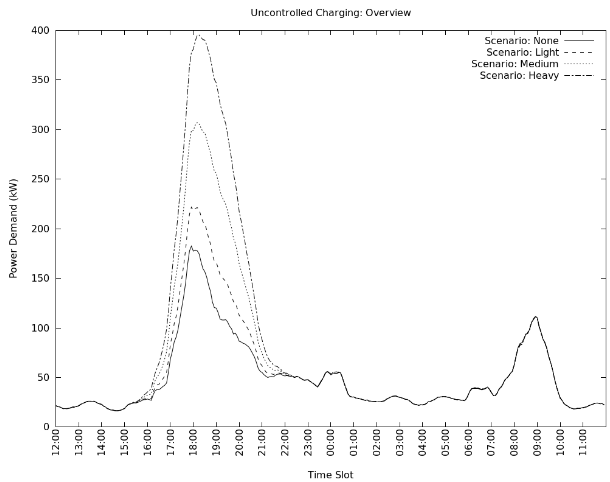
B. Controlled charging

In this section we discuss the results of the smart charging algorithms. First we discuss their performance in terms of their impact on the peak load of the resulting load profiles. Next we discuss their performance in terms of their impact on the flatness of the resulting load profiles. Fig. 4b gives a graphical overview of the results in the form of average load profiles. An average load profile is calculated from the 100 repetitions of each scenario: the load during a time slot is the average of the load during that time slot from the 100 repetitions.

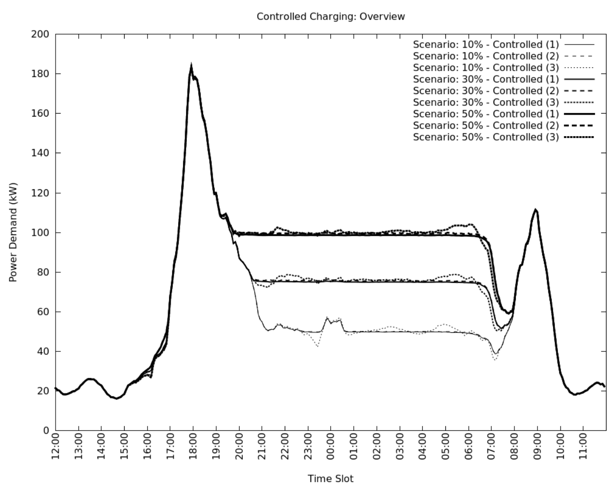
1) Peak load: Table II shows the impact for each variant the smart charging algorithm on the peak load. All of them achieve the same performance regarding peak load reduction: the peak load originating from uncontrolled charging can be completely shifted in time for each scenario. This means that the observed peak load of approximately 191 kW is solely the result of the uncontrollable loads. This also illustrated by Fig. 4b.

2) Load profile flatness: The impact on the peak load of the load profiles is identical for each extension of the algorithm, however the impact on the load profile flatness is not the same.

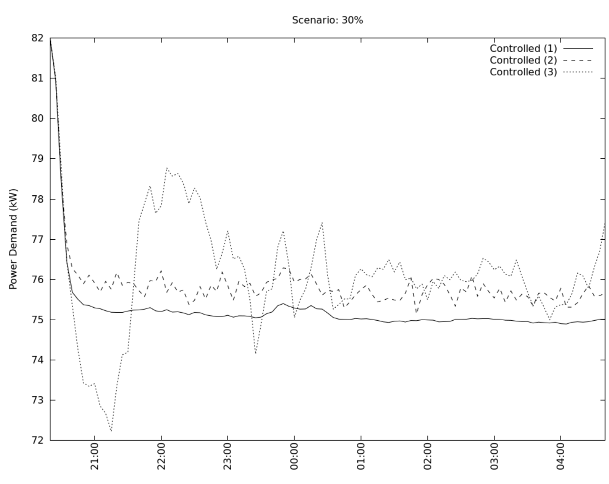
We first consider the algorithm with variable charging rates and the algorithm with a constant charging rate. Both algorithms allow the charging process to be split up in multiple parts by interrupting it. The average standard deviation between the values of the load profile is for both algorithms



(a) Uncontrolled



(b) Controlled



(c) Controlled: Details

Fig. 4. Controlled (1): variable charging rate + interruptions, Controlled (2) fixed charging rate + interruptions, Controlled (3) fixed charging rate + no interruptions

TABLE I
IMPACT OF UNCONTROLLED CHARGING ON LOAD PROFILE

Scenario	PEV penetration	Peak Load	Standard Deviation
No vehicles	0%	191 kW	37.36 kW
Light	10%	233 kW	48.71 kW
Medium	30%	318 kW	72.17 kW
Heavy	50&	408 kW	97.19 kW

TABLE II
IMPACT OF CONTROLLED CHARGING ON THE PEAK LOAD. EACH SMART CHARGING ALGORITHM EXTENSION RESULTED IN THE SAME PEAK LOAD, THEREFORE WE HAVE GROUPED THE RESULTS UNDER ONE CATEGORY: ”CONTROLLED”.

Scenario	Algorithm	min	avg	max	stdev
None	/	169	191	235	12.29
Light	Uncontrolled	198	233	274	15.63
	Controlled	161	191	231	14.38
Medium	Uncontrolled	294	318	352	14.57
	Controlled	162	191	224	14.05
Heavy	Uncontrolled	375	408	438	14.54
	Controlled	157	191	230	12.45

TABLE III
IMPACT OF THE MINIMUM RUNTIME CONSTRAINT ON THE FLATNESS OF THE LOAD PROFILE.

MR	Light	Medium	Heavy
3	35.12 kW	35.49 kW	39.70 kW
6	35.13 kW	35.52 kW	39.82 kW
9	35.14 kW	35.56 kW	39.90 kW
12	35.15 kW	35.58 kW	39.95 kW
15	35.16 kW	35.60 kW	40.00 kW
18	35.18 kW	35.64 kW	40.04 kW

aproximately 35.10 kW in the light scenario. However the difference becomes larger for the medium and heavy scenarios. The algorithm which assumes a variable charging speed results in a load profile with standard deviation of 35.38 kW in the medium scenario (30% PEV), and 39.38 kW in the heavy scenario (50% PEV). The algorithm that assumes only one charging speed results in a standard deviation of 35.47 kW in the light scenario, and 39.64 kW in the heavy scenario. This indicates that limiting the charger to one charging rate has a negative effect on the load profile variability (as we expected).

We reduced the amount of freedom of control by adding an additional constraint, the minimum runtime, that specifies how long the charger should be turned on before it can be turned off again. We still assume that only a single charging rate is assumed. The results shown in Table III indicate that the flatness of the load profile is reduced, however the difference is relatively small. The average standard deviation for the light scenario ranges from 35.12 kW to 35.18 kW, for the medium scenario from 35.49 to 35.64, and for the heavy scenario from 39.70 kW to 40.04 kW.

Attaining a flat load profile clearly is further impeded when we assume that the charging process can not be interrupted, which is an extreme case of the previous extension to the algorithm: the minimum runtime equals the total time required to fully charge the vehicle. Now, the average standard deviation between the values of the load profiles is approximately 35.19 kW in the light scenario, 35.66 kW in the medium scenario, and 40.06 kW in the heavy scenario. This indicates that not allowing interruptions has a negative impact on the variability of the load profile.

Fig. 4c illustrates the discussed results. The algorithm with the most flexibility results in a nearly flat profile, while reducing the flexibility results in a more spiked profile.

C. Discussion

The results indicate that uncontrolled charging has a negative impact on the peak load and flatness of the load profile for the considered scenarios. Each extension was able to achieve the same performance with respect to peak load reduction: the peak load originating from uncontrolled charging can be completely shifted in time. However the results were not the same when considering the flatness of the load profile. The results indicate that while the difference is relatively small, the average standard deviation between the values of the load profiles becomes higher for a non-adjustable charger speed and longer charging blocks.

VI. CONCLUSIONS AND FUTURE WORK

The work presented in this paper discussed several extensions to the algorithm proposed in [6] that change the control freedom of the algorithm, which reflects varying complexity of the required control interface to the charger. The results indicate that significant improvements over uncontrolled charging can be achieved by controlled charging, even when the flexiblity (and hence hardware complexity) of the chargers is reduced: even when charging always happens at full power, in a contiguous period of time, the aggregate load profile does not differ much from when more flexibility is added. However, the algorithms make some assumptions that need further research, i.e. the power demand predictions. It is not clear what the impact of prediction errors will be. Further research will have to show if the algorithms are resilient enough or can be made so. The algorithms presented in this work do not consider fairness as a constraint. It is for example possible that the charging process of some vehicles is spread over a large period of time, while others are charged in a short time period. (Note that assessment of algorithm complexity has been omitted from this paper due to space limitations.)

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