Deriving Electric Vehicle Charge Profiles from Driving Statistics

R.A.Verzijlbergh, Z.Lukszo, E.Veldman, J.G.Slootweg, M.Ilic

Abstract—**The impacts of EV charging on electricity grids is becoming an increasingly important subject of study, but detailed knowledge about the future charging profiles of EVs appears to be missing. In this study we construct EV charge profiles based upon a large dataset of driving patterns. We consider both controlled and uncontrolled charging scenarios, where the main rationale of the controlled charging scenario is to shift the EV electricity demand away from the standard household peak. We show that applying charge control results in only slightly higher peaks compared to the situation without EVs, whereas in the uncontrolled case, the peaks will be significantly higher. Moreover, it is shown that the aggregated charge profiles give a good approximation for the demand of approximately 50 EVs or more. The EV charge profiles can be used as a tool for future network planning and EV impact studies.**

Index Terms—**Electric vehicles, smart grids, power system planning, load management.**

I. Introduction

Electric vehicles (EVs) could be an important contribution to the reduction of greenhouse gases in the transport sector [1]. If the number of electric vehicles grows substantially, the impacts on the power system of charging these vehicles will do so as well. Since this is recognized widely, one observes an increasing number of studies on the impacts of electric vehicles on the power system. Whereas some studies focus on the impacts on the distribution networks, see e.g. [2] and [3], others consider effects on the regional or national power system level, e.g. [4] and [5]. Regardless of the focus of the study, it is crucial to accurately model the expected electricity demand of the EVs, because that determines to a large extent the impact on the various aspects of the power system.

A realistic model of the future charging behavior of EVs appears, however, to be missing. Most EV impact studies either use very stylized versions of charging profiles, or use stochastic approaches that are only loosely inspired by driving patterns. The most notable efforts to construct charge profiles based on actual driving patterns are described in [6] and [7]. In the latter paper, the aggregated EV demand profiles are also used as input for a stochastic approach on analysing EV impacts on grid assets. A detailed description of how the charge profiles have been constructed is, however, not given in these papers.

This study thus aims to provide and analyse realistic charge profiles of EVs, based on an extensive dataset of current driving behavior [8]. As EVs are also considered to be an important building block of smart grids [9], we consider both controlled and uncontrolled charging. The controlled charging profile is inspired by the fact that, inherently, the peak of household demand and EV demand would coincide because they both follow the daily commuting cycles. The main rationale of controlled charging is therefore to shift the EV charging peak away from the normal household peak. This reduces the combined peak of households and EVs and possibly enables higher penetrations of EVs without having to replace network components. In [3] the profiles described in this paper have been used to show that controlled charging can lead to a significant reduction of overloaded network components.

II. Research method

A. Standardized load profiles

The idea of using aggregated EV charge profiles is inspired by the standardized household demand profiles that are used for network planning in the Netherlands [10]. Electricity demand by a single household is naturally unpredictable due to its stochastic nature, but for a large number of houses a more predictable pattern arises. To model the load on e.g. a feeder cable with a certain number of households connected to it, one uses the standardized household profile multiplied by the number of houses on that cable. The standardized profiles are usually expressed as a time series of a dimensionless fraction of the yearly demand. To obtain the actual predicted load of a household expressed in kW, the timeseries are multiplied by the yearly electricity demand of that household – a number that is usually known by distribution netwok operators (DNOs). Furthermore, the time series span every hour of the year, to account for seasonal differences in load profiles. Fig. 1 shows the standardized profile for December 1st for a household with the average Dutch yearly electricity usage of 3500 kWh.

In this paper we propose to use the same method to model the electricity demand of EV charging. Based on transportation

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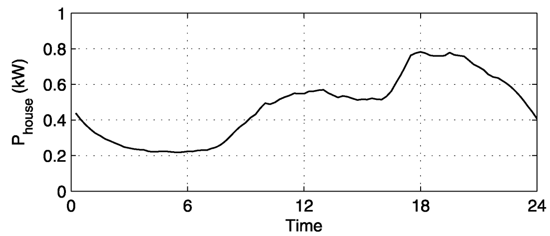

Fig. 1. Standardized household electricity demand on December 1st.

data, we construct an aggregated standardized load profile of a large number of EVs. This aggregated profile can then be adjusted to represent the demand profile of a single EV or a group of EVs.

B. Transportation data

The Mobility Research Netherlands gives a large dataset of individual trips by various transport means. The data is collected by means of a survey of roughly 40.000 people in the Netherlands [8]. The dataset consists of over 130.000 individual movements (one way trips), from which approximately 40.000 are car movements of roughly 18.000 individuals. The most important variables that have been used to construct the different charge profiles are (for each of the 18.000 individual cars): daily driving distance, home arrival time and home departure time.

To get some initial insights in the driving patterns, Fig. 2 shows the probability distribution of car trips based on daily driving distance and the time at which the *last* arrival at home takes place; two important parameters in the construction of the charge profiles. From Fig. 2 it can be concluded that on average, the majority of car drivers covers only modest distances. Furthermore, it is noteworthy that the distribution of the shorter trips shows two distinct peaks, one around noon and one around 1800h. Apparently, a significant fraction of the people tend to use their car only during the morning, since we have considered only the *last* arrival time at home. For the longer distances, the time of the last arrival at home is mostly in the early evening or late afternoon. This can intuitively be understood by considering the daily commuting cycle of driving to work in the morning and arriving back home in the evening.

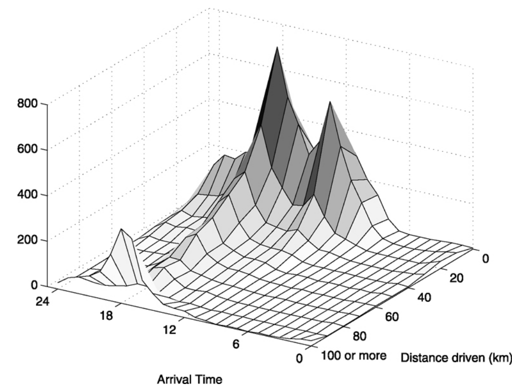

Fig. 2. Distribution of times at which cars arrive at home.

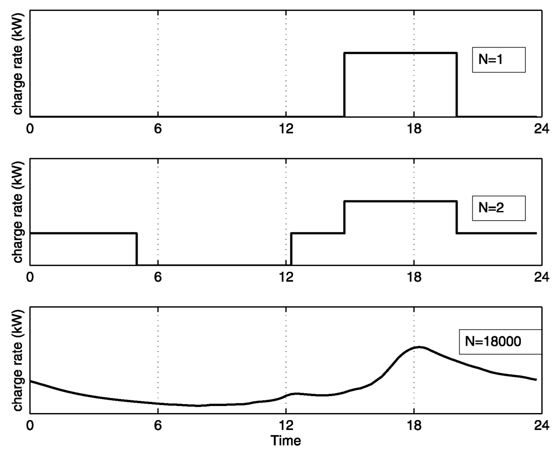

Fig. 3. Schematic representation of the construction of the aggregated charge profiles from individual car energy needs in the uncontrolled, 3kW charging scenario.

III. Results

A. Uncontrolled charging with fixed charge rate

The simplest possible charge scheme is where people plug in their EV after their last arrival at home and start charging with a fixed rate until the battery is full. The energy need of a single car and thus the duration of charging depends on the daily driving distance: an EV efficiency of 5km/kWh is assumed. The power drawn by one individual EV will equal a block wave, where the height is given by the charge rate and the beginning and endpoints are determined by the home arrival time and daily driving distance. The aggregate load of two EVs with different driving distances and arrival times will be the sum of two block waves; for a large number of EVs the aggregate load will be the sum of all block waves. Fig. 3 schematically depicts this method for a fixed charge rate of 3kW. The aggregate profile of a large number of EVs, shown in the bottom graph of Fig. 3, clearly correlates with the driving patterns of Fig. 2, and, more importantly, also with the typical household demand shown in Fig. 1.

For an increased charge rate of 10kW, the method is identical, but a different aggregated profile will emerge, see Fig. 4. The single block waves of which the aggregate profile is composed are shorter, but greater in magnitude. The aggregate profile correlates with the arrival time distribution even closer, because the smoothing effect is more moderate.

B. Slow charging

In a simple form of a more sophisticated charging scheme, the car user specifies the time of departure of the next trip. The battery will then be charged with the lowest possible, but constant charge rate, so that at the specified time the battery will just be full. For this form of charging, three variables need to be known: daily driving distance, arrival time at home and departure time of the next trip. Once again, we assume that the arrival time reflects the last trip arrival time. For one individual car, the charge rate P_0 will be the energy need E_{car}

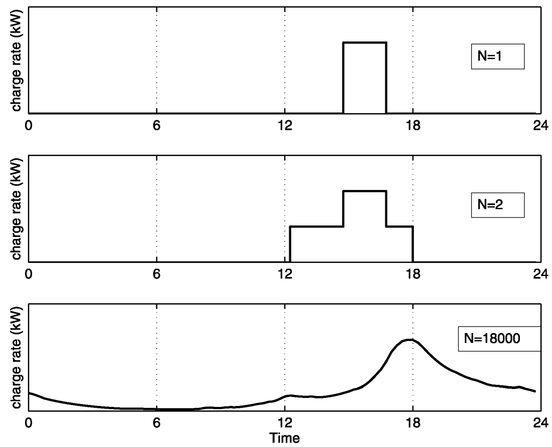

Fig. 4. Schematic representation of the construction of the aggregated charge profiles from individual car energy needs in the uncontrolled, 10kW charging scenario.

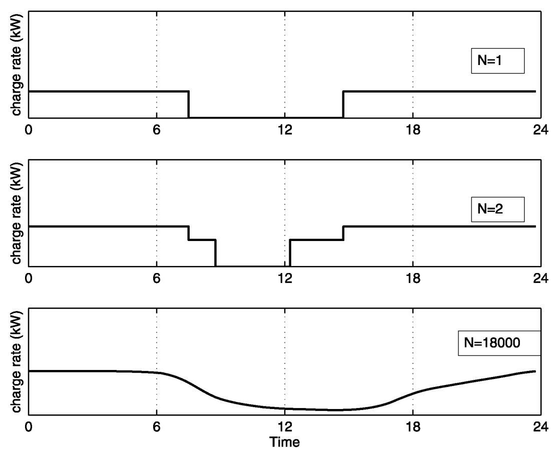

Fig. 5. Schematic representation of the construction of the aggregated charge profiles from individual car energy needs in the controlled slow charging scenario.

of the vehicle, determined by its daily driving distance, divided by the time it will be plugged in until the next trip T_{charge}, such that $E_{car} = P_0 T_{charge}$. Fig. 5 depicts how this method will lead to an aggregated charge profile. The aggregated profile is minimal during the day, builds up slowly in the evening hours and is more or less constant during the night. In the morning it decreases quite rapidly, as most cars will depart from home.

C. Controlled charging

In the controlled charging scenario, the charge rate is variable and depends on the network load. The basis for this method is the standardized household load shown in Fig. 1. The underlying idea is that EVs are non time-critical loads and charging can be postponed as long as the battery is full at the next trip departure. This freedom can then be used to relieve the networks, which means in concrete terms that the bulk of the energy will be transferred during the night hours. The method by which the controlled charge profile is formed is closely related to the previous case of slow charging. Again, charging is spread out over the largest possible timespan, but this time the charge rate is not constant as in the slow

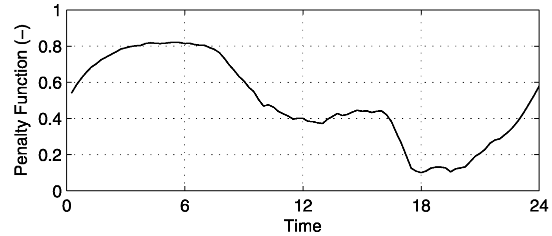

Fig. 6. Penalty function for the controlled charge signal with a value of $C = 1.1$.

charging case. Instead, the constant charge rate is multiplied by a penalty function that is inversely proportional to the standardized household demand, see Fig. 6.

The penalty function is given by

$$f(t) = C - \frac{P_{house}(t)}{P_{max,house}} \tag{1}$$

where C is a constant that determines how much the sum of the household load and the EV load can exceed the household peak only. In principle, if $C = 1$, the new total load of household and EV is never higher than the household load only. To study the effect of a group of EVs on e.g. a distribution feeder, it seems somewhat unrealistic to assume all EVs can be controlled perfectly, so a value of $C = 1.1$ is chosen. In this way, the peak value of the households and EVs will still be approximately 10% higher than that of the household alone. To fullfill the energy needs of an individual car, the integral of instantaneous charge rate $P_{car}(t)$ has to equal the energy corresponding to the driven distance. In the previous cases, this condition was automatically fullfilled because either the duration of charging or the charge rate was explicitly based on that energy need. Here, we have multiplied by the penalty function $f(t)$, so the charge rate should be normalized by the integral of this function:

$$P_{car}(t) = P_0 \frac{f(t)}{\int_{T_{charge}} f(t)dt} \tag{2}$$

where P_0 is determined by the available charge time T_{charge} between home arrival and departure and the car's energy need.

For a single EV, this leads to a variable charge rate as depicted in the top graph of Fig. 7. Analogous to the other cases, the aggregated profile is the sum of all individual car profiles. The aggregated profile clearly shows that the bulk of the energy transfer is now shifted to the night.

D. Comparison

Similar to use of the standardized household profiles, the EV charge profiles need to be multiplied with a specific EV's daily energy need to obtain a daily profile in kW. To compare the different charge profiles, the uncontrolled 3kW, uncontrolled 10kW and the controlled profile have been plotted in Fig. 8 for an energy need of 6kWh, which is equivalent to 30 km, approximately the average Dutch daily driving distance. A few observations can be made from this figure. Most markedly, in the uncontrolled scenarios there is a very distinct evening peak

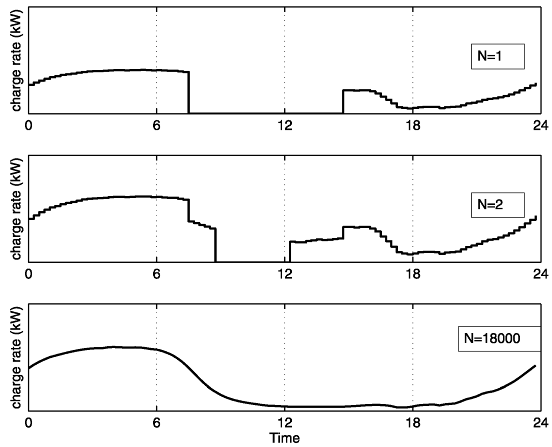

Fig. 7. Schematic representation of the construction of the aggregated charge profiles from individual car energy needs in the controlled intelligent charging scenario.

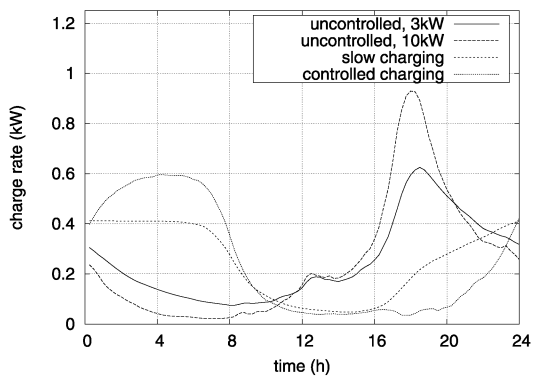

Fig. 8. Different aggregated EV charge profiles for one single EV with the average daily driving distance of 30km.

in the demand, which is not surprising considering the distribution of home arrival times shown in Fig. 2. Furthermore, the difference between the 3kW and 10kW scenario, especially the difference between the magnitude of the peaks, is quite modest. This can be understood realizing that allthough the charge rate is much higher, there is much less overlap in charging the different EVs. The profiles are in good agreement with the results of [7], where a peak of 0.7 kW is found for the power demand per vehicle.

In the controlled charging scenario the peak is found at night, when household electricity demand is lowest. In the slow charging scenario, the EV demand is also mainly shifted to the night, but already increases in the late afternoon and early evening hours, when household demand is high.

IV. Application of the EV charge profiles

A. Combined household and EV demand

For most practical purposes, one is interested in the total network load, which is the sum of the household profile and the EV charge profile. Fig. 9 shows the combined profiles, together with the standardized household profile only. In this figure, the load of one EV with the average driving distance of 30km is added to the standardized household profile with average electricity consumption of 3500 kWh per year. It can

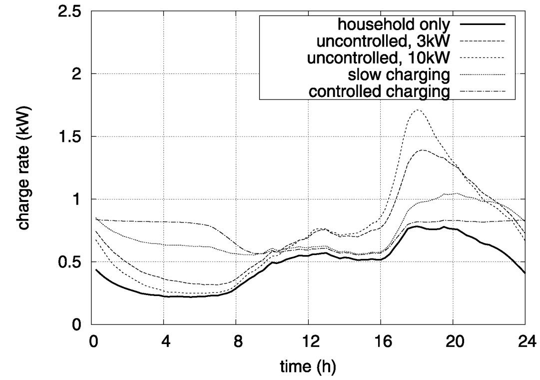

Fig. 9. Different charge profiles added to the standard household profile.

thus be interpreted as a standardized profile of a household owning one EV.

In this figure the effect of controlled charging is immediately clear: the total load remains more or less constant throughout the night and does hardly exceed the peak value of the household only. On the other hand, in the uncontrolled charging scenario, the combined peak is markedly higher than the household peak only: approximately two times higher in the 3kW scenario and even more in the 10kW scenario. The combined peak in the slow charging scenario is lower than in the uncontrolled scenarios, but still notably higher than the household peak.

It is interesting to invoke the rule of thumb that distribution networks in the Netherlands are approximately dimensioned on the basis of an aggregated peak of 1kW per household [11]. Comparing this to the standardized household profile, with a peak of approximately 0.7kW, one concludes that a distribution grid asset like an MV/LV transformer typically has a utilization factor of 70 %, which is close to the reported values, see e.g. [12].

In this light, the value of controlled charging immediately becomes clear: it can lead to a significant reduction of overloaded components in comparison with the uncontrolled charging scenario. In [3] the profiles derived in this papers have already been used to compare the number of overloaded LV cables and MV/LV distribution cables. For a specific scenario, it was found that controlled charging can lead to 25% less transformer replacements compared to the situation without charge control.

B. Applicability of aggregated profiles

The use of aggregated demand profiles is justified by the fact that for large numbers of loads, the variability of the individual load profiles vanishes. This can be formulated mathematically with the use of a coincidence factor, defined as:

$$g = \frac{\max P_{tot}}{\sum_{i=1}^{N} \max P_i} \tag{3}$$

where P_{tot} is the total power drawn by N loads and P_i is the power of the i^{th} load as depicted schematically in Fig. 10. The coincidence factor is also referred to as simultaneity factor and sometimes its reciprocal the diversity factor is used [13]. By definition, the coincidence factor of a single load is one. For

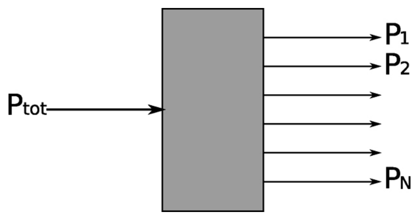

Fig. 10. Schematic representation of coincidence factor.

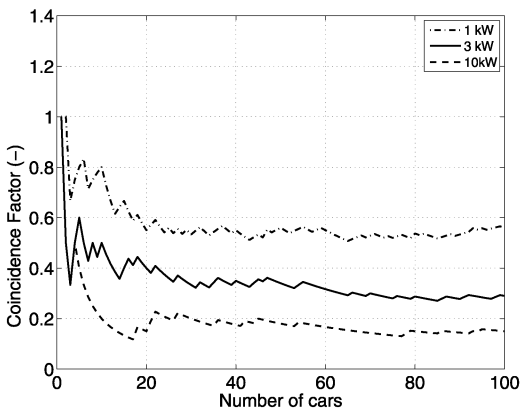

Fig. 11. Coincidence factor as a function of the number of cars.

large numbers of loads, the value of the coincidence factor of residential loads typically lies in the range 0.2-0.3, see e.g. [11] and [13]. These values, however, are based on historical measurements of household demand. Being a different load by nature, it is interesting to evaluate how the coincidence factor of EVs will depend on the number of vehicles. From this it is also possible to determine for what numbers of EVs it is justified to work with the aggregated profiles. Fig. 11 shows for three uncontrolled charging scenarios the coincidence factor as a function of the number of cars. First it can be concluded that the coincidence factor is more or less constant for a number of cars exceeding approximately 50. For the combined load of 50 or more EVs, one can thus safely work with the aggregated profiles. To consider the joint effect of a much smaller amounts of cars, one cannot readily use the aggregated profiles. This can be solved by either relying on stochastic methods, or, by multiplying the aggregated profile with an appropriate factor that can in principle be determined from Fig. 11. It is also observed that the coincidence factor shows a strong dependence on the charge rate of the individual EVs. This is caused by the fact that the probability that multiple EVs charge at the same time is small when charging times are short.

For the controlled charging scenarios, the coincidence factor has a value close to one for any number of EVs. This can be understood by realizing that it was explicitly imposed that the charging would take as long as possible. As a result, charging of almost all EVs overlaps. For these scenarios it is therefore justified to us the aggregated profile for any number of EVs.

V. Conclusions

EV charge profiles that can be used to study various impacts of EVs on the electric power system have been presented. The profiles are based upon data of current driving patterns. In the uncontrolled charging scenario's, there is a close correlation between the EV demand profiles and home arrival times. This coincides for a large part with the standard household electricity demand, because that too is dictated primarily by the typical daily commuting cycle. Because EVs can be considered flexible loads, we have also constructed controlled charging profiles, where most of the energy transfer has been shifted to the night hours. Although the work presented in this paper is primarily meant to be used for future studies of EV impacts, a number of conclusions can already be drawn. Most importantly, it is shown that controlled charging of EVs can severely reduce the peak of the combined demand of household and electric vehicle. This is an important notion, given the fact that most distribution networks have been designed on the basis of current household demand profiles. It is an indication that the replacement of large numbers of grid assets to cope with an increasing amount of electric vehicles can be reduced significantly.

A second essential result is that for most practical purposes, it is justified to work with the aggregated profiles. If one considers the combined effect of more than approximately 50 EVs, one can readily use the charge profiles presented in this paper. For numbers smaller than 50 EVs, one could either resort to stochastic methods or adjust the peak load by an appropriate value following from the coincidence factor. Future studies should provide more clarity regarding this issue.

The most important venue for future work is to use the EV charge profiles presented in this paper to study EV impacts on actual operational grids. This will provide information regarding necessary grid reinforcements, network losses, voltage problems and other network impacts, and, moreover, how these impacts can be reduced by controlled charging.

Using the profiles could also enhance knowledge of higher level system impacts of EVs such as increased need for production capacity, emissions and costs of EV charging following from unit dispatch models, or transmission network impacts. With regard to all these possible venues for future research, the emphasis should again be on how the controlled charging scenarios could relieve network and system level impacts of EVs. It should be noted, however, that the controlled charging scenario as presented in this paper, was explicitly based on the typical load of residential distribution networks. The load profile of the total national system load looks different than the typical household load, so this should be taken into account when comparing controlled and uncontrolled scenarios.

Next to being a tool for research purposes, the profiles can be of direct practical importance for distribution system operators because they can be used for distribution network planning. In that context, this method fits well with the current practice of using the standardized household profiles.

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