Probabilistic Modeling of Charging Profiles in Low Voltage Networks

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***Abstract*—This paper analyzes possibilities to create deterministic driving profiles from mobility survey data provided by the German government. Main objectives are to determine (a) the periods when the car is at home and (b) the driving distance and thus the amount of energy necessary to fully recharge the car. For this, the main challenge is to split the data into trips "departing from" and trips "returning to" home. This is achieved via the Monte-Carlo-Method under the key assumption that cars are at home early in the morning. The resulting journeys are grouped into daily driving profiles and then travel times and annual distance driven are validated by comparison with the original data.**
Furthermore, to evaluate the grid impact, a simultaneity factor is introduced assuming that the cars are charged immediately after each journey. The factor describes the percentage of electric vehicles charging at any given time. The maximum simultaneity is found late evening with a steady decrease into the night. An increase in charging power leads to a decrease in simultaneity. However when considering small grids the results become less predictable. Safety margins to keep necessary confidence intervals have to be included.
Besides electric vehicle charging, other factors which influence residential low voltage grids are household loads, photovoltaic systems and heat pumps. An already existing model of the University of Loughborough is expanded to consider interdependencies between factors affecting grid loads, such as correlations between driving profiles and household loads. The relative timedependent impact of each technology is shown and the importance of probabilistic modeling in small grids is evaluated. Large safety margins or load shifting through intelligent charging algorithms is needed to keep small grids inside operation boundaries.

I. Introduction

Low voltage grids were originally not designed to deal with additional loads caused by electric vehicle(EV)-charging or heat pumps. To limit necessary grid expansion and associated costs, the expected load due to EV-charging should be determined as realistically as possible. Therefore chapter II introduces a solution to create deterministic driving profiles from given survey data. A simultaneity factor is calculated in chapter III to evaluate grid impact depending on size, charging power and safety margins via the Monte-Carlo-Approach. Chapter IV discusses interconnectivity between different load affecting factors to show the importance of probabilistic modeling in low voltage grids (chapter V). Finally a summary an conclusion is given in chapter VI.

II. Driving-Profiles

The driving profiles are derived from the national mobility survey conducted by the German ministry of transport [1]. It contains basic information about weekday dependent driving behavior in half-hour intervals for four main activities. The activities include work, education, shopping and recreation. The goal is to create deterministic driving profiles from the given data. At first probability distributions for trips to and from the specified activity are derived. Secondly individual trips are created and validated via the Monte-Carlo-Approach. Finally the journeys are combined to represent typical daily driving routines.

A. Trip-Derivation

The report data does not distinguish between trips to and from the activity. Two methods depending on the activity type are used to derive specific driving intervals. The first method splits the given probabilities for the activities work and education in half due to long activity time durations. In the morning trips exclusively towards the activity take place, while in the evening cars return home. At midday the travel probabilities overlap to create a smoother transition.
For the activities "shopping" and "recreation" a second method is used because the activity length is assumed to be considerably shorter. The key assumption is that trips at 3:00 am are exclusively vehicles departing home. The number of departing cars at 3:30 am is calculated by subtracting the returning vehicles from the previous time interval at 3:00 am from all driving cars. At 4:00 am, returning trips consist of a fraction of vehicles departed at 3:00 am and those departed half an hour later. The rest of the day follows respectively.

The amount of returning vehicles is calculated by the activity length and probability distribution of the driving times. The driving times can be derived from the given driving distance distribution with a correlation function between travel distance and duration. Short trips usually have a lower average speed than longer ones. The developed function is shown in figure 1.

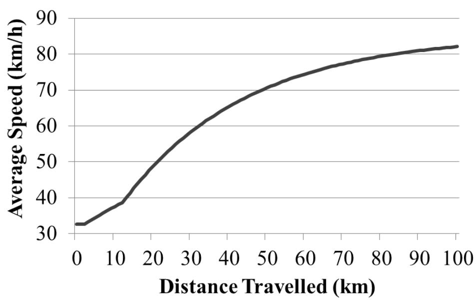

Fig. 1. Correlation function between average speed and distance traveled.

Further the activity length is assumed to be logarithmically distributed. At first mean value and deviation of

the logarithmic probability distribution are unknown. The study ”Freizeit-Monitor 2018” provides a first set point [2] for both values. Using the previously proposed method, the distribution of vehicles departing home is calculated. Afterwards, the combined distribution of trips to and from home is recreated by using the derived data via the Monte-Carlo-Approach. In the next step, the standard deviation of the recreated data from the original data is calculated.
The procedure is repeated with slightly different set point values for the activity length until a minimal standard deviation from the original data is obtained.

Figure 2 shows the original data and the final derived trips leaving home for recreational activities on weekdays. While in the morning almost all trips are departures form home, the situation is reversed in late evening. Throughout the day the distribution is almost equal for cars leaving and returning home. It is noteworthy that the chosen method slightly underestimates trips away from home at night because the activity and driving distribution stay fixed throughout the day. Usually the activity length decreases towards the end of the day. To reduce computational complexity this effect is not taken into consideration.

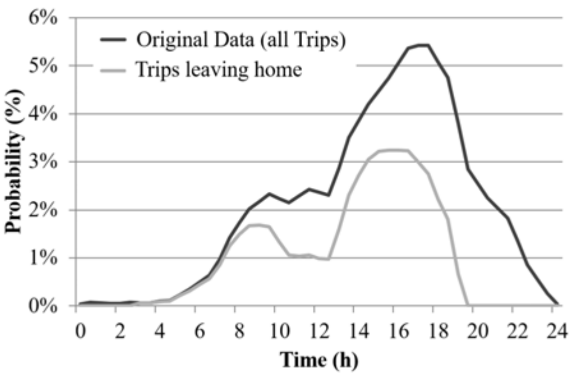

Fig. 2. Comparison of distributions for trips starting home with the original data for recreational activities on weekdays.

B. Individual trips and validation

For each activity, the probability of cars leaving home is known from the previous chapter. In the next step, individual trips are created. At first the probabilities for vehicles leaving home for each activity are combined to an overall probability. Based on the Monte-Carlo-Approach, the function is integrated into the corresponding distribution function and subsequently inverted. A specific departure time is created via a uniform random number. Figure 3 illustrates this procedure.

Several thousand departure times at the households are created. For the selected departure times, the activity distribution is known and the activity type determined by a new uniform random number. In case the chosen activity is shopping or recreation the previously developed logarithmic distribution is assessed via a new uniform random number to determine the activity length. The same procedure is used for the travel time. Simple addition of the departure time, travel time to the activity, and the activity length leads to the departure time back to the household.

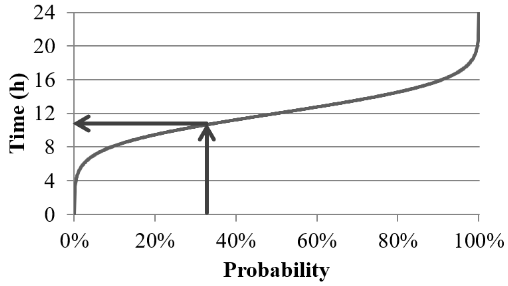

Fig. 3. Inverted distribution density function to calculate traveling times via a random number e.g. 0.32.

For the activities ”work” and ”education” the approach is different. In this case a probability density function for the starting time of the return trip is given instead of the activity length. Plausibility dictates, that the return trip must take place after the trip towards the activity. Additionally very short and very long activity times are uncommon and in some cases even prohibited by labor law. Therefore certain travel combinations must be avoided. In order to do so a recursive method is used. At first the total number of trips for each activity type is determined. According to the amount of journeys, return trips are computed without time restrictions. This pool is used to exclusively match the trips to and from the activity within the defined time restrictions. For each journey leaving home a match is searched out of the pool. In case no match can be made with any remaining return trip in the pool, already existing matches are broken up in case the new match is within the constrains.

Following the calculation of individual trips, these trips are validated via the Monte-Carlo-Method. All journeys are then transferred into a distribution showing the probabilty of a trip at each half-hour interval of the day. Figure 4 visualizes the results in comparison to the original data set for a Sunday. The standard deviation is 0.38%. On Saturdays and workdays even better results can be achieved, due to a higher proportion of work and educational activities which differ less from the original data.

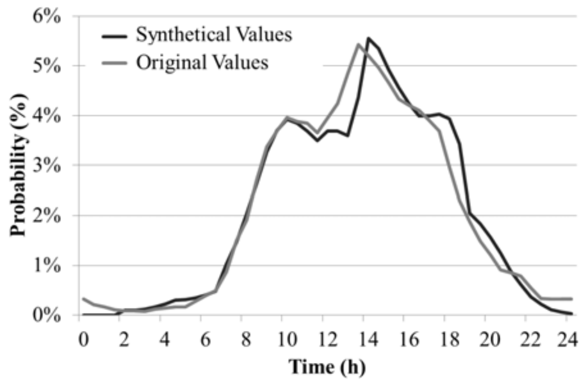

Fig. 4. Comparison of accumulated data by Monte-Carlo-Method with the original data for all activities combined on a Sunday.

In order to determine the required arrival times back home, the departure times of the return trips are extended by the traveling times in a final step.

C. Driving routines

Cars are often used more than once a day and are used more on weekdays than on weekends. The underlying report [1] contains information about the trip distribution depending on the type of day and it condenses the percentage of cars being used more than twice a day into one category. Therefore individual daily driving profiles designed in this paper consist of zero to three trips. A further constraint is that trips made by one car must be consecutive. Furthermore it is assumed that the minimal waiting time between two trips averages to 30 minutes. The already created individual trips are matched in a recursive manner similar to the traveling time match for the activities work and education described in the previous chapter. The key difference is that not all journeys have to be matched.

The resulting driving routines are validated by comparison with data regarding average travel distances per year and vehicle. For each day of the week an average travel distance can be obtained. The daily averages are then multiplied by 52 weeks for an average yearly traveled distance of 14089 km. The obtained result differs by 1.9% or 270 km from the original data supplied by the report.

III. Charging impact

As previously concluded, vehicles leave and return at different time intervals. To evaluate the charging impact, a simultaneity factor similar to the ones used for household loads is introduced. It describes the percentage of EV's charging at a given time. While the chance of all vehicles charging at the same time is relatively high for a small amount of EV's contained in the grid, the simultaneity factor decreases with an increasing number of EV's.

At first the time dependency of the simultaneity factor is evaluated for very large grids. In networks containing an infinite amount of electric vehicles the confidence intervals are the same and therefore is the maximum simultaneity factor per time step known. A network containing one million electric vehicles is chosen to simulate this effect. It is assumed that the vehicles charge with 3.7 or 11 kW respectively directly after arriving back home. In case the charging time until the next departure is insufficient to fully charge the vehicle, the remaining energy gap is charged after the next return home. The battery is assumed to be of sufficient size and the grid is able to provide the necessary energy at all times.

Figure 5 illustrates the percentage of charging vehicles on a weekday depending on the time of day and the chosen charging power. A higher charging power leads to a lower simultaneity. The cars are charged faster and therefore charging overlaps tend to decrease. Still the grid impact increases from 0.58 kW maximum impact per car for slow-charging to 0.72 kW for fast-charging. Even though the charging power increases threefold the grid impact only increases by 24%. It should be noted that in reality cars are not charged directly after each trip and in consequence the simultaneity could change due to different behavior of car owners. A more advanced approach is discussed in a follow up paper [3].

Typical low voltage networks only contain a few electric vehicles due to a small number of connected customers. The general time dependency of the previously described

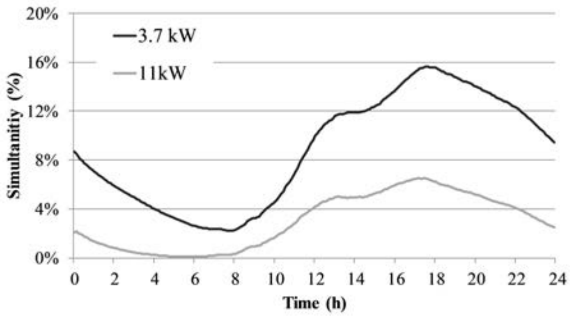

Fig. 5. Simultaneity factor of direct EV-charging for large grids.

simultaneity factor for very large grids stays the same, but yields an overall increase for smaller grids.

Figure 6 illustrates the importance of confidence intervals. In case only 10 electric vehicles are owned in a distributin grid and charged from time to time with 11 kW, we can observe in 99.99% of all cases, that at maximum 6 cars will charge at the same time. 99.73% of the time only 5 cars or less are charging, while 95% of the time 4 cars or less are drawing power. It becomes clear that only in extremely rare cases all 10 cars would charge at the same time. Flexible charging algorithms could absorb the grid impact of rare charging scenarios by reducing the charging power in times of necessity [3]. The grid does not have to be able to handle the full charging power anymore.

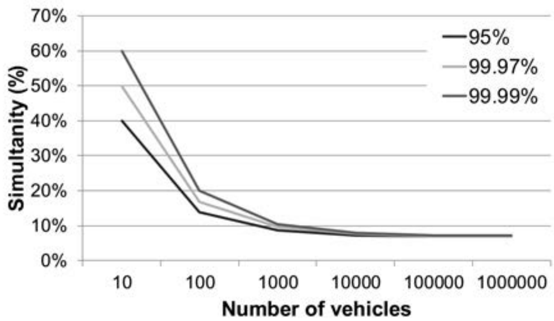

Fig. 6. Simultanity factor of 11 kW EV-charging directly after arrival for varying connected vehicles while considering different convidence intervalls.

With increasing amount of EV's in the network it becomes implausible that all vehicles are charged at the same time. The reserved power for EV-charging can be reduced without inducing safety risks. Never the less, the model does not take into account local effects such as employment at the same company, which could increase the simultaneity of journeys due to equal work schedules. Therefore the simultaneity-factor should only be used for network evaluation for grids containing 1000 or more EV's without flexible charging algorithms to handle network overload without considering confidence intervalls.

IV. Cross-influential-connection

Alongside EV-charging, low voltage grids in residential areas are influenced by regular household loads, potential photovoltaic systems and heat pumps. All grid impacting factors are interconnected.

While a car is in use, the driver is not home and therefore household loads are reduced as well as internal heat gains. A reduction in internal heat gains in consequence leads to an increase in heat pump power consumption.
Unblocked by clouds, sun radiation leads to an increase in outside and building temperature, which lowers heating demand provided by the heat pump, while at the same time PV-output rises. Furthermore sun radiation influences light bulb usage, which in turn reduces internal heat gains.

Most correlations are already implemented in the household model of the University of Loughborough used in this paper [4]. Individual grid impact is calculated for each household in one minute time intervals via a bottom up approach. The following chapters describe the implementation of missing links and improvements on the existing model.

A. Household load adaption

The program provided by the University of Loughborough operates under the assumption that all appliances are turned off at midnight. Therefore, the household loads just before and just after midnight are not consistent when considering the average over a large quantity of houses. To overcome this issue, some appliances are started inside their respected cycle.
For illustration purposes the usage of an appliance is set to 40 minutes (Figure 7). Afterwards the activity is not performed for another 60 minutes. In the first time interval of the day a uniform random number between 0 and 1 is created. In this example it equals 0.3. Therefore, the appliance is in use and 30% of the activity cycle is already completed at this point. The remaining activity length is 10 minutes. In conclusion some appliances are used at midnight while others are turned off and thus the average household load is consistent when crossing midnight. In the next step, the real individual activity length of each appliance is calculated by the already existing algorithm of the model.

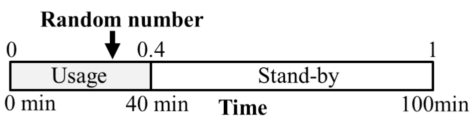

Fig. 7. Exemplary consistency assumption at midnight for a given household load.

B. Driving-Profile-Link

As previously described, it is implausible that driving schedules have no influence on household loads. The number of residents at home must be adapted according to the number of used electric vehicles. Depending on the household size and regional location, different car densities are provided by the "Mobility in Germany" report [1]. While in urban areas fewer cars per household exist, the link between driving profiles and household load does grow stronger in rural areas.

The model of the University of Loughborough already contains information about time dependencies of people staying home via a transition probability matrix, but it does not specify the purpose of residential activity outside of the house. While a vehicle is being used, at least one resident cannot be home at the same time.
To determine if the number of residents at home is too high, a uniform random number is created. In case the percentage of residents at home is above the generated value the number is reduced by one. Otherwise no adaption occurs.

C. Heat pump

While no substantial changes are necessary on the photovoltaic model, the heat demand model designed by the University of Loughborough has to be extended. Originally it only provides a model for conventional heating systems. The greatest difference lies in the heat distribution. While conventional radiators provide a very dynamic heat transfer, heat pumps should use much slower floor heating for better efficiency. The heat controllers and essential start values and assumptions have to be adjusted. Previously the heat emitter temperature was chosen at random for the first time interval. Floor heat emitters need to be close to equilibrium so no drastic changes in room temperature occur in the first hours of the day, due to high heat capacity of the emitter.

During normal operation the room temperature is allowed to change within given boundaries. Once the room temperature is below the set point, the heat pump starts working at full capacity for maximum efficiency. The amount of power drawn from the grid is restricted by the heat pump size, while the heat output depends on the outside temperature as seen in equation 1 [5]. T_{ol} stands for the outlet temperature of the heat pump and is set to 40 °C for room heating and to 60 °C for warm water production. The outside temperature T_o is already implemented in the existing model. In consequence, all variables of the thermodynamic model are known.

$$\dot{Q} = (0.0008 \cdot (T_{ol} - T_o)^2 - 0.138 \cdot (T_{ol} - T_o) + 7.4545) \cdot P \quad (1)$$

V. Importance of probability

With the adaption of the model of the University of Loughborough all grid loads are known. For simplification reasons the power factor is assumed to be 1. To assess the highest grid impact a clouded winter day is chosen without PV-generation and full penetration of electric vehicles and heat pumps. To show general dependencies the average load of a very large number of households is compared to an exemplary grid containing only 100 households (figure 8).

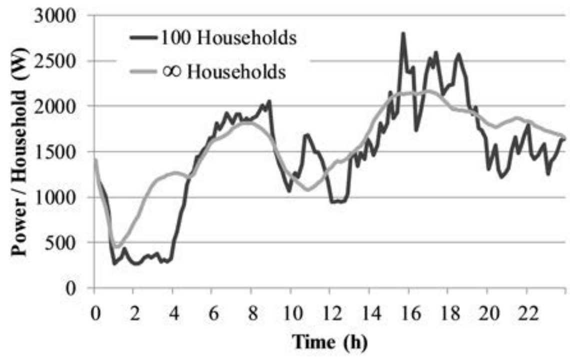

Fig. 8. Comparison of averages for a very large number of households with 100 households.

As clearly seen in the graph, grid load fluctuations of small grids are higher than in large grids. These fluctuations are mostly affected by vehicle charging, while heat pumps and household loads already follow a smoother transition for the chosen low voltage grid size. Considering a confidence interval of 99.73% the maximum grid load increases from 2165 W for very large networks to 2961 W. Therefore it is not recommended to calculate small grids based on simultaneity factors alone. Confidence intervals to include rare load accumulations should be considered as well by using probabilistic methods.

VI. Summary

This paper presented a method to create discrete driving profiles out of report data. Main difficulties were the creation of probabilities for cars leaving and returning home depending on the activity type. With the use of two different methods the creation of the profiles was validated successfully. Furthermore a simultaneity factor for EV-charging was introduced.

It was shown, that an increase in charging power leads to a decrease of the simultaneity factor and thus in total an under-proportional increase of maximum grid load. The dependency between the number of EV contained in a grid and confidence intervals led to the conclusion that in case of less than 1000 connected EV's in the network, probability analysis is important. The same holds true when considering all relevant loads in residential low voltage grids even after introducing inter-dependencies.

References

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