Probabilistic analysis of voltage bands stressed by electric mobility

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Abstract-- **This contribution proposes a method to analyze the capabilities of low voltage grids to meet the demands of additional loads due to electric mobility. Probabilistic load models for both the domestic and electric vehicle loads are developed to give insight into the stochastic nature of load distribution and voltage bands. The results not only provide the maximum voltage deviations, but their probability of occurrence during a given period of time. With this information, a recommendation for future grid planning can be developed, which takes into account the increasing load caused by electric mobility. Furthermore, a load management system is proposed to reduce maximum load thus avoiding costs for increasing feeder capacities.**

***Index Terms*— electric vehicles, load flow, load modeling, power system planning, probability density function, statistical analysis, voltage control**

I. Introduction

The upcoming wide spread distribution of electric vehicles (EV) will provide new challenges for power grids as the demand for energy will increase. This raises the question, whether it is possible for the current grid to meet the new requirements without major investments. On the other side, electric mobility may have mitigating effects on the grid peak load as well, because battery storage in EV may be used to balance loads between peak and base load times. Renewable energies, which not necessarily supply energy when it is needed, will intensify the need for load balancing.

For future grid planning, it is necessary to know what impact electric mobility will have especially on distribution grids. The most important issue is that - assuming no charge control - many vehicles may be charged simultaneously in evening hours after work. This is exactly the time, where the grid is already at its peak load.

This paper analyzes under which conditions there will come up grid constraints in near future due to electric mobility and when they are to be expected. This is achieved by applying certain scenarios for future development of EV and simulating a typical low voltage grid.

In a first step, load models are developed for domestic loads and electric vehicles to be able to represent their varying nature correctly in a load flow calculation. These load models can either be based on deterministic standard load profiles or probabilistic loads and are discussed in section II. The difference and increase in detail due to probabilistic load models in load flow calculation is analyzed in section III. Here, a detailed view on the probability of occurrence of line loadings and voltages at a certain grid node is given. Section IV analyzes the effects of electric mobility on future grid planning and the increase in peak load demand on distribution feeders for a low number of households and vehicles.

II. Load Modeling

To be able to simulate a low voltage grid, load models of different loads in that grid are necessary. This includes commercial, domestic and industrial loads as well as the load of electric vehicles. This section describes the models used for the assessment of the impact on low voltage grids of electric vehicles.

A. Domestic Load

Domestic load models are necessary for grid calculation and planning and are state of the art. They are used, for example, for sizing transformers and power lines. This subsection will show possibilities for domestic load models.

1) Load Profile

Load profiles are used by energy suppliers to estimate the hourly demand of their customers, whose energy consumption is usually measured on a yearly basis. This hourly data is used to determine the supplier obligation on retail markets, which must be covered by the supplier. These profiles are scaled to have an energy consumption of 1,000 kWh per year. There is a profile for different load types (e.g. domestic, agricultural, commercial loads), differentiated each season and 3 types of weekdays (workdays, Saturday and Sunday) [1]. In Fig. 1 three winter profiles for domestic loads are shown.

It becomes apparent, that the peak in winter is on workdays at about 6:30 pm. However, the peak on Saturdays at 12:00 am is almost as high.

As mentioned, these profiles are used to estimate the contribution of a large number of similar customers to the system load curve. For a collection of customers, they need to be scaled accordingly to the customers' energy consumption. To fit the calculated maximum load value to the measured peak load data at urban MV/LV grid transformers, for example, coincidence factors are applied, which describe the ratio of the coincident, maximum demand of two or more loads to the sum of their noncoincident maximum demand for a given period. It is less than or equal to one. Load profiles help to give an overview of the situation in a certain grid.

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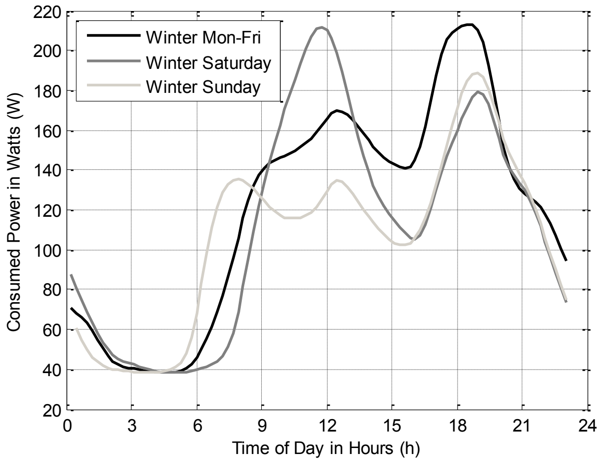

Fig. 1. Domestic standard load profiles for households in winter.

2) Probabilistic Load

For an in depth analysis of voltage bands, it is necessary to have a decent knowledge of the distribution and statistical nature of the load. When looking at a small number of households and EVs, the momentary load may differ a lot compared to the averaged load profiles. To account for this, load models of individual households and of small groups of these loads are required, e.g. a certain number of households at one feeder. A probabilistic approach for a domestic load model is investigated in [2], where a probability density function is used to describe the nature of the load to a certain time step, which can be acquired of measurement data. Fig. 2 shows an exemplary histogram of the load distribution of measured domestic load data at 7:00 pm on a workday in winter. The loads are average values for 15 minute time intervals. The data was collected in the scope of a publicly funded project within the German E-Energy Research Program [3]. The measurement data is used throughout this paper.

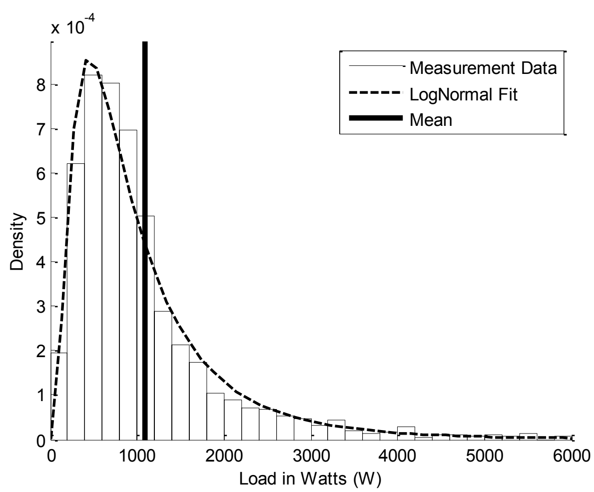

Fig. 2. Histogram of measured domestic load data at 7:00 pm with mean and probability density function fit.

The marked mean of the load distribution would be the value of a corresponding load profile. Evidently, much higher loads may occur locally on a feeder than given by a standard load profile, as the figure shows. Furthermore, the measured data can be fitted by different distribution functions. In this case, the log-normal distribution fits best, which means that the logarithm of the occurring loads is normally distributed. The probability density function of the log-normal distribution can be described by

$$f_x(\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x-\mu)^2}{2\sigma}}, \quad x > 0.$$

In Fig. 2, the parameters for the fit at 7:00 pm are $\mu = 6.69531$ and $\sigma = 0.771546$. However, other publications [4] show that for different measurement data of household loads often the Beta or Weibull distribution yields a better fit.

The fitted distribution can now be used for voltage drop calculations on low voltage and medium voltage feeders [5], [6] or for a probabilistic Monte Carlo load flow calculation.

B. E-Mobility Load

While the load profile for households is well known and commonly used for grid planning, the load profile for electric vehicles needs to be derived based on plausible considerations. The load of electric vehicles is modeled under the assumption that in the starting phase of their market entry they mainly will be charged at home. It is assumed that the car starts charging immediately when arriving at home. However, this may change with the introduction of a load management system, which may alter the load profiles. Furthermore, assumptions need to be made regarding the charging power and grid penetration of electric mobility.

1) Probabilistic Load

By analyzing the mobility behavior of today's car owners, one can assess a charging profile by taking into account the arrival time at home and an average daily traveled distance for the amount of energy, which needs to be charged, like depicted in Fig. 3.

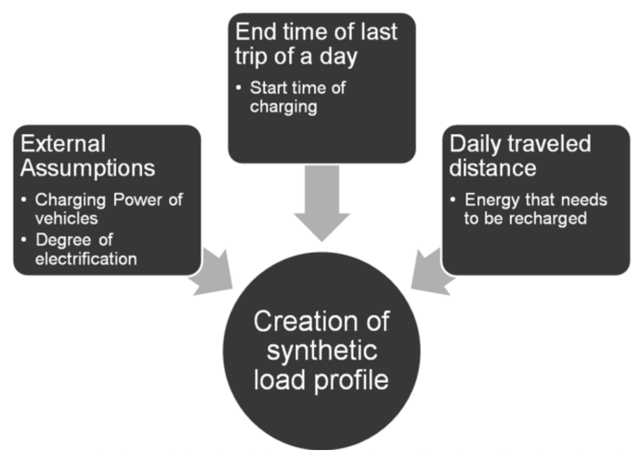

Fig. 3. Description of the algorithm for creation of load profiles for electric vehicles.

First of all, the assumptions regarding charging power and degree of electrification play a major role for the generation of synthetic loads. For Germany, the government is looking to have one million electric vehicles on the road by 2020 and over five million by 2030 [7]. That represents roughly 2.5% of the total car population for 2020 and 12.5% for 2030 respectively. Regarding the charging power, there are different possibilities of charging. When the car is charged at a normal plug, 1 phase protected with a 16 A fuse at 230 V, the vehicle can be charged with up to 3.7 kW. Table I shows the upper limits for different types of connections.

TABLE I
MAXIMUM CHARGING POWER FOR ELECTRIC VEHICLES IN GERMANY

Charging Current	1x16 A	3x16 A	3x32 A	3x63 A
Max. Charging Power	3.7 kW	11.0 kW	22.1 kW	43.5 kW

How fast the demand for charging power will rise is difficult to say. Charging power also may be different for charging at home and for rapid charging at a service station, if this is acceptable for reduced charging times. In this paper, it is assumed that a rated power of 11 kW should be supplied by a common domestic 3 phase grid connection.

Beside this, it is necessary to know when electric vehicles will arrive at home and will usually be charged, considering that there is no load management system in place in the starting phase of electric vehicles. For EVs, the time of arrival of a single car is a stochastic variable following the probability density function given by the time of arrival of the total car population. These data can be acquired from survey data, which was collected in [8]. In this survey, German households were monitored with regard to their mobility behavior. Fig. 4 shows the time of arrival after the last trip of the day. Most people's last trip of the day ends at 6:00 pm and it is suspected that they arrive at home and would start to charge their electric vehicle.

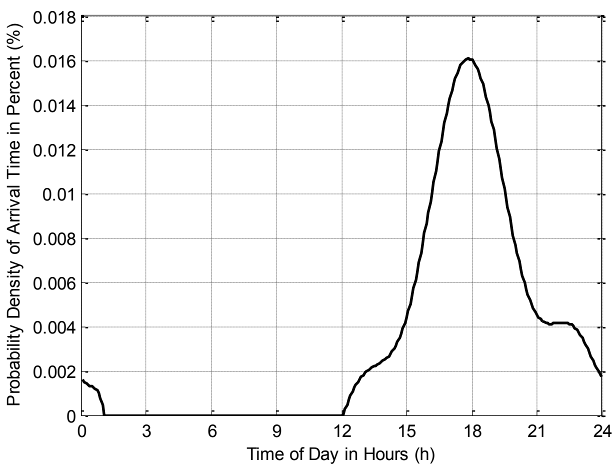

Fig. 4. Probability density function of the arrival time after the last trip of a day with 5 minute sampling (survey data [8]).

Beyond that, it is important for how long each vehicle will be charged. This is determined by the daily travelled distance and the energy consumption per kilometer, which is roughly estimated to be about 20 kWh/100 km. In [8] the households were asked for their daily travelled distance as well. These data can be fitted well by the generalized Pareto distribution function. The daily travelled distance is shown in the first row, while the percentage of occurrence is shown in the second row of Tab. II. In the third row, the values of the fitted generalized Pareto distribution function are shown and it becomes apparent, that the deviations are negligible. The generalized Pareto distribution function is described by

$$f_x(\xi,\mu,\sigma) = \begin{cases} 1-\left(1+\dfrac{\xi(x-\mu)}{\sigma}\right)^{-\frac{1}{\xi}}, & for\ \xi \neq 0 \\ 1-\ exp\left(-\dfrac{(x-\mu)}{\sigma}\right), & for\ \xi = 0 \end{cases}$$

with the parameters: $\xi = 0.43381, \sigma = 28.577$ and $\mu = 0$.

TABLE II
PARETO FIT OF SURVEY DATA OF DAILY TRAVELLED DISTANCES

Distance in km	0-1	1-10	10-20	20-40	40-65	65-100	100-200	200 +
Survey in %	3.5	24.3	18.0	20.9	12.9	8.7	6.7	4.5
Pareto Fit in %	3.5	24.6	17.9	20.6	12.8	8.6	7.9	3.3

It is to be pointed out that Table II only includes distances above 0 km. 29.9% of the vehicle population is not moved per day. The average travelled daily distance of the 70.1% moving cars is about 50.1 km, the mean of the fitted Pareto function. With the help of the Pareto distribution fit, it is possible to draw specific values for the daily travelled distance, although the survey data have such a coarse resolution.

Finally, with this information a probabilistic load for a single electric vehicle can be calculated like shown in Fig. 3 by following these steps:

- draw a uniformly distributed random variable to decide, whether the vehicle is driving at all (only 70.1% of vehicles are moved per day),
- draw random variable accordingly to the PDF for the arrival time to set the starting time for charging,
- draw random variable accordingly to the PDF for the daily travelled distance to know the necessary amount of energy for a fully charged battery.

Therefore, the stochastically generated load for a single vehicle is rectangular: zero until the car arrives at home, at specified charging power for the time needed to recharge the battery and zero afterwards, when the battery is fully charged. This is assumed, although batteries reduce their charging power while reaching full charge. This is, because car manufacturers limit the cycle depth of vehicle batteries to about 20% to 80% state of charge to increase life time. In this range full charging power is feasible.

The battery capacity is not separately taken into account. Instead the possible range is limited to 300 km. If a larger daily travelled distance is drawn, it is reduced to 300 km. This inherently limits the size of the battery to 300 km * 20 kWh/100 km = 60 kWh.

2) Load Profile

Load profiles are only valid when considering large quantities of loads. When looking at a single load as probabilistic process, the load profile is the mean or the expected value of that process. However, the variance may be relatively high. Therefore, there may be a significant deviation of a single load to the load profile. Still, when looking at a large number of loads, the mean will be very close to the load profile.

Based on the methodology of the precedent section, load profiles can be derived by repeating the described methodology to generate stochastic load profiles for a large number of vehicles and calculating the average. Load profiles for different charging rates are shown in Fig. 5.

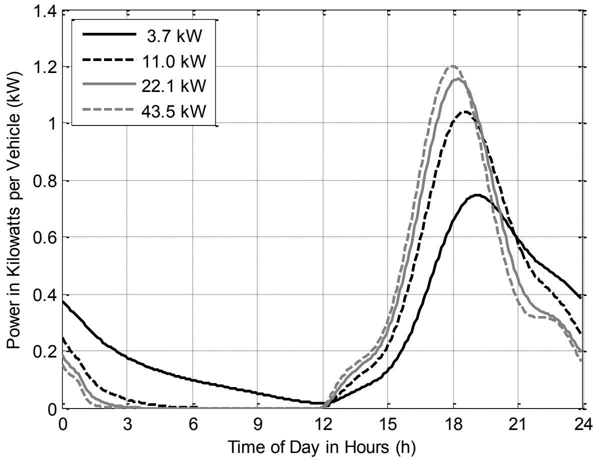

Fig. 5. Load profiles for electric mobility and different charging rates derived by the accumulation of synthetic probabilistic loads for single vehicles.

The maxima of the load profiles occur between 6:00 and 7:00 pm. With an increasing charging power, the peak shifts to earlier times and is a little higher. Interestingly, the maxima, especially from 22.1 kW to 43.5 kW, only increase a little while the charging power is doubled. This is, because faster charging results in less vehicles charging simultaneously.

These profiles can be used for grid simulation and be applied for every vehicle. Although this causes the vehicles to have a load with a coincidence factor of 1, it yields sufficient accurate results for large aggregations of vehicles, e. g. when simulating medium voltage grids. What number of vehicles is necessary to be able to use a standard load profile instead of probabilistic single vehicle loads, is investigated in section IV, Fig. 9. There, we analyze how far the peak load of an increasing number of vehicles is apart from the standard load profile.

C. *Combination of Domestic and Electric Vehicle Loads*

Electric vehicles will be mainly charged at home in the beginning. The number of vehicles is directly dependent on the number of households in a low voltage grid. In Germany, for example, there are 1.3 cars per household in rural areas and 1.2 cars in urban areas [8]. By extending the algorithm described before, one can generate combined profiles for households and electric vehicles together. This can be achieved by drawing a random variable for the number of vehicles present at the currently looked at household. Furthermore, it must be decided randomly, whether the car is electric or not, depending on the degree of electrification. If it is electric, the process described earlier can be continued and the profile for the electric vehicle is added to the one of the households.

Like this, a daily profile for, e.g. 5 households and 6 electric vehicles (electric and non-electric) can be generated under the assumptions of a certain charging power, a certain degree of electrification, a probability density function (PDF) for the daily traveled distance and a PDF for the time of arrival. Furthermore, a probability of a certain load on one feeder with a small amount of electric vehicles and households can be calculated. This will be elaborated in section IV regarding the consequences for future grid planning.

III. Load Flow Calculation using different load models

For the analysis of low voltage grids, usually standard load profiles are used. Results of simulations with averaged load profiles show that - depending on the number of EV charged simultaneously - minor problems with transformer overload occur. The main problem, however, will be under voltage due to the increased load [9]. Especially regarding the results for voltage drop calculations, it is to be expected that the simulation with probabilistic load models will yield results with a much higher precision by taking into account the probability of coincidental loads locally and temporally at one feeder, for example. This is necessary, because the simulation with standard load profiles assumes a homogenization of loads and does not take into account local accumulations of electric vehicles at one feeder.

The simulations were carried out using an urban low voltage grid within the city of Stuttgart, Germany. It consists of two 800 kVA transformers feeding the grid, roughly 900 households, 500 kW commercial load, 800 kW night storage heater load and 120 kW of minor loads like street lighting. The commercial, night storage and minor loads are implemented with standard load profiles due to the absence of measurement data, which would enable a probabilistic model. However, these loads are known to have a high coincident factor and therefore the improved model would only have negligible influence on further voltage drops. It is assumed, that there are roughly 1,080 vehicles present. Fig. 6 shows the results of different simulations. Three scenarios are depicted. The first is modeled without electric vehicles. The second and third assume 12.5% electric vehicles, while in the second scenario they were charged with 3.7 kW and in the third with 22.1 kW. Each scenario was simulated using probabilistic load models and standard load profiles, represented by the two bars in Fig. 6. For each simulation, the maximum voltage drop ΔU from the urban grid transformer to the nodes is shown. There is only a slight decrease in voltage drop when simulating without e-mobility. However, considering e-mobility, the voltage drop with probabilistic load models is a lot higher.

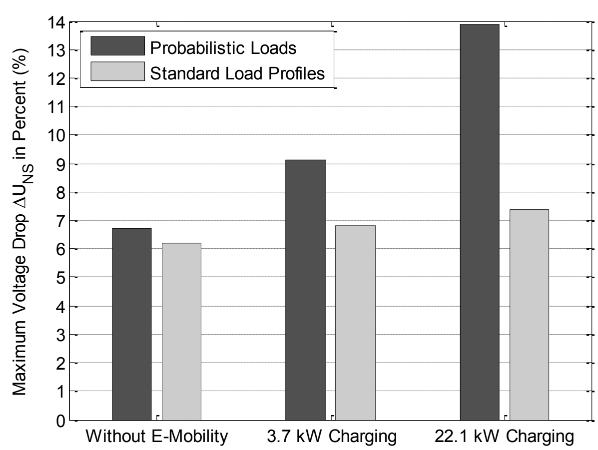

Fig. 6. Maximum voltage drop simulating with probabilistic loads and standard load profiles with 12.5% electric vehicles.

Looking at this situation in detail, it can be found that the voltage drop for probabilistic loads depicted in Fig. 6 is possible but does not occur very often. It is the maximum drop that occurred during the simulation. Fig. 7 shows the occuring voltages at an exemplary node in more detail.

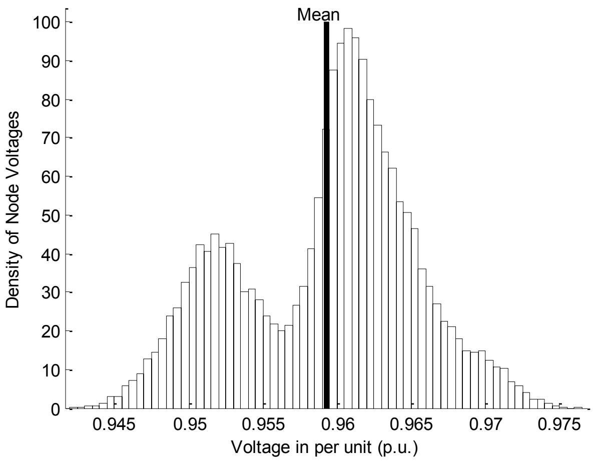

Fig. 7. Exemplary node voltages resulting from a load flow calculation using probabilistic load models.

At this node, the mean voltage is at 0.959 p.u., although it becomes apparent that the occuring voltages are widely spread by about ±0.15 p.u. and twin peaked. All voltage values are given referring to a value of 1.0 p.u. at the LV bus of the MV/LV transformer substation. To reach a reasonable conclusion taking into account the probability of occurrence of loads and voltages, one can specify a level of confidence or conversely a risk value.Thus the statement is possible that there is only a 5% chance for the voltages at this node to be below 0.9490 p.u., or a 1% chance for the voltages to be below 0.9464 p.u.. These results can now be used to decide, whether grid reinforcement is necessary at this node or not and is more accurate than the simulation with standard load profiles.

Interestingly, Fig. 6. shows that without e-mobility there is not a big difference between the simulations with probabilistic loads and standard load profiles. Therefore, probabilistic load flow only brings small increases in precision over the simulation with standard load profiles. For the simulation with electric vehicles, however, it is advisable to use probabilistic load models. This is due to the high deviation of single vehicle profiles compared to the standard load profile for electric vehicles. Looking at Fig. 5, the load profile for 43.5 kW only reaches 1.2 kW on average, while single cars are charging with up to 43.5 kW. This is a significant difference for voltage drop on the corresponding feeder, where that specific car is connected to the grid.

IV. CONSEQUENCES FOR FUTURE GRID PLANNING

The rising share of electric vehicles will inevitably lead to an increase in peak load of households. Because it is unknown, which households will have an EV, it is necessary to account for the probability of occurrence of an EV in each household with regard to the degree of electrification of vehicles. In this section, the results of domestic and electric vehicle load modeling are combined to develop recommendations for future grid planning and feeder design.

For the derivation of load profiles for electric vehicles in section II, the generation of a daily profile for a single vehicle was conducted many times. To derive, what loads may occur on a single feeder in a low voltage grid with, for example, 10 electric vehicles connected, a daily profile for the vehicles is calculated. With their chance to be electric, their PDF for the time of arrival and their PDF for the daily travelled distance, this daily profile is stochastic. Doing this multiple times and taking the maximum of every daily profile yields a distribution of peak loads, which is depicted in Fig. 8 for different numbers of vehicles.

The circle depicts the median of the peak loads of all profiles. The thicker box begins at the 25th percentile and ends with the 75th percentile. The thinner box begins at the smallest and ends at the largest occurring peak load. For example, for only one vehicle, this peak load will always be 11 kW. And if infinite profiles were generated, the thinner box would always reach 11 kW, because it is always possible but very improbable that all vehicles charge simultaneously. It is clear that the expected peak load per vehicle decreases with an increasing number of vehicles, because they tend to charge more evenly distributed. With small populations, it is more probable that vehicles charge simultaneously. The limit of the median as the number of vehicles goes to infinity is the peak load of the standard load profiles depicted in Fig. 5. Furthermore, the 25th and 75th percentile would have the same value as the median.

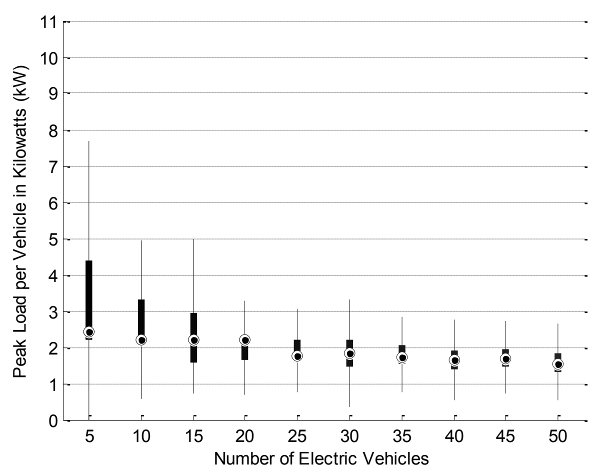

Fig. 8. Probability distribution of peak loads occurring with a certain number of vehicles charging each with 11 kW with random times and durations (10,000 Iterations for each number of vehicles).

Fig. 9 shows the described median for larger number of vehicles divided by the peak load of the standard load profile for electric vehicles. This helps to assess the difference of a simulation with standard load profiles and probabilistic single loads. For example, when looking at a low voltage grid with 600 electric vehicles charging with 3.7 kW, the simulation with probabilistic single loads will result in an increased peak load at the transformer of about 5%.

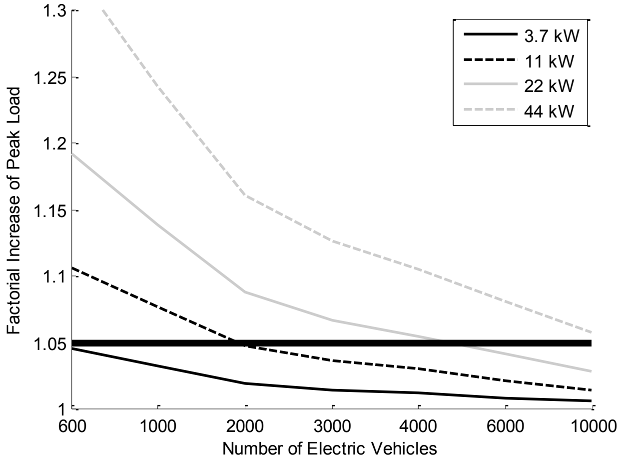

Fig. 9. Factorial increase of peak load due to the usage of probabilistic single load profiles for EV instead of standard load profiles.

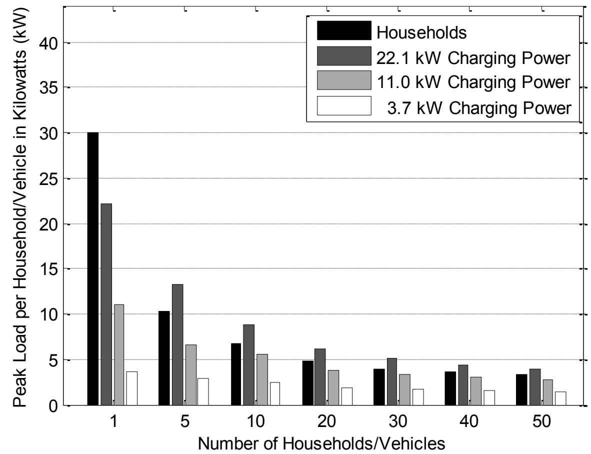

Fig. 10. Comparison of peak loads between households and electric vehicles with different charging power.

Charging the vehicles with 11 kW will already result in an increase of 10% compared to the simulation with standard load profiles. This comparison helps to decide from when on it is feasible to use standard load profiles instead of probabilistic single loads. If a 5% deviation of peak loads would be acceptable, a number of 2,000 vehicles charging with 11 kW is necessary to use a standard load profile instead. For 3.7 kW charging, already 600 vehicles would be sufficient. Looking at the considered low voltage grid in section III, a number of 900 households and therefore about 1,080 vehicles already represents a large low voltage grid. However, a degree of electrification of 55.5% would be needed for the necessary 600 electric vehicles to justify the use of standard load profiles. Therefore, standard load profiles are only recommended for the simulation of medium voltage grids.

Similar considerations are already made regarding domestic load profiles to be able to design the necessary peak load capacity of a feeder connecting a certain number of households. By defining a certain risk, one can assess a load threshold for the expected peak load for a certain number of vehicles, which is not exceeded. The peak loads for domestic loads and electric vehicle loads using a risk of 1% are depicted in Fig. 10. This means, that only in 1% of cases the actual load exceeds the depicted one. The choice of a smaller risk results in an increase of peak load per vehicle.

Interestingly, the peak load of vehicles surpasses the peak load of households when charging with 22.1 kW and for larger number of households the peak of 11.0 kW charging is almost as high as the one of the households. This confirms the assumption, that electric vehicles will increase the necessary peak load for households significantly. However, these values are only valid when looking solely at electric vehicles or at domestic loads, but not in combination. The values cannot just be added, because that would assume their respective peak loads to occur at the same time.

To determine the resulting peak load of domestic loads combined with electric mobility, loads for households are chosen randomly from measurement data.

In a next step, it is randomly determined how many electric vehicles are present depending on the degree of electrification. Finally, a probabilistic load model for each of the vehicles is added to the load of households. Fig. 11 shows the result of 99% percentile peak loads over the number of households with 2.5% (scenario for 2020) and without electric mobility. Fig. 12 shows the same results for a degree of electrification of 12.5% (scenario 2030).

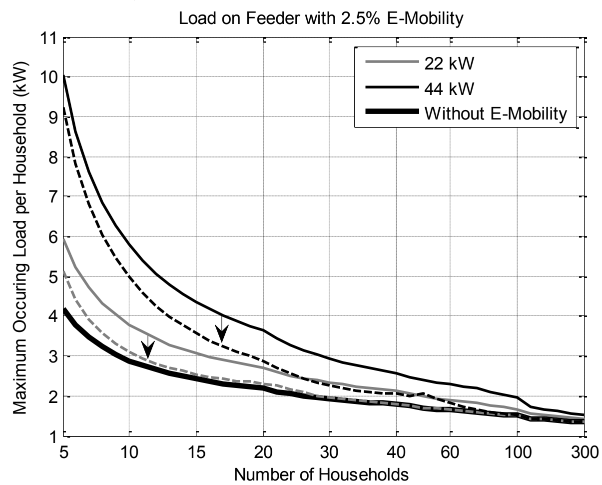

Fig. 11. Necessary peak load capacity of LV Feeder with 2.5% EV (dashed lines depict load management system with according charging power).

The continuous lines represent electric vehicles charging without load management while the dashed lines represent electric vehicles charged with a simple load management system, which is easily applied and does not need communication. This load management system selects a uniformly distributed end time for each vehicle between 0:00 am and 5:00. The beginning of charge is delayed until the remaining time is just sufficient for the necessary energy to be recharged until the end time.

Fig. 11 and 12 show a remarkable increase of peak load demand of households due to e-mobility. However, in the scenario for 2020 with 2.5% degree of electrification in Fig. 11, there is no significant effect up to a charging power of 11.0 kW. Starting with 22 kW, there is a noteworthy increase.

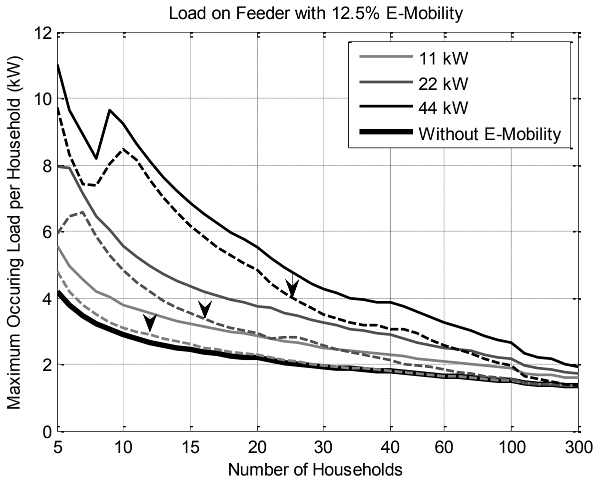

Fig. 12. Necessary peak load capacity of LV Feeder with 12.5% EV (dashed lines depict load management system with according charging power).

For Fig. 12 with 12.5% electrification, there is already a major effect on peak load demand starting with a charging power of 11 kW. However, these effects can be mitigated by the simple load management system, as described above. The effect of the load management system is shown by the arrows, which show the reduction from the continuous to the dashed line for a certain charging power.

A more sophisticated load management system may even achieve further peak loading reduction. For example, if there is a load measurement on the feeder, the load management system could charge the vehicles only when the measurement is below a certain load. Regarding the energy, the grid has enough capacity to charge the vehicles. Only the peak load exceeds the technically admissible limits. This load management may reduce the resulting curves in Fig. 11 and 12 even to the level of the basic curve without e-mobility. However, LV grid monitoring and communication are necessary to deliver a load measurement at the feeder to the corresponding vehicles. Furthermore, the charge of vehicles is slightly delayed compared to the uncontrolled case, where the vehicles are charged immediately on connecting to the grid.

The deployment of such a load management system not only mitigates the effect of e-mobility on occurring peak load on cables and power lines, but decreases major voltage drops thus allowing cost savings by reducing the grid capacity required. By applying the detailed probabilistic load model for electric vehicles, one can assess and compare the costs and benefits associated with the introduction of different load management systems.

V. Conclusions

To analyze the effects of e-mobility on voltage bands, a detailed knowledge of the probability of occurrence of loads is necessary. This paper shows the importance of different load models on the outcome of a load flow calculation for grid analysis, developing a load model for electric vehicles. This was done by taking into account the mobility behavior of car owners acquired by survey data, especially with regard to their daily travelled distances and time of arrival, when the vehicle most likely will start charging. This probabilistic load model accounts for local clusters of electric vehicles connected to a certain feeder. Additionally, it accounts for temporal accumulations of vehicles returning home and starting charging simultaneously, as well. This probabilistic load model provides significantly better results for the probability of occurrence of voltages and even transformer loads than the simulation with standard load profiles. It was shown that the application of standard load profiles for e-mobility is not valid for less than around 1,000 electric vehicles and therefore cannot be used even for large low voltage grids. Standard load profiles should only be used for the simulation of medium voltage grids. Although even in this case, the artificial coincident factor of 1 introduces inaccuracies inherently and probabilistic loads for single vehicles are still advantageous.

Furthermore, the findings of this contribution help to assess the condition of a grid concerning an increasing market share of electric vehicles. Especially the results regarding the load profile and single load probabilities of electric vehicles may improve future grid planning, which has to take into account new technologies like e-mobility and possible load management systems. In addition, the detailed knowledge of voltage bands can benefit grid operation as well. By utilizing the detailed view on voltages, different load management strategies can easily be compared regarding their costs and viability.

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VII. Biographies

Alexander C. Probst was born in Bremen, Germany, on September 16, 1983. He received the Diploma degree in Engineering Cybernetics, Mechanical Engineering from University of Stuttgart in 2009.

In 2009 he started to work at the Institute of Power Transmission and High Voltage Technology at the University of Stuttgart, where he currently pursues a doctoral degree.

His current research interests are the influence of electric mobility on future distribution grids, grid planning and providing ancillary services by load management systems controlling the charging of vehicles.

Martin Braun is Juniorprofessor for „Smart Power Grids“ at the at the University of Stuttgart, Germany. In parallel he manages, since January 2009 the research group ‘Decentralized Ancillary Services’ at Fraunhofer-Institute for Wind Energy and Energy System Technology (IWES) in Kassel, Germany. He studied Electrical Engineering and Economics at the University of Stuttgart and received a European Ph.D. at the University of Kassel. His research activities focus on technical and economical analyses of the integration of distributed generators, storage and loads into the electrical power system.

Jürgen Backes was born in Neunkirchen (Saar), Germany on May 22, 1965. After receiving his Diploma in Electrical Power Systems Engineering at the University of Saarland, Saarbruecken, Germany, in 1991, he started his research in the field of “Probabilistic Reliability Analysis and its application to distribution network planning” at the University of Saarland and received his PhD degree in 1998. From 1997 to 2006 J. Backes had been developing power systems analysis software and performing Power Systems consulting with different companies in Germany and Switzerland. Since 2006 he is working in the Technical Asset Management of EnBW Regional AG, a distribution system operator in the Federal State of Baden-Wuerttemberg, Germany.

Stefan Tenbohlen received the Diploma and Dr.-Ing. degrees from the Technical University of Aachen, Germany, in 1992 and 1997, respectively.

1997 he joined AREVA Schorch Transformatoren GmbH, Monchengladbach, Germany, where he was responsible for basic research and product development and in this function working in the field of on-line monitoring of power transformers. From 2002 to 2004 he was the head of the electrical and mechanical design department. 2004 he was appointed to a professorship and head of the institute of Power Transmission and High Voltage Technology of the University of Stuttgart, Germany. In this position his main research fields are diagnostic of equipment of power transmission, development of high voltage measurement technique, behavior of gas insulated insulation systems and different aspects of electromagnetic compatibility (EMC).

Prof. Tenbohlen holds several patents and published more than 200 papers. He is member of the IEEE, CIGRE and VDE ETG. He is convener of CIGRE WG A2.37 (Transformer Reliability Survey) and member of CIGRE A2 (Power Transformers), and several other international working groups.