Electric Vehicle and Heat Pump Hosting Capacity Assessment for a German 25,000-noded Distribution Network

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***Abstract*—This paper examines the impact of different penetration levels for electric vehicles (EVs) and heat pumps (HPs) on a large-scale German distribution network. The network comprises two HV/MV transformers supplying 150 LV grids. Based on GIS data the entirety of the network down to each household has been modelled. Based on maximum coincidence factors for electric vehicle charging and heat pump operation, the share of the network experiencing overloading and undervoltage problems has been identified to show which levels of new consumers the network can safely accommodate under current planning guidelines. The method can be replicated on other distribution network and can provide distribution system operators with a useful tool to examine the readiness level of distribution networks to cope with an electrification of the mobility and heating sector. The results show that MV/LV transformers and voltage problems on the MV grid are the most prominent issues while voltage problems on the LV grids become only relevant at very high penetration levels. Overloading of lines occurs only in few cases, with MV lines somewhat more affected than LV lines.**

Keywords—Electric vehicles, heat pumps, hosting capacity, distribution network, overloading, voltage violations, coincidence factor, load flow

I. Electric Vehicles and Heat Pumps in Distribution Networks

In order to shift away from fossil fuels towards cleaner sources of energy, there has been increasing effort on the electrification of passenger cars as well as the usage of heat pumps, that are powered by a future decarbonized power grid, e.g. relying on renewable energy sources such as solar and wind power. As a consequence, simulation studies regularly suggest scenarios with penetration rates of up to 80 % and higher until 2050 or earlier, e.g. [1]. New electric vehicles (EVs) and heat pumps (HPs) will add to the existing load of the individual household. It is therefore imperative to review today's distribution networks about their capability to accommodate envisioned EV and HP penetration levels.

There have been a great number of investigations on low voltage (LV) distribution grids to assess the impact of the new consumers. With high charging power to recharge the EV quickly as well as high power input requirements for heat pumps, network assets risk being overloaded and voltage violations outside the stipulated 0.9 to 1.1 p.u. voltage band may occur. For example, [2] assesses a 70 % EV penetration limit for a single LV network in the UK based on real EV charging behavior data. [3] analyses the impact on LV/MV transformers and MV line loadings, using simplified grid topologies. [4] evaluates the impact of EV charging on HV/MV substations for the city of Porto, Portugal.

Overall, only few assessments focus on a combined evaluation of the LV and MV grids. However, the simultaneous charging or heating behavior of large customer groups can impact voltages also in other parts of the network and therefore a build-up effect may become apparent. [5] evaluated such a network spanning across multiple voltage levels and comprising 5,000 nodes. However, the analysis focused on the impact of photovoltaic systems as the network was able to accommodate a 100 % EV penetration.

This paper aims to extend on previous limitations, further enabled by increasing computational capabilities as well as improving data availability of distribution system operators (DSOs) regarding the mapping of distribution grids. Hence, such detailed analyses have become possible in recent years, allowing for the simulation of large distribution grids comprising several 10,000s up to 100,000s nodes.

In this paper, a 25,000-noded network is simulated using a probabilistic approach. Random EV and HP distributions are introduced based on the simulated penetration level and maximum coincidence factors for concurrent EV charging and HP operation applied. Such coincidence factors can be derived from EV charging data (e.g. from the UK project My Electric Avenue [6]) or by probabilistic modelling based on driving statistics (e.g. [7]). By running load flow calculations on the network in DIgSILENT PowerFactory, overloading and undervoltage problems are identified. The simulations are repeated in a Monte-Carlo approach to account for uncertainty in the location of new EV and HP demand.

The results indicate the hosting capacity of the network with regards to EV and HP uptake, i.e. showing which share of network assets experience overloading and undervoltage violations. This gives the DSO an assessment which penetration levels the network can safely accommodate and which network parts will be affected first and most severely. With the information at hand, planning guidelines can be improved and long-term plans composed to upgrade and extend the current distribution network. It further helps to understand the need for smart control of electric vehicles and heat pumps.

II. Model Setup and Assumptions

A. GIS-based distribution network import

The 25,000-noded distribution network was provided by the German DSO EWR Netz GmbH and can be seen in Fig. 1. It is supplied by two 110 kV/20 kV transformers with a capacity of 45 MVA each. However, the network has only a peak load of 14 MW as the HV/MV transformer have been upgraded to accommodate 66 MW of wind power and 19 MWp of solar power, most of which is installed close to the HV/MV substation. Almost 10,000 customers, predominantly households, are supplied by a total of 150 MV/LV transformers. The network is operated mostly radial and 90 % of the LV network as well as 80 % of the MV network is cabled.

The network data has been automatically imported into DIgSILENT PowerFactory from the Geographic Information System (GIS) of EWR Netz GmbH. Major challenges represented locating and fixing errors in the GIS data, such as missing connections, erroneous cable types, etc. This enabled the display and calculation of the entire network, from the HV/MV transformers down to the 10,000 households connected at 400 V level.

On top of the existing customer loads, electric vehicles and heat pumps are added to the network. Assumptions on their technical characteristics as well as their locational distribution are described in the following.

B. Technical characteristics of electric vehicles, heat pumps and existing customer loads

Nowadays, home charging of EVs ranges typically from 3.7 kW to 22 kW. Most users may opt to choose higher charging power than 3.7 kW for the convenience of shorter charging times, as charging overnight may occasionally not be sufficient to fully recharge the EV after long driving distances. A home charging station with 22 kW requires the approval of the DSO. Therefore, 11 kW has been chosen as the most likely charging power level applied in German distribution networks. Further, a power factor of 0.98 lagging has been assumed.

The power input of the HP may also vary depending on the type of the HP and the dwelling's heating requirements. It has been assumed to be 4.6 kW based on [1]. Further, a power factor of 0.8 lagging has been chosen.

Non-household customers have been modelled with standard load profiles. Household customers were randomly assigned with one of 74 household profiles measured by HTW Berlin [8] and scaled to each respective yearly household demand. A random time in the evening between 5 and 8 pm is chosen to determine the demand of regular appliances. At this time typically the peak load occurs and may in particular concur with EV peak charging demand.

C. Electric vehicle and heat pump distribution

The distribution of HPs is based on the household distribution, with each household having the same probability for the installation of a heat pump. The total number of heat pumps add up to the respective HP penetration that was modelled. A HP penetration of 100 % corresponds with every single household receiving one heat pump.

The distribution of EVs is based on socio-economic analysis. A score from 1 to 10 is applied to each household to indicate the likelihood of an EV purchase by the respective household. The score is calculated on different household indicators such as housing situation, the residents' age, their family situation, income levels, political orientation, existing solar rooftop plants, etc. A score of e.g. 5 has been assumed to have five times the likelihood compared to a score of 1. The EV owners are selected based on this likelihood

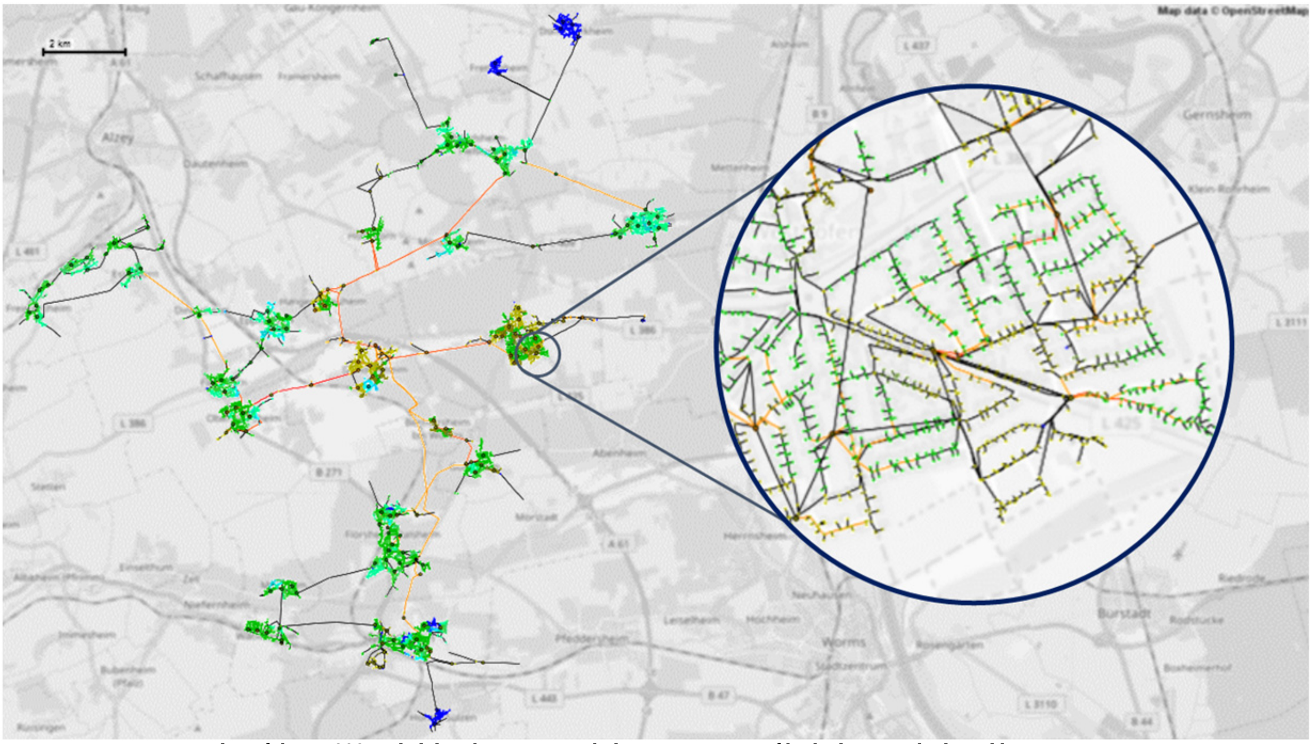

Fig. 1: Display of the 25,000-noded distribution network during a situation of high electric vehicle and heat pump penetration

distribution. A small likelihood is added that a second or even third EV is charging at the same household. The total number of EVs add up to the EV penetration that was modelled. An EV penetration of 100 % corresponds with all cars being electric. With a car ownership of 0.52 cars per person, there are estimated to be 12,420 cars in the area.

During each simulation run, the distribution of EVs and HPs is reshuffled. Through this Monte-Carlo approach, also worst-case situations with unfavorable EV and HP distributions are reflected.

D. *Simultaneous/concurrent charging and heating*

Depending on the time of return, different people will plug their EV in for charging at different times. Similarly, not all heat pumps will typically be switched on at the same time. This relationship can be expressed through the coincidence factor, seen in Fig. 2. It is based on [1] and [9] and determined by stochastic simulation of driving behavior and thermal load profiles. It expresses the maximum concurrence throughout a year with a 95 % confidence interval. This means, that the maximum coincidence factor should only occur in one of 20 years. This is deemed as a satisfactory confidence level for DSOs. Charging data in the future are important to validate such coincidence factors.

As can be seen, if only few EVs or HPs are considered, a high concurrence applies. However, with increasing number of units, the coincidence factor decreases, as concurrent charging or HP operation becomes less likely. Furthermore, the HP coincidence factor is higher than the EV coincidence factor, as HP operation is mainly determined by cold spells that impact all households. The EV charging behavior of users, on the other hand, is more random and depends on factors such as return times and travel distances, therefore showing much lower concurrences.

III. Modelling Approach

A. *Separate consideration of different network levels*

While the coincidence factor is a simple and convenient tool to quickly assess the impact of a number of EVs or HPs on a network segment, it cannot be used to examine the impact across multiple voltage levels.

For example, to assess the impact of EVs on a single LV feeder, a high coincidence factor has to be assumed that corresponds with the low number of EV owners in this grid segment. On the other hand, if the impact of EVs on the HV/MV transformer is evaluated, a low coincidence factor must be assumed as only a small percentage of EVs will charge at the same time if the number of EVs is in the hundreds.

Therefore, the hosting capacity is performed on four different levels:

- LV feeders
- MV/LV transformer
- MV feeders
- HV/MV transformer

Each level is simulated with the maximum EV and HP coincidence factor and subsequently assessed regarding any undervoltage or overloading violations on the respective evaluation level.

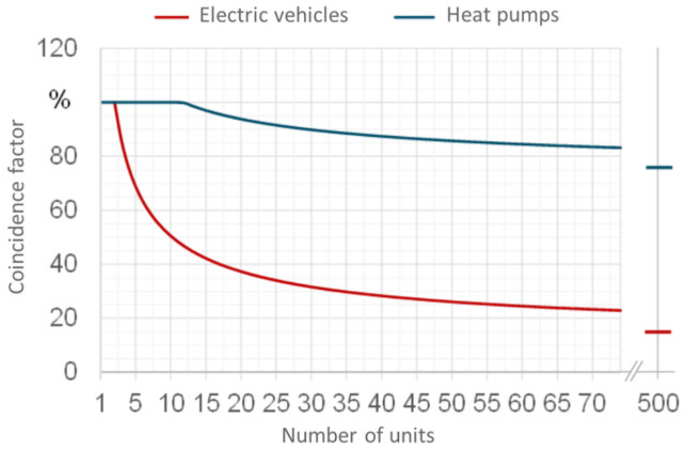

Fig. 2: Maximum coincidence factor for different numbers of electric vehicles and heat pumps, based on [1] and [9]

B. *Applied thresholds for overloading and voltage violations*

During each separate simulation of network levels with the applied maximum coincidence factors, the share of network assets experiencing overloading or voltage violations is noted. Table 1 gives the thresholds, above which a undervoltage or overloading violation is noted. They are in line with the planning guidelines of EWR Netz GmbH.

In the MV grid and above, network assets are typically not loaded above 60 % to maintain n-1 redundancy. This means, in the case of a contingency, assets are allowed to be overloaded up to 120 % for a short time. In the LV grid the n-1 criterion is usually not applied.

Further, according to standard EN 50160 the voltage in distribution networks should be kept within 0.9 to 1.1 p.u. A common practice is to classify a maximum voltage drop and rise for each respective network level. Hence, through load flow calculation it is checked which MV nodes experience voltage drops larger than 5 % with reference to the MV busbar of the HV/MV transformer. Similarly, any LV nodes are checked if they exhibit voltage drops larger than 5 %

Table 1: Applied planning thresholds for voltage and loading violations according to DSO guidelines

Overloading	HV/MV transformers	> 60 % loading
	MV lines	> 60 % loading
	MV/LV transformers	> 100 % loading
	LV lines	> 100 % loading
Undervoltage	MV grid	> 5 % voltage drop
	LV grid	> 5 % voltage drop

with reference to the LV busbar of the MV/LV transformer.

IV. Results

Fig. 3 shows the results for different EV and HP penetration levels from 0 % to 100 %. Some results have been omitted due to convergence problems of the load flow algorithm with too high penetration levels.

The heat maps show the share of elements that exhibit a voltage or overloading violation. For example, a 100 % EV penetration without heat pumps would result in:

- Voltage drops greater than 5 % on 5 % of LV nodes and on 13 % of MV nodes;
- No overloading problems on LV lines but on 6 % of MV lines;
- The overloading of 40 % of all MV/LV transformers;
- No overloading of the two HV/MV transformers

As can be seen, the MV/LV transformers are the most severely impacted by increasing EV and HP penetrations, with most of them getting overloaded at higher penetration levels. The first transformers are already overloaded at low EV and HP penetration levels, with e.g. 12 % of MV/LV transformers overloaded at 20 % EV combined with 20 % HP penetration.

The MV grid also shows high voltage drops, resulting in large parts of the network facing voltage drops higher than 5 %. Overloading of MV lines occurs also to a smaller degree as the 60 % loading threshold is surpassed.

Voltage violations occur also to some degree on LV grids. However, it seems to be relatively robust against high penetration of EVs and HPs, with e.g. only 20 % of nodes experiencing voltage drops greater than 5 % in the 100 % EV + 40 % HP case. Lastly, almost no overloading above 100 % occurs on LV lines.

Furthermore, it can be seen that on the LV level the impact of EVs is similar to the impact of HPs. However, at the MV level, HPs pose bigger problems compared to EVs. For example, a 100 % HP penetration leads to large voltage drops in 47 % of MV lines, while a 100 % EV penetration only leads to large voltage drops in 13 % of MV lines.

While the EV charging power (with 11 kW) is more than double the power input of the heat pumps (with 4.6 kW), the coincidence factor is much lower for EVs. This is more pronounced for large numbers of EVs and HPs, where the coincidence factor of HPs is about 4 to 5 times the one of EVs.

V. Discussion

The greatest impacts of EVs and HPs in this particular distribution network are on MV/LV transformers as well as on the voltage of the MV grid. Improved voltage control methods could further extend the current guidelines on voltage drops per voltage level, reducing the need for reinforcements due to voltage constraints. However, to prohibit the overloading of MV/LV transformers, advanced control concepts for electric vehicles and heat pumps are

EV penetration →

HP penetration ↓

LV_U	0%	20%	40%	60%	80%	100%
0%	0%	0%	0%	1%	3%	5%
20%	0%	0%	2%	5%	8%	13%
40%	0%	2%	6%	10%	15%	20%
60%	1%	7%	12%	17%		
80%	4%	13%	19%			
100%	9%	20%				

MV_U	0%	20%	40%	60%	80%	100%
0%	0%	0%	0%	0%	1%	13%
20%	0%	0%	1%	8%	23%	31%
40%	1%	5%	19%	28%	39%	44%
60%	17%	29%	37%	44%		
80%	39%	43%	47%			
100%	47%	50%				

LV_I	0%	20%	40%	60%	80%	100%
0%	0%	0%	0%	0%	0%	0%
20%	0%	0%	0%	0%	0%	1%
40%	0%	0%	0%	1%	1%	3%
60%	0%	0%	1%	2%		
80%	0%	1%	2%			
100%	1%	2%				

MV_I	0%	20%	40%	60%	80%	100%
0%	0%	0%	0%	1%	2%	6%
20%	0%	0%	1%	5%	10%	15%
40%	1%	3%	8%	13%	17%	19%
60%	7%	13%	16%	18%		
80%	16%	18%	19%			
100%	19%	22%				

MV/LV	0%	20%	40%	60%	80%	100%
0%	0%	1%	5%	15%	26%	40%
20%	1%	12%	23%	33%	44%	50%
40%	8%	30%	39%	48%	55%	62%
60%	25%	45%	53%	61%		
80%	40%	56%	65%			
100%	54%	65%				

HV/MV	0%	20%	40%	60%	80%	100%
0%	0%	0%	0%	0%	0%	0%
20%	0%	0%	0%	0%	0%	0%
40%	0%	0%	0%	0%	0%	0%
60%	0%	0%	0%	0%		
80%	0%	0%	0%			
100%	0%	0%				

Fig. 3: Share of network assets experiencing overloading or voltage violations for different penetration levels of electric vehicles and heat pumps. LV_U = Voltage violations in the LV grid; LV_I = Overloading in the LV grid; MV/LV = Overloading of MV/LV transformers; MV_U = Voltage violations in the MV grid; MV_I = Overloading in the MV grid; HV/MV = Overloading of HV/MV transformers

necessary to alleviate the need for grid reinforcements (e.g. [10]).

Further, a number of MV lines were affected by loadings above 60 %, resulting in overloading violations according to the specified thresholds. The 60 % threshold due to n-1 redundancy may however be subject may be subject to future discussions, as the power output of controllable loads such as EVs and HPs could be limited by the DSO during n-1 events. This would reduce the oversizing of MV assets to ensure n-1 security.

The LV grids, on the other hand, are only impacted at very high EV and HP penetration levels that are not expected within the next decade. Hence, necessary investment into LV grid extensions would be limited to accommodate such high EV and HP penetration levels.

Lastly, as the HV/MV transformers are largely oversized to accommodate large wind power plants close to the substation, no overloading is occurring here. However, in other networks this may often not be the case.

Even though this distribution network is not representative for Germany, the method is replicable and can be used by distribution system operators to evaluate the readiness levels of their distribution network for EV and HP uptake.

It should finally be noted that for cases of concurrent EV and HP penetration, the results are a worst-case estimation as EV and HP peak demand will in most times not occur at the same time. A more thorough analysis with combined EV/HP coincidence factors based on stochastic simulation would be required to resolve this.

VI. Conclusions

This paper shows the impact of electric vehicles and heat pumps on a large German distribution network with 25,000 nodes and a peak load of 14 MW. It evaluates the impact across multiple voltage levels, from the single household to the two HV/MV transformers supplying the network.

Severe overloading of MV/LV transformers are expected, with the first overloaded transformers being encountered at EV and HP penetration levels above 20 %. Further, large voltage drops on the MV lines are expected that may be critical for grid operation. Voltage problems in the LV grids are less severe, with major problems only arising at a combination of both high EV and HP penetrations, and overloading in LV grids is negligible.

The novelty of the paper lies in assessing distribution networks on a large scale, with simple methods such as maximum coincidence factors. Such methods give distribution system operators the tools to evaluate the readiness level of their distribution network to accommodate high EV and HP penetration levels.

This in turn improves their planning principles and helps in their decision-making to appropriately investigate mitigation measures such as smart EV charging and HP control, improved voltage control concepts, and increased distribution grid monitoring.

Uncertainties lie in particular in the determination of the maximum coincidence factors. The curves used in this paper (see Fig. 2) have been obtained through rigorous stochastic simulations based on driving statistics and thermal heat demand, however, they need to be verified through actual EV charging and HP operational data in the future.

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