Grid Integration Studies for eMobility Scenarios with Comparison of Probabilistic Charging Models to Simultaneity Factors

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***Abstract*—One major challenge of the mobility transition to Battery Electric Vehicles (BEVs) is the integration of charging infrastructure into distribution grids. The resulting increase in power demand can lead to overloadings and voltage band violations. A common method to estimate the simultaneous power demand of BEVs is the usage of simultaneity factors. This is a reasonable approach for a large number of vehicles. However it is questionable, how precise the results are for small numbers of vehicles - e.g. in low-voltage grid feeders.**

In this paper we present a method for conducting grid integration studies in real integrated low- and medium-voltage grid models in the context of eMobility. A special focus is the comparison of a probabilistic distribution approach for BEV charging in low-voltage grids vs. the usage of simultaneity factors. The probabilistic method uses a pool of BEV charging profiles and places them randomly in an LV grid to derive worst-case situations. Necessary grid reinforcement and expansion as well as their cost are then estimated with an automated approach based on a heuristic optimization algorithm. Additionally we compare different charging scenarios like residential charging, public fast charging and dedicated grids for charging stations.

The results show, that the application of simultaneity factors can cause large deviations in regard to violations, as well as necessary grid reinforcement and expansion compared to the probabilistic approach. Especially local weak spots in LV feeders often cannot be identified when using common simultaneity factors for all BEVs in a low-voltage grid. This leads to a possible underestimation of reinforcement and expansion cost. Furthermore the cost of integrating charging infrastructure into the grid varies widely between the different scenarios considered.

I. Introduction

In the upcoming decades the mobility sector of many countries is expected to undergo a transition to Battery Electric Vehicles (BEVs). In 2009, the German government e.g. proposed a target of one million BEVs by 2020 [1]. Due to low growth rates of BEVs, the achievement of this target has become questionable. However, significantly higher growth rates and thus even higher vehicle numbers are required and expected in the near future in order to achieve the goals of the Paris Agreement on Climate Change. This of course means a massive increase in demand for charging infrastructure which will directly affect distribution grids. The additional power consumption could lead to overloadings and voltage band violations. Therefore grid integration studies play a very important role in assessing the distribution grids' capacity for (additional) charging stations and possibly necessary grid reinforcements. In order to conduct those kinds of studies valid worst case assumptions for the maximum power flow caused by charging BEVs are needed. Since, at least in the absence of market induced effects, it is very unlikely, that all vehicles in a grid charge at the same time with their rated charging power, a common method is the usage of simultaneity factors. These factors decrease the specific power consumption according to the number of simultaneously charging vehicles. It is questionable however, how well-suited this approach is for small numbers of vehicles. Additionally, at this point in time it is still very much unclear how exactly the future charging infrastructure and charging behaviour are going to look like.

In the upcoming sections we introduce a method for conducting grid integration studies in the context of eMobility. We provide a detailed comparison of simultaneity factors vs. a probabilistic approach based on BEV charging profiles. Furthermore various charging infrastructure concepts are presented. Finally, we describe a method for evaluating and comparing the grid integration cost caused by these different approaches and scenarios.

II. Modelling of BEV charging

In this section we present a comparison of a probabilistic distribution approach for modelling BEV charging in real low- and medium-voltage grids vs. the usage of simultaneity factors. Furthermore we describe different charging infrastructure scenarios that are referred to in the following sections.

A. BEV charging profiles

In this paper we use simulated BEV charging profiles. They are derived from measurements of real charging processes of BEVs in order to represent their characteristic charging behaviours. For modeling the charging process it is assumed, that typical lithium-ion batteries that are used in BEVs are only charged with their rated current until they reach a state of charge (SoC) of about 80 percent. Above 80 percent SoC the charging current decreases and so does the charging power as shown in Figure 1.

Necessary parameters to simulate charging profiles according to these characteristics are the SoC at the beginning of the charging process, the maximum usable battery capacity and the maximum rated charging current. The distribution

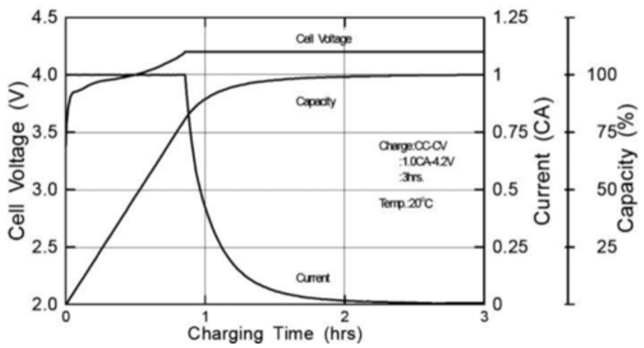


Fig. 1. Charging behaviour of li-ion batteries [2]

of the last two parameters is based on market shares of BEVs in Germany in the year 2016 [3]. The initial SoC however depends on the BEV owners' usage behaviour and the energy demand of the vehicles. The usage behaviour of vehicle owners is assumed according to a German mobility study which was conducted in 2008 [4]. This study surveyed more than 60,000 individuals for their everyday's mobility data like time of day, travelled distances and means of transport. The result is a model for providing realistic BEV charging profiles representing the distribution of different models of vehicles and usage behaviours in Germany. This model was used to generate 10,000 charging profiles for the time span from 5 to 8 pm on a weekday where the charging worst-case is assumed to occur. Since the main goal in this paper is comparing the usage of charging profiles vs. simultaneity factors, for simplicity reasons only vehicles with a maximum charging power of 22 kW are considered. However, generating charging profiles for other charging powers like 11 kW, 3.7 kW or combinations of them would be possible as well. Figure 2 shows a sample of 25 charging profiles in the time span from 7 to 8 pm where every row of the graph depicts a single charging profile. It can be seen that in this example only three vehicles simultaneously charge with their maximum power, whereas the majority of vehicles does not need to charge at all.

Fig. 2. Sample of 25 BEV charging profiles

B. Probabilistic distribution approach

The generated charging profiles are used to create realistic worst-case scenarios for distribution grids. This is achieved by randomly choosing (with replacement) one of the 10,000 profiles for every charging point in the grid. The positions of the charging points are fixed and will not be varied in this process. Charging vehicles are represented by static loads with the power consumption of their chosen profiles at 7:30 pm. After setting all load power values, a power flow calculation is performed in order to retain the highest line loading and the lowest bus voltage per feeder, as well as the highest transformer loading. All grid calculations are done with pandapower, an open source tool for power system modeling, analysis and optimization [5]. This process is repeated for 100,000 iterations to identify the worst-case values regarding violations of loading and voltage limits.

C. Calculation of simultaneity factors

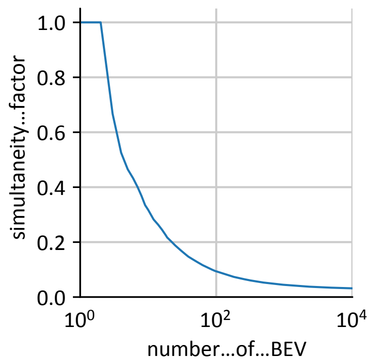


Fig. 3. Simultaneity factors for 1 to 10,000 BEVs

For a meaningful comparison of the probabilistic distribution approach described in Subsection II-B with the usage of simultaneity factors, these factors need to be calculated from the same pool of charging profiles. For every number n of BEVs, n charging profiles are randomly chosen. Then the sum of the power flow of all charging profiles at 7:30 pm is calculated and divided by n times the vehicles rated charging power, which in this case is 22 kW. This is performed for 100,000 iterations. Finally the 99.99th percentile is chosen as the simultaneity factor for n simultaneously charging vehicles to sort out extreme outliers. With this method we calculate the simultaneity factors for all numbers of vehicles from 1 to 10,000. The resulting curve is shown in Figure 3. It can be seen that the simultaneity factor is 1.0 for one and two vehicles and converges to around 0.03 for larger numbers.

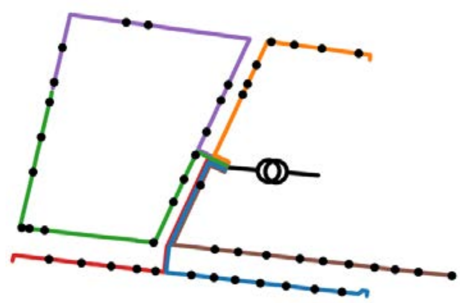


Fig. 4. Exemplary low-voltage grid

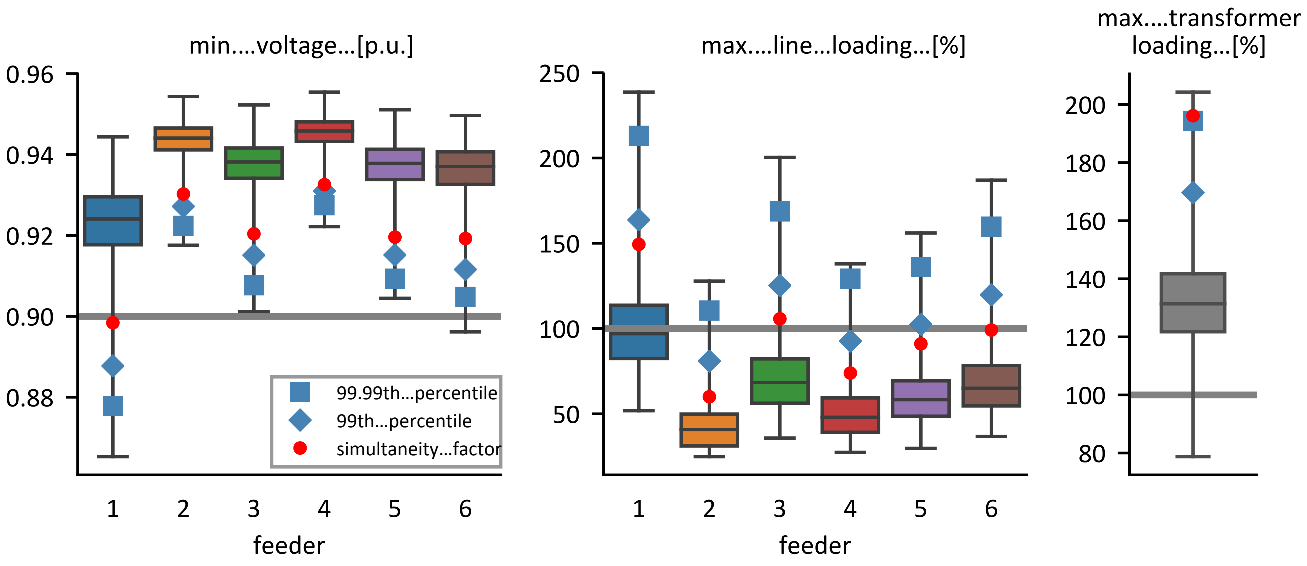


Fig. 5. Comparison of simultaneity factors vs. probabilistic distribution approach in one LV grid

D. Application and comparison in real grid models

Both approaches for modelling BEV charging are applied and compared in 13 real low-voltage grids and one real medium-voltage grid. The medium-voltage grid is an urban grid, the low-voltage grids supply a mixture of different settlement structures. All grid models are provided by the German DSO Stadtwerke Kiel. Following common grid planning practices the simultaneity factors are calculated per grid and not per single feeder. This means, that the simultaneous power flow of all BEVs in a grid is determined by applying the same simultaneity factor.

Figure 4 shows a plot of one of the 13 low-voltage grids with the six feeders plotted in different colors and the low-voltage connection points plotted as black circles. The BEVs are randomly distributed in all grids. It is assumed, that the total number of vehicles in a grid equals the number of households, which is currently approximately the case in Germany [6]. The probability for a connection point to get assigned a vehicle corresponds with the percentage of households of the connection point compared to the sum of all households in the grid.

So if a connection point supplies five percent of all households that are supplied by the whole grid, its estimated value of BEVs is five percent of all vehicles distributed in the grid. Figure 5 shows a comparison of the probabilistic distribution approach vs. simultaneity factors for this exact grid. The distribution of the minimum bus voltage, the maximum line loading and the maximum transformer loading per low-voltage feeder over all 100,000 iterations (see Subsection II-B) are visualized as boxplots. The whiskers show the absolute minimum and maximum values, the boxes show the 25th, 75th percentile and the median. Additionally the 99th, 99.99th percentile and the values when using simultaneity factors are depicted. The exact values can also be found in Table I. The color coding of the boxes matches the feeders in Figure 4. In this particular example the LV grid supplies about 500 households in an urban area. The lowest number

TABLE I
SIMULTANEITY FACTOR AND PERCENTILE VALUES OF FIGURE 5

feeder	min. voltage [p.u.] max. loading [%]	simult. factor	99th percentile	99.99th percentile
1	bus voltage	0.8984	0.8877	0.8778
	line loading	149.35	163.68	213.00
2	bus voltage	0.9302	0.9271	0.9223
	line loading	60.00	80.91	110.55
3	bus voltage	0.9204	0.9151	0.9076
	line loading	105.71	125.28	168.69
4	bus voltage	0.9325	0.9310	0.9274
	line loading	73.89	92.65	129.26
5	bus voltage	0.9196	0.9151	0.9093
	line loading	91.04	102.45	136.11
6	bus voltage	0.9192	0.9115	0.9048
	line loading	99.12	119.82	159.74
all	transformer loading	196.17	169.65	194.39

of BEVs in a single feeder is 48, the highest one is 116. It can be seen, that for these numbers of vehicles the approach based on simultaneity factors tends to underestimate the worst-case power flow caused by simultaneously charging vehicles. In all six feeders the minimum voltage is lower and the maximum line loading is higher when using the 99.99th or even the 99th percentile of the probabilistic distribution approach. Only for the transformer loading the simultaneity factor value matches the 99.99th percentile value. This indicates, that simultaneity factors are suited for larger numbers of vehicles, since the transformer loading is caused by the aggregated number of vehicles of all feeders in the grid.

This is not only the case for this particular low-voltage grid. Figure 6 shows a comparison of the simultaneity factor values and the 99.99th percentile values for all 67 feeders of all 13 low-voltage grids. The distributions of minimum voltages, maximum line loading and maximum transformer loading are shown as boxplots. The voltages are given in per unit, the loading in percent. In regard to the medians of

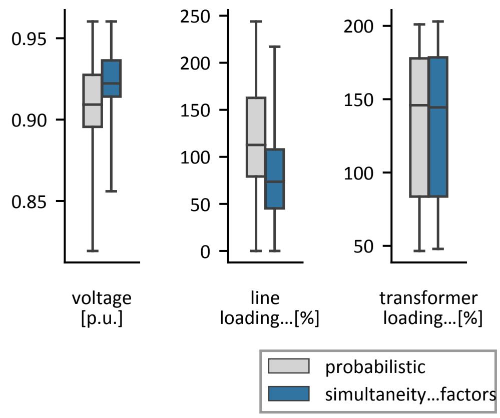


Fig. 6. Comparison of simultaneity factors vs. probabilistic distribution approach in all 13 low-voltage grids

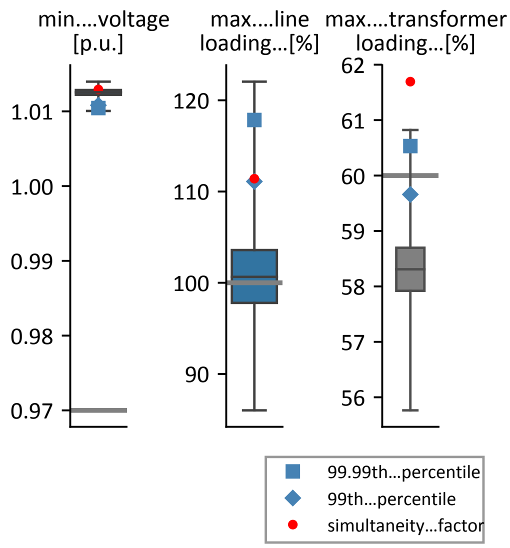


Fig. 7. Difference between simultaneity factors vs. probabilistic distribution approach in one medium-voltage grid.

the boxes, the probabilistic distribution approach results in 0.01 p.u. lower minimum voltages and 40 percentage points higher line loading compared to using simultaneity factors. The transformer loading however only deviates by around 0.1 percentage points, which matches the results shown in Figure 5.

Figure 7 shows the same comparison as Figure 5 in the medium-voltage grid. For clarity reasons only the aggregated results over all feeders are displayed, since the grid contains 16 medium-voltage feeders. The total amount of BEVs in the whole grid is 23,000 in this case. The results differ from the comparison in the low-voltage networks. The difference in minimum voltage between the 99.99th percentile and the simultaneity factor value is around 0.1 p.u. Regarding line loading, the 99th percentile value and the simultaneity factor value are nearly equal. The difference to the 99.99th percentile value amounts to about 5 percentage points. The transformer loading is only about 1 percentage point higher when using simultaneity factors compared to the 99.99th percentile value. At least in this medium-voltage grid, simultaneity factors appear to be a reasonable approach for estimating worst-case scenarios. This allows to conclude, that simultaneity factors seem to be better suited for larger numbers of BEVs in MV grids with aggregated LV grids.

E. Alternative charging infrastructure concepts

Residential charging of BEVs, which is assumed in the previous subsections, is only one of different possible charging infrastructure scenarios. Alternative charging concepts, that will also be considered, are described in the following sections. These concepts are not necessarily realistic in the very near future but could nonetheless play an important role in future scenarios with a high penetration of BEVs.

1) Autonomous driving: One major goal pursued by many car manufacturers and technology companies are fully autonomous vehicles. This could also have an impact on charging infrastructures. Autonomous vehicles would allow placement of charging stations in areas with sufficient grid capacities, e.g. close to substations. In this paper, we consider a scenario, where all vehicles distributed in the grid (see Subsection II-D), coordinated by an automatic guidance system autonomously move to charging stations when they need to charge. The charging stations are directly connected to the HV/MV substation.

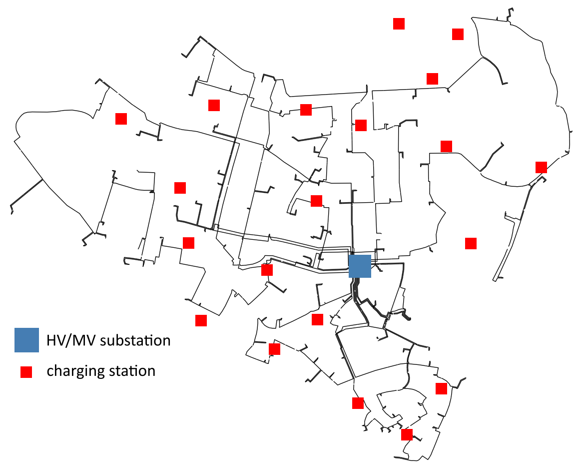


Fig. 8. Exemplary distribution of fast charging station in the medium-voltage grid.

2) Fast charging stations: Another possibility is a growing number of fast charging stations that allow recharging vehicles in relatively short amounts of time, similar to refueling conventional cars. The electric car manufacturer Tesla already runs a network of fast charging stations, which can provide up to 145 kW per charging point [7]. In 2018 ABB unveiled 350 kW chargers, that e.g. Porsche already announced to use in its future cars and Enercon opened its first prototype of a 350 kw charging station [8], [9], [10]. Figure 8 shows an exemplary distribution of fast charging stations in the medium-voltage grid. Their grid integration will be demonstrated in the next section. In this paper we assume a number of 20 fast charging stations for the whole medium-voltage grid and each station provides six 350 kW charging points. Because of the relatively small number of simultaneously available charging points, we assume a high simultaneity factor of 0.9. The fast charging stations are

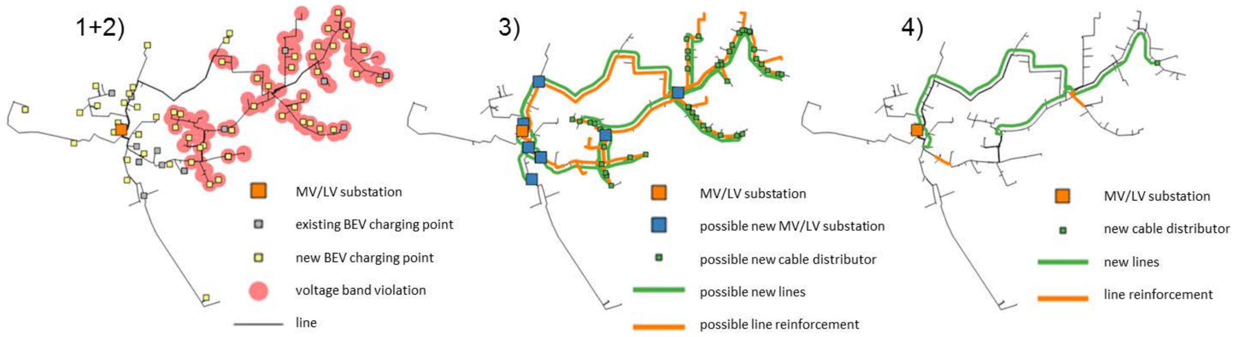


Fig. 9. Automated grid planning in an exemplary LV grid

randomly distributed in the grid with a minimum distance of 300 meters. We also compare two different grid integration scenarios for the fast charging stations: a) direct integration into the existing grid (direct connections to the HV/MV substations are possible) and b) dedicated medium-voltage feeders for the charging stations, with a lower voltage limit of 0.8 p.u. and no (n-1) security.

III. Reinforcement and expansion cost

In this section we combine the earlier described low- and medium-voltage grids as well as the methods for implementing BEV charging worst-case scenarios with probabilistic scenario variations and an heuristic optimization algorithm. The result is a method to assess necessary grid reinforcement and expansion measures, as well as their cost, due to BEV charging in an integrated low- and medium-voltage grid model.

A. Integrated low and medium-voltage grid model

Residential charging of BEVs can cause potential violations in low-voltage grids, in the connected medium-voltage grid as well as in HV/MV and MV/LV substations. For this reason an integrated grid model is needed in order to be able to assess all potential reinforcement and expansion cost. The medium-voltage grid used in this paper supplies 86 low-voltage grids. Since not all 86 low-voltage grid models are available, we use the 13 low-voltage grids described in Subsection II-D as substitutes. We use the six grid characteristics rated transformer power, maximum measured transformer load, number of low-voltage connection points, number of households, total line length and number of feeders to match each of the original 86 low-voltage grids to one of the substitutes. To do so, we calculate a similarity index for all 86 original low-voltage grids. The original grids then were substituted with the "most similar" of the 13 low-voltage grids according to the similarity indices.

B. Probabilistic BEV integration scenarios

As described in Subsection II-B, the spatial distribution of BEVs in the grid model occurs probabilistically according to the number of households per connection point. In the next step, the worst-case simultaneous power consumption is determined, either with the probabilistic distribution of charging profiles (see Subsection II-B) or with simultaneity factors (see Subsection II-C). This approach alone does not consider that the distribution of the simultaneously needed charging power is not the only impact factor on reinforcement and expansion cost. The spatial distribution of the charging points itself can also have a significant influence whether and where grid reinforcement and expansion is necessary. For this reason we consider ten different probabilistic BEV distribution variations for each low- and medium-voltage grid as well as for each charging infrastructure scenario. Regarding the residential charging scenario this means, that ten different spatial variations of residential charging points are generated. For each of these ten variations we then determine the worst-case simultaneous charging situation. For the 13 low-voltage grids this is done with both approaches (see Subsections II-B and II-C). For the medium-voltage grid we only use the simultaneity factors, since the comparison in Subsection II-D showed, that they are reasonably well suited in this particular case. Accordingly 10 spatial distribution variations of fast charging stations are randomly determined considering a minimum distance as described in Subsection II-E2. The amount of ten variations was chosen in order to demonstrate the resulting distribution of reinforcement and expansion cost while limiting the necessary computational time. For better assessment of possible uncertainties in predicted scenarios it is advised to consider a higher number of variations. In a grid integration study that was conducted for the state of Hesse in 2018, a similar approach with 50 variations was applied [11].

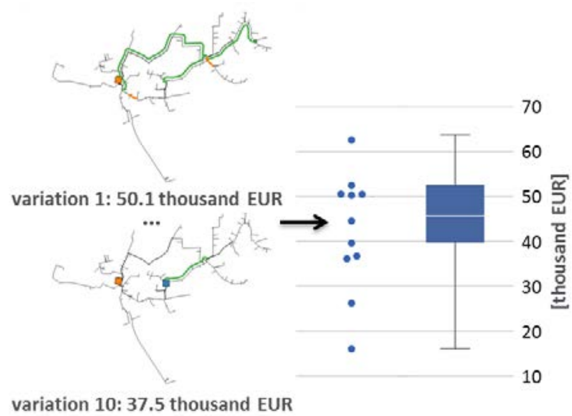


Fig. 10. Distribution of grid reinforcement and expansion cost in an exemplary LV grid.

C. Automated grid planning

The combination of all previously described grids, distribution variations and charging infrastructure scenarios leads to a number of 170 cases for which we need to assess the necessary reinforcement and expansion measures as well as their investment cost. For this number of cases manual planning is not a feasible option. Instead, an automated scalable approach is necessary. This is why we use an automated heuristic optimization approach which is described in detail in [12]. 170 grid planning cases is a comparatively low number. However the same method was already utilized in [11] for more than 700 real grids, 50 distribution variations, various scenarios and smart grid technology analyses, leading to several million of necessary grid planning cases.

The basic method is illustrated in Figure 9 and works as follows:

1) Scenario implementation: Additional loads are added to the grid model. In this paper this is performed with the methods described in the subsections II-B and III-B.

2) Analysis of possible violations: Load flow calculations of all load cases to identify bus voltage violations, line and transformer overloading.

3) Identification of possible reinforcement and expansion measures: All measures, that could possibly mitigate the violations are identified. This can include replacement and/or addition of lines and transformers, founding new substations as well as switching measures for topological optimization.

4) Heuristic optimization: An heuristic optimization process is used to search the optimum subset of measures, that solves all violations with the least cost possible. When this is performed for all ten BEV distribution variations, the result is a distribution of ten possible grid reinforcement and expansion costs as exemplarily shown in Figure 10. The cost distribution is shown as a boxplot. The whiskers represent the absolute lowest/highest values. The box shows the 25th, 75th percentile and the median cost.

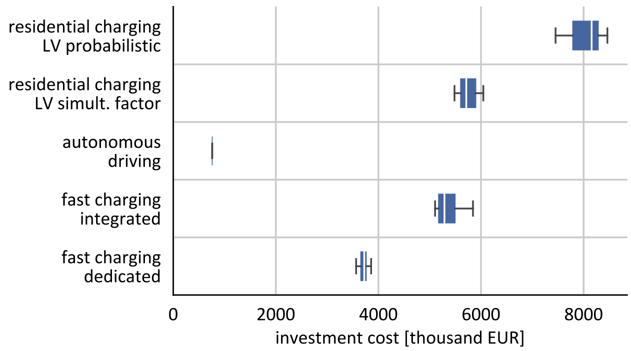


Fig. 11. Total grid reinforcement and expansion cost of all BEV charging infrastructure scenarios

D. Results

Figure 11 shows the grid reinforcement and expansion cost distribution for all investigated scenarios (see Subsection II-E). The depicted values include the total cost occurring in all relevant voltage levels. In case of the residential charging scenario those are the LV and the MV level as well as HV/MV and MV/LV substations. Furthermore for this scenario two different results are shown: The reinforcement and expansion cost when applying the probabilistic BEV distribution approach for the LV grids and the cost when using simultaneity factors in all voltage levels.

Regarding the probabilistic variant, the median cost is around 8.2 million Euro (7.5 to 8.5 million Euro). When using simultaneity factors in the LV grids the investment cost is overall lower (median 5.7 million) and the range of spread is narrower (5.5 to 6 million Euro). This indicates, that simultaneity factors underestimating voltage band and loading violations directly translates into underestimating grid reinforcement and expansion cost. Furthermore the resulting costs do not vary much. The median cost at the MV and HV/MV level is 2.1 million Euro, ranging from 2 to 2.2 million Euro. Figure 12 emphasizes these findings by providing a more detailed comparison between both

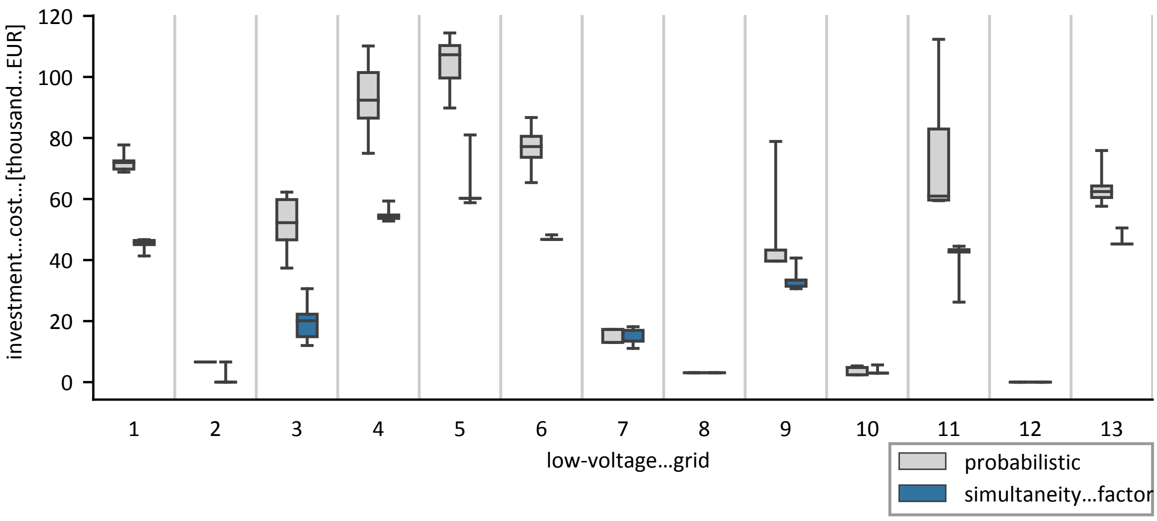


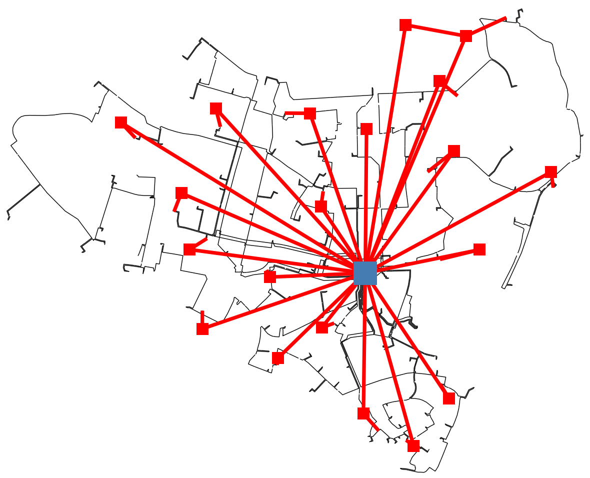
Fig. 12. Comparison of simultaneity factors vs. probabilistic distribution approach in all 13 LV grids

approaches. The Figure compares the reinforcement and expansion cost of all 13 LV grids.

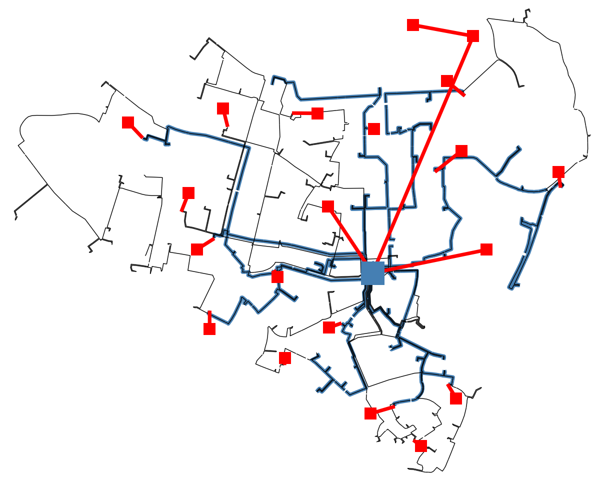
For 11 of 13 grids the probabilistic approach leads to higher investment cost (based on the median). For the remaining two grids the investment cost does not differ between both methods. Additionally in 8 of 13 cases the probabilistic approach leads to higher maximum investment cost as well as a higher spread of cost. Based on the medians of the boxes, the median difference between both approaches is about 17,000 Euro. The maximum difference in cost is 47,000 Euro.

The median cost of the autonomous driving scenario is around 800,000 Euro with no variation at all. Since in this scenario all BEVs are assumed to autonomously move to charging stations that are directly connected to the HV/MV substation, there are no cost for line reinforcement or additional lines, no voltage violations and no low-voltage reinforcement cost. The absolute number of BEVs is constant (one per household, see II-B), so all ten distribution variations only cause transformer overloading in the substation. Additional cost for mileage and coordination of the autonomous vehicles are not considered.

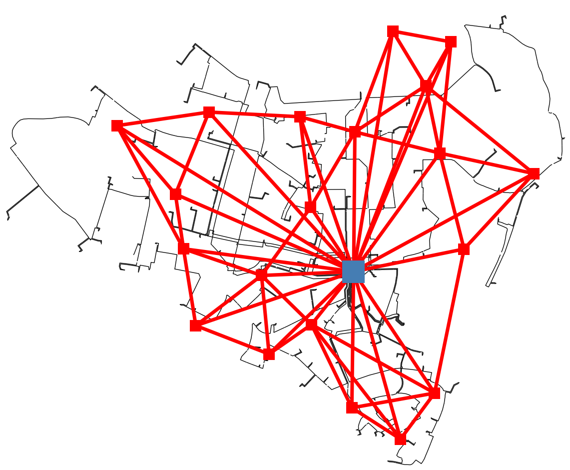
The median cost for the integrated scenario is around 5.3 million Euro, ranging from 5.1 to 5.8 million Euro. In comparison the investment cost for the scenario ”fast charging dedicated” is far more consistent and overall lower. The median is around 3.7 million Euro, ranging from 3.6 to 3.9 million Euro. One reason for the comparatively wider cost distribution in the integrated scenario is, that the integration cost of fast charging stations into the existing grid is highly dependant on spatial distribution of the fast charging stations. Figure 13a shows an example of all possible connections for integrating the fast charging stations into the medium-voltage grid. Each charging station can be connected to the nearest medium-voltage connection point or to the substation. Direct connections to the substation are depicted as straight lines, however the actual implementation considers a detour factor of 1.5. The solution determined by the heuristic optimization (see Subsection III-C4) can be seen in Figure 13b. In this specific distribution variation most of the charging stations are connected to the existing grid while only four charging stations get directly connected to the substation. The more charging stations are connected to grid areas with lower capacities, the higher the grid integration cost.



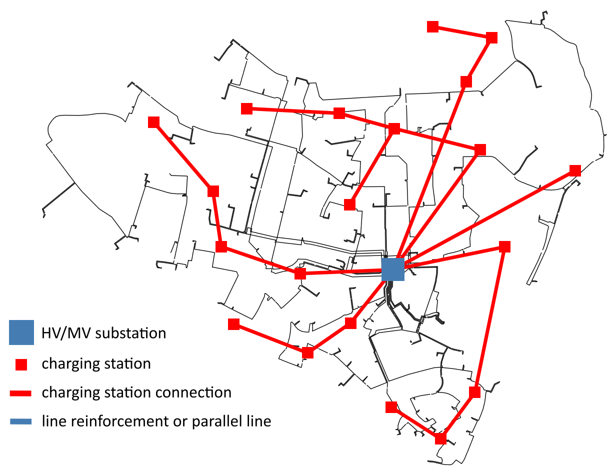
(a) All possible connections to the existing MV grid



(b) Grid integration solution determined by the heuristic optimization



(c) All possible connections for a dedicated fast charging grid



(d) Dedicated grid solution chosen by the heuristic optimization

Fig. 13. Comparison of integrating fast charging stations into the existing MV grid vs. a dedicated fast charging MV grid

For the "dedicated" scenario however, this effect only has a small influence on the investment cost. Figure 13c shows all possible connections for a dedicated fast charging infrastructure. Each fast charging station can be connected to the three closest neighboured charging stations as well as to the substation. Figure 13d displays the solution determined by the heuristic optimization. In this scenario the fast charging stations are not integrated into the existing MV grid while connections between the charging stations are possible. As a result investment cost are mostly independent from the spatial distribution of charging stations which is one possible explanation for the low spread in investment cost between the distribution variations. For interpretation of these results it is important to note, that the results of the fast charging scenarios are not directly comparable to the residential charging and the autonomous driving scenarios. In this paper it was our main goal to demonstrate fundamentally different charging concepts and not to to analyze, whether the two charging infrastructures can serve the same needs. Since it is not to be expected that one single charging concept will prevail, grid integration studies with a realistic combination of different charging infrastructure types would be a fruitful area for further work.

IV. Summary and Conclusion

This paper introduces an approach for conducting grid integration studies for eMobility scenarios in real distribution grids. A special focus is the comparison of a probabilistic distribution approach based on BEV charging profiles vs. the usage of simultaneity factors. The comparison shows, that simultaneity factors tend to underestimate the simultaneous power demand of small numbers of BEVs especially in LV feeders. As a result, voltage violations and line overloading are possibly underestimated as well. When assessing MV/LV substation transformer loadings or violations in MV grids, the results of both approaches are quite similar. This indicates, that simultaneity factors are potentially well suited for larger numbers of vehicles. A specific limit for the suitability of simultaneity factors however cannot be derived from the results of this paper which could be an object of further research. The methods for assessing worst-case BEV charging scenarios are applied in an integrated low- and medium-voltage grid. In order to consider the influence of spatial distribution of BEVs on grid violations, ten different probabilistic BEV distribution variations are used. Furthermore multiple charging infrastructure scenarios like residential charging, autonomous driving and fast charging stations are implemented. The grid reinforcement and expansion cost are determined with an automated heuristic optimization approach. The resulting investment cost shows, that the usage of simultaneity factors leads to significantly lower reinforcement and expansion cost as well as narrower cost distributions. The autonomous driving scenario shows cost saving potentials compared to the residential charging scenario.

It is important to note though, that this is not a realistic scenario in the near future and we did not consider all cost aspects associated with autonomous vehicles.

Regarding the fast charging scenarios a dedicated charging infrastructure with separate feeders from the existing grid shows to be less expensive and more predictable in cost, due to a less distinctive dependence on spatial distribution of the charging stations.

This paper mainly focused on demonstrating and comparing different methodologies and fundamentally different scenarios for grid integration studies in the context of eMobility. Based on this work, a further study could assess grid integration cost for a more realistic scenario, combining different types of charging infrastructure. Since the presented automated grid planning method already proved to allow a much higher number of grid planning cases, this would allow including more grids and BEV distribution variations to further increase the significance of the achieved results.

Acknowledgment

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