Methods for Assessing Worst-Case Scenarios for Distribution Grids in the Context of Electric Mobility

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***Abstract*—On last year's E-Mobility Integration Symposium we demonstrated a comprehensive approach for conducting grid integration studies in the context of electric mobility, including probabilistic modelling of vehicle charging, an analysis of simultaneity factor approaches as well as automated grid reinforcement. In this paper we present further research, that puts a greater focus on modelling and identification of realistic worst-case grid situations caused by EVs, charging in real low-voltage (LV) grid models. The proposed probabilistic method uses a pool of EV charging profiles and repeatedly places them randomly in a grid. The resulting distribution of different grid states contains all information that is necessary to derive realistic worst-case situations as well as the probabilities of their occurrence. Since probabilistic methods require a relatively high amount of computational resources, we present an acceleration of this approach based on artificial neural networks. In addition we demonstrate improved procedures for using simultaneity factors in order to asses worst-case grid situations in LV grids. The presented methods aim at a good balance between accuracy and practical feasibility. Especially the simultaneity factor based method is suitable for application in conventional grid planning processes in any common commercial grid planning software, while achieving similar worst-case estimations compared to the probabilistic method. The result of this work is a versatile toolkit for a variety of different use cases.**

I. Introduction

Planning distribution grids requires accurate, reliable and practical methods for assessing possible worst-case situations in order to prevent grid congestions. Scenarios of expected worst-cases - e.g. the point in time with the highest expected transformer loading - are the basis for planning decisions, like reinforcement of an overloaded line or transformer. Usually these situations are a result of high numbers of decentralised loads or generators, that are simultaneously active in the same grid. Especially in grids with increasing numbers of EV charging points, it can be very challenging to predict the maximum simultaneous power flow caused by charging vehicles and where in the grid it might occur. Additionally, simultaneities of different load/generator types have to be considered. Over- or underestimation of these worst-case simultaneities can result in over-/under-dimensioned distribution grids, that are either unreliable or cost-inefficient. Therefore, the goal is not to find the absolute worst-case that possibly could occur but rather to identify congestion situations, that might arise with a low, but realistic probability.

In practice the usage of simultaneity factors is the most common method to consider those simultaneities in grid planning. These factors estimate the maximum simultaneous power flow of loads or generators by multiplying their rated power with a constant factor, that decreases with a higher number of simultaneously active units. As we showed in [1] this approach is not suitable for predicting worst-case situations in LV grid feeders. Nevertheless, improved methods based on simultaneity factors would be very desirable due to the high feasibility of their application in real world grid planning processes.

In the following sections we present further research on different methods for worst-case assessments in LV grids. Based on [1] we demonstrate a probabilistic approach, that uses load profiles of EV charging processes and households in order to determine worst-case bus voltages as well as line/transformer loadings in LV grids. In addition we show, that this approach can be accelerated by predicting load flow results with artificial neural networks instead of calculating them. Finally, we present a way to achieve better worst-case estimations when using simultaneity factors, that can easily be applied in conventional grid planning processes using common commercial planning software. All methods are applied on eleven real LV grids in order to compare the resulting worst-case assessments as well as their suitability and feasibility for different use cases.

II. Approaches for Assessing Worst-Case Scenarios

In this section we present the fundamental methodology of the probabilistic and the simultaneity factor approaches demonstrated in this paper. Both the probabilistic as well as the simultaneity factor methods use a pool of simulated load profiles that contains 10,000 EV charging profiles and 10,000 household profiles. The EV charging profiles are generated based on a variety of different technical properties like capacities and charging characteristics of typical lithium-ion batteries as well as statistical data on mobility behaviour of vehicle owners (for more information see [1]). For all charging profiles a maximum rated power of 11 kW is assumed. The household profiles were generated using the load profile generator available at [2]. They represent households of different sizes, different demographic characteristics and different consumer behaviours. The considered profiles comprise the time window from 6:00 p.m. to 7:30 p.m. in one-minute-resolution (91 time steps) on a week day. The EV and household profiles and their described properties were chosen to present a comprehensible and

meaningful comparison of different approaches for worst-case assessments considering the simultaneity of multiple load types in LV grids. In general, all presented methods can be applied on any combination and number of profile types (EVs, households, PV, etc.), different EV charging powers (3.7 kW, 22 kW, 50 kW, etc.) as well as different time windows and time resolutions.

A. Probabilistic Distribution Approach

The probabilistic approach, as visualised in Figure 1, randomly chooses one of the 10,000 profiles of the appropriate type for each EV and each household in the grid. Next, for each time step in the chosen profiles all loads in the grid are set to the given power values and a power flow calculation is performed in order to determine the resulting line/transformer loadings and bus voltages. For all grid calculations the open source software pandapower [3] is used. After calculating the power flow results for all time steps, the highest line loading and lowest bus voltage per feeder as well as the highest transformer loading is stored. This process is repeated for a high number of probabilistic iterations n with a new random sample of chosen profiles in each iteration. The result is a distribution of n lowest bus voltages and highest line loadings per feeder as well as n highest transformer loadings. From this distribution a certain percentile is chosen in order to represent a realistic worst-case situation for the transformer and for each individual feeder. In this paper the 99.99th percentile of maximum loadings and the 0.01th percentile of minimum voltages are chosen. This means, that for example out of 100,000 evenings (represented by a time window between 6 and 7:30 p.m.), the evenings with the 10th highest loadings and 10th lowest voltages are chosen to represent a realistic worst-case situation that the grid should be dimensioned for. The choice of a worst-case percentile however depends on the specific use case, the remaining risk a DSO is willing to base its planing premises on and whether potentially overdimensioning the grid is an acceptable option. If e.g. demand side management of charging EVs is available to mitigate situations with very high simultaneities, a lower worst-case percentile could be sufficient.

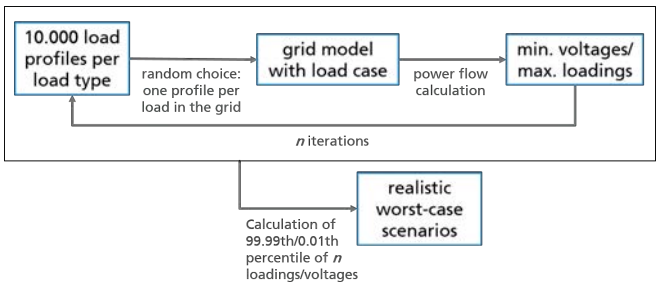


Fig. 1. Block diagram of the probabilistic approach

B. Enhancements of the Simultaneity Factor Method

Global Simultaneity Factors: The simultaneity factors applied in this paper are calculated based on the same EV and household profiles that are used for the probabilistic approach. As shown in Figure 2, for every number of loads l between 1 and 10,000, l profiles for each load type are

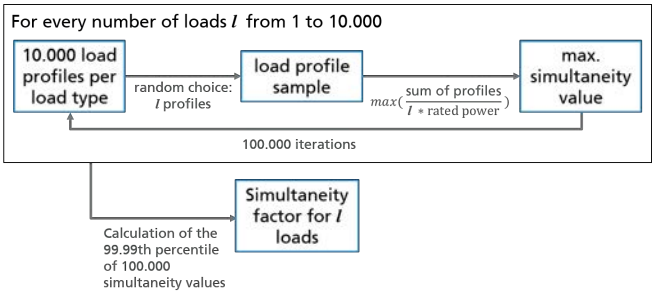


Fig. 2. Block diagram of the simultaneity factor calculation

randomly chosen. Then the sum per time step is calculated and divided by l times the maximum rated power of the specific load type (11 kW for EVs, 14.5 kW for households) in order to calculate the simultaneity value for every time step in the sum profile. Analogous to the probabilistic method, the worst-case simultaneity value for this specific combination of profiles is stored. This process is repeated 100,000 times resulting in 100,000 simultaneity values. The 99.99th percentile of these values is then chosen to represent the worst-case simultaneity for l simultaneously active loads.

If the simultaneity factors for the different types of loads are determined independently this neglects the dependencies of their simultaneities and can lead to a severe overestimation of the maximum simultaneous power flow. Figure 3 shows the importance of considering dependencies of the simultaneities of different load types. In this figure the simultaneity factors for 1 to 10,000 simultaneously active loads are plotted as simultaneity curves. The blue and red curves show the individual simultaneities for EVs (11 kW) and households. When these factors are applied individually - that means dependencies of the simultaneities between these load types are not considered - the outcome is the purple curve. It can be seen, that the usage of the individual factors leads to an overestimation, especially for 100 loads or less, which often is the case in LV grid feeders.

In order to incorporate the dependencies of these simul-

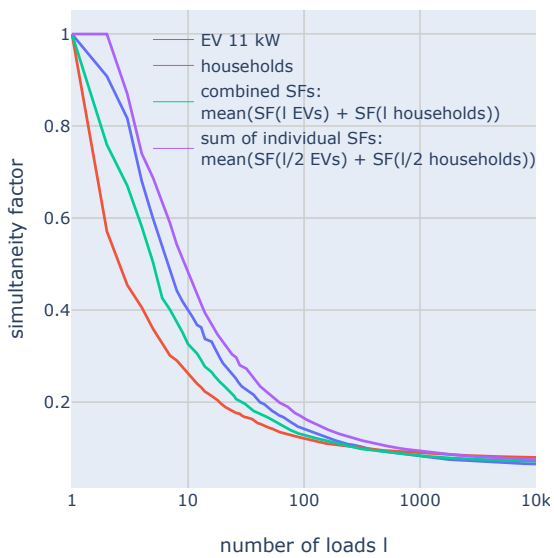


Fig. 3. Simultaneity factors for 1 to 10,000 loads

taneities, it is necessary to base their calculation on repeatedly choosing random profiles in the given mix ratio. For example, in this paper a fixed ratio of one EV per household is assumed. Under the assumption that the simultaneities of different load types are independent, a simultaneity factor for 5 EVs and 5 households can then be determined by repeatedly choosing 5 random profiles of each load type and calculating their simultaneity like described before. The green curve in Figure 3 shows the combined simultaneity. All considerd factors in this paper are combined factors. Since simultaneity curves are grid independent, they can be precalculated for different combinations of load types and different mix rations between them, which still makes their application very feasible.

Feeder Specific Simultaneity Factors: Using simultaneity factors in practical grid planning usually means, that one factor is determined for the total number of loads in the grid and this factor then is globally applied to all of them, as depicted in Figure 4a and 4b. As we showed in [1] this approach is suitable for assessing worst-cases in MV grids or for MV/LV transformer loadings, that usually are caused by more than 100 simultaneously active loads. For assessing worst-case bus voltages and line loadings in LV grid feeders however, global simultaneity factors lead to significant underestimations of these values. One reason for this effect is that bus voltages and line loadings in a LV grid feeder are mainly affected by the power flow originating from loads in the feeder itself. Since the number of loads in a feeder is lower than the total number of loads in the grid, higher worst-case simultaneities are to be expected. A way to consider this, is to determine and apply the simultaneity factors for each feeder individually. This however overestimates the maximum transformer loading and therefore the maximum voltage drop in the transformer, which also affects the estimated minimum bus voltage in all feeders (see Figure 4c).

Feeder Specific Simultaneity Factors + Separated Feeders: A possible way to mitigate this is to modify the grid model like shown in Figure 4d. In the modified grid model all LV feeders are isolated from each other, connected to the external grid by an exact copy of the original transformer. This allows applying feeder specific simultaneity factors without affecting other feeders. In order to match the transformer loading and voltage drop in the transformer of the case with global simultaneity factors (Figure 4b), an additional load is connected at the LV busbar of the transformer, compensating the difference between total feeder load and total grid load, determined by applying global simultaneity factors.

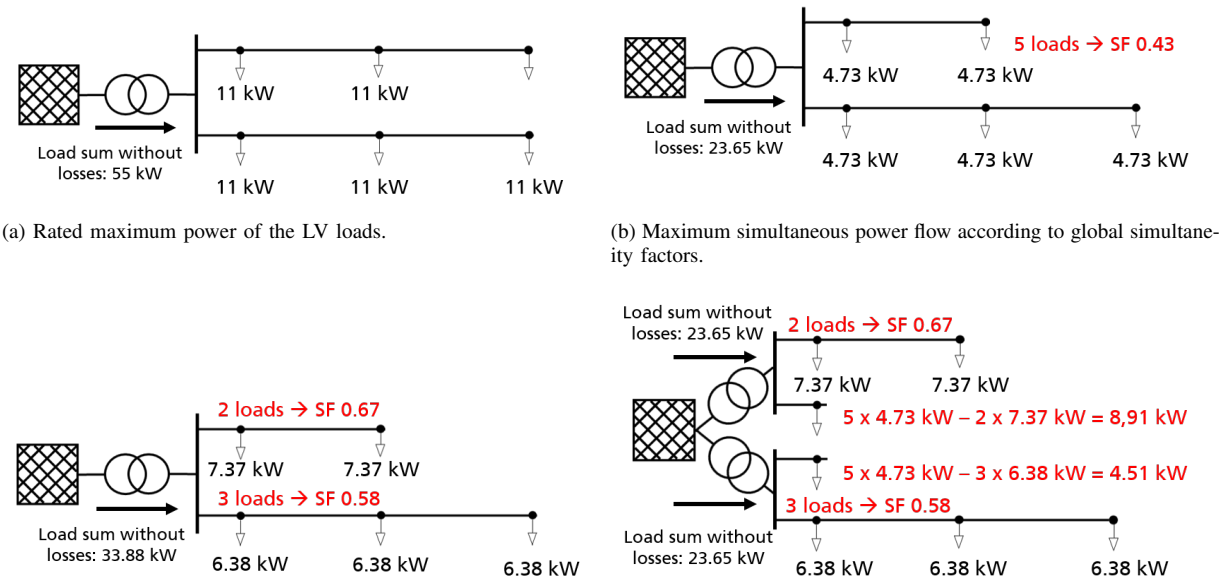
III. Application and Comparison in Real LV Grids

In this section we apply the aforementioned approaches for worst-case assessment on eleven real LV grids in order to compare, if they produce similar worst-case assessments. The grid models were provided by the German DSO Stadtwerke Kiel. They contain a variety of different sizes and settlement structures - the smallest grid has two feeders and supplies twelve households, while the largest grid includes seven feeders and 620 households.

As mentioned in Section II, it is assumed, that every household owns an EV that is exclusively charged at home. However this assumption is no requirement for the presented approaches and they could be applied on any other scenario just as well.

A. Probabilistic Approach - Number of Necessary Iterations

A fundamental question when applying the probabilistic method is, what size the probabilistically determined sample of voltages and line/transformer loadings, that is used to derive a worst-case situation, should have. As described in section II-A a sample of the size n consists of n independently calculated lowest bus voltages and highest line/transformer loadings. From this sample a certain percentile - in this



(a) Rated maximum power of the LV loads.

(b) Maximum simultaneous power flow according to global simultaneity factors.

(c) Maximum simultaneous power flow according to feeder specific simultaneity factors

(d) Maximum simultaneous power flow according to feeder specific simultaneity factors with separated feeders.

Fig. 4. Different simultaneity factor variants in an exemplary two feeder LV grid

case the 99.99th/0.01th percentile - is calculated to represent a realistic worst-case situation regarding loadings/voltages in a grid. However, it follows that this percentile value itself is a random variable that depends on the specific sample of loadings/voltages that was drawn. That means, when the worst-case percentile is repeatedly determined it differs slightly from calculation to calculation. The result is a distribution of values for the worst-case percentiles. This distribution of worst-case percentiles is grid specific. With increasing sample sizes the variance of the calculated percentiles decreases and the median of their distribution approaches the true percentile value of the basic population of all possible loadings/voltages. So the question is: How many samples of minimal voltages/maximal loadings should be drawn at least, to make sure that the probabilistically determined worst-case percentile is within an acceptable range of the actual percentile of the basic population?

Confidence Intervals: A common way to quantify this range are confidence intervals (CIs). CIs quantifiy the level of confidence that a statistical value of an unknown population - in our case a specific percentile - is contained within the interval. Usually they are calculated based on a random sample of an unknown population and some information about its type of distribution (e.g. normal distribution). The higher the desired level of confidence is, the wider is the CI. A 99% CI e.g. means, that 99 percent of all possible CIs contain the true value [4]. The type of distribution of these worst-case percentiles however is unknown. Moreover, the empirical investigation of the distribution of worst-case percentiles for different specific sample sizes of voltages/loadings would be impractical due to the high amount of necessary computing time. To investigate the distribution of worst-case percentiles based on sample size of 100,000 voltages/loadings e.g., would require to calculate a high number of independent samples each containing 100,000 voltages/loadings.

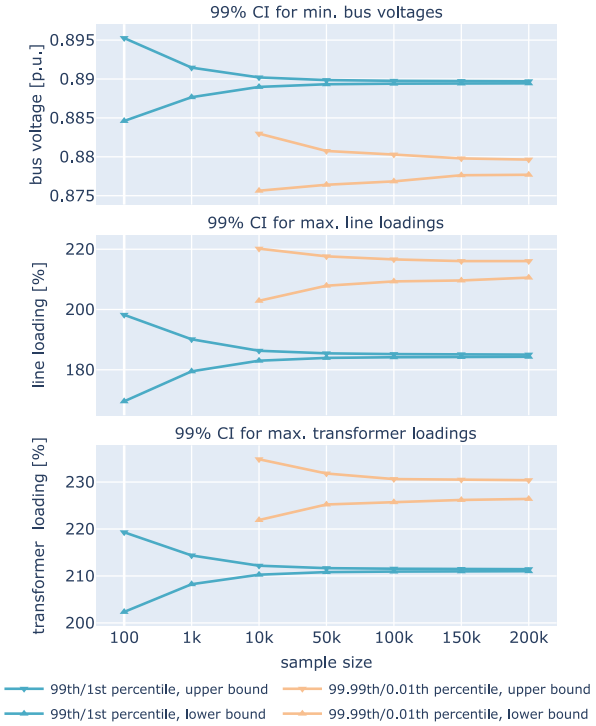


Fig. 5. Worst-case value confidence intervals for 100 to 200,000 probabilistic iterations in one LV grid

Bootstrap Resampling: Therefore, we use a method called bootstrap resampling, to derive CIs for the worst-case percentiles [5]. To this end, for each of the eleven LV grids, a sample of 200,000 minimum voltages and maximum line/transformer loadings is calculated. This sample is then used instead of the unknown basic population. That means, the consecutive sampling is done based on this (known) population. Specifically, samples of different sampling sizes are drawn 10,000 times each. Finally, since now the basic population is known for each sampling size the 99% CI

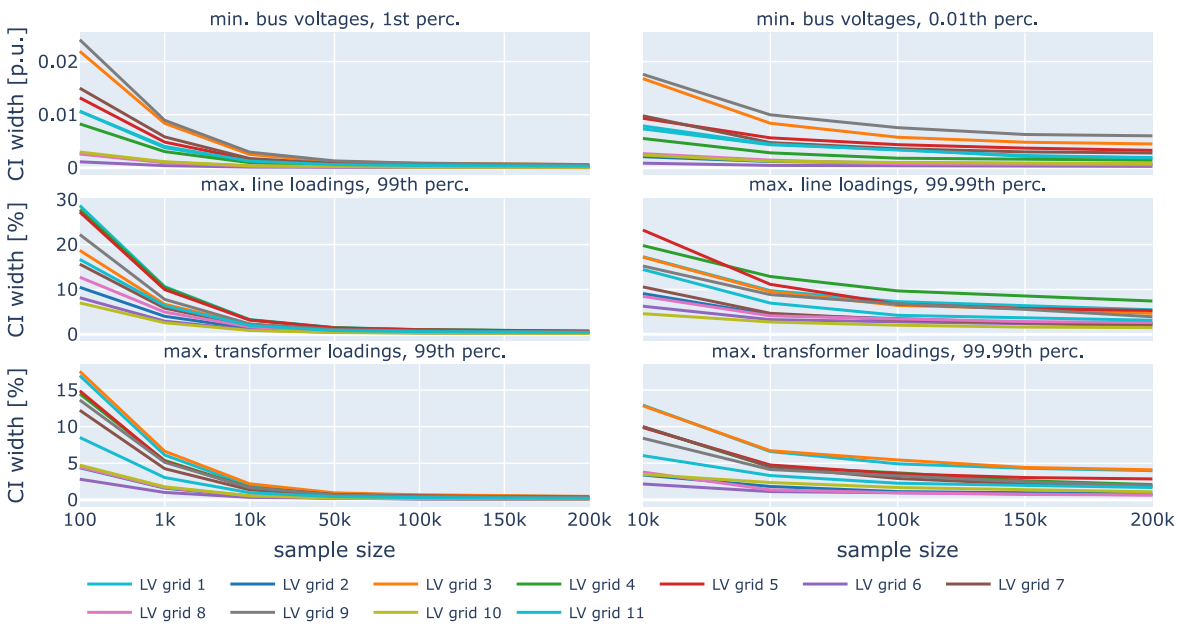


Fig. 6. Widths of worst-case value confidence intervals in eleven LV grids

can be determined. Figure 5 shows the CIs for the 99th/1st (blue curves) and 99.99/0.01th (orange curves) percentiles of minimum bus voltages and maximum line/transformer loadings, for different sampling sizes between 100 and 200,000 in a single LV grid. It can be seen, that the widths of the CIs for the 99th/1st percentiles decrease with increasing sample sizes. The same is true for 99.99th/0.01th percentile CIs, but they are overall wider.

Figure 6 visualises these CI widths for both percentiles calculated for all eleven LV grids. At a sample size of 10,000, the 99th/1st percentile CI widths of all grids are below 0.005 p.u. for the minimum voltage and below 5 percent for the maximum line/transformer loadings. For bigger sample sizes, the additional decrease of CI widths is much smaller. For the 99.99th/0.01th percentile this occurs at a sample size between 50,000 and 100,000 samples. Based on these results it can be concluded, that sample sizes of 10,000 voltages/loadings for the 99th/1st percentile and 100,000 for the 99.99th/0.01th percentile are a good trade-off of necessary computational resources and the potential error between the probabilistically determined and the actual percentile values.

B. Probabilistic Approach vs. Simultaneity Factors

In this section the probabilistic approach introduced in section II-A and the different variants of simultaneity factor methods of section II-B are applied and compared in eleven real LV grids. The probabilistically determined 99.99th/0.01th percentile values of minimum voltages and maximum loadings are used as a benchmark in order to investigate, if methods based on simultaneity factors can achieve comparable worst-case assessments.

Detailed Comparison in a Single LV Grid: Figure 7 shows the minimum voltages and maximum line/transformer loadings per feeder in a single LV grid. The boxplots represent the results of 100,000 probabilistic iterations. The diamond shaped markers indicate the 99.99th/0.01th percentile of these values. Additionally blue, orange and green markers indicate the respective value when determined with the different simultaneity factor variants that are applied globally, feeder specific and feeder specific with separated feeders (see Figure 4). The results show, that in this grid the global simultaneity factors underestimate minimum voltages and maximum line loadings compared to the probabilistic 99.99th/0.01th percentile. The transformer loading however is almost exactly matched. Feeder specific factors overestimate minimum voltages and transformer loading, but match the line loading percentile. Only the feeder specific factors based on a grid model with separated feeders achieve an overall good assessment of worst-case voltages as well as line/transformer loadings.

Comparison in Eleven LV Grids: Figure 8 extends this comparison to all eleven grids. The figure shows the relative deviation between the 99.99th/0.01th probabilistic percentile and the three simultaneity factor variants regarding voltages, line and transformer loadings over 50 feeders and eleven transformers. 75 percent line loading according to the probabilistic approach and 90 percent according to the simultaneity factor e.g., would result in a 20 percent positive deviation in this graph.

The overall results confirm what was indicated for the single grid in Figure 7. Global simultaneity factors (blue boxes) significantly underestimate minimum voltages and maximum line loadings in ten of the eleven LV grids. The median deviation regarding voltages is 0.7 percent with a maximum deviation of 4.4 percent. Line loadings are underestimated by 32 percent at the median and 66 percent at the maximum. Maximum transformer loadings are assessed very well: The median deviation amounts to -0.03 percent with a maximum of 7.8 percent and only two results exceed a deviation of 2 percent.

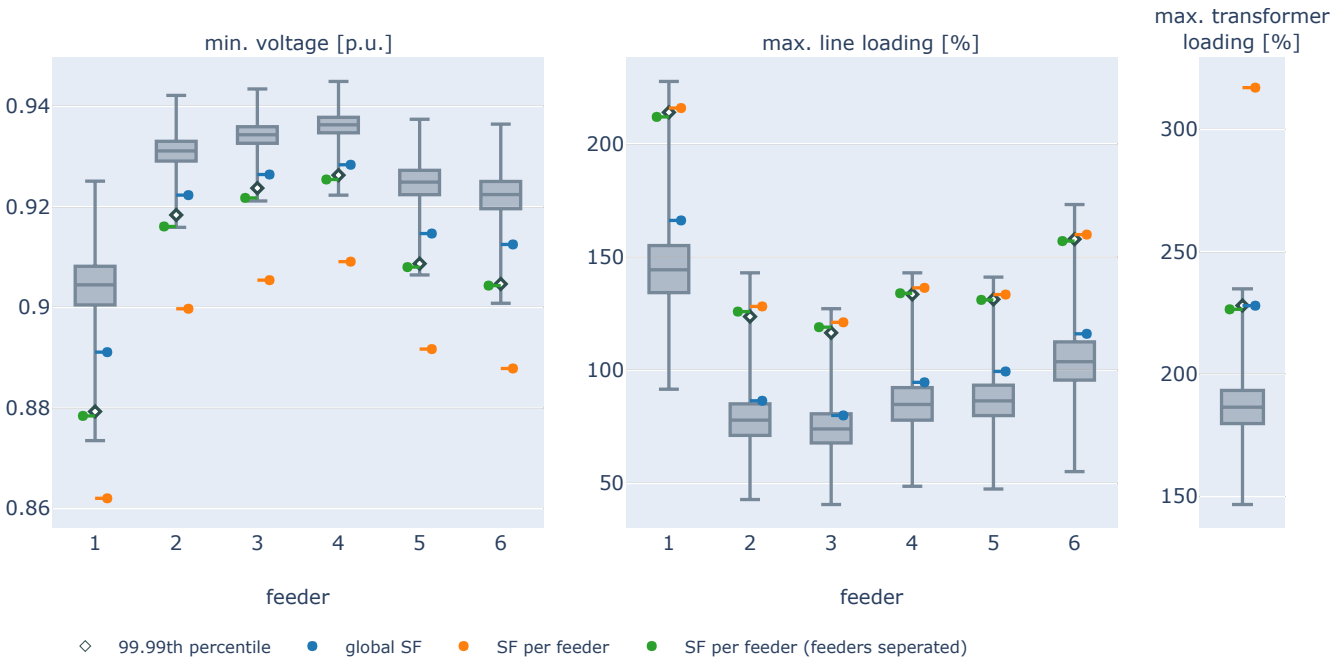


Fig. 7. Comparison of simultaneity factors vs. probabilistic distribution approach in one LV grid

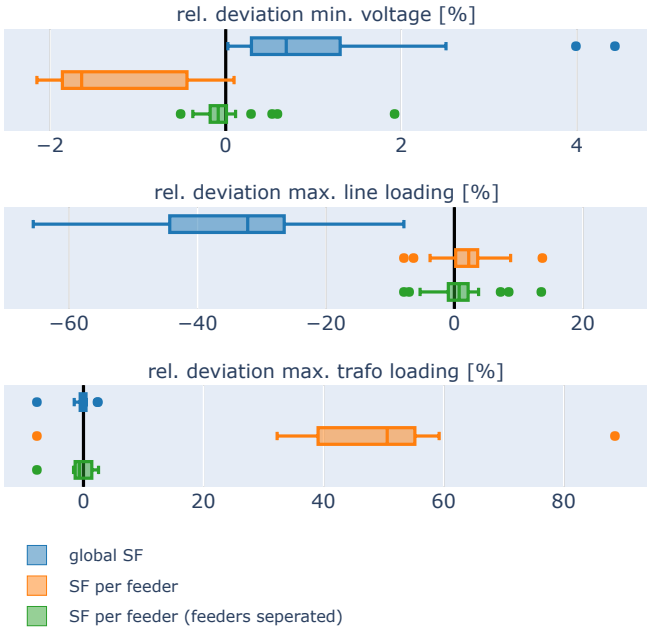


Fig. 8. Relative deviation of simultaneity factor values to 99.99th/0.01th percentiles of the probabilistic approach in eleven LV grids

Feeder specific factors (orange boxes) overestimate minimum voltages (median deviation -1.6 percent, maximum deviation -2.2 percent) as well as maximum transformer loadings (median 51 percent, maximum 89 percent), while the estimation of maximum line loadings is relatively close to the probabilistic percentile values (median 2.2 percent, maximum 13.7 percent).

Feeder specific factors applied on grid models with separated feeders (green boxes) achieve the best assessments of minimum voltages (median deviation 0.3 percent, maximum deviation 1.9 percent) and maximum line loadings (median 0.75 percent, maximum 13.5 percent). The estimations of maximum transformer loadings are also very close to the probabilistic percentile values (median -0.7 percent, maximum 7.8 percent). Compared to the results based on global simultaneity factors there are minor differences in the worst-case estimations, although both variants lead to the same load sum per transformer. This can be explained with slightly lower transmission losses in the separated grid models, since the replacement loads, that represent the simultaneity with the loads of other feeders, are connected directly to the LV busbar of the transformer (see Figure 4).

Conclusion: Overall it can be concluded, that feeder specific simultaneity factors with separated feeders obtain good results in assessing minimum bus voltages and maximum line/transformer loadings that are comparable to the worst-case results determined with the probabilistic approach. In addition, applying the simultaneity factor method is very fast and simple: Given precalculated simultaneity factors, modifying the grid model and calculating the power flow results only takes seconds with an automatable software like pandapower compared to several hours for the probabilistic approach. The main advantage however is, that the enhanced simultaneity factor method is feasible for practical applications in conventional grid planning processes, and can be used in any common commercial grid planning software like PowerFactory or Sincal.

C. Accelerated Probabilistic Approach based on Artificial Neural Networks

As demonstrated in the previous section, simultaneity factor methods can be adapted in a way, so that they achieve very similar worst-case assessments to the probabilistic approach while being relatively simple as well as time and resource efficient in application. These advantages make using simultaneity factors in grid planning very practical and attractive. Depending on the use case however, that method cannot completely replace the probabilistic approach, due to some inherent disadvantages.

Motivation and Use Cases: The presented separation of LV feeders can only be performed in radial grids. As a consequence, this simultaneity factor method is not suitable for assessing worst-case bus voltages and line loadings in meshed grids. An additional complication arises, when the investigated grids include a high number of different combinations of loads and generators with a variety of different mix ratios. For each number of simultaneously active loads as well as each individual combination of load types and mix ratios, a simultaneity factor has to be calculated, which could compromise the practicality of this method. Furthermore for some use cases, not only the worst-case power flow at single points in time is of interest, but the power flow during a whole time window. For analysing operational strategies like the potential of demand side management of EV charging points in order to reduce load peaks, while ensuring that every vehicle gets fully charged, the specific worst-case combination of load profiles is needed. Finally, simultaneity factor methods allow no conclusions, where in a feeder how many loads are expected to be simultaneously active in the worst-case situation, since the rated power of all loads in a feeder is multiplied with the same factor.

In these cases the probabilistic approach is still needed, which requires a high amount of computing time. Obtaining the results of 100,000 probabilistic iterations for a single LV grid based on load profiles containing 91 time steps e.g., demands 9,100,000 power flow calculations, as well as processing and storing the results. On a typical notebook CPU these calculations take several hours (single-core) depending on the grid size. While for some research applications this might be feasible, in many practical grid planning use cases it is not. Thus a way to accelerate the probabilistic method while obtaining comparable results is desirable.

Prediction of Power Flow Results: The calculation of several million power flows takes up the majority of time in this process. As shown in [6], a promising approach is the prediction of the power flow results by means of an artificial neural network (ANN) instead of actually calculating them. For this purpose, we use the open-source machine learning Python library scikit-learn [7]. An ANN can be trained to learn the relation between an input and an output vector based on a set of training data. After that, the ANN can be used to predict the output for input vectors, that were not contained in the training data. In our case, for each of the eleven LV grids, the ANN was trained on 10,000 iterations of the probabilistic approach, which comprise 910,000 load

vectors (10,000 load profile samples with 91 time steps each) as input data and 910,000 output vectors of the resulting bus voltages, line and transformer loadings for all buses, lines and transformer in the grid. Finally 8,190,000 additional load vectors (90,000 probabilistic iterations) were given as inputs to the ANN in order to predict the regarding power flow results.

Calculated vs. Predicted Results: Figure 9 shows a comparison of the calculated and the predicted results of 100,000 probabilistic iterations of a single LV grid. Analogous to Figure 7, the blue boxes visualize the calculated 100,000 lowest voltages and 100,000 highest line loadings per feeder, as well as the 100,000 highest transformer loadings. The orange boxes show the results predicted by the ANN based on the same load vectors as input data. For both result types the 99.99th/0.01th worst-case percentiles are marked. It can be seen, that even though the ANN slightly underestimates the minimum voltages and maximum loadings in all feeders and for the transformer, the overall results are very similar. Regarding the worst-case percentiles, the largest deviation between calculated and predicted values are 0.01 percent for the minimum voltages, 3.5 percent for the maximum line loadings and 1 percent for the maximum transformer loadings.

Figure 10 summarizes the same comparison over all feeders and transformers of all eleven LV grids. Comparable to Figure 8 it presents the relative deviations between the predicted worst-case percentile values and the calculated ones for minimum voltages as well as maximum line and transformer loadings. Again, positive deviations indicate, that the predicted values are higher than the calculated ones. The comparison shows, that overall the ANN achieves a good prediction of the worst-case percentiles. Regarding voltages the median deviation amounts to 0.28 percent with a maximum deviation of 0.58 percent. Line loadings (median deviation -0.94 percent, maximum deviation 4.6 percent) and transformer loadings (median -0.9 percent, maximum -2.65 percent) are also predicted with a relatively low error.

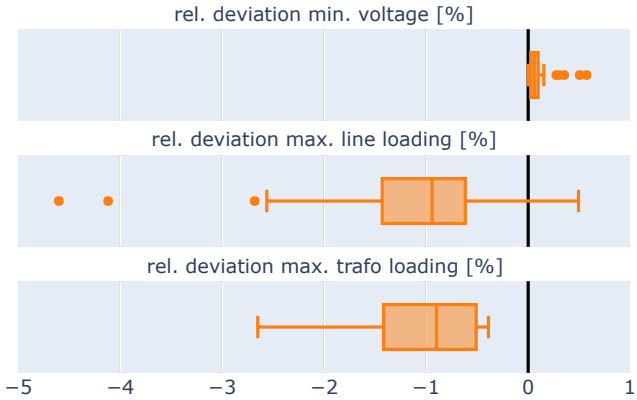


Fig. 10. Relative deviation of the predicted 99.99th/0.01th percentiles values to the calculated ones in eleven LV grids

Conclusion: Including the time for training the ANN and predicting the power flow results, calculating only the results of 10,000 probabilistic iterations and predicting the results of the remaining 90,000 requires about 15 percent of the time that would be necessary, if the whole 100,000 iterations were calculated. Once the ANN has been trained to predict the power flow results of a specific grid, the results of 100,000 probabilistic iterations can be predicted in a couple of minutes while the calculation of these results requires several hours. Since the predicted results prove to be very similar to the calculated ones for the investigated grids, accelerating the probabilistic method by means of an ANN seems to be a promising approach to increase its practical feasibility.

IV. Summary and Conclusion

The goal of the work presented in this paper is the investigation and further development of practical methods for accurately assessing realistic worst-case situations in real LV grids. These methods aim to be feasible for real world grid planning applications with a focus on the grid

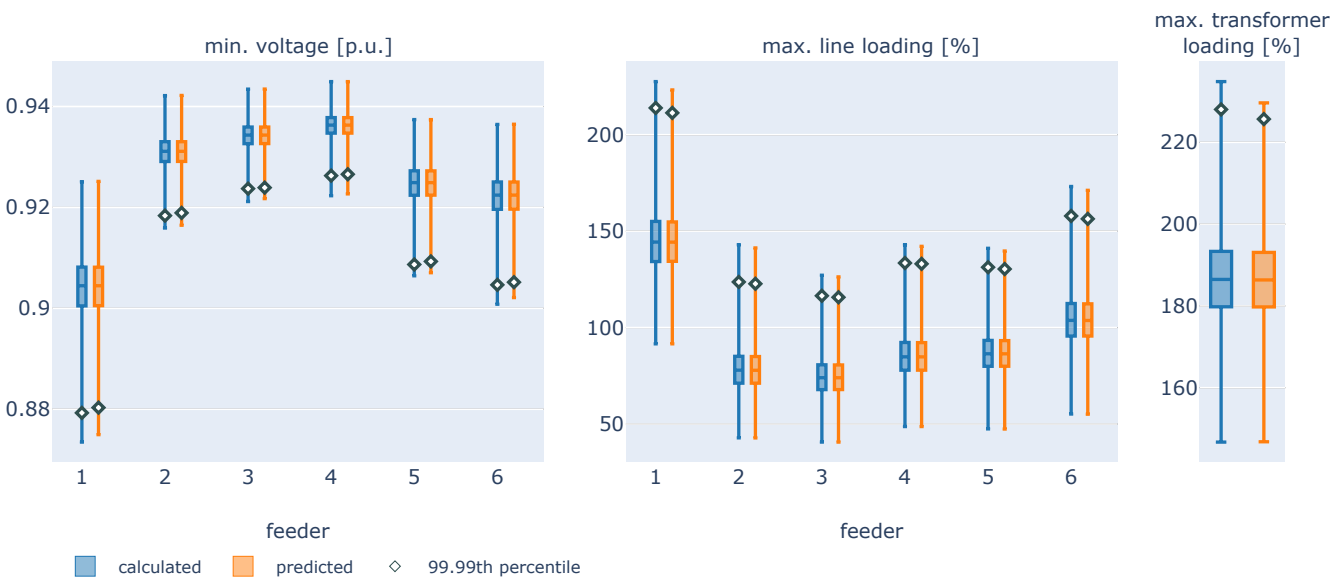


Fig. 9. Comparison of calculated vs. predicted worst-case values in one LV grid

integration of EV charging infrastructure. Resulting from further research based on [1], two approaches are introduced and compared.

The first one is a probabilistic approach, that repeatedly allocates randomly chosen load profiles to every load in a grid. The results of this approach are used as a benchmark for an enhanced simultaneity factor method, that modifies grid models to separate their feeders and than applies feeder specific simultaneity factors. Compared to previous work, both approaches now allow worst-case assessments considering a combination of different load types. In addition, the probabilistic method can now investigate time windows of arbitrary sizes instead of assuming a fixed worst-case point in time. Both the probabilistic approach and the simultaneity factor method use the same pool of EV charging profiles and household profiles in order to investigate worst-case bus voltages, line and transformer loadings, caused by the power demand of these two load types. An analysis of the simultaneity between the EV profiles and household profiles reveals, that the maximum simultaneous power flow is largely overestimated when using individually determined simultaneity factors for EVs and households in grid planning. This requires combined simultaneity factors for different load types, that consider dependencies between their worst-case simultaneities. The probabilistic approach and the simultaneity factor methods are applied on eleven real LV grids, in order to compare the determined worst-case assessments.

The comparison shows, that feeder specific simultaneity factors applied on a modified grid model with separated feeders achieve a good estimation of the probabilistic worst-case assessment. However their application is much simpler and requires only a fraction of the computational resources. Other than conventional simultaneity factor methods, this method obtains equally good estimations of worst-case voltages, line loadings and transformer loadings. As a result, this method is feasible for integration in practical grid planning processes and can be used in any common commercial grid planning software.

For some specific use cases however, like meshed grids or grids with a large variety of combinations of different load types, the simultaneity factor method is not applicable. The probabilistic method on the other hand requires a relatively high amount of time and computational resources. Therefore, an approach to accelerate the probabilistic method by means of an artificial neural network is presented. The results predicted by the neural network show only minor deviations to the calculated ones, while being determined in about 85 percent less time including training. Once the neural network is trained on a specific grid, it allows to predict worst-case assessments in a few minutes compared to several hours when calculating them. The presented results indicate, that the demonstrated approaches are a good basis for a versatile toolkit, that allows practical, realistic worst-case assessments, feasible for a variety of different grid planning use cases in the context of electric mobility.

Future studies should aim to apply these methods on a larger number of grids and more complex scenarios. Especially the accelerated probabilistic approach based on artificial neural networks should be further validated. Furthermore it should be investigated, if filtering the randomly chosen load profiles would be an alternative way to decrease the computational time required by the probabilistic method, by reducing the number of iterations that needs to be calculated.

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