Generating worst-case scenarios by randomly distributing loads for risk assessment in low voltage residential electricity grids

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In order to assess the capacity of low voltage electricity grids different grid operation cases are usually analyzed. These cases are used to identify weaknesses in the grid, evaluate the risks involved and subsequently facilitate the integration of new loads such as electric vehicles or heat pumps which are joining these grids in an increasing degree. This study suggests a random load allocation algorithm to create realistic worst-case scenarios for grid operation without the need for historical load data or reverting to load profiles. This is achieved by distributing loads asymmetrically across all three phases so that they comply with grid codes and burden the local transformer moderately. In this way, a multitude of feasible load scenarios is generated and evaluated. A metric is proposed to select those scenarios which lead to a critical operation state of the grid. The generated worst-case scenarios can be used to evaluate the potential capacity and risks of integrating new consumers into grids. This is demonstrated in a use case where electric vehicles are integrated into the investigated grid at half of all connection points. The analysis shows that the grid is additionally stressed and the reinforcement of cables or charge management would be required to facilitate the safe operation of the grid with additional loads.

Keywords: worst-case scenarios, random loads, asymmetric loads, risk assessment, low voltage electricity grid

1. Introduction

By the year 2050 Germany aims to reduce its overall greenhouse gas emissions by 85% to 90% compared to the year 1990 (BMUB, 2016). Electrization and sector coupling, i. e. between heat, transportation and electricity, are two important measures to realise the goal of decarbonization in the energy sector. Meanwhile the Grid Development Plan estimates that there will be up to 10 million electric vehicles and 4.1 million heat pumps in Germany by year 2030 (Transmission Grid Operators in Germany, 2019). By the end of year 2019, the number of electric vehicles as well as heat pumps are less than half a million (KBA, 2020; bwp, 2020), which suggests a significant increase of power demand in the low voltage grid in the near future.

It is necessary to assess the grid capacity before integrating these new consumers into the grid, so that risks like overloading of equipment, brownouts or blackouts can be anticipated and prevented. However, the operation status of the equipment and the state of the grid in residential areas are barely known to operators. High or low load conditions depend highly on individual customer behaviours. Sensors, which provide operators with live measurements of their grid, are usually solely found at local transformer stations, especially for low voltage grids. There they record voltage and loading information of the transformer but knowledge about how the current load and generation affects the underlying grid stays hidden.

Modeling loads and their uncertainties is a typical problem in the area of probabilistic powerflow. Short-term (a few month or less) power demands are independent from each other because different types of customers are connected to the grid. However, power demands are also correlated because customers may possess similar behavioral patterns or are affected by same weather conditions. This partial correlation was modelled by several researchers as a superposition of a totally correlated discrete set of means and independent variations, which were normally distributed (Allan et al., 1976; Chen et al., 2008; Billinton and Huang, 2008; Liu et al., 2013; Sheng and Wang, 2019). The authors based their analysis on historical data and in parts predictional load data as well, which however are generally not available for low voltage residential areas.

In the present study, a quick assessment of low voltage residential electricity grids is realised by generating demands randomly. The availability of historical load data or reversion of representative load profiles is not required for the allocation of demands. The allocated random asymmetric demands comply with the regulation of grid codes and burden the local transformer moderately. By using this method, a multitude of realistic load scenarios is generated and evaluated. A metric is proposed to select those scenarios which lead to a

Proceedings of the 30th European Safety and Reliability Conference and
the 15th Probabilistic Safety Assessment and Management Conference.
Edited by Piero Baraldi, Francesco Di Maio and Enrico Zio

ISBN: 981-973-0000-00-0 :: doi: 10.3850/981-973-0000-00-0_output

critical operation state of the grid. This universal procedure is used to identify the weaknesses of a given low voltage grid structure and to evaluate the potential capacity and risks which the integration of new consumers into grids might pose.

This paper is structured as follows: First, the method to distribute power demands randomly is introduced in section 2. In section 3 the results of modeling in a residential network are described, of which the worst-case scenarios are selected and discussed based on different concerning risk metrics. A simple use case that illustrates the integration of electric vehicles is tested on one of the worst-case scenarios. The concluding remarks are given in section 4.

2. Method

2.1. *Load allocation algorithm*

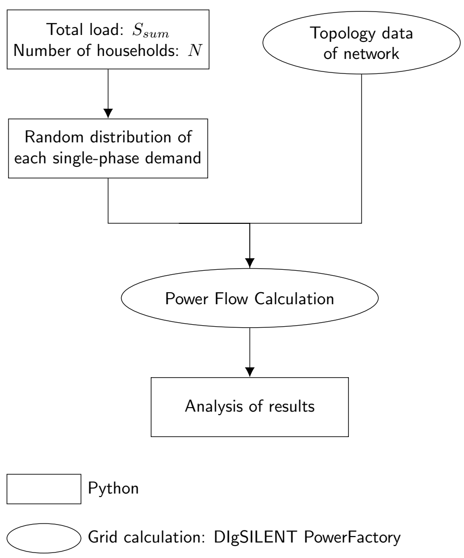

Fig. 1. Schematic of the method

In order to determine worst-case load scenarios for a given grid topology, a probabilistic load allocation algorithm was devised. It is explained below and illustrated in figure 1:

(i) Define input parameters: Network data, total power demand S_{sum}, number of households N.
(ii) Generate a vector of length N with random variables, which refers to a set of apparent powers S_i for N-households, so that:

$$\sum_{i=1}^{N} S_i = S_{sum} \tag{1}$$

where S_i is the power demand of the i_{th} household in the grid.
(iii) Unlike balanced loads in transmission grids, power demands in the low voltage grids are unbalanced across three phases. However, loads larger than 4.6 kVA must be connected into the network symmetrically according to VDE-AR-N 4100:2019-04. So for the calculation, we split each S_i into S_{iA}, S_{iB}, S_{iC} randomly, which refers to the single-phase demand of each household and meets the following Equation 2 and 3.

$$S_{iA} + S_{iB} + S_{iC} = S_i \tag{2}$$

$$\max(S_{iA}, S_{iB}, S_{iC}) - \min(S_{iA}, S_{iB}, S_{iC}) < 4.6 \text{ kVA} \tag{3}$$

(iv) Assign a random power factor ($\cos\varphi_{iA}$, $\cos\varphi_{iB}$, $\cos\varphi_{iC}$) between 0.94 and 0.98 to each single-phase demand (S_{iA}, S_{iB}, S_{iC}). Then a scenario of random demands for the network is generated, which is a $N \times 6$ dimensional matrix for all N households.
(v) Obtain the state of the network under the generated scenario: Carry out an asymmetrical power-flow calculation using a suitable tool, such as grid simulation software DIgSILENT PowerFactory.
(vi) Export the scenario and its corresponding power-flow results for post-analysis.
(vii) Repeat the preceding process i. e. step (ii) to step (vi), to generate a significant amount of scenarios and network states which can be compared and analysed.

2.2. *Low voltage grid structure*

In order to test the method, a network model of a low voltage grid was required to conduct power-flow calculations with different load distributions. While the method can be used in any low voltage grid, we decided to use a topology from the MONA 2030 reference topologies, which reproduce features of real networks, but are otherwise fictional, usable under a Creative Commons license and well documented (FfE e. V., 2019).

The residential network "MONA 14" was chosen and its topology is shown in figure 2. There are 45 house connection points in the network and the rated power of the transformer is 630 kVA. The windings of the transformer are delta-wye connected. For our study, a neutral wire is provided on the secondary side and grounded.

2.3. *Assumptions for load distribution*

We assume that each connection point supplies two households ($N = 90$) and the total load is defined to be 347 kVA, which constitutes 55% of

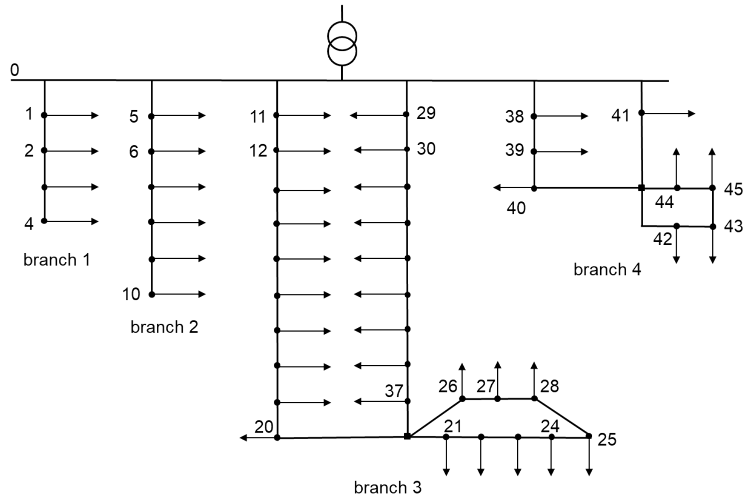

Fig. 2. Topology of network “MONA 14” (FfE e. V., 2019)

the rated transformer power, so that $\sum_{i=1}^{90} S_i = 347$ kVA.

2.3.1. *Unbalanced random load distribution*

3000 independent scenarios of randomly generated demands were created, based on the proposed method in section 2.1. An asymmetric power-flow calculation was carried out for each scenario.

2.3.2. *Balanced load distribution*

A basic scenario with a symmetric load distribution was generated additionally, which is used as a reference for the state of the network under balanced conditions. It is used later on to compare scenarios and determine how far the operation state of the network will be aggravated under the generated random scenario. For this distribution, power demand at every connection point is simplified to a three-phase 7.7 kVA load, so that the total load accounts for 55% of the transformer rated power. An unified power factor of 0.95 is assigned to each load considering the experience from Strunz et al. (2014) for European residential loads.

2.4. *Risk metrics*

For our study it is assumed that the low voltage residential network is connected to the infinite power grid, so that dynamic voltage and frequency stability of the network is guaranteed and therefore not further addressed.

However, considering the increased integration of new power consumers like electric cars and heat pumps, overloading of equipment is concerned. It decreases the energy efficiency due to power loss in form of heat or may trip the overload relay, which leads to local or even regional power cuts. Meanwhile, power quality indicators in terms of voltage amplitude (RMS value) and voltage unbalance are included in the analysis.

The results of the power-flow calculations are analyzed and discussed based on the mentioned metrics in the following chapter.

3. Results and discussion

For the quantification of risks, the states of the network in terms of the loading of cables, loading of transformer, voltage amplitude and voltage unbalance in each case are identified and summarized for the 3000 cases. The corresponding worst-case scenarios are selected and discussed.

3.1. *Cable loading*

All cables were assessed for their loading in every scenario. As the power demands were unsymmetrical, loading of a cable refers to the maximal loading of one of the three phases.

The most heavily loaded cable in each case was identified. They are either cable 0-11, cable 11-12 or cable 0-29 among the 3000 cases. This is the expected outcome because these are the first cables leading to the branch with the most households, i. e. the majority of power flows through these cables.

The loading status of the most stressed cable in each case was also identified. The histogram in figure 3 shows the distribution of the maximal loading of cable for all 3000 cases. It can be seen that the majority of the maximal loading is located between 62% and 75%. Moreover, there are 384 cases in which the most stressed cable is higher than 75% loaded. In the worst-case scenario, which occurred in the $2826th$ random distribution of demands (named *Case A*), the cable 11-12 was 93.61% loaded. Figure 4 shows the corresponding power demand at every connection point in this worst-case, in which the demands vary from 1.1 kW to 16.1 kW.

3.2. *Voltage amplitude*

According to DIN EN 50160:2011-02 (2011), the 10-min average value of the voltage amplitude must be held within 10% of the nominal voltage, i. e. [0.9, 1.1] p. u.. Some operators prefer a range of [0.95-1.05] p. u. during normal operation, so that there is a buffer for emergencies. As the network is loaded in an unbalanced way, the voltage amplitude u_m for analysis is defined as the mean value of the single-phase voltages:

$$u_m = (u_a + u_b + u_c)/3 \tag{4}$$

The connection point with minimal voltage amplitude is identified for each case. Among all cases, the lowest voltage always appeared at bus 24, 25, 27 or bus 28. These connection points are located at the end of the branch with the most households connected.

The distribution of the minimal voltage amplitude from each case is shown in figure 5. Among them, 372 cases violate the lower boundary of 0.95 p. u.. The $2315th$ distribution of demands produced the worst-case scenario (named *Case B*) at bus 25 with a voltage amplitude of 0.944 p. u.. The corresponding power demand at each bus for this scenario is shown in figure 6. In this scenario the demands vary from 2.6 kW to 12.7 kW.

3.3. *Voltage unbalance*

On the other hand, the 10-min average value of voltage unbalance must be within 2% to comply with DIN EN 50160:2011-02. The voltage unbalance ε_u is calculated as follows:

$$\varepsilon_u = \frac{u_2}{u_1} \times 100\% \tag{5}$$

where u_2 is the negative-sequence voltage, u_1 is the positive-sequence voltage. The histogram of the maximal voltage unbalance from each scenario is shown in figure 7. The worst-case scenario resulted from the $859th$ scenario (named *Case C*) with a highest voltage unbalance of 1.0% at connection point 27. Figure 8 depicts the corre-

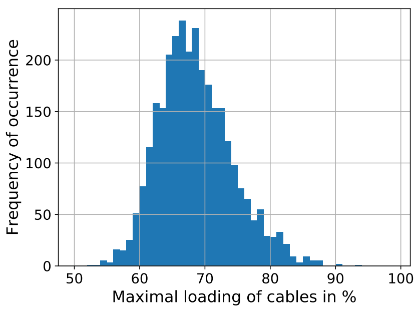

Fig. 3. Histogram of the loading status of the cable with the highest load in each scenario

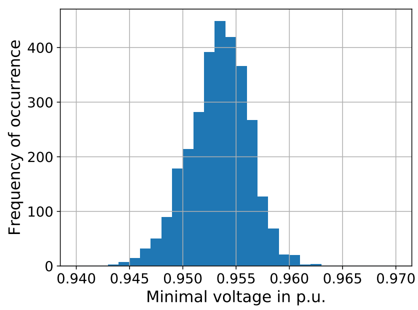

Fig. 5. Histogram of the minimal voltage amplitude in each case

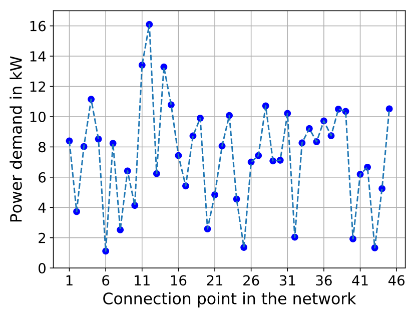

Fig. 4. Power demand at every connection point for the worst-case scenario in Fig. 3

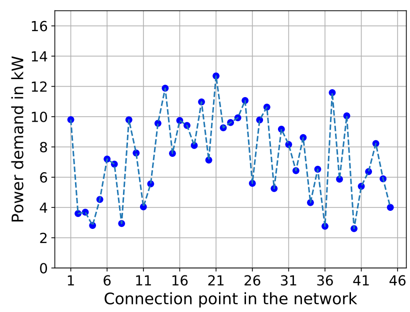

Fig. 6. Power demand at every connection point for the worst-case scenario in Fig. 5

sponding power demand at every connection point in this scenario. The randomly generated demands range from 1.5 kW to 12.0 kW. The analysis indicates that the network is not heavily stressed in terms of voltage unbalance. One important reason is the beneficial delta-wye connection of the local transformer.

3.4. *Transformer loading*

Another metric for the criticality of a demand scenario is the resulting loading status of the transformer. The loading status of a transformer in the simulation tool DIgSILENT PowerFactory (2019) is defined as follows:

$$\text{loading} = \max\left(\frac{I_{bushv}}{I_{nomhv}}, \frac{I_{buslv}}{I_{nomlv}}\right) \times 100\% \quad (6)$$

where I_{bushv}, I_{buslv} are the magnitudes of the current of the high and low voltage side respectively. For an unbalanced power-flow calculation the highest current across three phases is used. I_{nomhv} and I_{nomlv} are the nominal currents of the high and low voltage side respectively. Figure 9 describes the loading of the transformer from each case. As the demands were connected asymmetrically, the loading of the transformer is larger than 55% in all cases. The worst-case scenario appeared in the $2971th$ distribution of demands (named *Case D*) and resulted in a loading of 70.85%. This high asymmetric loading accelerates the aging and reduces the useful life of transformer. The corresponding power demand at each bus of this distribution is shown in figure 10. Here the demands vary from 1.0 kW to 13.6 kW.

3.5. *Correlation between voltage amplitude and unbalance*

The voltage amplitude and voltage unbalance at each bus for all 3000 cases is illustrated in Figure 11 and Figure 12 respectively. The figures show the result space and thus the range of voltage and unbalance magnitudes for every connection point. It can be seen that both voltage amplitudes and unbalances between bus 21 and bus 28 show a wider range between maximum and minimum observed values than at other buses. This indicates that, for the given network, this area can be considered less robust.

Both metrics are correlated, i. e. buses with high voltage unbalance factors show a higher pos-

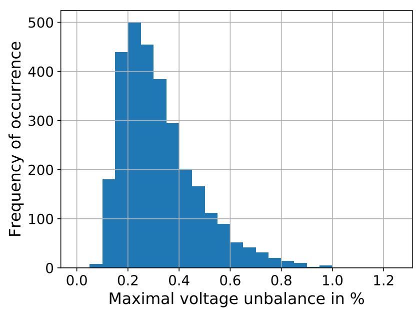

Fig. 7. Histogram of the maximal voltage unbalance in each scenario

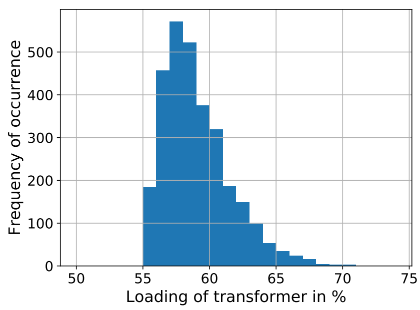

Fig. 9. Histogram of the loading status of transformer in each scenario

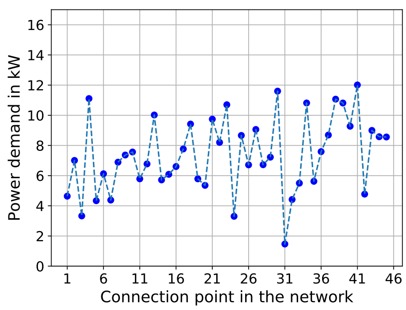

Fig. 8. Power demand at every connection point for the worst-case scenario in Fig. 7

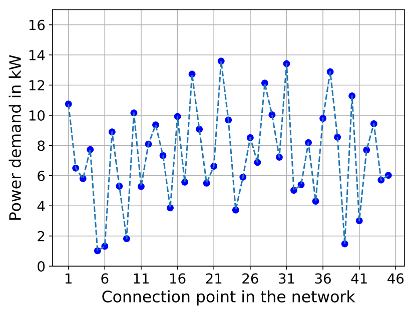

Fig. 10. Power demand at every connection point for the worst-case scenario in Fig. 9

sibility to exhibit low voltage amplitudes in some scenarios. The Pearson correlation coefficient between minimal values for voltage amplitudes and maximal values for voltage unbalance for every connection point is -0.99. This negative correlation is shown in Figure 13.

Comparing the difference between the maximum voltage range and maximum voltage unbalance range for each connection point also yields a high Pearson correlation coefficient of 0.98. The positive correlation is shown in Figure 14 together with the fitted linear regression line.

3.6. *Summary of worst-case scenarios*

As described in section 2.3, a scenario with symmetric loads was generated as a base case. After performing the load-flow calculation, the minimal voltage amplitude was 0.953 p. u. at bus 28, the cable 11-12 was most heavily loaded with a loading of 61.2% and the transformer was 55.05% loaded.

The selected worst-case scenarios based on defined risk metrics are listed and compared to the symmetric base scenario in table 1. Case A resulted in the heaviest loading of cable 11-12 with a loading of 93.61%, which is more than 30% higher than in the base scenario. The lowest voltage amplitude of 0.944 p. u. was from Case B at connection point 25 and is 0.01 p. u. lower than in the symmetric scenario. Case C lead to the highest voltage unbalance of 1.0% at bus 27. Moreover, the transformer was most stressed in Case D with a loading of 70.85%, which is about 15% higher than in the base scenario.

Although the selected worst-case scenario seem to be edge case from each histogram, we still regard them as realistic because their asymmetric distribution of loads comply with grid codes. Furthermore, from the distribution of loads for each worst-case scenario shown in Fig. 4, Fig. 6, Fig. 8 and Fig. 10, we can see that the loads vary in a reasonable range. There are neither extremely high demands nor concentration of demands at the end of the longest branch, which can theoretically lead to the worst static operation states for the given network structure in terms of low voltage amplitude and high loading of equipment, but these cases would be less likely to occur in reality.

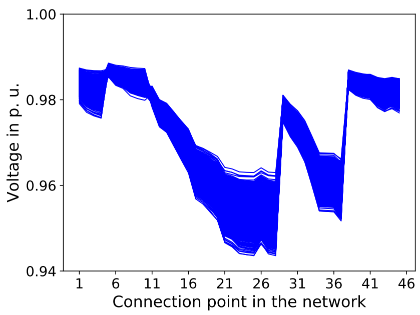

Fig. 11. Voltage amplitudes at every connection point for all 3000 scenarios

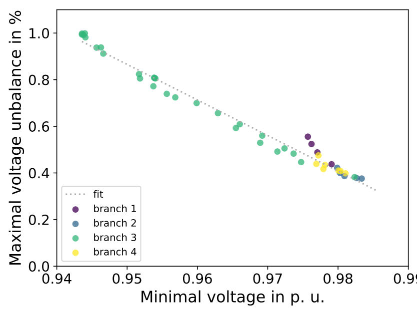

Fig. 13. Minimal voltage and maximal unbalance pairs for all connection points over all 3000 scenarios with linear fit

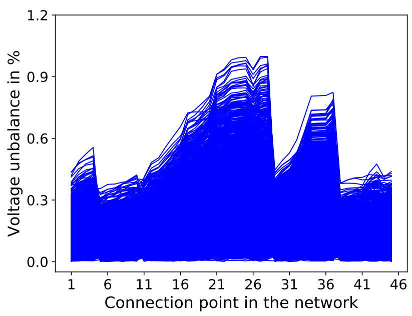

Fig. 12. Voltage unbalance at every connection point for all 3000 scenarios

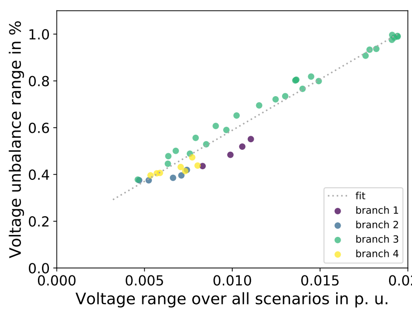

Fig. 14. Maximal ranges of voltage magnitude and unbalance for each connection point over all 3000 scenarios with linear fit

Table 1. Worst-case scenarios for different risk metrics

Scenario	Symmetric	Case A	Case B	Case C	Case D
Total load (kVA)	347	347	347	347	347
Max. cable loading (%)	61.18	93.61	83.35	86.68	87.98
Min. voltage amplitude (p. u.)	0.953	0.951	0.944	0.951	0.947
Max. voltage unbalance (%)	0	0.77	0.68	1.0	0.74
Transformer loading (%)	55.05	69.32	61.41	67.47	70.85

Note: Among all 3000 scenarios: Case A leads to maximal loading of cable; Case B leads to minimal voltage amplitude; Case C leads to maximal voltage unbalance; Case D leads to maximal loading of transformer

3.7. *Use case: Integration of electric vehicles*

We took one of the worst cases from table 1 to assess how a worst-case scenario for load demand could help planning decisions regarding the integration of electric vehicles into the grid. Case B was selected for this analysis. It resulted in the lowest minimal voltage among all scenarios, which might get worse with the introduction of additional loads in form of electric vehicles. A simple scenario for this situation is that half of the connection points supplies an electric car with a symmetric demand of 3.7 kW, which is a common charging power of electric cars (BNetzA, 2018). With this setup, the loading of the transformer reached 75.5%. Seven cables in the network were loaded higher than 80%. Among them, the most heavily loaded cable was cable 11-12 with a loading of 98.6% . If this was a real grid situation, it would be advisable to upgrade this cable or to manage charging timeslots in order to guarantee a reliable power supply under all circumstances. The maximal voltage unbalance ($\varepsilon_u = 0.73\%$) and minimal voltage amplitude ($u_m = 0.933$ p. u.) occurred at bus 25 and bus 27 respectively. The results are summarized in table 2.

Table 2. Scenario B with integration of electric vehicles

Scenario	Case B	Case B with EVs
Total load (kVA)	347	432
Max. cable loading (%)	83.35	98.56
Min. voltage amplitude (p. u.)	0.944	0.933
Max. voltage unbalance (%)	0.68	0.73
Transformer loading (%)	61.41	75.5

4. Conclusion and outlook

For evaluating the network capacity and risks of integrating new consumers like electric cars and heat pumps, a method to generate realistic random demand scenarios is proposed, where the asymmetric distribution of single-phase loads complies with the regulation of grid codes. The worst-case scenarios are selected according to the risk metrics, i. e. high loading of transformer, high loading of cables, minimal voltage amplitude (RMS value) and maximal voltage unbalance.

As the method is used to evaluate capacity and risks of integrating more power demands into grids, distributed generators like photovoltaic systems are not considered. The significance of the grid evaluation depends on grid structures and input parameters, which can be adjusted considering various grid topologies and load conditions to acquire the corresponding worst-case scenarios. For this analysis we assumed that in the given radial network each connection point supplies two households and that the total load does not exceed 55% of the rated transformer power.

The presented use case utilises an identified worst-case scenario to assess the feasibility of integrating electric vehicles into the existing grid structure. It is shown that under the chosen grid status, the metric values indicate that some grid related action is required to guarantee that the integration of electric cars does not impair the safe operation of the grid.

Acknowledgement

The authors acknowledge the the financial support from the German Federal Ministry for Economic Affairs and Energy, as well as Project Management Jülich within the project “IKTfree – Hochverfügbarer Verteilungsnetzbetrieb bei Störung der IKT-Infrastruktur im Smart Grid”. The authors are solely responsible for the content of this publication.

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