Determination of the Line Parameters of Electrical Distribution Grids based on Smart Meter Data

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Abstract

Due to the decarbonization of the energy sector and the associated integration of new electrical loads and generators such as electric vehicles or PV systems, grid operators must switch to active grid operation management. This includes the control of both flexible loads and generation systems based on the knowledge of important grid parameters such as resource utilization and node voltage. Smart meters are therefore increasingly being integrated into the low-voltage level in order to determine the grid status from the recorded measurement data and the grid topology as a basis for active grid operation management. However, a current problem is that a large proportion of the line parameters, such as the line resistance, are not sufficiently digitized and in some cases incorrect, so that it is unclear at which currents line overloads occur. Within the framework of sensitivity analyses using synthetically generated smart meter data, this study investigates the influence of measurement uncertainties on the quality of the determination of the line parameters using a method based on multiple linear regression and the voltage drop along lines. This study shows that line parameter determination based on measurement data, using the here presented approach, is applicable in practice for lines with high voltage drops.

1. Introduction

In order to achieve the statutory climate targets, the expansion of decentralized energy generation plants and new types of consumers, particularly at the lower voltage levels, is strongly motivated. However, these plants and generators pose challenges for the originally passively designed distribution grids due to possible higher utilization of operating resources or voltage band violations. A switch to actively operated distribution grids based on grid status determinations is therefore necessary.

Smart meters are increasingly being installed at the low-voltage level in order to determine the status of the grids, e.g. through state estimation, and thus enable active control of the systems. These record the electrical parameters (voltage, current, active and reactive power) of the grid at regular intervals. In this context, it must be noted that measured values are always subject to measurement uncertainties, which are propagated through the further processing procedure. The grid status can then be determined based on the measured values and the grid topology. However, the grid topology is often not digitized in sufficient quality nowadays. Consequently, essential parameters such as the line impedances are missing or are only available with inaccuracies. Methods for determining the grid topology and line parameters are therefore the subject of current research.

This article examines the influence of measurement uncertainties on the quality of the determination of line parameters. A method for determining the line parameters based on the voltage drop along the lines using multiple linear regression is used. This study uses synthetically generated measurement data to investigate the influence of measurement uncertainties of different magnitudes.

The structure of this paper is as follows. In Section 2, a literature review of various methods used in research to determine line parameters is given, thus differentiating the research contribution of this study from the existing literature. Section 3 explains the data basis of this study and the process steps used to determine the line parameters in more detail. Section 4 then provides an overview of the various results and draws initial conclusions about the influence of measurement uncertainties in the determination of line parameters. Finally, the results are summarized in Section 5 and an outlook is given.

2. Review of Literature

Various approaches for determining line parameters in distribution grids can be found in the literature. A large number of algorithms determine the line parameters, the ohmic active resistance R and the reactive resistance X, on the basis of historical voltage, active and reactive power measured values from smart meters. Based on this, either regression models or neural grids can be used to estimate the parameters.

First, a numerical method for identifying the grid topology and determining the line parameters is presented in Reference [1]. Historical voltage, active and reactive power amplitudes at the grid nodes are used as the data basis. An approximate estimate of the topology and line parameters is obtained on the basis of linear regression. In a further step, the parameters R and X are considered as variables in the

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power flow calculation and approximately optimized to their actual values in a special version of the Newton-Raphson iteration. In addition, the topology is corrected at each iteration. The presented method is tested on the medium-voltage grids IEEE 33-bus feeder and 123-bus feeder with real measured values considering measurement uncertainties. Therefore, the results cannot be transferred to low voltage.

In Reference [2], an optimization method for determining R and X assuming a known grid topology is presented. For this purpose, a cost function is formed from the described non-linear equations, whereby the minimization of the cost functions by means of particle swarm optimization achieves optimal results for the line impedances. The results presented are based on real grid areas with real measured values, so that no generally valid statements can be made.

In Reference [3], a method based on a neural grid and stochastic gradient descent is presented. This requires initial parameter estimates from a geographic information system to be optimized. Physical transition functions based on nonlinear power flow are developed to replace the transition functions based on deep neural grids in the graphical neural grid. The result of the graphical learning model are estimated node voltage values of the smart metering systems. The gradient of the loss function of the voltage values is then calculated as a function of the resistance and reactance parameters of the lines using an iterative method. Finally, the estimates of the line parameters are calculated according to the principle of stochastic gradient descent in order to minimize the deviations between the voltage values generated from the graphical learning model and the actual measured voltage values. The method takes measurement uncertainties into account, but is only applied to IEEE 13- and 17-bus feeder medium-voltage grids.

Finally, Reference [4] presents a method for determining the line parameters R and X on the basis of a multiple linear regression model. The mathematical basis for this model is the linearized voltage drop on a line, which is used as a multiple linear regression model. The method shows results for a medium-voltage grid, including low-voltage grids, and takes into account the presence of measurement uncertainties.

In summary, it can be said that there are different methods for determining line impedances, but not on a publicly available database for the low-voltage level. The methods presented use different grid models for which it is uncertain whether they represent the broad mass of grid structures that occur in reality. Due to the scalability also for larger grid models and the comparatively simple implementation in practice, the method of multiple linear regression is used in this study according to Reference [4].

In comparison to the studies presented, a publicly available database is used here, which depicts representative grid structures at the low-voltage level [5]. This ensures that the results are reproducible and that no grid structure is neglected. Measurement uncertainties of different orders of magnitude are added to the synthetically generated measurement data. This allows the influence of measurement uncertainties to be determined in sensitivity analyses and requirements to be placed on the measurement technology for implementation in reality. This distinguishes the presented work from the existing literature.

3. Data and Methodology

In this chapter the data basis and data generation for the line parameter determination algorithm are presented. First, the grid models used and the synthetic load profiles are discussed. As a next step, the calculation of the voltage drop along the lines and the problem solving using multiple linear regression are explained.

3.1. Data Generation

This study uses SimBench grids as the data basis [5]. SimBench is a publicly available database of synthetic grids developed on the basis of real grid structures and parameters. Table 1 provides an overview of the SimBench low-voltage grids used and their properties. The low-voltage grids are available in three scenarios, with scenario 0 corresponding to the current supply task in Germany. Scenarios 1 and 2 describe future supply tasks with increased numbers of decentralized generation plants, battery storage systems, charging stations and heat pumps. In the low-voltage grids, only underground cables are used as lines, with the same type of cable always being used within a grid. Two different cable types with $R'_1 = 0.2067\frac{\Omega}{km}$, $X'_1 = 0.0804\frac{\Omega}{km}$ (type 1) and $R'_2 = 0.1267\frac{\Omega}{km}$, $X'_2 = 0.0798\frac{\Omega}{km}$ (type 2) are used across the grid models. Based on the probabilistic load and generation profiles, an annual load flow calculation is carried out with a time resolution of 15 minutes. This means that the relevant grid status data (node voltage, line currents, active and reactive power) is available in sufficient quality for all time steps.

Table 1 - Overview of the structural parameters of the low-voltage grids [5].

Grid Model	**1**	**2**	**3**	**4**	**5**	**6**
Grid structure		Rural		Semiurban		Urban
Number of nodes	15	97	129	44	111	59
Number of lines	13	95	127	42	109	57
Total cable length [km]	0.56	1.47	2.35	0.746	1.79	1.078
Mean cable length [m]	43.05	15.44	18.52	17.76	16.42	18.9
Cable type	1	1	1	1	2	2

In order to take into account, the influence of real measurement technology, statistical measurement uncertainties are added to the node time series as part of sensitivity analyses. The statistical measurement uncertainties are simulated as Gaussian-distributed random numbers. It must be noted that, in accordance with DIN EN 60359 [6], the measurement uncertainties specified in the data sheets of the measurement technology correspond to the maximum tolerable measurement uncertainties. To map this accordingly, the measurement uncertainties are mapped in a 3σ interval.

3.2. Voltage Drop along Lines

Based on the measured voltage, active and reactive power values at the nodes, the voltage drop along the lines is calculated in the following step, which is used as input data for the multiple linear regression model.
First of all, when calculating the voltage drop along the line, it must be taken into account that the amount of the complex voltage drop is not the same as the difference between the amounts of the node voltages. The active power flows on the lines essentially lead to differences in the phase angles of the complex node voltages and the reactive power flows lead to differences in their magnitude. [6]
In order to calculate the complex voltage drop, the behaviour of the lines in the low voltage must first be examined more closely. Due to the low voltages at the low-voltage level, the capacitance coating of underground cables C' is of little significance. In addition, the cross-reactances of the capacitances for short-length cables in low-voltage grids are sufficiently large compared to the loads. The capacitive currents, i.e. the load currents of the cables, decrease with decreasing voltage level, so that they are negligible at the low-voltage level. This means that the capacitance coating for low-voltage earth cables can be neglected, resulting in the equivalent circuit diagram for low-voltage cables shown in Figure 1, leading to an ohmic inductive behaviour of the cables. [7, 8]

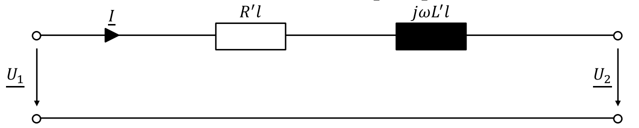

Figure 1 Equivalent circuit diagram of an electrically short cable in the low-voltage level, according to [8]

Therefore, an approximation of the complex voltage drop, according to Figure 1, can be introduced for the low-voltage level in Eq. (1), with $R = R'l$ and $X = \omega L'l$.

$$\begin{aligned} \Delta\underline{U} &= \underline{U}_1 - \underline{U}_2 = \underline{I}(R + jX) \\ \Delta\underline{U} &= (I_W - jI_B)(R + jX) \\ \Delta\underline{U} &= I_W R + I_B X + j(I_W X - I_B R) \end{aligned} \qquad (1)$$

with $I_W = \frac{P}{U}$ and $I_B = \frac{Q}{U}$.

The voltage drop $\Delta\underline{U}$ can then be decomposed into a longitudinal voltage U_l and a transverse voltage U_q, as shown in Figure 2.

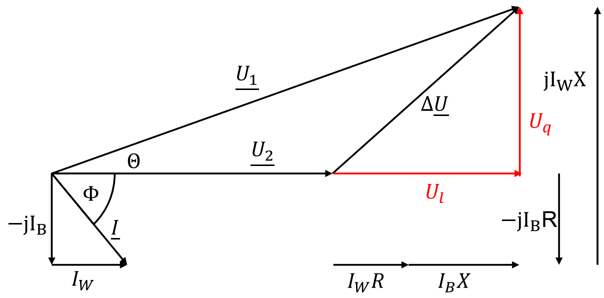

Figure 2 Pointer diagram of an electrically short line with resistive/inductive load

For an ohmic-inductive load current, the longitudinal and transverse stresses are calculated according to Eq. (2). For an ohmic-capacitive load current, the two signs in Eq. (2) must be reversed accordingly. Furthermore, the relationship in Eq. (3) applies approximately for small angles Θ assuming $U_q \ll U_2 + U_l$.

$$\begin{aligned} U_l &= I_W R + I_B X \\ U_q &= I_W X - I_B R \end{aligned} \qquad (2)$$

$$|\Delta\underline{U}| = \Delta U \approx U_1 - U_2 = \sqrt{(U_2 + U_l)^2 + U_q^2} - U_2 \qquad (3)$$

This results in the relationship shown in Eq. (4), which depicts the system of multiple linear regression.

$$\begin{aligned} \Delta U &\approx U_1 - U_2 = U_l \\ U_1 - U_2 &= I_W R + I_B X \end{aligned} \qquad (4)$$

3.3. Multiple Linear Regression

Once the calculation of the input data has been completed and the regression equation has been set up using Eq. (4), it must be solved. The multiple linear regression model is solved using the least squares method. Here, the sum of the squared residuals is minimized according to Eq. (5), with $\boldsymbol{i = 1,..,M}$ being the number of measurements and $\boldsymbol{N}$ the number of parameters $\boldsymbol{\beta}$ to be determined. The coefficients $\boldsymbol{\beta}$ are determined in such a way that the variance around the regression is minimized.

$$\begin{aligned} S(\beta_0, \dots, \beta_N) &= \sum_{i=1}^{M} (y_i - \tilde{y}_i)^2 \\ &= \sum_{i=1}^{M} \left(y_i - \beta_0 - \dots - \beta_N x_{N,i}\right)^2 \rightarrow min \end{aligned} \qquad (5)$$

4. Results

In this chapter the results of the line parameter estimation for six different low voltages grids are presented. Furthermore, the influence of measurement uncertainties is investigated in the scope of sensitivity analysis.

4.1. Line Parameter Determination

In the following, we examine the results of parameter determination with precise resolution of the measured values for different supply tasks. As an evaluation variable, we look at the absolute percentage difference between the determined and the real line parameters depending on the grid model. Figure 3 and Figure 4 show the percentage deviations of the determined parameters R_{est} and X_{est} from the original parameters R_{orig} and X_{orig}. It can be seen that the model determines the line parameters with a high degree of accuracy and delivers reliable results when the data is precise. For both R and X, at least half of the estimates across all grids and scenarios have deviations close to zero percent. In addition, all regression equations have a coefficient of determination of $R^2 \approx 1$, meaning that there is a linear relationship between the endogenous and exogenous variables.

A direct comparison of the two parameters shows that X is generally subject to higher errors than R. This is due to the X/R ratio, which is always less than one in the low-voltage grids used. Accordingly, R is the more dominant factor and is determined with higher accuracy.

Furthermore, a closer look at the grid models across the various scenarios shows that the uncertainty for both parameters increases with each scenario. In particular, a change in the scattering ranges is evident, while the medians remain largely constant. This trend is partly due to the increase in PV systems and battery storage systems. In addition to the increased bidirectional power flow, the active components of the power flows increase significantly and the reactive components increase slightly due to the decentralized feed-in to the grid, which leads to a change in the voltage drops. In particular in the grids in which the number of PV systems and battery storage systems increases significantly (e.g. grids 1, 5 when switching from scenario 0 to 1), an increase in the spread widths can be seen.

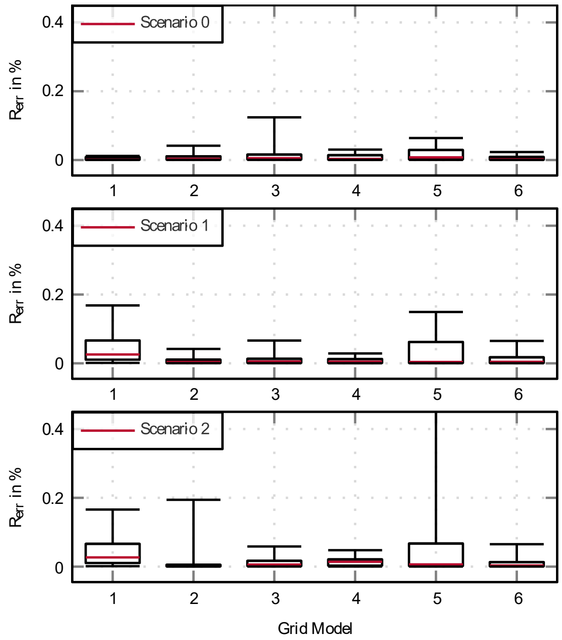

Figure 3 Deviation in percent of the determined resistances R from the original line parameters for the six different grid models for three supply scenarios.

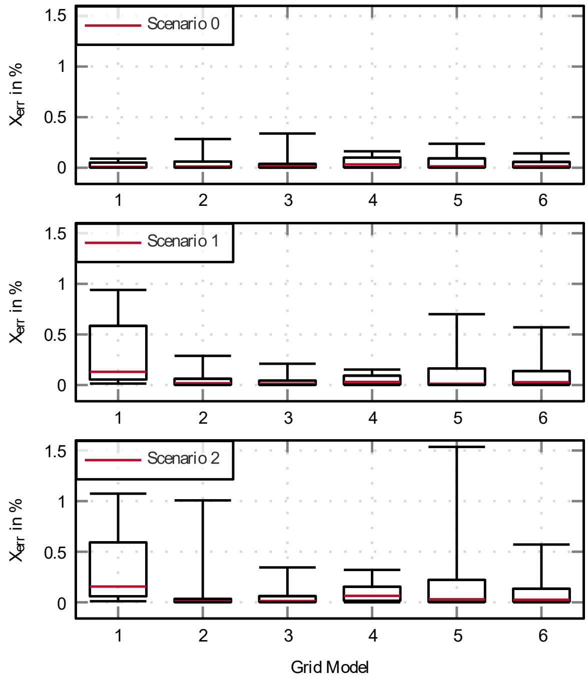

Figure 4 Deviation in percent of the determined resistances X from the original line parameters for the six different grid models for three supply scenarios.

4.2. Influence of Measurement Uncertainties

Sensitivity analyses are used to investigate the robustness of the developed method against measurement uncertainties.

First, the influence of rounding the input data to a certain number of decimal places is investigated. Figure 5 shows the median of the percentage deviation from R for all six grid models as a function of the number of decimal places for scenario 0. It can be seen that the parameter determination delivers significantly better results from a rounding to three decimal places. When rounding to one decimal place, which corresponds to the accuracy of real measured values from smart meters, the quality drops significantly [9]. This behaviour is due to the strong change in the voltage drops caused by the rounding of the node voltage amplitudes. Depending on the similarity of the voltage amplitudes of neighbouring grid nodes, there are sometimes very small voltage drops, so that the rounding causes the voltage drops to be either significantly larger or smaller than they actually are. This leads to the conclusion that low voltage drops are a critical factor of the model.

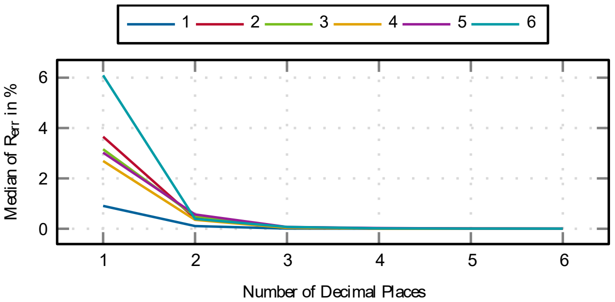

Figure 5 Influence of the number of decimal places on the quality of the line parameter determination of R.

In the following analysis, the influence of statistical measurement uncertainties on the quality of parameter determination is examined. As the influence of real measurement technology is to be mapped, the input data is first rounded to one decimal place, according to [9], and measurement uncertainties are then added to the time series. Figure 6 shows the quality of the parameter determination of R for the six grid models in scenario 0 as a function of the added measurement uncertainties. It can be seen that the quality decreases significantly with increasing measurement uncertainties, which is in line with the expectations. The curve can in turn be explained by the influence of the measurement uncertainties on the voltage drops. Due to error propagation, the maximum absolute measurement uncertainties of the amplitude values are added together when calculating the voltage drops, resulting in larger measurement uncertainties than actual voltage drops. When looking at the reconstruction qualities of individual lines, it can be seen that the percentage deviation is significantly lower for lines with a high voltage drop. It can therefore be observed that the cables with the highest voltage drops are also those for which R and X can be determined most reliably. Since the lines with high voltage drops in particular are most likely to lead to voltage band problems and their parameter determination shows satisfactory results, implementation in practice is also possible with measurement uncertainties.

The same patterns and statements emerge for the other future scenarios and the impedance parameter X, whereby the results are slightly improved due to the slightly higher voltage drops in the future as a result of the increase in loads in scenarios 1 and 2.

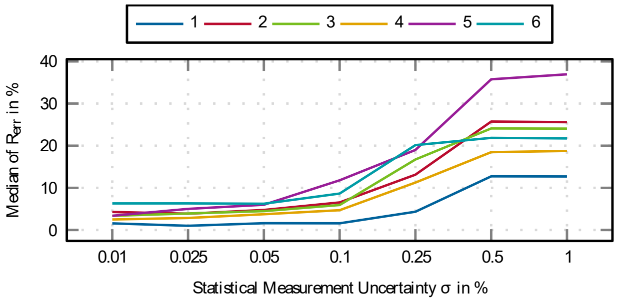

Figure 6 Influence of the statistical measurement uncertainty on the quality of the line parameter determination of R with a fixed number of one decimal place.

5. Conclusion

This paper presents a study on the influence of measurement uncertainties on the quality of the determination of line parameters using multiple linear regression based on the voltage drop along lines.

Exemplary results show that the line parameters with precise amplitude values of the nodal voltage, nodal active power and nodal reactive power time series are determined almost error-free. Within the framework of the sensitivity analysis, it is shown that the rounding of the amplitude values and the addition of measurement uncertainties, as is the case with real measured values from smart metering systems, have a significant influence on the quality of the results. Low voltage drops in particular are strongly distorted by the rounding of the amplitude values and the addition of measurement uncertainties, while the line currents remain largely unchanged. In comparison, when determining the parameters of lines with high voltage drops, there are small deviations between real and estimated parameters. As these lines in particular tend to have voltage band problems, the method can be used in practice in these cases even if measurement uncertainties are present.

A simplification made in this work is the limitation of the one-phase equivalent circuit diagram. Since power grids are usually designed with three phases, an extension of the simulation models and methodology to three phases should be considered. Due to the higher information density in three-phase systems, an improvement of the estimates can be expected. In addition, power grids are increasingly operated in meshed form, so the methodology and analyses should be extended to meshed grid structures.

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