IMPACT OF THREE-PHASE PSEUDO-MEASUREMENT GENERATION FROM SMART METER DATA ON DISTRIBUTION GRID STATE ESTIMATION

Moritz CRAMER, Philipp GOERGENS,
Fabian POTRATZ, Armin SCHNETTLER
RWTH Aachen University – Germany
cramer@ifht.rwth-aachen.de

Stefan WILLING

RWE Deutschland AG - Germany
stefan.willing@rwe.com

ABSTRACT

This paper addresses the modelling of unknown power values, so-called pseudo-measurements, for the use in distribution grid state estimation. Historical load data from smart metering devices in private households and photovoltaic systems is analysed regarding phase distribution, reactive power and correlation between different generators. Based on this, methods for pseudo-measurement generation are developed and tested in combination with state estimation. Depending on the active power a corresponding value for the power factor has been found that enables the modelling of reactive power by using lookup tables. The high correlation in relative PV feed-in can be represented by assumption of equal standardized power. The developed methods are validated by simulation on the basis of an electric distribution grid. It is shown that phase distribution in pseudo-measurements is of minor importance, while the developed methods improve the quality of the distribution system state estimation result.

INTRODUCTION

The increasing penetration of low and medium voltage grids with distributed energy resources (DER) calls for new concepts in distribution grid operation [1]. Secure and reliable active distribution grid operation requires information on current power system state as the basis of control decisions. For this purpose state estimation (SE) is well established in transmission grid operation. In contrast to the transmission grid, distribution system state estimation (DSSE) lacks real-time measurement data [2] and thus the SE changes from an overdetermined weighted-least-squares (WLS) application to an underdetermined problem. As loads and DER in the low-voltage (LV) level are often not symmetrical, three-phase state estimation is required [3]. In order to solve the WLS problem, missing measurements can be compensated using historical data, so called pseudo-measurements (PM). However, both the asymmetry and power factor of low voltage loads and generation are typically unknown. The introduction of smart meter technology, also known as advanced metering infrastructure (AMI), allows thorough analysis of load and generation behaviour of low voltage customers and has been proven beneficial in distribution system analysis [4]. This paper investigates the application of three-phase PM generated from AMI data in DSSE with respect to the resulting estimation quality.

DISTRIBUTION SYSTEM STATE ESTIMATION MODEL

State estimation based on WLS algorithms calculates the most likely system state by minimizing the estimation error [5]. Equation (1) shows the objective function that minimizes the sum of squared deviations between the measurement value z and the estimate h(x) resulting from the state vector x for every measurement i, weighted with w, over m measurements.

$$\min J(x) = \sum_{i=1}^{m} \frac{\left(z_i - h_i(x)\right)^2}{W_{ii}} \tag{1}$$

Equation (1) can be rewritten to

$$\min J = \frac{1}{2}[z - h(x)]^T[W^{-1}][z - h(x)] \tag{2}$$

Where W is the weighting matrix associated with the measurements. Generally, the elements of W correspond to the variances of each measurement.
The optimization problem can be solved iteratively using the delta of the state vector from iteration k to k+1

$$\Delta x = [G(x_k)][H^T\, W^{-1}][z - h(x_k)] \tag{3}$$

where H is the Jacobian matrix

$$H(x_k) = \left[\frac{\partial h(x_k)}{\partial (x_k)}\right] \tag{4}$$

and G is the Gain matrix

$$G(x_k) = [H^T(x_k)\, W^{-1}\, H(x_k)]^{-1} \tag{5}$$

If the increment Δx is smaller than a predefined convergence level, the final estimate for the given situation is achieved.
Furthermore, the unbalanced, i.e. not symmetrical, character of loads and DER in the LV level makes the simplification of positive sequence component estimation insufficient. For that matter, three-phase current-based state estimation has proven to be a suitable solution [6]. Based on the formulation in [7] the system state vector x_φ comprises the currents $I_{1\text{-}n}$ of every branch in the grid and the slack bus voltage U_{slack} for every phase φ

$$x_\varphi = \begin{pmatrix} U_{slack,\varphi} \\ I_{1,\varphi} \\ I_{2,\varphi} \\ \vdots \\ I_{n,\varphi} \end{pmatrix} \qquad \varphi = 1,2,3 \qquad (6)$$

Besides direct measurement of the branch currents, the DSSE model makes use of branch power flow measurements, nodal voltage measurements and power injection measurements, i.e. power consumed or generated at a node. In order to solve the WLS problem, missing measurements can be compensated by two types of measurements:

- Virtual Measurements
- Pseudo-Measurements

Virtual measurements make use of information regarding customers in the grid, for example zero-injection measurements at nodes where no customer (load or generation) is connected [8]. In this case a real measurement would not add any benefit. Because of the high certainty of virtual measurements, they are weighted strongly.

In contrast to this, so called PM, using historical data, are providing the solver with the required information of active and reactive power per phase of the unmeasured nodes to make the grid observable [9]. Therefore PM have the same form as power injection measurements and are brought to the branch current form in the state vector. Since no historical measurement data for the unknown bus exists, PM are generated from data of similar loads. These PM are of high uncertainty and thus have a low weight in the estimation process. However, bad PM will reduce estimation accuracy.

PSEUDO MEASUREMENT MODELLING OF LOADS

For this purpose, AMI data in five second resolution for three-phase active and reactive power of over 100 households in one LV grid is analysed regarding load unbalance and power factor in relation to the sum of active power.

Symmetry of Loads

The three phases in the low-voltage grid are not loaded equally due to single-phase loads and generation. To characterize this asymmetry a power asymmetry factor is calculated. Since the AMI are not measuring the phase angle a fixed angular difference is assumed between the phases and thus only the effect of the amplitude of current or apparent power on the asymmetry is considered [10]. No distinctive relation could be found in the data. Both, the power asymmetry factor and the phase distribution, i.e. the relation of active power of the three phases, do not display clear patterns. Therefore phase distribution of loads does not expand into PM generation in this paper.

Reactive Power of Loads

The investigation of the direct dependence of active power and the power factor, cos (phi), is carried out by means of rank correlation coefficients according to Spearman and Kendall. The majority of households exhibits a medium to high correlation. The data displays a non-linear positive correlation between power factor and total active power. The average power factor increases with active power and strives for greater values against 1 while the standard deviation decreases. The assumption of a fixed power factor for households cannot be confirmed based on the measured values [10]. In order to generate reactive power PM, a lookup table (LUT) that includes the average power factor for a given active power is generated. This allows a fast calculation of the reactive power value for any active power value occurring.

PSEUDO MEASUREMENT MODELLING OF PV-FEED-IN

The investigated residential area in total comprises 17 photovoltaic (PV) systems with an installed power ranging from 3 to 19 kW. A separate detection of active power always takes place at the entry points of the photovoltaic systems. The temporal resolution of 50s of these measurements is substantially smaller than in the load measurements.

The correlation of the power feed-in of the multiple PV systems included in the network has been examined using Pearson (r) and concordance correlation coefficients (CCC). Figure 1 shows the course of the standardized feed-in, i.e. the momentary power in relation to the power at a specified time for every PV system, of two exemplary PV systems.

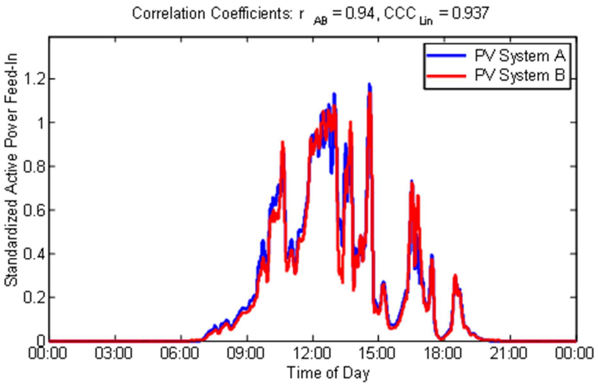

Figure 1: Relative Active Power of two Systems

The similar course is reflected in high correlation coefficients. These calculations can be carried out in pairs between all PV systems. Correlation coefficient values above 0.95 characterize the consistently high correlation. Therefore in PM generation it is assumed, that if one PV system is measured, the others can be modelled using the identical relative power. By taking the mean value of the relative power of up to three measured PV systems the PM will be even of higher quality. Considering more than three PV systems will give no benefit. The PV systems site is of minor importance.

EVALUATION OF DEVELOPED PSEUDO-MEASUREMENTS IN DSSE

To obtain a reference value for the predictive accuracy of the existing SE software, a load case from the grid is selected. Based on the grid data, such as topology and line impedances, the actual network state is calculated using three-phase power flow software for the exemplary load case, i.e. under the assumption of perfect knowledge of all nodal powers. The grid state for this load case is estimated by the DSSE software and repeated 100 times in order to handle the random character of measurement errors. The estimation accuracy is then determined by the root mean square error (RMSE) between the estimate and the reference value of all state variables.

Low Voltage Feeder Test-Case

The validation of the developed method is based on a section of a LV grid of a residential area in Southern Germany. The grid segment is of radial structure and consists of 86 nodes and 85 edges. It comprises private households in single-family houses and 8 PV systems distributed along the feeder. Underground cables with lengths between 10 and 116 meters connect the nodes.

Reference Case Results

The exemplary measurement setup consists of two power injection measurements, at node 21 and 74, that also measure node voltage magnitude. At node 21 there is PV feed-in and in this scenario it serves as the reference measurement for the standardized active power feed-in when modelling the PM of other generators. Furthermore, there is another voltage magnitude measurement, two power flow measurements and a branch current magnitude measurement.

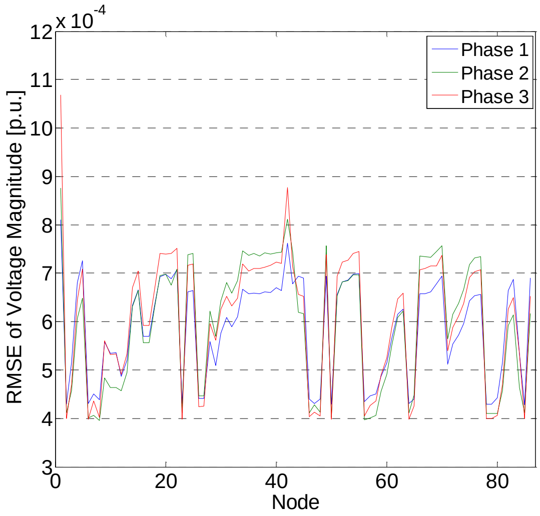

Figure 2: Error in Nodal Voltage Estimation

Assuming the slack node voltage magnitude is at one per-unit, the three-phase power flow results in voltage profile with a voltage magnitude between 0.997 [p.u] and 1.020 [p.u.]. **Figure 2** and **Figure 3** show the DSSE results of the typical simulative approach of modelling PM by adding noise to the exact results. The RMSE of the branch current magnitudes (maximum and the mean value) is slightly lower than the RMSE for the nodal voltages. Generally, a high estimation accuracy is achieved.

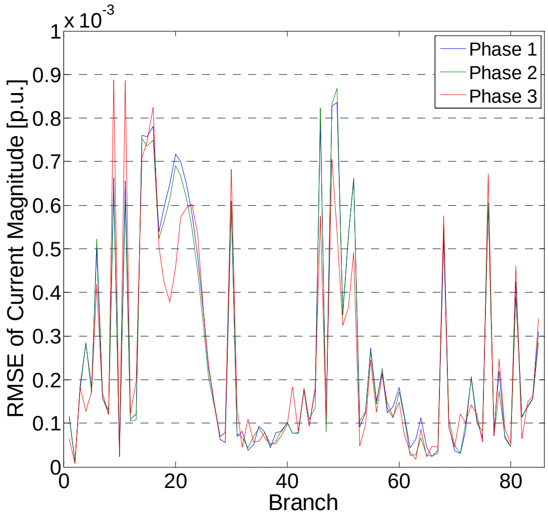

Figure 3: Error in Branch Current Estimation

Here, the knowledge of the exact values for active and reactive power is neglected, as it would be from a real-world grid operator's point of view. Contrary, the sum of active power for every node with a PM is estimated using the exact value and then manipulated with noise. Based on this aggregated value, the active and reactive power for every phase is modelled according to the respective method.

Impact of Phase Distribution

For the evaluation of the impact of phase distribution three different setups are compared. Since no valid modelling for asymmetry could be derived, the comparison comprises symmetrical, random and exact phase distribution. Exact phase distribution describes the case where the estimated, noisy sum of active power is distributed on the phases identical to the reference case. Therefore this serves as the evaluation of the importance of correct modelling of load asymmetry. The reactive power is modelled using the LUT. **Figure 4** shows the maximum and mean RMSE of nodal voltages. Random phase distribution has a considerably higher estimation error than the use of symmetrical loads which results in voltage errors close to the exact phase distribution.

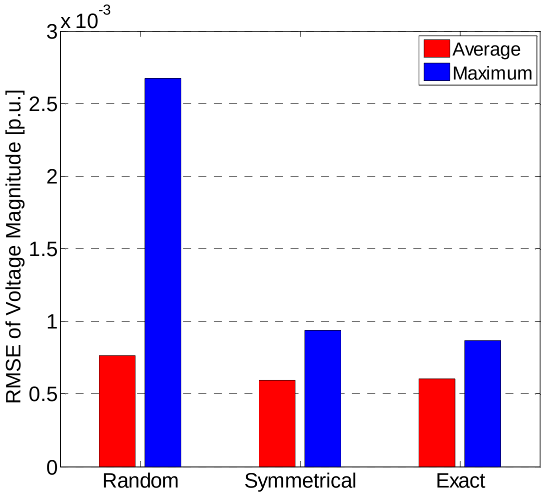

Figure 4: Voltage Error for Different Phase Distributions

In **Figure 5** the average and maximum RMSE of branch current magnitudes are shown. The behaviour is similar to the one found for the nodal voltages. However the mean values are significantly lower and the symmetrical case even reduces the maximum RMSE compared to the exact phase distribution, likely due to a better (random) estimate of the aggregated active power for all phases.

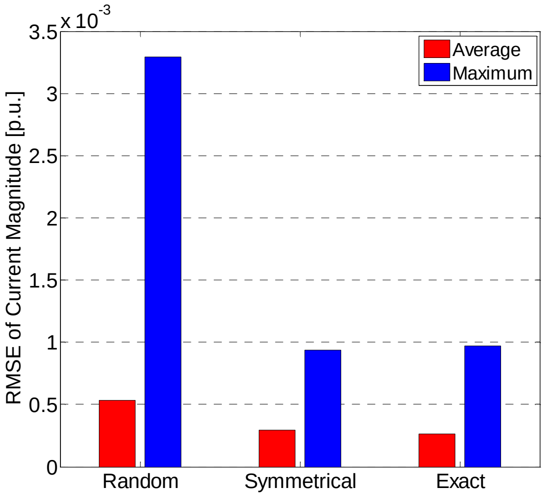

Figure 5: Current Error for Different Phase Distributions

From the results it can be concluded that knowledge of the exact phase distribution of the loads is not of essential benefit for state estimation PM modelling, especially compared to the case when assuming a symmetrical load.

Impact of Reactive Power Modelling

For the impact assessment of reactive power modelling three different ways of PM generation are compared. In the comparison a static cos(phi) of 0.95, the assumption of no reactive power, i.e. cos(phi)=1, and the modelling using the LUT as described earlier, are evaluated. For this investigation the exact knowledge of phase distribution is assumed. **Figure 6** shows the node voltage magnitude RMSE. While the average error is independent of the PM reactive power modelling, the maximum RMSE can be reduced significantly using the LUT.

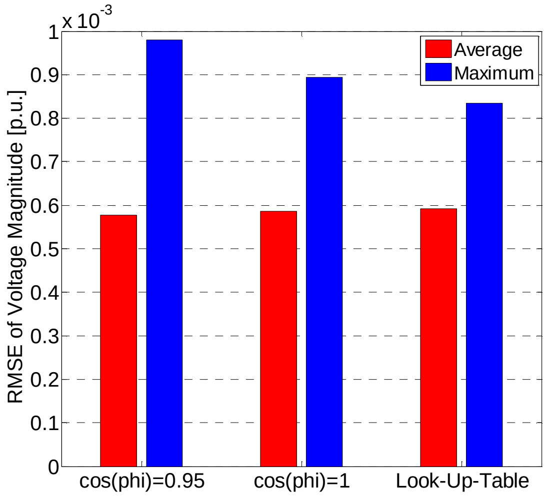

Figure 6: Voltage Error for Different Q Modeling

Figure 7 shows the branch current magnitude error for the different PM generation models. The LUT again performs better than the assumption of no reactive power. However, considering the maximum error, the static power factor has the lowest RMSE.

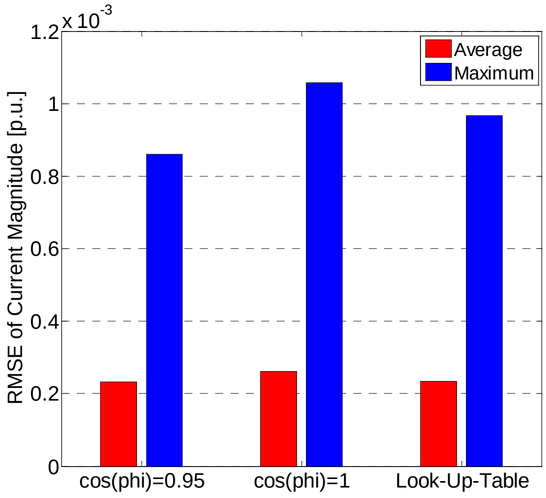

Figure 7: Current Error for Different Q Modelling

Regarding the average estimation error, the reactive power modelling of PM does not have an effect. The use of LUT provides a suitable method of PM generation.

Impact of PV Feed-In Modelling

Finally, the impact of PV feed-in modelling is investigated by comparison of standard simulative approach, as described above, a random value between 0 and the peak power of the PV system and identical standardized active power. It has to be noted, that the first case in reality cannot be achieved, since it is based on the knowledge of the exact power. The reactive power is modelled using the LUT, while the exact phase distribution is assumed for the loads.

In **Figure 8** the effect of PV modelling on the nodal voltage magnitude is shown. The case using the correlation of feed-in exhibits the lowest error, especially considering the maximum RMSE.

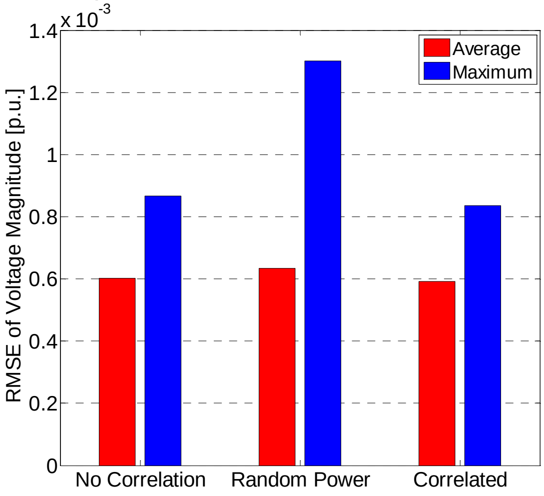

Figure 8: Voltage Error for Different PV Modelling

For the branch current magnitude RMSE the average values are lower, while the maximum values increase (**Figure 9**). Again, modelling the PM by assuming the identical relative active power shows the best performance.

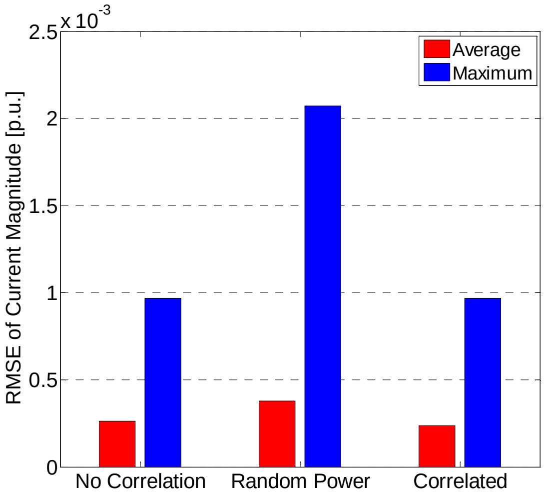

Figure 9: Current Error for Different PV Modelling

While using a random value between 0 and the peak power for every PV system feed-in displays high RMSE, due to the high correlation the assumption of identical standardized power for all PV systems is found to be a suitable method for PM modelling of PV systems.

CONCLUSION AND OUTLOOK

In the analysis of AMI data in a low voltage grid no typical pattern for phase distribution, especially no distinct relation with the sum of active power could be found. In contrast to this, the reactive power showed clear dependence, with the power factor being positively correlated with the active power. This was used to model the PM for reactive power of loads by lookup tables. In the analysis PV systems in the investigated area showed a high correlation between their relative active power feed-in. Therefore for PM modelling of PV feed-in the relative power of all systems is assumed equal.

Applying the above described modelling approaches to the DSSE test case, both the PV modelling and the LUT showed good performance with regard to the resulting estimation errors. In contrast to this the knowledge of phase distribution only has a minor impact on the estimation error. Use of indirect measurements, meta information, e.g. time of day, and probabilistic estimation methods [11] of active power sum are essential for real time application and might further reduce the estimation errors.

ACKNOWLEDGEMENT

The authors would like to thank RWE Deutschland AG and LVN for providing data of measurement and corresponding grid topology.

REFERENCES

[1] Willing, S.; et al.: “Improving quality of supply and usage of assets in distribution grids by introducing a “Smart Operator””, CIRED Conference, Stockholm, 2013

[2] Manitsas, E.; et al.: “Modelling of Pseudo-Measurements for Distribution System State Estimation”, CIRED Seminar, Frankfurt, 2008

[3] Baran, M.E.; Kelly, A.: “A branch-current-based state estimation method for distribution systems”, IEEE Trans. Power Systems, vol. 10, 483-491, Feb. 1995

[4] Aritt, R.; Dugan, R.: “Comparing Load Estimation Methods for Distribution System Analysis”, CIRED Conference, Stockholm, 2013

[5] Abur, A.; Gomez Exposito, A.: "Power System State Estimation, Theory and Implementation", Marcel Dekker Inc., New York, USA, 2004

[6] Baran, M.E.: "Challenges in State Estimation on Distribution Systems", IEEE Power Engineering Society (PES) Summer Meeting 2001, vol. 1, 429–433, 2001.

[7] Pau, M.; Pegoraro, P.A.; Sulis, S.: "WLS distribution system state estimator based on voltages or branch-currents: Accuracy and performance comparison", IEEE I2MTC Conference, 493–498, May 2013.

[9] Ghosh, A.K.; Lubkeman, D.L.; Johnes, R.H.: "Load Modeling for Distribution Circuit State Estimation", IEEE Trans. Power Del., vol. 12, 999–1005, Apr 1997.

[8] Peres, W.; et al.: “Branch Current Based State Estimation: Equality-Constrained WLS and Augmented Matrix Approaches”, Anais do XX Congresso Brasileiro de Automática, Belo Horizonte, 3198-3205, Sep. 2014

[10] Potratz, F.; Cramer, M.: “Analysis of the Active and Reactive Power Behavior of Private Households”, Annual Report, Institute for High Voltage Technology at RWTH Aachen University, 56-61, 2014

[11] Gödde, M.; et al.: ”Analysis of a Convolution Method for the Assessment of Distribution Grids within Probabilistic Power Flow Calculation”, CIRED Workshop, Rome, 2014