FIELD TEST OF A LINEAR THREE-PHASE LOW VOLTAGE STATE ESTIMATION SYSTEM BASED ON SMART METER DATA

Dominik WAERESCH, Robert BRANDALIK, Wolfram H. WELLSSOW
TU Kaiserslautern
Kaiserslautern, Germany
waeresch@eit.uni-kl.de

Joern JORDAN
IDS Gmbh
Ettlingen, Germany
joern.jordan@ids.de

Rolf BISCHLER, Nelia SCHNEIDER
Stadtwerke Kaiserslautern Versorgungs-AG
Kaiserslautern, Germany
rolf.bischler@swk-kl.de

ABSTRACT

The area-wide installation of smart meters in low voltage (LV) grids prospectively provides information about the relevant operational system parameters, e.g. complex node voltages and line loads. Under the condition of neglected house to grid connection lines, a positive local measurement redundancy at every network node is obtainable. In general, this enables the implementation of special three-phase LV state estimation (SE) systems with the ability of bad data detection. In the future, such SE systems might be the basis for closed-loop network control systems without any operator interventions.

This paper proposes a concept for a LV state estimation system based on smart meter data. In contrast to other approaches, a linear SE algorithm is used, so that the SE system is not prone to convergence issues. Input variables are voltage and current magnitudes as well as active and reactive currents. The bad data detection process is generally based on the well-known method of normalized residuals. To ensure correctly applied network topologies also in meshed networks, a novel algorithm for detecting topology faults is used. The presented results gathered from simulations and a field test are promising, showing appropriate accuracies and bad data detection probabilities especially for voltage magnitude and active current bad data.

INTRODUCTION

Due to the prospectively area-wide installation of smart meters in low voltage (LV) grids and the implementation of smart meter communication systems, distribution system operators (DSOs) have additional information about the relevant operational system parameters, e.g. complex node voltages and line loads, at almost every customer node in the future. Hence, by neglecting the house to grid connection lines and referring voltage and current measurements to network nodes, a positive local measurement redundancy at every network node is obtainable. Thus, special three-phase LV state estimation (SE) systems can be implemented to achieve also a bad data detection ability. In the future, such SE systems might be necessary for LV network operation when a closed-loop network control without any operator interventions should take place. In this context, classical SE algorithms known from high voltage (HV) grids cannot be used due to other measurement variables and the need for a three-phase SE [1]. Also, the neutral conductor should be always considered in the SE process [2]. Due to these reasons, special LV state estimation algorithms must be developed and applied in practice. The SE systems shall estimate the network state with sufficient accuracy so that other applications such as line load monitoring and the determination of network control parameters are feasible.

LOW VOLTAGE STATE ESTIMATION CONCEPT BASED ON SMART METER DATA

Field Test Project 'SmartSCADA'

The development of a SE system for LV grids was the purpose of the field test project 'SmartSCADA', which was funded by the German Federal Ministry for Economic Affairs and Energy. The project with the five partners University of Kaiserslautern, IDS GmbH, the DSO Stadtwerke Kaiserslautern Versorgungs-AG, Meteocontrol GmbH and COMback GmbH went from March 2013 to the end of 2016 and included a smart meter rollout in a semi-urban LV grid and the development of a LV state estimation algorithm based on smart meter data and PV-feed-in-forecasts. Furthermore, an algorithm for the detection of topology faults, e.g. conductor breaks or blown fuses in cable distributors, had to be developed to ensure correctly applied network topologies also in meshed networks. Finally, the developed algorithm had to be applied and tested on a SCADA system in real-life operation.

For the development of the LV state estimation algorithm based on smart meter data, real measurements from a field test were used. Therefore, a meshed LV network from the local DSO Stadtwerke Kaiserslautern with 120 loads and 24 PV systems was chosen as a test grid due to its high penetration with PV systems. Smart meters have been installed at 110 house connections and voltage and current magnitudes as well as active and reactive currents with sign are measured. The measurement interval was chosen to ten minutes for loads and five minutes for PV systems. The data are send via power line communication to a data concentrator and are forwarded to the DSO [2].

Characteristics of LV State Estimation

Conventional SE algorithms known from HV grids are usually not usable for LV grids because of a lack of measurement equipment at network nodes resulting in a negative measurement redundancy. This is shown by the definition of the measurement redundancy η with the number of independent measurements M and the number of nodes N in a network [1]:

$$\eta = \frac{M}{2N-1} - 1 \tag{1}$$

As experience shows for effective compensation of measurement errors and especially bad data, the measurement redundancy η should attain values of at least 1 [1]. But in contrast to HV grids, η cannot be easily increased by additional branch measurements because LV grids often consist of buried cables. Due to that, the more or less only way for increasing η is to neglect the house to grid connection lines and refer all voltage and current measurements from customer nodes to the respective network nodes [2]. Experience shows, that this simplification usually leads to measurement redundancies $\eta > 0.5$, so that a bad data detection is possible.

Another essential difference in LV state estimation is the need for three-phase SE due to asymmetric system states and neutral wire currents [3]. This implies that the computational effort is significantly higher than for single-phase SE systems. Regarding this, SE systems for LV grids should be based on linear optimization problems, as the solution can be obtained without any iterations [4]. This is usually not possible when solving a nonlinear optimization problem.

Preprocessing of Smart Meter Data

Measurement data can contain errors for various reasons. Therefore, plausibility checks and possibly data fault correction algorithms are important to get a reliable database. Within the project, checks are done concerning missing measurement values. Furthermore, voltage and current values are compared against specific permissible ranges. The measured current values are checked against the rated currents of fuses installed at the point of common coupling. Following the plausibility check, the as false identified values are substituted by more accurate replacement values which are determined e.g. from surrounding network nodes or load profiles.

In order to achieve sufficient SE results, it is inevitable that the network topology as well as household connections are correctly mapped onto the mathematical network model. But in real grid operation unexpected deviations between actual network topology and mathematical model cannot be excluded. Thus, these so-called topology faults (TFs), which often remain undetected in meshed LV grids, obviously must be identified before running the SE algorithm. In this context, a new, simple and efficient topology fault detection algorithm has been developed which localizes TFs only on the basis on measured voltage magnitude measurements and statistical methods. The basic idea behind the algorithm is, that if no TF exist, the absolute voltage magnitude difference between two connected network nodes close to each other is limited to a specific value. The limit depends especially on Pearsons's correlation coefficient of the respective voltage magnitude time series, which is typically nearly one. Basically, a TF probably exist, if the voltage magnitude difference between two network nodes close to each other exceeds the mathematically derived detection limit. Detailed information about the algorithm is given in [5].

Developed LV State Estimation Algorithm

Within the field test project, a linear SE algorithm has been developed. This means that the SE is based on voltage and current magnitudes as well as active and reactive current measurements. The benefit is that the algorithm is fast and not prone to convergence problems. The accuracy compared to nonlinear approaches is still adequate enough due to typically small voltage angles in LV networks. Due to usually asymmetric loads the LV SE system has to be applied for three-phase network states. In this context, the three-phase optimization problem is formulated in symmetrical components (SC) with a positive ('1'), negative ('2') and a zero ('0') sequence system [6]. For all transformations, it is assumed that the angles between the line-to-ground voltages are 120° which is a permissible assumption for LV grids. The three-phase system state vector $\mathbf{x}$ in algebraic form is defined in SC as (2). Here $\mathbf{u}_{s,re}$, $\mathbf{u}_{s,im}$ are the vectors with all real and imaginary parts of the complex node voltages $\underline{U}_{s,i}$ at network nodes i in SC system s.

$$\mathbf{x} = \begin{bmatrix} \mathbf{u}_{1,re}^T & \mathbf{u}_{1,im}^T & \mathbf{u}_{2,re}^T & \mathbf{u}_{2,im}^T & \mathbf{u}_{0,re}^T & \mathbf{u}_{0,im}^T \end{bmatrix}^T \tag{2}$$

Assuming the weighted least square (WLS) method the general objective function $J(\hat{\mathbf{x}})$ with the estimated system state $\hat{\mathbf{x}}$, the measurement value z_k and the measurement variance σ_k^2 can be described by (3). Thereby the row vector $\mathbf{h}_k^T$ relates measurement z_k to the state vector $\mathbf{x}$.

$$J(\hat{\mathbf{x}}) = \sum_{k=1}^{M} \frac{\left(z_k - \hat{z}_k\right)^2}{\sigma_k^2} = \sum_{k=1}^{M} \frac{\left(z_k - \mathbf{h}_k^T \cdot \hat{\mathbf{x}}\right)^2}{\sigma_k^2} \tag{3}$$

In matrix form the objective function results in (4), where $\mathbf{z}$ is the measurement vector in SC (5), $\mathbf{H}$ the measurement model matrix with the linear functions $\mathbf{h}_k$ (6) and where $\mathbf{R}$ contains the measurement variances (7).

$$J(\mathbf{x}) = \left(\mathbf{z} - \mathbf{H} \cdot \mathbf{x}\right)^T \cdot \mathbf{R}^{-1} \cdot \left(\mathbf{z} - \mathbf{H} \cdot \mathbf{x}\right) \tag{4}$$

$$\mathbf{z} = \left[z_1 \ \cdots \ z_k \ \cdots \ z_M\right]^T \tag{5}$$

$$\mathbf{H} = \left[\mathbf{h}_1 \ \cdots \ \mathbf{h}_k \ \cdots \ \mathbf{h}_M\right]^T \tag{6}$$

$$\mathbf{R} = \text{diag}\left\{\sigma_1^2 \cdots \sigma_k^2 \cdots \sigma_M^2\right\} \tag{7}$$

The solution of the WLS optimization problem can be in general obtained by using the well-known augmented matrix approach [1]. The idea behind is to separate the virtual measurements, e.g. sum of currents at a node equals zero, from the regular measurements and write them as equality constraints. Representing virtual measurements with $\mathbf{C} \cdot \mathbf{x}$ and the estimated regular measurements with $\mathbf{H}_R \cdot \mathbf{x}$ the WLS problem can be formulated as shown in (8-10). Here, $\mathbf{r}$ represents the difference vector between actual and estimated values of regular measurements which is called the residual vector. In the end, it can be formulated as a Lagrangian function as shown in (11).

$$\text{minimize} \quad J(\mathbf{x}) = \mathbf{r}^T \mathbf{R}^{-1} \mathbf{r} \tag{8}$$

$$\text{subject to} \quad \mathbf{C} \cdot \mathbf{x} = 0 \tag{9}$$

$$\text{and} \quad \mathbf{r} - \mathbf{z} + \mathbf{H}_R \cdot \mathbf{x} = 0 \tag{10}$$

$$\mathcal{L} = J(\mathbf{x}) - \boldsymbol{\lambda}^T \cdot (\mathbf{C} \cdot \mathbf{x}) - \boldsymbol{\mu}^T \cdot (\mathbf{r} - \mathbf{z} + \mathbf{H}_R \cdot \mathbf{x}) \tag{11}$$

Due to two equality constraints, (11) has two sets of Lagrangian multipliers, which are often denoted as $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. The Lagrangian function can also be written as a linear matrix optimization problem, which is shown in (12). Here the coefficient matrix is called Hachtel's or augmented matrix. It has good mathematical properties, especially when applying an additional weighting factor α for adjusting $\mathbf{R}$ [1]. The fundamental structure of the measurement Jacobian matrix $\mathbf{H}_R$ in SC is like the nodal admittance matrix and described in detail in [6].

$$\begin{bmatrix} \alpha \cdot \mathbf{R} & \mathbf{H}_R & 0 \\ \mathbf{H}_R^T & 0 & \mathbf{C}^T \\ 0 & \mathbf{C} & 0 \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{\mu} \\ \mathbf{x} \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \mathbf{z} \\ 0 \\ 0 \end{bmatrix} \tag{12}$$

Bad Data Detection Process

An essential task of the SE system is the bad data (BD) detection and localization within the input data set. In HV grids, the BD localization is usually based on the well-known normalized residual method shown in (13). Here, the residuals r_k of all measurements k are normalized with the respective residual standard deviations $\sigma_{r,k} = \sqrt{\Omega_{kk}}$ [1]. The values $\sigma_{r,k}$ can be obtained by the residual covariance matrix $\boldsymbol{\Omega}$ as shown in (14) to (15).

$$r_k^N = \frac{r_k}{\sqrt{\Omega_{kk}}} = \frac{z_k - \hat{z}_k}{\sqrt{\Omega_{kk}}} \tag{13}$$

$$\boldsymbol{\Omega} = \frac{1}{\alpha} \cdot \mathbf{R} \cdot \mathbf{A}_1 \cdot \mathbf{R} \tag{14}$$

$$\begin{bmatrix} \alpha \cdot \mathbf{R} & \mathbf{H}_R & \mathbf{0} \\ \mathbf{H}_R^T & \mathbf{0} & \mathbf{C}^T \\ \mathbf{0} & \mathbf{C} & \mathbf{0} \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2^T & \mathbf{A}_3^T \\ \mathbf{A}_2 & \mathbf{A}_4 & \mathbf{A}_5^T \\ \mathbf{A}_3 & \mathbf{A}_5 & \mathbf{A}_6 \end{bmatrix} \tag{15}$$

Regarding the three-phase SE with formulation in symmetrical components, a complex residual with real part $r_{k,s,re,t}$ and imaginary part $r_{k,s,im,t}$ exist for each and every SC system s={1,2,3} and time step t. The respective residual standard deviations are denoted as $\sigma_{r,k,s}$. At first, the residuals in SC can be retransformed in phase quantities with the well-known SC-retransformation matrix $\underline{T}^{-1}$ as shown basically in (16). The normalization of the residuals in phase quantities is then appropriately done by using the same residual standard deviation $\sigma_{r,k,120}$ for each SC system s. This value should be chosen to the maximum value of the residual standard deviations $\sigma_{r,k,s}$ as shown in (17) [6].

$$\begin{bmatrix} r^N_{k,L1,re,t} + j\, r^N_{k,L1,im,t} \\ r^N_{k,L2,re,t} + j\, r^N_{k,L2,im,t} \\ r^N_{k,L3,re,t} + j\, r^N_{k,L3,im,t} \end{bmatrix} = \frac{1}{\sqrt{3} \cdot \sigma_{r,k,120}} \cdot \underline{T}^{-1} \cdot \begin{bmatrix} r_{k,1,re,t} + j\, r_{k,1,im,t} \\ r_{k,2,re,t} + j\, r_{k,2,im,t} \\ r_{k,0,re,t} + j\, r_{k,0,im,t} \end{bmatrix} \tag{16}$$

$$\sigma_{r,k,120} = \max \begin{Bmatrix} \sigma_{r,k,1,re}, \sigma_{r,k,1,im}, \\ \sigma_{r,k,2,re}, \sigma_{r,k,2,im}, \\ \sigma_{r,k,0,re}, \sigma_{r,k,0,im} \end{Bmatrix} \tag{17}$$

Finally, the bad data localization is done by comparing the normalized residuals with specific chosen detection limits ε for each measurement variable. If a bad data exists, then the respective normalized residual at the related network node shows the largest values. Usually, the measurement which was indicated as bad data is replaced by an as adequate as possible substitution value. If current bad data occur, the entire current measurement data set, i.e. active and reactive currents and current magnitude, of the related phase Lx, x ϵ{1,2,3}, should be replaced. The entire bad data localization and replacement process should be repeated as long as bad data are identified. Further information about the applied algorithm is given in [7].

SIMULATIVE SYSTEM VERIFICATION

Test Environment and Parameters

The described algorithm is implemented within the Matlab R2015 software environment and tested with smart meter data from the above-mentioned measurement campaign. Smart meter measurement variables are voltage and current magnitudes as well as active and reactive currents. Furthermore, voltage magnitude as well as active and reactive current measurements at the three main feeders at the secondary substation are available.

The measurement redundancy for the considered network amounts to $\eta = 0.9$. For the replacement of bad data additional PV feed-in predictions and load values are available. The standard deviations σ_e of the measurement errors are assumed as 0.2 V for measured voltage magnitudes and 0.1 A for measured current values. The SE time interval has been chosen to ten minutes.

SE Algorithm Accuracy

For the investigation of the SE algorithm accuracy, power flow calculations (PFC) performed in PSS®SINCAL 10.0 environment are used to provide exact network states for some time steps. The scenarios of the PFC are based on smart meter measurements so that the analysis is done for realistic network states. The PFC results, which are assumed as true values, are then modified by superimposing normal distributed measurement errors with standard deviations as mentioned before. The so derived data set consists of synthetic measurement values which are used as input data for the SE algorithm.

The SE accuracy is analyzed by comparing the SE results with the measurements and the true values. The comparison results show that the related normalized residuals are normally distributed with reasonable residual standard deviations. Thus, a correct function of SE algorithm can be assumed [8].

Bad Data Detection Probability

The analysis of the BD localization process is done outgoing from the mentioned synthetic measurement data sets based on smart meter data. In this context, six representative BD scenarios have been used to derive the BD detection limits $\varepsilon_U = 2.3$ for voltage magnitude measurements and $\varepsilon_I = 2.0$ for current measurements [8].

In the next step, investigations have been done regarding the localization of single BD of all considered measurement types, i.e. voltage and current magnitudes and active and reactive currents. It turned out, that the detection of voltage magnitude BD is almost independent from the detection of current BD and that it is very reliable with a detection probability of nearly 100 % for BD values greater 1 V. Also, current magnitude BD values greater than 1 A can be localized with a probability of over 90 %. The detection of active and reactive current BD is worse compared to the mentioned BD types, especially if the absolute current is nearly zero. Nevertheless, high BD values are localized in most cases especially in the presence of high absolute currents.

Further investigations were done concerning the detection of multiple BD. A realistic time series over 14 month was used and random multiple BD were inserted. For the analysis, it was distinguished between cases with a single BD (denoted as case '1 BD'), two BD ('2 BD'), three BD ('3 BD') and at least four BD ('4+ BD'). The relevant results are shown in Figure 1 and 2. Thus, as said before, the detection of voltage magnitude BD is almost independent from current BD and very reliable. The respective detection probability increases

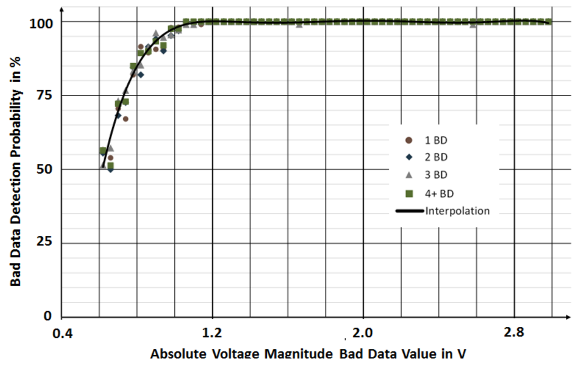

Figure 1. Detection probability of voltage magnitude BD as a function of the BD value and the number of BDs

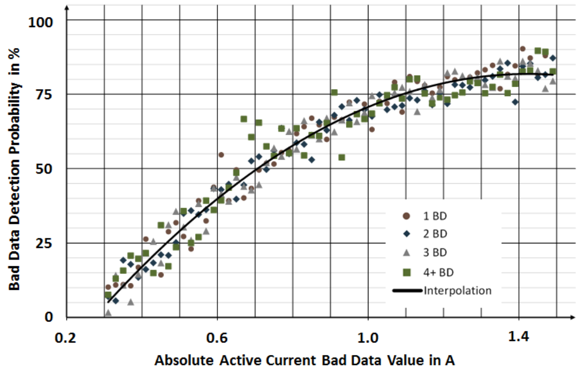

Figure 2. Detection probability of active current BD as a function of the BD value and the number of BDs

with the BD value starting from $3\sigma_U = 0.6$ V. The detection probability of active current BD is also adequate as shown in Figure 2. However, high BD values are necessary to achieve detection probabilities over 80 %. This is due to high dependencies between active and reactive currents. Also, the low local measurement redundancies for currents are an important reason.

FIELD TEST

The verification of the SE accuracy in real grid operation was done by installing additional measurement devices in three cable distributors and comparing the comparative voltage magnitude and absolute current measurements with the values estimated by the SE system. The measurement interval has been chosen to ten minutes. Figure 3 and Figure 4 show the differences between estimated values and with index 'Comp-Meas' denoted comparative measurements. According to that, the voltage magnitude estimation accuracy is within a range of ±1.4 V. In terms of the localization of voltage limit violations this might be an adequate range. Also, the estimation accuracy of absolute branch currents might be sufficient with values of approximately ±20 A, since they imply small absolute voltage drops between directly connected network nodes of 0.1 V for a line length of 50 m and a line type NAYCWY 3x185mm².

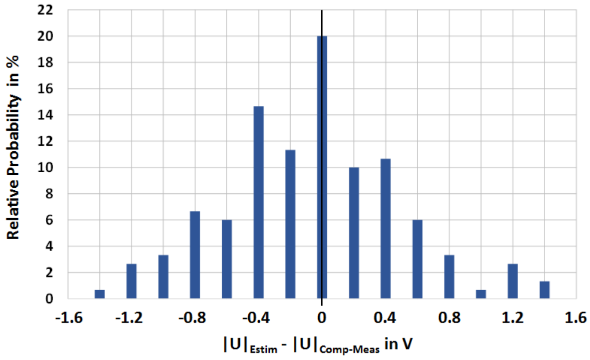

Figure 3. Relative frequency of the difference between estimated and additionally measured voltage magnitudes

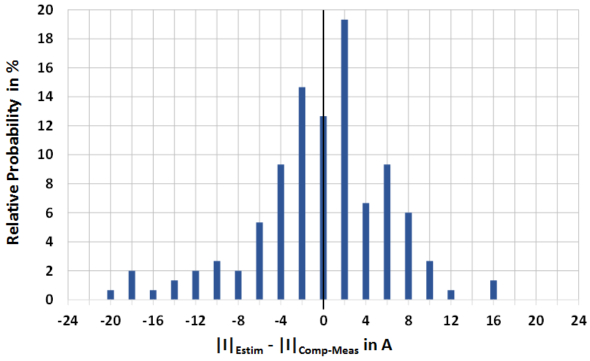

Figure 4. Relative frequency of the difference between estimated and additionally measured absolute currents

Most probably all determined accuracies are adequate enough to use the SE results as the basis for a closed-loop network control without any operator intervention. Note that, different from transmission systems, control actions in LV grids will be taken only in case of limit violations but not for optimizing the system with respect to any objective function.
The verification of the BD detection process within the field test was done by inserting BDs into the SE input data set and checking, whether the BDs are correctly localized. It turned out, that voltage magnitude BD can be reliably detected as determined in the simulative system verification before. Also, most of the current BDs have been correctly localized. Only in case of low absolute currents it is possible, that a BD is not detected. Finally, the results are very promising, so that a correct function of the BD detection process is assumed.

CONCLUSION

The preliminary results of the developed SE algorithm tested by various simulations and within a field test are very promising. They show that a probable future rollout of smart meters at every household connection can provide a way for estimating the state of LV networks, if the data acquisition at customers is allowed. The increased measurement redundancy leads to the fact that bad data analysis works great for voltage measurements and good for current measurements.

The estimation accuracy for voltage magnitudes and branch currents is assumed adequate for a closed-loop network control without any operator intervention. Note that in LV systems control actions target at avoiding limit violations only, not at achieving any optimized operational parameter as is the case in transmission systems. Further investigations should be done concerning the generation of pseudo measurements for unmeasured loads. This is important, as in some countries, e.g. Germany, it is prospectively only partly allowed to measure loads at household customers.

REFERENCES

[1] A. Abur, 2004, *Power System State Estimation*, CRC Press, Boca Raton, USA

[2] R. Brandalik, W.H. Wellssow, D. Waeresch., J. Jordan, R. Bischler, N. Schneider, 2015, ‘State Estimation in Low Voltage Grids based on Smart meter Data and Photovoltaic Feed-In-Forecast’, *Proceedings 23rd CIRED, Lyon/France*

[3] A. Rankovic, B.M. Maksimovic, A.T. Saric, 2014, ‘A three-phase state estimation in active distribution systems’, *International Journal of Electrical Power and Energy Systems, Vol.54, Elsevier*

[4] D.A. Haughton, G.T. Heydt, 2013, ‘A Linaer State Estimation Formulation for Smart Distribution Systems’, *IEEE Transactions on Power Apparatus and Systems, Vol.28, No. 2*

[5] D. Waeresch, 2016, ‘Topology Fault Detection in Low Voltage Grids based on Statistical Analyses of Smart Meter Data’, *IEEE ISGT Europe 2016, Ljubljana/Slovenia*

[6] J. Jordan, R. Bischler, N. Schneider, W.H. Wellssow, R. Brandalik, D. Waeresch, 2015, ‘Linear state estimation in low voltage grids based on smart meter data’, *Proceedings IEEE Powertech, Eindhoven/Netherlands*

[7] R. Brandalik, D. Waeresch., W.H. Wellssow, J. Jordan, R. Bischler, N. Schneider, 2016, ‘Bad Data Processing for Low Voltage State Estimation Systems based on Smart Meter Data’, *Proceedings CIRED Workshop, Helsinki/Finland*

[8] D. Waeresch., R. Brandalik, W.H. Wellssow, J. Jordan, R. Bischler, N. Schneider, 2016, ‘Linear state estimation in low voltage grids based on smart meter data’, *Proceedings CIGRE Session 2016, Paris/France*

Supported by:
Federal Ministry of Economics and Technology
on the basis of a decision by the German Bundestag

The project ‚SmartSCADA“ is funded by the German Federal Ministry of Economic Affairs and Energy within the 6th Energy Research Program; reference number: 0325583E