

## METER PLACEMENT FOR LOW VOLTAGE SYSTEM STATE ESTIMATION WITH DISTRIBUTED GENERATION

Ahmad ABDEL-MAJEED  
Stefan TENBOHLEN  
University of Stuttgart-IEH  
ahmad.abdel-majeed@ieh.uni-stuttgart.de

Daniel SCHÖLLHORN  
EnBW Regional AG  
d.schoellhorn@enbw.com

Martin Braun  
University of Kassel  
Fraunhofer IWES  
martin.braun@uni-kassel.de

### ABSTRACT

*Accurate and reliable state estimation is the core stone for flexible operation and control of active smart grids. Through the current expansion of integrating DG units in low voltage networks, the network operation is becoming more complex than before. However, real-time monitoring and control through state estimation is a routine task for the transmission system operators (TSO's) due to the availability of measurement data. The distribution system operators (DSO's) are trying to extend their monitoring and control for medium and low voltage network in order to enable smart grid applications. With the current rollout of smart meters, which are considered a key component of future smart grids, there would be enough metering data in the distribution networks (voltage, current, active and reactive power consumption and generation) available at every customer connection point. This paper aims to develop a method to solve the problem of meter placement for low voltage system state estimation through deciding which measurement data from the installed smart meters should be considered in the state estimation algorithms in order to improve on the uncertainty of the estimated voltage and its phase angle at every node in the network.*

### INTRODUCTION

In Germany, the number of small scale distributed generation (DG) units especially from renewable energy has increased sharply in the recent years and will continue to grow up significantly in the near future, especially the share of wind and solar energy in the total amount of energy generation through a targeted support from the federal government. Due to the low production capacities of DG units from renewable energy, they are normally connected to the medium or low voltage network, and this results in problems of power quality and compliance with the voltage range [1]. Therefore, in order to keep the distribution networks under control, the actual state of their network is required. It can be obtained by state estimation techniques.

However, in distribution networks, there are only few measurement points in the network compared to number of the nodes. A direct transfer of traditional state estimation metering placement method to the low voltage network is not possible due to the different network

characteristics between transmission and distribution networks which are described in detail in [2].

Taking the current rollout of the smart meter into consideration, this problem can be solved through using the real time measurements from smart meters. The distribution system operators may not need to install a smart meter at every customer connection point, or to communicate with all smart meters to use their measurement data for state estimation. So the target of this paper is to develop a method which can help the DSO chose the best measuring point to place a smart meter or to communicate with a smart meter which is already installed there.

### SUGGESTED MEASUREMENT PLACEMENT METHODS

Most of the existing measurement placement methods were developed and tested for the transmission network. Schweppe *et al.* proposed metering placement method based on reduction the variance of the estimated state variables [3]. Shaifu *et al.* proposed an approach to place a given number of measurements to reduce the voltage magnitude deviation to those busbars which are not measured based on a series of load flow simulations [4]. Singh *et al.* have proposed a meter placement algorithm based on the properties of the error covariance matrix for distribution networks with distributed generation [5]. Cobelo *et al.* proposed an algorithm which is based on reducing the state estimation error for the voltage and its phase angle below a certain threshold [6]. Most of the proposed methods are suitable for both high and medium voltage networks but not yet tested and verified to the low voltage networks. This paper will investigate a metering placement method for the low voltage network based on [6].

### POWER SYSTEM STATE ESTIMATION

Power system state estimation is commonly based on the weighted least square method, where the state variables (voltage magnitude and its phase angle) are determined by the minimization of the square of the error of all measurements.

The basic equation which relates the measurements with the state variables is

$$z = h(x) + e$$

where

$z$  is the measurement vector,  
 $x$  is the state variables vector,

$h$  is the system of nonlinear power flow equations,  
 $e$  is the measurement error vector.

Every measurement is associated with a specific weight to quantify the degree of trust for that type of measurement (real, pseudo and virtual measurement). The WLS method aims to minimize the weighted difference between the calculated states and the measurements values based on the equation

$$\text{Min } J(x) = \sum_{i=1}^m [z_i - h_i(x)]^T W [z_i - h_i(x)]$$

where

$J(x)$  is the minimization function,  
 $x$  is the state variables vector (voltage magnitude and its angle),  
 $m$  is the number of measurements,  
 $z_i$  is the measurement vector,  
 $h_i$  is the system of nonlinear power flow equations,  
 $W$  is the weighting matrix.

The best estimation of the network states is obtained when the gradient of  $J(x)$  becomes zero. The system of power equations  $h(x)$  is not linear and need to be solved iteratively through the equation

$$\Delta x = (H^T W H)^{-1} H^T W [z - h(x)]$$

where  $H$  is the Jacobian matrix of  $h(x)$ . This equation converges when all elements of  $\Delta x$  are close to zero between two iterations.  $(H^T W H)$  is called the gain matrix  $G$ .

## THE PLACEMENT METHOD

The suggested measurement placement method in [6] is based on exploiting the properties of the error covariance matrix on improving the uncertainty of the estimated state variables on nodes where no measurements are available. The uncertainty can be calculated using the equation (assuming the measurement data are within 3 standard deviation with confidence intervals of 99.73%):

$$\text{Uncertainty}(\%) = \pm \frac{300 \cdot \sigma}{\text{mean}}$$

where  $\sigma$  is the standard deviation of the state variables (the diagonal elements of  $G^{-1}$ ).  $\text{mean}$  is the state variable values in this case.

The methodology which will be used in this paper for a low voltage network is based on creating a worst case scenario where no real time measurements are available in the network, and then by adding additional real time measurements in order to achieve the maximum sum of improvements on the uncertainty for the whole feeder.

## CASE STUDY SONDERBUCH

The network "Sonderbuch" shown in Figure 1 is a low voltage network in the south of Germany which is characterized with high penetration of PV units. The R/X ratios for the cables in this network are in the range

between 2.89 and 7.72. 50% of the customers and PV systems are equipped with smart meters which are able to send the power injection measurements (active and reactive) and voltage measurements every 15 minutes. The available measurements in the network are real time measurements from smart meters at every customer connection point, and pseudo measurements as a standard customer load profile for Germany  $H_0$  in addition to the power and voltage measurements at the low voltage side of the transformer in the substation. Pseudo measurements are modelled with 50% accuracy; real time measurement will be modelled as 3% and 1% accuracy for power measurements (P, Q) and voltage measurement respectively. In this paper, power measurements will always refer to both active and reactive measurements.

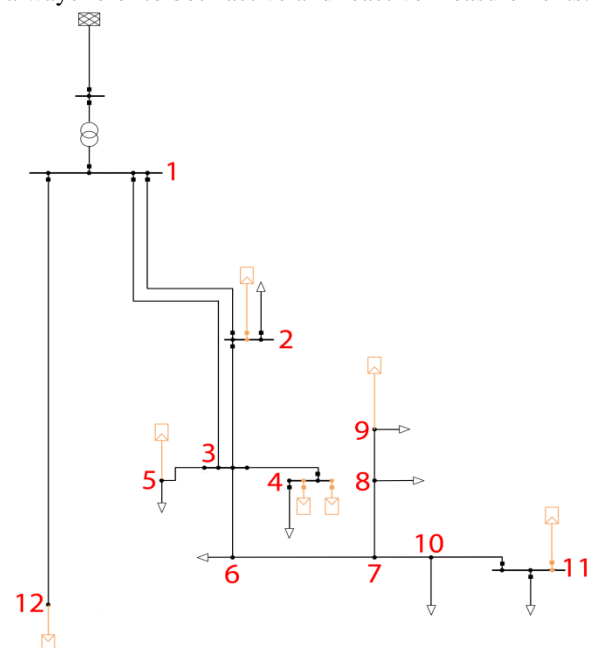


Figure 1 Investigated network topology

## CASE STUDIES

All the simulations were done as a worst case scenario for 10<sup>th</sup> of April 2012 at 12:00 where the PV units had their maximum generation for that month.

As a reference case, all measurements in this network will be modelled as pseudo measurements. Then real time measurements (power and voltage) will be added to evaluate their effect on the overall uncertainty of the state variables. The effect of cable length and R/X ratio on the uncertainty will be also analysed.

The simulations will be divided into 4 cases, the first case will analyse the effect of R/X ratio and the cable length on the state variables uncertainty. The second case will investigate which type of measurement (voltage or power) is suitable for this radial low voltage grid. The third case will analyse the best placement for real time measurement in case that many loads and PV systems are connected to the same feeder. The fourth case will analyse

the best measurement type in case of a PV-system or load which is directly connected to the substation.

**Case 1 (Effect of Cable R/X ratio)**

In order to study the effect of the R/X ratio on the estimated value uncertainty, simulations were done to the node 12 and with different values of R/X ratios as shown in table 1. The original cable type is NAYY-J 4\*150 SE, further low voltage cable types with different R/X ratio with the same length have been simulated. The uncertainty results are shown in table 1. It can be seen that the uncertainty for both voltage and phase angle estimation is not directly related to the value of the R/X ratio of the cable but directly proportional to the value of R in case of estimated voltage uncertainty and X in case of estimated phase angle uncertainty. Therefore, the cable length is also directly proportional to the value of the uncertainty.

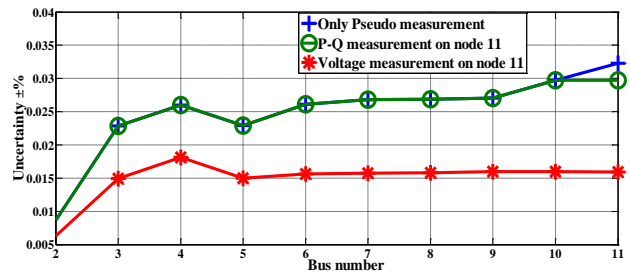
**Table 1 State variables uncertainty in with different types of low voltage cables.**

Cable type	R/X		Uncertainty	
	R	X	Voltage	Angle
<b>NFA2X 4*35 RM</b>	12,16		0.3990%	0.0282%
	0.876	0.072		
<b>NFA2X 4*70 RM</b>	5,40		0.1065%	0.0100%
	0.443	0.082		
<b>NAYY-J 4*50 SE</b>	7,72		0.2194%	0.0172%
	0.641	0.083		
<b>NAYY-J 4*150 SE</b>	2,58		0.0234%	0.0047%
	0.206	0.08		
<b>AI 25</b>	3,46		0.7004%	0.1048%
	1.18	0.341		
<b>AI 50</b>	1,86		0.1919%	0.0649%
	0.594	0.319		

**Case 2 (Type of measurement)**

In this case the measurement type (voltage or power injection measurements) will be investigated in order to decide which suitable for low voltage radial networks.

In order to evaluate this case, three simulations were done; the first one was done only with Pseudo measurements without adding any real time measurement to the feeder (nodes from 2-11), the second one was done by adding a voltage measurement on node 11, the third one was done by adding power measurement on node 11. The simulation results are shown in figure 3. It can be seen that adding real time voltage-measurement has improved the voltage uncertainty for the whole feeder while adding real time power-measurement has just improved the voltage uncertainty only at node 11. The same results have also been found for phase angle estimation.



**Figure 2 Voltage uncertainty values with different measurement type.**

**Case 3 (Best measurement location and combination)**

In order to evaluate the best location of the voltage measurements in this feeder (nodes from 2-11), a selected number of simulations were done with 18 different measurement quantity, combinations and locations as shown in table 2.

**Table 2 Measurement combinations and locations**

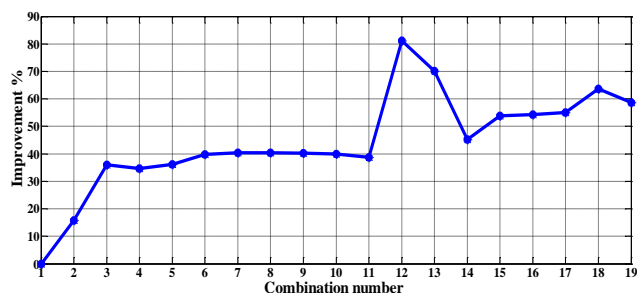
Combination number	Measurements
1	Only Pseudo
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
10	10
11	11
12	2,3,4,5,6,7,8,9,10,11
13	2,4,5,9,11
14	2,11
15	4,11
16	5,11
17	9,11
18	4,9,11
19	2,9,11

To measure the improvements of the uncertainty along the feeder, the sum of the percentage improvements in the uncertainty for all nodes was calculated according to the following equation:

$$Improvement (\%) = \sum_{i=1}^n \frac{Uncertainty_{pseudo} - Uncertainty_i}{Uncertainty_{pseudo}} * 100\%$$

Where *n* is the number of nodes.

Combination number 1 will be the reference simulation for comparison (the case where pseudo measurement was assumed at all nodes). The improvement in uncertainty in every node is compared with this reference case and shown in figure 4.



**Figure 3 Improvement of voltage estimation with different measurement number, combinations and locations.**

As seen in the figure, the best sum of improvement obtained (81.1%) when adding real time measurements to all nodes measurement but this case may not be economical and a minimisation of the number of real time measurements is needed. However, in case of adding one real time voltage measurement, all locations from nodes 3-11 have good improvement results, but the best location for this measurement was obtained either at node 6, 7, 8, 9 or 10 (40%). In case of adding two real time voltage measurements the best combination was obtained at nodes 9 and 11(55.1%). In case of adding three real time voltage measurements the best combination was obtained at nodes 4, 9, 11(63.6%). It was noted that best locations were obtained mostly when placing the measurements near the start and end of the feeder and on nodes where the PV-systems with the highest installed peak power are installed.

#### **Case 4 (PV-system directly connected to the substation)**

In this case where the PV-system is directly connected to the low voltage side of the substation as the PV system at node 12, three simulations were done in order to find the best measurement type first by simulating Pseudo measurement as a reference, the second by adding voltage measurement and the third by adding power injection measurement. The simulation results show that adding power injection measurement has improved the uncertainty of the estimated voltage and its phase angle by 64% and 47% respectively. While adding voltage measurement has improved the estimated voltage and its phase angle uncertainty by 97% and 60% respectively, this indicate that power measurement has better influence on the uncertainty in this case where PV system is directly connected to the substation. Similar results were also obtained by simulating a load which is directly connected to the substation.

#### **SUMMARY AND CONCLUSION**

The paper describes a method for meter placement in radial low voltage networks taking into consideration the current roll-out of smart meters through deciding which measurement data from the installed smart meters should be considered in the state estimation algorithms in order to improve the uncertainty of the estimated voltage and

its phase angle at every node in the network.

The results of the 4 cases which have considered a radial low voltage network were explained in detail. It can be seen that in the radial low voltage networks which is characterised by high R/X ratio, the uncertainty of the estimated voltage and its phase angle was directly proportional to the value of R and X respectively. The uncertainty of the estimated state variables was also proportional to cable length. It was found, in the case of a feeder along which many loads and PV-systems are connected, the voltage measurement on one node has improved the uncertainty for estimating the voltage and its phase angle for all nodes on the feeder, while the power injection measurement has only improved the uncertainty at the node where the real-time measurement was added. On the other hand, in case that the PV-system or load is directly connected to the substation, the power injection measurements shows better improvement for the measurement uncertainty for the estimated voltage and its phase angle rather than adding voltage measurement. These results could be helpful for the DSO's in order to decide which measurement data from the already installed smart meters should be considered in the state estimation or to install new smart meters.

However, other factors which have not yet been included in this paper should also be considered together with the state variable uncertainty for an optimal placement method for radial low voltage network such as minimizing the sum of residuals for the state variables.

#### **REFERENCES**

- [1] Abdel-Majeed, Ahmad, Robert Viereck, Fred Oechsle, Martin Braun, and Stefan Tenbohlen. "Effects of Distributed Generators from Renewable Energy on the Protection System in Distribution Networks." In Universities' Power Engineering Conference (UPEC), Proceedings of 2011 46th International, VDE, 2011.
- [2] Abdel-Majeed, Ahmad; Braun, Martin; , "Low voltage system state estimation using smart meters," Universities Power Engineering Conference (UPEC), 2012 47th International, vol., no., pp.1-6, 4-7 Sept. 2012.
- [3] Schweppe, Fred C. "Power system static-state estimation, Part III: Implementation." Power Apparatus and Systems, IEEE Transactions on 1 (1970): 130-135.
- [4] Shafiu, A., N. Jenkins, and G. Strbac. "Measurement location for state estimation of distribution networks with generation." Generation, Transmission and Distribution, IEE Proceedings-. Vol. 152. No. 2. IET, 2005.
- [5] Singh, Ravindra, Bikash C. Pal, and Richard B. Vinter. "Measurement placement in distribution system state estimation." Power Systems, IEEE Transactions on 24.2 (2009): 668-675.
- [6] Cobelo, Inigo, Ahmed Shafiu, Nick Jenkins, and Goran Strbac. "State estimation of networks with distributed generation." European transactions on electrical power 17, no. 1 (2007): 21-36.