METER PLACEMENT IMPACT ON DISTRIBUTION SYSTEM STATE ESTIMATION

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ABSTRACT

This paper discusses the criteria that must be considered for the placement of new measurements in distribution networks in order to obtain the best state estimation performances. A better network state monitoring will improve all the other network management tasks.
The impacts of the measurement device placement on the state estimation accuracy and on the bad data detection capabilities are illustrated. To ease the comparison of different measurement sets, a visualization method of the expected performances of the state estimator is presented. The paper finally gives measurement placement recommendations based from a literature review and our experience gained from simulations.

INTRODUCTION

In the near future, more and more measurement devices will be installed in the distribution system. The reason for the installation of these devices is to improve the network observability that is necessary to operate the system closer to its limits.
For instance, more distributed generation can be integrated into the grid if an enhanced monitoring system is used: the network voltage that is disturbed by the distributed generators must be first monitored with an acceptable percentage of errors before the appropriate volt/var control can be performed.
To get the most benefit of these new measurements, state estimation is a necessary tool. Indeed, state estimation will take into account the full measurement redundancy to estimate the most likely network state and because state estimation can be used for bad data detection or for topology error identification.
For cost reasons, the number of these new measurement devices will be limited and measurement placement strategies are needed to take the most benefit of these additional measurements.
For this purpose, this paper attempts to answer two questions:

- What criteria must be considered when installing sensors in the distribution grid?
- How many sensors must be placed, and for what result?

The paper first recalls the fundamentals of state estimation. Second it presents the measurement placement criteria that must be considered during the measurement design stage.
Third, a visualization technique that can help the user to understand the benefits of additional measurement devices, and allow him to select the best measurement placement scenarios amongst different possibilities is presented. The visualization and the placement impact on bad data detection capabilities are illustrated.
Finally, we conclude the paper with some measurement device placement recommendations based from our observations and a short literature review.

STATE ESTIMATION

From redundant measurements, the state of the system (x), which is the complex voltage at every node, is estimated by solving a weighted least square problem:

$$\hat{x} = \arg\min J(x) \qquad (1)$$

With $J(x) = (z - h(x))^T R^{-1} (z - h(x)) \approx \sum_i \frac{1}{\sigma_i^2} (z_i - h_i(x))^2$

Where *J(x)* is the cost function that must be minimized over *x*, *z* is the measurement vector, *h(x)* is the measurement model and *R* is the covariance matrix of the measurements.
Typical measurements are voltage magnitude, current magnitude and active and reactive power. Because there are generally few real-time measurements, load forecasts (also called pseudo-measurements) are added to make the system observable. The network model can be single or three phase to consider the unbalance.

Solution

The minimization of the cost function is a nonlinear optimization problem that is usually solved using the iterative Newton-Raphson method.
In addition to the state estimate, the state estimator provides also a measure of the state estimate uncertainty (its covariance matrix, $\mathrm{cov}(\hat{x})$) that is function of the accuracy of the measurements (σ_i in (1)) and of the measurement set.
The optimization will result in the most likely state estimate (maximum likelihood estimator) if the measurement noise is 'well-behaved' (zero-mean and normal distribution). If this is not the case, for instance because of bad input data (defective measurement device or wrong network configuration assumed), the bad data must be detected and eliminated. Otherwise the estimator will result in a significantly biased state estimate. That is why network configuration errors and bad data suppression routines are essential stages of the state estimation.
Details about the implementation of state estimators can be found in any power systems textbook.

METER PLACEMENT IMPACT

The number of measurements, their locations and the measurement type will strongly impact the performances of the state estimator on different aspects whose are presented

below. These measurement placement criteria can be considered during the measurement design state: they can be evaluated in order to select the better measurement placement scenarios amongst different possibilities.
The cost criterion is essential during the measurement design stage but it is not discussed in this paper.

Observability

Unlike in transmission systems, the observability of distribution networks without pseudo-measurements cannot be obtained in an economic manner. Thus it is not a design criterion for distribution systems.
However, if possible, the number of pseudo-measurements should be minimized since they are less reliable than actual measurements. Nevertheless, the maximization of the state estimation accuracy will tend positively toward reducing the number of pseudo-measurement as well. This is the topic of the next section.

Accuracy of the state estimate

The purpose of state estimation is to obtain the most accurate network state given the redundant measurements. In practice, the true state estimation accuracy is never known since the error-free measurements are unknown. In this context, the maximization of the accuracy of the state estimate is done via the minimization of the state uncertainty.
This measurement design criterion is often used in the literature [1][2]. The measure of accuracy can be the average or the maximal value of the nodes voltage magnitude or the lines flow standard deviation, or a combination of both. These statistics are easily calculated as a byproduct of the state estimation.
To ease the comparison of different measurement sets, the visualization of the state uncertainty on the map of the network is implemented. This will be further explained and illustrated in the second part of this paper.

Bad data detection and identification capabilities

The measurement redundancy provides a mean for increased accuracy of the state estimate, but is also a mean to detect and possibly identify bad data, such as a defective sensor, a bad load forecast or a network configuration error. The bad data detection and identification method consists to analyze the residuals ($\hat{r}_i = z_i - h_i(\hat{x})$) and their statistical properties via a chi square test on the cost function ($J(\hat{x})$) and the values of the normalized residuals ($\hat{r}_i / std(\hat{r}_i)$).
We stress that if the bad data indicators don't detect the presence of a bad data, doesn't mean there is no bad data; but that given our measurement set, the estimator doesn't detect one. The capabilities of bad data detection and identification depend strongly on the measurement set.
To design a measurement set robust against bad data, one method proposed in the transmission system literature is to choose the measurement location so that the number of critical measurements is reduced [1]. Critical measurements are measurements on which there is no redundancy, and if removed, they lead to an unobservable system. Therefore it is not possible to detect a bad data on critical measurements. But in distribution, as long as there is a pseudo-measurement for each load, the network will be still observable when flow measurements are removed. In theory, bad data on flow measurements are thus always detectable. But in practice, since the load models are quiet uncertain, the detection of some bad data could be more difficult with some measurement configurations than others.
The identification of leverage point measurements can be used as a measure of the bad data detection capabilities of a measurement set in distribution state estimation. A measurement set that minimizes the number of leverage points will be indeed more robust [2].
Leverage point measurements are measurements 'close to be critical'. They have a high impact on the state estimate, and if bad, they will attract the estimate toward them making the residuals low, which will make difficult the detection of bad data on those measurements. Leverage measurements are characterized by an estimated standard deviation of their residual close to zero. Unfortunately, it is difficult to set the threshold that defines what is close to zero.
Lastly, because distribution systems have simple topologies, we can remark that delimiting similar size of load groups will make the bad data detection capabilities of the estimator uniform in the network. Moreover, the minimization of the state uncertainty explained in the previous section will also probably increase the bad data detection capabilities of the estimator.

Network configuration error identification

Network configuration errors can occur when the telemetered status of a tie switch is wrong, or when the switch status is not updated by the dispatcher after several manual operations.
Performing state estimation with a wrong topology will certainly result in a biased result. It could also result in high residuals, which can be detected with a chi square test, if the measurement set is well designed. In worst cases, the estimator will not detect a problem or not converge.
To detect topology errors, the transmission system approach, which consists to analyse the residual characteristics to pinpoint the switch in error, is not realistic in distribution because of the lower measurement redundancy.
A more suitable approach for distribution, although more time consuming, was proposed in [3]. It consists to test all the switches in doubt in different state estimation and keep the topology that result in the state estimation with the lowest cost function. If no topology results in low residuals, we can safely assume that there is a bad data with the base topology.
In any case, for the topology processing to be effective, the accuracy on flow estimates at the level of switches in doubt must be relatively high, which is function of the measurement set. Therefore, either the load forecasts must be accurate, or flow measurements must be placed relatively close to the switches that may be in doubt. This is thus another concern for the measurement placement.
We remark however that the topology error identification methods will not work with low loading: if the actual flow through a closed switch is close to zero, assuming it open will give also a state estimation with low residuals.
Given the limitation of those methods, if the switch changes often of state, monitoring its status directly is of course a good alternative.

Convergence

Convergence of state estimation, which is a nonlinear optimization problem, is not guaranteed. It can be negatively affected by some factors that may be avoided. It was explained in [4] that nondirectionnal measurements such as current magnitude may cause convergence problems if the flow direction in uncertain. This can be caused typically because of a loop topology or distributed generation. Similar problems can occur if the power factor is very uncertain, for instance because the status of some capacitor banks is unknown. Therefore, if the flow direction is generally unknown, directional measurements should be used.

Robustness

Finally the robustness to a meter loss because of a device failure or a communication failure can be evaluated with the criteria presented above when one measurement is discarded from the measurement set (sort of N-1).

ILLUSTRATIVE EXAMPLES

State uncertainty

To illustrate the measurement placement impact on the state uncertainty, a simulated network is considered with two different measurement sets.

The single line diagram of the medium voltage (20kV) distribution test system is shown on Fig. 1. The network is composed of 8.55 km of underground cables and 14.2 km of overhead lines. The total loading of the feeder is 7.1 MVA. On each node a load is connected (with consumptions varying between 0.1 and 1MW). Three distributed generators are present; DG3 is generating 0.1MW and the two others 2.5MW.

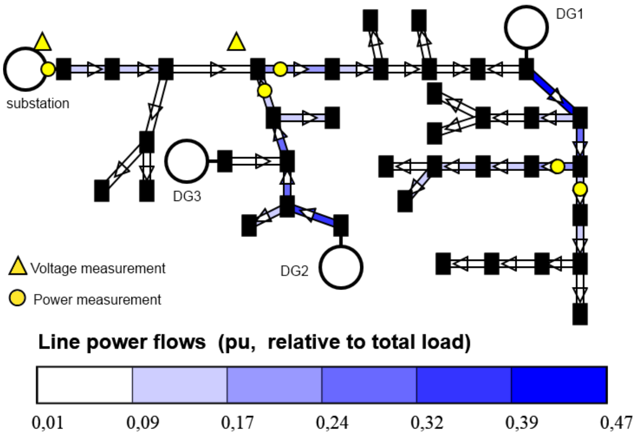

Figure 1 State of the network with measurement devices shown (set 1)

To present the state of the network and its uncertainty, a third dimension on a map of the network is added. The third dimension can be used to plot the network state, the residuals, the state uncertainty or to point out leverage point or critical measurements. For clarity, we choose to represent the third dimension with colours. Such visualization should be used as complement to tabular outputs and will ease the comparison of different measurement placement strategies.

In the next examples, state estimation was performed with measurements obtained from a load flow solution. Since we consider error-free measurements, the two measurement sets give the same state estimate. The flow repartition is shown on Fig. 1, where each line is coloured as a function of the power flow. Colouring the nodes with the voltage magnitude estimates or voltage standard deviation can be also performed, but is not shown here.

The state uncertainty is strongly impacted by the standard deviation of the measurements.

In these estimations, the assumed standard deviations of the load models are set to 1/3 of the average load (one load model is available for each node). The standard deviations of the distributed generators models are set to 10% of the mean generation. Lastly, the standard deviations of the actual measurements (voltage and power) are set to 1% of the measured values.

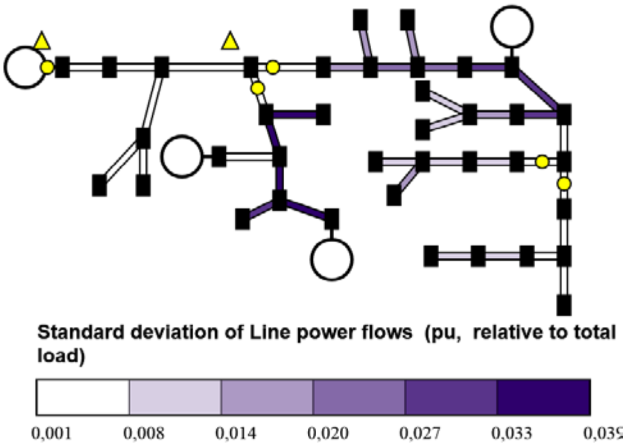

Figure 2 Uncertainty of the power flows with first measurement set (set 1)

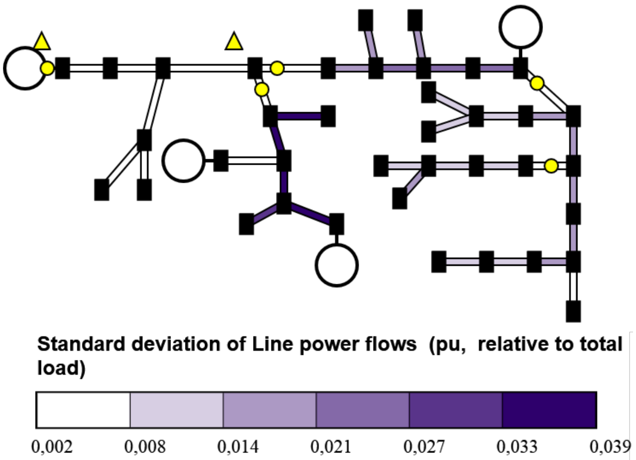

Figure 3 Uncertainty of the power flows with one power meter location changed (set 2)

The standard deviations of the flows estimates with the first measurement set (two voltage and five power measurements, plus load and DG models) are shown on Fig. 2.

We can clearly see that the uncertainty about the flow estimate is very low on line segments with power meters; then the uncertainty increases due to the uncertain load or DG injection. At the ending sections of the feeder, the uncertainty is approximately equal to the load (or DG) uncertainty connected at the terminal node.

When changing the location of one power meter (set 2), the flow uncertainty is changed, see Fig. 3. In this case, the flow uncertainty is more uniform in the network and is probably a better solution concerning the accuracy criterion.
The uncertainty about the voltage estimate is nearly not affected by this change of power meter location. The voltage standard deviation is in fact nearly uniform in the network and is equal to $1\% \big/ \sqrt{2} = 0.007$ pu (1% of voltage measurement standard deviation with two measurement device).
From our experience with the use of this visualization, we observed that:

- Additional voltage measurements decrease the voltage uncertainty everywhere in the network.
- Additional flow measurements decrease the power flow uncertainty in neighbouring line segments. The uncertainty on the flow repartition away from the measurements is mainly function of the load forecast uncertainty.
- Because the lines impedances are relatively low in distribution, the coupling is low between the voltage and the power uncertainties: additional voltage measurements have little effect on the power flow uncertainties and vice-versa.

Bad data detection and identification capabilities

To illustrate the bad data detection and identification capabilities of the different measurement sets, DG1 (see Fig. 1), actually generating 2.5MW, is assumed to be disconnected when performing state estimation. The resulting cost function and largest normalized residual (LNR) for both measurement sets are show on table 1.

	Set 1	**Set 2**
Cost function	354	720
LNR	12	17

Table 1 Bad data indicators when a DG is assumed to be disconnected while it is not

In both cases, the normalized residuals indicate as bad (normalized residual > 3) the loads delimited by the series measurements in the same load group of DG1. It is thus not possible to identify exactly which load is bad.
We can see that set 2 is more sensitive to this bad data than set 1, because the cost increases more and that the number of suspected loads is lower.
However, set 2 will perform better to detect some other types of bad data. A measure of the bad data detection capabilities could be done by the calculation the leverage point measurements.
Simple meter design rules can make the estimator more robust to bad data, this is explained below.

CONCLUSION

This paper discusses the different criteria that must be considered for the measurement design in distribution state estimation. These criteria are: cost, accuracy of the state estimate, bad data detection and identification capabilities, abilities of network configuration error detection, and robustness of the algorithm in convergence and to a meter loss.
The illustrations clearly showed the gain of accuracy when better measurement devices locations are used. The visualization tool could be used as a basis of justification for the installation of additional measurement devices and help the user during the selection of the new measurement device locations. Adding user interactivity would be a good improvement to this tool.
Because distribution networks have simple topologies (weakly meshed), we think that measurement placement strategies close to be optimal can be obtained with simple heuristic rules:

- From the visualization of the state estimation accuracy, the user can place voltage measurement where the voltage deviation is too high.
- For the power flows, a similar rule can be used. But for simple topologies, the placement of the flow measurements so that they delimit similar amount of load will give very good results. It was also suggested in [5].
- Use directional measurements (power instead of current) when the flow direction is a priori unknown.
- Monitor the injection of big and intermittent distributed generation units.
- Place power meters close to tie switches to ease the monitoring of their status.

We can remark that the two first rules will also increase the bad data detection capabilities.
As concluding remark, there is a real benefit for the operator to have accurate load models because it will improve all the state estimation functions, those can be improved for instance from measurement campaigns.

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