DETECTION OF MEASUREMENTS ERRORS WITH A DISTRIBUTION NETWORK STATE ESTIMATION FUNCTION

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ABSTRACT

Existing electricity distribution management systems (DMS) have been designed using operational and algorithmic procedures that are highly centralised. As more of the distribution network becomes active, accurately estimating the state of the system becomes essential and therefore DMS must include functions to achieve the required near to real-time state estimation. Distribution State Estimation using sensors data and load models as input data can help improve the network observability required by Advanced Distribution Automation function. One of the important objectives of state estimation algorithms is also to be able to detect erroneous measurement data. This information is firstly used in order to reject this data as inputs of the estimation process but also to help identify faulty sensors for scheduling their repair or their replacement.

This paper presents different techniques which can be applied to distribution state estimation to detect and identify faulty sensors.

INTRODUCTION

Distribution networks are facing technical constraints and uncertainties: Distribution network operators (DNOs) need to improve the quality of service, integrate high penetrations of distributed generation (which includes highly variable wind and solar generation), forecast energy flow, and improve efficiency, all while maintaining stable voltage at an acceptable level under all loading and operating conditions. A coordinated and smart approach is therefore required to help solve these challenges. The development of Advanced distribution automation functions in distribution control centre tools, such as Volt and VAr optimization, optimal network reconfiguration, and security analysis will bring improvements to network operation.

However, until recently, only few sources of monitoring existed on the electric distribution system, and relatively few devices included remote control to achieve the established operating objectives. This approach was acceptable because the distribution system was relatively static in nature, with well-understood and predictable load and voltage profiles, no significant penetration of active components such as distributed generation, and virtually no need to reconfigure the feeders or alter controller settings under normal circumstances. Sébastien GRENARD EDF R&D – France sebastien.grenard@edf.fr

Today, however, the lack of monitoring in distribution networks is a barrier to the implementation of the corresponding automation functions. On the other hand, a full monitoring of the distribution network is not economically realistic. Therefore, there is a need for intermediate solutions such as the use of a distribution state estimator (DSE), the selective deployment of low-cost sensors at suitable nodes in the network, and the use of smart metering information when available.

Therefore, Distribution State Estimation (DSE) will be at the heart of future Distribution Management Systems (DMS) and a necessary step towards the Smart Grid. The algorithm of distribution state estimation is a non linear optimization that uses a limited number of measurements (which may be of different types : voltages, currents, active/reactive power) acquired by a SCADA, combined with the network model in order to estimate the electrical state of the network in "real time" (in the range of 1 to 3 minutes). Such information becomes essential for Distribution Network Operators (DNOs) in order for example to detect and deal with voltage constraints arising due to the connection of Distributed Generation in the MV and LV networks. The results obtained with the distribution state estimation algorithm are then used as input data by the algorithm of real-time functions which make decision on controller settings in the network.

One of the important objectives of state estimation algorithms is also to be able to detect erroneous measurement data. This information is firstly used in order to reject this data as inputs of the estimation process but also to help identify faulty sensors for scheduling their repair or their replacement. It also improves the accuracy of results of DSE used by real-time functions.

After a description of the issues related to the accuracy of input data used by distribution state estimation algorithms, this paper presents different techniques which can be applied to detect data provided by fault sensors. The advantages and drawbacks of each technique are presented: limit of the possible error detection for different types of sensors, impact on distribution state estimation performances and calculation time. The results of different case studies run on a real MV distribution feeder are presented.

ESTIMATION DISTRIBITION STATE **FUNCTION (DSE)**

Network state estimator uses the set of available measurements in order to estimate the system state. Measurements used by the DSE are classified according to three families :

- real measurements,
- pseudo-measurements, -
- virtual measurements.

Real measurements are metered on the system and synchronously retrieved by the SCADA, pseudomeasurements are load models; virtual measurements are additional values used when the value is clearly identified (for instance, zero load injections at nodes with no load connected).

The DSE algorithm is defined by an objective function subject to the measurements model previously described and a constraint equation linking virtual measurements to the state variable V (amplitude and phase angle of voltage at each node). Therefore, the goal of DSE is to determine an estimate of V that minimizes this objective function. The latter is expressed as the function of the measurement residuals $\rho(r_i)$ subject to constraints given by the measurement equations.

 ${\stackrel{\Lambda}{V}} = \arg\min J(V) = \sum_{i=1}^{m} \rho(r_i)$ objective function

subject to :

equation considering the ith real or $z_i = h_i(V) + r_i$ pseudo-measurement equation

c(V) = [0]equality constraints equation corresponding to virtual measurements

The performance of the DSE function is directly related to the accuracy of its input data: sensors' measurement, load models and network model. Any errors in measurements could therefore alter the expected accuracy of DSE results. Random errors characterizing the pre-defined class of sensors are generally present. These are normally eliminated by the state estimation algorithm thanks to the suitable redundancy of measurements. However, larger unexpected errors could also appear: they can be due to drifts or biases directly affecting sensors installed in the network or bad communication of the information from the sensor's Remote SCADA Terminal Unit to the through the telecommunication support. To make sure that such large errors do not impact DSE results, several methods can be applied.

METHODS APPLIED FOR DETECTION AND IDENTIFICATION MEASUREMENTS OF **ERRORS**

Post treatment of outliers

This method consists of analysing the results obtained by the distribution state estimation function. The analysis is made through two main steps:

- Khi-2 test: it is used to identify the possible • presence of bad measurement data
- Comparison of the normalised residue with a predefined threshold for each measurement if the Khi-2 test was positive

The principle of Khi-2 test is a statistical method which consists in checking the value of the objective function J(V)at the end of the DSE algorithm process. The value of J(V), calculated only with real measurements, must follow a Khi-2 distribution: if the probability of having a value of J(V) is above a pre-defined threshold, it could be expected that an outlier is present.

It is important to mention that this step is not entirely necessary. However, it helps improve the computation time of the process if no outliers are present. It avoids the non necessary comparison of all normalised residues which is time consuming.

The normalised residue is defined by:

$$r_i^N = \frac{|r_i|}{\sqrt{\Omega_{ii}}}$$

where : $r_i = z_i - h_i(V)$ and Ω is the covariance matrix corresponding to all residues. The value of each normalized residue is compared with a pre-defined threshold. Only the values of normalized residues corresponding to real measurements are considered and compared with the predefined threshold. If the value is above the threshold, the corresponding measurement data is removed from the input data of the distribution state estimation algorithm. The process of state estimation function is then re-launched with a pseudo-measurement used instead of the realmeasurement.

Use of an M-estimator for measurements errors detection

This method consists in filtering the bad measurement data directly within the state estimation algorithm. The bad data are detected during the iterations of the algorithm. The Huber M-estimator is chosen in this paper.

This approach is designed for automatically detecting measurements with rapidly growing residuals and suppressing their influence on the state estimate. To do so, the weight applied to each residue $(\Phi(r_i))$ depends upon the value of the residue (see references [1] and [2]). If the residue is below a given threshold,

if
$$\left| \frac{r_i}{\sigma_i} \right| \le$$
 threshold then $\Phi(r_i) = \frac{1}{\sigma_i^2}$
else $\Phi(r_i) = \frac{\frac{a}{\sigma_i} signe(r_i)}{r_i}$

Where σ_i corresponds to the assumed error variance of the

ith sensor. In other words, WLS (Weighted least squares) is applied when the residue is below the threshold and WLA (Weighted Least Absolute Value) otherwise. The Mestimator is only applied to real-measurements.

CASE STUDIES

Both techniques previously explained have been applied through Matlab simulations to a real classic MV distribution feeder. They have been applied on a given operating point of the network. The network model is considered to be entirely precise.

In this paper, the figures are built as follows: a suitable accuracy of state estimation corresponds to the following performance: amongst 500 estimations on the same network operating point, we consider as an example in this paper that voltage amplitude and angle should be within a boundary of $\pm 1\%$ of the real time value. The following DSE performances are assessed by adding progressively several P/Q/V sensors at MV/LV substations of the MV feeder.

- the green curve is related to the minimum performance,

- the red curve corresponds of the mean performance,
- the blue curve represents the maximum performance

The first configuration corresponds to a P/Q/V sensor at the feeder head. Figure 1 shows the performance of the algorithm on voltage amplitude and angle when no abnormal errors are applied to sensors (it is considered that P/Q/V sensors have an accuracy of 1%).



Figure 1 DSE performances without abnormal measurement errors

Performances of the post treatment methodology

In order to assess the performance of the post treatment methodology, an "abnormal" error is applied to one of the sensor. In this case study a 5% error is applied to the voltage sensor added in configuration 3 (see Figures 2 and 3). All other sensors keep the supposed accuracy of 1%. Without the post treatment, larger errors are obtained in the estimation of voltage amplitude in configuration. This mitigated by two solutions:

i) Applying the post-treatment (see Figure 3)

ii) Adding more sensors (with three more sensors in

configuration 6, the initial performance is obtained)







Performance of the M-estimator approach

Similarly to the previous methodology, the comparison is made between applying the basic DSE formulation and the Huber M-estimator formulation on a case where an abnormal error of 5% is applied to a voltage sensor. All other sensors keep the supposed accuracy of 1%.

Figure 4 depicts the results obtained when the Huber Mestimator is applied to the same case as in Figures 2 and 3. One can see that the performances obtained with the post

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treatment are slightly better. However, the computation time of the post treatment solution is much longer than the application of the Huber M-estimator.



Figure 4 Results with Huber M-estimator

Similar case studies have been performed while applying abnormal errors at two different voltage sensors in the network. The results are similar: applying either methodologies help detect the large "abnormal" errors of 5% on both sensors. Moreover, the performances in terms of results accuracy are only slightly different.

It is important to underline that the natural interactions between measurements can reduce the efficiency of the algorithms of detection and identification of bad data. However, these interactions decrease with the number of sensors installed in the network. Thus, only the addition of a relatively little number of sensors in Figure 2 (case study without bad data treatment) preserved the DSE performances. But it is no longer the case depending on the multiplicity, nature and amplitude of outliers (Figure 6). Thus, in presence of bad data, the algorithms studied are required in order to maintain the quality of each estimate with a reduced number of sensors (Figure 5).



Figure 5 : Results with Huber M-estimator - drift and bias of 5% are applied to two sensors



Figure 6 : Results without bad data treatment- drift and bias of 5% are applied to two sensors-

CONCLUSIONS

This paper has presented the importance of Distribution State estimation in the future and how they will use different types of measurements in the network (real measurements and pseudo-measurements). One of the important objectives of state estimation algorithms is also to be able to detect erroneous measurement data.

This paper has presented two different possible approaches which have been simulated on a real MV feeder:

- Post treatment approach
- Huber M-estimator

The results of the case study illustrate the performances of both approaches in improving the results of voltage amplitude estimation when an abnormal voltage measurement of 5% is applied to a sensor in the network. Even though slightly better results are obtained with the post treatment approach, the Huber M-estimator could be more appropriate for a real application as its computation time is much faster. However, sensors data retrieved from a DSE experiment will help consolidate this study and its conclusions as utilities have currently no feedback on MV network sensors reliability.

REFERENCES

- [1] A. Abur, A.G. Exposito, 2004, *Power System State Estimation*, Editions Marcel Dekker
- [2] O. Chilard, S. Grenard, 2009, "Distribution State Estimation based on voltage state variables", *CIRED* 2009, Prague, paper 0524A
- [3] S. Grenard, O. Devaux, O. Carré, O. Huet., 2011, "Advanced distribution applications for operations", *Powersteering IEEE PowerEnergy J ournal* sept-oct 2011, 133-139.