VOLTAGE MANAGEMENT IN THE PRESENCE OF DISTRIBUTED ENERGY RESOURCES – FIELD IMPLEMENTATION OF A ROBUST DISTRIBUTION STATE ESTIMATOR WITH ERRORS IN SENSOR DATA

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ABSTRACT

In order to improve the resilience of Dynamic Voltage Regulation, lever, currently experimented by Enedis (the French DSO) in several French demonstrators, EDF R&D developed and tested an M-state estimator.
This paper presents the main results of the M-estimator operational experimentation which are positive so far. These results assess the industrialization possibility of Dynamic Voltage Regulation Lever on Enedis Networks as a means to increase the DSO network hosting capacity of Distributed Energy Resources (DER).

INTRODUCTION

Dynamic Voltage Regulation based on centralized setting of On Load Tap Changer (OLTC) set point is one lever Enedis (the French DSO) experiments to increase the DER[1] hosting capacity of its MV networks. In this frame, Enedis entrusted to EDF R&D the development of Voltage Regulation algorithms based on a Weighted Least Square (WLS) Distribution State Estimator (DSE). The DSE uses sensor-based measurements and pseudo-measurements to determine the network state at any time and to allow the OLTC dynamic management.

The VENTEEA experimentation (a French Demonstrator supported by ADEME[2]) showed that the DSE behaviour can be strongly affected by sensor outliers. These bad data could be due to many reasons such as sensor misuse or failure. As the occurrences of this bad data are not negligible, the DSE accuracy became inacceptable to Enedis and a way to improve the DSE algorithm had to be found. This paper deals with improving the robustness of the DSE against sensor errors and failures.
EDF R&D studied, then implemented an M-estimator running alongside the operational WLS estimator on a substation and relevant MV networks of the Smart Grid Vendée demonstrator. This paper introduces the M-estimator (maximum likelihood type) principle, the way it deals with measurements errors, how to set it up, and the outcomes achieved by both simulation and field tests. It also compares the results of the M-estimator against the WLS state estimator.

1 Distributed Energy Resource
2 French Agency for Environment and Energy Mastering

FROM A DSE TOWARDS A M-DSE

In order to estimate the electric state of the distribution network in "real time"[3], the DSE solves a non-linear optimization problem. It looks for the state vector x which minimizes an objective function J(x) selected in advance. The state vector chosen for our Distributed State Estimator is composed of the voltage amplitude and phase angle at each node.

$$\hat{x} = \arg\min J(x)$$
$$with\ J(x) = \sum_{i=1}^{m} \rho(r_i) + k_{nec} * c(x)^T * c(x)$$
$$where\ \rho(r_i) = \left(\frac{r_i}{\sigma_i}\right)^2$$
$$k_{nec}\ is\ a\ weighting\ factor$$
$$subject\ to:\ z_i = h_i(x) + r_i$$

For this purpose, network observability (z_i) – so called network measurement in the following - and a network model ($h_i(x)$) are needed. Three kinds of network observability are used:

- real measurements
- pseudo-measurements
- virtual measurements ($c(x)$)

The first ones are coming from field voltage and/or "power sensors", the second ones refer to active and reactive power forecasting for secondary substations and the last ones are for nodes without production or consumption (P=0 and Q=0).
A weight (σ_i) is given to each measurement depending on the measured value and the sensor's precision (1% for voltage measurements, 3% for power measurements and 50% for pseudo-measurements).

The current objective function is a Weighted Least Square method. It is efficient regarding noisy measurements but unfortunately not regarding outliers. That's why, we looked for a more robust estimator, an M-estimator (M-DSE).

3 Calculations are made every 10 minutes

The M-estimator

The particular feature of an M-estimator is that it changes its objective function for real measurements depending on the value of a standardized residue. The latter is the difference between the measured value and its estimation, divided by a weight in accordance with the sensor's precision. We implemented the Schweppe Hubert Generalized M estimator (SHGM). Details can be found on the book reference [1]. This estimator switches between a Weighted Least Square function and a Weighted Least Absolute (WLA) function.
This method detects the outliers upstream in order to give them a reduced weight in the optimization problem. In this way, the M-estimator benefits from the strengths of both the Weighted Least Square and the Weighted Least Absolute estimators.

Indeed, the Weighted Least Absolute function is more efficient for dealing with bad data such as biased measurements. From now on, we have:

$$\rho(r_i) = \begin{cases} \frac{1}{2} * \frac{{r_i}^2}{{\sigma_i}^2} & if \ \left|\frac{r_i}{\sigma_i}\right| < a \\ a * \left|\frac{r_i}{\sigma_i}\right| - \frac{1}{2} * a^2 & otherwise \end{cases}$$

$$If \ r_i \ is \ a \ pseudo - measure, \rho(r_i) = \frac{1}{2} * \frac{{r_i}^2}{{\sigma_i}^2}$$

Finally, the choice of the objective function is adjusted thanks to a parameter "a". If the standardized residue is bigger than "a", the algorithm will select the WLA function, otherwise it will keep the WLS function. Generally, the parameter "a" is fixed between 1 and 4. The smaller the parameter "a" is, the more selective we are about what we consider as an outlier. After running some tests and in order to avoid considering a value below the sensor's precision as an outlier, we decided to set the "a" parameter to 3 for our implementation.

SIMULATION RESULTS ON VENTEEA

Simulations consisted in introducing errors / bias on sensors outputs and to observe the impact on M-estimator results compared to the standard estimator; they were run on historical data sets issued from the voltage regulation experiment on VENTEEA demonstrator. Simulations where conducted with a unique error prone sensor per feeder and different bias levels (1, 5 and 10 %) and with several malfunctioning sensors per feeder.

With only one biased sensor

Table 1 shows the mean percentage of successful estimations for 100 draws in VENTEEA network, with both the WLS estimator and the M-estimator.

		No bias	1% bias	5% bias	10% bias
Feeder A	WLS	100	100	45	0
	M	100	100	100	100
Feeder B	WLS	100	100	82	0
	M	100	100	100	100

Table 1: Percentage of successful estimations (with less than 1% error)

With several biased sensors

We ran some simulations with cases studies representing real observed cases. In table 2, the feeder 1, 2 and 3 have respectively 4, 5 and 6 voltage sensors.
We made the following simulations with 1000 random data draws:

1. Bias of -1% on a sensor et -10% on a second one
2. Bias of -10% on a sensor et -10% on a second one
3. Additional bias of -10% on a third sensor

Simulation	1	2	3
Feeder 1	70	0	0
Feeder 2	100	88	0
Feeder 3	100	100	0

Table 2: Mean percentage of successful estimations by node with the M-estimator (with less than 1% error)

The M-estimator performance depends on the number of sensors available on the feeder. As long as there are more normally running sensors than faulty ones, the M-estimator is able to overcome the issue in most of the cases, even with important biases. In case most sensors on the same feeder are defective, the M-estimator tends to consider the good ones as the bad ones and conversely.

The WLS estimator didn't perform well with several biased sensors on the same feeder. The weight of the outliers was then too important and degraded the WLS DSE results far from the 1% mark.

After these first satisfactory results of the M-estimator on the Matlab simulations, Enedis decided to have it implemented in operational conditions in the control systems covering the Smart Grid Vendée demonstrator areas (in open loop first and in closed loop afterwards).

FIELD IMPLEMENTATION

The WLS Distributed State Estimator was first implemented in 2016 on the VENTEEA demonstrator in *Vendeuvre-sur-Barse* primary substation. This primary substation comprises one 20 MVA HV/MV transformer with 5 MV feeders. With a biased sensor, the conclusions showed that despite a substantial tendency to mitigate the error, it was still necessary to improve the results especially when the bias was important or there were several sensors biased. The other main results are available in the reference document [2].

Smart Grid Vendée network

In 2018, the WLS DSE was tested operationally in the wider and more complex demonstrator *Smart Grid Vendée,* on PALLUAU primary substation which has two 36 MVA transformers feeding 16 MV feeders. On these networks, MV producers connected capacity are 20.6 MW on the first transformers and 17 MW on the second one. These producers are mainly a mix of wind farms and solar panel farms.
36 secondary substations in the area were equipped with voltage and power sensors with an average of 3 to 4 by feeder (excluding dedicated feeders and short feeders).
In addition, voltage, active power and reactive power measurements are available at the primary substation for each feeder and at each MV DER site.
After a few months of observation on the WLS estimator and some improvements on its inputs, the M-estimator was put into operation in parallel.

Results with a biased sensor

We first observed the efficiency of the M-estimator when a sensor drifted suddenly, sending voltage value at 18.5 kV on a 20 kV network. Figure 1 bellow illustrates this issue: the sensor is first running normally (blue curve), then, without any event or fault on the network, the sensor starts to send extremely low voltage values. The WLS DSE results (grey curve) were directly impacted, they drop by 500 V representing almost a 3% error. Meanwhile, the M-DSE results were not affected, staying under the goal of 1% precision that Enedis requires. The 1% requirement is necessary for being able to send the optimal setting point to the On Load Tap Changer while taking into account uncertainties in the control chain and the operational margins against voltage regulatory limits.

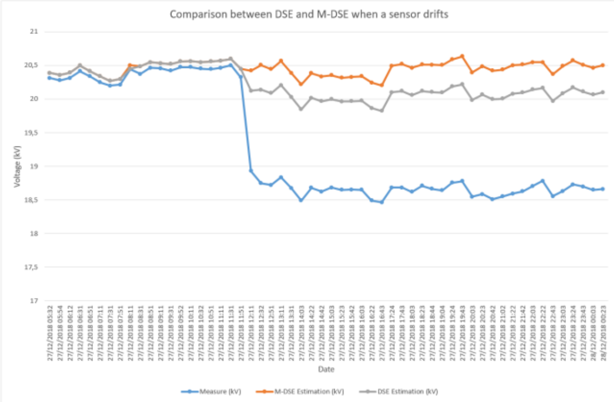

Figure 1: Comparison between estimators estimation when a sensor drifts

The impacts of the drift was also noticed on the DSE results for the other sensors on the same feeder. Figure 2 shows the estimations results on a downstream sensor. Once the first sensor values drop, the DSE estimations on the second sensor are instantly affected and drop as well.

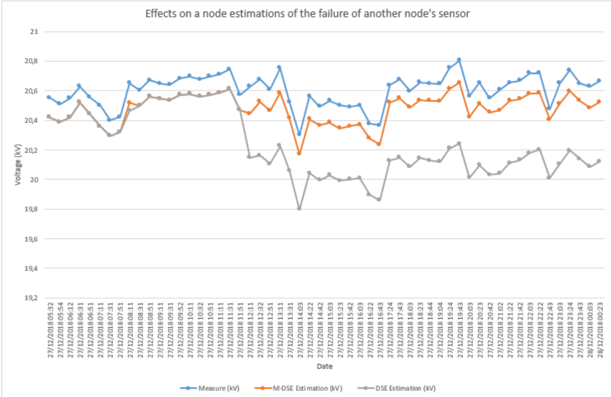

Figure 2: Effect on a node estimations of the failure of another node's sensor

Results in a normal situation

Even when sensors are working properly, we still notice an improvement with the M-estimator results in some cases. Effectively, for example in a feeder with 2 sensors, we observed on both sensors that the estimations were slightly better with the M-estimator than with the classic one. A 50 V gain on the gap between estimation and measurement was obtained. Results are shown on figure 3.

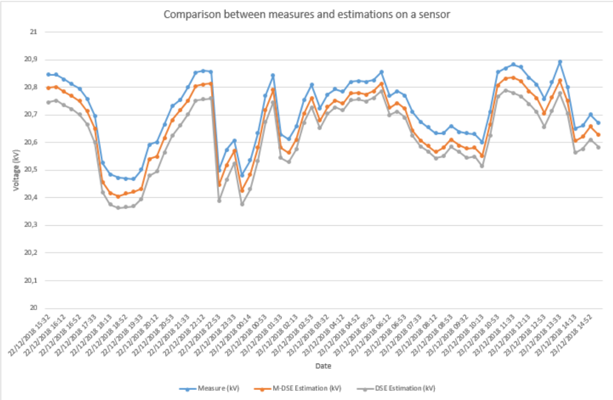

Figure 3: Comparison between measures and estimations on a sensor

Detection of sensors failures

We wanted to go further and use the M-estimator algorithm in order to detect a sensor failure. So, we recorded in a matrix the objective function chosen at each step of the estimation (Weight Least Square or Weight Least Absolute). For small biases, the DSE can switch between the two functions. But, when an important bias occurs on a sensor, the objective function selected by the M-estimator will always be the Weight Least Absolute. Thus, it would be possible to use this information to suspect a failure on a sensor and trigger a maintenance action for preserving the DSE results.

CONCLUSION AND PERSPECTIVES

This paper illustrates the reliability and efficiency gains given by the M-DSE compared to the standard (WLS only) DSE. The M-DSE gains were operationally proven on Enedis Smart Grid Vendée demonstrator by the beginning of 2019.

The standard DSE might be largely affected by sensors drifts or failures that were more frequent than expected during Enedis experiments. Our implementation of an M-estimator has proven us that it is a viable solution for solving this problem. For any given bias, the M-estimator performs better than the WLS estimator and therefore manage to eliminate bad data, as long as there are more “healthy” data than erroneous ones.

Finally, the M-estimator also makes it possible to realize preventive maintenance by using the flag “right” or “assumed false” allocated to each sensor at each estimation. It is thus possible to quickly detect a defective sensor and promptly react to preserve DSE performances.

Enedis is planning to implement the DSE and the regulation function in 10 primary substations all over France in 2019. Following this experimentation, Enedis will deploy the M-estimator instead of the WLS estimator to feed the dynamic Voltage Regulation function on MV networks.

The M-estimator achievement is of a major importance for Enedis since it is a key feature in the industrial deployment of the dynamic voltage regulation lever to increase the DER hosting capacity of MV networks.

REFERENCES

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[2] D. Croteau, O. Carré, 2017, "Distribution State Estimation: Outcomes from a field implementation aimed at tackling MV voltage mastering in the presence of DER", *CIRED conference*, Glasgow, Paper 0420