PERFORMANCE EVALUATION OF DISTRIBUTION SYSTEM STATE ESTIMATOR USING DIFFERENT MEASUREMENT DEVICES

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ABSTRACT

State estimators, used to monitoring transmission networks, are not widely applied to distribution systems. Before deploying such a system, DSOs want to evaluate its performances in field conditions. In this paper, different uncertainty sources are considered. Device measurement error is modelled by a normal distribution function, and measurement delays or loss of communication are emulated by simulations. This paper introduces a tool to evaluate the performance of a state estimator, applied on a 102-node real LV network of the Swiss DSO Romande Energie, with 40 smarts meters and three GridEye monitoring devices, a new GPS synchronized high precision measurement device. The method consists in the comparison between load flow calculations and an estimator using a weighted least squares formulation. Uncertainties are added to the load flow results and a selection of them are considered as measurements. Thereby, the performance is evaluated for different simulation cases: meters placements, GridEye cells placements and different datasets for each measurement device can be selected. The simulations are based on several snapshots representing different times of the day.

INTRODUCTION

Smart metering roll-out in Switzerland

As the smart meter concept definition is being finalized, distribution system operators (DSOs) are ready for the upcoming roll-out. Major DSOs have started pilots to evaluate technologies and solutions. Nevertheless, the roll-out will only start once the security standards and certification process will be defined in Switzerland. Smart meters are part of the measures included in Swiss Energy Strategy 2050. In Switzerland, the roll-out of smart meters would be profitable for the country's economy: the devices and their installation will represent a cost of one billion francs until 2035, while the implied economic benefits should reach between 1.5 and 2.5 billion. This is the conclusion of an impact assessment carried out on behalf of the Swiss Federal Office of Energy (SFOE) [1].

The revision of the Ordinance on Electricity Supply came into effect on 1 January 2018 and required Swiss DSOs to equip 80% of their measuring points with smart meters by 2027. The deployment of meters also provides an opportunity to review internal processes and to manage network investments.

REeL Demonstrator

The REeL ("réseau en équilibre local") project is a demonstration project carried out by Romande Energie in partnership with an academic consortium. The aim is to demonstrate technology developments in a real distribution system. Activities cover grid management and monitoring, flexibility management, FDIR and electricity market and services to the end consumers.

The activity covered in this paper is related to the use of smart metering data for system operation purposes. State estimation based on smart meter data has been proposed since the early stages of SmartGrid concepts. In this study, the conditions for the validity of such a state estimator are investigated from the perspective of the deployment strategy of the DSO: how many smart meters are required to reach a given target precision? Is a combination with other measurement devices beneficial? Which characteristics of smart meters will be influencing the performance of the state estimator?

Regulation and data protection

Switzerland has already defined the minimum technical requirements for smart meters. Active and reactive energy measurement, load curves calculations with a sampling period of 15 minutes and recording them for at least 60 days are specified characteristics. Smart meters should have at least two interfaces: one is reserved for bidirectional communication with a data processing system and the other one allows the end customer to read the measured values and the load curves. A digital communication system ensuring automatic data transmission between the meter and the data processing system is also required. These technical requirements contribute to ensure a positive cost-benefit ratio of future measuring systems. The security and data protection guidelines are the responsibility of the Federal Institute of Metrology.

STATE OF THE ART

Distribution system state estimation

State estimation (SE) is a robust way to monitor transmission systems [2]. The interest to apply this concept to distribution systems is rising. On the one hand, bidirectional power flows increase DSOs requires better knowledge of power flows in the systems. On the other hand, smart meters are deployed at all end customer points. However, some fundamental differences between transmission and distribution systems have to be considered before the application of SE to distribution systems. The radial topology of distribution systems seems to affect the stability of SE algorithms. Advanced numerical methods like Hachtel's augmented matrix [3] and globally convergent methods [4] have been developed to address these problems. A method to diagnose the SE numerical stability via the analysis of the condition number has also been presented [5]. Compared to transmission systems, phase current are relatively unbalanced. This fact leads to three-phase SE formulations [6], more accurate but also more time-consuming for computation. The smart meter, widely deployed in distribution systems, has to be a cheap device. Time reference in these devices is then not as accurate as transmission measurement tools like phasor measurement units. Some more accurate measurement devices could be deployed, but DSOs need a way to place them at the most strategical nodes. A few studies have been carried out to find the best measurement placements [7] and to evaluate the uncertainties propagation of measurement due to meters placement and accuracy [8]. In this article, a method to evaluate the performance of a standard formulated SE (Newton-Raphson algorithm in sense of weighted least squares) is presented, taking into account different uncertainties propagation and different accuracy of measurements.

Observability in distribution networks

Distribution grids have been traditionally operated almost without any monitoring devices, and the "safe" sizing of the grid infrastructures and the unidirectional power flows have allowed DSOs to operate their grids in a safe way. The limited resources for network reinforcements, the increase of the distributed energy generation due to the environmental concerns and the energy transition policies, the raise of uncertainty in spatial-temporal energy balance due to increase of stochastic production and consumption raise the challenges for the secure and reliable operation of distribution networks. Moreover, deregulated electricity markets in which the end customers are getting more reactive roles, and higher risk of power outages due to extreme weather events and climate change, increase the need for network observability. DSOs, responsible for the operation of distribution grids, are looking for affordable and scalable solutions for the network supervision which provides them the access to the network statistics, power quality status, fault identification and location, and assets status monitoring. Further applications are needed by bringing added value to the monitoring data for asset management and network planning. A suitable solution for the network supervision can make use of the available smart meter data along with the data of advanced metering infrastructure to improve the distribution grid observability.

Communication

Within the wide choice of communication means to transfer smart meters data to the data process system, the combination of PLC and cellular network is found to be an efficient way. PLC G3 is a good communication channel in urban dense area using no external service suppliers whereas GPRS/LTE meters allow remote electricity delivery points to be read thanks to the good cellular coverage in the country. PLC G3 performance is good enough today in most scenarii but still need fine tuning to achieve near real time responsiveness. Disturbances on the network are inherent but a well-tuned algorithm can differentiate communication from power network faults. Furthermore, PLC G3 can still be improved using other larger bands like FCC-2 instead of Cenelec A. Despite FCC-2 band usage being subject to strict conditions, it can be an answer to some situations.

STUDY CASE DESCRIPTION

Studied network description

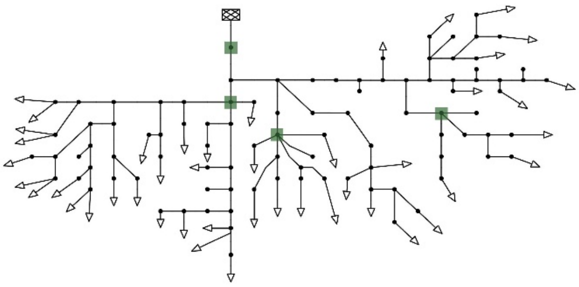

Fig. 1: Study case LV network, with the green squares being the GridEye cells

The studied network is a part of the distribution system of the Swiss DSO Romande Energie, with 100 lines and 101 nodes in a radial topology. It is an interesting case because this network is a part of the REeL demonstrator and is equipped with smart meters. This network feeds an outer-urban residential area and in most cases several customers are aggregated behind a main meter for the entire building. In the used representation, 40 connection points are considered for the 157 end customers. Five residential PV generators are also active in this network. Smart meters are typically placed at the extremities of the network (at end consumer/producer connection points), since more accurate measurement tools (here GridEye cells) can be placed at more central and strategical points of the network. Practically, there are three points where physical dimensions permitted to place GridEye cells (green squares in Fig. 1) in this grid.

Load and production profiles

One of the studied uncertainty source comes from the measurements sampling period and is closely linked with the dynamic of the system state. Simulations have to consider not only one load case, but also loads and productions profiles during the day. Load profiles are generated with the tool called *loadprofilegenerator*, presented in [9], for the 157 end customers, with one point per minute. Accurate measurements are available at the secondary side of the MV/LV transformer (cf. Fig. 2) with one point every ten minutes. The 157 generated load profiles are then weighted and interpolated in a way that their sum matches the total power measured at the secondary side of the transformer, respecting conditions (1) and (2). Finally, these 157 profiles are aggregated into 40 main connection points (MCP), considering the information about the number of end consumers per main connection point (cf. Fig. 2) and respecting conditions (3) and (4).

$$P_{TOT} = \sum_{i=1}^{157} P_{Customer,i} \quad (1) \qquad P_{TOT} = \sum_{i=1}^{40} P_{MCP,j} \quad (3)$$

$$Q_{TOT} = \sum_{i=1}^{157} Q_{Customer,i} \quad (2) \qquad Q_{TOT} = \sum_{i=1}^{40} Q_{MCP,j} \quad (4)$$

For the production profiles, the Liu-Jordan model, already integrated in PowerFactory environment, is used considering meteorological data history at the closest station and the geographical orientation of each PV panel.

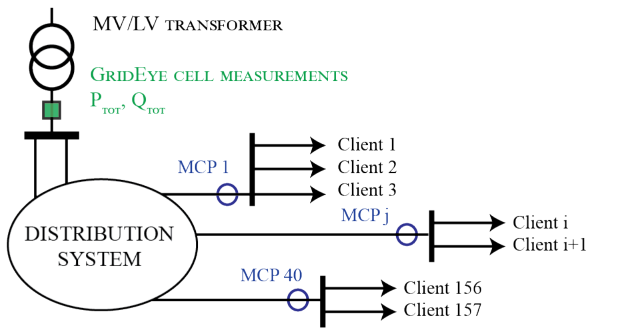

Fig. 2: Aggregation of main connection points and end customers

Measurement devices

New generation smart meters (Landis+Gyr E450) are considered to evaluate the state estimator performances. These devices are certified with the accuracy class 1 (IEC), which means that the accuracy of the energy measurements is 1%. These tools can measure the power transit, as well as the voltage module, at the node where they are placed. The types of measurements and the accuracies considered for smart meters are summarized in Table 1.

Table 1: Accuracies considered for smart meters

Measurement	***Accuracy***
Voltage module	2%
Injected/consumed active power	1%
Injected/consumed reactive power	1%

GridEye cells are more accurate tools than smart meters. Equipped with a GPS synchronization, this tool can measure accurately the voltage angle, as well as three power flows in the branches that are adjacent to the node where they are placed. The types of measurements and the accuracies considered for GridEye cells are summarized in Table 2.

Table 2: Accuracies considered for GridEye cells

Measurement	***Accuracy***
Voltage module	0.1 %
Voltage angle	0.1 %
Branch currents (max. three branches)	1%

METHOD

The method used to evaluate the state estimation performance, illustrated in Fig. 3, consists in the comparison between results of power flow calculations executed with the PowerFactory® software, considered as the true values, and the results of the state estimator, implemented in the MatLab® environment. The network model is provided to both the power flow environment and the state estimator. Load and production scenarii feed PowerFactory and only the results corresponding to the measurements of smart meters and GridEye cells are transmitted to the state estimator. Therefore the PowerFactory simulation is a proxy for the measurements made in the real network after the deployment of the smart meters. After a data processing to introduce simulated uncertainties, the measurements feed the estimator and the estimated results are compared with the power flow results, considered as true.

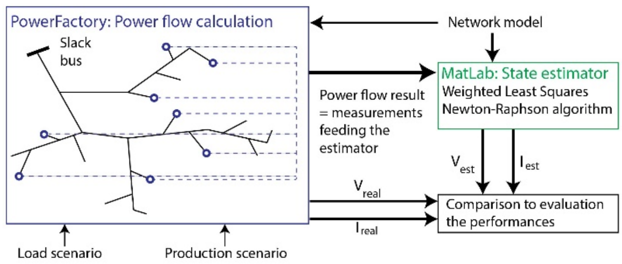

Fig. 3: Performance evaluation method

Performance criteria are defined based on the node voltage and the branch current estimation errors, expressed by (5) and (6).

$$e_{V,i} = V_{est,i} - V_{real,i} \quad (5) \qquad e_{I,j} = I_{est,j} - I_{real,j} \quad (6)$$

Where $e_{V,i}$ is the error between the voltage considered as the true value $V_{real,i}$ at node i and its estimated value $V_{est,i}$, since $e_{I,j}$ is the error between the current considered as the true value $I_{real,j}$ in branch j and its estimated value $I_{est,j}$. For N nodes, the mean average voltage error MAE_V and the maximal voltage error max_V are determined using (7) and (8), respectively.

$$MAE_V = \frac{1}{N}\sum_{i=1}^{N}\|e_{v,i}\| \quad (7) \qquad max_V = \max(\|e_{v,i}\|)_{i=1}^{N} \quad (8)$$

For B branches, the mean average current error MAE_I and the maximal current error max_I can by determined using (9) and (10), respectively.

$$MAE_I = \frac{1}{B}\sum_{j=1}^{B}\|e_{I,j}\| \quad (9) \qquad max_I = \max(\|e_{I,j}\|)_{j=1}^{B} \quad (10)$$

RESULTS AND INTERPRETATION

Effect of the measurement uncertainty

Measurement uncertainties are emulated by the introduction of a Gaussian distribution of error, with a standard deviation corresponding to the accuracy values exposed in Table 1 and Table 2 for smart meters and GridEye cells, respectively. The estimation is repeated 100 times for 40 different instants of the day, and the repartition of the voltage mean error of each node is exposed at Fig. 4.

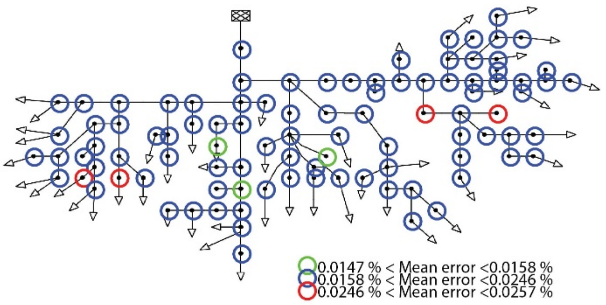

Fig. 4: Repartition of the voltage mean error of each node due to measurement uncertainty.

Globally, these uncertainties induce a maximal voltage error raising 0.3% of the rated voltage and the maximal current error goes up to 3.7% of the rated current of the line, which is considered as an acceptable accuracy performance in terms of congestion monitoring.

Effect of the used dataset

Communication channels, especially PLC, have baud rate limitations and only the most relevant data has to be transferred from meters to the central system. Hence, DSOs want to know which dataset is the most suitable to feed a state estimator. Performance defined by formula (5) to (10), are exposed for twelve datasets at Table 3, and each dataset has been used for 50 estimation repetitions at eight different instants in the day.

From these results, two main findings can be highlighted: smart meter voltage module measurement and GridEye cells phase measurement does not improve performances significantly, since the implied massive transfer risks to congest the communication channel and to increase the computing time of the WLS SE algorithm drastically.

Table 3: Resulting performance for twelve different datasets

	Dataset, smart meters	Dataset, GridEye cells	max_I [%I_N]	MAE_I [%I_N]	max_V [%U_N]	MEA_V [%U_N]
A0	P_{inj},Q_{inj},$\|V\|$	-	2.3	0.15	0.14	0.020
A1	P_{inj},Q_{inj},$\|V\|$	$\|V\|$	3.9	0.14	0.19	0.015
A2	P_{inj},Q_{inj},$\|V\|$	$\|I\|$	4.0	0.13	0.17	0.012
A3	P_{inj},Q_{inj},$\|V\|$	$\|V\|$, $\|I\|$	3.1	0.13	0.16	0.012
A4	P_{inj},Q_{inj},$\|V\|$	$\|V\|$,$arg(V)$	4.3	0.14	0.17	0.015
A5	P_{inj},Q_{inj},$\|V\|$	$\|V\|$,$arg(V)$,$\|I\|$	3.6	0.13	0.20	0.012
B0	P_{inj}, Q_{inj}	-	4.2	0.14	0.16	0.016
B1	P_{inj}, Q_{inj}	$\|V\|$	4.0	0.14	0.20	0.015
B2	P_{inj}, Q_{inj}	$\|I\|$	3.6	0.13	0.14	0.012
B3	P_{inj}, Q_{inj}	$\|V\|$, $\|I\|$	3.8	0.13	0.16	0.012
B4	P_{inj}, Q_{inj}	$\|V\|$,$arg(V)$	3.8	0.14	0.18	0.015
B5	P_{inj}, Q_{inj}	$\|V\|$,$arg(V)$,$\|I\|$	3.3	0.13	0.18	0.012

Effect of the sampling period

Smart meter data is typically transmitted to the central system as energy indexes for every 15 minutes interval. From this data, the estimator could be fed with values of active and reactive powers which are averaged on a period of 15 minutes. Based on the generated profiles described above, the performances of a DSSE fed with instantaneous values (cf. Fig. 5) and with averaged values (cf. Fig. 6) are compared. These simulations are executed considering the dataset B0 defined in Table 3.

Fig. 5: Accuracy for instantaneous measurements

When fed with averaged values, the SE performance depend on the dynamic of the network: at several instants in the day (for example around midday), modification of the load and production profiles imply significant deterioration of the SE performance.

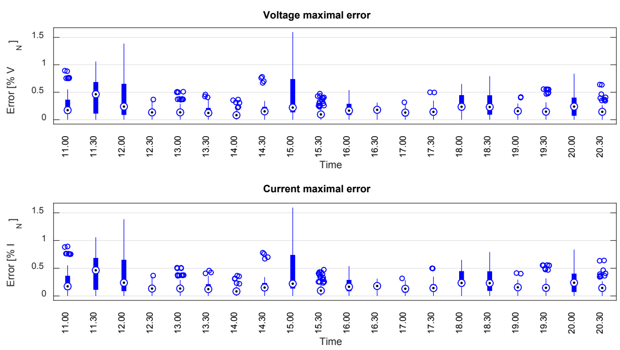

Fig. 6: Accuracy with a sampling period of 15 minutes

Effect of the penetration rate

The penetration rate is defined by the ratio between the number of considered smart meters and the number of nodes at the extremities of the radial network. The minimal penetration rate of meters can be evaluated to obtain a minimal accuracy performance in 95% of the cases. The benefits of more accurate measurement devices have been determined for different cases: eight snapshots and one hundred pseudo-random combinations of meters placements for each penetration rate for both the following cases: (1) without GridEye cells in nodes; (2) when GridEye cells are installed at the three possible places in the network. The resulting performance, summarized in Fig. 7, can be used directly for DSO decision making: ensuring a maximal voltage error of 1% in 95% of the cases involve a penetration rate higher than 87% when no other measurement device is implemented in the grid. With three GridEye cells installed at the available LV cabinet in this network, this rate is lowered to 64%. The current evaluation accuracy is influenced similarly. In all the simulated cases, it is assumed that the reference voltage, defined at the secondary side of the transformer, is known.

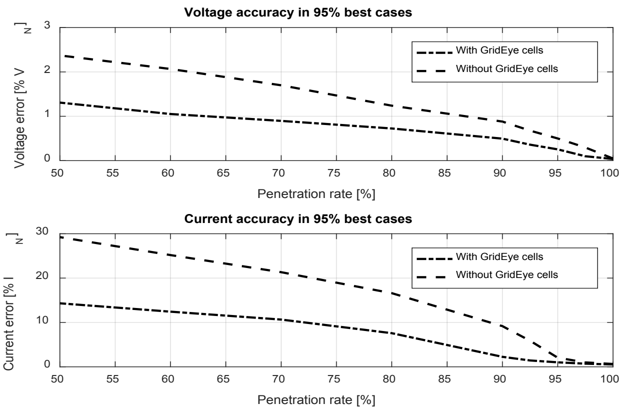

Fig. 7: Evaluated performance evolution with the smart meter penetration rate

PERSPECTIVES

The simulations and results presented in this study indicate that state estimation, especially when data from several measurement systems is combined, can yield valuable information for the network planner and operator. However, practical factors like data throughput, accuracy and synchronism require high effort to be addressed. For this reason, attention will next be paid to other possible usage scenarii for smart metering data without the need for state estimation. These possible usage scenarii include outage management (identification and location / affected area of an outage), offline analyses carried out with historical data and the use of on-event alerts for specific power quality or outage related issues. The last and final step will be the demonstration of the selected features in the real-world demonstration area currently set up by Romande Energie and its partners.

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