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REEL Demo – Romande Energie ELectric network in local balance Demonstrator

Deliverable: 3c Validation of the use of smart meter measurements for grid analysis

Demo site: Rolle

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1. Description of deliverable and goal

1.1. Executive summary

State estimation is used in high-voltage networks as a real-time network analysis method to convert measurement data into network operating points. As an established method in the high voltage networks, this work process aims to expand this method for the low-voltage networks.

State estimation is a mathematical optimization process, which produces expected outputs based on provided inputs. As such, the aim is to minimize the error between the produced outputs and the provided inputs, which are the measurement points within the network. By establishing the connections between the network parameters, the optimization formula aims to minimize the difference between expected and provided outputs. This procedure is typically a non-linear optimization.

The main outcomes of this deliverable are summarized below:

1. **Development of a linear state estimation method for the low-voltage grid**. The main goal of this work is to overcome the non-linearity and its ensued problems, by developing a linear state estimation method for the low-voltage grid. To further enhance the computation time, a network reduction algorithm is also implemented, which reduces the network size. This aids in also visually understanding the network and its respective outputs.
2. **Operation under different measurement device unit inputs**. To acquire state estimation outputs, GridEye devices and smart meters are necessary, since smart meter only provide the aggregate energy consumption outputs of the three phases. The device incompatibility between devices of different timeframes is tackled. Also, since GridEye devices contain per-phase information, distribution of smart meters into per-phase consumption, as well as estimating the reactive power consumption of every smart meter device, is achieved.
3. **Acquiring higher-resolution outputs based on GridEye devices**. The provided measurements are on different timeframes, thus, an algorithm to adjust measurements of the lower resolution and quality smart meters towards the GridEye devices is developed. High-quality 10-minute state estimation outputs are produced.

State estimation methods have specific input requirements. Nevertheless, if more data are available, the state estimation method produces higher quality and more reliable outputs. For the developed method, the minimum requirements are:

- Network topology and parameters including cable resistance, reactance, susceptance, cable nominal capacity.
- Smart meters (node location and consumptions). Smart meter measurements consist of aggregated measurements at different points of the network. Due to privacy issues, there are some aggregated smart meters, whose provided location is instead a cabinet. This serves as a method to provide the total consumption data, while hiding the nodal location of individual consumers at nodes. The smart meter consumptions are provided as an aggregate for the three phases. Measurement availability is 15 minutes.
- GridEye device information at transformer level (node location, voltage, current and active/reactive power). GridEye measurements are provided by default every 10 minutes, although it is configurable.

The test network is the city of Rolle, where GridEye and smart meters devices are both deployed. The validation process comprises of direct comparison with the respective power flow outputs within the same network.

In addition to these activities, DEPsys has collaborated with HEIA-FR and Romande Energie to study and develop an efficient method for fault localization in LV grids using smart meters and GridEye. The results of this work are not presented in this

1.2. Research question

The main research question addressed in this work is to make use of existing smart metering data for analysis of low-voltage network. The outcomes of the developed state estimation algorithm for the low-voltage network are evaluated.

This work addresses the applicability of state estimation for cases of aggregated smart meters. The aggregated smart meters can be categorized into two groups: i) aggregated smart meters retaining their original location and ii) aggregated smart meters whose provided locations are different from their original position, which serves to ensure customer’s privacy. This procedure does not affect the total energy consumption of the network and is done by the smart meter data provider.

This assessment also provides insights on state estimation under multiple data sources of different timeframes. Finally, the importance of higher-resolution outputs, based on the timeframe of the device of the higher-resolution, is appraised. As such, neglected spikes due to lower-resolution measurements, can be noted numerically and visually.

1.3. Novelty of the proposed solutions compared to the state-of-art

The importance of state estimation in the operation of the power system led to research in its advancement towards the distribution grids. Currently, there are various state estimation methods. The method of choice depends on the measurement availability, provided data type of measurements and the desired optimization method. The typical method of state estimation consists of a non-linear weighted least-square optimization, where a linearization process is necessary. At this linearized point, a Newton-Raphson procedure produces outcomes, which depend on the pre-set convergence criteria. Thus, the iterative procedure is not only computationally costly, but also potentially non-converging.

This work presents an alternative method for state estimation, where the outcome is produced linearly, without requiring further data inputs than the typical method would require. This is achieved by a reformulation of the states of the network. The optimization is still a weighted least square optimization, but the process becomes a series of matrix multiplications, instead of an iterative single-point solution. Moreover, since the optimization matrix contains network topology and parameters information, it only requires partial update for every timestamp, instead of a new matrix formulation per linearized point for every timestamp.

Moreover, this work sets the basis for acquiring higher-resolution measurements from lower-resolution ones from different measurement device units. Thus, every device can collaborate to produce outputs, based on the outputs of the GridEye device on the transformer level.

The outcomes of this method are validated using field measurements provided by GridEye and smart meter measurements in a low-voltage grid of Rolle.

1.4. Description

Power systems are becoming more dynamic and distribution grids will play a bigger role in the future, due to the vital part of distributed generation in the total energy production. This shift is bound to be bigger in the future and adaptations are necessary for all the responsible parties. Thus, energy market-related functions, which are produced typically by the outputs of state estimation algorithms, are gathering more traction.

State estimation provides valuable insights about the network's operating conditions. The produced outputs are typically voltage and current values for all nodes and branches within the network. These outputs are the basis for other functions that operators use, since energy models and network applications outputs are yielded by the products of state estimation.

For the high and medium voltage network, the inputs are usually the SCADA outputs. This is different to the low-voltage one, where the measurement availability is scarce and less accurate. The adaptation towards the low-voltage network requires smart meters.

Originally, state estimation is an iterative process, that tries to minimize the objective function within a linearized point by a Newton-Raphson solver. Developed for the higher voltage network, which contains more measurement units than the LV one, its advantages lie in cases of high measurement redundancy. The non-linear procedure has two inherent problems. First and foremost, the computation time is quite higher than any linear solver. Moreover, convergence is not always ensued for cases where iterations are required.

The developed method relies on reformulation of the states. This reformulation requires more measurements to achieve observability. These additional measurements aid to build a linear reformulated matrix. Nevertheless, by smartly creating assumptions on some of the measurements, the observability conditions are met without requiring additional measurements or imposing any issues in the quality of the outcomes. To achieve this, low weights to the assumed measurement points are induced, that overall do not hinder the algorithm's performance. As mentioned, state estimation operates better with more measurements available, nevertheless, can still produce quality outputs at cases where observability condition is met. The available devices in the network are GridEye devices and smart meters. The collaboration between these measurements is necessary to produce high-quality outputs. GridEye are installed devices at MV/LV transformer and some LV cabinets. These provide quality information every 10 minutes, regarding the voltage, the current and power consumptions per phase.

Thus, the balance between the phases is depicted, which is useful for acquiring insight about the smart meter allocation within the network.

Smart meter measurements are also provided, which indicate the location of installation and their energy consumption on a 15-minute time frame basis. The provided consumption is the three-phase consumption. Smart meters are categorized into two different groups, one containing smart meters whose node position is correctly provided and another group, which instead provides aggregated smart meter data at cabinet positions. For clarification, the aggregated smart meters whose provided location is a cabinet are indicated as 'FDR', while aggregated smart meters who retain their original position are indicated as 'BRP'. This is done to simplify the annotation of the smart meters and to visually comprehend the provided inputs in a graph. This differentiation between the smart meter groups is shown in Figure 1.

Since GridEye outputs are higher-quality and resolution than the smart meters, they are vital to the state estimation. GridEye devices constitute the basis for acquiring the smart meter's consumption of active and reactive power per phase. Since smart meter provide energy consumed for the summation of the three phases, GridEye power consumption per phase provide an indication of the per phase consumption, as well as accurate reactive power consumption estimations.

Additionally, this work tackles the issue of multiple timeframes of provided data. Since GridEye measurements and smart meter measurements are provided every 10 and 15 minutes respectively, the common approach would be to run state estimation for the common timeframe of 30 minutes. This work, thus, focuses on acquiring high-resolution 10-minute outputs, by correlating the total of aggregated smart meter inputs to the GridEye device installed on the transformer. This way, smart meters consumptions are not only correlated to the correct phase, but they can be used in the 10-minute window of the GridEye devices. This adaptation provides voltage and current peaks and spikes, which would otherwise be unnoticeable.

The network of the test case is shown in Figure 1. Originally, the network constitutes of 143 nodes. Initially, 176 smart meter devices are installed in the network, distributed within 41 nodes. Since smart meters represent customer consumption, many smart meters can be aggregated to specific nodes. As such, 134 of the smart meters are distributed within 15 nodes as smart meters aggregated at their existing node (BRP). The rest of the smart meters are aggregated in the 3 cabinets and transformer nodes, to ensure privacy of the customers (FDR). These contain aggregated data of smart meters in different locations, which are aggregated to an artificially created node within the network.

After the reduction process, 27 nodes are fully able to describe the network, in which 18 are nodes of consumption. The reduced network, containing the outcomes of state estimation, is illustrated in Figure 2.

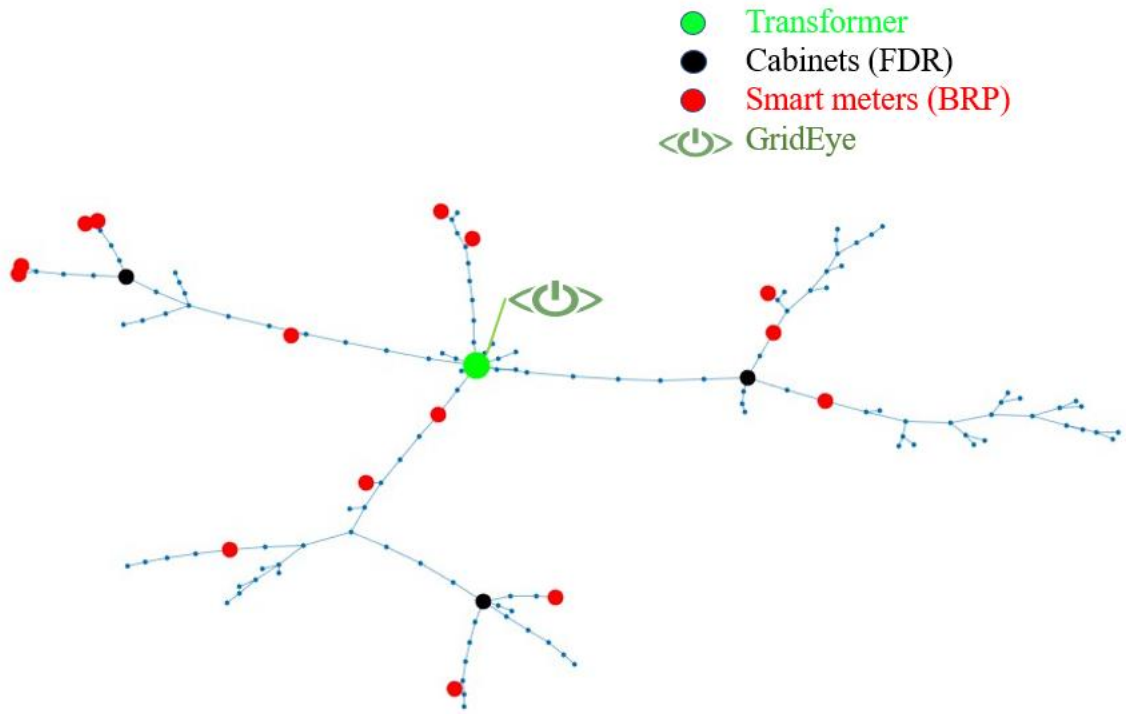

Figure 1. Test case network and positions of various measurement devices.

2. Achievement of deliverable:

2.1. Date

This work is accomplished during 2018 and 2019.

2.2. Demonstration of the deliverable

The main outcome of the analysis is the combination of data provided by different measurement systems. The outcomes almost perfectly match the inputs provided in the state estimation (highest error is 0.0016V or 0.0006% for node voltage and 0.02A or 0.017% for branch current). Even when noise is manually introduced based on the levels of trust of the GridEye device, the output error does not exceed the introduced error. The computation time is faster for the linear state estimation compared to the power flow, as typical power flow is iterative.

The outputs of state estimation are visualized in Figure 2, where the branch current with respect to the nominal line current of each line is depicted, as well as the voltage for the nodes. This figure shows the results for one specific timestamp and is used to visualize the outcomes of the method.

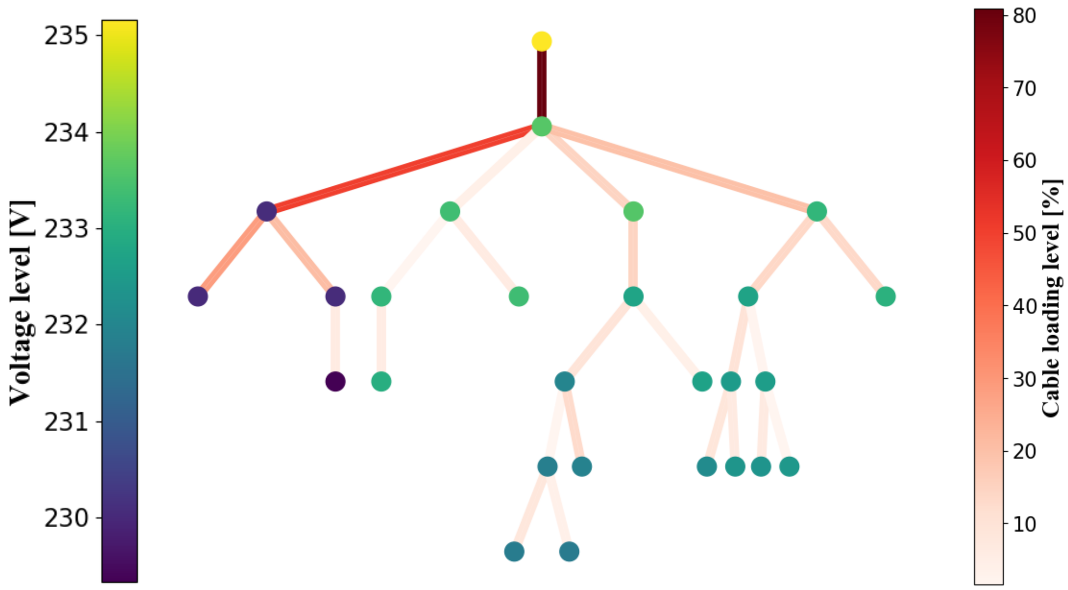

Figure 2. State estimation voltage and current outputs

Moreover, instead of using only the common-time frames of the measurement devices (every 30 minutes), another goal is to provide deeper insight based on provided measurement data by the GridEye timeframe (10 minutes). By assuming consumed power as a uniform distribution, higher-resolution estimates are achieved. The advantages of higher-resolution state estimation lie in acquiring the network's operating conditions. This can be noted in Figure 3, where the 10-minute state estimation is more insightful, as some voltage and current peaks would be unnoticed otherwise. Figure 3 consists of estimated outputs for one node, which represents several smart meter devices, for both voltage and current.

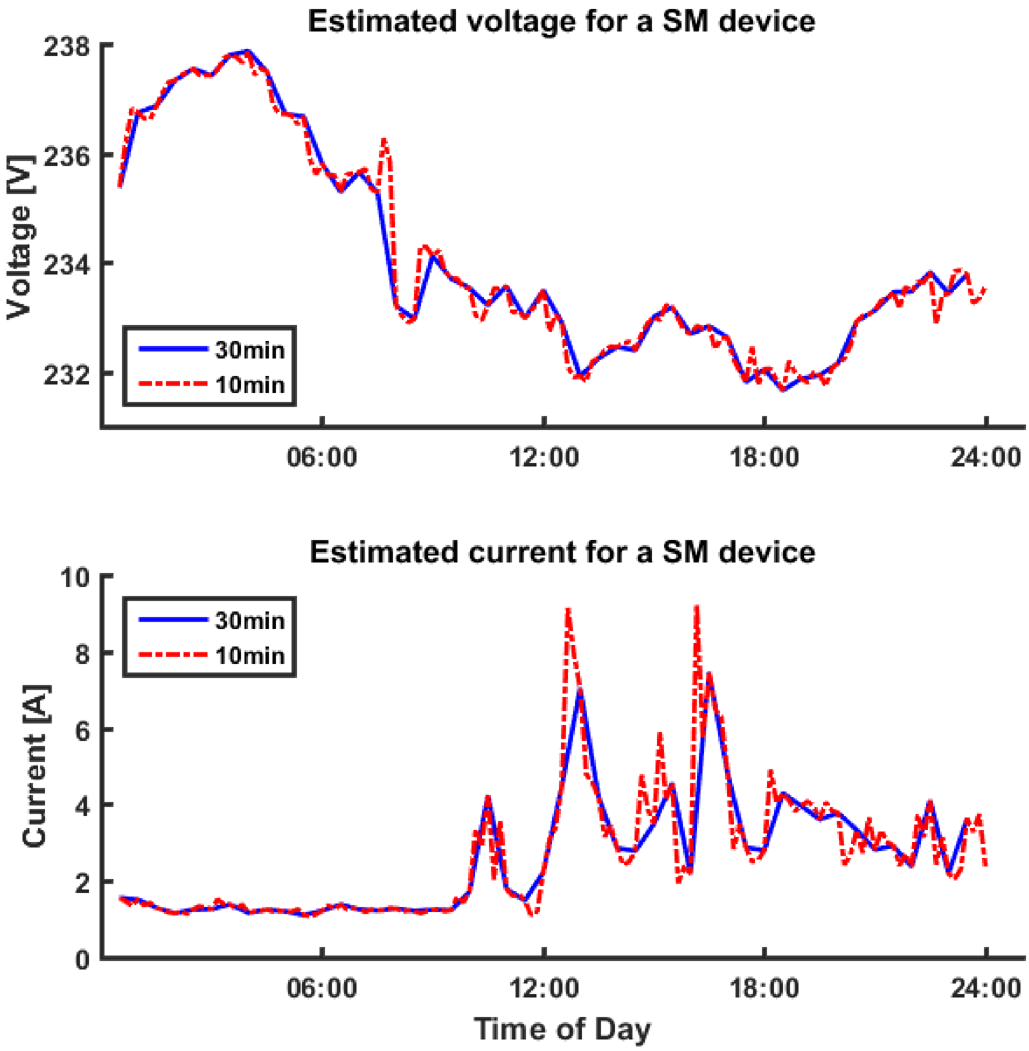

Figure 3. Estimated voltage and current of a smart meter device for different time-resolution within a day

3. Impact

The results of this deliverable show how to make use of smart metering data along with grid measurements for the analysis of low voltage networks and monitoring of its secure and safe operation.