Real-time Measurements and their Effects on State Estimation of Distribution Power System

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Abstract—This paper aims at analyzing the potential value of using different real-time metering and measuring instruments applied in the low voltage distribution networks for state-estimation. An algorithm is presented to evaluate different combinations of metering data using a tailored state estimator. It is followed by a case study based on the proposed algorithm. A real distribution grid feeder with different types of meters installed either in the cabinets or at the customer side is selected for simulation and analysis. Standard load templates are used to initiate the state estimation. The deviations between the estimated values (voltage and injected power) and the measurements are applied to state estimation. The deviations between the estimated values (voltage and injected power) and the measurements are applied to state estimation. Eventually, some suggestions are provided for the distribution grid operators on placing the real-time meters in the distribution grid.

I. INTRODUCTION

The challenges introduced by the increasing integration of Distributed Energy Resources (DERs) and new components, push forward the necessity of additional real-time monitoring system (referring to the concept that the operation states are updated frequently comparing to the original energy billing system) in the distribution grids, especially in low voltage level (LV). Conventionally, the Distribution System Operators (DSOs) use Velander Correlation to estimate the peak load, given the load templates (i.e., pseudo inputs). Appareently, these challenges cannot be sufficiently handled via this method. The DSOs are facing a trade-off problem between the visibility of the grid with a large quantity of active units (new patterns) and the investment on metering system. To improve the grid visibility, several key factors need to be addressed:

- **Customer side smart meters**: The smart meters are installed at the customer side to enable the hourly billing. Average power in hourly (or higher) resolution is measurable. In some advanced meters, voltage and reactive power can be measured as well. For political reasons, a large scale roll-out is anticipated in the near future.

- **Remote meters on grid side**: Similar to the solution in the transmission grid (as well as some MV distribution grids), the remote meters are installed in the substations and some special nodes. Three-phase voltage, current, and power injection can be measured in hourly (or several-minute) intervals. Compared to the smart meters, they are much more expensive.

- **Pseudo measurements**: In unobservable areas or without any measuring points, the estimation will fully depend on the existing knowledge of the grid (i.e., pseudo measurements, like historical data, load templates, nominal voltage value, average power factor, etc.). A better estimation result can be obtained if the pseudo measurements are improved.

- **State estimation method**: Given the above inputs, DSOs can apply the state estimation (SE) to obtain the best approximation of the operation states. However, due to the unique features of the LV grid (i.e., a huge number of nodes, radial topology, non-ignorable resistance of the cables, etc.), the traditional estimation algorithm (e.g., method introduced in [1]) is not applicable for the distribution grid estimation. The methodology has been improved by taking into account the features of the distribution grid in [2] and [3], i.e., the pseudo measurements with around 20% uncertainty are considered as a complementary set for SE, and a three phase asymmetrical grid model is used. Furthermore, some advises are provided on placing the meters for grid operation [4]. Paper [5] studies the influence of smart meters with advanced features onto SE and suggests on the optimal positions considering the grid features and the numbers of meters. However, new problems arise, if the state estimator inputs consist of a flexible combinations of pseudo data, real measurements, which vary temporally and spatially, or if the measured objects delivered from different sources are different from each other in terms of voltage, power, etc. Thus, a valid state estimator is necessary to enable the evaluation of different metering portfolios, to maximize the potential values of various metering options.

Hence, an evaluation procedure is proposed for the accuracy of the estimation with respect to the number of meters and their locations in the grid. In this procedure, a tailored state estimator is developed and used.

II. EVALUATION ALGORITHM

A. Evaluation Procedure

To calculate the level of accuracy of the distribution grid SE, using certain portfolios of limited numbers of meters, simulations are conducted, following Fig. 1. The block “Traditional state estimation” indicates the current knowledge on the distribution grid from the DSOs, including the information...
Fig. 1. The evaluation procedure (Area 1: the reference case; Area 2: the designed cases for measurements, i.e., certain portfolios of measurements; Area 3: comparison and analysis).

of annual billing-data and a 24-hour load template, estimated on the basis of consumer type. Based on the comparisons of various cases, i.e., different sets of available measurements, the relation between the numbers of meters or different locations are analysed by statistical approaches. The accuracy level is given by the following equation:

\[
\text{accy} = \frac{1}{n} \sum_{i=1}^{n} \left| \text{err}_{\text{trad},i} - |\text{err}_i| \right|
\]  

(1)

where, \(i\) is the index of the selected state variables, and \(\text{err}\) is given by SEs compared to the real states. \(\text{err}_{\text{trad},i}\) gives the reference value of errors for the evaluation by following the procedure described by Area 1 in Fig. 1. \(\text{err}_i\) represent the errors when a certain portfolio of measurements are involved in the estimation (Fig. 1 Area 2). Thus, the designed portfolios and the corresponding meters can be evaluated as in Area 3.

B. State estimation (SE) Approach

Within the proposed evaluation procedure, the tailored SE approach is designed and used for the simulations (see Fig. 2). The approach allows the possibility of several data sources for SE. Before running the simulation, the data are matched with the lowest sampling time, and the possible time drift is checked with redundant values. The measurement set consists of two subsets: the real measurements (e.g., power flow information, voltage magnitudes and angles), and the pseudo measurements (e.g., load templates, predefined power factor). In the first step, the load profiles are updated if the corresponding measurements are available. The weighting factors in SE are decided by the specification of the measurement uncertainty in the technical sheets.

In the second step, the hybrid backward-forward power flow (see Fig. 3) is conducted based on the available information. The LV feeder is usually in a radial topology. Thus, the backward-forward method [6] can be applied. This hybrid backward-forward method can converge very fast in the first few iterations, and is not sensitive to the initial values and the starting point. By using this method, the pseudo measurements in the unobservable areas can be adjusted according to the available information, i.e., the errors of the pseudo measurements is reduced. This step provides good initial values for the later estimation.

Similar to the traditional SE algorithm, voltage, current and power could be regarded as the estimation variables. If there are some redundant measurements to minimize the errors, SE is applied. In the third step, by minimising the errors between the available measured value and estimated value using Weighted Least Square (WLS) method, the program will update the SE results. The objective function is as follows:

\[
J(x) = (z - H(x))^TW(z - H(x))
\]  

(2)

where

- \(z\) is the measurement vector;
- \(x\) is the state vector;
- \(H\) is the transformation matrix, containing the linearised relations in power flow;
- \(W\) is the weighting factor matrix, determined by the estimated uncertainty of the measurements, i.e., relative accuracy. Different combinations of available measurements are provided for the calculations. Subsequently, the errors, as compared to the "Real state" (Fig. 2), are further assessed.
A. Network topology

The test network is a real LV feeder in Denmark [7]. It consists of 13 nodes, 69 customers (involving 7 customer types), and 3 PV systems. The nominal line-line voltage is 0.4kV. The topology is shown in Fig. 4. Two sources of the measurements are investigated in this paper: remote meters in the cabinets and smart meters at the customer side. Among these 13 nodes, 5 remote meters are installed in the cabinets; the smart meters are installed at all customers’ residence; and 5 additional smart meters are installed in the terminal nodes to measure the voltage. All the lines are underground cables with certain properties. The total length of the cables is 840 m.

B. Measurements

The remote meters measure three phase voltage magnitude, current magnitude, and active power flow. The data is logged in the database by sending SMS every 10 minutes. The smart meters deliver the average active power on hourly basis (three phases in total) via wireless internet. The additional 5 smart meters log the three phase voltage in 10-minute intervals. Currently, separate databases and different formats are used to store the measurements. One-day measurements (18th April 2013) are used in the following simulations.

The missing rate of the remote meter data is around 1% – 10%, but the missing strings are seldom consecutive. The missing rate of smart meters is very low. The valid range of current values in the remote meters is 2.5A to 400A, which also affect the power measurements. The uncertainty of the measurements are listed as follows:

- Remote meters: ±2%;
- Power measurements from smart meters: ±1%;
- Voltage measurements from smart meters: ±5%.

Accordingly, the weighting factor of values used in SE should be chosen depending on the data source.

C. Pseudo measurements

When the information is not sufficient to support SE, the pseudo measurements are involved in the calculations. TABLE I lists several pseudo measurements.

A notable issue while doing the simulations is that the measured active power is much less than what is assumed in the load templates. Fig. 5 shows the real measurements and the template values of a certain load category. Apparently, the error is very large and varying significantly (which violate the hypothesis in the normal SE approach [2] and [3]). By comparing the real and pseudo measurements, it is concluded that the errors in the weekends are larger. To accommodate such pseudo measurements, the SE approach should be robust to avoid non-convergence.

D. Scenarios

To evaluate the effect of different combinations of available real-time measurements, several scenarios are defined based on the set-up stated as above:

Sc. 1 Reference scenario: using only pseudo measurements;
Sc. 2 Full observation: using all collected measurements;
Sc. 3 Power measurements from all smart meters available with one additional voltage measurement from either Node 1 (3a) or Node 3 (3b) as the reference voltage (the measurements from different metering types);
Sc. 4 Power + voltage measurements on a single node (i.e., 2, 3, 5, 6, 7, 9, 11, 12, 13) available (4a – 4i, respectively);

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pseudo Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage</td>
<td>nominal value 230V</td>
</tr>
<tr>
<td>Active power</td>
<td>load template –</td>
</tr>
<tr>
<td>Power factor</td>
<td>constant value 0.95</td>
</tr>
</tbody>
</table>

Fig. 5. The load template vs. real measurements
TABLE II
THE PORTFOLIO OF MEASUREMENTS IN EACH SCENARIO

<table>
<thead>
<tr>
<th>Sc.</th>
<th>Remote meter (Power-flow)</th>
<th>Remote meter (Voltage)</th>
<th>Smart meter (Power)</th>
<th>Smart meter (Voltage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>2</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>3a</td>
<td>–</td>
<td>Node 1</td>
<td>All</td>
<td>–</td>
</tr>
<tr>
<td>3b</td>
<td>–</td>
<td>–</td>
<td>All</td>
<td>Node 3</td>
</tr>
<tr>
<td>4</td>
<td>Single node (PF + U)</td>
<td>–</td>
<td>–</td>
<td>All</td>
</tr>
<tr>
<td>5</td>
<td>–</td>
<td>–</td>
<td>All</td>
<td>–</td>
</tr>
<tr>
<td>6</td>
<td>All</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Sc. 5 All measurements from smart meters are available; Sc. 6 All measurements from remote meters are available. The scenarios are summed in TABLE II.

IV. RESULTS AND ANALYSIS

A. Effect of the types of measurements

Fig. 6 shows the modified power flow results (i.e., the injected power and the voltage). The two plots on the left show the values at each bus in Hour 1, and the two plots on the right show the values at the connecting point (Node 1) in each hour. The huge difference between the load templates and the real power consumption leads to a large difference in the injected power values comparing Sc. 1 and Sc. 3, which may lead to problems on plausibility and observability or biased estimation result. However, the shape of diurnal variation is similar. The real values is about 20% of the template values for all customers. Thus, the load templates need to be modified to obtain a reasonable prediction of the load consumption. This error significantly affects the accuracy level of the feeder’s SE, not only on the injected power but also on the voltage (see Fig. 7: Sc. 1, Sc. 3a, and Sc. 3b).

The voltage drop along the feeder is reduced in Sc. 3 because of less power flow in the feeder. The voltage magnitudes depend mainly on the one and only voltage measurement, i.e., voltage on Node 1 (Sc. 3a) and on Node 3 (Sc. 3b). It replaces the pseudo measurement (the nominal value as 1 p.u.) on Node 1 as a reference voltage to derive the remaining node voltages. Since the voltage values on Node 1 and Node 3 are from different sources, the results show a large difference between Sc. 3a and Sc. 3b. The accuracy of the voltage estimation is strongly dependent on the available voltage measurement, as there is no redundant measurement in these scenarios. Comparing the accuracy level of the voltage in Fig. 7, it is obvious that the estimation result is biased by the less accurate voltage value on Node 3.

B. Effect of the position of measurements

In Sc. 4, the meters (with voltage and load) are assigned to the selected nodes one by one. In Fig. 7 it is observed that if the load size is larger, a higher improvement is achieved. The accuracy level of the injected power obtains 8% point improvement with one meter installed in the feeder, whereas the accuracy level of the voltage is improved approximately 15% point. The improvement of accyU is due to two reasons: less power loss led by the updated load, and the available voltage measurement. Comparing the sub-scenarios in Sc. 3, it is seen that a higher accuracy is obtained if the node with meters is in the beginning of the feeder.

C. Smart meter vs. remote meter

Fig. 8 shows the simulation results of Sc. 5 and Sc. 6, where two types of meters with different measuring specifications...
and locations (Fig. 4) are used. The difference of the voltage estimates is almost constant along the feeder and in time, while it is not the same for the injected power. This phenomenon indicates that there might be calibrating errors, which can be simply removed by recalibrating the meters. There would be a big risk for voltage regulation solutions if such errors exist. Looking at the accuracy level of Sc. 5 and Sc. 6 in Fig. 7, the same results can be derived. By having all of measurements available, a better estimation can be achieved.

D. Impacts of the metering data

While processing the measurements, some critical issues regarding the metering data are identified, which need to be solved in practice:

- About 4% of the data from the remote meters is missing due to the unstable delivery of SMS service. The missing data is usually not consecutive and, thus, can be estimated from the neighbouring time instants. Otherwise, the corresponding node is regarded as non-measurable.
- The valid measuring range should be adapted to the load or the feeder size, to send effective values to the estimator. The invalid measurements in the remote meters with regard to the current and power, is around 30% (less than 2.5 A) due to the improper measuring range.
- The coordination between different sources could be a risk on SE, not only due to the time step and the accuracy of values, but also due to the reason that SE results may be biased by the less accurate source (e.g., Sc. 5 and Sc. 6). Moreover, the synchronization of the clocks and the calibration of different data sources will lead to the problem of convergence.

V. CONCLUSION

This paper presents to what extent the estimation of the grid operation can be improved by using different types of real-time measurements in the LV distribution grids. With a better estimation of the LV grid states, people can gain some knowledge on the DER behaviours. It also enables the reliable delivery of DER services to the grid. An evaluating algorithm is described to estimate their values in a LV feeder, in which a hybrid SE approach is presented to handle multiple sources of the input values. Different combinations of measurements, obtained from the real test feeder, are implemented in the estimation. The accuracy level for each scenario is calculated. The increasing numbers of meters or more types of measurements improve the overall accuracy of the estimation. The redundant values can help on minimizing the measuring errors. The accuracy of the injected power depends on the error between the available power data and the corresponding load templates used in the estimation. Power factors and the unsymmetrical loads at the measuring nodes also affect the accuracy. A higher accuracy of voltage can be anticipated if the single voltage metering point is placed near the transformer. Different sources of data and data quality are the barriers for the SE approach. In the lack-of-measurement situations, the insufficient data would potentially bias the estimation results. In addition, the load template should be updated to approach the real conditions of the feeder for various purposes (e.g., grid planning).

From the results, it can be suggested that a further pre-processing stage should be embedded in the estimation approach to obtain a robust SE. Based on the fact of the data quality, a method to tune the weighting factor is important for an automatic SE program.

REFERENCES