LV NETWORK STATE ESTIMATION USING DECOUPLED LOAD-FLOW ALGORITHM

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ABSTRACT

This paper presents a novel decoupled method for the power-flow expressions which are used as a part of the state-estimation algorithm at the low-voltage distribution level. The proposed simplifications are based on the particular characteristics of the low-voltage distribution network. The state-estimation results, obtained with the simplified method, are compared to the results of the state estimation with the classical power-flow equations.

INTRODUCTION

As a consequence of the new types of loads, increasing storage and DG penetration, the distribution networks are currently facing a transition from the poorly monitored passive systems towards more observable networks equipped with controllable elements. Thus, some of new functionalities have to be introduced to the distribution networks, one of them being the state estimation (SE). The purpose of the SE algorithm is to use the available imprecise measurements from the network and then calculate estimates of the state variables. Estimator relies on the known network topology and the load-flow equations.

In order to decrease the computational burden of the algorithm and speed up the estimation process, load-flow equations can be simplified, which is an already known procedure from the transmission network (TN). Those simplifications, however, cannot be directly used for the distribution network (DN) load-flow calculation, because of the differences between the two network types.

NETWORK CHARACTERISTICS

Characteristics of the DN, such as element electrical parameters, loading, available measurements…, are considerably different from those in the TN. Dissimilarity level usually increases, as the voltage level of the network under the consideration decreases. Namely, the main difference is in the impedance ratio R/X value, which becomes significant in the DN [1]–[3]. Moreover, the amount of the measurements available in the DN is low and loading is highly unbalanced. DNs usually operate radially (open-loop) and there is also a diversity between the different DN types (say urban vs. rural DN).

STATE ESTIMATION

The most widely used method for the SE algorithm is the classical Weighted Least Squares (WLS) method. Its use for the TN SE was introduced by Schweppe [4]–[6] in the 1970's. The method has proven itself to be reliable and quite fast using the appropriate amount and accuracy of the input data. The method itself and its derivatives were already a subject of a number of different papers [1], [7]–[9], and only crucial information about the method and the SE algorithm itself is to be repeated here.

State Estimator algorithm

The objective of the SE algorithm is to provide realistic estimates of the network state variables. With all the state variables being known, the network state is considered to be defined. The inputs to the SE are the measurements of the network variables (powers and voltages) and the network topology (Ybus, switch statuses). Measurements can be either real (from the network), or pseudo/virtual, which are estimated based on the historical measurements or zero-injection buses.

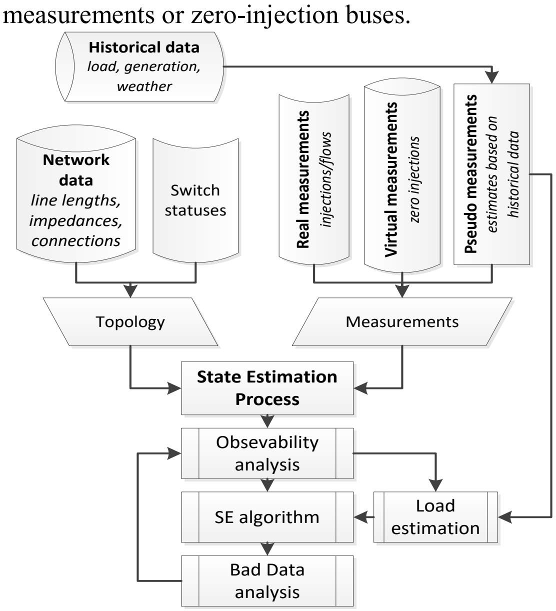

Fig 1: State Estimation functions

The SE process is graphically presented in Fig 1. It consists from different sub-functions, such as topology processor, observability analyser, bad data processor and of course the SE algorithm utilised with appropriate method [10], [11].

The relation between the vector of the network measurements $\boldsymbol{z}$, and the vector of state variables $\boldsymbol{x}$, is given with a following expression:

$$\boldsymbol{z} = \boldsymbol{h}(\boldsymbol{x}) + \boldsymbol{r}, \qquad (1)$$

where $\boldsymbol{h}$ is the nonlinear function determined by the network admittance matrix $\boldsymbol{Y_{bus}}$ and the Kirchoff's laws and $\boldsymbol{r}$ is the residual vector of the measurement errors. Purpose of the SE is the estimation of the state vector $\boldsymbol{x}$ using the chosen method.

WLS method

By utilization of the WLS method the state of the network can be defined by minimization of the following objective function $\mathbf{J}(\boldsymbol{x})$:

$$minimize\colon \mathbf{J}(\boldsymbol{x}) = \boldsymbol{W}\boldsymbol{r}^2 = \boldsymbol{W}\big(\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})\big)^2, \qquad (2)$$

where $\boldsymbol{W}$ is the diagonal matrix of measurements weights defined as the inverse of the measurement variance matrix $\boldsymbol{R}$. The problem is solved iteratively using the following expressions [7]:

$$\Delta\boldsymbol{z}^k = \boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x}^k), \qquad (3)$$
$$\boldsymbol{G}\Delta\boldsymbol{x}^k = \boldsymbol{H}^T\boldsymbol{W}\Delta\boldsymbol{z}^k, \qquad (4)$$
$$\Delta\boldsymbol{x}^{k+1} = \boldsymbol{x}^k + \Delta\boldsymbol{x}^k, \qquad (5)$$

where $\boldsymbol{H} = \frac{\partial \boldsymbol{h}(\boldsymbol{x})}{\partial \boldsymbol{x}}$ is the measurement Jacobbian and k is the number of iteration. The product of the measurement Jacobbian and $\boldsymbol{G}$ is the gain matrix $\boldsymbol{G} = \boldsymbol{H}^T\boldsymbol{W}\boldsymbol{H}$. The iterative process is stopped, when the following condition is fulfilled $|\Delta\boldsymbol{x}| \leq \varepsilon$. A mathematical explanation of the method can be found in [4].

DECOUPLING

The state vector is defined as

$$\boldsymbol{x} = [\boldsymbol{\theta} \quad \boldsymbol{V}]^T, \qquad (6)$$

and the vector of measurements is

$$\boldsymbol{z} = \left[\boldsymbol{P_{ii}} \quad \boldsymbol{P_{ij}} \quad \boldsymbol{Q_{ii}} \quad \boldsymbol{Q_{ij}} \quad \boldsymbol{V_{ii}}\right]^T. \qquad (7)$$

The Jacobian matrix $\boldsymbol{H}$ can then be written as:

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{H_{P\theta}} & \boldsymbol{H_{PV}} \\ \boldsymbol{H_{Q\theta}} & \boldsymbol{H_{QV}} \end{bmatrix}, \qquad (8)$$

and the gain matrix $\boldsymbol{G}$ utilising the same nomenclature as:

$$\boldsymbol{G} = \begin{bmatrix} \boldsymbol{G_{P\theta}} & \boldsymbol{G_{PV}} \\ \boldsymbol{G_{Q\theta}} & \boldsymbol{G_{QV}} \end{bmatrix}. \qquad (9)$$

Algorithm decoupling (decouple the gain $\boldsymbol{G}$ only) neglects the off-diagonal elements of the gain matrix $\boldsymbol{G_{PV}}, \boldsymbol{G_{Q\theta}}$. The expression from (4) then yields the following decoupled estimation algorithm:

$$\boldsymbol{G_{PQ}}\Delta\boldsymbol{\theta}^k = \boldsymbol{\Delta A}, \qquad (10)$$
$$\boldsymbol{G_{QV}}\Delta\boldsymbol{V}^k = \boldsymbol{\Delta R}, \qquad (11)$$

The right hand side of the expressions are as follows:

$$\boldsymbol{\Delta A} = \left[\boldsymbol{H_{P\theta}^T} \quad \boldsymbol{H_{Q\theta}^T}\right]\boldsymbol{W}\Delta\boldsymbol{z}, \qquad (12)$$
$$\boldsymbol{\Delta R} = \left[\boldsymbol{H_{PV}^T} \quad \boldsymbol{H_{QV}^T}\right]\boldsymbol{W}\Delta\boldsymbol{z}, \qquad (13)$$

In a TN solution procedure, $\boldsymbol{H_{PV}}, \boldsymbol{H_{Q\theta}}$ submatrices can be neglected due to the specific characteristics of those networks, namely low values of R/X ratios [3], [12]. Neglecting of the off-diagonal elements in the Jacobian matrix (model decoupling) also simplifies the right hand side expressions (12) and (13) to:

$$\boldsymbol{\Delta A} = \boldsymbol{H_{P\theta}^T}\boldsymbol{W_P}\,[\Delta\boldsymbol{P_{ii}} \quad \Delta\boldsymbol{P_{ij}}]^T, \qquad (14)$$
$$\boldsymbol{\Delta R} = \boldsymbol{H_{QV}^T}\boldsymbol{W_{QV}}[\Delta\boldsymbol{Q_{ii}} \quad \Delta\boldsymbol{Q_{ij}} \quad \Delta\boldsymbol{V}]^T, \qquad (15)$$

The characteristics of the DN are quite different, as already explained also in this paper. Therefore, different assumptions apply to the simplified load-flow equations. This leads to neglecting the $\boldsymbol{H_{P\theta}}, \boldsymbol{H_{QV}}$ and $\boldsymbol{G_{P\theta}}, \boldsymbol{G_{QV}}$ submatrices. Consequently, expression from (4) simplifies to the following decoupled Distribution System State Estimation (DSSE) algorithm:

$$\boldsymbol{G_{PV}}\Delta\boldsymbol{V}^k = \boldsymbol{\Delta A}, \qquad (16)$$
$$\boldsymbol{G_{Q\theta}}\Delta\boldsymbol{\theta}^k = \boldsymbol{\Delta R}, \qquad (17)$$

There is also a difference in model decoupling, when compared to the Transmission System State Estimation (TSSE). Inspection of the values of the Jacobian matrix $\boldsymbol{H}$ shows a higher coupling between $\boldsymbol{P} - \boldsymbol{V}$ and $\boldsymbol{Q} - \boldsymbol{\theta}$ submatrices, which is opposite to the TSSE. Consequently the diagonal values are neglected and the right hand side of the equations (16) and (17) are as follows:

$$\boldsymbol{\Delta A} = \boldsymbol{H_{PV}^T}\boldsymbol{W_{PV}}[\Delta\boldsymbol{P_{ii}} \quad \Delta\boldsymbol{P_{ij}} \quad \Delta\boldsymbol{V}]^T, \qquad (18)$$
$$\boldsymbol{\Delta R} = \boldsymbol{H_{Q\theta}^T}\boldsymbol{W_Q}\,[\Delta\boldsymbol{Q_{ii}} \quad \Delta\boldsymbol{Q_{ij}}]^T. \qquad (19)$$

There is a similarity between these two expressions, when compared to the TN decoupling ones shown with equations (14) and (15).
Besides the decoupling itself, another simplification was introduced into our method. Based on the network impedance ratio, all the imaginary parts of the admittance matrices were neglected. This additionally simplifies the developed algorithm.

SIMULATION NETWORK

For the testing purposes of the developed decoupled method a simulation network model was developed, based on a real unbalanced 3+N-phased Slovenian LV network. The single-line scheme of the modelled LV network is shown in Fig 2.

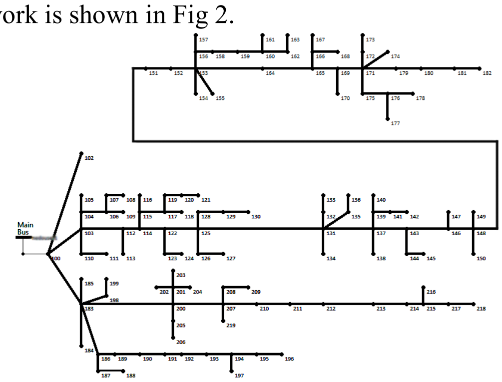

Fig 2: Test network scheme

The network consists of 119 buses and supplies 77 loads.

There are both, 3-phase and single-phase loads in the network.
The model of the network is built in the OpenDSS software which is run as a Matlab routine. Load power injections are defined with Matlab from the database of the real measurements. Network measurements (powers and voltages) are extracted from the OpenDSS simulation and Gaussian noise is added in order to simulate the real network conditions.
No bad data is considered in this case, since only the comparison of the two different power-flow algorithms is of importance, rather than the robustness of the SE algorithm itself. The estimated network voltages are compared with the initial values from the simulation and both methods are compared in terms of the computation time and accuracy.

RESULTS

The outputs from the classical and the decoupled WLS LV SE are compared in this section. Both estimators use active and reactive injections with added noise and some voltage magnitudes as inputs, but no power flow values. All measurements were given a random Gaussian noise with zero mean $\mu_{PQV} = 0$, and standard deviation value for power measurements $\sigma_{PQ} = 0.1$ and for voltages $\sigma_V = 0.01$.

Classical WLS method

Classical WLS method SE voltage profiles for different LV busses of all three phases are presented in Fig 3. The voltage imbalance can be observed. The red line shows the real voltage profile from the simulation, while with blue the estimated voltage profile is presented. Yellow circles are the node voltage amplitudes, which formed the input to the SE algorithm. One can notice, that these values are erroneous due to the added noise. A black dashed line is a depiction of a $\pm 1\%$ deviation from the real voltage profile.

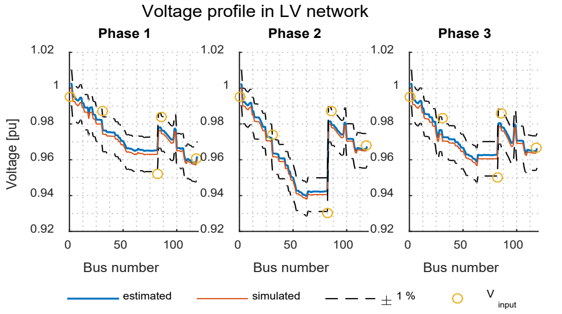

Fig 3: Classical WLS SE voltage profile, one time step

As it can be seen, the SE error is small. Maximal deviation between simulated and estimated voltage equals to $\Delta V_{max} = 0.28$ %.
Results for the 960 consecutive 15-minute steps are presented hereafter (exactly 10 successive days). Estimation is performed separately for each phase. Simulated voltage profile versus the estimated one, for a random LV network node, is shown in Fig 4. One can notice that both profiles match quite well.

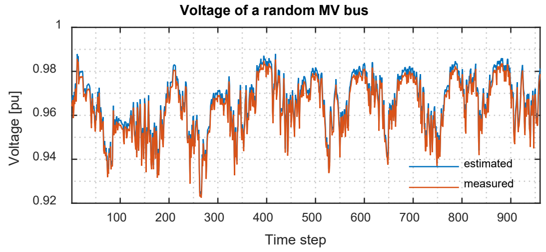

Fig 4: Estimated and simulated voltage of one LV node, 10 days

In the end also the profile of the maximum estimation error for each time step is presented in Fig 5. It can be seen, that the error remains under the $\Delta\hat{V}_{max} = 0.3$ % boundary.

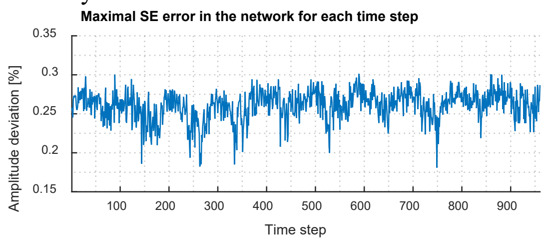

Fig 5: Maximal percent SE error for each step

Estimation of each phase is timed for each step and the median estimation time equals to $t_{SEmed} = 3.7$ s. The SE duration and error will be compared with the decoupled method.

Decoupled WLS method

The presentation of results of the developed decoupled WLS method is presented next.
SE results, in terms of voltage profile for different LV busses, all three phases and for the same time step as in case of the classical WLS (Fig 3) are presented in Fig 6. The color scheme is retained, so the red line represents the real voltage profile from the simulated network. Blue line shows the estimated voltage profile. Yellow circles are the node voltage amplitudes, which were given to the SE algorithm. Also here, the simulated values are subjected to the same white noise. A black dashed line is a representation of a $\pm 1\%$ deviation from the real voltage profile.

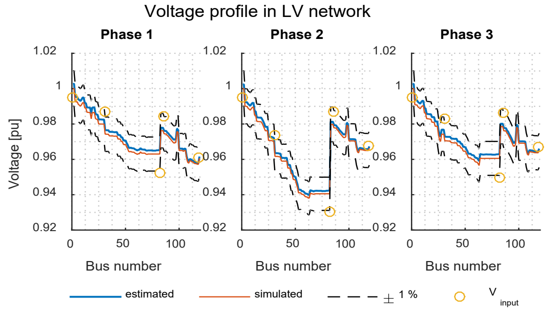

Fig 6: Decoupled WLS State estimation voltage profile, one time step

Compared to the previous classical method, the estimation error for this time step retains almost the same with its max value equal to $\Delta V_{max} = 0.3$ %.

The results for the decoupled LV DSSE for the same 10 days as in case of the classical SE are presented hereafter. The simulated voltage profile versus the estimated one, for a random LV network node is presented in Fig 7. The chosen node is the same, as in case of classical SE. One can notice that both profiles match quite well.

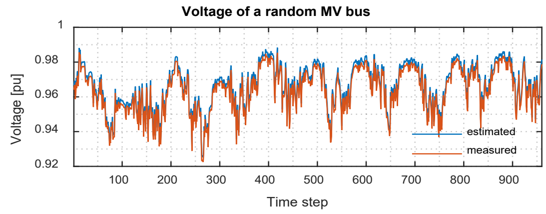

Fig 7: Estimated and simulated voltage of one LV node, 10 days

The profile of maximum estimation error for each time step is presented in Fig 8. When compared to the classical SE error profile in Fig 5, one can notice a bit different shape. Error values during the heavy loading tend to increase compared to the classical SE, however, maximal error for the observed period is still below 1% with its value being $\Delta\hat{V}_{max} = 0.95$ %. The median iteration time for the decoupled SE equals to $t_{SEmed} = 1.7$ s.

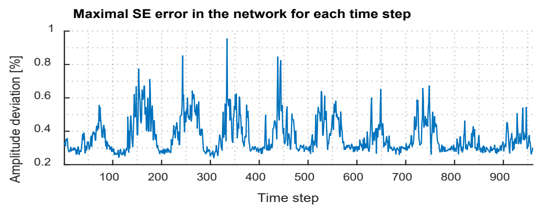

Fig 8: Maximal percent SE error for each step

CONCLUSIONS AND FURTHER WORK

In order to prove the decrease in the computational burdensomeness of the developed decoupled algorithm in comparison with the classical one, SE iteration times for both methods are presented in Fig 9. Decrease in iteration times using the decoupled method is noticeable. Decoupled SE takes about 46 % of the classical SE time.

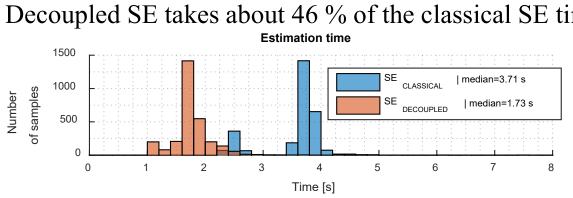

Fig 9: SE iteration time distribution comparison

Estimated voltage amplitude error for both methods is shown in Fig 10, for the same time step. It can be seen that the values of the error in the network remain the same.

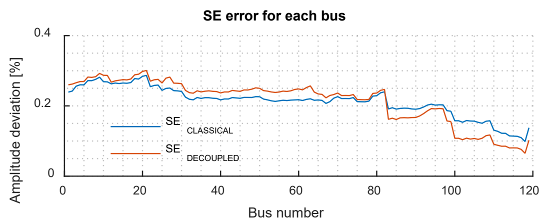

Fig 10: SE voltage error comparison, same time step and phase

We can conclude that the presented method has a potential for improvement of the DSSE, since it requires less computational resources and at the same time it results in accurate estimates.

Further work will focus on the analysis of the developed method robustness with development of the bad data functionality. Derivative of the presented method is planned for the field testing in a real DSSE application.

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