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State Estimation in Medium Voltage Distribution Networks using Pseudo Measurements

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SUMMARY

Transition from fossil fuels to sustainable sources of energy like wind and solar is the need of the hour. All over the globe, plans are in motion to achieve this goal. This implies addition of new elements to the grid in the form of Distributed Energy Resources (DERs). These affect the working of distribution grids and to ensure reliable as well as safe operation, it is important to keep a track on the grid's state regularly which is essential to a Distribution System Operator (DSO). For this very reason, Distribution System State Estimator (DSSE) has been introduced and has been a prominent topic of interest. Because of lack in observability of the network owing to unavailability of measurements and the stochastic load profiles of the distribution network, DSSE poses its own challenges. Therefore, it is necessary to validate the working of a suitable DSSE that is affected by the continuous changes in the grid. By selecting a suitable algorithm, this paper attempts to solve the observability issue by introduction of pseudo-measurements. The work in this paper comprises of sensitivity analysis of Weighted Least Squares (WLS) algorithm tested on two medium voltage networks in the Netherlands with the help of modelling from Gaia software for an Enexis network and a part of Stedin's distribution network with limited measuring devices data available. Different types of inputs are taken to test the working of the algorithm in case of Stedin's network and in case of Enexis network, the peak load moment of the day is tested with the available month data comparing it with the mean value. The results obtained illustrate the effectiveness of the selected algorithm for DSSE and are important for the DSOs to make critical decisions when needed for grid operation.

KEYWORDS

State Estimation, Medium Voltage Networks, Distribution System Operator, Weighted least squares, Distributed Energy Resources.

INTRODUCTION

Over the past few years, the energy demand is increasing rapidly and there is an observed rise in dispersed generation which will affect the grid gradually. Integration of DERs, Electric Vehicles (EV) and microgrids coupled with the rise in prosumers in the market implies that system operators will need to play an active role to deal with the unpredictable nature of the network [1].

To overcome the inflexibility of power flow, Schweppe [2] introduced State Estimation (SE) as an alternate method to classical load flow first in transmission systems. The overview of the network can be determined with the help of a state estimator which receives measurement data from the DMS like Supervisory Control and Data Acquisition (SCADA) system that collects and analyses near real-time distribution network information. The output from the state estimator which is the heart of DMS, enables to further perform important functions like security and contingency analysis. This in turn helps in monitoring and having control over most of the devices like circuit breakers, switches and so on in the substation. A stark contrast between the transmission and distribution network state estimation is the structure of networks and availability of measurements. Firstly, the operation of distribution networks is mostly radial. Secondly, in transmission systems the redundancy of measurements makes state estimation of networks rather easier. Limited monitoring of the network is a challenge in the case of distribution networks. The fact that the available measurements are limited led to the introduction of pseudo-measurements which are filled in to make the overall system observable and thus perform SE. These pseudo-measurements have higher uncertainty which leads to larger variance in the formulated measurements. Therefore a suitable algorithm should be selected that is capable of handling such uncertainty in measurements. Various researchers have been working on SE of distribution networks in recent years and have come up with a number of formulations. A summary of these recent developments is given in [3].

The main contribution of this paper is in applying stochastic power flow simulation of Low Voltage (LV) networks to generate pseudo-measurements for SE of Medium Voltage (MV) networks. This is different from the usual bottom up approach [4] where smart meter data of households is added up to get total power at the secondary side of the MV/LV transformer. The LV networks models used in this paper include all details of the network topology and parameters of connecting LV cables with households being modelled stochastically. The results of stochastic power flow results in Gaia are validated with measurements and used as an input to the SE module in Vision Network Analysis.

DISTRIBUTION SYSTEM STATE ESTIMATION (DSSE)

In the past twenty years, the concept of DSSE has been in focus due to the increasing uncertainty caused by the integration of DERs in the grid. The most conventional method for state estimation is the Weighted Least Squares (WLS) Method.

The measurements provided by the devices can have a few anomalies due to various reasons be it manual or a systematic error. Various mathematical formulations have been proposed to further increase the robustness of the system in the event of facing bad data (outliers). All these formulations consider the measurement function as **h** and the state vector **x** which is connected to the measurement vector **z** as shown in Equation (1) where **r** is the residual or the error measurement vector:

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

These various formulations have been tested and compared in [5]. The advantages and disadvantages of these algorithms are summarized in Table 1. Overall, LMS, LTS, LAV and GM algorithms though robust against bad data lack efficiency in dealing with the high uncertainty in measurements and are computationally expensive. Also a good estimator needs to have small or non-existent bias which refers to the mean of the error estimate to be zero and be consistent which implies that the error estimate statistically corresponds to the measurement error variance. For this very reason, WLS method is best suitable for state estimation studies and is widely used assuming there is no bad data [6].

Table 1. Comparison of Algorithms

Algorithm	Advantages	Disadvantages
Weighted Least Squares (WLS)	Simple, widely used.	Fails in presence of bad data.
Least Median of Squares (LMS)	Robust against bad data.	Requires high redundancy of measurements
Least Trimmed Squares (LTS)	Robust against bad data.	High memory requirement.
Least Absolute Value (LAV)	Robust against bad data.	High cost in computation. Sensitive to measurement uncertainty.
Generalized Maximum Likelihood (GM)	Robust against bad data.	Sensitive to parameter selection.

Depending on the availability of measured variables and the choice of Power Flow (PF) (AC or DC), the Measurement Jacobian is formulated. Many types of formulations are available in literature. Two of the most used ones are the Voltage based and Branch Current based DSSE approaches. A comparison of the two approaches has been done in [5] and it is seen that a faster convergence is observed in voltage based approach than in a current based approach. One other factor that stands out in favour of the voltage based approach is having the Jacobian matrix being independent to the states as compared to the current based approach. The robust performance on all kinds of networks and sensitivity towards network impedance is also an advantage of the voltage based approach. Considering all these factors, the voltage based WLS is the clear choice.

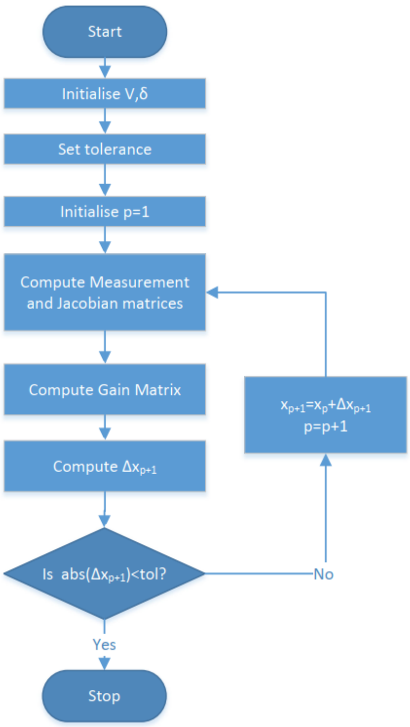


Figure 1. Flow Chart of WLS

The main purpose of state estimation technique is to make sure that the state of the power system is always known. The bus voltages and angles are considered as the state of the system which have to be calculated. The real and reactive power injections as well as the real and reactive power flows along with bus voltage magnitudes and magnitude of current flows are considered. The modelling of the entire WLS Estimation algorithm is based upon [7] in which it has been explained in detail. A flowchart of the algorithm can be found in Figure 1.

The study systems considered on which WLS algorithm is tested upon are described below:

STUDY SYSTEMS CONSIDERED

Two networks are considered with the first network corresponding to a typical Dutch medium voltage distribution network, where the measuring device data is available at the secondary side of an MV/LV transformer for few of the transformer stations. In the second network, the measuring devices data is available for several nodes connected to LV network and the data for remaining ones are generated using Gaia software [8] which models the LV network behind an MV/LV transformer explicitly. It is assumed that the grid topology remains constant and free from faults and failure in components. The second network is tested with a prototype of state estimation in Vision Network Analysis [8].

Network 1

An anonymized and downsized MV distribution network owned by Stedin B.V., a Dutch DSO, is taken. The grid contains a 50/13 kV transformer in the primary substation which is considered as the slack node. Step down transformers corresponding to 13/0.4 kV voltage level are used along with 50/13 kV transformer at the primary substation. The network has been modelled in Vision Network Analysis as shown in Figure 2.

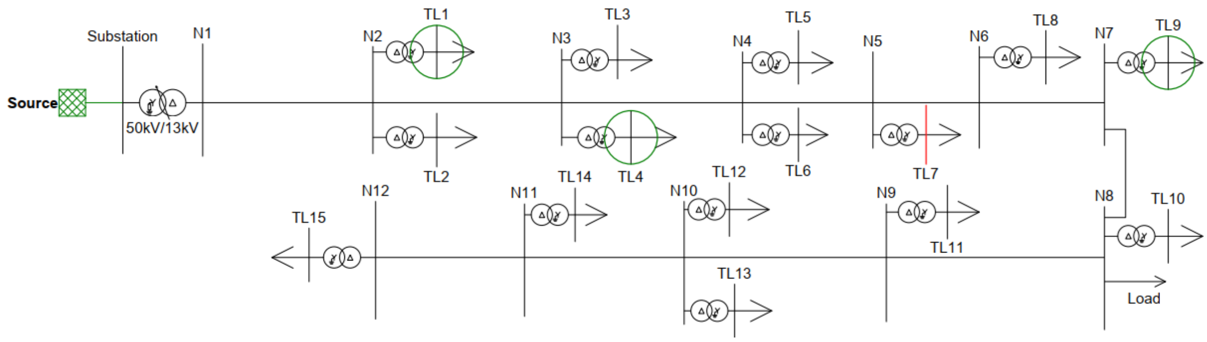


Figure 2. MV test network of Stedin in Vision Network Analysis

The network comprises of 28 nodes with 15 of them connected to household loads and one to a large load. The measuring devices data for few of these loads are available and for the other loads, a general estimate of the loading profile over the entire year is available (artificially created by the company experts based on information about number and type of LV customers connected) which can be used as a basis for generating pseudo-measurements. The red node is where the comparison of voltage magnitudes is done and the green circled nodes are where available voltage measurements are considered later on for analysis.

Network 2

An anonymized MV distribution network owned by Enexis B.V., is considered as the second test network. The grid contains a primary substation which is considered as the slack node. Step down transformers corresponding to 10/0.4 kV are used at various nodes as shown in Figure 3.

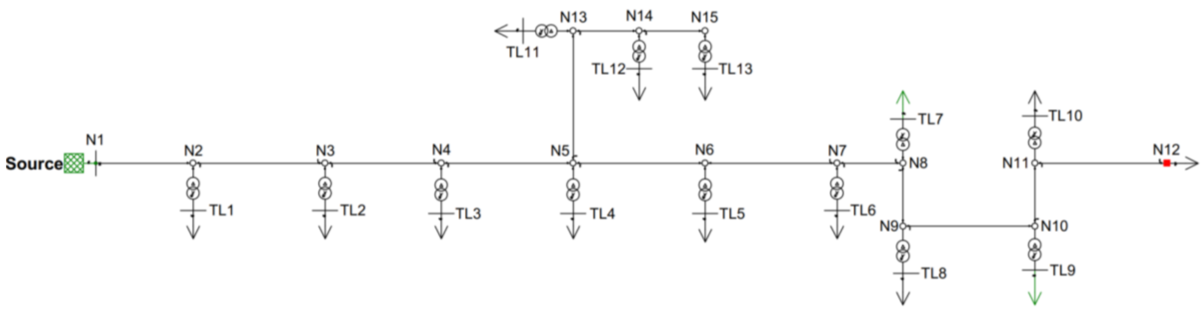


Figure 3. MV test network of Enexis in Vision Network Analysis

The network comprises of 28 nodes with 13 of them connected to LV network equivalent loads and one to a MV level consumer (N12). The measuring devices data for few of these loads (at the secondary side of MV/LV distribution transformer) are available and for the other loads, a general overview of the loading profile over the entire year is generated on a quarterly basis using Gaia software which models LV network and the stochastic behavior of the households. The green loads are the ones where active power values are compared later on (TL7 and TL9).

MEASUREMENT MODELLING

The measurements available in a distribution system fall rather short in terms of requirement to make the network observable. Based on the availability and type of measurements, they are essentially classified into three types namely: **Real**, **Virtual** and **Pseudo** measurements as described in [6]. The two types of network modelling techniques that have been performed on the selected networks are briefly described below.

Measurement Devices Data

The network in Figure 2 has data from the measuring device on the secondary side of MV/LV transformers and the historical energy consumption data with which an average load profile for the entire year has been estimated. In distribution networks, the measuring devices are placed at few of those nodes and therefore it is possible to get the total power injection at those nodes. It is to be noted that the values from a meter correspond to all loads behind MV/LV transformer and not a single household. It is in fact not possible to get this data from each of the nodes (neighborhoods) at every instant.

Ten of the sixteen nodes with equivalent loads have measuring devices installed. The other six nodes with loads have load power profiles that have been generated for the whole year using a bottom up approach. These load profiles are considered to calculate the variance and the mean value of power injections for the required time frame. With the measuring devices data, it is further analyzed how a change in input variables can affect the estimated results. The algorithm's response to redundancy and type of measurement being used as an input can be recognized which can prove to be quite instrumental in implementing the state estimator for real world applications.

Generating pseudo-measurements using stochastic LV network power flow

Power system as a whole is a very large interconnected network. However, modelling of the whole network in all details is not feasible due to very large dimension of the model. Therefore, the part of the most interest, MV distribution network in this case, is modelled in detail, while other parts are represented in form of equivalents. HV network is typically modelled as a voltage source for power flow/state estimation studies, since a specific MV network is of a very small influence on the much stronger HV transmission system. HV network can be considered as an infinitely strong source in this case. LV networks connected to MV/LV transformers are usually represented in the form of equivalent loads representing aggregated model of a neighborhood connected to LV network.

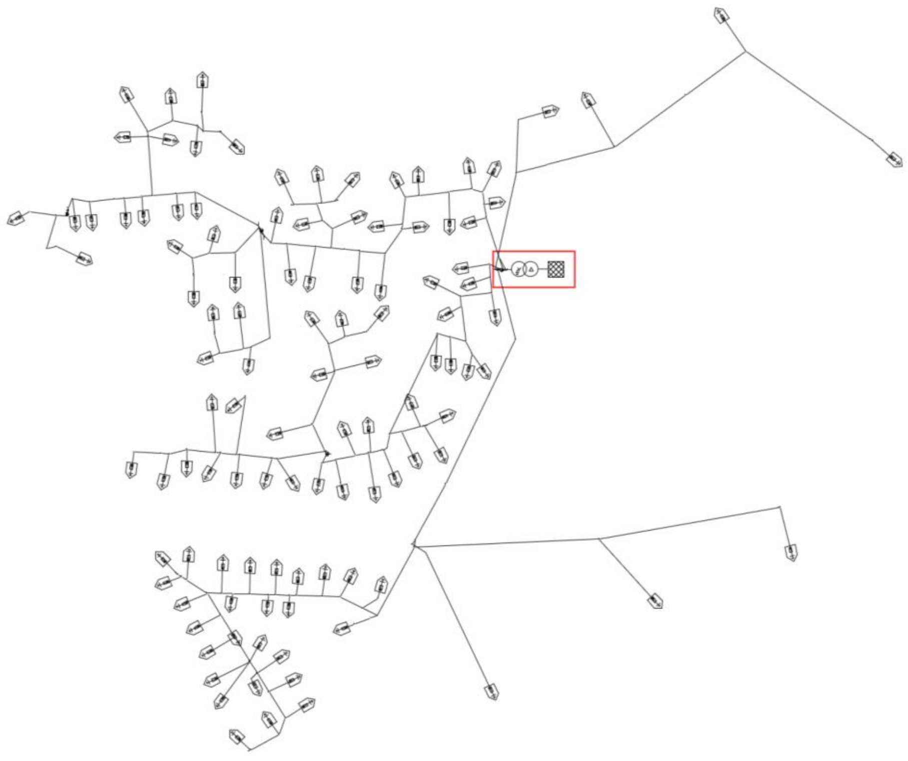


Figure 4. Example of LV network model in Gaia (red rectangle: MV/LV transformer)

Detailed models of LV networks for the Dutch DSOs are generated as well as updated in Gaia LV modelling software. LV network models in Gaia are generated automatically based on Geographic Information System (GIS) data and databases used by the DSOs. These equivalents used by DSOs are mostly obtained via a rough estimation of power based on the number and type of customers connected. In case if detailed smart meter data of LV-connected customers is available (which might be troublesome due to privacy concerns), the total power is obtained as the sum of powers of all customers connected to a specific MV/LV transformer. Such approaches have a drawback that the actual LV network is not modelled at all. LV cables have relatively large resistance that results in significant network losses compared to the energy consumed. Further, network unbalance and asymmetry of the cable admittance matrix are ignored. The LV network itself is considered as a black box model in the typical bottom-up approach. The modelling would be much more precise if the actual LV network structure can be modelled and simulated. Detailed modelling of LV networks is proposed in this paper for generating pseudo-measurement data used later on for SE of MV networks.

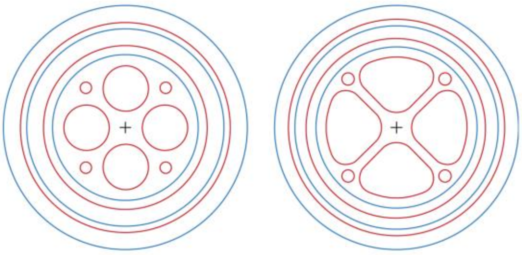


Figure 5. Schematic cross-sections of round and sector-shaped 9-wire LV cables

The networks are then checked for integrity using automated procedure, and those where potential data issues have been detected, are checked manually. An example of LV network model in Gaia is shown in Figure 4. The network is modelled starting from the neighborhood MV/LV transformer (indicated with red rectangle) going down to and including the level of individual households. LV cables in Gaia are modelled using 5- or 9-wire model (depending on whether a cable has additional conductors used for public lighting) with mutual inductances between each pair of the conductors and the cable sheath. An example of cross-section of 9-wire cables is shown in Figure 5. A household in Gaia model is connected to a cable exactly as it is done in reality: the phase wire of a household is connected to a proper phase (in a single phase case), neutral (N) and Protective Earth (PE) wires of household and cable are also properly connected with each other, and the grounding resistance is modelled where it is present [9]. A household is represented using stochastic Gaussian Mixture (GM) load model – probability density function (PDF) of active power that changes its shape based on the month, working or weekend day, and a quarter of an hour throughout the day (see Figure 6). Each household is assigned a specific GM model type based on its yearly energy consumption, type of house and other available data. No detailed smart meter data is used due to privacy concerns. Large individual appliances (photovoltaics, electric vehicle charging point, heat pump, etc.) can be modelled by their own time-varying PDF's.

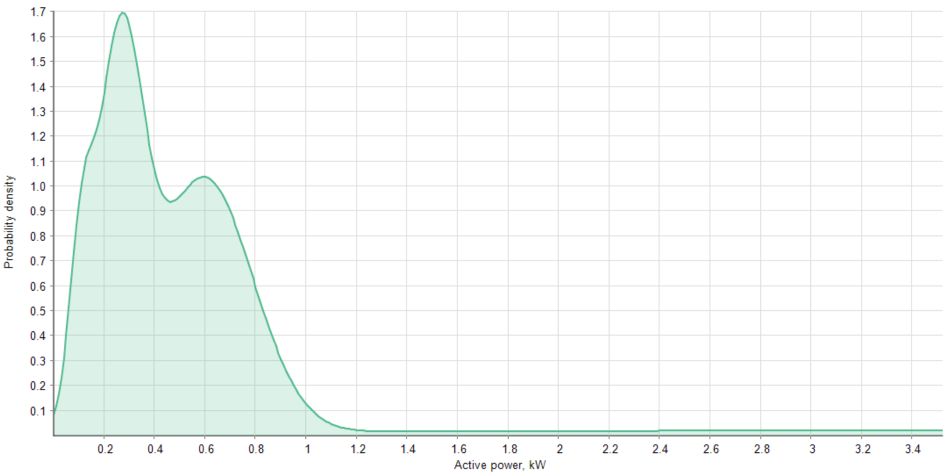


Figure 6. Probability density function of an active power of a household during weekend of January at 19:00

PDF's of households and appliances are used for Latin hypercube based Monte Carlo random sampling, which provides active powers necessary to perform a (deterministic) power flow calculation in a LV network. This process is repeated many times so that representative statistical data can be obtained for probability distributions of currents, powers and voltages in all network branches/nodes. In this way the stochastic power flow calculation for LV network in Gaia can be performed for each specific time instant of a year.

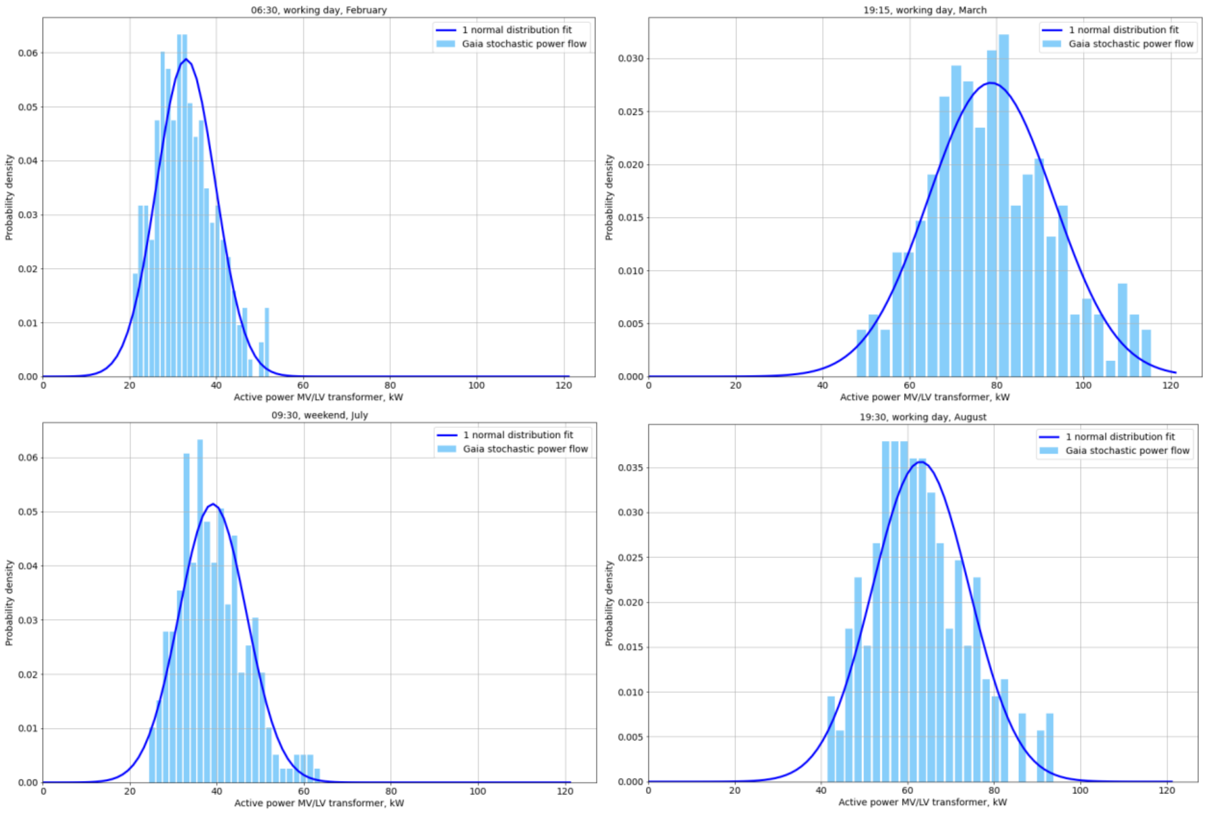


Figure 7. Examples of normal distribution fitting of Gaia stochastic power flow results

The results of this calculation at the LV side of the MV/LV transformer can be used in order to generate pseudo-measurements for SE in MV networks in case the exact measurement data is not available. Histogram of the active power of the transformer at specific time instant can be approximated by a normal PDF providing mean and variance values necessary for WLS SE. Examples of such fitting are illustrated in Figure 7. Fitting using single normal distribution is not perfect, GM model with several normal distributions would give a better fit, but applying GM model to WLS SE is not trivial and, for the time being, is considered as a subject for future research.

Statistical test of the algorithm

To check if the algorithm is indeed effective for distribution network applications, a statistical test is done. The two measures used are bias and consistency which are described below and summarized from [6] and a detailed test has been done for a Dutch distribution network in [10].

I. **Bias:** Statistical bias is said to exist if the estimated parameter is not systematically different. If the expected error is zero, then the estimator is said to be unbiased. Equation (2) shows the desired property of an unbiased estimator:

$$\boldsymbol{E}[(\boldsymbol{x_t} - \boldsymbol{\hat{x}_t})] = \boldsymbol{0} \tag{2}$$

II. **Consistency:** In statistics, an algorithm or a procedure which adheres to certain confidence intervals upon tests with a hypothesis is sought after. An estimator is consistent if the estimates converge in probability to the value the estimator is designed to estimate. One of the measures for consistency is the normalized state error squared variable ($\boldsymbol{\epsilon}$) shown in

Equation (3) where $\hat{R}_x$ is the estimated error covariance matrix. $\boldsymbol{\epsilon}$ should lie within a certain interval as obtained from the χ^2-table as it is a multivariate case [6]:

$$\boldsymbol{\epsilon} = (\boldsymbol{x_t} - \boldsymbol{\hat{x}_t})^{\boldsymbol{T}} \boldsymbol{\hat{R}_x^{-1}} (\boldsymbol{x_t} - \boldsymbol{\hat{x}_t}) \tag{3}$$

RESULTS

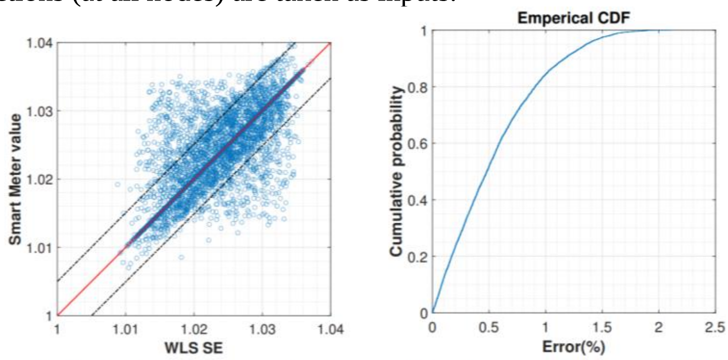
Network 1 with Measuring Devices Data

The network shown in Figure 2 is considered first. Load profiles over the whole year which have been artificially generated by the DSO are available. The resolution of available measurements is five minutes apart. The nodes that require pseudo-measurements are TL8, TL10, TL11, TL12, TL13 and the Load which is obtained from the load profiles available. For the other nodes the power injections and voltage magnitudes at few of them are available.

The state estimation algorithm is implemented for a duration of thirty days for the network. The estimation is done with two scenarios: the first one being without any voltage magnitude measurements considered and the second one with few voltage magnitude measurements considered as inputs. The true values are already available in the form of measurement data from the device at bus TL7 against which the results are compared. Significant difference in the quality of estimates is observed in these two scenarios.

Without voltage measurements

The network is shown in Figure 2 with the highlighted node in red being the voltage bus i.e., bus 20 (TL7) for which the plot shown in Figure 8 corresponds to. Multiple simulations are run for the entire month and the obtained values from state estimation are compared with the already available data from the measuring device (smart meter for a group of LV network households) for the same time period. In this scenario, no voltage magnitude measurements available are considered to perform state estimation. Only the power injections (at all nodes) are taken as inputs.



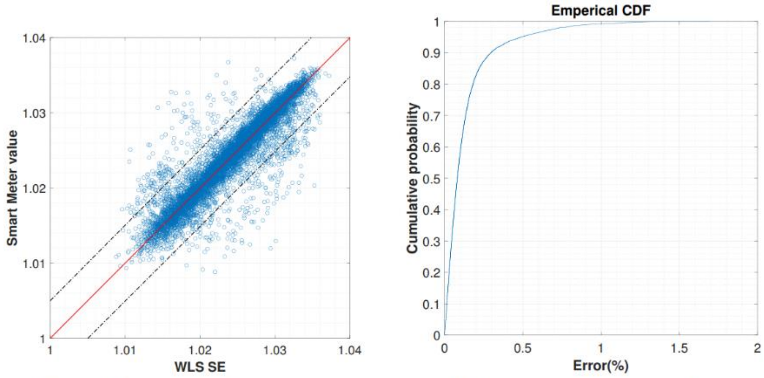
(a) Scatter plot of actual value vs estimated value (b) Absolute mean error percentage ECDF

Figure 8. Voltage comparison and error probability at bus 20 without voltage measurements

The absolute mean error percentage for each of the instances is also plotted for bus 20 (TL7) in an empirical cumulative probability density plot. From this plot, it is further observed that the error is quite low and the algorithm is indeed effective for this network.

With voltage measurements

Further analysis is done taking into consideration few of the voltage magnitudes data from the measuring devices and state estimation is performed on the network. The nodes whose voltage magnitudes are taken as additional measurement input (TL1, TL4 and TL9) are shown in Figure 2 indicated by the circles in green.



(a) Scatter plot of actual value vs estimated value

(b) Absolute mean error percentage ECDF

Figure 9. Voltage comparison and error probability at bus 20 with voltage measurements

The scatter plot in Figure 9 indicates the closeness of the state estimation algorithm value in comparison to the measuring device (smart meter for a group of LV networks) value. It is observed that the similarity of values increases significantly as compared to the previous case. This shows that with consideration of voltages which are known at few points in the grid, a significant improvement in estimation precision is obtained. The estimated states correspond most likely to more accurate system states. This implies that it is possible to estimate the other quantities in the grid more precisely as well.

Network 2 with Gaia software usage for pseudo-measurements

The network shown in Figure 3 is the second case considered which belongs to Enexis B.V. and is tested with a prototype of state estimation module in Vision NA. The only measurements available are for the nodes TL5, TL7 and TL9. For the other nodes along with TL7 and TL9 (the green nodes in Figure 3), the Gaia software is used to obtain histograms of the active and reactive powers at the secondary side of MV/LV transformer for each time instant. The Gaia data is then approximated by normal PDF where means and standard deviations are used as pseudo-measurements for state estimation in the MV network. Gaia performs calculations for a typical working day of the month with an assumption that the pattern is repeating for all the working days (similarly for weekends). The measurement data available at TL7 and TL9 is used to validate the result obtained at peak load moment.

Only the month of April 2021 is considered owing to availability of detailed measurements for this month. The load peak moment of April is observed to be typically around 18:00. The distribution of transformer active powers at this moment of time for working days of April are plotted from the measurement data and compared with the state estimation value obtained. It is observed that for all the cases where measurement data is available for comparison, the value obtained from state estimation calculations is close to the mean value of measurement data.

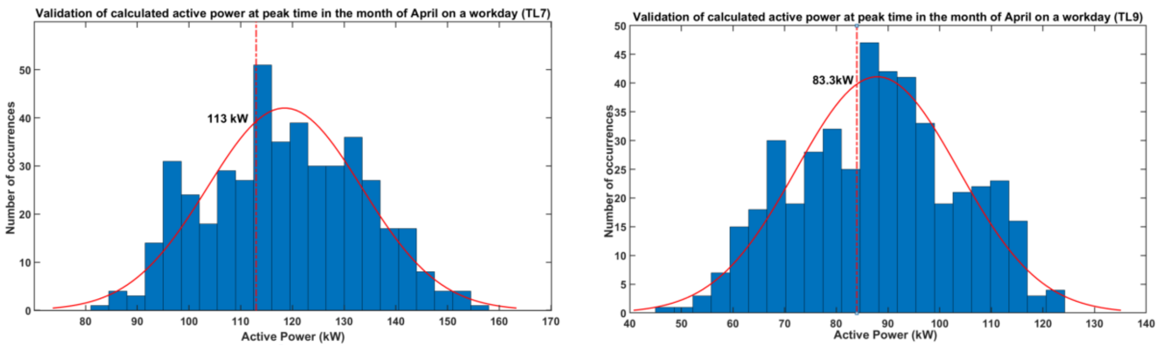


Figure 10. Validation of active power calculated at peak time of the day in April

In Figure 10, validation performed for two of the nodes of the network TL7 and TL9 is plotted. Histogram of available measurement data (working days in April at peak load moment, i.e., 18:00) is illustrated with blue bars. The estimated values of active power at load peak moment for TL7 and TL9 nodes are 113 kW and 83.3 kW, respectively (shown with red dashed vertical lines). These values are close to the mean values which are determined from the PDF approximations of stochastic LV power flow simulation results of Gaia (solid red lines). This reflects the algorithm's efficiency. To perform extensive validation, it is necessary that more data is available and further tests should be done. This is considered as a subject of future work.

CONCLUSION

The working of WLS algorithm on the networks using synthetic data and measuring devices data is verified. The algorithm is implemented and tested on the Dutch MV networks consisting mostly of underground cables. With the help of Stedin's network and measurement data, the effect of type of input measurement on state estimation precision has been evidently demonstrated. In the case of Enexis network, a detailed way of generating pseudo-measurements for the nodes with missing data using stochastic power flow simulation of LV networks is proposed, and a validation with available data is done to verify the estimated powers at MV equivalent loads. The proposed method is more reliable than the traditional bottom-up approach since LV networks are modelled in a much more detailed way. Future work will include interfacing of Phase to Phase computational software with the measurement systems and extensive validation of the estimator on large scale MV networks of the Dutch DSOs.

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