PROBABILISTIC VOLTAGE ESTIMATION FOR THE ACTIVE CONTROL OF DISTRIBUTION NETWORKS

Fabio BIGNUCOLO
University of Padua – Italy
bignucolo@die.unipd.it

Roberto CALDON
University of Padua – Italy
caldon@die.unipd.it

Marco VALENTE
University of Padua – Italy
marco.valente@studenti.unipd.it

ABSTRACT

A procedure allowing a reliable State Estimation (SE) for active distribution networks, without requiring remote on-line measurements, is presented. It is based on load modelling techniques and Discrete Step Communications (DSCs) for Distributed Generation (DG).
Aim of the paper is to demonstrate the possibility of maintaining the state estimation performances with reasonable management costs for Distribution System Operators (DSOs).

INTRODUCTION

The penetration of Distributed Generation (DG) into existing distribution networks is currently limited by the traditional passive methods of network management. Integrating DG, indeed, presents a number of technical challenges. In particular, the redeployment of power flow heavily modifies the voltage profiles that may dramatically rise in the neighbourhood of the generator connection points.
In order to increase the connectible capacity, a Distribution Management System (DMS) controller is necessary for managing actively the network voltage. A DMS scheme provides for acquisition of the network data, process of information and communication of control signals to the devices involved in the network voltage management. Possible control actions are transformer tap variations, reactive devices regulation (i.e. capacitor banks insertion) and DG output control (namely active and reactive power).
At present, real time measurements in each node of a distribution network are not feasible, so an adjustment of traditional State Estimation algorithms including a great number of pseudo-measurements seems to be necessary.

PERFORMING A STATE ESTIMATION ON DISTRIBUTION NETWORKS

State Estimation procedures are used from long time in transmission systems to assess the network operating conditions. To this aim a large number of real time measurements are required and are obtained from a fully integrated SCADA system. This results in an over-determined problem in which the measurements redundancy allows the application of plausibility check and bad data detection tools. In this context, the SE non-linear optimization algorithm processes the redundant data in order to provide the best estimate of the system voltages and phase angles. The most used SE technique consists of a weighted least squares minimisation problem, in which the measurements errors are weighted by the inverse of the measurements variances (that are defined as the square of the standard deviations σ_i), as shown in (1):

$$\min \sum_{i=1}^{m} \left(\frac{z_i - \mu_i}{\sigma_i} \right)^2 \qquad (1)$$

where z_i is the ith measured value, μ_i is the ith calculated (estimated) value and σ_i is the ith measurement standard deviation. Usually, the minimization leads to an iterative (Gauss-Newton) process and the state variables are updated with the most recent values until the convergence is reached. The algorithm, extensively using matrix computation, supplies the estimate of voltage magnitude and phase angle for each node of the network and the corresponding uncertainty of the estimated quantities [1].
Unfortunately, different reasons prevent a straightforward application of these techniques to distribution networks. The Medium Voltage (MV) and Low Voltage (LV) systems are extremely wide with a great number of nodes and lack a complete SCADA system. At present, the availability of real time measurements is often limited to the Primary Substation (PS) (like MV bus-bar voltage and P-Q flows on the outgoing feeders). In this case a large number of so-called “pseudo-measurements” has to be used to guarantee the network observability. Pseudo-measures may represent estimates of load consumptions or DG injections and are usually afflicted by a high uncertainty, due to the impracticability of a widespread measurement system (even if a sort of correlation between different customer loads can be considered [2]). High levels of uncertainty negatively affect the accuracy of voltage estimates, preventing an effective control of network voltages.
Two different strategies may be adopted to ensure a suitable reduction of the estimated voltages uncertainties:
– introduction of further remote on-line measurements; in particular, the installation of further voltage measurements in critical nodes produces the best results in reducing the degree of uncertainty [3]; suitable algorithms provide the optimized measurements location;

– reduction of pseudo-measurements uncertainty by using load modelling or other techniques.

The first solution involves the complete design of a suitable and reliable communication network, that may imply high DSO realization and management costs.

LOAD MODELLING TECHNIQUES USING LOCAL MEASUREMENTS

Different levels of loads knowledge have been investigated [5]. The base condition (that actually is not a load modelling technique) provides a fix value of active power (P) and reactive power (Q) absorption for each node (e.g. defined as the 50 % of the load rated power) with a high level of uncertainty (for example ± 100 % or more [6]).

A first load modelling technique makes use of power flow measurements (P,Q) performed on the sending ends of feeders: each load consumption is calculated by sharing out the measured power flow according to the rated power of loads (or MV/LV transformer rating in case), as shown in (2):

$$P_{i,t} = \left(P_{F,t} - P_{L,t} - \sum_{k}^{N_{GD,t}} P_{DG,k,t} \right) \left(\frac{P_{n,i,t}}{\sum_{i=1}^{N_t} P_{n,i,t}} \right) \qquad (2)$$

where $P_{i,t}$ and $P_{n,i,t}$ are respectively the assigned active power absorption and the rated power of the overall load at node i belonging to the tth feeder, while $P_{F,t}$ is the power flow measured in PS for the tth feeder, $P_{L,t}$ represents the overall estimated losses for the tth feeder and $P_{GD,k,t}$ is the power injection of the kth GD plant connected to the tth feeder. A similar formula is considered for the reactive power $Q_{i,t}$.

Using daily load curves for specific load types guarantees a suitable improvement to account the real-time nature of loads. These trends, named in literature as Load Profiles (LPs), are typically divided into load classes and obtained through statistical analyses of historical data, depending on season, day of the week, temperature and further influential parameters [5]. Alternatively these curves may be provided by short term load forecast techniques (e.g. neural networks) [7]. Daily LPs are defined, for a specific time, as a mean normalized value and an uncertainty range, like shown in Figure 1. Considering multiple load classes generalizes the load modelling problem allowing to analyse separately the contribution of each load in each node of the distribution network. Based on the LPs knowledge, the load power consumption $P_{i,t,c}$ can be expressed as:

$$P_{i,t,c} = \left(P_{F,t} - P_{L,t} - \sum_{k}^{N_{GD,t}} P_{DG,k,t} \right) \left(\frac{LP_{i,t,c} \cdot P_{n,i,t,c}}{\sum_{i=1}^{N_t} \left(LP_{i,t,c} \cdot P_{n,i,t,c} \right)} \right) \qquad (3)$$

where $LP_{i,t,c}$ represents the instantaneous mean value of the assigned curve for the load connected to the ith bus-bar of the tth feeder and belonging to the cth load class. As a consequence, for the ith node, the total demand is a summation of load demands over all the load classes (4).

$$P_{i,t} = \sum_{c=1}^{Nc} P_{i,t,c} \qquad (4)$$

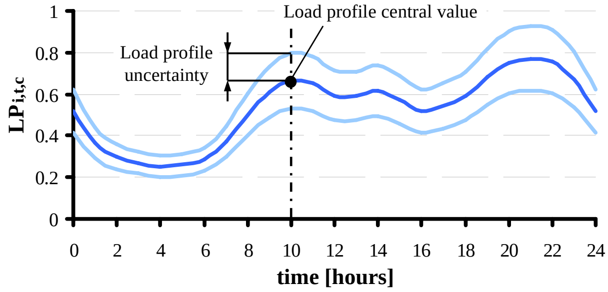

Fig. 1: Example of Load Profile (for the "domestic load" class)

Another way to assess the instantaneous absorption of each load uses billing data to calculate the Average Daily Customer demand (ADC). In case the daily trends are not considered, the measured power flow absorbed by the entire feeder is scaled as follow:

$$P_{i,t} = \left(P_{F,t} - P_{L,t} - \sum_{k}^{N_{GD,t}} P_{DG,k,t} \right) \left(\frac{ADC_{i,t}}{\sum_{i=1}^{N_t} ADC_{i,t}} \right) \qquad (5)$$

It is important to note that this method is more accurate that the former one that uses only rated power, contemplating the real loading of each customer. However, it does not consider load daily fluctuation and requires a complete knowledge of customer connectivity [5].

To avoid the load daily trend issue, eq. (5) is modified introducing class specific Load Model Factors (LMFs), which are energy-normalized curves representing the relative daily demand variation between different classes. Adopting LMF trends, each load consumption can be assess as :

$$P_{i,t,c} = \left(P_{F,t} - P_{L,t} - \sum_{k}^{N_{GD,t}} P_{DG,k,t} \right) \left(\frac{LMF_{i,t,c} \cdot ADC_{i,t,c}}{\sum_{i=1}^{N_t} LMF_{i,t,c} \cdot ADC_{i,t,c}} \right) \qquad (6)$$

where $LMF_{i,t,c}$ represents the mean value of the distribution of the energy consumption which, time by time, is associated to the cth class of load that participates to the overall load requirement of ith node belonging to the tth feeder, similarly to LPs.

The most suitable technique to be adopted depends case by case on the availability of network information and on the cost of data collection.

DISCRETE COMMUNICATIONS OF DISPERSED GENERATION STATE

Referring to DG plants, the DSO can not be based on the knowledge of typical generation curves like done for loads. Especially for renewable source units (i.e. wind farms), only a remote on-line measurement may provide the real status and the actual generation value of DG plants. On the other hand, this is an additional variable cost for the DSO in actively managing the distribution network.

Besides, several research works in literature demonstrates that the effectiveness of the insertion of further power-flow measurements is sensibly lower then voltage measurements one [3]. To this aim the paper proposes the DGs outputs detection through Discrete Step Communications (DSCs) between DGs and the PS. The DSO may require an information about the actual value of the dispersed plants injections in case they vary more than a defined step (see Figure 2). In this way, the DSO knows the DG status and the active and reactive generations by a step trend. The standard deviation of the step trend corresponds to the step width.

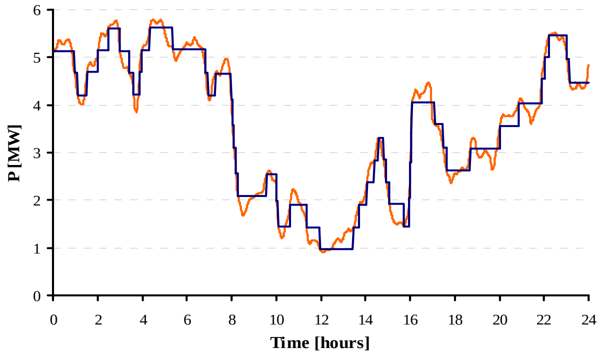

Fig. 2: DSC technique for a wind farm (absolute step width mode)

The method may assume a relative value of step width (as a percentage of the actual generated power) or an absolute step width (as a fraction of the rated power of the plant).

Referring to the case study analysed below, Figure 3 shows that the most suitable step value to obtain a tolerable uncertainty and to limit the management cost may be between 5 % and 10 % of the rated power of each DG plant.

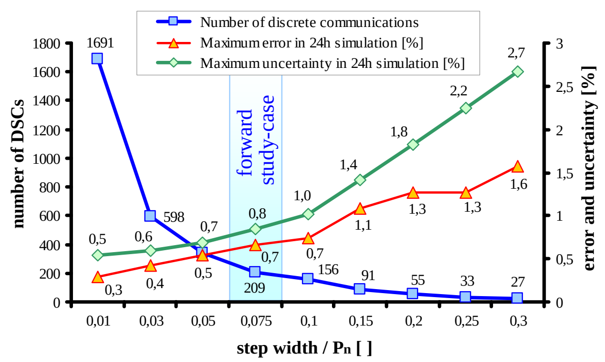

Fig. 3: DG step width Vs. SE uncertainty, and management cost

CASE STUDY

The application of a probabilistic state estimation based only on Primary substation on-line measurements has been simulated.

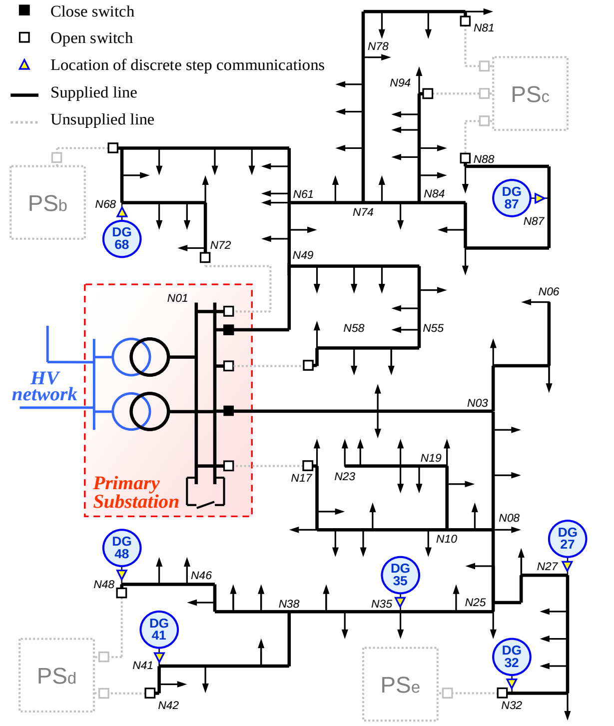

Fig. 4: 20 kV distribution network model

Two radial managed feeders with rated voltage V_n = 20 [kV] compose the case study network (Figure 4). Total load connected to Feeder A is 13.34 [MW] / 3.21 [Mvar], while the sum of DGs maximum outputs is 19.00 [MW]. Conversely the upper feeder (Feeder B) shows a lower DG penetration level: the total connected load is 11.54 [MW] / 2.69 [Mvar], while the maximum generable power is 7.00 [MW] from DG68 and DG87 units. Realistic daily trends for loads and DG generations are implemented to obtain a reliable 24h simulation. Both renewable and not-renewable DGs are considered to test the effectiveness of the state estimation algorithm based on load modelling and DSCs (Figure 2 shows the active output of the wind park DG48).

The hypothesis of sole voltage monitoring in PS (with uncertainty 0.5%) determines a growing uncertainty profiles moving from the PS to the feeder ends.

Figure 5 represents the structure of the simulation procedure. Random functions define the actual power injections node by node according to the daily LPs and the DG production trends. The values of local voltage and power flow measurements obtained from a load flow calculation are provided as input of the SE tool. At the end of the 24h simulation, "real" and estimated voltages are compared time by time to analyse both the errors and the uncertainties trends.

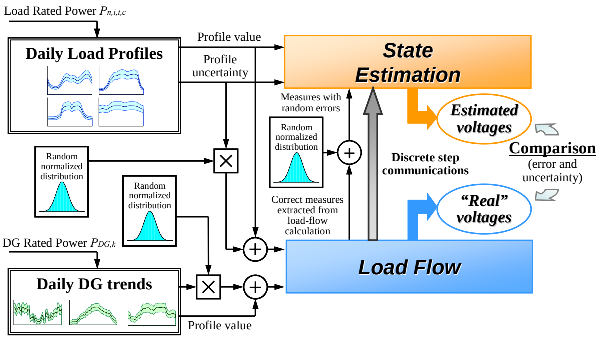

Fig. 5: Basic structure of the daily simulation

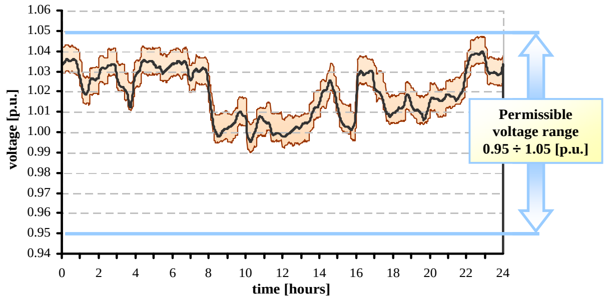

Fig. 7: "Real" voltage daily trend compared to the uncertainty band (bus-bar N48)

Figure 6 reports, for each bus-bar, the maximum uncertainty obtained during the 24h simulation where daily load trends and various DG generation patterns are considered. The uncertainty profile demonstrates the impact of DG penetration level on voltage uncertainty. By observing the trend of each feeder, it appears that the sole load-modelling implementation using the formula (3) (red line) obtains tolerable uncertainty values during all the simulation in case the overall generated power is sensibly lower than the overall load (Feeder B). Vice versa, if the DG output exceeds the load consumption (Feeder A), a technique to partially know the DG state has to be implemented.

DSCs and load modelling techniques do not require high costs for the DSO, but allows a great uncertainty reduction in distribution network state evaluation, especially in the outermost bus-bar. In the 24h simulation, for the node N48 (where the higher voltage uncertainty is detected) Figure 7 shows the "real" voltage trend compared with the state estimation range. The accuracy of the network voltage estimation is fully demonstrated in the whole distribution system.

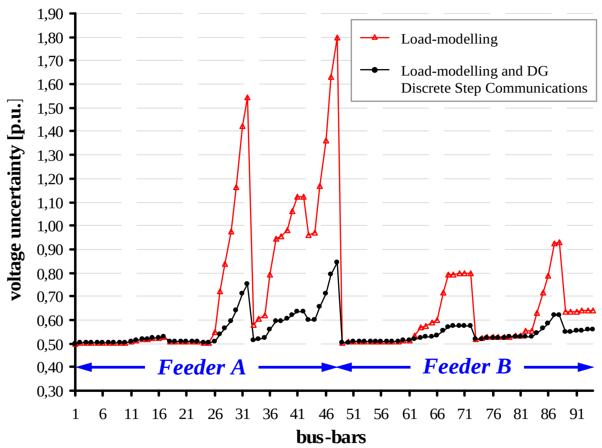

Fig. 6: Effect of DSC application on voltage uncertainty profiles

Table 1: DSC results of a daily simulation

DG plant		Type	Number of required DSCs
Feeder A	DG27	CHP Gas Engine	23
	DG32	Hydro plant	26
	DG35	CHP Gas Engine	17
	DG41	CHP Micro-turbine	25
	DG48	Wind farm	50
Feeder B	DG68	CHP Micro-turbine	19
	DG87	Wind farm	49
Overall			**209**

DISCUSSION AND CONCLUSIONS

The voltage estimation in distribution network is one of the most strategic topics for the application of a DSM active controller which enhances the DG penetration level and can reduce the reinforcement of the system.

The application of State Estimation tools to distribution networks has some critical aspects mainly dependent on the lack in on-line measurements availability. In this work a solution is proposed that mixes the load modeling techniques (based on historical data analysis or on short-term load forecasting) and the partial knowledge of the DG plants status through Discrete Step Communications.

The proposed methodology demonstrates its validity applied to a real radial distribution network. The number of required DSCs during a daily simulation also indicates the suitable communication technique to adopt and its likely costs.

REFERENCES

[1] A. Abur, A.G. Exposito, 2004, *Power System State Estimation – Theory and Implementation*, Dekker, New York, US.

[2] K. Li, 1995, "State estimation for power distribution system and measurement impacts", *IEEE Trans. on Power Sys.* vol. 11, 911-916.

[3] A. Shafiu, N. Jenkins, G. Strbac, 2005, "Measurement location for state estimation of distribution networks with generation", *IEE Proc. Gener. Transm. Distrib.* vol. 152/2, 240-246.

[4] H. Li, B. Yunus, G. Strbac, 2005, "The impact of communications channel availability on distribution state estimator", *Proceedings 18th CIRED*, Turin 6-8 June 2005

[5] A.K. Ghosh, D.L. Lubkeman, R.H. Jones, 1996, "Load modeling for distribution circuit state estimation", *IEEE Trans. Power Del.* vol. 12, 999-1005.

[6] C.M. Hird, H. Leite, N. Jenkins, H. Li, 2004, "Network voltage controller for distributed generation", *IEE Proc. Gener. Transm. Distrib.* vol. 151/2, 150-156.

[7] H.S. Hippert, C.E. Pedreira, R. C. Souza, 2001, "Neural networks for short-term load forecasting: a review and evaluation", *IEEE Trans. on Power Sys.* vol. 16, 44-55.