Distributed state estimation for multi-agent based active distribution networks

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Abstract—Along with the large-scale implementation of distributed generators, the current distribution networks have changed gradually from passive to active operation. State estimation plays a vital role to facilitate this transition. In this paper, a suitable state estimation method for the active network design is proposed. The method takes advantages of the multi-agent system technology to compute iteratively local state variables by neighbors’ data measurements. The accuracy and complexity of the proposed estimation are investigated through on-line simulation with a 5-bus test network.

Index Terms-- State estimation, distributed state estimation, multi-agent system, active network, distributed generation.

I. NOMENCLATURE

$x$ System state vector.

$x_a$ Local state vector.

$x_b$ Boundary state vector.

$z$ Measurement vector.

$m_i$ Number of branches connected to bus $i$.

$h$ Function vector relating measurements to system state.

$G$ Gain matrix.

$H$ Jacobian matrix.

$R$ Variance vector of the measurement errors.

$R_{i}^{meas}$ Voltage measurement variance at bus $i$.

$R_{ij}$ Voltage estimation variance at bus $i$ from bus $j$.

$R_{ij}$ Angle estimation variance between bus $i$ and bus $j$.

$V_i^{meas}$ Voltage magnitude measurement.

$\sigma_i^{meas}$ Variance of voltage magnitude measurement.

$\bar{V}_i$ Estimated voltage magnitude.

$\bar{\theta}_i$ Estimated different angle.

II. INTRODUCTION

Due to the limited number of measurements and the rather passive way of operation, monitoring capabilities of the current distribution network are still undeveloped. The foreseen large-scale implementation of distributed generation (DGs) challenges the distribution networks in coping with bidirectional power flows, voltage variations, fault level increases, protection selectivity, power quality and stability. Consequently, the concept of Active Network (AN) based on decentralize operation of local area networks has been mentioned as a possible solution for those problems [1]. The AN concept provides local and intelligent control functions for each cell (local area network). To enable these functions, each cell in AN must not only be observable locally but also strengthen the monitoring capabilities of the whole system. Obviously, development of a suitable state estimator will become a crucial element.

State estimation (SE) was firstly introduced by Schweppes and Wildes with a classical weighted least square (WLS) method [2]. In an effort to reduce computation burden, several hierarchical state estimation methods were proposed and summarized in [3]. Under the power system deregulation with emerging tasks for the network operators on all voltage levels, distributed state estimation (DSE) has drawn more and more interests [4]. In [5], Ebrahimian and Baldick introduced a robust DSE algorithm based on linearized augmented Lagrangians for overlapping bus boundaries. In [6], a straightforward and effective algorithm for overlapping tie-line boundaries was presented by Conejo et al. The method applies iteration steps to estimate local state variables as long as the boundary state variables do not change significantly. A global state estimation for both the transmission and distribution systems proposed in [7] by Sun and Zhang is also based on the iteration technique. In the past, a concept of an ultra fast decentralized state estimation for the large electric power system was presented in [8] by Zaborsky et al. Given at each bus a microprocessor, the bus state variables can be calculated by processing local bus information and its neighbours’ information. With the support of a strong communication system, this method can increase significantly the computation speed.

In a different approach, the Extended Kalman Filtering (EKF) theory has been applied for network parameter estimation [9], static state estimation [10], and dynamic state estimation [11]. However, EKF needs to collect recursively
time-historic data, update covariance vectors and treat heavy computation matrix. Those steps mitigate applications of EKF in the real large-scale power system.

A DSE method based on multi-agent system (MAS), i.e., an application of information and communication technologies, was presented in [12] by Nordman and Lehtonen. By exchanging messages among substation agents, the method has shown significant advantages in state estimation computation, bad data detection and identification steps. Nevertheless, the research has just been concerned on novel aspects, i.e., illustrating a feasibility of the concept with current sensors.

This paper elaborates on the idea of a distributed state estimation method, which was mentioned in [8]. Our main contribution is utilizing the advantages of MAS application and iteration techniques to improve the performance of state estimation in distribution networks suitable for the design of ANs. On-line simulations are implemented to investigate effectiveness and complexity of the proposed method. The organization of this paper is as follows: Section II describes details about a MAS based Active Network; Section III describes the proposed DSE; Section IV shows case studies with on-line simulations; Section IV draws out the main conclusions.

III. MULTI-AGENT BASED ACTIVE NETWORK

A. Active Distribution Network

As aforementioned, encouragement for developing more DGs causes many problems for the distribution networks. Some new concepts, such as Microgrid, Autonomous Network, Active Network, and Smart Grid, have been developed to deal with these challenges [1], [13-16]. Although differing in approach and scale implementation, they share the same objective of changing the current distribution networks from passive to active operation. The AN concept is described more in detail in this research.

Basically, an AN is built up from several cells, i.e., local sub-networks. Within each cell, an additional control layer is established. Hence, they can operate autonomously as Microgrid or Autonomous Network. This development of cell control layers will facilitate the increase of DG penetration. Redundant interconnections among the cells are essential to ensure connection between areas of power supply and demand. Obviously, the transition to AN requires a more meshed configuration in the distribution network.

B. Multi-Agent System based control architecture

MAS is considered as a suitable technology to enable the autonomous functioning of the cells in the AN. The MAS technology is based on the concept of intelligent agents, which are defined as entities (software or hardware) being able to react to changes in their environments and to interact with other agents [17]. A possible configuration of a MAS-based Active Network is shown in Fig.1 [18]. Each distribution substation represents for a cell, which includes load consumption and DGs. Active components of the cell, i.e., controllable loads and generators, are managed by representative agents. Through a master agent of the cell, those agents can communicate with other cells’ agents of the AN.

IV. DISTRIBUTED STATE ESTIMATION FOR ACTIVE NETWORKS

A. Background of State Estimation

As a fundamental technique used for SE, the classical WLS aims to find the log-likelihood function by solving following problem [20]:

$$
\text{Minimize: } J(x) = \left[ z - h(x) \right]^T R^{-1} \left[ z - h(x) \right]
$$

The application of a Gauss-Newton method for non-linear optimal conditions leads to an iterative solution as shown below:
\[
\Delta x^{k+1} = [G]^{-1} \cdot H^T \left( x^k \right) \cdot R^{-1} \cdot \left[ z - h \left( x^k \right) \right]
\]
(2)

where:
\[
H \left( x^k \right) = \frac{\partial h \left( x^k \right)}{\partial x^k}
\]
is the Jacobian matrix,
\[
G = H^T \left( x^k \right) \cdot R^{-1} \cdot H \left( x^k \right)
\]
is the Gain matrix.

Computation of the gain matrix for a large-scale power system is extremely heavy, which limits the application of the WLS method only to the transmission systems. Hence, several improvements were proposed to reduce the computation burden, for instance, a decoupled formulation or DC estimation. For the same purpose, DSE represents above centralized state estimation problem (1) by decentralized state estimation problems as follows [6]:

Minimize: \[
\sum_{a=1}^{\delta} J \left( x_a \right) + \sum_{a=1}^{\delta} \sum_{i \in B \left( a \right)} J \left( x_a, x_i \right)
\]
(3)

By dividing the centralized state estimation problem into smaller decentralized objective functions, the local state estimation can be implemented with scaled down size of the computation matrices.

B. State Estimation for a MAS based structure

When the AN is based on a MAS based control structure, SE plays a vital role to enable actuators in the control system of the AN. Depending on the control stages, i.e., cell control level, or AN control level, SE of the cell processes its own real-time and pseudo measurement information and coordinates with neighbors to get whole network state variables.

A state estimation scheme among the cells is shown in Fig.3. The SE agent of each cell performs three functions. Firstly it collects measurements of the local network area, for example, \([V_i, P_{ij}, Q_{ij}]\). In case of lacking some measurements, pseudo-measurements are replaced.

![DSE Agent of the Active Network](image)

These data are used in the coordination phase to estimate state variables for the neighbor cells, for instance, \([V_j', \theta_j]\). With the knowledge about the line impedance from \(i\) to \(j\), the state variables \([V_j', \theta_j]\) can be computed straightforward by a classic WLS method in (1)-(2). The variances of these local state variables, \([\sigma_j', \tau_j]\), can be obtained by the diagonal elements of \([G^{-1}]\) [21]. Note that the size of the gain matrix in this case is just \(3 \times 3\). For further computation, these state values with their variances are then considered as “pseudo-measurement” values with a Normal distribution:

\[
N \left( V_j', \sigma_j'^2 \right), \quad N \left( \theta_j, \tau_j^2 \right)
\]

As the coordination function allows exchanging these information between the cells, each cell will have a list of “pseudo-measurement” data as follows:

\[
\left[ V_{j1}^{\text{meas}}, V_{j2}^{\text{meas}}, \ldots, V_{jm}^{\text{meas}}, \theta_{j1}, \ldots, \theta_{jm} \right]
\]

with their variances:

\[
\left[ \sigma_{j1}^{\text{meas}}, \sigma_{j2}^{\text{meas}}, \ldots, \sigma_{jm}^{\text{meas}}, \tau_{j1}, \ldots, \tau_{jm} \right]
\]

where \(m_i\) is a number of the neighbor cell connected to cell \(i\); \(V_{j1}^{\text{meas}}\) and \(\sigma_{j1}^{\text{meas}}\) are real-time measurements (pseudo-measurements) of the voltage magnitude at reference bus of cell \(i\).

These array data are sent to the management layer which deploys the DSE function. Regarding the voltage magnitude data, the state estimation in (1) is then rewritten as:

Minimize: \[
J \left( V_i \right) = \frac{\left( V_{ij}^{\text{meas}} - \overline{V}_i \right)^2}{R_{ij}^{\text{meas}}} + \sum_{j=1}^{m} \frac{\left( V_{ij} - \overline{V}_i \right)^2}{R_{ij}^i}
\]
(4)

where:

\[
R_{ij}^{\text{meas}} = \left( \frac{1}{\sigma_{ij}^{\text{meas}}} \right)^2; \quad R_{ij}^i = \left( \frac{1}{\sigma_{ij}^i} \right)^2.
\]

The first order optimality condition yields:

\[
\frac{\partial J \left( V_i \right)}{\partial V_i} = \frac{V_{ij}^{\text{meas}} - \overline{V}_i}{R_{ij}^{\text{meas}}} + \sum_{j=1}^{m} \frac{V_{ij} - \overline{V}_i}{R_{ij}^i} = 0
\]
(5)

It leads to the maximum likelihood estimation as follows:

\[
\overline{V}_i = \frac{R_{ij}^{\text{meas}} V_{ij}^{\text{meas}} + \sum_{j=1}^{m} R_{ij}^i V_{ij}}{R_{ij}^{\text{meas}} + \sum_{j=1}^{m} R_{ij}^i}
\]
(6)

Similarly, the maximum likelihood estimation for the bus voltage angles is formed by the following equation:

\[
\overline{\theta}_j = \frac{R_{ij} \theta_{ij} + R_{ij} \overline{\theta}_j}{R_{ij} + R_{ij}}
\]
(7)

where:

\[
R_{ij} = \left( \frac{1}{\tau_{ij}} \right)^2.
\]

These new local state variables are compared with the prior values, i.e., \([V_i^0, \theta_i^0, \ldots, \theta_i^m]\). If there is no big change, the algorithm stops. Otherwise, it updates new local state variables as the prior state variables and sends backward information to the coordination layer to repeat the iterative loop until the local state variables converge.

As can be seen from the proposed DSE procedure, the coordination task is performed before the local state estimation is done while other DSE methods are in a contrary direction.
C. Topology Analysis

On a AN level, the proposed DSE considers each cell as a bus. An overall topology analysis is then determined by the status of interconnection line measurements. The operation status is defined with the criteria described in [4].

Agent $A_i$ checks if the local current measurement $|I_{ij}| = 0$, then it sends a query-if message to the neighbor agent $A_j$. After receiving the message, $A_j$ checks its local current measurement and defines status of the branch $i-j$. This status is also sent to $A_i$ by a confirm message. The message sequences for each interaction are illustrated on the sequence diagram in Fig.4.

V. CASE STUDIES

An on-line simulation is performed with a 5-bus test network, as shown in Fig.5, under Matlab/Simulink and Java Agent Development Framework (JADE) platform [22]. Data of the 5-bus test network are provided in Table I-II. In the Matlab/Simulink simulation, each bus of the 5-bus test network consists of an embedded function block. The embedded function block is a part of the agent which is connected with the MAS platform (JADE) during the simulation period. The local measurements of each bus are transferred through this block to be processed at the MAS platform.

A. Normal operation with measurement noise

Under normal operation, the bus voltage and real power flow are steady-state values. Those values, however, are distorted by noises from bad data sources, i.e., measurements devices, or communication channels. They cause so-called variances and bad data for estimation. In this simulation, the measured data of the bus voltages and power flows are polluted with distributed random fluctuations, 0.004 and 0.008pu respectively. In addition, 15% deviations from the standard values are injected in $V_2$ and $P_{23}$ as a bad data effect. These data are shown concretely in Fig.6.

Through the embedded function, 100 samples of the measurements are collected to generate the mean and standard deviation of the Normal distribution. Pseudo-measurements are used to replace missing measurements with large variance. These data are then transferred to the MAS platform to deploy the algorithm of DSE. The communication period, i.e., from the first time of sending information to the MAS platform to the second one, is about 40ms.

![Fig. 5. Single line diagram of 5-bus test network.](image)

![Fig. 4. Sequence Diagram for Topology Analysis.](image)

![Fig.6. Measured values with noise.](image)

Fig. 7 shows the results of the state estimation after 200ms. In the first period, 0–80ms, the embedded functions gather measured data and generate information for the MAS
platform. The values shown in this period are the differences between the true values and pre-estimated values. These pre-estimated values might be the nominal values or can be taken from a previous stage of estimation. In the period from 80–120ms, estimated data are obtained. Note that these values are estimated taking into account bad data injection. After 120ms, new estimation values are yielded when the bad data disappears. At the end of the simulation, the voltage differences and the active power differences are less than 0.1%.

B. Network topology change

At \( t = 10 \)ms, the switches at two ends of the line 2-4 open. Consequently, there is no power flow through line 2-4, as shown in Fig.8. In the two first communication periods, the measurements of the network in normal state are still processed. As a result, the differences of voltage magnitude and real power flow are significant in these periods, as shown in Fig.9. Naturally, the largest tolerance comes from the estimation values of \( V_4 \) (1.2%) and \( P_{24} \) (2.5%). At the same time, the SE agents have detected the network topology change by checking current measurements. New measurements are used to yield updated state variables which reach closely to the true values in the next communication periods. At the end of the simulation, all of the differences are ensured less than 0.1%.

Fig.8. Measured values with noise – Case of network work topology change.

Fig.7. Differences of estimations from true values.

Fig.9. Differences of estimations from true values – Case of network topology change.
C. Increased load consumption

In this case, the bad data influence is not taken into account. At $t = 60\text{ms}$, the load demand of bus 5 increases 20%. It causes voltage oscillations and power flow changes which are shown in Fig.10. As can be seen from Fig.11, the percentage values of voltage estimation differences swing to the voltage oscillation from 60-120ms. After $t = 120\text{ms}$, the algorithm estimates a new state of the network. At the end of the simulation, the voltage differences and the active power differences are less than 0.6%.

VI. CONCLUSION

This paper proposes an adequate state estimation method for MAS based Active Network. The performance of the proposed method is investigated through an on-line simulation. With the support of MAS, the state estimation function can be straightforward implemented in a distributed way. It can give accurate estimation not only on the steady state but also adapt itself to network changes.

Basically, the proposed DSE method is using a WLS technique to estimate local voltage and angle differences. However, the scale of the computation matrix with only two interactive buses inside the SE cells and SE agents taking care of the interconnection lines is much smaller than with central SE and other DSE methods. In addition, each typical bus of the power system is connected generally with maximum four other buses. Therefore, the processors of each bus can get convergence within few loops. Distributed and parallel working of processor improves significantly the computation time. The proposed estimation is suitable for a meshed configuration of the AN, which includes more than one interconnection between each pair of the cells. Depending on the availability of communication, the method is able to work locally inside the cells or also globally for the whole AN.

Further work needs more concern on other aspects of DSE, i.e., observability analysis, and bad data detection and identification. Based on the MAS structure, it is expected to yield promising solutions regarding these technical problems.

VII. REFERENCES


VIII. Biographies

Phuong H. Nguyen was born in Hanoi, Vietnam in 1980. He received his M.Eng. in Electrical Engineering from the Asian Institute of Technology, Thailand in 2004. From 2004 to 2006 he worked as a researcher at the Power Engineering Consulting Company No. 1, Electricity of Vietnam. In the end of 2006 he joined the Electrical Power System Research group at Eindhoven University of Technology, the Netherlands as a Phd student. He is working under the framework of the “Electrical Infrastructure of the Future” project.

Wil L. Kling (M’95) was born in Heesch, The Netherlands in 1950. He received the M.Sc. degree in electrical engineering from the Eindhoven University of Technology, The Netherlands, in 1978. From 1978 to 1983 he worked with Kema and from 1983 to 1998 with Sep. Since then he is with TenneT, the Dutch Transmission System Operator, as senior engineer for network planning and network strategy. Since 1993 he is a part-time Professor at the Delft University of Technology and since 2000 he is also a part-time Professor in the Electric Power Systems Group at the Eindhoven University of Technology, The Netherlands. From December 2008 he is appointed as a full-time professor and a chair of EPS group at the Eindhoven University of Technology. He is leading research programs on distributed generation, integration of wind power, network concepts and reliability.

Mr. Kling is involved in scientific organizations such as Cigre and IEEE. He is the Dutch Representative in the Cigre Study Committee C6 Distribution Systems and Dispersed Generation.