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State estimation for wind farms including the wind turbine generator models

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ABSTRACT

Wind farms can be analyzed using state estimation methods, which can be used to obtain its running state, including several aspects that cannot be easily obtained using other methods (e.g., capacitor bank aging) Using these methods on these types of networks is strongly affected by decoupling between active and reactive power and by a radial configuration, which is typical. For example, this decoupling affects its observability and robustness as well as the technical feasibility of the results. To overcome these drawbacks, an extended state estimation method is proposed in which the models for the different wind turbine technologies have been incorporated. These models have been mainly generated from measurement data using neural networks and polynomial fitting; these models do not require parameter values, which are rarely available from manufacturers. Furthermore, the resulting equations for modeling wind turbines are easily integrated into the state estimator due to their simplicity and derivatives.Thus, a method that guarantees feasible results, at least for wind turbines, was generated with increased observability robustness.

The method was tested using measurement data from the Sotavento Wind Park, which has wind turbines with different types of technologies.

1. Introduction

The statuses of the network and wind turbine generators (WTGs) are useful for evaluating the proper working conditions of a wind park; the data from Supervisory Control and Data Acquisition (SCADA) can be used and are usually implemented in this type of installation. However, directly using measured data can generate errors associated with measurement errors and communication failures, among other concerns. Furthermore, it can only be obtained values directly calculated from measurements; thus, several relevant factors (e.g., capacitor aging) cannot usually be available. In this context, state estimation (SE) methods can overcome these problems.

State estimation (SE) is a method for obtaining the state variables of a network from a set of measurements [1,2]. Usually, the measurements are the active and reactive power flowing through the branches and injected at nodes as well as the magnitude of the nodes' voltage. Apart from obtaining the network state, this type of analysis could be useful for analyzing other aspects related to the system operation (e.g., out-of-service WTGs, aging capacitor banks, communication failures and energy loss estimates).

When an SE method is applied, it must be considered that a wind farm network is usually in a radial configuration, and the electrical measurements are only conducted on the low voltage side of the wind turbines (WTGs) and the high voltage side of the substation. Thus, the common measurements are the voltage at the nodes, the active and reactive power generated by the WTGs and the active and reactive power injected into the transmission network through the substation. A state estimator in this type of network has little redundancy because it only includes nodal measurements, and the active power (voltage angles) is strongly decoupled from the reactive power (voltage magnitudes). Therefore, the resulting system has a weak observability; this means that if the measurements in only one WTG are not available, then the system may not be observable. Furthermore, there is no guarantee that the results are technically feasible (e.g., due to out-of-range values, unrealistic power flows and values that are incompatible with WTG operation) because the WTG behavior (e.g., the PQ model of asynchronous machines) is not included in the method.

To overcome the aforementioned drawbacks, this paper proposes to include functions that model the WTG behavior (i.e.,

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Nomenclature

k	number of iterations
x	state vector (module U_i and θ_i nodal voltage phase)
h	functions that relate measurements to state variables
z^m	measurements vector
ε	errors vector
d	constraints vector
$c(x)$	functions of the constraints vector
W	inverse covariance matrix
H	Jacobian matrix of the functions $h(x)$, in $x^{(i)}$
C	constraint matrix
$\Delta z^{(i)}$	vector measurement errors z^m
P_i	active power injected at node i
Q_i	reactive power injected at node i
Q_{Ci}	reactive power generated by capacitors in node i
U_i^m	measurement of the voltage at node i
P_i^m	measurement of the active power injected at node i
Q_i^m	measurement of the reactive power injected at node i
Q_{Ci}^m	measurement of the reactive power generated by the capacitors in node i
n	number of nodes in the network
N	set of nodes in the system
nn_R	reference node for voltage angles
N_{Um}	set of nodes with voltage measurements
N_{Pm}	set of nodes with injected active power measurements
N_{Qm}	set of nodes with injected reactive power measurements
N_{null}	set of nodes with virtual measurements (null injected active and reactive power)
N_e	set of nodes with active and reactive power that belongs to the extended state vector
$N_{e,FSWT}$	set of nodes for FSWTs
$N_{e,VSWT-DFIGs}$	set of stator-side nodes in VSWT-DFIGs
$N_{e,VSWT-DFIGr}$	set of rotor-side nodes in VSWT-DFIGs
$N_{e,VSWT-SG}$	set of nodes for VSWT-SGs
$X_{(N)}^m$	vector of measurements X_i^m at nodes N; thus,$X_{(N)}^m = [\ldots \quad X_i^m \quad \ldots] \quad i\in N$

functions that establish the relationship between voltage, active power and reactive power in WTGs) in the state estimation equations. These relationships are not usually included in a classic state estimation [3]; they are only partially considered in certain power flow analyses [4,5,6].

To model WTGs, equations can be used that typically include the slip as input data and several assumptions about the generator behavior (e.g., the relationship between power and slip) [7,8]. Using these equations has certain disadvantages: the need for slip measurements; the equation parameters are usually unknown; and finally, the additional complexity in the state estimator does not guarantee enhanced redundancy.

To overcome those problems, herein, WTGs were modeled using polynomial fitting techniques and *back-propagation neural networks* (*BPNNs*) [9,10]. Thus, the input data for the proposed state estimator are the network parameters and measurements; the latter are used for WTG modeling and during SE. The resulting models, polynomial equations and BPNNs can easily be integrated into the SE due to their simplicity and derivatives. To integrate these functions into the state estimator, a method is proposed that increases the number of state variables, including the variables active and reactive power of wind turbines, and uses the WTG models as restrictions. As a result, the state estimation problem becomes a constrained optimization problem [11,12]. The main advantage of the proposed model is that the decoupling between P–V and between Q-δ disappears, the system redundancy is increased, and the results obtained are technically feasible due to inclusion of the WTG models.

To demonstrate its operation, the proposed method was applied to the Sotavento Experimental Wind Farm S.A. (http://www.sotaventogalicia.com) [13,14]. This farm is dedicated to D&I of wind power and includes nine different types of 24 WTGs, including fixed-speed and variable-speed wind turbines.

2. Static state estimation

2.1. Classical state estimator

Static state estimation (SE) consists of calculating a set of variables (state variables) from a set of network measurements. Usually, the measurements are at the magnitude of the node voltages, the active and reactive power flow in branches and the active and reactive power injection in nodes. On the other hand, the state variables are the magnitude and angle of the node voltages. When the state variables are known, any electric variable in any element of the network can be obtained. A diagram of the classical SE methodology is shown in Fig. 1.

In SE, the measurements are considered erroneous with the following behavior:

1. The histogram of the error values can be approximated using a normal pdf with the mean μ and standard deviation σ: $N(\mu,\sigma)$.
2. The expectation of errors is zero: $E[e_i] = 0$.
3. The errors are independent: $E[e_i \cdot e_j] = 0$; thus, it can be defined as a diagonal covariance matrix, where the main diagonal is the standard deviation vector:

$$Cov(e) = E\left[e \cdot e^T\right] = W^{-1} = diag\left\{\sigma_1^2, \sigma_2^2, \ldots, \sigma_m^2\right\}. \tag{1}$$

The SE method consists of calculating the state vector x such that the error between the measured values and those obtained from the estimator is minimized. According to previous paragraphs, assuming that measurements have an associated error (ε), the following system of equations can be written [1]:

$$z^m = h(x) + \varepsilon. \tag{2}$$

Therefore, the following index must be minimized [10]:

$$\min\{J(x)\} = \min\left\{[z - h(x)]^T \cdot W \cdot [z - h(x)]\right\}. \tag{3}$$

The method to minimize this term is the weighted least squares method. The state vector can be obtained by iteratively solving the following system of equations:

$$\begin{gathered}\left(H^T\left(x^{(k)}\right) \cdot W \cdot H\left(x^{(k)}\right)\right) \cdot \Delta x^{(k)} = H^T\left(x^{(k)}\right) \cdot W \cdot \left(\Delta z^{(k)}\right) \\ x^{(k+1)} = x^{(k)} + \Delta x^{(k)}\end{gathered} \tag{4}$$

$$\Delta z^{(k)} = z^m - h\left(x^{(k)}\right). \tag{5}$$

For a wind farm, the state vector is formed by the angle of voltage at every network node except the reference node n_R and the