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Robust state estimation for power systems via moving horizon strategy

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ABSTRACT

In this paper, I propose a re-weighted moving horizon estimation (RMHE) to improve the robustness for power systems. The RMHE reduces its sensitivity to the outliers by updating their error variances real-time and re-weighting their contributions adaptively for robust power system state estimation (PSSE). Compared with the common robust state estimators such as the Quadratic-Constant (QC), Quadratic-Linear (QL), Square-Root (SR), Multiple-Segment (MS) and Least Absolute Value (LAV) estimator, one advance of RMHE is that the RMHE incorporates the uncertainty of process model and the arrival cost term during the optimization process. Constraints on states are also taken into account. The influence of the outliers can be further mitigated. Simulations on the IEEE 14-bus system show that the RMHE can obtain estimated results with smaller errors even when the outliers are present.

1. Introduction

The most common assumption of measurement noise used in power system state estimation (PSSE) is Gaussian. However, the Gaussian noise assumption is only an approximation to reality [1]. When the system meets transient data in steady-state measurements, instrument failure, human error or model nonlinearity [1,2], non-Gaussian measurement error could be generated. Such outliers that are far away from the expected measuring data raise the potential risk of misleading the estimation result [3]. The influence of bad data or outliers on the estimated results and one method to suppress the bad measurements during the iterative process has been proposed in [4]. Robust estimators with different objective functions such as the Quadratic-Constant (QC), Quadratic-Linear (QL), Square-Root (SR) and Multiple-Segment (MS) estimator have also been introduced to solve this kind of problem [5–7]. Moreover, robust estimation has also been applied to such systems that all measurements are collected from phasor measurement units (PMUs) [8–10].

The Moving Horizon Estimation (MHE) aims to solve at each time instant an optimization problem by using a limited amount of most recent information [11]. The states are estimated by minimizing an overall objective function which consists of sensor model error, process model error, and error in the state estimate at the beginning of the window [12]. The constraints on states have also been exploited in the optimization process. This can overcome the issues such as the suboptimal estimates or instability of the error dynamics [13]. By having these constraints in the optimization, MHE is more robust to the measurement outliers. [14] propose one kind of robust MHE. It generates a robust estimate by separately minimizing a set of least-squares cost functions, where the measurements affected by outliers are left out. Finally the estimation result associated with the lowest cost is chosen. One drawback of this method is that the observability of estimator cannot be guaranteed when some measurements are deleted.

In this paper, after combining the advantages of the MHE and the robust estimators such as QC, QL, SR and MS, a re-weighted MHE (RMHE) algorithm is proposed for robust PSSE. The RMHE uses the same method proposed in [15,4,16] to deal with the outliers, where the variances of outliers are updated online based on the measurements. The weights of the outliers will be mitigated but the observability of estimator is not influenced. Moreover, the constraints are exploited in the optimization process in order to alleviate the influence of outliers. In order to accelerate the performance of RMHE, the Alternating Direction Method of Multipliers (ADMM) is adapted to solve the quadratic problem based on RMHE. The ADMM is a powerful algorithm for solving structured convex optimization problems. It provides a structured way of decomposing very large problems into smaller-subproblems that can be solved efficiently [17]. Numerical simulations with the IEEE 14-bus benchmark system show the effectiveness of RMHE.

This paper is organized as follows. The robust state estimation problem is formulated in Section 2. The RMHE algorithm is

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Nomenclature

State variables

x	State vector
$\hat{x}$	Estimated state
V_i^r	Real part of the voltage phasor at bus i
V_i^{im}	Imaginary part of the voltage phasor at bus i
w	Process noise

Measurements and noise

z	Measurements from Phasor Measurement Unit
v	Measurement noise

Functions

$e_{i,k}$	The ith measurement residual at time step k
$\rho(e_{i,k})$	Chosen function of $e_{i,k}$
J	Cost function
$f_i(v_i)$	Probability density function of v_i
H	Measurement matrix
$W_{i,k}$	Weighting factor for ith measurement at time step k
Ψ	Derivative of J w.r.t. $\hat{x}$

Numbers and others

m	Number of measurements in 1 batch
n	Number of states
N	Number of batches
i	Measurement index
t, k	Time index
q	Iteration index
(k)	Iteration index in ADMM
a_i	First threshold for traditional estimator i
b_i	Second threshold for traditional estimator i
r_i	Third threshold for traditional estimator i
σ_i	Standard deviation of measurement noise v_i
R	Diagonal matrix
P	state covariance matrix
$\mathbf{x}$	Vector $[\hat{x}_{t-N}^T \cdots \hat{x}_t^T]^T$
Z	Vector $[z_{t-N}^T \cdots z_t^T]^T$
ρ_0	The penalty parameter in ADMM algorithm
$r^{(k+1)}$	The primal residuals in ADMM algorithm
$s^{(k+1)}$	The dual residuals in ADMM algorithm

proposed in Section 3. The simulations on IEEE 14-bus system is given in Section 4. Finally the conclusions are made in Section 5.

2. Robust state estimation

2.1. Measurement model and state equation

This paper use rectangular coordinates. The linear measurement model based on the PMUs [8] is given by

$$z_t = Hx_t + v_t, \tag{1}$$

where t is the time step and $z \in \mathbb{R}^m$ is the measurement vector composed of the real and imaginary components of bus voltage (or the line current) phasors. The state vector is given as $x = [V_1^r \cdots V_n^r\ V_1^{im} \cdots V_n^{im}]^T \in \mathbb{R}^n$, in which V_i^r and V_i^{im} $(i = 1, \ldots, \frac{n}{2})$ are the real and imaginary components of the bus voltage phasors, respectively. v is assumed to be noise with zero mean.

Specially the ith measurement is given by

$$z_{i,t} = H_i x_t + v_{i,t}, \tag{2}$$

where the subscript i is the index and v_i is uncorrelated between different measurements.

In this paper, the following assumptions are held:

Assumption 1. The local state estimation is performed using the measurement data collected within the same system-wide updating time interval.

Assumption 2. The system is observable by PMUs and matrix $G = H^T H$ is full rank.

The following simplified process model is considered for the state estimation problem [18,19]:

$$x_{t+1} = Ax_t + w_t, \tag{3}$$

where A is assumed to be an identity matrix [18] and w_t represents the zero-mean disturbance with variance $Q > 0$.

2.2. Robust estimators

In this section we will discuss different types of M-estimators [5]. A traditional power system may be considered as a quasi-static system [18,20] because load demands change slowly and hence the state changes slowly, i.e. $x_{t-N} \approx \cdots \approx x_t \approx x$. Given $N + 1$ sets of measurements $z_{i,k}$, $k = t - N, \ldots, t$ collected from $i = 1, \ldots, m$ measurements, the state x can be estimated by minimizing the cost function as follows:

$$J = \sum_{i=1}^{m} \sum_{k=t-N}^{t} \rho(e_{i,k}), \tag{4}$$

where $e_{i,k}$ is the measurement residual,

$$e_{i,k} = z_{i,k} - H_i \hat{x}. \tag{5}$$

Eq. (5) gives $\frac{\partial e_{i,k}}{\partial \hat{x}} = -(H_i)^T$. Differentiating the above cost function (4) with respect to $\hat{x}$,

$$\begin{aligned} \frac{\partial J}{\partial \hat{x}} = \Psi(E) &= \frac{\partial J}{\partial e_{i,k}} \frac{\partial e_{i,k}}{\partial \hat{x}} \\ &= \sum_{i=1}^{m} \sum_{k=t-N}^{t} \frac{\partial \rho(e_{i,k})}{\partial e_{i,k}} \frac{1}{e_{i,k}} e_{i,k} \frac{\partial e_{i,k}}{\partial \hat{x}_k} \\ &= -\sum_{i=1}^{m} \sum_{k=t-N}^{t} W_{i,k} e_{i,k} (H_i)^T, \end{aligned} \tag{6}$$

where

$$W_{i,k} = \sum_{i=1}^{m} \sum_{k=t-N}^{t} \frac{\partial \rho(e_{i,k})}{\partial e_{i,k}} \frac{1}{e_{i,k}}. \tag{7}$$

Using Eq. (5), $\Psi(E)$ can also be written by

$$\begin{aligned} \Psi(E) &= -\sum_{i=1}^{m} \sum_{k=t-N}^{t} W_{i,k} (z_{i,k} - H_i \hat{x})(H_i)^T \\ &= -\bar{H}^T W E \\ &= -\bar{H}^T W (Z - \bar{H}\hat{x}), \end{aligned} \tag{8}$$

where

$$\bar{H} = \left[H^T \cdots H^T\right]^T \in \mathbb{R}^{(N+1)m \times n},$$

$$Z = \left[z_{t-N}^T \cdots z_t^T\right]^T \in \mathbb{R}^{(N+1)m},$$

$$E = \left[e_{t-N}^T \cdots e_t^T\right]^T \in \mathbb{R}^{(N+1)m},$$

$$W = \operatorname{diag}\left(W_{1,t-N}, \ldots, W_{m,t-N}, \ldots, W_{1,t}, \ldots, W_{m,t}\right) \in \mathbb{R}^{(N+1)m \times (N+1)m}.$$