Turkish Journal of Electrical Engineering & Computer Sciences
http://journals.tubitak.gov.tr/elektrik/
Research Article
Turk J Elec Eng & Comp Sci
(2017) 25: 3143 – 3151

doi:10.3906/elk-1603-261

Robust local parameter estimator based on least absolute value estimator

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Received: 25.03.2016 • **Accepted/Published Online:** 23.12.2016 • **Final Version:** 30.07.2017

Abstract: Changes in weather conditions such as temperature and humidity, miscommunication between the control center and circuit breaker transducers and tap changers, and inaccurate manufacturing data may cause parameter errors. Because of incorrect parameters, the state estimator may provide biased state estimates, which may lead to many serious economic and operational results. In order to prevent that, one must identify and correct those parameter errors. This work proposes a local parameter estimator based on the least absolute value (LAV) estimator, which is known to be robust against bad measurements, i.e. measurements with gross error. Considering the increasing number of phasor measurement units (PMUs), as well as their fast refresh rate and high accuracy, the proposed method will employ PMU measurements in local parameter estimation. In general, a PMU measures the current phasor flowing through a branch and the voltage phasor of the sending bus of that branch. However, those two measurements are not sufficient to estimate the parameters of the considered branch. Therefore, multiple measurements taken at different time instants will be used in the parameter estimation process for measurement redundancy, assuming that the line parameters and transformer taps are constant. The proposed method also assumes that the state estimates are available. The LAV estimator is computationally expensive, but it provides unbiased state estimates even in the presence of bad data, provided that enough measurement redundancy is available. This deficiency will be eliminated by performing local parameter estimation.

Key words: Phasor measurement units, least absolute value estimator, robust parameter estimation, local parameter estimation

1. Introduction

State estimation (SE) in power systems is one of the most essential functions of energy management systems (EMS) in maintaining the reliability of the whole system operation [1]. SE assumes a true model of the power system [1–4], and hence the knowledge of system topology and true values of the line and transformer parameters are extremely important for SE accuracy [1–7]. However, system parameters such as line series impedance and shunt admittance values, as well as the transformer taps, may be inaccurate [8], which may bias the estimates. Those biased state estimates may yield serious results, since EMS applications and decision routines depend on those estimates. This paper proposes a local parameter estimation method that uses phasor measurement unit (PMU) measurements. The parameter estimation problem is solved using a robust least absolute value (LAV) (or least absolute deviations, LAD) estimator, which enables unbiased estimates to be obtained without performing a bad data process.

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Performance of programs that run on the EMS depends strongly on the parameters. Topological errors can be identified easily in SE, which may be treated as parameter errors, while the small errors in the parameters such as branch impedance will create reliability problems [9]. Parameter estimation methods in the literature can be separated into two subgroups, namely off-line methods [5–13] and online methods [14–19]. Those methods depend on the well-known least squares (LS) estimator [1]. However, LS is a nonrobust estimator, such that even a single bad measurement in the data set may skew the parameter estimates. Therefore, one needs to run a bad-data detection process, such as normalized residual test [20], in order to detect and identify bad data, which will add extra computation time. This paper proposes using the LAV estimator, which is robust against measurements with gross error and yet computationally competitive with the LS estimator [21,22]. The LAV estimator, which is defined in Section 2 in detail, can be expressed as a linear programming (LP) problem. Reformulating the problem as a LP provides the state estimator the advantage of noise filtering as well as bad-data elimination. The LP problem can be solved using the simplex method, which can improve the computational performance.

The LAV estimator, which is an L-1 norm estimator, is computationally expensive for nonlinear problem formulations due to the iterative solution scheme, though it is robust against bad measurements in the presence of enough measurement redundancy [23]. However, performing local parameter estimation can compensate for this deficiency, which is a very small problem compared to the state estimation problem. Note that, although the system states and the PMU measurements are linearly related, the parameter estimation problem is a nonlinear problem, since the vector to be estimated consists of not only the parameters of the considered branch or transformer, but also the bus voltages of the sending and the receiving ends of the considered branch or transformer. Therefore, for computational efficiency, the size of the problem should be kept at a minimum. Once the parameter estimation problem is localized, the size of the problem decreases significantly, and hence the computational burden becomes insignificant. Note that if a LAV estimator is employed, a bad-data processor becomes unnecessary.

Considering the increasing number of PMUs in power grids, this paper proposes using PMU measurements in local parameter estimation. PMUs take synchronized bus voltage phasor and line current phasor measurements 30 times per second with respect to the global positioning system [24]. However, those two measurements are not sufficient to estimate the parameters of that branch or transformer. Therefore, multiple measurements taken in different time instants will be used in the parameter estimation process for measurement redundancy, assuming that the state estimates are also available.

This paper introduces a local parameter estimator that employs the robust LAV estimator. The developed method is capable of performing unbiased parameter estimation, even in the presence of gross errors associated with measurement data.

The paper is organized as follows: in Section 2, the proposed parameter estimation method will be explained in detail and in Section 3, simulations and the results of the comparison between LAV and LS estimators in terms of accuracy and computational performance will be presented. Section 4 concludes the paper.

2. Proposed method

EMS estimates either all parameters of a given power system or a subset of the system parameters, i.e. local parameter estimation [1]. Since estimating all system parameters has a high computational burden, local parameter estimation is preferred. Consider the two-bus system given in the Figure, where g_{12} is the series conductance, b_{12} is the series susceptance, and b_{11} is the charging-susceptance, which is assumed to be equal to b_{22}, of the transmission line between buses 1 and 2. The relation between the system parameters and the voltage and current phasor measurements taken by a PMU can be expressed as below, where V_k is the voltage phasor of bus k and I_{ij}^{meas} is the measured current phasor between buses 1 and 2. $Re\{y\} + jIm\{y\}$ represents the real and imaginary parts of phasor y.

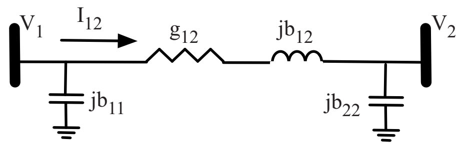

Figure. Two-bus sample system.

$$
\begin{aligned}
&I_{ij}^{meas} = Re\left\{I_{ij}^{meas}\right\} + jIm\left\{I_{ij}^{meas}\right\} \\
&Re\left\{I_{ij}^{meas}\right\} = g_{ij}\left(Re\left\{V_i\right\} - Re\left\{V_j\right\}\right) - \left(b_{ij} + b_{ii}\right) Im\left\{V_i\right\} + b_{ij} Im\left\{V_j\right\} \\
&Im\left\{I_{ij}^{meas}\right\} = g_{ij}\left(Im\left\{V_i\right\} - Im\left\{V_j\right\}\right) + \left(b_{ij} + b_{ii}\right) Re\left\{V_i\right\} - b_{ij} Re\left\{V_j\right\}
\end{aligned} \tag{1}
$$

As seen in Eq. (1), the number of measurements is not enough to estimate the three unknown parameters. Considering the fast refresh rate of PMU measurements (30 times/s) [25] and that system parameters remain the same for short durations, this paper proposes to use multiple PMU scans taken from the same measurement unit at consecutive time instants to solve the parameter estimation problem. Although at least 3 measurements are required for the solution of the parameter estimation problem, for a robust estimation at least 4 redundant measurements are needed [23]. Therefore, this work proposes the use of at least 7 measurement scans for single bad-data robustness. Thanks to the small size of the parameter estimation problem, the computational burden of the method is very small.

Despite being more accurate compared to the conventional measurements, PMUs may provide bad data. Using only the voltage and current phasor measurements obtained by a PMU makes the parameter estimation vulnerable. In order to improve the robustness of the parameter estimation, the state estimates of the system from the EMS state estimator are also employed as measurements.

The relation between the observations and the system states is formulated below.

$$z = h\left(x\right) + e \tag{2}$$

In Eq. (2), measurement vector z with size of $8n\times\ 1$ is defined as below, where measurements are taken at n different time instants:

$$z^T = \left[\begin{array}{cccccc} V^{m,r} & V^{m,i} & V^{e,i} & V^{e,i} & I^{m,r} & I^{m,i} \end{array}\right] \tag{3}$$

$V^{m,r}$ = vector of the real parts of the voltage phasor measurements taken at the sending end of the branch (1 $\times n$), $V^{m,i}$ = vector of the imaginary parts of the voltage phasor measurements taken at the sending end of the branch (1 $\times n$), $V^{e,r}$ = vector of the real parts of the voltage phasor estimates at the sending and receiving ends of the branch (1 × 2n), $V^{e,i}$ = vector of the imaginary parts of the voltage phasor estimates at the sending and receiving ends of the branch (1 × $2n$), $I^{m,r}$ = vector of real parts of the current phasor measurements from the sending end to the receiving end of the branch (1 $\times n$), and $I^{m,i}$ = vector of the imaginary parts of the current phasor measurements from the sending to the receiving end of the branch (1 $\times n$).

The state vector x with size $(4n + 3) \times 1$ is defined as follows:

$$x^T = \begin{bmatrix} V^r & V^i & g_{ij} & b_{ij} & b_{ii} \end{bmatrix} \tag{4}$$

V^r = vector of the real parts of the voltage phasors of the sending and receiving ends of the branch $(1 \times 2n)$, V^i = vector of the imaginary parts of the voltage phasors of the sending and receiving ends of the branch $(1 \times 2n)$, g_{ij} = series conductance of the branch (1×1), b_{ij} = series susceptance of the branch (1×1), b_{ii} = charging susceptance of the branch (1×1), z is nonlinearly related to the state vector x defined in Eq. (4) via the function $\mathrm{h}(x)$.

The state estimation problem is linear if the considered system is measured solely by PMUs. However, the parameter estimation problem is a nonlinear problem due to the relation between the states and parameters, and observations, as seen in Eq. (1). Therefore, an iterative solution should be employed. Although LS is a well-known and widely used method for state estimation [1], it is not a robust estimator, i.e. even a single piece of bad data may distort the estimates. If LS estimation is employed, postprocessing of measurement residuals for bad-data analysis should be carried out. Note that bad-data processing is computationally expensive.

This paper proposes the use of a robust LAV estimator. Although the iterative LAV estimator is computationally expensive [21], thanks to the small size of the proposed parameter estimation problem, the extra computational time will be negligible.

The objective function of the LAV estimator is defined as below for a system with m measurements and n states to be estimated, where r_i is the ith residual.

$$\sum_{i=1}^{m} |r_i| \tag{5}$$

The LAV optimization problem can be expressed as an equivalent LP problem by rearranging the equations and defining some new strictly nonnegative variables [1,21], as formulated below.

$$\begin{aligned} &\min \quad c^T y \\ &s.t. \quad My = b \\ &\qquad\quad \mathrm{y} \geq 0 \\ &c^T = \begin{bmatrix} Z_n & O_m \end{bmatrix}, \quad y = \begin{bmatrix} \Delta X_a^T & \Delta X_b^T & U^T & V^T \end{bmatrix}, \quad M = \begin{bmatrix} H & -H & I & -I \end{bmatrix}, \quad b = \Delta z \end{aligned} \tag{6}$$

In Eq. (6), Z_n is the $1 \times 2n$ vector consisting of zeros and O_m is the $1 \times 2m$ vector consisting of ones, where m is the number of measurements and $n$is the number of states. H is the Jacobian matrix, which is defined as the partial derivative of h(.) with respect to the states. ΔX_a and ΔX_b are $1 \times n$, and U and V are $1 \times m$ vectors, where

$$\begin{aligned} &\Delta x = \Delta X_a^T - \Delta X_b^T \\ &U^T - V^T = z - h\left(x^k\right) - H\left(x^k\right)\Delta x^k = \Delta z^k - H\left(x^k\right)\Delta x^k \end{aligned} \tag{7}$$

In Eq. (7), superscript k indicates the iteration number. The iterative solution procedure is summarized as: 1) initialize x_0, 2) solve the LP problem given in Eq. (6), 3) check if $\Delta x^k < \varepsilon$. If so, finish the iterative solution, otherwise $x^{k+1} = x^k + \Delta x^k$ and go to 1.

The LP estimation problem in Eq. (6) can be interpreted geometrically as minimizing the sum of moduli of distances of the solution to the measurement hyperplanes [26]. The resulting estimates lie on a point of intersection of n hyperplanes in n-dimensional space. Therefore, the LP-based LAV uses the set of n hyperplanes from the m available observations, where the objective function is minimized. Bad measurements are rejected provided that there are fewer than $m - n$ of them. The LAV estimation therefore combines automatic bad-data rejection with a useful degree of noise filtering [26].

3. Simulations and results

In this section, the 2-bus system given in Figure is employed for the simulations. For the simulation, g_{12} is assigned as 5.2246 pu, b_{12} is assigned as –15.646 pu, and b_{11} is assigned as 0.0528 pu. All case studies are conducted in MATLAB. In all scenarios, Gaussian error with zero mean and a standard deviation of 0.001 was added to the measurement sets and the simulations were conducted 1000 times.

3.1. Comparison of LS and LAV

In this scenario, no bad data were introduced into the measurement set. As seen in Table 1, both estimators converged to the true values in comparable durations. Note that no special effort is spent for estimator optimization. If bad data were associated with the measurement set, the computational time of the LS estimator would increase, while that of the LAV estimator would remain nearly the same [23]. This situation is visualized by the following scenario. It is assumed that the measurement set includes a bad measurement. A measurement is randomly selected as bad during the run of 1000 simulations. As also seen in Table 1, the estimates of LS are highly biased. If unbiased estimates are obtained by postprocessing the results, the solution time will increase significantly. Mean squared error (MSE) and estimator bias (EB) are defined as follows, where superscript e indicates an estimate.

Table 1. Comparison of LS and LAV.

		No bad data	With bad data
LS	MSE of g_{12}	0	7.62
	MSE of b_{12}	0	6.86
	MSE of b_{11}	0	0.067
	EB of g_{12}	0	–4.905
	EB of b_{12}	0	28.44
	EB of b_{11}	0	0.1052
	Mean duration	0.025 s	0.04 s
LAV	MSE of g_{12}	0	0
	MSE of b_{12}	0	0
	MSE of b_{11}	0	0
	EB of g_{12}	0	0
	EB of b_{12}	0	0
	EB of b_{11}	0	0
	Mean duration	0.050 s	0.045 s

*Values smaller than 1e-6 are assumed to be 0.

$$MSE = \frac{1}{n}\sum_{k=1}^{n}\left(x_k^e - x_k\right)^2 \tag{8}$$

$$EB = \frac{1}{n}\sum_{k=1}^{n} x_k^e - x_k \tag{9}$$

3.2. Performance evaluation with bad parameter data

In this scenario, it is assumed that the given parameter information is incorrect, such that the series susceptance was assumed to be 3 times larger than the true value. The simulation results are presented in Table 2. As seen in Table 2, the proposed method converged to the true values in acceptable duration with acceptable accuracy. Note that the increase in simulation duration and decrease in accuracy are caused by the incorrect initial values of the parameter estimation problem.

Table 2. Performance of the method with incorrect parameter values.

LAV	MSE of g_{12}	0.1655
	MSE of b_{12}	0.2527
	MSE of b_{11}	0.0151
	EB of g_{12}	0.0319
	EB of b_{12}	0.0604
	EB of b_{11}	–0.00011
	Mean duration	0.34 s

3.3. Performance evaluation with bad measurement

It is assumed that the given parameter information is correct and state estimation results are unbiased, but PMU provides bad data for both voltage and current. Table 3 presents the results for different amounts of bad data. As seen in Table 3, if the size of the observation matrix increases, i.e. more measurement scans are employed for parameter estimation, the robustness improves and the proposed method provides unbiased parameter estimates with larger number of bad measurements.

Table 3. Performance of the method with bad data.

Number of bad voltage and current measurement pair		1	2	2
Number of observation instants		7	7	8
LAV	MSE of g_{12}	0	10.219	0
	MSE of b_{12}	0	24.974	0
	MSE of b_{11}	0	0.8114	0
	EB of g_{12}	0	104.42	0
	EB of b_{12}	0	623.70	0
	EB of b_{11}	0	0.6583	0
	Mean duration	0.400 s	0.370 se	0.399 s

*Values smaller than 1*e*-6 are assumed to be 0.

3.4. Performance evaluation with bad state estimates

In this case, it is assumed that the given parameter information is correct, but the state estimator used in the system gives one a biased estimated of the bus voltage where the PMU is located (sending end voltage), i.e. the estimated value is identically equal to 0. Then the same scenario is applied to multiple biased estimates. As seen in Table 4, the proposed method maintains robustness until 6 biased estimates are employed in the parameter estimation problem. The last column of Table 4 presents the MSE results of the same observation set with 6 biased estimates; however, the observation set receives 8 measurement instants instead of 7. As seen in Table 4, if the number of observations is increased, the parameter estimation maintains robustness with larger amounts of bad data.

Table 4. Performance of the method with biased state estimates.

Number of biased estimates		1	2	3	4	6	6
Number of observation instants		7	7	7	7	7	8
LAV	MSE of g_{12}	0	0	0.014	0.45	23.653	0.014
	MSE of b_{12}	0	0	0.029	0.15	16.896	0.019
	MSE of b_{11}	0	0	0.011	0.15	1.4015	0.011
	EB of g_{12}	0	0	0.00019	0.20	559.05	0.00019
	EB of b_{12}	0	0	0.00085	0.023	285.48	0.00037
	EB of b_{11}	0	0	0.00012	0.024	1.943	0.00013
	Mean duration	0.273 s	0.263 s	0.301 s	0.304 s	0.338 s	0.267 s

*Values smaller than 1e-6 are assumed to be 0.

3.5. Transformer tap estimation

In this case, the parameters of a transformer, namely the transformer tap and leakage inductance in pu, are estimated. It is assumed that the given parameter information is correct, but the state estimator used in the system gives one a biased estimated of the bus voltage where the PMU is located (sending end voltage), i.e. the estimated value is identically equal to 0. Then the same scenario is applied to multiple biased estimates. As seen in Table 5, the proposed method maintains robustness until 6 biased estimates are employed in the parameter estimation problem. The last column of Table 5 presents the MSE results of the same observation set with 6 biased estimates; however, the observation set receives 8 measurement instants instead of 7.

Table 5. Performance of the method with biased state estimates.

Number of biased estimates		1	2	3	4	6	6
Number of observation instants		7	7	7	7	7	8
LAV	MSE of b_{12}	0	0	0	0	1.8641	0
	MSE of a	0	0	0	0	0.4103	0
	Mean duration	0.345 s	0.352 s	0.346 s	0.347 s	0.341 s	0.351 s

*Values smaller than 1e-6 are assumed to be 0.

As seen in Tables 4 and 5, if the number of observations is increased, the parameter estimation maintains robustness against larger amounts of bad data. Note that if the biased estimates are associated with the receiving end voltage, the tolerance of the proposed method will be lower. However, increasing the observation vector size will also make the proposed method robust against larger amounts of biased estimates. Considering the small size of the parameter estimation problem, the increased number of observations will not significantly affect the estimation performance.

4. Conclusion

This paper introduces a parameter estimator based on a robust LAV estimator. In order to increase computational performance, the estimation problem is developed locally, i.e. the estimation is applied to a single line measured by a PMU. Note that compared to LS, the LAV estimator is computationally expensive. However, considering the small size of the estimation problem as well as the performance of the LAV estimator under bad data and incorrect parameter conditions, the computational performances of both methods become competitive. The required measurement redundancy for the robustness is maintained using state estimates and multiple PMU scans.

The developed method can be used at the control center for each branch or transformer separately. Note that parameter estimation is not required to be performed as frequently as state estimation. Therefore, for computational ease, parameter estimation of each branch and transformer can be performed one at a time.

Parameter errors are generally flagged as bad measurements in state estimation. Using a reliable parameter estimator will increase trust in the measurements and enable a more reliable system operation.

The simulations and the numerical results show that as the size of the observation set increases, i.e. using more time scans instead of 7 scans, the robustness of the proposed method improves, which does not add a significant computational burden to the proposed method.

The preliminary results of this work were presented in [27], which compares LS and the proposed method, assuming unbiased state estimates. This work analyzed the proposed method with biased state estimates. Moreover, performance with transformer taps and the effect of increasing the sample size were also introduced.

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