Identification of Network Parameter Errors

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***Abstract*—This paper describes a simple yet effective method for identifying incorrect parameters associated with the power network model. The proposed method has the desired property of distinguishing between bad analog measurements and incorrect network parameters, even when they appear simultaneously. This is accomplished without expanding the state or the measurement vectors. There is also no need to apriori specify a suspect parameter set. All these features are verified via simulations that are carried out using different size test systems for various possible cases. Implementation of the method involves minor changes in the weighted least squares state estimation code, hence it can be easily integrated into existing state estimators as an added feature.**

***Index Terms* — Lagrange multipliers, power system state estimation, parameter errors.**

I. Introduction

ALL the energy management system (EMS) applications make use of the network model in the mathematical formulation of their problem. Transmission line resistances, reactances and charging capacitances, transformer reactances and tap values, shunt capacitor/reactor values are examples of network parameters that are required to build the network model. Among the EMS applications, state estimation plays an important role since it provides the network model for all other applications.

Traditionally, state estimation is carried out assuming that the correct network model is known. Therefore, any inconsistencies detected during the estimation process will be blamed on the analog measurement errors. Errors in network model may be due to topology and/or parameter errors.

The influence of the parameter errors on the state estimation solution is studied in detail in [1, 2]. Existing methods of parameter error identification are of two types [1]. The first type is based on residual sensitivity analysis [3]-[9], where the sensitivities of the measurement residuals to the assumed parameter errors are used for identification. This analysis is performed on the solved state estimation case and therefore the core state estimation code will remain untouched. This is the main advantage of this type of approach. The second type uses a state vector augmented by additional variables which are the suspected parameters. This approach can be implemented in two different ways, one using the static normal equations [2], [10]-[16], and the other using the Kalman filter theory [17]-[24].

Topology errors on the other hand, involve incorrect status information for circuit breakers and several methods are proposed so far for their detection and identification [25-29]. Among these methods, a recent one which is based on a reduced system model and the use of Lagrange multipliers [28, 29] addresses the main shortcoming of the previously proposed methods by eliminating the need to identify a suspect substation before topology error identification.

In this paper, a new parameter error identification method which complements the topology error identification method of [29] is proposed. This method is based on the Lagrange multipliers of the parameter constraints. A set of additional variables which correspond to the errors in the network parameters is introduced into the state estimation problem. However, direct estimation of these variables is avoided by the proposed formulation. Following the traditional state estimation solution, measurement residuals are used to calculate the Lagrange multipliers associated with the parameter errors. If these are found to be significant, then the associated parameter will be suspected of being in error. The main advantage of this method is that the normalized measurement residuals and parameter error Lagrange multipliers can be computed, allowing their identification even when they appear simultaneously. The first part of the proposed procedure is based only on the conventional WLS state estimation solution, however the subsequent error identification and correction procedures will have to be implemented and integrated into the existing code. There is no need to specify a suspect set of parameters apriori, since the method will readily identify the erroneous parameters along with any existing bad measurements.

The paper is organized such that section II presents the proposed formulation and solution of the parameter error identification problem. Implementation details and the results of simulations are given in Section III. Section IV concludes the paper.

II. Proposed method

1. Problem Formulation

Consider the measurement model:

$$z = h(x, p_e) + e \tag{1}$$

where:

z is the measurement vector,

$h(x, p_e)$ is the nonlinear function relating the measurements

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to the system states and network parameter errors,
x is the system state vector including voltage magnitudes and phase angles,
p_e is the vector containing network parameter errors,
e is the vector of measurement errors.

Buses with no generation or load, will provide free and exact measurements as zero power injections. These can be treated as equality constraints given by:

$$c(x, p_e) = 0 \tag{2}$$

Network parameter vector will be modeled as:

$$p = p_t + p_e \tag{3}$$

where p and p_t are the assumed and true network parameter vectors. Network parameter errors are normally assumed to be zero by the state estimator. Therefore, for error free operation, the following equality constraint on network parameter errors will be used:

$$p_e = 0 \tag{4}$$

The weighted least squares (WLS) state estimation problem in the presence of network parameter errors and equality constraints can then be formulated as the following optimization problem:

$$\begin{aligned} \text{Minimize} \quad & J(x) = \tfrac{1}{2} r^t W r \\ \text{Subject to} \quad & c(x, p_e) = 0 \\ & p_e = 0 \end{aligned} \tag{5}$$

where:
$r = z - h(x, p_e)$ is the measurement residual vector,
W is the diagonal matrix whose inverse is the measurement error covariance matrix, cov(e).

Applying the method of Lagrange multipliers, the following Lagrangian can be defined for the optimization problem of (5):

$$L = \frac{1}{2} r^t W r - \mu^t c(x, p_e) - \lambda^t p_e \tag{6}$$

Applying the first order optimality conditions:

$$\frac{\partial L}{\partial x} = H_x^t W r + C_x^t \mu = 0 \tag{7}$$

$$\frac{\partial L}{\partial p} = H_p^t W r + C_p^t \mu + \lambda = 0 \tag{8}$$

$$\frac{\partial L}{\partial \mu} = c(x, p_e) = 0 \tag{9}$$

$$\frac{\partial L}{\partial \lambda} = p_e = 0 \tag{10}$$

where:

$$H_x = \frac{\partial h(x, p_e)}{\partial x} \tag{11}$$

$$C_x = \frac{\partial c(x, p_e)}{\partial x} \tag{12}$$

$$H_p = \frac{\partial h(x, p_e)}{\partial p_e} \tag{13}$$

$$C_p = \frac{\partial c(x, p_e)}{\partial p_e} \tag{14}$$

μ and λ are the Lagrange multipliers for the equality constraints (2) and (4).

Equation (8) can be used to express λ in terms of μ and r :

$$\lambda = S \cdot \begin{bmatrix} r \\ \mu \end{bmatrix} \tag{15}$$

where:

$$S = -\begin{bmatrix} W H_p \\ C_p \end{bmatrix}^t \tag{16}$$

is the parameter sensitivity matrix.

Equality constraint (4) allows substitution of p_e in (7)-(9). Denoting $h(x,0)$ and $c(x,0)$ by $h_0(x)$, $c_0(x)$ respectively, the measurement equations will take the following form:

$$z = h_0(x) + e \tag{17}$$

$$c_0(x) = 0 \tag{18}$$

Note that (17) and (18) are the conventional measurement and zero injection equations used by the state estimators. They do not include parameter errors as explicit variables. Substituting the first order Taylor approximations for $h_0(x)$ and $c_0(x)$, the following linear equations will be obtained:

$$H_x \cdot \Delta x + r = \Delta z \tag{19}$$

$$C_x \cdot \Delta x = -c_0(x_0) \tag{20}$$

where:
$\Delta x = x - x_0$, x_0 being the initial guess for the system state vector
$\Delta z = z - h_0(x_0)$.

Using (7), (19), and (20), the following equation will be obtained:

$$\begin{bmatrix} 0 & H_x^t W & C_x^t \\ H_x & I & 0 \\ C_x & 0 & 0 \end{bmatrix} \bullet \begin{bmatrix} \Delta x \\ r \\ \mu \end{bmatrix} = \begin{bmatrix} 0 \\ \Delta z \\ -c_0(x_0) \end{bmatrix} \tag{21}$$

This equation is the same equation used for iterative solution of the conventional WLS state estimation problem. Hence, the solution for the measurement residuals r and the Lagrange multipliers for the zero injections μ can be obtained first by iteratively solving (21). Once the state estimation algorithm successfully converges, (15) can be used to recover the Lagrange multiplier vector λ associated with the parameter errors.

2. *Computation of the Normalized Lagrange Multiplier λ^N*

Since the main aim of this work is to identify parameter errors, the validity of the constraint (10) will have to be tested. This can be done based on the Lagrange multiplier vector λ associated with the parameter error vector p_e. In order to test the significance of a given λ_i value, it will be normalized using its covariance matrix cov(λ), which can be obtained as in [30] and also described below.

Letting $u = [r \quad \mu]^T$ and using (15):

$$\Lambda = \mathrm{cov}(\lambda) = S \cdot \mathrm{cov}(u) \cdot S^t \tag{22}$$

The covariance of u, *cov(u)* can be calculated by first expressing r and μ in terms of the measurement mismatch. To do that, let the inverse of the coefficient matrix in (21) be given in partitioned form as follows:

$$\begin{bmatrix} 0 & H_x^t W & C_x^t \\ H_x & I & 0 \\ C_x & 0 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} E_1 & E_2 & E_3 \\ E_4 & E_5 & E_6 \\ E_7 & E_8 & E_9 \end{bmatrix} \tag{23}$$

Noting that $c_0(x)=0$ at the solution, (21) will yield the following expressions for r and μ:

$$r = E_5 \cdot \Delta z \tag{24}$$

$$\mu = E_8 \cdot \Delta z \tag{25}$$

Let $\Psi = [E_5 \quad E_8]^T$, then:

$$u = \Psi \cdot \Delta z \tag{26}$$

$$\mathrm{cov}(u) = \Psi \cdot W^{-1} \cdot \Psi^t \tag{27}$$

The Lagrange multipliers for the parameter errors can then be normalized using the diagonal elements of the covariance matrix Λ defined in (22):

$$\lambda_i^N = \frac{\lambda_i}{\sqrt{\Lambda(i,i)}} \tag{28}$$

for all $i = 1 \ldots k$, where k is the total number of network parameters whose errors are to be identified.

Note that, the denominator in (28) will be zero for cases where local measurement redundancy does not allow detection of errors in parameter i. One such case is when all measurements that are functions of a parameter are critical. The other obvious one is when there are no measurements that are functions of a parameter.

3. Correction of the Parameter in Error

After the parameter in error is identified, this specific parameter can be corrected by estimating its true value simultaneously with the other state variables [1]. In order to accomplish this, the state vetor is augmented by the suspicious parameter p, yielding the following new state vector, v:

$$v = [x_1, x_2, \ldots, x_n \mid p] \tag{29}$$

where:

$x_1, \ldots, x_n$ are the conventional state variables, and

p is the parameter previously identified as erroneous.

Solution of the state estimation problem will yield not only the state estimates but the estimated value of the suspect parameter as well.

4. Error Identification/Correction Algorithm

The above formulation can be used to develop an algorithm to detect, identify and eliminate network parameter errors as well as bad data. Such an algorithm is proposed below:

Step 1. WLS State Estimation.

This is the WLS state estimation problem as currently solved by existing software. In addition to the measurement residual vector r, the solution will provide the Lagrange multiplier vector μ of zero injections if they are treated as equality constraints in the state estimation formulation. The solution involves repeated solution of (21) until convergence. Note that all parameter errors are assumed to be zero and therefore ignored at this step.

Step 2. Bad Data and Parameter Error Identification.

Compute the normalized residuals r^N for the measurements as described in [31] and the normalized Lagrange multipliers λ^N for the parameter errors as in (28). Section II.2 illustrates the steps leading to (28).

Choose the larger one between the largest normalized residual and the largest normalized Lagrange multiplier.

- If the chosen value is below the identification threshold, then no bad data or parameter error will be suspected. A statistically reasonable threshold to use is 3.0, which is the one used in all simulations presented in the next section.
- Else, the measurement or the parameter corresponding to the chosen largest value will be identified as the source of the error.

Step 3. Correction of the Parameter Error.

If a measurement is identified as bad, it is removed from the measurement set. Equivalently, its value can be corrected using a linear approximation for the estimated measurement error [31].

If a parameter is identified as erroneous, it is corrected by estimating its value by the method described in section II.3 using the augmented state vector defined as (29). Substitute the estimated parameter value for the old one and go to Step 1.

Note that bad data and parameter errors are processed simultaneously. This is possible provided that there is sufficient measurement redundancy and the parameter errors are not strongly correlated with the bad data. Since parameter errors are persistent whereas bad data usually appears in a single scan, the likelihood of simultaneously having strongly interacting bad data and parameter errors is small. Furthermore, using this approach there is no need to specify which parameter is to be tested for errors, apriori state estimation. Those three steps are seperated from each other. Step 2 uses the results of the normal state estimation done in Step 1, the set of suspicious parameters can be easily changed in Step 2 and without requiring re-estimation of the system states.

III. Simulation Results

The above described parameter error identification procedure is implemented and tested on IEEE 14, 30 and 57 bus test systems. Different cases are simulated where errors are introduced in transmission line parameters, transformer taps, shunt capacitors and analog measurements. Both single errors and simultaneously occurring errors in analog measurements and parameters are simulated. Performance of the method as well as its limitations is illustrated through these examples.

1. Case 1: Line impedance or measurement error

This case presents single errors in transmission line impedances or analog measurements. The method is shown to differentiate between these different types of errors and to correctly identify the error. The simulated errors for the three test systems are listed in Table 1, where the tests A and B are carried out as follows:

Test A: An error is introduced in the line parameter listed in Table 1; all analog measurements are error free.

Test B: No parameter errors are introduced; all measurements are error free except for the listed flow in Table 1.

Table 1 Simulated Parameter and Measurement Errors

Test System	Bad Parameter/Meas.	
	Test A	Test B
14-bus	r_{4-5}	q_{4-5}
30-bus	x_{5-7}	p_{5-7}
57-bus	r_{4-6}	q_{4-6}

Tables 2-4 show the sorted normalized residuals r^N and normalized Lagrange multipliers λ^N, obtained during the tests of Table 1.

Table 2 Results of Error Identification - 14-bus System

Test A		Test B	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
r_{4-5}	7.88	q_{4-5}	12.02
r_{2-4}	5.98	q_5	8.61
r_{2-5}	4.84	q_4	6.57
q_{4-5}	4.81	x_{4-5}	5.35
t_{5-6}	4.59	x_{2-4}	4.18

Table 3 Results of Error Identification - 30-bus System

Test A		Test B	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
x_{5-7}	25.47	p_{5-7}	19.50
x_{7-6}	22.01	r_{5-7}	12.34
x_{2-5}	21.92	p_5	10.56
r_{7-6}	15.78	q_6	9.97
r_{2-5}	15.42	x_{7-6}	9.86

Table 4 Results of Error Identification - 57-bus System

Test A		Test B	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
r_{4-6}	14.82	q_{4-6}	8.78
q_{4-6}	9.65	r_{4-6}	5.96
r_{3-4}	7.37	x_{5-6}	4.22
r_{4-5}	7.09	s_4	4.01
p_{4-6}	6.79	q_4	4.01

For Test A, the estimated parameter values based on the procedure of section II.3 are shown in Table 5 for all three tested systems.

As evident from the above, single line impedance errors as well as single analog measurement errors can be identified and corrected by this approach.

Table 5 Estimated and True Parameters of Line Impedances

Test system	Bad Parameter	Estimated Parameter	True Parameter
14-bus	r_{4-5}	0.01355	0.01355
30-bus	x_{5-7}	0.11593	0.11600
57-bus	r_{4-6}	0.04295	0.04300

2. Case 2: Transformer tap or measurement error

This case presents single errors in transformer taps or analog measurements. Errors are simulated for the 57-bus test system, where the tests A and B are carried out as follows:

Test A: A 1% error is introduced in the transformer tap value t_{13-49}; all analog measurements are error free.

Test B: No parameter errors are introduced; all measurements are error free except for the flow p_{13-49}.

Table 6 Tap and Measurement Error Identification

Test A		Test B	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
t_{13-49}	63.19	p_{13-49}	18.52
q_{13-49}	53.48	x_{13-49}	6.71
x_{13-49}	48.69	r_{48-49}	6.37
x_{48-49}	25.60	p_{49}	6.17
r_{46-47}	20.03	x_{14-46}	5.58

Again, for Test A, the estimated value of the wrong parameter is shown in Table 7.

Table 7 Estimated and True Parameters of Taps

Test system	Bad Parameter	Estimated Parameter	True Parameter
57-bus	t_{13-49}	0.89502	0.89500

As in case 1, the method successfully identifies and corrects transformer tap errors, while maintaining its ability to identify any errors appearing in analog measurements.

3. Case 3: Errors in shunt capacitor/reactor parameters

Errors in the parameters of shunt devices such as capacitors or reactors can be detected but not identified. The reason is the lack of redundancy, i.e. there is only one measurement, namely the reactive power injection at the corresponding bus, whose expression contains this parameter. Hence, when there is an error in this injection measurement or an error in shunt device parameter, this error will be detected, but its source can not be identified. The injection measurement and the parameter constraint constitute a critical pair. This case illustrates two examples of this limitation for 14 and 30 bus test systems.

Errors are introduced in the shunt susceptances at bus 9 (s_9) and at bus 24 (s_{24}) of 14 and 30 bus systems respectively. The normalized residuals and Lagrange multipliers are given in sorted form in Table 8. Note that the reactive injection measurements and shunt susceptances have identical normalized values, indicating that they constitute a critical pair whose errors can not be identified.

Table 8 Shunt Susceptance Errors

14-bus system		30-bus system	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
s_9	5.80	s_{24}	12.72
q_9	5.80	q_{24}	12.72
q_{9-10}	3.05	q_{22-24}	5.78
t_{4-9}	2.51	q_{22}	5.23
q_{14}	2.05	q_{23-24}	4.65

The estimated and true parameter values are shown in Table 9.

Table 9 Estimated and True Parameters of Shunt Susceptances

Test system	Bad Parameter	Estimated Parameter	True Parameter
14-bus	s_9	0.1900	0.1900
30-bus	s_{24}	0.0432	0.0430

4. Case 4: Simultaneous errors

This case shows the identification of multiple errors occurring simultaneously in the 14-bus system. Errors are simulated in the reactance of the transmission line 2-4, tap of the transformer 4-9 and the power flow measurement in line 4-2. Largest normalized value test is used to identify these errors one at a time. Results of normalized value tests for each error identification cycle are presented in Table 10.

Table 10 Multiple Error Identification Results

Error identification cycle					
1st		2nd		3rd	
z/ p	***r^N / λ^N***	***z/ p***	***r^N / λ^N***	***z/ p***	***r^N / λ^N***
x_{2-4}	60.56	t_{4-9}	23.87	p_{4-2}	5.07
p_{4-2}	46.48	p_{9-4}	17.99	p_3	3.75
x_{4-5}	40.49	t_{4-7}	10.00	p_4	3.02
x_{2-5}	30.24	r_{7-9}	9.78	r_{2-4}	2.86
t_{4-9}	25.00	p_4	9.68	p_{4-5}	2.25
Identified and Eliminated error					
x_{2-4}		t_{4-9}		p_{4-2}	

When corrected, the parameter values are found as shown in Table 11. Notice that when there are multiple errors in the network parameters as well as analog measurements, repeated application of the largest normalized value test can identify errors one by one as shown in Table 10. However, due to the interaction between multiple parameter errors, sequential correction of parameter errors may yield approximate values as in Table 11. This approximation error can be minimized by executing an extra estimation solution where all identified parameters are included simultaneously in the augmented state vector. The results for this case are shown in Table 12. Note that, the results in Table 12 are more accurate than those given in Table 11.

Table 11 Estimated and True Parameters of Multiple Errors

Step	Bad Parameter	Estimated Parameter	True Parameter
1st	x_{2-4}	0.17400	0.17632
2nd	t_{4-9}	0.96015	0.96000

Table 12 Simultaneous Estimation of all identified parameters

Bad Parameter	Estimated Parameter	True Parameter
x_{2-4}	0.17633	0.17632
t_{4-9}	0.96000	0.96000

Similar to the case of the multiple interacting and conforming bad data, there may be situations where strongly interacting parameter and analog measurement errors can not be identified due to error masking. Such cases are however rare and can not be handled by this method.

5. Case 5: Inherent Limitations: Multiple Solutions

Identification of errors in network parameters is inherently limited by the available set of measurements as well as the system topology. The limitation is due to the possibility of multiple solutions corresponding to two or more parameter errors which affect the same subset of measurements.

Consider two network parameters p_1,p_2 and their erroneous values p_1^a,p_2^b. If two different solutions x^a, x^b yielding the same objective function value can be found such that:

$J(x^a,p_1^a,p_2) = J(x^b,p_1,p_2^b)$

then, the WLS state estimator will equally likely converge to either one of these solutions. Hence, it will not be possible to identify which of these two parameters is actually in error.

One such situation is illustrated by the following two tests that are carried out on IEEE 14-bus system whose diagram and measurements are shown in Figure 1:

Test A: The reactance x_{6-12} for line 6-12 is incorrect; all measurements are exact.

Test B: The reactance x_{12-13} for line 12-13 is incorrect; all measurements are exact.

The incorrect parameters for the two neighboring lines are chosen as shown in Table 13. These two parameter errors will be detectable but not identifiable. Either one of the parameters can be identified as incorrect depending upon the initial conditions used in the iterative solution of the state estimation problem.

In Test A, the proposed method correctly identified x_{6-12} as the erroneous parameter, while in Test B, the same algorithm still identified the same parameter instead of the incorrect parameter x_{12-13} as bad data. The reason can be easily seen by looking at the almost identical objective function values corresponding to the two tests in Table 13. As shown in Table 14, in Test B, x_{6-12} is identified instead of the real parameter in error, x_{12-13}. The estimated states for the two test cases are shown in Table 15. Note that the two estimates differ very little, only at the buses incident to the branches with parameter errors, namely buses 6, 12 and 13.

Table 13 Objective Function Values for Tests A and B

	Erroneous Parameter	Assumed Value	True Value	$J(x)$
Test A	x_{6-12}	0.23656	0.25581	14.7064
Test B	x_{12-13}	0.29988	0.19988	14.7068

Table 14 Error Identification of Series Lines

Test A		Test B	
Measurement/ Parameter	***Normalized residual / λ^N***	***Measurement/ Parameter***	***Normalized residual / λ^N***
x_{6-12}	3.8291	x_{6-12}	3.8280
x_{12-13}	3.8250	x_{12-13}	3.8148
x_{6-13}	2.8902	x_{6-13}	2.7479
p_{6-12}	2.4126	p_{12-13}	2.5182
p_{12-13}	2.3390	p_{6-12}	2.4759

Table 15 Estimated States for Tests A and B

Bus No:	Test A		Test B	
	V	***θ***	***V***	***θ***
1	1.0600	0	1.0600	0
2	1.0450	-5.2379	1.0450	-5.2382
3	1.0100	-13.1662	1.0100	-13.1669
4	1.0159	-10.8853	1.0159	-10.8858
5	1.0180	-9.2395	1.0180	-9.2403
6	1.0700	-14.8812	1.0700	-14.8857
7	1.0679	-14.6357	1.0678	-14.6355
8	1.0900	-16.4757	1.0900	-16.4758
9	1.0606	-16.0028	1.0605	-16.0023
10	1.0547	-16.0920	1.0547	-16.0922
11	1.0588	-15.6241	1.0587	-15.6260
12	1.0558	-15.7289	1.0559	-15.7184
13	1.0510	-15.8867	1.0510	-15.8656
14	1.0384	-16.9473	1.0384	-16.9403

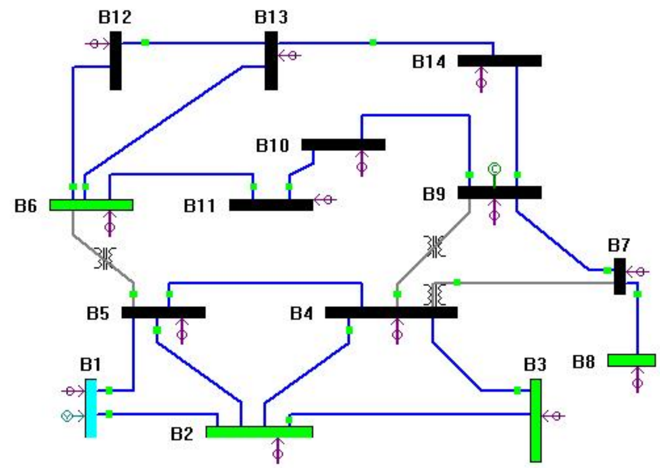

FIG 1. IEEE 14-BUS SYSTEM

IV. CONCLUSIONS

This paper presents a method for identifying network parameter errors even in the presence of bad analog measurements. The parameter error identification is accomplished by formulating the parameter errors as zero equality constraints and then testing the significance of the associated Lagrange multipliers. These are computed from the normalized measurement residuals obtained by the WLS state estimation. The method can deal with mixed type multiple errors in measurements and network parameters. There is also no need to specify a set of suspect parameters before state estimation. Once the parameter error is identified, its correct value is estimated using the augmented state estimation method. Several examples are simulated to illustrate the effectiveness of the method. The paper also shows the inherent limitations of error identification for certain special cases. The method can be readily implemented as a user defined option by modifying an existing WLS state estimation code.

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VI. Biographies

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