Network Branch Parameter Validation Based on a Decoupled State/Parameter Estimator and Historical Data

M. R. M. Castillo, *Student Member, IEEE*, J. B. A. London Jr, *Member, IEEE,* and N. G. Bretas, *Senior Member, IEEE*

Abstract— This paper proposes an efficient off-line approach for dealing with power network branch parameters errors, that comprises three phases. In Phase 1 the branches suspected to be with errors are identified through an Identification-Index Vector (IIV), where each element of IIV is the ratio between the number of measurements incident to each branch, whose normalized residuals are larger than one specified threshold value, and the total number of measurement incident to each branch of the network. Using several measurement snapshots, the suspicious branches parameters are estimated, in a sequential form, in Phase 2. In order to do that, it is proposed a decoupled augmented state estimator which increases the V-θ state vector for the inclusion of suspicious branch parameters. Phase 3 enables the validation of the estimative obtained in Phase 2, via a conventional Weighted Least Squares State Estimator. Several simulation results (with the IEEE 14, 30 and 57 bus systems) have demonstrated the high correctness and reliability of the proposed approach to lead with single and multiple parameter errors in adjacent and non-adjacent branches. The results obtained by the proposed approach were compared with those obtained by other existing methodology.

***Index Terms*—Power Systems, State Estimation, Branch Parameter Estimation.**

I. INTRODUCTION

ANY network parameter error degrades the results of a state estimator (SE). As a consequence, it also degrades the performance of other applications programs available in modern energy management systems (e.g., security analysis, economic dispatch, etc.).

Often, network parameter errors may occur mainly because of: inaccurate manufacturing data; network changes not properly updated in the data base; wrong or oversimplified calculation; disparity in values coming from data bases; and so on [1].

Parameter errors are less evident than both topological errors (incorrect topology information) and gross errors (errors on analogical measurements). Moreover, parameter errors may not be identified for a long period of time leading to permanent errors in the results provided by the SE.

The more attentions have been paid to the estimation of network parameters, which becomes very important in power system analysis as state estimation and topology estimation, and many literatures [2]-[14] have contributed to this problem. The methods for network parameter estimation can be classified as two kinds, one is the residual sensitivity analysis based on the relation between the residuals and measurement errors during the state estimation process to identify a group of lines whose parameters might be in error [3]-[7]. However, those techniques can be applied only if the set of lines whose parameters need to be determined is small; results deteriorate rapidly as the number of uncertain parameters increases. While the other uses an augmented state vector (the usual V-θ state vector is augmented with additional variables representing suspicious parameters to be estimated) and do a simultaneous state and parameter estimation. Depending on the way the augmented state is estimated, two groups of methods can be distinguished: (i) those using the static normal equations [8]-[10], and (ii) those using the kalman filter theory [11]-[13].Both of the methods mentioned above are greatly related to the accuracy of measurement data.

Although the literature on parameter estimation is not very extensive, it can be said that a common characteristic is that they only attempt, either directly or sequentially, to estimate the parameters of a few transmission lines [2]. Thus, a practical method to estimate in a systematic way the parameters of all elements of the transmission system is not available nowadays.

This paper presents an off-line approach that enables network branch parameters errors identification and estimation. The idea is to use several measurement snapshots, in order to estimate the suspicious series branch parameters in a sequential form, taking advantage of the fact that those parameters can be considered time-invariant for the time period of those measurement snapshots [1].

This paper is organized as follows: Section II revisits the Weighted Least Squares normal equations for the conventional state estimation, as well as the largest normalized residuals test for gross error detection and identification; Section III presents the proposed approach; Section IV presents the tests results obtained with IEEE-14, 30 and 57 bus systems, and finally Section V shows the conclusion.

II. CONVENTIONAL STATE ESTIMATION BASED ON THE NORMAL EQUATIONS

Power system state estimation is closely related to the statistics regression methods. The non-linear equations relating the *(mx1)* measurement vector z and the $(n_e\ x1)$ V-θ state vector x_e are:

$$z = h(x_e) + w \quad (1)$$

where w is an *(mx1)* random noise vector with zero mean jointly Gaussian distribution and *h(.)* is a vector-valued non-linear function that relates the measurements to the system states. Through the conventional Weighted Least Square (WLS) approach, the state vector x_e is estimated by recursively forming the Jacobian matrix $H(x_e) = \partial h(x_e) / \partial x_e$, and solving the gain matrix equations:

$$G\Delta x_e = H^t W(z - h(x_e)) \tag{2}$$

with $G = H^t WH$, where W is the diagonal matrix representing the inverse of the covariance matrix of w.

The residual vector r, defined as being the difference between z and the corresponding filtered quantities $\hat{z}$, is normalized and submitted to a validation test

$$r(k)^N = \frac{|r(k)|}{\sigma_r(k)} \leq \lambda \ (threshold\ value), \tag{3}$$

where $r(k)^N$ is the largest among all $r(i)^N, i = 1, \ldots, m$; $\sigma_r(k) = \sqrt{\Omega(k,k)}$ is the Standard Deviation of the k^{th} component of the residuals vector; and Ω is the residual covariance matrix given by

$$\Omega = W^{-1} - HG^{-1}H^t . \tag{4}$$

If $r(k)^N > \lambda$, the measurement with gross error is detected and the k^{th} measurement will be the one with gross error (usually $\lambda = 3$ [1]).

III. Proposed Approach

The proposed approach comprises three phases: Phase 1 – Identification of Suspicious branches; Phase 2 – Suspicious parameters estimation; and Phase 3 – Validation of suspicious parameters estimative.

A. Phase 1 – Identification of suspicious branches

A parameter error has the same effect on the estimated state as a set of correlated gross errors acting on all the measurements adjacent to the erroneous branch, namely the power flow measurements at that branch and the power injection measurements at the edge nodes [1]. As a consequence, if a branch parameter error is large enough, the measurements adjacent to that branch will likely have the normalized residuals above a pre-established limit.

The proposed approach enables suspicious branch identification through the analysis of the measurement normalized residuals. Observe that as the proposed approach is off-line, it is possible to select particular recorded snapshots free of both measurement gross errors and topological errors.

The proposed approach for the identification of suspicious branches uses three vectors: Measurement-to-Branch Vector (MBV); Suspicious-Branches Vector (SBV); and Identification-Index Vector (IIV), all of them with dimension *(n_lx1)*, where n_l is the number of branches of the system.

MBV shows how many measurements are incident to each branch of the system ($MBV(i) = j$ indicates that there are j measurements incident (or related) to branch i)[1]. SBV indicates how many measurements incident to each one of the branches have normalized residuals larger than a specified threshold ($SBV(i) = k$ indicates that there are k measurements incident to branch i with normalized residual larger than a specified threshold). Each element of IIV is the ratio between the corresponding elements of SBV and MBV, that is, $IIV(i) = {SBV(i)}/{MBV(i)}$. All the branches k with $IIV(k) \neq 0$ will be classified as suspicious branches. However, the proposed approach gives more attention to those branches with $IIV(k) \geq 0.5$.

Fig. 1 presents the flowchart of the proposed approach, where: LSB is a List of Suspicious Branches, and LSBE is a List of Suspicious Branches whose parameters were Estimated and Validated.

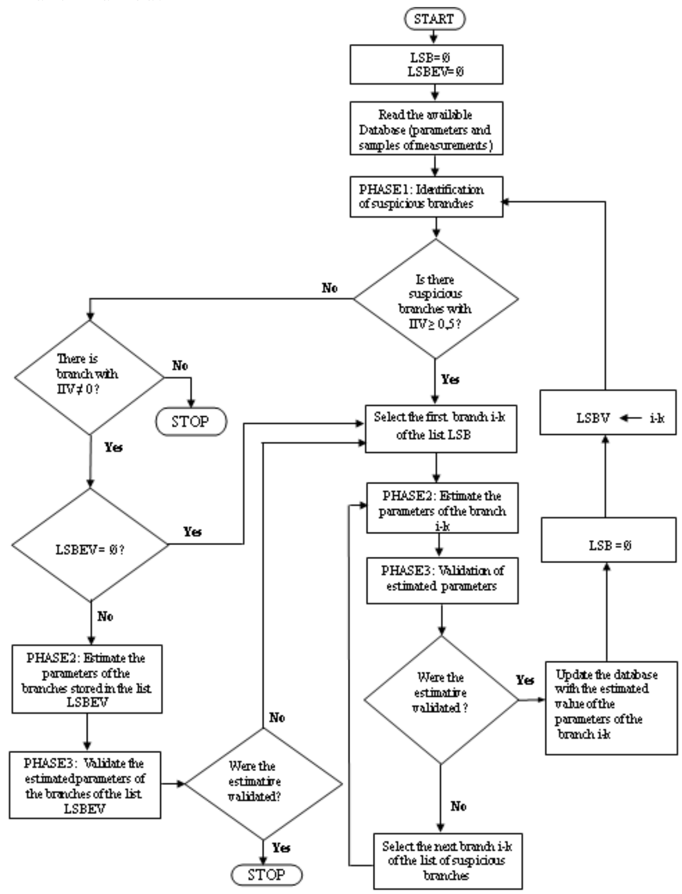

Figure 1. Flowchart of the proposed approach

Considering those three vectors, the proposed algorithm for the identification of suspicious branches can be summarized as follows:

Step 1: For a given snapshot of measurement initialize the MBV;

Step 2: Run the conventional weighted least square (WLS) state estimator and obtain the measurement normalized residuals;

Step 3: If there are normalized residuals larger than the

[1] A measurement is incident (or related) to a branch if it is either a power flow measurement at that branch or a power injection measurement at the terminal nodes of that branch.

detection threshold go to the next step (usually this value is equal to 3 [1]). Otherwise, end the algorithm.

Step 4: Through the measurements with the normalized residuals larger than the detection threshold initialize the SBV and compute IIV.

Step 5: Form a list of suspicious branches sorted according the value of the corresponding IIV element. In case of suspicious branches with the same IIV, the branch with the highest normalized residual will be considered the most suspicious.

B. Phase 2 – Suspicious parameters estimation

The proposed off-line approach uses an augmented state estimator, here called parameter/state estimator, which increases the V-θ state vector (nodal voltage magnitudes and phase angles) for the inclusion of series parameters of the suspicious branches. The normal equations technique is used to deal with the augmented model. In order to enable reliable estimates, the estimation process is executed using sequential measurements of several snapshots.

The idea is to use measurements of several snapshots and estimate the suspicious series branch parameters in a sequential form, taking advantage of the fact that those parameters can be considered time-invariant [1].

In general, the following procedure is proposed:

Snapshot 1: initialize all bus voltages at flat start and the suspicious parameters with the available values. Considering the measurements available in this snapshot (z^1), estimate the V-θ state variables ($\hat{x}_e^{\,1}$) and the suspicious parameters ($\hat{p}^1$), using the parameter/state estimator mentioned above;

Snapshot 2: initialize all bus voltages at flat start (as in snapshot 1), but the suspicious parameters are now initialized with the values estimated in the previous snapshot ($\hat{p}^1$). Considering the measurements available in this snapshot (z^2), estimate the V-θ state variables ($\hat{x}_e^{\,2}$) and the suspicious parameters ($\hat{p}^2$).

The stopping criterion of the proposed procedure is the comparison between the magnitude of the suspicious parameter correction vector, obtained in two sequential snapshots ($\Delta\hat{\underline{p}}^k = \left|\hat{\underline{p}}^k - \hat{\underline{p}}^{k-1}\right|$), and a pre-established limit for the corrections. In this paper, every time a suspicious parameter correction obtained in two sequential snapshots ($\Delta\hat{p}_i^{\,k} = \left|\hat{p}_i^{\,k} - \hat{p}_i^{\,k-1}\right|$) is below 0.01, the corresponding parameter is removed from the augmented vector, that is, the estimated value has converged to the parameter value ($\hat{p}_i = \hat{p}_i^{\,k}$).

The proposed parameter/state estimator works in a decoupled way, i.e., for each snapshot *k* the solutions for the complex voltage ($\Delta\underline{V}^k$) and suspicious parameters ($\Delta\underline{P}^k$) updates are obtained alternately and convergence is tested based on the maximum changes in both of these arrays (see next section).

C. Decoupled Parameter/State Estimator Formulation

Observe that the proposed decoupled state/parameter estimator will be applied to each of the available snapshots in a sequential way, as described in section III.B. As a consequence, for each measurement snapshot it increases the V-θ state vector, here called Augmented State Vector (x_{Aug}), with the suspicious series branch parameters. Considering the proposed decoupling, x_{Aug} can be partitioned as $x_{Aug} = (x_e, x_p)$, and equation (1) becomes:

$$z = h_{Aug}(x_e, x_p) + w, \tag{5}$$

where x_e is the *(n_ex1)* V-θ state vector; x_p is the *(n_px1)* suspicious parameter vector; $h_{Aug}(.)$ is a vector-valued non-linear function that relates the measurements to the *(Nx1)* system augmented states, and n_e, n_p, and N are, respectively, the number of V-θ state variables, suspicious parameters, and augmented variables to be estimated.

Through the WLS approach the augmented state vector x_{Aug} is estimated by recursively forming the decoupled augmented Jacobian matrix

$$H(x_{Aug}) = \frac{\partial h(x_{Aug})}{\partial x_{Aug}} = \begin{bmatrix} \dfrac{\partial h(x_{Aug})}{\partial x_e} & \dfrac{\partial h(x_{Aug})}{\partial x_p} \end{bmatrix} \underset{=}{\Delta} \begin{bmatrix} H_e & H_p \end{bmatrix}, \tag{6}$$

where H_e and H_p are, respectively, the Jacobian matrices of h_{Aug} with respect to x_e and x_p; and solving sequentially, for x_e and x_p, the decoupled augmented Gain equation using the basic Gauss-Newton iterative process. To the *ν-th* iteration one has:

$$G_e \Delta\underline{x}_e^{\,\nu} = H_e^T W[z - h(\underline{x}_e^{\,\nu}, \underline{x}_p^{\,\nu})] \tag{7}$$

$$G_p \Delta\underline{x}_p^{\,\nu} = H_p^T W[z - h(\underline{x}_e^{\,\nu+1}, \underline{x}_p^{\,\nu})] \tag{8}$$

where:

$$G_e = [H_e]^t[W][H_e] = \begin{bmatrix} G_v & G_{v\theta} \\ G_{\theta v} & G_\theta \end{bmatrix} \tag{9}$$

and

$$G_p = [H_p]^t[W][H_p] = [G_p]. \tag{10}$$

The steps of the proposed decoupled state/parameter estimator algorithm are given below:

Step 1: Start iterations, set the iteration index $\nu = 0$.

Step 2: Initialize all bus voltages at flat start and the suspicious parameter vector considering the available values.

Step 3: Solve $G_e \Delta\underline{x}_e^{\,\nu} = H_e^T W[z - h(\underline{x}_e^{\,\nu}, \underline{x}_p^{\,\nu})]$.

Step 4: Update $\underline{x}_e^{\,\nu+1} = \underline{x}_e^{\,\nu} + \Delta\underline{x}_e^{\,\nu}$.

Step 5: Solve $G_p \Delta\underline{x}_p^{\,\nu} = H_p^T W[z - h(\underline{x}_e^{\,\nu+1}, \underline{x}_p^{\,\nu})]$.

Step 6: Check if $\Delta\underline{x}_e$ and $\Delta\underline{x}_p$ are lower than the convergence tolerance. If so, stop. Else, continue.

Step 7: Update $\underline{x}_p^{\,\nu+1} = \underline{x}_p^{\,\nu} + \Delta\underline{x}_p^{\,\nu}$, $\nu = \nu + 1$, and go to step 3.

The parameters to be estimated by the proposed approach are the series conductances (G_{km}) and susceptances (B_{km}) of long and medium length transmission lines. In the π-model these lines are characterized by non-zero shunt susceptances.

Consequently, a system with "*L*" branches corresponding to those transmission lines and "*nb*" buses has "*N=2nb-1+2L*" Augmented States to be estimated.

In order to improve the conditioning of matrices G_e and G_p, the row and column scaling method was implemented to solve equations (7) and (8).

D. Phase 3 – Validation of suspicious parameters estimative

This phase is necessary because, in reality to the effect of parameter error smearing; the identification process of suspicious branches (Phase 1) can fail, that is, it can incorrectly classify one branch as suspicious. As a consequence, after the parameters of the most suspicious branches are estimated, it is necessary to validate those estimative.

To validate the estimate of the parameter of a given branch of the network, a conventional WLS state estimation is used considering the same measurement snapshot considered in Phase 1, so that it is processed considering the estimated value of that branch obtained in Phase 2, and not the available value in the database. After that, the IIV of that suspicious branch is calculated again. If this IIV do not decrease, in relation to that obtained in Phase 1, it means that branch was incorrectly indicated as suspicious branch. Otherwise, that estimative is validated.

IV. Tests Results

This section presents the numerical results of the application of the proposed approach to the IEEE 14, 30 and 57 bus systems (the parameters of those systems can be downloaded from [16]). Several simulations have been carried out using those systems. However, due to space limitations, only three representative scenarios will be considered here.

The initial conditions were constructed in the following way:

-Initial Parameters: errors were added only to the parameters that will be estimated. These errors are 30% of the correct values;

- To simulate measurements of several snapshots, a temporary evolution of the system load associated with one typical load profile was considered. The curve of load of each bus of the system is composed of a percentage of the total load of the system;
- Measurement values of each snapshot: these values were obtained from an exact load flow solution to which normally distributed noise was added. The measurement noise was assumed to have zero mean and standard deviation "σ" given by: $\sigma = \frac{pr * fe}{3}$, where *fe* is the meter full scale; *pr* is the meter precision (in this paper *pr = 2%*).
- In order to apply the proposed approach, twenty sets of measurements were generated to simulate twenty consecutives snapshots.

Remark 1: The values of measurements and parameters will be in p.u.

Test 1: In this test the proposed approach is applied to the IEEE 14 bus system (the topology and the correct parameter values of this system can be downloaded from [16]). Multiple parameter errors are added simultaneously to the series admittance of branches 1-5, 2-3 and 2-4 (errors of 30% of the correct values of both series conductance and susceptance of those branches). Observe that the branches 2-3 and 2-4 are adjacent.

Appling the proposed approach it is obtained (see Flowchart presented in Fig. 1):

Phase 1: Identification of suspicious branches

The first step in this phase is to initialize the MBV. After that, a conventional WLS estimator is processed and the measurement residuals are calculated. Through the measurements with normalized residuals larger than 3, the algorithm initializes the SBV, and computes the IIV. Checking the non-zero elements in IIV, a list of suspicious branches is formed.

Table I presents the list of suspicious branches *i* with $IIV(i) \geq 0.5$.

Branch 2-3 is selected to be estimated.

TABLE I

List of Suspicious Branches with $IIV(i) \geq 0.5$ – Scenario 1

Branch *i*	*MBV(i)*	*SBV(i)*	*IIV(i)*
2-3	10	7	0.7
1-5	10	7	0.7
3-4	10	7	0.7
2-5	10	7	0.7
2-4	10	7	0.7
4-5	10	6	0.6

Phase 2: Suspicious parameters estimation

The value 1.0011-j4.2455 pu for the estimate of branch 2-3 series admittance is obtained.

As previously mentioned, to apply the proposed approach twenty sets of measurements were generated to simulate twenty consecutive snapshots. However, in the fourth snapshot the stopping criterion was satisfied in the execution of Phase 2.

Phase 3 – Validation of suspicious parameters estimative

Those estimative are validated. Then, the database is updated, that is, the available series parameters of the branch 2-3 are substituted by the estimated values. The list of candidate branches is eliminated (LSB = ϕ); Branch 2-3 is stored in the List of Suspicious Branches whose parameters were Estimated and Validated (LSBEV ←2-3).

Phase 1: Identification of suspicious branches

Table II presents the list of suspicious branches *i* with $IIV(i) \geq 0.5$.

Branch 2-5 is selected to be estimated.

Phase 2: Suspicious parameters estimation

The branch 2-5 series admittance is estimated.

Phase 3 – Validation of suspicious parameters estimative

The estimative of the series parameters of the branch 2-5 are not validated. The next branch on the list of suspicious branches is selected (branch 1-5).

TABLE II
LIST OF SUSPICIOUS BRANCHES WITH $IIV(i) \geq 0.5$ – SCENARIO 1

Branch *i*	*MBV(i)*	*SBV(i)*	*IIV(i)*
2-5	10	7	0.7
1-5	10	7	0.7
2-4	10	6	0.6
3-4	10	6	0.6
2-3	10	6	0.6
1-2	10	6	0.6

Phase 2: Suspicious parameters estimation

The value 0.9701-j3.9816 pu for the estimate of branch 1-5 series admittance is obtained. In this phase the stopping criterion was satisfied in the eighth snapshot.

Phase 3 – Validation of suspicious parameters estimative

Those estimative are validated. Then, the database is updated, that is, the available series parameters of the branch 1-5 are substituted by the estimated values. The list of candidate branches is eliminated (LSB = ϕ); Branch 1-5 is stored in the List of Suspicious Branches whose parameters were Estimated and Validated (LSBEV ←1-5).

Phase 1: Identification of suspicious branches

Branch 2-4 is the first branch in the new list of suspicious branches *i* with $IIV(i) \geq 0.5$.

Phase 2: Suspicious parameters estimation

The value 1.5948-j4.8227 pu for the estimate of branch 2-4 series admittance is obtained. In this phase the stopping criterion was satisfied in the third snapshot.

Phase 3 – Validation of suspicious parameters estimative

Those estimative are validated. Then, the database is updated, that is, the available series parameters of the branch 2-4 are substituted by the estimated values. The list of candidate branches is eliminated (LSB = ϕ); Branch 2-4 is stored in the List of Suspicious Branches whose parameters were Estimated and Validated (LSBEV ←2-4).

Phase 1: Identification of suspicious branches

There is branches identified as suspicious, but none of them has $IIV(i) \geq 0.5$. The list LREV is not empty.

Phase 2: Suspicious parameters estimation

The parameters of the branch stored in the list LSBEV are estimated (branches 2-3, 1-5 and 2-4). The stopping criterion was satisfied in the fourth snapshot.

Phase 3 – Validation of suspicious parameters estimative

In the Validation process those estimative are validated; Stop.

Table III presents the correct values, the initial values and the estimated values of the series impedances of the branches1-5, 2-3 and 2-4. The values of the estimated parameters were corrected from 30% to less than 1%, mainly the conductance of the branch 2-3.

Table IV presents the state (complex voltage) estimated by the conventional WLS estimator processing the same measurement set but submitted to three condition in terms of parameter values of the series admittance of branches 1-5, 2-3 and 2-4: (i) with errors in the series admittance of those branches (errors of 30% of the correct values of both series conductance and susceptance of those branches) (Column 2); (ii) the values considered to the series admittance of branches 1-5, 2-3 and 2-4 are those estimated by the proposed approach (Column 3); and (iii) without errors in the series admittance of branches 1-5, 2-3 and 2-4 (Column 4).

It is important to oserve that the state estimative obtained by the conventional WLS estimator making use of the estimated values of the series admittance of branches1-5, 2-3 and 2-4, presented in Column 3 of Table IV, are very close to the state estimative obtained by it making use of the correct values of those parameters, presented in Column 3 of Table IV.

TABLE III
SIMULATION RESULTS – SCENARIO 1

	Initial*	**Estimated**	**Correct**	**% of correction**
G_{15}	0.7891	1.0364	1.0258	1.02
B_{15}	-3.2577	-4.2495	-4.2350	0.34
G_{23}	0.8731	1.1349	1.1350	0.01
B_{23}	-3.6783	-4.7925	-4.7818	0.22
G_{24}	1.2969	1.6886	1.6860	0.15
B_{24}	-3.9353	-5.1092	-5.1158	0.13

* The initial values are contaminated with errors of 30% of the correct values

TABLE IV
SIMULATION RESULTS – SCENARIO 1

	Parameters with errors	Parameters estimated	Parameters with the correct values
θ1(rad)	0.0000	0.0000	0.0000
θ2 (rad)	-0.0850	-0.0869	-0.0870
θ3 (rad)	-0.2379	-0.2220	-0.2222
θ4 (rad)	-0.1949	-0.1800	-0.1800
θ5 (rad)	-0.1680	-0.1531	-0.1532
θ6 (rad)	-0.2612	-0.2483	-0.2483
θ7(rad)	-0.2468	-0.2333	-0.2333
θ8 (rad)	-0.2468	-0.2333	-0.2333
θ9 (rad)	-0.2737	-0.2609	-0.2609
θ10(rad)	-0.2764	-0.2637	-0.2637
θ11(rad)	-0.2711	-0.2583	-0.2583
θ12(rad)	-0.2758	-0.2632	-0.2633
θ13(rad)	-0.2772	-0.2646	-0.2647
θ14(rad)	-0.2923	-0.2800	-0.2800
V1 (pu)	1.0732	1.0595	1.0595
V2 (pu)	1.0583	1.0444	1.0444
V3 (pu)	1.0177	1.0094	1.0094
V4 (pu)	1.0256	1.0170	1.0171
V5 (pu)	1.0274	1.0189	1.0189
V6 (pu)	1.0785	1.0693	1.0694
V7 (pu)	1.0700	1.0608	1.0609
V8 (pu)	1.0983	1.0892	1.0893
V9 (pu)	1.0646	1.0553	1.0554
V10 (pu)	1.0597	1.0504	1.0504
V11(pu)	1.0655	1.0562	1.0563
V12(pu)	1.0638	1.0544	1.0545
V13(pu)	1.0591	1.0497	1.0498
V14(pu)	1.0444	1.0349	1.0350

Test 2: In this test it will be analyzed the capacity of the proposed approach to obtain good estimative for different percentages of errors in the parameters of a certain branch of

the IEEE 30 bus system, as well as it was accomplished in [4]. The topology and the correct parameter values of that system can be downloaded from [16].

Three situations will be considered:

Situation 1: Errors only in the serie susceptance of the branch 10-20 (errors from 5% to 80% of the correct values). The correct value of that parameter is 3.9854 p.u.

Table V presents: the value of that parameter processed by the proposed approach, that is with error, (Column 2); the percentage of errors applied in that parameter (Column 3); the estimated values (Column 4); and the percentage of correction (Column 5).

TABLE V
SIMULATION RESULTS – SITUATION 1

Case	Initial Values	% error (original)	Estimated Value (b)	% of correction
1	-3.7850	5	-3.9622	0.5821
2	-3.5850	10	-3.9620	0.5871
3	-3.1850	20	-3.9621	0.5846
4	-2.3850	40	-3.9620	0.5871
5	-0.7850	80	-3.9619	0.5897

Situation 2: Errors only in the serie susceptance of the branch 2-4 (errors from 5% to 80% of the correct values). The correct value of that parameter is -5.1974p.u.

Table VI presents: the value of that parameter processed by the proposed approach, that is with error, (Column 2); the percentage of errors applied in that parameter (Column 3); the estimated values (Column 4); and the percentage of correction (Column 5).

TABLE VI
SIMULATION RESULTS – SITUATION 2

Case	Initial Values	% error (original)	Estimated Value (b)	% of correction
1	-5.4570	5	-5.1922	0.1001
2	-5.7170	10	-5.1919	0.1058
3	-6.2380	20	-5.1920	0.1039
4	-7.2740	40	-5.1921	0.1020
5	-9.3870	80	-5.1919	0.1058

It is important to observe that the proposed approach allows correcting the error significantly in the parameter, even in the presence of an error of up to 80%.

In the Tables VII and VIII, are the results of the application of the parameter estimation method proposed in [4], for analysis of situations 1 and 2, respectively.

Remark that, the method proposed in [4] is based on the residual sensitivity analysis.

Test 3: Multiple parameter errors in the conductance and susceptances series of the adjacent branches 4-5 and 9-10 of the IEEE 57-bus system (errors of 30% of the correct values).

Table IX presents the correct values, the initial values and the estimated values of the series impedances of the branches 4-5 and 9-10. The values of the estimated parameters were corrected from 30% to less than 0.01%, mainly the serie suceptance of the branch 4-5.

TABLE VII
SIMULATION RESULTS – SITUATION 1 (PROPOSED ESTIMATOR IN [4])

Correct Value b=-3.9854				
Case	**Initial Condition**	**% error (original)**	**Estimated Value (b)**	**% of correction**
1	-3.7850	5	-3.9700	0.38
2	-3.5850	10	-3.9500	0.88
3	-3.1850	20	-3.8930	2.30
4	-2.3850	40	-3.6850	7.51
5	-0.7850	80	-2.5310	36.47

TABLE VIII
SIMULATION RESULTS – SITUATION 2 (PROPOSED ESTIMATOR IN [4])

Correct Value b=5.1974				
Case	**Initial Condition**	**% error (original)**	**Estimated Value (b)**	**% of correction**
1	-5.4570	5	-5.1920	0.10
2	-5.7170	10	-5.1870	0.19
3	-6.2380	20	-5.1760	0.43
4	-7.2740	40	-5.1480	0.96
5	-9.3870	80	-5.0820	2.23

TABLE IX
SIMULATION RESULTS – SCENARIO 3

	Initial*	Estimated	Correct	% of correction
G_{4-5}	3.8091	2.9499	2.9301	0.67
B_{4-5}	-8.0449	-6.1878	-6.1884	0.01
G_{9-10}	1.6232	1.2444	1.2486	0.33
B_{9-10}	7.3859	-5.6535	-5.6815	0.49
* The initial values are contaminated with errors of 30% of the correct values				

V. CONCLUSIONS

This paper presented an efficient and practical off-line approach to validate (parameter error identification and correction) series branch parameters of power system based on historical series of data.

The augmented state vector is estimated in a decoupled way, offering more robustness to the estimation algorithm as it avoids the ill-conditioning of the gain matrix.

In order to show the potentiality of the proposed approach, test results were presented, considering scenarios with multiple parameter errors in adjacent and non-adjacent branches.

Appreciating the results obtained in all the completed tests, we can affirm that:

- The proposed approach makes possible good estimative, even in the presence of one or more errors in the series parameters of transmission lines, the same as adjacent lines;
- Through the propose approach, it is possible to obtain good estimative for different percentages of errors in a parameter, even in the presence of measurements with noise;
- Comparing the results obtained by the proposed approach, as were shown in the Tables V and VI, with those obtained by the method proposed in [4], and shown in the Tables VII and VIII, we have proved the viability of that methodology. It is important to highlight, however, that, using these results as the

basis; we cannot affirm that our approach is superior to the method developed in [4]. This is because, the group of measurements used in that reference was not presented; it is not possible to accomplish a more accurate comparison between the two methodologies of estimation of parameters. However, in any way, it is already an indicative of the viability of the proposed approach.

VI. Acknowledgment

The authors would like to acknowledge FAPESP for the financial support given to this research.

VII. References

[1] A. Abur and A. G. Expósito, "Power system state estimation: Theory and implementation". Marcel & Dekker Publishers, Nova York, EUA, 2004.

[2] P. Zarco and A.G. Expósito, "Power System Parameter Estimation: A Survey," IEEE Transactions on power systems, Vol. 15, N° 1, pp. 216-222, Feb. 2000.

[3] D. Fletcher and W. Stadlin, "Transformer tap position estimation," IEEE Transactions on power systems, vol. PAS-102, n°. 11, pp. 3680-3686, Nov. 1983.

[4] W. Liu, F. Wu, and S. Lun, "Estimation of parameter errors from measurement residuals in state estimation," IEEE Transactions on power systems, vol. 7, n°. 1, pp. 81-89, Feb. 1992.

[5] R. Smith, "Transformer tap estimation at Florida power corporation," IEEE Transactions on power systems, vol. PAS-104, n°. 12, pp. 3442-3445, Dec. 1985.

[6] T. Van Cutsem and V. Quintana, "Real-time processing of transformer tap positions," IEE proceeding, vol. 135, pp. 31-40, Jan. 1988.

[7] M. B. Do Coutto Filho, J.C. Stacchini de Souza and E.B.M. Meza "Off-line validation of power network branch parameters" IET Generation, Transmission & Distribution, 2008, Vol. 2, Nº 6, pp. 892-905

[8] M. Allam and M. Laughton, "A general algorithm for estimating power system variables and networks parameters," in Proc. IEEK PES Summer Meeting, Anaheim, CA, 1974, Paper C74 331.5.

[9] O. Alsac, N. Vempati, B. Stott, and A. Monticelli, "Generalized state estimation," IEEE Transactions on power systems, Vol. 13, N° 3, pp. 1069-1075, Aug, 1998.

[10] W. Liu and S. Lim, "Parameter error identification and estimation in power system state estimation," IEEE Transactions on power systems, Vol. 10, N° 1, pp. 200-209, Feb. 1995.

[11] A. Debs, "Estimation of steady-state power system model parameters," IEEE Transactions on power systems, Vol. PAS-93, N° 5, pp. 1260-1268, Sep./Oct.1974.

[12] E. Handschin and E. Kliokys, "Transformer tap position estimation and bad data detection using dynamic signal modeling," IEEE Transactions on power systems, Vol. 10, N° 2, pp. 810-817, May. 1995.

[13] I. Slutsker and K. Clements, "Real Time recursive parameter estimation in energy management systems," IEEE Transactions on power systems, Vol. 11, N° 3, pp. 1393-1399, Aug. 1996.

[14] N. Logic and G. T. Heydt, "An Approach to Network Parameter Estimation in Power System State Estimation" Electric Power Components and Systems, 33: 1191-1201,2005.

[15] A. Monticelli "State estimation in electric power systems". Kluwer Academic Publishers, Massachusetts, USA, 1999.

[16] Power System test case achieve: University of Washington, htpp://www.ee.washington.edu/research/pstca.

VIII. Biographies

Madeleine Rocio Medrano Castillo received the B.S.E.E degree from San Agustin National University of Arequipa, Perú, in 2002, and the M.S.E.E. (2006) degree from E.E.S.C.- University of Sao Paulo, Brazil, both in Electrical Engineering. She is currently the Ph.D. degree at the same University. Her research interest includes parameter estimation of line transmission and state estimation in electrical power system.

Joao Bosco Augusto London Junior (S'1997-M'02) received the B.S.E.E. degree from the Federal University of Mato Grosso, Brazil, in 1994. The M.S.E.E. in 1997 from E.E.S.C. - University of Sao Paulo, Brazil, and the Ph.D. degree in 2000 from E.P. - University of Sao Paulo, both in Electrical Engineering. He is currently Assistant Professor at the E.E.S.C. - University of Sao Paulo. His main areas of interest are power system state estimation, distribution system reconfiguration, and application of sparsity techniques to power system analysis.

Newton G. Bretas (M'1976, SM'1989) received the Ph.D. degree from University of Missouri, Columbia, USA in 1981. He became Full Professor of the University of Sao Paulo, Brazil, in 1989. His work has been primarily concerned with power system analysis, transient stability using direct methods as well as power system state estimation. Dr. Bretas has also interest in energy restoration using ANN and GA for distribution systems.