Power System Parameter Estimation: A Survey

Pedro Zarco and Antonio Gómez Expósito

Abstract—**This paper deals with the problem of network parameter errors in state estimation. First of all, some experimental results are presented showing the influence of these errors on the performance of Weighted Least Squares state estimators. Secondly, the preliminary step of identifying suspicious network parameters is briefly discussed. A classification of the techniques proposed in the literature to estimate parameter errors is then suggested, followed by a description of the main ideas behind each method. Finally, a discussion is included on the possibilities and limitations of every class of methods.**

Index Terms—**Parameter errors, state estimation, transformer tap positions.**

I. Introduction

STATE Estimators (SE) are the heart of modern Energy Management Systems (EMS). The performance of any other application program (e.g., security analysis, economic dispatch, etc.) strongly depends on the accuracy of data provided by the SE. Resorting to field measurements, network parameters (R, L, etc.), network topology (breaker positions, etc.), and other available information, the SE takes advantage of the redundancy in the measurement set to filter the noise inevitably associated with the measurement process. The Weighted Least Squares (WLS) is the preferred approach to solve the resulting model, due to its well-known statistical properties.

Incorrect topological information normally produces large errors in the estimated measurements and can be easily identified. However, branch impedance errors are less evident and may lead to permanent errors in the data provided by the SE for a long time without being detected.

This paper is intended to describe the state of the art on the parameter estimation problem. Section II presents some data showing how a single parameter error may locally deteriorate the performance of the SE. Section III is devoted to the preliminary step of identifying suspicious network parameters. A classification of the methods presented so far for parameter estimation is proposed in Section IV. The two main categories of methods are reviewed in Sections V and VI, followed by a summary of published results and a discussion in Sections VII and VIII.

II. Influence of Parameter Errors

Network parameters (branch impedances or tap changer positions) may be incorrect as a result of inaccurate manufacturing data, miscalibration, tap changer being locally modified without knowledge of the control center, etc., and may produce:

- A significant degradation of the results provided by the SE and, therefore, of the conclusions arrived at by other applications, like security assessment.
- Acceptable measurements being detected as bad data owing to its lack of consistency with network parameters.
- A loss of confidence in the SE by the operator.

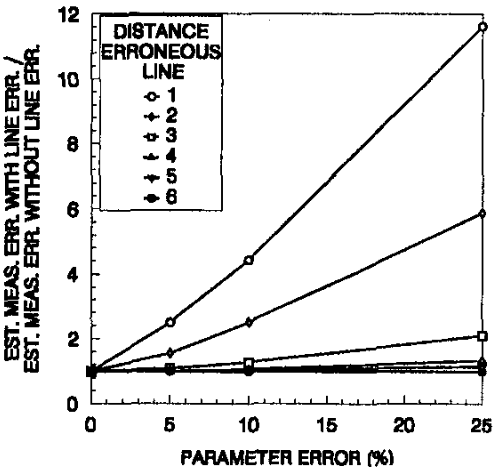

Fig. 1. Influence of a single parameter error on estimated measurements at different *distances*.

Although most papers on parameter estimation (PE) briefly refer to the importance of including this function within the SE, in order to prevent the consequences mentioned above, only a few of them [24], [29], [30], [32], [35], contain any data supporting this claim. Reference [6] presents some field experiences obtained during the process of bringing the state estimation function on line. Specially, [35] performs a complete study about the influence of parameter errors on the state estimation, analyzing the most important factors. Also, [17] presents a brief review of the PE problem.

Fig. 1 shows the ratio between the average estimated measurement error when a single line susceptance is erroneous and the same average when the susceptance is correct. This ratio is computed by considering measurements at different distances to the erroneous susceptance. Measurements at *distance 1* refer to the power flows of the erroneous line, as well as the power injections and voltages of its edge buses (adjacent set). Measurements at *distance 2* are those directly related to measurements at *distance 1*, and so on.

The simulations have been carried out on the IEEE 14-node network and represent different load flow situations with maximum measurement redundancy. As the IEEE 14-node network comprises 20 branches, and each point in the figure is the average of 60 state estimation runs with different measurement values (for the results to be statistically significant), each line has been tested 3 times. Error levels produced by class 1 transducers have been simulated.

The following conclusions may be obtained:

- Despite the high redundancy and the fact that a single parameter is erroneous, a significant overall deterioration can be noticed as the parameter error grows.
- The error's influence decreases with the distance to the involved branch. In practice, this influence is negligible at distances equal to or larger than 4, which means that the process of estimating a certain parameter is of a local nature.
- The harmful influence is more noticeable when the available measurements are more accurate, although this cannot be observed in the figure (see [35]).

III. Parameter Error Identification

From the SE point of view, a parameter error has the same effect as a set of correlated errors acting on all the measurements involved in the erroneous branch, namely the power flow measurements located on the branch and the power injection measurements located at the ending nodes. This results from a simple manipulation of the basic measurement model [23]:

$$z_s = h_s(x, p_0) + v_s = h_s(x, p) + [h_s(x, p_0) - h_s(x, p)] + v_s \tag{1}$$

where z is the measurement vector, x the state vector (bus voltage magnitudes and bus phase angles), h the nonlinear functions relating the measurement and state vectors, v the measurement error vector, p the true value of the network parameter, p_0 the erroneous value of the network parameter and the subscript s refers to the involved measurements only.

The term in square brackets in (1) acts as an equivalent additional measurement error. If the parameter error is large enough, this term will generally cause bad data detection and the involved measurements will most probably be among those having the largest residuals [22], [23], [34]. The equivalent measurement error can be linearized as:

$$h_s(x, p_0) - h_s(x, p) \approx \left[\frac{\partial h_s}{\partial p}\right] e_p \tag{2}$$

$e_p = p_0 - p$ being the parameter error.

Therefore, those branches whose involved measurements have a large normalized residual are suspicious, and the PE will be focused specially on those branches.

Reference [18] assumes that bad data has been identified and removed previously so that a persistent presence of a bias term in certain measurement residuals is an indication of the existence of parameter errors.

The identification method proposed in [19] is also based on the fact that an unexpected large normalized residual may indicate that something is not correct in the neighborhood of that measurement. Once a set of suspicious branches have been detected, the suspicious parameters are estimated.

The method presented in [13] and [31] to estimate transformer tap positions, is applied when the difference between the calculated and telemetered reactive power flows through the transformer is higher than a preset tolerance.

Finally, measurement, parameter, and configuration errors on the input data of a SE are identified by means of suitable statistical tests in [1].

IV. Methods for Network Parameter Estimation

Since Schweppe published his seminal work on SE in 1970 [26], [27], many other researchers have directed their efforts toward this topic [12]. Comparatively, the number of papers devoted to the PE problem is modest. Methods for network PE may be classified as follows [36]:

- Methods based on residual sensitivity analysis [13], [18], [21]–[23], [31], [34]
- Methods augmenting the state vector:
  Solution using normal equations [2]–[4], [7], [19], [25], [33], [35].
  Solution based on Kalman filter theory [5], [8], [10], [11], [16], [28]–[30].

This classification emphasizes the most outstanding difference between each class of methods, namely whether or not the state vector is augmented with additional variables representing suspicious parameters, indicating also the particular methodology followed to solve the resulting model.

V. Methods Based on Residual Sensitivity Analysis

These methods make use of the conventional state vector and perform the PE process when the SE has finished.

The method presented in [22], [23], and [34] is based on the sensitivity relationship between residuals and measurement errors [15]:

$$r = S_r v \tag{3}$$

where S_r is the residual sensitivity matrix, given by [20]:

$$S_r = I - HG^{-1}H^T W \tag{4}$$

and

$$G = H^T WH \tag{5}$$

is the gain matrix. A linear relationship can be established between the involved measurement residuals r_s and the parameter error e_p by means of (1)–(3):

$$r_s = \left((S_r)_{ss}\frac{\partial h_s}{\partial p}\right) e_p + \overline{r}_s \tag{6}$$

where $(S_r)_{ss}$ is the $(s \times s)$ submatrix of S_r corresponding to the s involved measurements and r_s is the residual vector that would be obtained in absence of any parameter errors.

Equation (6) can be interpreted as a linear model linking some measurement residuals r_s to an unknown parameter error e_p in the presence of noise $\overline{r}_s$. This makes the determination of e_p a local estimation problem.

The approach adopted in [18] is also based on measurement residuals and a bias vector which combines the effect of parameter errors and the state of the system. The estimation is performed in two steps: The first step estimates a bias vector while parameter errors are obtained at the second step from a sequence of bias vectors formerly computed. The main difference with [22], [23], and [34] is that the bias vector is expressed in terms of line flows.

The method proposed in [13], applied later in [31], is intended to estimate transformer tap positions and exploits the coupling between this parameter and the residual of the reactive power flow through the transformer.

Reference [21] presents also a transformer tap estimation algorithm but uses the estimated and measured voltages in order to generate a new tap position.

VI. Methods Augmenting the State Vector

These methods augment the state vector with suspicious parameters as if they were independent variables. This way, parameters are estimated along with bus voltage magnitudes and bus phase angles.

Two different alternatives have been used to deal with the resulting augmented model:

- Normal equations.
- Kalman filter theory.

A. *Solution Using Normal Equations*

The most straightforward approach to solve the WLS state estimator is by means of the normal equations,

$$G\Delta x = H^t W \Delta z. \tag{7}$$

The method proposed in [33] adds transformer taps to the state vector. Consequently, new columns are appended to the Jacobian whose elements are the partial derivatives of the measured quantities with respect to the newly defined state variables.

If there are measurements associated with the tap variables to be estimated, additional elements will be appended to the measurement vector and both the Jacobian and the measurement covariance matrices will have as many extra rows as new measurements have been appended.

Initially, transformer taps are modeled as continuous variables and a best fit is calculated. Then, the best fit is set to its nearest feasible discrete tap position and is later removed from the state vector. The normal equations are solved again allowing changes in the state vector resulting from the discretization of the taps. One or several transformer taps can be estimated simultaneously.

A similar method is described in [19], but the incremental flows due to parameter errors are used as part of the unknown state variables. Parameter errors are subsequently calculated in terms of these associated flows.

More than two decades ago, the augmented state vector was used in [2] and [3] to estimate all Y_{bus} elements in polar form.

Other class of methods, designed for off-line estimation of constant parameters, resort to several measurement snapshots to increase the redundancy around the suspicious parameters [25],

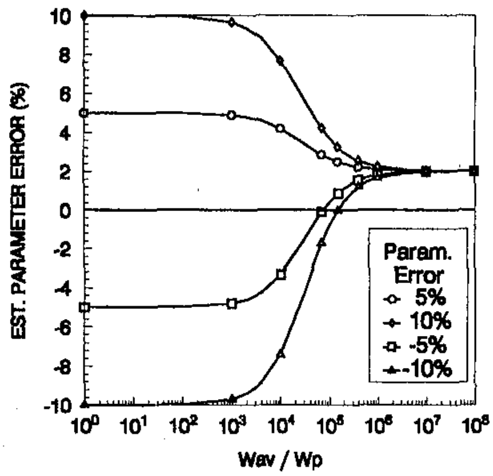

Fig. 2. Estimated line susceptance error versus relative parameter weight (IEEE 14-bus network, line 7–9).

[35]. Assuming q simultaneous samples are handled, the state and measurement vectors are:

$$x = [x(1),\, x(2),\, \cdots,\, x(q),\, p]^t \tag{8}$$

$$z = [z(1),\, z(2),\, \cdots,\, z(q)]^t \tag{9}$$

where $x(k)$ is the state vector corresponding to the kth sample, $z(k)$ is the measurement vector corresponding to the kth sample, and p is the parameter vector.

The available values of suspicious parameters are included as extra measurements in [25]. However, it is shown in [35] that the estimated parameters may be badly influenced by the weighting factors adopted for this extra information.

Fig. 2 illustrates what happens when a broad range of weighting factors (w_p) are assigned to the initial parameter value (in this case, the series susceptance corresponding to line 7–9 of the 14-bus network). The estimated parameter error is represented versus the ratio w_{av}/w_p, where w_{av} is the average of the measurement weighting factors. Four initial parameter errors are considered ($\pm 5\%$, $\pm 10\%$). The rightmost part of the figure shows the parameter error (about 2%) that would be estimated solely based on regular measurements (whose mean error is 3.2% in this example). When the ratio w_{av}/w_p is smaller than 10^3, the influence of the initial parameter value is determinant and there is no way to improve the estimated value. Only when this ratio is around 10^5 (in this example) could a better parameter estimation be expected, provided the initial error was negative. Note that it is not advisable to estimate parameters whose initial error (e.g., 1% in this case) is smaller than the average measurement error. As shown in Fig. 3 for a different line, the estimated parameter error may be negative as well, but the former conclusions still apply (this time, the average measurement error is 3.8%).

When only regular measurements are considered, the objective function becomes:

$$J(x,\, p) = \sum_{k=1}^{q} \sum_{i=1}^{m} w_i [z_i(k) - h_i(x(k),\, p)]^2. \tag{10}$$

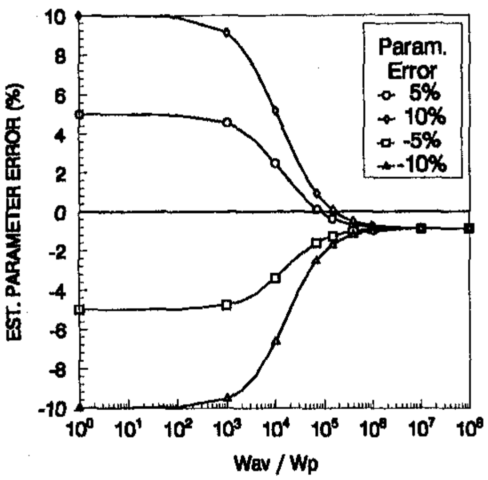

Fig. 3. Estimated line susceptance error versus relative parameter l p. Then, the objective function becomes weight (IEEE 14-bus network, line 10–11).

The Jacobian matrix of this enlarged model has the following structure

$$H = \begin{bmatrix} H(1) & & & & h_p(1) \\ & H(2) & & & h_p(2) \\ & & \ddots & & \vdots \\ & & & H(q) & h_p(q) \end{bmatrix} \qquad (11)$$

which, upon substitution in (5), leads to a bordered-block-diagonal gain matrix

$$G = \begin{bmatrix} G(1) & & & & g_p(1) \\ & G(2) & & & g_p(2) \\ & & \ddots & & \vdots \\ & & & G(q) & g_p(q) \\ g_p^t(1) & g_p^t(2) & \cdots & g_p^t(q) & G_{pp} \end{bmatrix}. \qquad (12)$$

At each iteration, this huge gain matrix must be formed and factorized in order to obtain the state vector correction Δx. Although this seems to be, computationally, a prohibitive task, a method especially tailored to the resulting block-diagonal structure can be applied whose overhead cost is modest compared to the sequential processing of all snapshots [35]. In addition, taking advantage of the local nature of the parameter estimation problem, the computational effort can be significantly reduced if only a small observable subnetwork surrounding every suspicious branch, along with the reduced set of related measurements, is included in the model.

B. Solution Based on Kalman Filter Theory

The method presented in [10] is intended to estimate transmission line admittances, transformer taps, biases in the measurements, and standard deviations of measurement errors.

At every time sample k, the measurements are related to the states by

$$z(k) = h(x(k),\, k,\, p) + v(k) \qquad (13)$$

where h is made dependent on k explicitly to reflect the possibility of network changes from one time sample to the next. The parameters are assumed constant for the entire time period under consideration.

In order to estimate the state vector, it is necessary to minimize the following objective function:

$$J = \sum_{i=1}^{m} [z_i(k) - h_i(x(k),\, k,\, p)]^T \cdot W(z_i(k) - h_i(x(k),\, k,\, p)]. \qquad (14)$$

If *a priori* information about the parameter vector is available, p_0, it can be used as a pseudo-measurement

$$p_0 = p + e_p \qquad (15)$$

where e_p is an error vector with zero mean and covariance R_p. Then, the objective function becomes

$$J_1 = (p - p_0)^T R_p^{-1} (p - p_0) + J. \qquad (16)$$

This algorithm, based on Kalman filter theory, is recursive in the sense that at time sample k, only the vector $z(k)$ is considered together with updated previous estimates of the parameters and their covariances.

In [11], all the information acquired during the testing period is resorted to in order to estimate state variables and parameters.

References [28]–[30] present two important differences with respect to [10]:

- The problem is localized into several small observable subnetworks containing the unknown parameters.
- Parameters are modeled as Markov processes, thereby allowing estimation of time-varying parameters.

The method assumes that the probability density functions of the *a priori* parameter estimate errors, state variables, and measurement errors are Gaussian with zero mean, leading to an adaptive parameter estimator. It starts by estimating only few highly telemetered branches. As impedance parameters of those branches become established, they are used to extend the process to less metered branches and so on. The solution will ultimately include all network branches with adequate redundancy excluding only those for which a reliable parameter estimation can not be performed.

References [5], [8], and [16], also based on Kalman filter theory, augment the state vector with those parameters leading to large residuals.

VII. Summary of Published Results

A fair and comprehensive comparison of the several approaches proposed so far for PE, based solely on published results, is virtually impossible, because the reported experiments refer to different scenarios and, what is equally important, vital information on the input data is many times missing. When the results are obtained from actual snapshots, the true state is logically unknown, and the only possible conclusion is that both $J(\hat{x})$ and the normalized residuals benefit from the inclusion of suspect parameters in the state vector (in fact, the more degrees of freedom, the lower the value of the objective function). This kind of experiment is more appropriate when transformer taps are estimated, because their actual values can be readily checked on site. Most frequently, however, results are obtained by simulation, in which case the accuracy of the estimated parameters can be better assessed. Unfortunately, several outstanding contributions omit the information on the simulated measurement noise adopted for the experiments. In what follows, some of the most significant results reported in the literature will be summarized.

The oldest results on the use of the Kalman filter for PE can be found in [10] and [11]. Simulation results in [10] originate from two experiments where over 10 parameters contaminated with 3–10% errors are simultaneously estimated. After a few filtering cycles, the estimated parameters are very close to the exact ones. Another BPA subnetwork is tested in [11] by means of actual snapshots. When all parameters are estimated, the value of $J(\hat{x})$ is an order of magnitude smaller and statistically unacceptable normalized residuals virtually disappear. A few estimated parameters differ from the available values by more than 10%. The accuracy of the simulated measurements is, however missing in [10]. In [11], an expression for the error variance is given, but the variables appearing in the formula (e.g., the full scales) are not provided. An interesting conclusion of this work, confirmed also in [32] and [35], is that small errors in line conductance and shunt capacitance are of little consequence.

In [18], a single line susceptance is perturbed and 2% random errors are added to all measurements. An undesirable feature of the method is that the estimated parameter error significantly grows with the error of the initial value, as a consequence of the linearized model adopted. Much better results are obtained in [19], where both simulated and real-time measurements are used in several experiments. The most complex case reported contains two nearby erroneous branches as well as a bad measurement (two branches away) in the presence of 3% random noise.

The Kalman filter is extensively tested in [30], where time-varying parameters are dealt with for the first time. In an outstanding experiment, all parameters are significantly contaminated (100% random errors) and very accurate results are obtained (again, no information is provided on the noise level associated with measurement samples). Another noticeable experiment consists of estimating the parameters of 99 branches based on 168 actual snapshots. The experiment concludes that the error of 10% transfer admittances exceeds 50%. These preliminary results, however, should be accepted with caution, because other sources of inaccuracy could influence the estimated values.

The IEEE 14-bus network is used in [35] to test the normal equations when the state vector is augmented with suspicious parameters. It is concluded that, irrespective of the initial parameter errors, the accuracy of the estimated parameters is proportional to both the accuracy of the measurement samples and the local redundancy. In turn, the local redundancy improves in proportion to the number of snapshots simultaneously used. Table I summarizes the filtering capability of this approach. Similar results are obtained when 5 out of 20 branches are erroneous, but the method is not intended to estimate all branch parameters.

The latest results are presented in reference [4], which is not devoted exclusively to the PE problem. The reported experiment refers to a huge network containing three separated branches with wrong series impedances. Gross errors are simulated on the power flow measurements of one of the corrupted branches

TABLE I

ESTIMATED PARAMETER ERRORS FOR DIFFERENT MEASUREMENT ERROR LEVELS: (a) AVERAGE. MEASUREMENT. ERROR (%), and (b) ESTIMATED. PARAMETER ERROR (%).

Snapshots	(a)	(b)	(a/b)
7	14.26	3.27	4.4
	8.56	1.95	4.4
	2.85	.65	4.4
4	14.20	4.38	3.2
	8.52	2.65	3.2
	2.84	.90	3.2
1	13.53	8.73	1.5
	8.10	5.27	1.5
	2.70	1.70	1.6

whose local redundancy is relatively low. While the initial parameter errors are significantly reduced, some relative errors still remain high (no information is given on the measurement accuracy).

Some interesting results have also been presented regarding the estimation of transformer taps. In [21], the taps of 25 transformers are simultaneously estimated by means of real-time measurements. The average and largest errors reported are 1.5 and 6 steps respectively. The method strongly relies on the presence and accuracy of voltage measurements. Similar results are presented in [22] for single tap errors, including a case in which both the reactance and the tap position of the same transformer are erroneous. In [33], one and two transformer taps are successfully estimated from actual snapshots whose accuracy is not provided. Finally, a dynamic filter is applied in [16] to estimate three transformer taps (two of them adjacent). Robustness of the algorithm to measurement noise is tested, including a gross error on one of the reactive power flows.

VIII. DISCUSSION

It can be stated that methods which augment the state vector have clearly surpassed those based on residual sensitivity analysis. Nevertheless, the latter approach is still necessary in the process of identifying suspect branches. It is also evident that, resorting to several snapshots, either sequentially or at once, provides a more robust way of updating the data base. It is not yet clear, however, whether a recursive filtering algorithm, or whether the conventional scheme based on the normal equations, is the best choice in all circumstances. In the authors' opinion, the Kalman filter may be more suitable to estimate time-varying parameters, while the simplicity of the standard WLS approach makes it more attractive to estimate constant parameters. Another controversial issue refers to whether a few selected parameters (including transformer taps) should be estimated, or whether the estimation process should be adaptively extended to eventually include all network branches with adequate local redundancy. A tentative answer to this question can be given by looking at the results presented above. It can be concluded (see Table I) that, for a given redundancy, the estimated parameter errors are proportional to the average measurement error. Consequently, if very accurate measurements are available, the estimated parameter values will probably be better than those available in the data base. But the opposite may also happen; a rather good branch parameter can be updated with a less accurate value if poor measurements are involved in the estimation process. Therefore, this risk should be kept in mind when deciding which parameters should be estimated.

Finally, all the proposed methods will provide poor estimates of parameters in the presence of persistent nearby gross errors that remain undetected.

The following comments reflect to some extent the authors' experience on this topic [35], [36]:

- Methods based on residual sensitivity analysis can be simply inserted at the end of the SE process, without having to modify any of the major routines which constitute the estimator. Among the several techniques which augment the state vector, those based on the ordinary normal equations are simpler to implement than the Kalman filter and require only straightforward modifications to the existing code. When the available information on the parameter value is not appended to the model as an extra measurement, the Jacobian becomes ill-conditioned at flat start. Hence, in order to elude this potential problem, the state vector should be enlarged only after the first iteration.
- Any method, irrespective of the technique adopted, requires that a certain measurement redundancy be locally available. Power flow measurements are particularly relevant in this regard, while the influence of injection measurements is, on average, much less noticeable.
- Estimation of transformer tap positions, like detection of topology errors, is inherently an on-line process. However, off-line processing may be a more adequate approach to estimate those branch parameters which remain essentially constant over time, like inductance and capacitance. Fluctuations of line resistance due to temperature changes may be significant, but errors affecting this parameter have been shown to be less influential on the SE performance [32], [35]. Additionally, if representative temperatures were recorded along with every sample, then it would be possible to refer the time-varying resistance to the constant value corresponding to a reference temperature. Off-line processing offers the following advantages [24], [35]:

Parameter values can be routinely improved on a batch computer by resorting to the last recorded snapshots, without interfering with the execution of the SE or any other EMS critical application. There is no need to modify the code running on line.

Computational issues are of secondary importance compared to optimality of the estimated values. Hence, irrespective of its complexity, the method deemed the most appropriate in every case can be chosen.

As parameter errors are permanent, no constraints are imposed on selecting a particular recorded snapshot. One or several related snapshots can be discarded if measurement redundancy is locally insufficient or the existence of bad data is suspected. This "healthy" snapshot selection process can be as sophisticated (i.e., costly) as required. Similarly, selection of suspicious parameters can be based on a longer historical series of data.

Simultaneously using several snapshots increase locally the redundancy because the additional parameter variables are shared by all network states. This would be quite a cumbersome process if carried out on line.

IX. Conclusions

In this paper, the network parameter estimation problem has been reviewed. Some experimental data have been first presented showing that a single parameter error may significantly deteriorate the accuracy of estimated measurements around the erroneous branch. Then, the important subtopic of suspicious branch identification has been briefly addressed.

A classification of existing methods for network parameter estimation has been later proposed. Two main approaches can be identified: On the one hand, methods which rely *a posteriori* upon the relationship between measurement residuals and parameter errors. On the other hand, methods which consider *a priori* suspicious parameters as additional state variables.

Some final comments are provided on the adequacy and limitations of each category of methods, regarding the type of parameter being estimated.

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