An Approach to Evaluate Modern Fault Location Methods for Power Distribution Systems

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***Abstract*—This paper presents an approach to assess automatic fault location methods in power distribution systems. The proposed approach allows to consider the aleatory errors inherent to calculated, forecasted and measured values, typically required by the fault location methods for a more realistic and consistent evaluation. These errors can follow different mathematical distributions, according their source and the assumptions made. In order to demonstrate the proposed approach, a real power distribution system is considered, and additionally, one method that requires measurements at the power substation and one method that requires sparse voltage measurements are assessed.**

***Index Terms*—Aleatory erros, Fault location, Power distribution systems.**

I. Introduction

Faults or short-circuits are the main source of interruptions in power supply of distribution systems. Therefore, the development of efficient automatic fault location methods are of great interest for power utilities. The fault location approaches can be classified according to the information required. If meters are not available, the fault location is based on screening of customer complaints and visual inspection of the system [1]. The classical impedance based methods requires measurements obtained at the substation and, the system topology and parameters. These methods are based on circuit simplifications and approximations regarding the loads [2], [3]. More recently, a number of methods based on measurements have been proposed. Apart from measurements in substation, these methods requires additional sparse meters, the system topology, parameters and loads [4], [5], [8], however, they do not require simplifications on the system.

According to literature, the automatic fault location approaches are generally evaluated considering that perfect measurements, parameters and loads, when required, are available [2], [3], [5], [7]. Usually, fault location methods are evaluated considering different types of faults, values of resistances and fault positions. Thus, for each simulated fault, the calculated fault position is compared to the actual fault position and an error is obtained. In some cases, different load levels are considered, however, errors in load forecasting, measurements and system parameters are rarely modeled and assessed [4]–[8].

In this context, this paper presents an approach to assess automatic fault location methods in power distribution systems. This approach allows to consider the aleatory errors inherent to calculated, forecasted and measured values. Therefore, it is aligned with the trends of the modern smart grids and results in a more realistic and consistent evaluation of fault location methods. The aleatory errors can follow different mathematical distributions, according to the assumptions made. Typically, normal and uniform distributions assumed [8], [13]. Monte Carlo simulations are used to statistically assess the fault location methods. In order to demonstrate the proposed approach, it is applied to the impedance based method proposed in [3] and to the measurement based method proposed in [8]. These methods were chosen due to its different natures and required data.

This paper is organized as follows. In the next section, both fault location methods are briefly described and its requirements are discussed. In section III the main sources of errors related to fault location methods are highlighted and quantified. In section IV, the main results are presented and discussed. Finally, in section V the conclusions are drawn.

II. Fault Location Approaches and Requirements

In this section the two fault location methods assessed in this paper are described. The impedance based method proposed in [3] and the measurement based method proposed in [8] were chosen. In the first method, the voltages and currents at fundamental frequency measured at the substation before and during the fault are used with the system topology and line parameters to calculate the impedance and, consequently, the distance between the substation and the fault location [3]. This method requires the same type of information and is based on similar circuit simplifications assumed by classical impedance approaches, therefore, it can be classified as a classical approach [2]–[5]. The second method requires the system topology and parameters, a set of sparse voltage amplitudes measured before and during the fault as well as the loads [6], [8]. This method can be classified as a method for modern systems, since it requires more measurements, communication infrastructure and it doesn't assumes circuit simplifications.

A. Method of Morales et al. [3]

This method performs a scanning on the branches of the power distribution system calculating the fault reactance in different locations. Assuming the fault impedance is mostly resistive, the fault location is that associated to the smallest calculated reactance. In this method the loads are aggregated and allocated in a terminal bus. The equivalent power distribution system is simplified and represented according to Fig. 1, where the aggregated loads are represented by a diagonal matrix $\mathbf{Z}_L$, the analyzed branch is represented by the impedance matrix $\mathbf{Z}$, and $\mathbf{Z}_u$ and $\mathbf{Z}_d$ indicates, respectively, the branches upstream and downstream the analyzed branch.

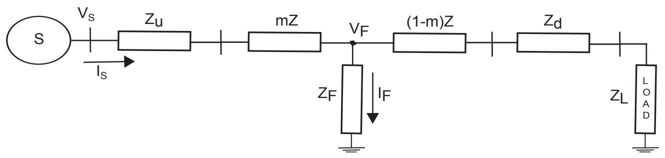

Fig. 1. Simplified network adopted by Morales et al. [3].

Since the aggregated loads, $\mathbf{Z}_L$, are calculated from currents and voltages measured at substation and branch parameters, the accuracy of this method is affected by errors in measurements and system parameters.

B. Method of Trindade et al. [8]

Unlike impedance based methods that provide the fault position, this method provides the bus closest to the fault location. This method is based on short-circuit theory and amplitude voltage sags measured on several buses. Based on a voltage sag measured in bus *i*, the fault current for a fault on bus k is calculated by (1), where $\mathbf{Z}_{ik}$ is the 3×3 impedance sub-matrix associated to buses i and k, and P stands for pre-fault measurements.

$$\mathbf{I}_{F(k)} = (\mathbf{Z}_{ik})^{-1} \cdot \left(\mathbf{V}_i^P - \mathbf{V}_i\right) \tag{1}$$

If N_v voltage meters are available, N_v fault currents can be calculated based on the assumption that the bus k is the closest to the fault. If the fault is close to bus k, all of the N_v calculated fault currents are expected to present very similar values, which are close to the actual fault current. On the other hand, if the fault is far from bus k, there will be an error on the fault current calculated from the measurements obtained in the i-th bus. Based on the aforementioned concept, a fault-location index δ_k can be used to identify the bus closest to the fault. This index is defined by (2).

$$\delta_k = \sum_{n=1}^{N_v} \left(\left| \mathbf{I}_{F(k)}^n - \overline{\mathbf{I}_{F(k)}} \right| \right) \tag{2}$$

where $\mathbf{I}_{F(k)}^n$ is the fault current calculated from (1) considering the meter *n* allocated on bus *i*, and $\overline{\mathbf{I}_{F(k)}}$ is the average of all fault currents calculated assuming a fault on bus k. Therefore, the lower δ_k is associated with the faulted bus. This method requires the three-phase bus impedance matrix including the load impedances and sparse voltage measurements, therefore, its performance can be affected by errors in lines and loads parameters and amplitude voltage measurements.

III. Evaluating Fault Location Methods

A literature review indicates that fault location approaches are generally evaluated considering that perfect measurements, parameters and loads, when required, are available [2], [3], [5], [7]. Frequently, fault location methods are evaluated considering different fault resistances and positions. For each simulated fault, the calculated position is compared to the actual fault position and an error is obtained. In some cases, different load levels are evaluated, however, errors in load forecasting, measurements and parameters are rarely modeled and evaluated [5]–[8].

As stated before, the performance of fault location approaches can be affected by inaccuracies in measurements, system parameters and loads. In the following, the main source of errors are discussed and quantified according to typical values recommended in literature and it is proposed a simple approach to estimate these errors. This proposed approach allows to consider the aleatory errors inherent to measured and forecasted values. This proposal derives from the measurement theory and it can results in a more realistic and consistent evaluation of fault location methods. The aleatory errors can follow different mathematical distributions, according to the assumptions made. Thus, for example, for measurements and loads the errors can follow a normal distribution [8], [13], while for parameters the errors can follow normal or uniform distributions, depending on the source of the errors.

A. Errors in Measurements and Loads

Errors in measurements are associated with the accuracy of metering system including meters, instrument transformer, A/D converters, connection cables, sensors and the communication infrastructure [10]. In practice, just the main of these effects are considered, since most of them are hard to be modeled. Currently, the typical accuracy of meters are between 0.1% to 2% for magnitudes and $\pm 2°$ for phase angles [17]. The errors associated with the instrument transformers are in general lower than 1.2% [16]. On the other hand, the errors associated with load forecasting depends on the quality of the available data. According to literature, these errors can range from 20% to 50% if data comes from measured monthly consumption and can range from 2% to 10% if the data comes from low voltage smart meters [13]–[15].

B. Error in Parameters

The errors in parameters can be adequately represented by errors in the length of the cables. A very common source of errors in parameters are associated with typos during database building. Besides that, errors can be associated to weather and operational conditions. The weather and load conditions can change the temperature of the cables, changing their lengths and, consequently, the resistance and reactance of these cables. According to literature, the length of the cables can vary up to 3% depending on the weather and load conditions [11]. Another very important operational aspect that can cause errors in parameters is the frequency of the voltages and currents of the system. According to literature, power distribution systems operating above their surge impedance loading and hence absorbing more reactive power can operate with frequencies ranging form 47.5 to 53 Hz for countries whose nominal frequency is 50 Hz [12], which means that the frequency in power distribution systems can vary up to $\pm 6\%$ from values calculated in nominal frequencies. As the reactances are function of this frequency, they can change during operation.

C. Estimating the Errors

The actual measurements, loads and parameters will be generated by adding aleatory errors to their true values. Therefore,

$$z_i^{actual} = z_i^{true} + b_i \times \sigma_i \tag{3}$$

where z_i^{true} is the true value of i-th measurement, load or parameter. The true values for measurements will be obtained from simulation, for example, using ATP (*Alternative Transient Program*), while the true values for loads and parameters will be obtained from database. Considering a normal distribution, the value σ_i is the standard deviation of the i-th measurement, load or parameter and will be defined according to typical errors associated to these values. Finally, b_i is a randomly generated number following a specified mathematical distribution, for instance, $b_i \in$ N(0, 1) for a normal distribution with zero mean and unitary standard deviation [13], [14].

The standard deviation associated to amplitude measurements obtained from modern digital meters, forecasted loads as well as parameters is computed from (4), where $\rho = 3$ for a normal distribution and $e_{\%}$ is the error associated with measurements, loads or parameters. The standard deviations associated with measured angles will be calculated according to (5). For an uniform distribution, ρ is set to 1 and, therefore, σ_i is the maximum error of the i-th measurement, load or parameter.

$$\sigma_i = \frac{z_i^{true} \times e_{\%}}{\rho \times 100} \tag{4}$$

$$\sigma_i = \frac{e_{angle}}{\rho} \tag{5}$$

In this paper, $e_{\%}$ will be set to 2% for amplitude measurements, 3% for the length of the cables, and 20% or 50% for forecasted loads. For the phase angles, e_{angle}, will be set to $2°$. These values were specified according to literature recommendation, however, they need to be adequate to the features of each power distribution system.

IV. Case Study

The simulations were performed in a real-life overhead three-phase 13.8 kV, 7.065 MVA, 4270 meters long distribution feeder containing 134 nodes shown in Fig. 2 [6]. This feeder was modeled in ATP (Alternative Transient Program) [9], where the faults were simulated. The available meters are indicated in figure.

Both fault location methods were assessed by applying single-phase faults to buses 4, 17, 26, 38, 56, 63, 67, 82, 90, 98, 103, 107, 115 and 123 with fault resistance equal to 1Ω. The errors presented in figures are calculated by $|d_{calc} - d_{act}|$, where d_{calc} is the calculated distance and d_{act} is the actual distance of the faults. In order to conduct a fair evaluation, 100 simulations considering aleatory errors were simulated for each fault position. In the results, the ideal case refers to simulations considering the perfect loads, measurements and parameters.

The results are presented considering one method at a time. The methods are not compared since this is out of the scope of this paper.

A. Method of Morales et al. [3]

As discussed previously, this method can be affected by errors in measurements and parameters. For that, aleatory errors following normal and uniform distributions are assessed.

1) Errors in Measurements: Fig. 3 presents the errors in the fault location while the errors in measurements follow a normal distribution and the true values are used for parameters. It is possible to observe that the mean errors for fault location increase for all simulated faults. The far the fault is from substation, the bigger the scattering of the fault location errors.

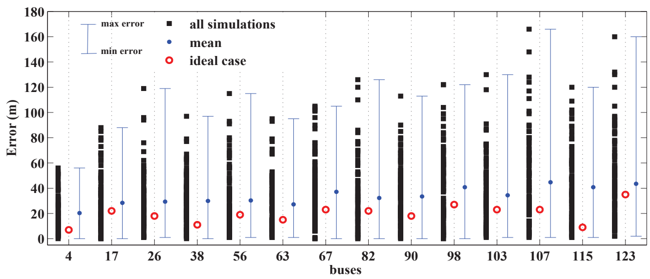

Fig. 3. Errors in fault location with errors in measurements - normal distribution.

The fault location errors considering that the errors in measurements follow an uniform distribution are shown in Fig. 4. In general, it can be observed that the errors increase regarding the uniform distribution. For instance, in bus 56 the maximum error increased from 120 to 200 meters. The maximum fault location error increase from 170 to 300 meters, which is distinguished, since the maximum length of the feeder is 4270 meters. Therefore, the way the measurements errors are considered, can significantly change the conclusions about the performance of this approach.

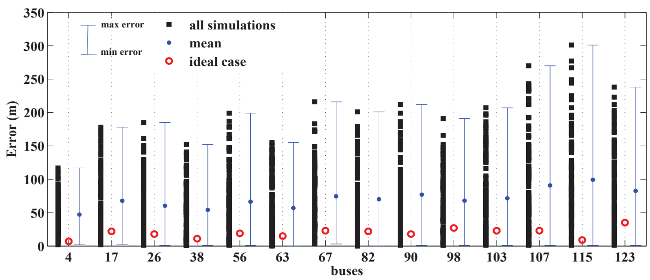

Fig. 4. Errors in fault location with errors in measurements - uniform distribution.

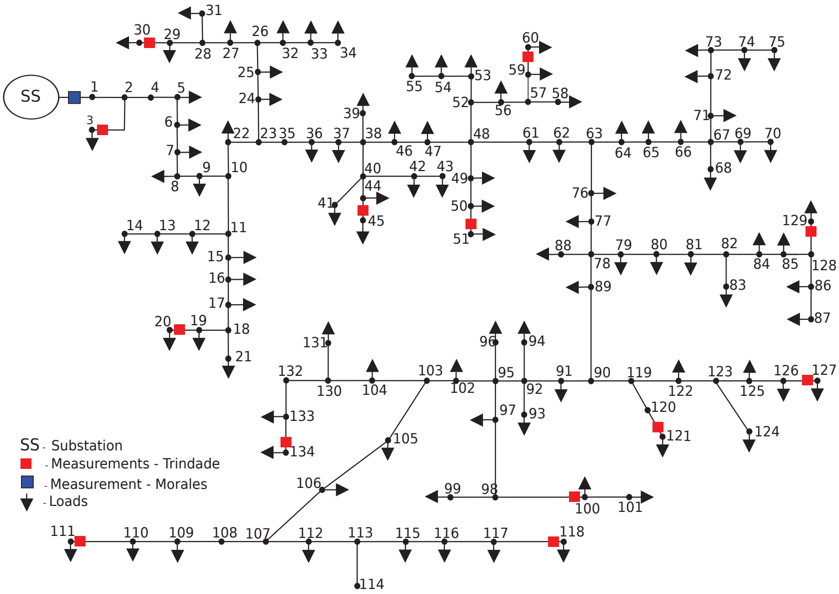

Fig. 2. Real power distribution system (134 nodes).

2) *Errors in Parameters:* Fig. 5 shows that the accuracy of this method is slightly affected by the errors in line parameters. Note that the error for the ideal case is close to the mean error obtained after 100 simulations. Besides, the scattering of the errors is low. These results were obtained considering that the errors follow a normal distribution and the true values were adopted for measurements.

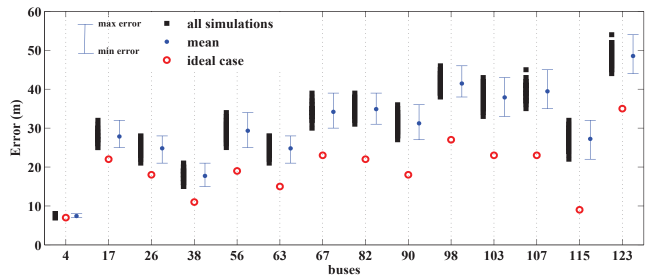

Fig. 5. Errors in fault location with errors in line parameters - normal distribuiton.

Results obtained assuming an uniform distribution and aleatory errors in parameters are presented in Fig. 6. As it can be observed, similarly to the previous case, the errors in the line parameters does not significantly affect the accuracy of this method.

Comparing the results presented in this section, it can be observed that the scattering of the fault location errors obtained considering aleatory errors in line parameters are smaller compared to the scattering of the fault location errors obtained considering aleatory errors in measurements. Therefore, the errors in measurements are more significant than the errors in parameters for the method proposed by Morales et al. in [3].

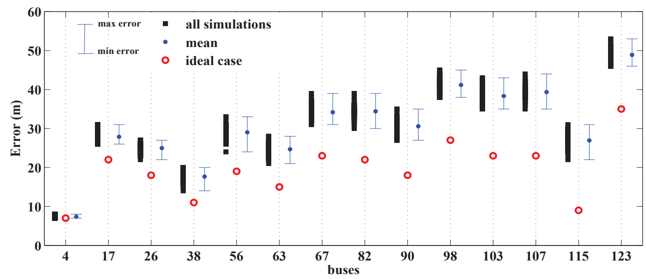

Fig. 6. Errors in fault location with errors in line parameters - uniform distribuiton.

B. Method of Trindade et al. [8]

This method can be affected by the set of measurements available, as well as by the errors in measurements, line parameters and loads. The effects of these errors are assessed in this section.

1) *Errors in Measurements:* Fig. 7 presents the errors in the fault location for the method proposed by Trindade et al. while the aleatory errors in measurements follow a normal distribution. The true values are assumed for the remaining data. Remember that this method indicates the bus closest to the fault instead of the fault position.

The fault location errors assuming that the errors in measurements follow an uniform distribution are shown in the Fig. 8.

Comparing Fig. 7 and Fig. 8, it can be observed that, in general, the uniform distribution results in slightly bigger errors for fault location. For instance, the maximum error in bus 98 increased from 250 to 400 meters, while in bus 38 the fault location error remained in 250 meters. This discrepant behavior is highly associated to the number and position of the available

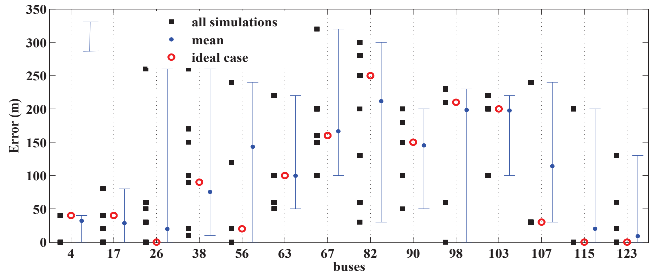

Fig. 7. Errors in fault location with errors in measurements - normal distribution.

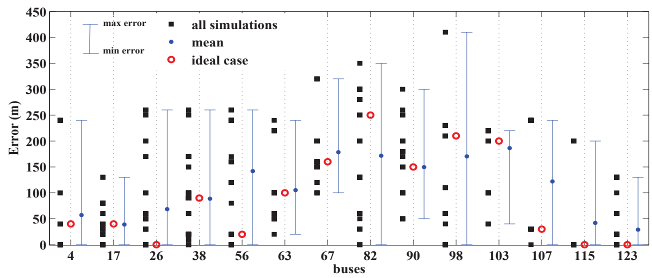

Fig. 8. Errors in fault location with errors in measurements - uniform distribution.

measurements. Additionally, the uniform distribution results in bigger fault location errors if the measurements contain errors.

2) Errors in Parameters: Fig. 9 shows the accuracy of this method with the errors in line parameters following a normal distribution. According to this figure, the errors in line parameters have affected only the fault location on the buses 17 and 56. The same general behavior can be observed if the errors in parameters follow an uniform distribution, as can be seen in Fig. 10. For instance, in this case, buses 17, 56 and 107 has presented errors in fault location. Therefore, as in the method proposed by Morales, errors in line parameters are not significate for this method.

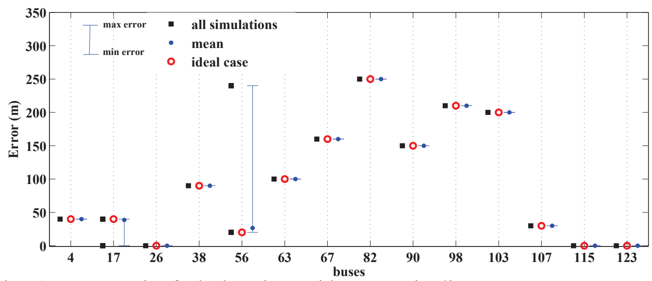

Fig. 9. Errors in fault location with errors in line parameters - normal distribution.

3) Errors in Loads: The method proposed by Trindade et al. requires the impedance matrices to perform short circuit calculations. Therefore, aleatory errors following a normal distribution were added in the load impedances. In general, the load forecasting depends on the available data and the adopted approach. In this section, the errors $e_{\%}$ were considered equal to $\pm 20\%$ and $\pm 50\%$. Fig. 11 and Fig. 12 show the

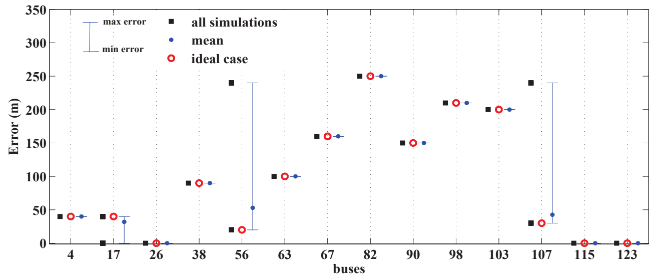

Fig. 10. Errors in fault location with errors in line parameters - uniform distribution.

fault location errors assuming that the errors in loads follow a normal distribution. In general, it can be observed that this fault location method is not significantly affected by the errors in load impedances. The results considering an uniform distribution and $e_{\%} = \pm 50\%$ are shown in Fig. 13. In this case, the aleatory errors in loads just affect the fault location errors in buses 17, 56 and 107.

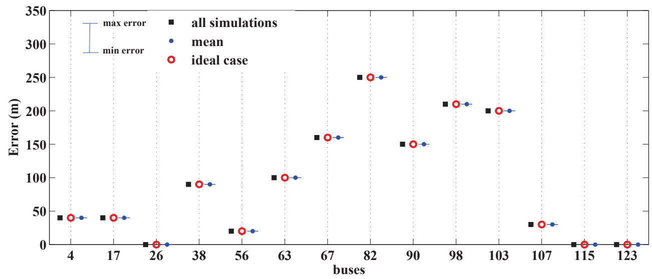

Fig. 11. Errors in fault location with ± 20 errors in loads - normal distribution.

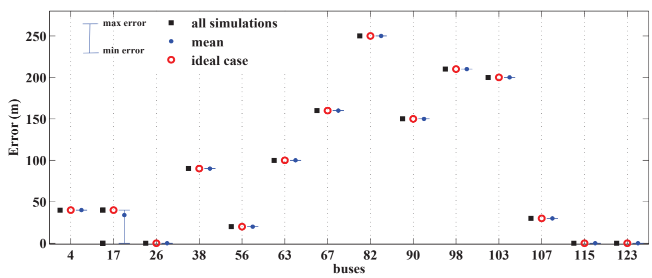

Fig. 12. Errors in fault location with ± 50 errors in loads - normal distribution.

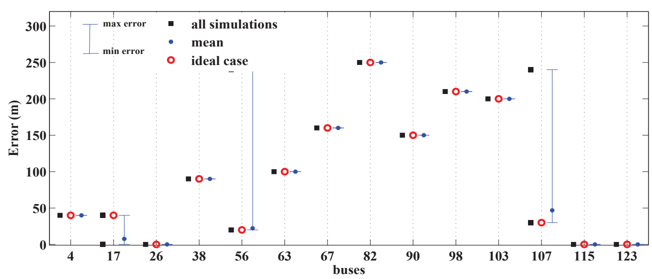

Fig. 13. Errors in fault location with ± 50 errors in loads - uniform distribution.

Comparing the results presented in this section, it can be observed that the aleatory errors in measurement are more significant than the aleatory errors in load and parameters for the method proposed by Trindade et al. in [8].

V. Conclusions

An approach that allows assessing the impact of the aleatory errors inherent to calculated, forecasted and measured values in automatic fault location methods was presented. Thus, the errors in measurements, parameters and loads can be adequately considered, which leads to a more realistic evaluation of the fault location methods. Therefore, the proposed approach is aligned with the trends and requirements of the modern smart grids. The aleatory errors can be modeled according to different mathematical distributions, depending on the source of the errors and on the assumptions made. For instance, the errors in line parameters, measurements and forecasted loads can be modeled by normal or uniform distributions. Therefore, in order to perform a more realistic and fair assessment of automatic fault locations methods, the proposed approach can be very useful.

In order to demonstrate the proposed approach, it was applied to the impedance based method proposed in [3] and to the measurement based method proposed in [8]. The results indicate that the several sources of errors can result in different impacts depending on the features of the method and on the power distribution system. In general, the following can be stated: (i) Uniform distributions leads to more conservative results; (ii) Despite the recommendations available in literature, the amplitude of the errors depends on the distribution power system and the measurements set; (iii) In the both assessed fault location methods, the errors in measurements seems to be the most important. However, for the measurement based method, this behavior depends on the number and the location of the voltage measurements available; (iv) In general, as observed for the evaluated methods, errors in parameters and load are less significant, however, this can not be generalized. Therefore, a complete analysis following the proposed approach is recommended for the evaluation of automatic fault location approaches.

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References

[1] IEEE Guide for Determining Fault Location on AC Transmission and Distribution Lines,” IEEE Std C37.114-2014 (Revision of IEEE Std C37.114-2004) , vol., no., pp.1,76, Jan. 30 2015 doi: 10.1109/IEEESTD.2015.7024095.

[2] D. Novosel, D. Hart, and J. Myllymaki, ”System for locating faults and estimating fault resistance in distribution networks with tapped loads”, *US Patent*, 5,839,093, pp- 279 - 288, December, 1998.

[3] G. Morales-Espaa, J. Mora-Florez, and H. Vargas-Torres, ”Fault location method based on the determination of the minimum fault reactance for uncertainty loaded and unbalanced power distribution systems”, *T&D Conference and Exposition: Latin America*, pp-803-809, 2010.

[4] Ramar, K.; Ngu, E.E., ”A new impedance-based fault location method for radial distribution systems”, *Power and Energy Society General Meeting, 2010 IEEE* , vol., no., pp.1,9, 25-29 July 2010, doi: 10.1109/PES.2010.5588189.

[5] G.D. Ferreira, D.S. Gazzana, A.S. Bretas, and A.S. Netto, ”A unified impedance-based fault location method for generalized distribution systems,” *PES General Meeting, IEEE* , vol., no., pp.1,8, 22-26 July 2012.

[6] R.A.F. Pereira, L.G.W. da Silva, M. Kezunovic, and J.R.S. Mantovani, ”Improved Fault Location on Distribution Feeders Based on Matching During-Fault Voltage Sags,” *Power Delivery, IEEE Transactions on* , vol.24, no.2, pp.852,862, April 2009.

[7] S.M. Brahma, ”Fault Location in Power Distribution System With Penetration of Distributed Generation,” *Power Delivery, IEEE Transactions on* , vol.26, no.3, pp.1545,1553, July 2011.

[8] F.C.L. Trindade, W. Freitas, J.C.M. Vieira, ”Fault Location in Distribution Systems Based on Smart Feeder Meters,” *Power Delivery, IEEE Transactions on* , vol.29, no.1, pp.251,260, Feb. 2014.

[9] Leuven EMTP Center, ”ALTERNATIVE TRANSIENTS PROGRAM Rule Book”, 1987.

[10] J. Zhu, A. Abur, M. J. Rice, G. T. Heydt, and S. Meliopoulos, ” Enhanced state estimators”, *Final project report*, PSERC, Nov. 2006.

[11] L. Weiner, P. Chiotti, and H. A. Wilhelm, ”Temperature Dependence of Electrical Resistivity of Metals”, *Technical Information Service, United states Atomic Energy Commission*, Ames Laboratory, Dec. 1956.

[12] A. S. Pabla, ”Electrical Power Distribution”,5ed, McGraw-Hill,2007.

[13] M. Yucra, F. Schmidt and M. C. de Almeida, ”Analysis of Bad Data Detection in Power System State Estimators Considering PMUs”, *PES General Meeting (PES)*, pp.1,5, 26-30 July 2015.

[14] J. Wu, Y. He, N. Jenkins,”A robust state estimator for medium voltage distribution networks, *Power Systems, IEEE Transactions on*, vol.28, no.2, pp.1008,1016, May 2013.

[15] Lihan He; Zhilin Wu; Zhihan Xu; Voloh, I., ”Fault location in distribution system with load uncertainty analysis,” Power System Technology (POWERCON), 2014 International Conference on , vol., no., pp.1595,1601, 20-22 Oct. 2014 doi: 10.1109/POWERCON.2014.6993899.

[16] IEEE Standard Requirements for Instrument Transformers, *IEEE Std C57.13-2008*, vol., no., pp.1,106, July 28 2008.

[17] Feeder Protection Relay SEL-751A Data Sheet, *Schweitzer Engineering Laboratories, Inc*.