Characterization of event databases for locating faults in radial power systems

Caracterización de bases de datos de eventos para localización de fallas en sistemas de potencia radiales

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Abstract

In this paper, an approach for characterizing event databases composed of voltage and current signals measured at a distribution substation during faults is presented. Voltage and current features or descriptors obtained from such signals and knowledge based methods are proposed for locating faults in power distribution systems. As it is shown, this is a simple, efficient and economical option that takes advantage of all the information directly related to the fault location contained in the signal measured at the distribution substation. The characterization proposed here constitutes a fundamental step towards the development of knowledge based methods. These are mixed with model based methods to obtain efficient and fast hybrid fault location algorithms to be applied in power distribution systems.

----- *Keywords:* Power quality, signal characterization, fault location, model based methods, knowledge based methods

Resumen

En este artículo se presenta una propuesta de caracterización de las bases de eventos compuestas por señales de tensión y de corriente medidas en la subestación de distribución ante circunstancias de falla. Se proponen por tanto, características o descriptores que pueden ser usados por los métodos basados en el conocimiento para la localización de fallas. Tal como se muestra, esta es una opción simple, eficiente y económica para aprovechar la información contenida en las bases de eventos y que está directamente relacionada con la localización de las fallas. La caracterización aquí propuesta es fundamental

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para el desarrollo de algoritmos híbridos de localización de fallas, rápidos y eficientes para sistemas de distribución de energía eléctrica.

----- *Palabras clave*: Calidad de potencia, caracterización de señales, localización de fallas, métodos basados en el modelo, métodos basados en el conocimiento
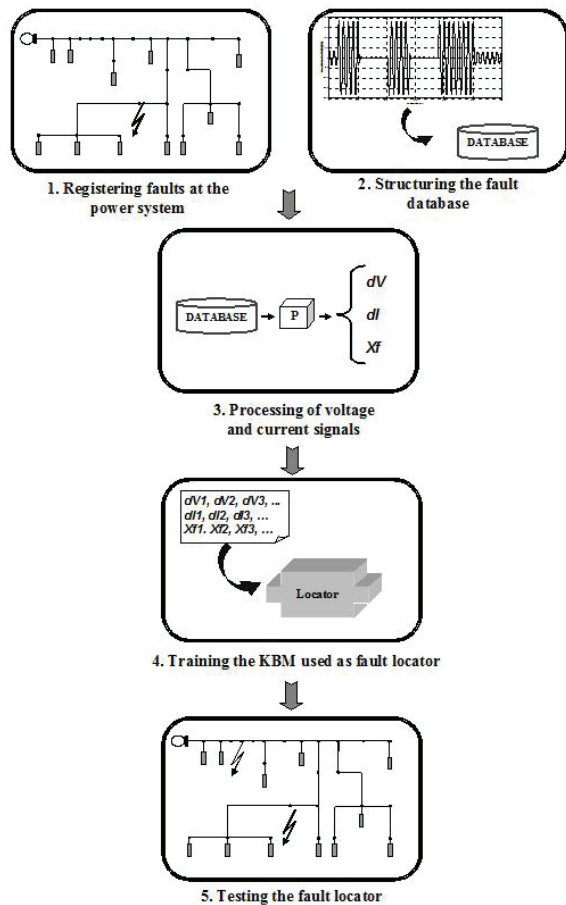
Introduction

Power lines at all voltage levels are prone to damage from electrical storms, breaks of insulators and short circuits due to trees and/or other external objects. In most of the cases, the fault is the direct consequence of a mechanical line damage which must be man-repaired to restore the power supply. Such a restoration process can be considerably improved if the location of the line damage is known, or at least, can be estimated with certain accuracy [1, 2]. Power quality requirements, in particular continuity of supply, implemented in connection to the deregulation of electricity markets have been motive of an increasing interest in studying the fault-location-problem in distribution systems. Faults and outages are related to power quality in terms of the continuity of supply indexes such as frequency and duration of interruptions. In the new deregulated environment, electrical utilities have to maintain adequate values of these indexes to be competitive under the open market conditions [1, 3]. Fault location techniques could help utilities to improve restoration process by giving reasonable accurate estimation of the faulted point. Fault location in power distribution systems is constrained to methods that use one terminal measurement. In general fault location methods can be classified in 1) knowledge based methods (KBM) [4-8], and 2) model based methods (MBM) [9-12]. KBM use a data base with information about protection devices, switches, current and voltage sensors condition, call recordings from customers, and samples of voltage and current measured at a substation. MBM use the fundamental voltage and current signals as measured at the substation together with the model of the power system to compute the impedance from substation to the fault location. Model based methods are more popular and better documented than knowledge based methods because of a less expensive implementation and operation. However model based methods are highly dependent on the network model and have multiple estimations of the possible fault location, because they only estimate one electrical distance from the substation to the fault location. Knowledge based methods are usually less precise than MBM but have the advantage of a low dependency on the network model and the capability to locate the faulted geographical zone in the power distribution system. Therefore, it seems apparent that hybrid methods can be developed to incorporate the advantages of both methodologies, solving the problem of multiple estimations and reducing the dependency on the network model. Most distribution networks have voltage and current signals measured at HV/MV substations only, and therefore it is imperative to develop methods that can extract useful characteristics from those signals. In order to take advantage of all the information related to the fault contained in the signals, current and voltage characteristics should be different from the RMS values commonly used by MBM. A good signal characterization technique helps in taking advantage of all the relevant information at the substation with almost no additional cost [1, 7, 13].

This work presents a fault location method based on the characterization of voltage and current signals, as measured at the substation during a fault in the power system. The characterization is based on the analysis of the transient and the steady state signals before, during and after the fault. Wavelet and Fourier transforms are used to determine the frequency and damping time of the transient in the RLC circuit from the substation to the fault location [14]. By means of an analysis of the current in a time window that includes

the states before, during and after a fault, the components α, β and *zero* can be obtained by using the Clark-Concordia transform and their relationship to the fault location distance can be estimated [5, 15]. Similarly, the change of load as seen from the substation can be measured, and then related to the distance to the fault [16, 17, 18]. As a result of this characterization, certain descriptors are obtained and used as input for knowledge based methods proposed to avoid the multiple estimation problem. These methods are a simple, efficient and economic alternative for fault location, based on information different from the RMS values of the voltage and current signals [1, 8]. The proposed fault location strategy follows the schematic representation presented in figure 1.

As shown in figure 1, step three is the fundamental part discussed in this paper.

In this work the strategy for characterization of the event database is also presented. It includes the analysis of the load variation, the admittance analysis as seen from the substation, the theoretical foundation for extracting duration and frequency of the transient signal and the Clark-Concordia transform used to analyze the α and β components. Additionaly, the knowledge based technique, trained as knowledge based method for fault location is presented. Finally, the test and the conclusions obtained from this research are given.

Features obtained from voltage and current registered during faults

Analysis of the system load

The analysis of the load change from prefault, fault and post fault signals is performed based on the relationship between this variation and the fault location. The identification of some characteristic loads in the analyzed distribution circuit will provide geographical information about the fault location.

Load modeling

There are four well known models used to represent the load and also to model the load variation during and after the fault [16].

Polynomial Model: Active and reactive power are computed as shown in (1).

$$P = a_0 + a_1|V| + a_2|V|^2 + ... \quad ;$$
$$Q = b_0 + b_1|V| + b_2|V|^2 + ... \tag{1}$$

This representation is acceptable for both, individual or aggregated loads.

Exponential model: Loads are obtained as a function of its nominal power values and its dependency on the voltage magnitude as it is presented in (2).

Figure 1 Proposed strategy for fault location based in characterization of event databases

$$S = P_n \left\| \frac{|V|}{|V_0|} \right\|^k + jQ_n \left\| \frac{|V|}{|V_0|} \right\|^l \qquad (2)$$

Where k and l are related to the load type, with values between 0 and 3.

Frequency dependent exponential model*:* Loads are seldom modeled to include the effects of frequency. If load is frequency dependent, this effect is included in the model, as shown in (3).

$$S(f,|V|) = P_n \left[\frac{\omega}{\omega_n} \right]^\delta \left[\frac{|V|}{|V_0|} \right]^k +$$
$$jQ_n \left[\frac{\omega}{\omega_n} \right]^\varepsilon \left[\frac{|V|}{|V_0|} \right]^l \qquad (3)$$

Where $\omega = 2\pi f$ and $\omega_n = 2\pi f_n$, f_n the nominal frequency. In this model, δ and ε are constants.

Statistical model: This model is suitable for modeling aggregate loads at a node, when daily, monthly or seasonal load profiles are known. A Gaussian normal distribution is assumed to represent the stochastic behavior of the loads, as it is presented in (4).

$$S = (P_n + k_p\delta) + j(Q_n + k_p\delta) \qquad (4)$$

Where the total active power has a probability of p, k_p is a coefficient related to p and δ is the standard deviation [18].

Aggregated load model at the power substation

Using the proposed models, it is possible to create an aggregate model with a single node, as seen from the substation, and shown in figure 2.

Using exponential models in the fault location problem, the equivalent power for the aggregate model at the substation before the fault is given in equation (5).

During the fault, the model of figure 2 varies due to the fault resistance, causing that the

power conditions turn into the equivalent model presented in figure 3.
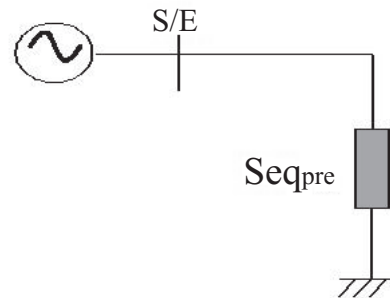

Figure 2 Load aggregate model at the substation

$$Seq_{pre} = P_n \left\| \frac{|V_{pre}|}{|V_0|} \right\|^k + jQ_n \left\| \frac{|V_{pre}|}{|V_0|} \right\|^l \qquad (5)$$
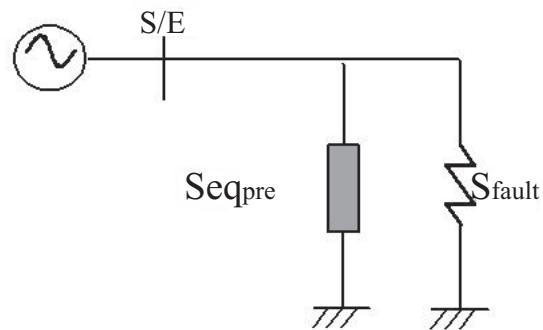

Figure 3 Load and fault aggregate model at the substation

Considering this model, a variation in the apparent power can be determined, as shown in equation (6).

$$Seq_{falla} = P_n \left\| \frac{|V_{fault}|}{|V_0|} \right\|^k + jQ_n \left\| \frac{|V_{fault}|}{|V_0|} \right\|^l +$$
$$P_f \left\| \frac{|V_{fault}|}{|V_0|} \right\|^{kf} + jQ_f \left\| \frac{|V_{fault}|}{|V_0|} \right\|^{lf} \qquad (6)$$

The variation in reactive power is used as descriptor, because it is associated to the power consumed by the line segment from the substation

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to the fault location. The approach considers that this change is not strongly related to the fault resistance, parameter which is unknown. Variation of reactive power is obtained from equations (5) and (6), to get (7).

$$\Delta Q = Q_n \left\| \frac{\left|V_{fault}\right| - \left|V_{pre}\right|}{\left|V_0\right|} \right\|^l + Q_f \left\| \frac{\left|V_{fault}\right|}{\left|V_0\right|} \right\|^f \quad (7)$$

For the steady state pre and post fault, the power variation can be used to find which load has been disconnected. This descriptor will provide geographical information about the fault location by means of the load characterization. Additionally, the variation in the power factor gives an additional indication on the load characteristics [17]. These two descriptors complement the geographical location of the fault, by identifying the load which has been removed from the distribution system.

Analysis of equivalent admittance

There are several models used to represent load admittances in transmission systems [9]. The one proposed here uses static load models, and it is given by (8), for any given node R

$$Y_R = G_R \left|V_R\right|^{np-2} + j\ B_R \left|V_R\right|^{nq-2} \quad (8)$$

Where:

V_R: Voltage at node R.

Y_R: Load admittance.

G_R, B_R: Constants proportional to conductance and susceptance respectively (estimated based on pre-fault values).

np, nq: Constants for active and reactive components of the load.

As with the analysis of the system load, the logical choice for descriptors is the variation of parameters np and nq on the aggregate model. This variation is caused by a pre-fault impedance equivalent to the system $Yeq\text{-}pre$, and the addition

of an admittance $1/Rf$, at the time of the fault, as presented in figure 4.
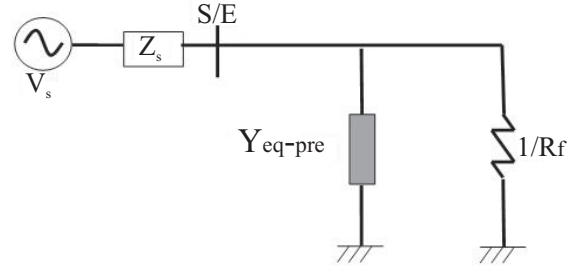
Figure 4 Aggregate model of impedances at the substation

Since the fault is typically resistive, an aggregate model at the substation can be adjusted to determine the variation in the apparent reactance as presented in (9).

$$\Delta X = \text{Im}\left(\frac{1}{\Delta Y_{S/E}}\right) = \text{Im}\left(\frac{1}{Y_{eq-pre} - Y_{eq-fault}}\right) \quad (9)$$

This value is used as one more descriptor to determine the distance to the fault by means of a knowledge based method.

Analysis of the coefficients α and β

The Clark-Concordia transform is applied to samples of line currents obtained during the fault. By applying the transform, components "alpha", "beta" and "zero" are obtained. Zero component is not used in this paper due its poor performance and following suggestions presented in previous fault locations approaches [5, 15]. The Clark-Concordia transform includes the three components, but since the third will not be used, the third row of the matrix [**Tc**] is neglected, as presented in (10)

$$\begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \quad (10)$$

An approximation of the eigenvalues of the matrix is used to interpret the set of current signals α and β after applying the *Tc* transform. In this way, line

currents are represented using the eigenvalues of the correlation matrix B. From (11) matrix A is computed using the transformation of the line currents. The number of significant samples corresponds to the number of rows of A, t_o is the initial time and Δt is the sampling interval.

$$A = \begin{bmatrix} i_\alpha(t_o) & i_\beta(t_o) \\ i_\alpha(t_o + \Delta t) & i_\beta(t_o + \Delta t) \\ ... & ... \\ i_\alpha(t_o + (n-1)\Delta t) & i_\beta(t_o + (n-1)\Delta t) \end{bmatrix} \quad (11)$$

Applying (12) the correlation matrix is computed.

$$B = A^T . A \quad (12)$$

Eigenvalues are obtained using the Matlab® *"eig(B)"* procedure, rendering the presentation (13)

$$[V,D] = eig(B) \quad (13)$$

Matrix D contains the eigenvalues for the two components of the current, as it is presented in (14)

$$D = \begin{bmatrix} \lambda_\alpha & 0 \\ 0 & \lambda_\beta \end{bmatrix} \quad (14)$$

The largest value in matrix D is then used to compute the distance to the fault *dist* from the distribution substation. In [15] the relation (15) is presented.

$$dist = a(\lambda)^k + b \quad (15)$$

Where a and b depend on the characteristics of the pre-fault load, and on the fault itself. The constant k classifies the fault, and it has the following values: $k=1$ for phase-ground, $k= -0.55$ for phase-phase-ground and $k=-0.552$ and $k=0.551$ for three phase faults [5, 15].

Since the maximum eigenvalue (λ) can be used to compute the distance to the fault, it is an important descriptor to be used in a knowledge-based method.

Characteristics obtained from transients signals

Power systems are built up of several components all of them can be modelled as one or more of the three basics circuit parameters: resistors R, capacitors C, inductors L. There is always a relation between the R, L, C parameters and the damping time and frequency of a transient signal and these characteristics are directly related to the distance from the distribution substation to the fault. Parameters L and C define the natural frequency of the transient oscillation. Damping time depends on parameters R, L and C in the circuit [14]. Since the frequency depends only on the equivalent L and C parameters of the faulted system, it can be used to find the distance from the distribution substation to the fault irrespective of the fault resistance. Additionally, by using the damping time it is possible to relate the frequency to the fault distance and resistance of the fault.

The proposed approach is based on the well know transient analysis [14]. It considers that the frequency and damping time of the transient caused by a fault is related to the parameters R, L and C from the substation to the fault location. To obtain these parameters two different time frequency analysis tools are used, namely Wavelet and Fourier transforms.

Wavelet Transform (WT)

This signal analysis method filters a signal in the time domain through low-pass and high-pass filters, eliminating low and high frequency components. The filtering is sequentially performed, and the procedure is carried out until the signal is decomposed in a predetermined number of components [19]. The discrete wavelet transform (DWT) of a N length input data sequence $f = \{f_n\} = \{f_0, f_1, ...f_{N-1}\}$, can be presented in a vector matrix form as in (16)

$$\varphi = W f \quad (16)$$

Where φ contains N wavelet coefficients, and W $(N$ x $N)$ is an orthogonal matrix consisting of row basis vectors. The basis vectors are specified by a set of numbers, called wavelet and scaling filter coefficients. Once a specific wavelet has been chosen, its coefficients are used to define two filters, the low-pass filter and the high-pass filter. Both types of filters use the same set of wavelet filter coefficients, but with alternating signs and in reversed order, meaning this pair of filters is the quadrature mirror filters. Low-pass and high-pass filters are also called the scaling and the wavelet filters, respectively. These filters are used to construct the filter matrices, denoted as L and H. To decompose the signal, a recursive approach known as pyramid algorithm is used. In this, the set of N input data is passed through the low-pass and high-pass filters; each output of the filter consists of N/2 wavelet coefficients. The output from low-pass filter is the approximation coefficients ($a^1 = \{a_0^1, a_1^1, ..., a_{N/2-1}^1 \}$) at the first level of decomposition. The output from high-pass filter is the detail coefficients ($d^1 = \{d_0^1, d_1^1, ..., d_{N/2-1}^1 \}$) at the first level of decomposition. The approximation coefficient a^1, can now be used as the data input for another pair of wavelet filters (identical with the first pair), generating sets of length N/4 of approximation ($a^2 = \{a_0^2, a_2^2, ..., a_{N/2-2}^2 \}$) and detail coefficients ($d^2 = \{d_0^2, d_2^2, ..., d_{N/2-2}^2 \}$) at the second level of decomposition. The process is continued until a desired level of decomposition. Since the original input data vector f is the approximation at the lowest resolution (decomposition 0), i.e., $a^0 = \{f\} = \{f_0, f_1, ...f_{N-1}\}$, then the DWT algorithm can be represented by (17)

$$a^m = L\,a^{m-1} \quad and \quad d^m = H\,a^{m-1} \quad (17)$$

Where m denotes the resolution level and $m = 1, 2,...,log_2 N$; and H and L denotes the high and low pass filter matrices respectively. The different resolutions for each level are related to the sampling interval. For level m the sampling interval is $2m$. As the sampling interval increases, resolution decreases and each approximation contains gradually less information. The difference in information between the approximations at level m and level $m–1$ is contained in the detail at level m. It is possible to use the approximation and detail coefficients to reconstruct (or synthesize) the original signal. The reconstruction process uses the recursion algorithm in reverse with conjugates of L and H [19]. To decompose signals, a particular class of functions called mother wavelets is used. Particularly in the case of power systems, the families Daubechies 4 and 8 are recommended due its similarity to transient signals. As a result of the decomposition process, the maximum energy detail for the high frequencies of the transient signal is obtained.
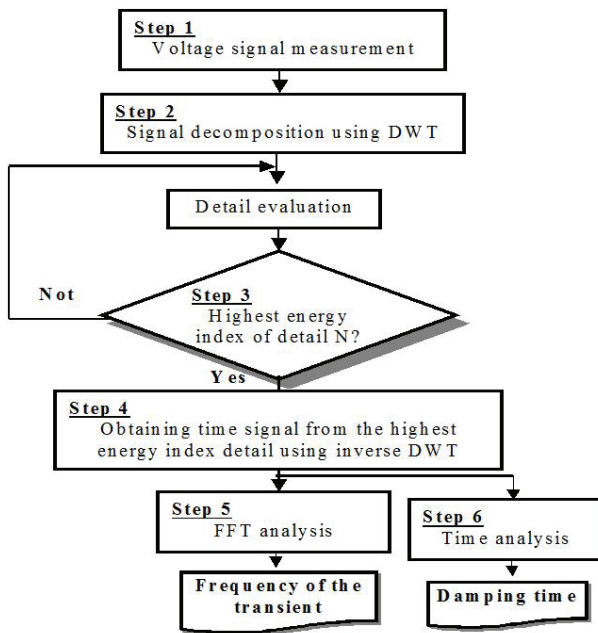
Fast Fourier Transform (FFT)

The maximum energy detail obtained using the DWT, is transformed into the time domain by means of the inverse DWT and it is then analyzed using the Fourier Transform [20]. The FFT is used here because it offers great accuracy to estimate the frequency of the composed transient signal.

Procedure to obtain the frequency of transient signals

The analysis of the fault transient seeks a frequency and a damping time associated to the distance to the fault. The transient signals of voltage are fed into the DWT [21] and next the maximum energy detail is transformed into the time domain and analyzed by using the FFT [22]. As a result, the transient frequency and the damping time are obtained. The procedure is presented in figure 5 and described as follows:

1) The voltage signal is measured at the distribution substation. The meter records the signal from two cycles before the fault in order to ensure capturing of the entire transient signal.

2) The signal is analyzed through DWT, to obtain a certain number of details. The original voltage signal is decomposed in the details which are considered to have the highest probability of finding the possible transient frequency.

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3) The signal detail with greatest wavelet index is picked up.

4) The detail obtained in the last step, is transformed into the time domain by using the inverse DTW.

5) The frequency of the time domain signal is obtained by the application of the FFT at the first cycles after the fault.

6) The damping time is computed from the time signal obtained in step four, as the time that takes for the signal to fall under the 2% threshold of its maximum peak.
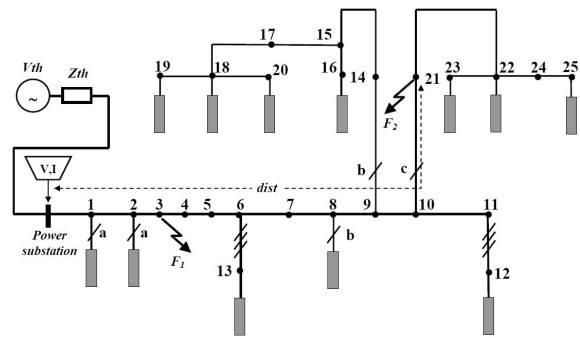

Figure 6 Power distribution system used to tests

The voltage signal in case of fault at node 3 was sampled at 125 kHz. Because of the sampling frequency the following information is obtained:

- Detail N.° 1 contains the signals with frequency between 31.25 and 62.5 kHz approximately;

- Detail N.° 2 corresponds to the signals with frequency between 16.625 and 31.25 kHz approximately;

- Detail N.° 3 contains the signals with frequency between 7.812 and 15.625 kHz approximately;

- Detail N.° 4 corresponds to the signals with frequency between 3.906 and 7.812 kHz approximately and,

- Detail N.° 5 corresponds to the signals with frequency between 1.953 and 3.906 kHz approximately.

By performing tests in the power system from figure 6, the possible transient frequencies were determined on the interval from 2 to 31 kHz. Therefore, the original voltage signal presented in figure 7 was decomposed in only five details, where the most representative are presented in figure 8.

From figure 8 it is possible to see that the highest energy coefficient is obtained from detail N.° 4. This signal detail is then transformed into the time domain by applying the inverse DWT. The signal obtained is then analyzed by using FFT giving the results presented in figure 9. Then, the obtained transient frequency is 5364.6 Hz.
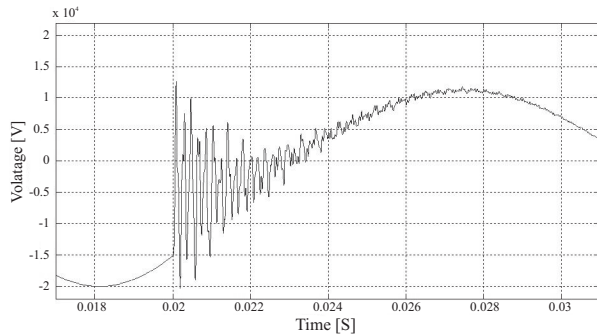

Figure 5 Procedure to obtain the frequency of transient signals

Example of transient analysis

Transient signals were generated using the ATP/ EMTP simulation software. Figure 6 shows a power distribution circuit from Saskatoon power, presented by R. Das in [9]. This particular circuit is used for testing the proposed method.

Referring to figure 6, a single phase to ground fault **F1**, involving phase B and a fault resistance of 10Ω was simulated at node 3.

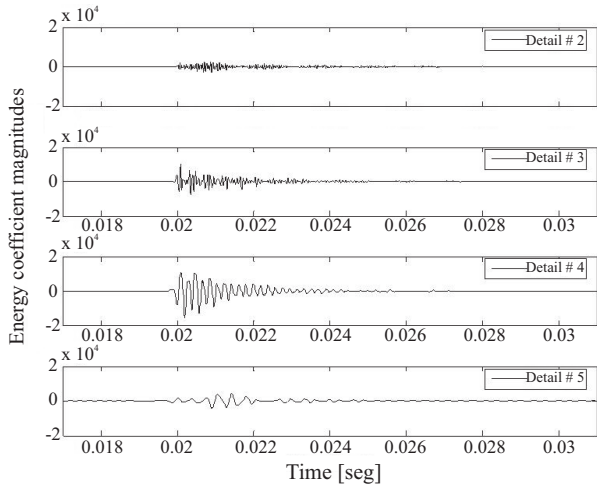**Figure 7** Voltage signal during a B single phase faul

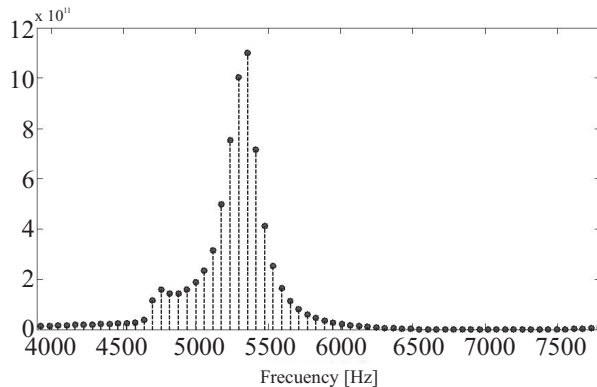**Figure 8** Wavelet details for B phase voltage signal

Figure 9 FFT analysis of the transient detail

The estimated damping time obtained from the proposed signal analysis is 8,54 ms. Finally, as previously presented the use of DWT is justified by the determination of transient signal features as frequency and damping time.

LAMDA as fault location method

For this approach one of several knowledge based methods was selected to perform the tests. This is a method based on hybrid connectives combining both the pure numeric and the pure symbolic classification algorithms, taking advantage of fuzzy logic and hybrid connectives [6]. LAMDA (Learning Algorithm for Multivariate Data Analysis) is proposed as knowledge based method to be fed with the obtained descriptors to determine the fault location. The following paragraphs resume the principle used in LAMDA. One object (**X**) has a number of characteristics called "descriptors"; these descriptors are used to describe the object. Every object is assigned to a "class" in the classification process. Class (c_i) is defined as the universe of descriptors, which characterize one set objects. MAD (Marginal Adequacy Degree) concept is a term related to how similar is one object descriptor to the same descriptor of a given class, and GAD (Global Adequacy Degree) is defined as the pertinence grade of one object to a given class [1, 6] as in fuzzy membership functions ($m_{ci}(x)$). In LAMDA, classification is performed according to similarity criteria computed in two stages. First MAD to each existing class is computed for each descriptor of an object. Second, these partial results are aggregated to get a GAD of an individual to a class. The former implementation of LAMDA includes a possibility function to estimate the descriptors distribution based on a "fuzzification" of the binomial probability function computed as (18) [6].

$$MAD_{c,d} = \rho_{c,d}^{X_{i,d}} \ (1-\rho_{c,d})^{(1-X_{i,d})} \qquad (18)$$

Where:

$\rho_{c,d} =$ Learning parameter for class **c** and descriptor **d**

$X_{i,d} =$ Descriptor **d** of individual **i**

GAD computation is performed as an interpolation between a t-norm and a t-conorm by means of the ψ parameter such that $\beta = 1$ represents the

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intersection and ψ = 0 means the union, as it is presented in (19).

$$GAD = \psi \ T(MAD) + (1-\psi) \ S(MAD) \quad (19)$$

The KBM here presented is used as regression toolbox for fault location, having obtained the results presented in section 4.

Results and discussion

In order to test the performance of the descriptors presented, several fault types, simulated by using different fault resistance values (0.5 – 40 Ω), in the test system depicted in figure 6. Tests were performed by using simulation due to the difficulty in obtaining a considerable amount data of actual fault registers, well correlated to the fault location and their resistance. A statistical learning method (LAMDA) was used to establish a relationship between the descriptors and the actual location of the fault. The complete process consists of five stages as depicted on figure 1. The first and second stages are devoted to the fault detection and measurement of the voltage and current signals. The third stage is the data preprocessing to obtain the descriptors. Having obtained the descriptors, a selection of some of these which best fit with the problem is performed at the fourth stage. The fourth stage consists of two specific processes: learning and classification of the sets of descriptors. Learning is performed using a special training data composed by sets of descriptors well characterized and strong related to the fault location. Having trained the classification tool, it is ready to classify new data, relating it to its fault location as it is performed at the last stage [1]. Figure 10 represents the partition of the fault database used for training and for testing the learning algorithm.

A set of 100 single phase faults was used as rough data to extract the training set of descriptors. This set contains faults with several values of fault resistance and location, selected considering faults distributed in all the nodes of the analyzed circuit. The training set contains representative data from most of the possible fault locations. Accordingly, the training set contains data of single phase faults located at 15 nodes, with fault resistance of 1, 10 and 30 Ω. Having obtained the set of fault registers, the descriptors presented in the previous sections as the transient frequency *(f)* from the voltage signal, the maximum eigenvalue computed by using the Clark Concordia transform *(λ)* from the currents signals and the variation of the apparent reactance *(Δx)*, are computed and used to train the LAMDA classification method.
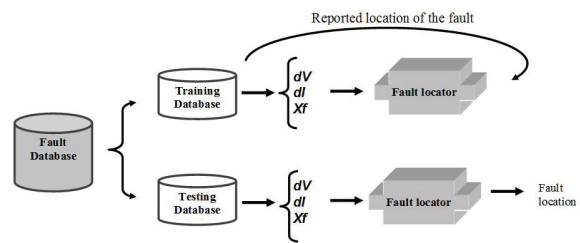
Figure 10 Subdivision of the fault database in two databases for training and testing the fault locator

As test set 47 fault registers, considering several values of fault resistance, locations and faulted phase were used. The worst results obtained by the KBM are presented on table 1.

The estimation errors are estimated as presented in (20).

$$e = \left| \frac{\text{Real distance - Estimated distance}}{\text{Feeder total length}} \right| \times 100 \quad (20)$$

These results show the good performance of the fault location method, estimating the faulted node and also the electrical distance. By using this first approximation, errors of around 10% in the distance estimation are observed. Also the faulted nodes were determined, having obtained errors in such nodes marked with an asterisk. As a first approximation, these results are considered satisfactory, and show the potential of signal characterization. Finally and according to simulations, best results have been obtained by using line voltages and currents which corresponds to a set of values measured during the sampling window of seven fundamental signal cycles, two before and five after the fault instant.

Table 1 Results of fault location in case of 21 different tests – Worst results

Real fault location		Estimation results	
Node	Fault distance [km]	Node	Estimated distance [km]
1	0.000	1	0.002
2	2.414	2	2.299
3	18.507	3	19.395
4	22.530	4	23.845
5	27.680	5	26.250
6	30.094	5*	28.502
7	34.600	6*	32.102
8	37.014	8	35.204
12	20.921	3*	19.221
13	30.094	13	28.245
14	32.508	13*	29.964
15	33.018	14*	31.005
16	34.922	15*	32.904
17	35.120	17	37.456
18	32.508	18	29.598
19	34.922	18*	31.065
20	35.727	18*	31.556
21	38.946	19*	34.121
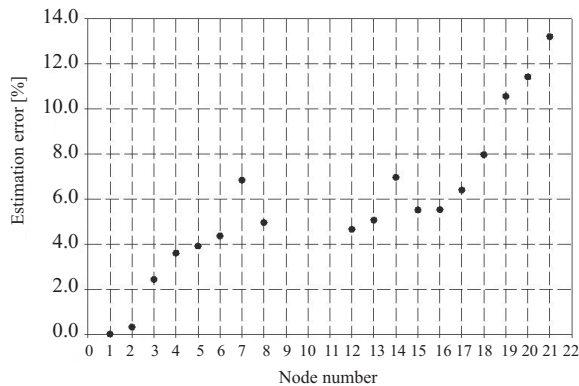
Figure 11 Estimation error at different faulted node

Conclusions

This paper proposes a signal characterization useful in fault location methods for radial power systems as distribution systems. Faults in such systems have to be located as quicker as possible so that repair can be done and power supply restored with minimum outage time. The theoretical basis for suitable selection of current and voltage descriptors to feed KBM in fault location problems are given in this paper. Some of the descriptors are directly related to the electrical distance to fault, such as the frequency of the transient, the α and β components and the admittance variation (Δx). A regression algorithm trained with these descriptors, gives accuracy to model based methods. The ideas and methods proposed in this work have been tested using computer simulations and show promissory results. We think that hybrid methods are feasible alternatives to present fault location methods offering not only accuracy but also cheap solutions to problems in distribution systems.

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