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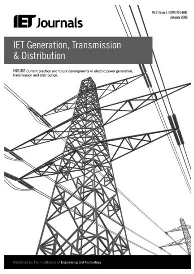

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Adaptive wavelets applied to fault classification on transmission lines

F.E. Pérez E. Orduña G. Guidi

Instituto de Energía Eléctrica, Universidad Nacional de San Juan, Av. Lib. Gral. San Martín 1109 Oeste (J5400ARL), San Juan, Argentina
E-mail: fperez@iee.unsj.edu.ar

Abstract: An adaptive wavelet algorithm (AWA) is presented, applied to classifying transitory events caused by faults in transmission lines. The algorithm generates the wavelets on the basis of the fundamental definitions of discrete wavelet transform (DWT) using a classification method based on probability such as the Bayesian linear discrimination analysis. A discriminant criterion shows the capacity of the method for distinguishing between fault types (classes). In order to do this, it only uses the current measurements of just one phase of the transmission line. The algorithm can be applied to high-speed transient-based protection (TBP) schemes that employ data windows shorter than one-fourth cycle of the fundamental frequency of the system. The results show a high level of success in the classification, even higher than the approach using mother wavelets pertaining to known families, such as Daubechies.

1 Introduction

The objective of protection systems is to detect and eliminate faults as fast as possible to minimise damage to the equipment and hazardous conditions for personnel. A simultaneous goal is to reduce the restoration time of the system and the costs associated with the fault. In order to achieve these objectives, the smallest number of equipment or electrical zones should be isolated so as to minimally affect both the continuity and quality electric service.

In general, the basic components of protection systems are:

- DC source: it ensures the operation of the protection system by isolating it from phenomena arising in the AC power system.
- Measurement transformer: it converts the sensed signals into the operative format of the protection relays.
- Protection relay: it receives the signals sent by the measurement transformers; it processes them and, finally, issues the commands to be executed.
- Circuit breaker: it is governed by the protection relay by means of auxiliary DC and AC circuits to switch-off the faulted component(s).

Since the transmission lines of a power system are the equipment where most faults arise [1], the emphasis will be laid on their protection system. Fig. 1 shows a basic representation of a protection system located at one of the transmission lines.

This work is focused on reducing the total fault-clearing time by decreasing the time required by the tasks of fault detection and classification. According to this aim, the data window used is more reduced (less than one-fourth cycle) than that of a 20 ms window (fundamental power frequency 50 Hz) for voltage and current measurement. These latter values are required by the distance digital relays using protection algorithms based on Fourier transforms. In the present proposal, processing is given, under the principle of transient-based protection (TBP) detailed in [2], only the current signals are processed, taking into account all their frequency components and using the concepts of discrete wavelet transform (DWT) and multi-resolution analysis (MRA) [3, 4].

In order to generate the wavelets to be used in the classification function, a mathematic algorithm called adaptive wavelet algorithm (AWA) [5] was implemented with MATLAB^{TM}.

The algorithm allows generating wavelets that classify the faults with a high level of success, closer to 100%, on the basis of the data obtained by measuring only the current of one of the phases of the transmission line for different kinds of faults.

Finally, with the purpose of highlighting the advantages of adaptive wavelets in the classification function, the results are contrasted with those obtained with mother wavelets procured from the Daubechies and Symlet families.

This paper is organised as follows. Section 2 offers a brief description of distance digital relays used currently to protect transmission lines. Section 3 describes the DWT and one of its variants known as Wavelet Packet. Section 4 gives brief details of the main features of the AWA and the associated tools. Section 5 indicates the modelled power system and describes the transmission line where the various fault types are simulated using the ATP/EMTP programme. In addition, aspects are also described as regards the data window, the sampling rate and the prior probabilities of

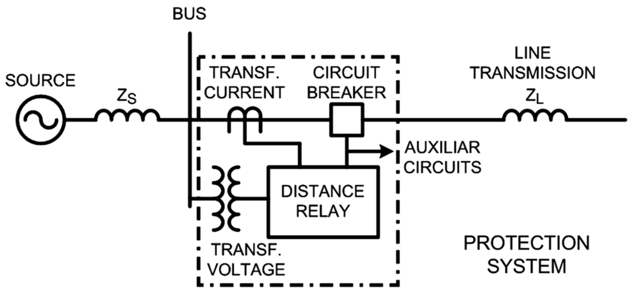

Fig. 1 *Line protection system*

each fault type needed to classify them. Section 6 shows the results for two applications. Finally, Section 7 presents the main conclusions of the work.

2 Distance relay

Since distance relays measure impedance, and that impedance is defined at a given frequency, distance relay filters must save only the fundamental frequency [6]. Analogical low-pass filters are combined with digital filters to make the voltage and current phasors at the fundamental system frequency, as shown in Fig. 2 for a distance relay.

Finite impulse response (FIR) filters are used in protective relays, and the most common FIR filters are Fourier recursive filters and Walsh-related filters. Least-squares and Kalman filters have been proposed for protection functions, without practical applications up to date [7].

FIR filters with less than a one-cycle window cannot reject all harmonics [6]. For this reason, only one-cycle window FIR filters are used. With voltage and current phasors calculated with one-cycle window data, evaluating the protection function inside of relay takes some microseconds. To sum up, the main component in relay operation time is the one-cycle window.

This research proposes to increase the operative speed of the relay using sample windows of less than one-cycle, considering all frequencies of electrical signals and analysing them with a variant of the DWT called wavelet packet.

3 Wavelet transform

The wavelet transform is a linear transform likewise the fast Fourier transform, although differing in that the window function (mother wavelet) used here is moved and dilated automatically during the analysis.

As a result, a better time–frequency resolution is attained for a given signal, as compared with the results given by the fast Fourier transform.

The wavelet transform has capabilities of providing accurate time location and classification of electrical transients in power systems [3], given the fact that it discloses the location in time domain of frequency components existing in a signal.

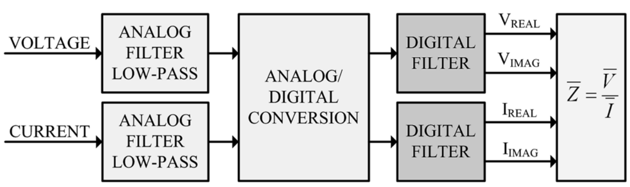

Fig. 2 *Filters for distance relay*

Continuous wavelet transform (CWT) for a given function $f(t)$ can be calculated as follows [8]

$$\mathrm{CWT}(f, a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) \mathrm{d}t \qquad (1)$$

where a and b are the scaling (dilation) and translation (time shift) constants, respectively, and ψ is the mother wavelet function. The DWT is given by

$$\mathrm{DWT}[f, m, n] = \frac{1}{\sqrt{a_o^m}} \sum_k \boldsymbol{f}[k] \psi^* \left(\frac{n - k a_o^m}{a_o^m} \right) \qquad (2)$$

where $\boldsymbol{f}[k]$ is the sampled waveform ($p \times 1$ vector), $a = a_o^m$ **Q1**
and $b = k a_o^m$ are the discretised parameters of scaling and translation, respectively.

The DWT is based on MRA or sub-band coding, which are detailed in Fig. 3. A discrete signal $\boldsymbol{f}[k]$ passes through two mid-band digital filters, one high-pass filter $\boldsymbol{g}[z]$ and another low-pass filter $\boldsymbol{h}[z]$, which produce the detail (***cDj***) and approximation (***cAj***) coefficients, respectively. These filters cover various frequency ranges depending on the decomposition level of the original signal (see Fig. 3*b*)

The analysis can be made up to a maximum level *jo* stated by the size p of the signal $\boldsymbol{f}[k]$. The pair of filters used for the analysis represent the mother wavelet of the DWT.

There is an ample range of mother wavelets: Haar, Daubechies, Morlet, Coiflet, bi-orthogonals etc, which can be chosen according to the specific application [9].

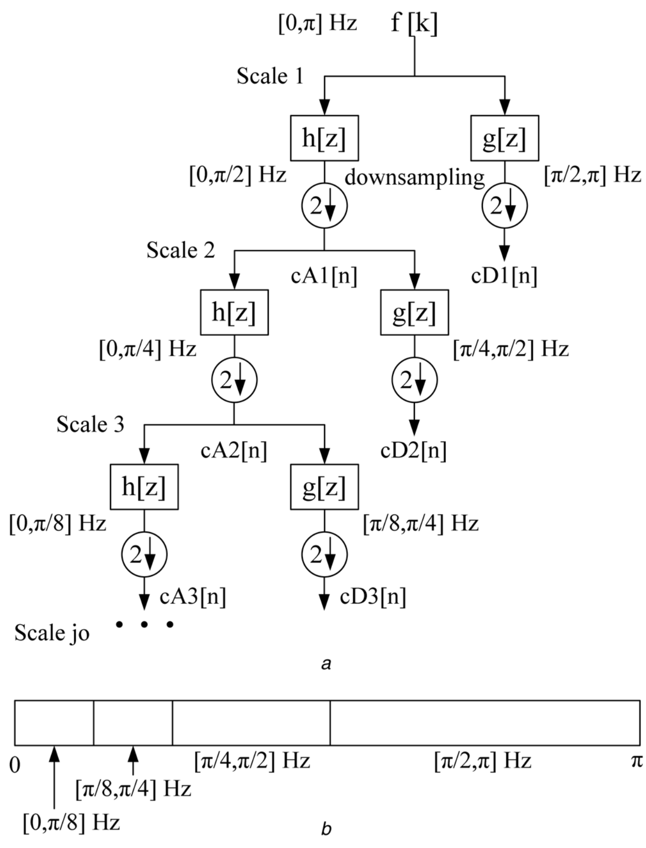

Fig. 3 **Q2**

a Wavelet filters bank and MRA
b Sub-band encoding for a signal $f[k]$ with sampling rate equal to 2π

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3.1 Wavelet packet

The wavelet packet (WP) method is a generalisation of the wavelet decomposition that offers a more convenient analysis for the signals, because both the approximation coefficient (low frequency) and the detail (high frequency) coefficients are processed through the pair of filters $\boldsymbol{h}[z]$ and $\boldsymbol{g}[z]$ shown in Fig. 3. In this way, it is possible to represent the signal $\boldsymbol{f}[k]$ with a greater number of frequency bands as compared with the number of bands used in DWT.

For the WP case, the frequency bands have the same size but cover different ranges.

Fig. 4*a* shows how the resulting signals from each filter are decomposed again by both filters (low- and high-pass), and action that can be repeated up to a maximum decomposition level *jo* determined likewise done in case of the DWT. This way, what is known as the WP tree is developed.

For the example of Fig. 4*a*, the signal analysis is made up to level 3. The original signal is represented by the coefficients of zero level and zero band (0, 0).

If the decomposition level is l and the highest frequency present in the original signal is π Hz, then the width of each frequency band corresponding to each node of the WP tree is $\pi/2^l$ [10]. Fig. 4*b* shows the various frequency bands that correspond to the resulting coefficients (l, t) of the WP, where l is the decomposed level 3 and t is the frequency band ($t \in 0, \ldots, 7$).

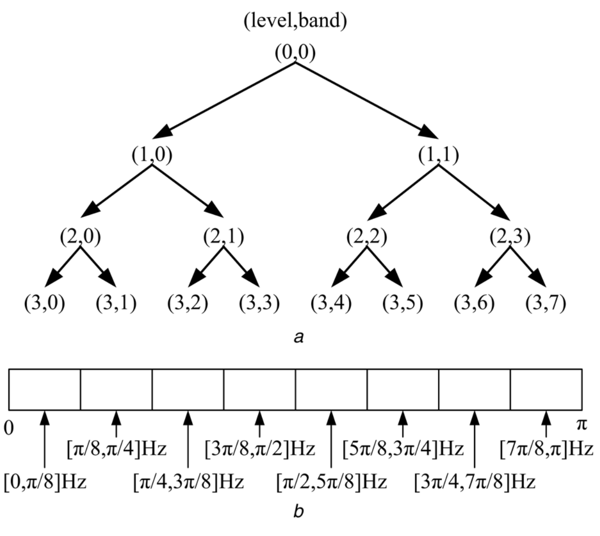
For research applications, the packet method is preferable because it allows analysing the high-frequency signals with finer detail, such as the currents arising in transient events caused by faults [11–14].

4 Adaptive wavelet algorithm

The adaptive wavelet algorithm (AWA) used in this paper is based on the work of [5]. It can be used for discriminant analysis.

Main features of this algorithm are:

- It is capable of generating wavelets composed by m filters, in contrast to the usual mother wavelets that employ only two filters.



Q2 **Fig. 4**

a Wavelet packet analysis
b Frequency-domain division of WP at level 3

- Through the DWT, it reduces the dimensionality of data and, at the same time; it keeps the greatest number of discriminant information.

The dimensionality is reduced by selecting some band of coefficients of DWT, or wavelet packet for our application. Then, the discriminant criterion will be based on the same coefficients.

4.1 Discriminant criterion

The adaptive wavelets are used to represent the signal in such a way that the discriminatory information be optimised. Therefore the adaptive wavelets are optimised in relation to a measurement that reflects the differences among classes [15]. The measure or discriminant criterion selected is the so-called 'leave-one-out' cross-validated quadratic probability measure (CVQPM), related to the classification methods based on probability; these allow attaining information on the accuracy of the classification and they can also reflect the capability they have to distinguish among classes.

The CVQPM is the average of an appreciation quadratic index a_Q that operates by comparing the probabilities of belonging of a given object to a pre-defined class $r \in 1, \ldots, R$ [16], and is formulated as follows

$$a_{Q/i}(i) = \frac{1}{2} + P_{/i}\left(r|\boldsymbol{x}_{i(r)}^{[l]}(t)\right) - \frac{1}{2}\sum_{r=1}^{R} P_{/i}\left(r|\boldsymbol{x}_{i}^{[l]}(t)\right)^2 \qquad (3)$$

$$\text{CVQPM} = \frac{1}{n}\sum_{i=1}^{n} a_{Q/i}(i) \qquad (4)$$

where $\boldsymbol{x}_{i(r)}^{[l]}(t)$ is the object for which the probabilities of belonging to each class are calculated, $P_{/i}(r|\boldsymbol{x}_{i(r)}^{[l]}(t))$ is the posterior probability for the true class of $\boldsymbol{x}_{i(r)}^{[l]}(t)$ and $P_{/i}(r|\boldsymbol{x}_{i}^{[l]}(t))$ is the posterior probability for $\boldsymbol{x}_{i}^{[l]}(t)$ belonging to class r.

With the 'leave-one-out' CVQPM (CVQPM from here on), Q3 the posterior probability that a given object belongs to a given class is attained when the co-variance matrices and the mean vectors have been computed in the absence of the mentioned object [4]. The sub-index $/i$ in every equation it appears, represents the absence of the object $\boldsymbol{x}_{i(r)}^{[l]}(t)$ in the calculus. The values of CVQPM range from zero to one. High values of CVQPM mean that the classes can be better distinguished [15].

4.2 Bayesian classification

In order to compute the posterior probabilities needed to obtain the factor a_Q the Bayesian classification is used, which considers the problem of assigning the object $\boldsymbol{x}_{i(r)}^{[l]}(t)$ within one of the predefined R classes.

For the case under study, each object represents a fault current consisting of p discrete measurements, and it is represented by the vector $\boldsymbol{x}_i = (x_{1i}, \ldots, x_{pi})^{\mathrm{T}}$. These data objects arising from the same r class (fault type) are stored as columns in the $p \times n_r$ matrix $\boldsymbol{X}$, where n_r is the number of objects. Then, the object to be classified $\boldsymbol{x}_{i(r)}^{[l]}(t)$ represents the coefficient set (l, t) of current signal $\boldsymbol{x}_i$ belonging to class r.

The Bayesian rules assign the object under classification into the class that maximises the posterior probability

$$P\left(r|\boldsymbol{x}_{i(r)}^{[l]}(t)\right) = \frac{p\left(\boldsymbol{x}_{i(r)}^{[l]}(t)|\, r\right)P(r)}{\sum_{r=1}^{R} p\left(\boldsymbol{x}_{i(r)}^{[l]}(t)|\, r\right)P(r)} \tag{5}$$

where $P(r)$ is the prior probability of each class that is assigned according to the statistical information of historical data, for our case. The probability density of class $p(\boldsymbol{x}_{i(r)}^{[l]}(t)|r)$ is assumed by following a multivariate normal distribution and is computed as

$$p\left(\boldsymbol{x}_{i(r)}^{[l]}(t)|r\right) = (2\pi)^{-p/2}|\boldsymbol{S}_{\text{pooled}}|^{-1/2} \cdot \exp\left[0.5(\boldsymbol{x}_{i(r)}^{[l]}(t) - \bar{\boldsymbol{x}}_{r/i}^{[l]}(t))^{\mathrm{T}}\boldsymbol{S}_{\text{pooled}}^{-1}\left(\boldsymbol{x}_{i(r)}^{[l]}(t) - \bar{\boldsymbol{x}}_{r/i}^{[l]}(t)\right)\right] \tag{6}$$

The mean vector $\bar{\boldsymbol{x}}_{r/i}^{[l]}(t)$ is calculated for each class, when the vector $\boldsymbol{x}_{i(r)}^{[l]}(t)$ is not present, and is expressed as follows

$$\bar{\boldsymbol{x}}_{r/i}^{[l]}(t) = \frac{1}{n_r - 1}\sum_{j=1}^{n_r-1} \boldsymbol{x}_{j(r)}^{[l]}(t) \tag{7}$$

The Bayesian linear discriminant analysis assumes that the co-variance matrices of class $\boldsymbol{S}_{\boldsymbol{r/i}}$ are equal to each other. Therefore in (6) they are substituted by a combined co-variance matrix $\boldsymbol{S}_{\text{pooled}}$, calculated as

$$\boldsymbol{S}_{\boldsymbol{r/i}} = \frac{\sum_{i=1}^{n_r}\left(\boldsymbol{x}_{i(r)}^{[l]}(t) - \bar{\boldsymbol{x}}_{r/i}^{[l]}(t)\right)\left(\boldsymbol{x}_{i(r)}^{[l]}(t) - \bar{\boldsymbol{x}}_{r/i}^{[l]}(t)\right)^{\mathrm{T}}}{n_r} \tag{8}$$

$$\boldsymbol{S}_{\text{pooled}} = \frac{\sum_{r=1}^{R} n_r \boldsymbol{S}_{\boldsymbol{r/i}}}{n} \tag{9}$$

The leave-one-out CVQPM is used because the classification of an object is done without interfering in the process, thus achieving an objective quantification of the classification.

Only the mathematical tools complementary to AWA have been described in this work. For more details about AWA refer to [5].

5 Application to the fault classification on transmission lines

In contrast to the distance digital relays that supervise the three phases of a transmission line, it is proposed here to measure only the current of just one phase, namely, phase A.

Regardless of whether or not the supervised phase participates in the fault, the generated wavelets must allow for correctly classifying the signals that build the databases for training and validation (see Section 5.2) in their respective classes.

5.1 Modelled transmission line

A 390 km, 500 kV transmission line called Mercedes-Colonia Elia was modelled, which is part of the Argentine Electrical System (fundamental power frequency 50 Hz). The electromagnetic transients programme ATP/EMTP was used, with the respective system generation and load equivalents for a normal operative state, and the frequency-dependent model was employed to model the transmission line [17].

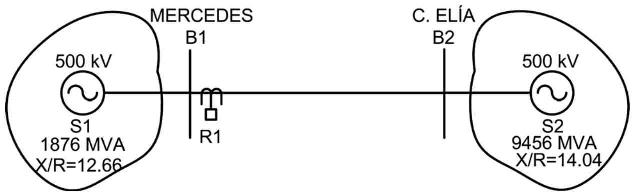


Fig. 5 *Simplified system configuration studied*

Fig. 5 is a rather simplified representation of the modelled system in ATP/EMTP. In fact, the modelled system in ATP/EMTP represents the Argentine Electrical System as an electric network containing 22 buses, 32 transmission lines, 13 equivalents circuits of smaller networks, 7 transformers and 9 generators.

Various fault types were simulated for every 5 km stretch of the line, which represented a total of 546 faults resulting from the current signals needed to build the database. These currents were metered by the relay R1, shown in Fig. 5.

5.2 Database

Since the current transformers show better frequency response than voltage transformers [18, 19], the methodology in this work will be applied only to current signals, although that, for simulations, there would be no problem in using voltage signals.

Taking the sinusoidal voltage signal of phase A as reference, a 30° (thirty degree) insertion fault angle is considered randomly to generate two current databases, one called the training database and the other the validation database.

The training base is composed by current signals of the various fault types simulated every 10 km that is kilometres 5, 15, 25, … , 385.

Likewise, the validation database is composed of the signals resulting from the faults simulated on kilometres 10, 20, 30, … , 390.

The various simulated fault types are:

- Single-phase faults with fault resistance $R_f = 0\ \Omega$
- Single-phase faults with fault resistance $R_f = 15\ \Omega$
- Single-phase faults with fault resistance $R_f = 40\ \Omega$
- Isolated two-phase faults
- Two-phase faults to ground with fault resistance $R_f = 5\ \Omega$ and
- Three-phase faults.

Using the training database and the AWA algorithm modified for our application, the wavelets are generated, which allow classifying the current signals with a success level coming close to 100%.

The validation database is useful to define more clearly the success level thus achieved by classifying the signals with the wavelets found in the procedure.

5.3 Sampling rate and time window

In order to capture all the information from fault-caused transient events simulated on the modelled line, after trying with several combinations from among the various sampling rates and different time windows, it was determined that a 2.048 ms window at a 500 KHz sampling rate (i.e. a 250 KHz Nyquist frequency) was needed to

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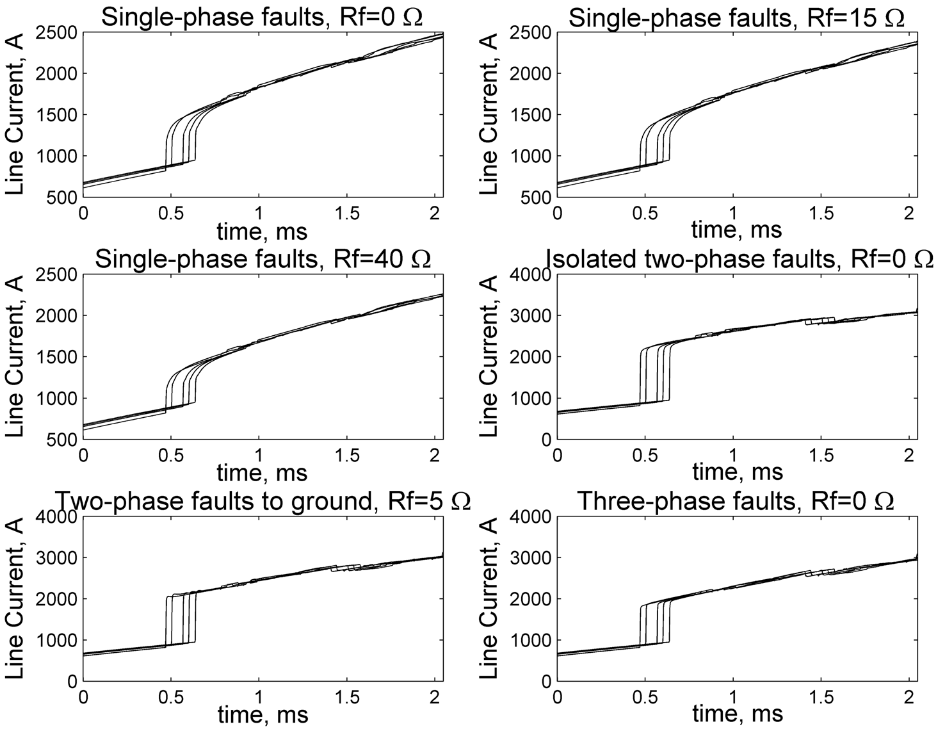

Fig. 6 *Five samples from each class of the training data with phase under fault*

achieve the target. In this way, the size of the discrete current signals corresponds to a vector of order 1024×1.

Fig. 6 shows five signals of each training data class with phase A under fault and the previously defined window time and sampling rate values.

5.4 Prior probabilities

The prior probabilities with regard to each class (fault type) were obtained from a study performed on Swedish and American power grids from 1967 to 1973.

Therefore using the statistical base of [20], the percentages of occurrence with regard to each fault type were considered as their respective prior probabilities. Table 1 summarises this for a 500 kV line.

6 Results

In order to better understand the adaptive wavelet methodology, first their concepts are applied to a database (training and validation) of four classes:

- Single-phase faults with fault resistance $R_f = 40\ \Omega$
- Isolated two-phase faults
- Two-phase faults to ground with fault resistance $R_f = 5\ \Omega$ and
- Three-phase faults.

Table 1 Prior probability of each type of fault to line of 500 kV

Fault	Percent, %
single-phase faults	93
isolated two-phase faults	2
two-phase faults to ground	4
three-phase faults	1

In a following step, the analysis is also made for the complete databases, that is, the set conformed by the six classes.

Both applications use as classifier the Bayesian linear discriminant analysis. The results achieved with the adaptive wavelets are compared with those produced with the corresponding Symlet and Daubechies mother wavelets.

After a previous analysis to determine the best level to distinguish between classes, the decomposition level $l = 3$ for the two applications was selected.

Previously performed analysis showed that for the chosen decomposition level (level 3), prior probabilities are only a requirement of the math model indicated in (5) since they have no influence on the fault classification. In this case, the classification only depends on the probability density given in (6). Therefore the posterior probability of whether or not a fault belongs to one of the fault types considered depends only on the probability density.

On the other hand, for decomposition levels equal to or greater than level 6, for each established frequency band, the fault classification is not possible since the probability density exerts no influence on the posterior probabilities. In these cases, the posterior probabilities are equal to the prior probabilities.

Thus, by choosing a suitable decomposition level, the fault classification algorithm proposed can be applied in a power system with different prior probabilities.

6.1 Database of four classes

The training and validation data have 39 samples or signals in each class.

As previously mentioned, the size of each discrete signal is 1024×1, corresponding to a 2.048 ms time window.

Using the training database for the case in which the supervised phase is under fault, the CVQPM produced using the coefficients $\{\boldsymbol{X}^{[l]}(t)\}_{t=0}^{t=2^l-1}$ both for the

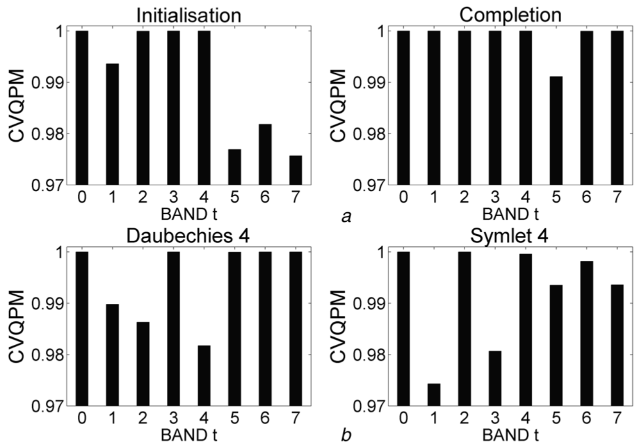

Fig. 7 *CVQPM for the coefficients* $\{x^{[3]}(t)\}_{t=0}^{t=7}$

a At initialisation and at completion of the AWA, optimisation of the discriminant measure was based on the coefficients $x^{[3]}(7)$ from band (3, 7)
b Using wavelets from the Daubechies and Symlet families

initialisation and the completion of the algorithm, with $l = 3$ can be seen in Fig. 7*a*.

The wavelets of this work resulted from two filters, one low-pass and another high-pass filter, of eight filter coefficients. Bands 0, 2, 3 and 4 of the WP produce the highest values of the CVQPM for initialisation because they are equal to 1. The remaining bands produce CVQPM values smaller than 1, but band 7 produces the lowest value of all, 0.9757. This means that the classifier would experience greater difficulties to distinguish among classes if the coefficients from this band were used.

For wavelet optimisation, then $t = 7$ is the chosen band so that when the algorithm finishes, the discriminant measurement for the coefficients (3, 7) is equal to 1. This also causes that the discriminant measurements of the remaining bands also get increased up to the value 1, except for band (3, 5) which reaches up to 0.9911. The fact that the CVQPM values of all bands are increased is a desirable result because the adaptive wavelet has been designed to optimise the CVQPM($\boldsymbol{X}^{[3]}(7)$).

In order to test the classification performance of the adaptive wavelets, coefficients were used from each band of level 3 of the WP as input data for the classifier, both for the initialisation and the completion of the algorithm. The results are summarised in Table 2. In the initialisation for the training data, the coefficients of band (3, 5) and (3, 7) give the lowest classification ratios, just 97.4%. In the completion, the classification percentage gets improved for all those bands whose initial classifications were lower than 100%.

To the same databases of phase under fault, Fig. 7*b* shows the discriminant measurement for each band of the level 3 of the WP using mother wavelets of eight filter coefficients: Daubechies 4 and Symlet 4. Table 2 shows the classification performance of these mother wavelets for each band (3, *t*), both for the training and the validation data.

Therefore by comparing the classification percentages, the benefits attained with the optimised adaptive wavelet become evident, over the performance shown with Daubechies 4 and Symlet 4.

A similar analysis with two-band wavelets and eight filter coefficients was made for the databases built with the current signals of phase C, which had no fault for all cases except for the three-phase fault.

The results associated with the wavelet designed to optimise the CVQPM of band (3, 2) are listed in Table 3, and those obtained with the predefined wavelets appear in Table 3.

The fact that current signals from phase C were used does not change the initial proposal of supervising only one of the line phases, because phase C would represent – in this case – the phase A free of fault in most cases except in three-phase fault.

This first application corresponds to a specific case where the signals that conform the database can be classified with high percentages, using the coefficients of any (3, *t*) band. On these accounts, the optimisation was performed considering the band having the lowest CVQPM.

For more general applications, with CVQPM values less than 1 for all WP bands, the usual procedure of the adaptive wavelet methodology regards the wavelet design on the CVQPM optimisation corresponding to the coefficients that produce the highest value in the initialisation. This fact will be explained furthermore in the following section, using the databases built with six classes.

6.2 Database of six classes

One of the main reasons for the importance of a correct classification of transmission line faults is the possible re-connection or auto-reclosure for single-phase fault, occurring as either the disconnection of the three phases of the line or just one phase when using single-pole circuit breakers. Q4

The auto-reclosure improves the power system transient stability [21], mainly if the line, where the single-phase fault occurs, is a member of the main high-voltage network.

In the case of a single-phase fault on a line where the auto-reclosure is possible, the system transitory stability is improved both by correctly discerning the fault type and by reducing the time taken in discerning this condition. In

Table 2 Percentage of correctly classified samples, using the coefficients $\{X^{[3]}(t)\}_{t=0}^{t=7}$ Q5

(i) % Correctly classified at initialisation									% Correctly classified at completion							
t	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
train	100	99.4	100	100	100	97.4	98.1	97.4	100	100	100	100	100	98.7	100	100
test	100	99.4	99.4	99.4	100	98.1	98.7	97.4	100	99.4	100	100	100	98.1	100	99.4
(ii) % Correctly classified with Daubechies 4									% Correctly classified with Symlet 4							
t	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
train	100	98.7	98.7	100	98.1	100	100	100	100	97.4	100	97.4	100	99.4	100	99.4
test	100	99.4	99.4	100	98.7	100	98.7	99.4	100	98.7	99.4	99.4	99.4	100	100	99.4

Note: (i) At initialisation and at completion of the AWA, optimisation of the discriminant measure was based on the coefficients $x^{[3]}$ (7) from band (3 ,7); (ii) using wavelets from the Daubechies and Symlet families

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Table 3 Percentage of correctly classified samples for a fault-free phase, using the coefficients $\{X^{[3]}(t)\}_{t=0}^{t=7}$

(i) % Correctly classified at initialisation									% Correctly classified at completion							
t	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
train	98.1	99.4	94.9	99.4	99.4	99.4	100	98.1	100	100	100	100	99.4	100	100	99.4
test	98.7	98.7	94.9	99.4	99.4	99.4	99.4	99.4	98.7	100	99.4	100	100	99.4	99.4	99.4
(ii) % Correctly classified with Daubechies 4									% Correctly classified with Symlet 4							
t	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
train	99.4	99.4	100	100	98.7	99.4	98.7	99.4	100	99.4	98.7	99.4	100	99.4	98.7	98.7
test	98.7	99.4	99.4	100	97.4	99.4	100	100	98.1	100	97.4	98.7	99.4	99.4	99.4	99.4

Note: (i) At initialisation and at completion of the AWA, optimisation of the discriminant measure was based on the coefficients $X^{[3]}$ (7) from band (3,7); (ii) using wavelets from the Daubechies and Symlet families

order to do this, data windows of smaller than one-fourth cycle of the fundamental frequency and the TBP principle are used.

At this point, it is worth remarking that purpose of this research is to build wavelets that allow appropriate classification of the current signals arising in different fault types in the shortest time possible.

Likewise, as done with the first application, the training and validation sets for each class are built using 39 discrete current signals of phase A. Each signal meets the requirements stated in Section 5.3.

In this example, it would also be important to highlight the advantages of using adaptive wavelets, rather than the predefined wavelets from Daubechies and Symlets families. With the first example, it was demonstrated that these predefined wavelets allow finding interesting results; but the adaptive wavelets have an even greater potential to keep improving the results. This is explained by the capability of these wavelets to become adapted to the problem at hand.

The example that now expounded is the optimisation of the discriminant measurement performed on band t of the WP, producing the highest CVQPM values in the initialisation of the algorithm, where $t \in 0, 1, \ldots, 2^l - 1$.

According to adjustments performed, the number of filter coefficients (N_f) of two-band adaptive wavelets is 8 and 16, respectively. The number of band coefficients ($N_{\text{coef}} = p/2^l$) used for classification is 128, which correspond to the decomposition level $l = 3$ of the WP.

Table 4 shows the various wavelets used to classify the databases, the decomposition levels of signals, the frequency bands of greater CVQPM and therefore the band on which the adaptive wavelet was optimised, the number of band coefficients that are used as input data to the classifier, the number of filter coefficients, the CVQPM of each wavelet and the percentage of correct classification of training and validation signals. As can be noted from this table, the CVQPM resulting from adaptive wavelets is greater than that achieved with Daubechies and Symlet families. All the training and validation signals are classified correctly by the adaptive wavelets, in contrast to the classification percentages attained with predefined wavelets.

Although in practical cases, this research is more interested in knowing the fault type occurring on the line, regardless of the fault resistance value, the CVQPM values presented here render information on the potential of wavelets, adaptive and traditional, used them with Bayesian linear discriminant analysis as classifier of signals pre-processed by WP tool. As a result of this, it attained to distinguish between faults of the same kind with various fault resistance.

Table 4 shows the results obtained with two-band wavelets and eight filter coefficients. Again, the CVQPM produced by the adaptive wavelet is greater than that achieved with the Daubechies and Symlet wavelet families.

Finally, Table 5 shows the results attained from the similar analysis done for the databases of phase C current signals.

Faults with various insertion angles were analysed using the adaptive wavelets found with eight filter coefficients, both for phase under fault and to fault-free phase, taking the coefficients of the band $t = 1$ to classify. Table 6 shows the results of this.

Only, when the supervised phase is not in fault, faults with an insertion angle of 240° present a CVQPM lower than 1 and its percentage of classification is 89.74%. The posterior probabilities indicate that all single-phase fault and three-phase fault were classified correctly, but some isolated two-phase faults and two-phase faults to ground were confused

Table 4 Classification results of faults supervising phase under fault using adaptive wavelets, and wavelets from the Daubechies and Symlet family

Wavelet	l	t	N_{coef}	N_f	CVQPM	% Correctly classified	
						Train	Test
(i) $N_f = 16$							
adaptive	3	1	128	16	1.00	100	100
Daubechies	3	3	128	16	0.98	97.8	98.2
Symlet	3	6	128	16	0.98	98.5	97.8
(ii) $N_f = 8$							
adaptive	3	1	128	8	1.00	100	100
Daubechies	3	3	128	8	0.98	98.2	98.5
Symlet	3	6	128	8	0.98	97.8	98.2

Table 5 Classification results of faults supervising fault-free phase using adaptive wavelets, and wavelets from the Daubechies and Symlet family

Wavelet	l	t	N_{coef}	N_f	CVQPM	% Correctly classified	
						Train	Test
(i) $N_f = 16$							
adaptive	3	1	128	16	1.00	100	100
Daubechies	3	5	128	16	0.98	98.9	97.8
Symlet	3	2	128	16	0.99	99.2	98.5
(ii) $N_f = 8$							
adaptive	3	1	128	8	1.00	100	100
Daubechies	3	7	128	8	0.99	99.6	98.5
Symlet	3	2	128	8	0.99	99.3	98.5

Table 6 Classification results of faults with various insertion angle, using adaptive wavelets found with $N_f = 8$

Insertion angle, deg	Phase A		Phase C	
	CVQPM	% Classification	CVQPM	% Classification
0	1.00	100.00	1.00	100.00
60	1.00	100.00	1.00	100.00
90	1.00	100.00	1.00	100.00
120	1.00	100.00	1.00	100.00
150	1.00	100.00	1.00	100.00
180	1.00	100.00	1.00	100.00
Q6 210	1.00	100.00	1.00	100.00
240	1.00	100.00	*0.93*	*89.74*
270	1.00	100.00	1.00	100.00
300	1.00	100.00	1.00	100.00
330	1.00	100.00	1.00	100.00

between them. This means that the auto-reclosure will be possible without any problem because the algorithm proposed never confuses multi-phase faults with single-phase to ground faults and all single-phase faults are not confused with another type of fault.

6.3 Comparison with existing techniques

The previous sections provide an AWA for fault classification on transmission lines. The existent classification techniques employ different math tools such as decision-tree (DT), support vector machine (SVM), artificial neural networks (ANN), fuzzy logic (FL), expert systems (ES), wavelet transform (WT) and combinations of them.

Results of some previous work, which use these tools, are summarised in Table 7. Results of the algorithm proposed in this paper, specifically with regard to the case in which the supervised phase is under fault, are also included.

The AWA shows superiority for the following reasons:

- Its high accurate fault classification that has been obtained by using the current signal of only one phase of the protected transmission line;
- The width of data window depends on length of the transmission line. Even though transmission line modelled in this work is the largest, the AWA uses a time window shorter than those used in other techniques and produces good accuracy.

Table 7 Comparison among classification methods

Classification methods	Voltage, kV	Line length, km	Required post-fault data (cycle)	Accuracy, %
reference [22]	400	300	not mentioned	100
reference [23]	–	–	1	100
reference [24]	230	300	1	98.12
reference [25]	400	300	1/2	97.84
reference [26]	500	300	1/2	100
reference [27]	400	150–240	1/4	99.53
reference [28]	400	300	2	99.91
reference [29]	400	300	1/4	99.26
reference [30]	400	100	1/10	100
		300	7/40	100
proposed	500	390	1/10	100

6.4 Observation

Although the advantages of auto-reclosure were noted on the stability in the case of single-phase fault, this work has contemplated the use of three-pole circuit breakers for the transmission line, because no allowance was made in identifying the faulted phase when supervising only one of the line phases. This may constitute a subject of work for the future.

7 Conclusions

This work remarks the advantages of using adaptive wavelets as analysis filters of a high-speed protection system for transmission lines.

Considering a protection system based on the TBP principle, the databases formed by the current signals from one of the phases of a system under fault conditions, the use of adaptive wavelets attain classification rates higher than those obtained with predefined wavelets originated in a known wavelet family.

For the 50 Hz power system modelled here, a significant decrease in the operation time of the protection relay is attained, because data windows of approximately 2 ms are required, as opposed to the 20 ms windows needed by the distance protection systems based on Fourier filters.

The high-speed protection systems are widely demanded at present owing to the expansion of power systems through international interconnections, or the inclusion of distributed generation into their grids, for safety and service quality issues.

The next research project will be oriented towards developing fast digital algorithms that include adaptive filters and their advantages for processing and classifying signals originating in faults.

Future research will involve an extension of this proposal that will regard additional considerations to that pointed out in Section 6.4, such as fault localisation, zone and directionality.

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9 References

1 Gómez-Expósito, A., Conejo, A., Cañizares, C.: 'Electric energy systems analysis and operation' (CRC Press, Boca Raton, 2009, 1st edn.)
2 Bo, Z.Q., Weller, G., Dai, F.T., Yang, Q.X.: 'Transient based protection for transmission lines'. Proc. Int. Conf. Power System Technology, Beijing, China, August 1998, pp. 1067–1071
3 Reddy, V.M., Rao, S.S., Mercede, F.J.: 'On the use of wavelets for the detection and analysis of power system transients'. IEEE Power Engineering Society Winter Meeting, New York, NY, USA, January–February 1999, pp. 1293–1299
4 Walczak, B.: 'Wavelets in chemistry' in 'Data handling in science and technology' (Elsevier Science B.V., Katowice, 1999, vol. 22, 1st edn.) Q7
5 Mallet, Y., Coomans, D., Kautsky, J., DeVel, O.: 'Classification using adaptive wavelets for feature extraction', *IEEE Trans. Pattern Anal. Mach. Intell.*, 1997, **19**, (10), pp. 1058–1066

6 Scheweitzer, E.O., Hou, D.: 'Filtering for protective relays'. 19th Annual Western Protective Relay Conf., Spokane, Washington, USA, October 1992, pp. 1–26
7 Altuve, J., Díaz, I., Vásquez, E.: 'Fourier and Walsh digital filtering algorithms for distance protection', *IEEE Trans. Power Syst.*, 1996, **11**, (1), pp. 457–462
8 Figueroa, M., Orduña, E.: 'Ultra-high-speed protection for medium voltage distribution networks with distributed generation'. Transmission and Distribution Conf. Exposition: Latin America IEEE/PES, Bogotá, Colombia, August 2008, pp. 1–8
9 Chein, W., Malik, O.P., Yin, X., Chen, D., Zhang, Z.: 'Study of wavelet-based ultra high speed directional transmission line protection', *IEEE Trans. Power Deliv.*, 2003, **18**, (4), pp. 1134–1139
10 Gao, J., Hu, G., Yao, X., Chang, R.: 'Anomaly detection of network traffic based on wavelet packet'. Asia-Pacific Conf. Communications (APCC '06), Busan, South Korea, August–September 2006, pp. 1–5
11 Bo, Z.Q., Aggarwal, R.K., Johns, A.T.: 'Non-unit protection of double circuit lines based on fault generated high frequency signals'. Second Int. Conf. Advances in Power System Control, Operation and Management, Hong Kong, December 1993, pp. 77–82
12 Bo, Z.Q., Aggarwal, R.K., Johns, A.T., Song, Y.H.: 'Spectrum analysis of fault-induced transients for the development of protection equipment'. Second Int. Conf. Advances in Power System Control, Operation and Management, Hong Kong, December 1993, pp. 72–76
13 (Power System Relaying Committee: 'Fault induced wave distortion of interest of relay engineers', *IEEE Trans. Power Appar. Syst.*, 1985, **PAS-104**, (12), pp. 3574–3584
14 Swift, G.W.: 'The spectra of fault-induced transients', *IEEE Trans. Power Appar. Syst.*, 1979, **PAS-98**, (3), pp. 940–947
15 Desmond, Ng., Tian, W.F., Withayachumnankul, W., Findlay, D., Ferguson, B., Abbott, D.: 'Classification of osteosarcoma T-ray responses using adaptive and rational wavelets for feature extraction'. Proc. SPIEComplex Systems II, Canberra, ACT, Australia, December 2007, vol. 6802, pp. 1–13
16 Chaparro, J.: 'Assessment of the main wavelet mothers to discriminate transients present in power systems'. MSc thesis, Universidad Nacional de Colombia-Sede Bogotá, 2009
17 Canadian/American EMTP User Group: 'Alternative Transients Program (ATP) rule book' (USA, 1987)
Q8
18 Bradley, D.A., Bodger, P.S., Hyland, P.R.: 'Harmonic response tests on voltage transducers for the New Zealand power system', *IEEE Trans. Power Appar. Syst.*, 1985, **PAS-104**, (7), pp. 1750–1756
19 So, E.: 'Harmonic measurements: current and voltage transducers'. Power Engineering Society Summer Meeting IEEE, Edmonton-Alta, Canada, July 1999, pp. 339–340
20 Ziegler, G.: 'Numerical distance protection: principles and applications' (SIEMENS, Publicis-MCD, 1999, 1st edn.)
21 Lin, X., Wang, R., Deng, X., Bo, Z.Q., Klimek, A.: 'A novel adaptive reclosure criterion for EHV transmission line'. IET Ninth Int. Conf. Developments in Power System Protection-DPSP, Glasgow, Scotland, March 2008, pp. 121–125
22 Reddy, M.J., Mohanta, D.K.: 'Adaptive-neuro-fuzzy inference system approach for transmission line fault classification and location incorporating effects of power swings', *IET Gener. Transm. Distrib.*, 2008, **2**, (2), pp. 235–244
23 Ravikumar, B., Thukaram, D., Khincha, H.P.: 'Application of support vector machines for fault diagnosis in power transmission system', *IET Gener. Transm. Distrib.*, 2008, **2**, (1), pp. 119–130
24 Samantaray, S.R.: 'Decision tree-based fault zone identification and fault classification in flexible AC transmissions-based transmission line', *IET Gener. Transm. Distrib.*, 2009, **3**, (5), pp. 425–436
25 Dash, P.K., Samantaray, S.R., Panda, G.: 'Fault classification and section identification of an advanced series-compensated transmission line using support vector machine', *IEEE Trans. Power Deliv.*, 2007, **22**, (1), pp. 67–73
26 He, Z., Fu, L., Lin, S., Bo, Z.: 'Fault detection and classification in EHV transmission line based on wavelet singular entropy', *IEEE Trans. Power Deliv.*, 2010, **25**, (4), pp. 2156–2163
27 Valsan, S.P., Swarup, K.S.: 'High-speed fault classification in power lines: theory and FPGA-based implementation', *IEEE Trans. Ind. Electron.*, 2009, **56**, (5), pp. 1793–1800
28 Upendar, J., Gupta, C.P., Singh, G.K., Ramakrishna, G.: 'PSO and ANN-based fault classification for protective relaying', *IET Gener. Transm. Distrib.*, 2010, **4**, (10), pp. 1197–1212
29 Samantaray, S.R., Dash, P.K.: 'Transmission line distance relaying using machine intelligence technique', *IET Gener. Transm. Distrib.*, 2008, **2**, (1), pp. 53–61
30 Jamehbozorg, A., Shahrtash, S.M.: 'A decision-tree-based method for fault classification in single-circuit transmission lines', *IEEE Trans. Power Deliv.*, 2010, **25**, (4), pp. 2190–2196

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Author Queries

F.E. Pérez, E. Orduña, G. Guidi

Q1 IEE style for matrices and vectors is to use bold italics. Please check that we have identified all instances.

Q2 Please provide the main caption for Figs. 3 and 4.

Q3 Is it okay to delete '(CVQPM from here on)'.

Q4 Okay as edited in the para 'One of the …… breakers'.

Q5 Please check and confirm the structure of Tables 2–5.

Q6 The commas used in the tabulation is changed to decimal point. Please confirm if it is okay.

Q7 Please provide the missing editor(s) name in ref. [4].

Q8 Please provide the missing publisher name in ref. [17].