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A NEW ADAPTIVE MOTHER WAVELET FOR ELECTROMAGNETIC TRANSIENT ANALYSIS

Daniel Guillén * — **Gina Idárraga-Ospina** * — **Camilo Cortes** **

Wavelet Transform (WT) is a powerful technique of signal processing, its applications in power systems have been increasing to evaluate power system conditions, such as faults, switching transients, power quality issues, among others. Electromagnetic transients in power systems are due to changes in the network configuration, producing non-periodic signals, which have to be identified to avoid power outages in normal operation or transient conditions. In this paper a methodology to develop a new adaptive mother wavelet for electromagnetic transient analysis is proposed. Classification is carried out with an innovative technique based on adaptive wavelets, where filter bank coefficients will be adapted until a discriminant criterion is optimized. Then, its corresponding filter coefficients will be used to get the new mother wavelet, named wavelet ET, which allowed to identify and to distinguish the high frequency information produced by different electromagnetic transients.

Keywords: wavelet transforms, mother wavelet, adaptive wavelets, electromagnetic transients, signal processing

1 INTRODUCTION

Power system conditions are continuously changing, those changes give as a result non-periodic signals that can be analyzed in order to know if there is a fault or transient condition into the power system. Most of the time, electrical signals (voltages and currents) are mixed with high frequency components, which can be used to identify transient phenomena from fault conditions. However, in conventional protection schemes, the high frequency information was neglected while the fundamental frequency (50 or 60 Hz) was used to evaluate the power system conditions [1], using the Fourier Transform (FT). However, Wavelet Transform (WT) applications have been introduced in protection schemes [2], where the high frequency information is analyzed to detect faults in power systems.

WT has been widely used in different applications of power systems for signal processing, because it has proved to be a powerful technique for analyzing non-periodic signals [3]. This fact has motivated the development of researches in different applications of power systems, where the high frequency components of signals are taken into account, such as in [4], where an algorithm based on transient energy in presented for distinguishing internal or external faults on transmission lines. In addition to this, high-speed protection for transmission lines using transient analysis has been developed based on wavelets [5, 6]. In distribution systems, a methodology for fault detection and classification based on high frequency components is presented in [7]. Moreover, WT has been applied to identify and classify power quality issues in power systems [8, 9].

Currently, WT applications in power systems have been used traditional mother wavelets, such as Daubechies, Symlet and Coiflet, generating a discussion about the selection of the best mother wavelet for a specific task. For instance, a comparison between different mother wavelets is presented in [10], with the aim of characterizing transients in power systems, concluding that more work is needed in order to choose the best wavelet for analyzing electromagnetic transients. Hence, this work presents a methodology of feature extraction for electromagnetic transients in a wide frequency spectrum, with the purpose of contributing to solve the discussion.

This study contributes to the analysis of electromagnetic transients in power systems, where a new mother wavelet is developed based on adaptive wavelets. In this way, the new wavelet can be used for analyzing different types of transient phenomena, such as capacitor bank switching, line energization and arcing faults. In fact, the the algorithm proposed by Mallat [11] is implemented to obtain the new mother wavelet, where the high frequency features produced by each type of transient are used to adapt the algorithm, which is based on the discrete wavelet transform (DWT) and multi-resolution theory. Therefore, the wavelet filter bank is parameterized using the multi-resolution theory and finally the high frequency information that will be used to optimize a discriminant criteria is obtained. Hence, to obtain the new mother wavelet, the filter bank will be gradually adapted until the high frequency information is optimized to identify properly electromagnetic transients. Moreover, filter bank coefficients are used to obtain the new mother wavelet, which can be used in different applications of power systems.

Universidad Autónoma de Nuevo León (UANL), Monterrey, N.L., México, guillenad@gmail.com, gidarraga@gmail.com; ** Universidad Nacional de Colombia, Sede Bogota, Colombia, caacortesgu@unal.edu.co

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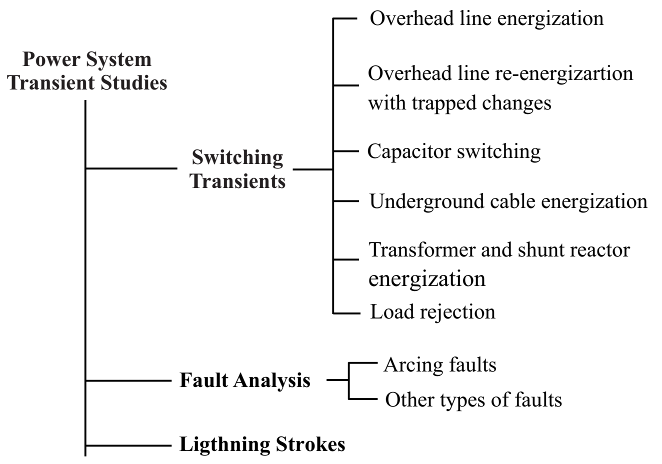

Fig. 1. Typical power system transient studies

2 ELECTROMAGNETIC TRANSIENTS

Most of the time, power system conditions are changing due to different load conditions or faults into the system. All changes produce a transient condition in the network until a new operation state is reached. In this regard, the cause of the transient condition should be identified, since it can affect the reliability and may produce damages in the system.

The general classification for transient studies in power systems is presented in Fig. 1, which includes capacitor switching, line energization and faults in transmission lines, among others [12]. Switching transients are normal operation conditions in power systems and they should not affect the continuity of the electrical supply. However, faults into the system must be identified as soon as possible to avoid damages in power equipment. Lightning strokes are studied in transient analysis since they can, or not, produce faults into the system. However, they are known as fast transients and they are may cause momentary or permanent interruptions on transmission or distribution circuits [13].

The protection schemes based on transient analysis have been increasing in the past decades. However, these schemes must be evaluated under different transient conditions, since they may produce false triggering when switching disturbances or lightning strokes occur [14]. Therefore, in order to contribute in the transient phenomena identification, three types of transient phenomena are addressed, *ie* arcing faults, capacitor switching and transmission line energization.

2.1 Frequency spectrum for transients

All electromagnetic transients in power systems have a wide frequency spectrum, which is different for fault conditions and switching transients. Then, transient studies have motivated to develop researches with the aim to characterize the frequency spectrum produced by the different transients in power systems.

Moreover, some researches have established the maximum frequencies for different transient phenomena. For instance, for transients originated by capacitor switching, it is expected that the maximum frequency in voltage and current signals is close to 46 kHz [15]. On the other hand, a frequency spectrum with a maximum frequency of 2 kHz is produced in transmission lines energization [16]. Finally, arcing faults, that are very common in power systems, can produce frequencies up to 1 kHz.

In this paper, the produced frequency spectrum by different transient conditions is used to design the mother wavelet, where the higher frequencies are used as fundamental information to gradually adapt it, until a discriminant criterion is optimized. Based on adaptive wavelets, the feature extraction for different electromagnetic transients is possible, while, at the same time, the discriminatory information is reduced. A wavelet is derived from a filter bank, and filter coefficients are used to compute the DWT, where high frequency components are extracted to obtain the new mother wavelet.

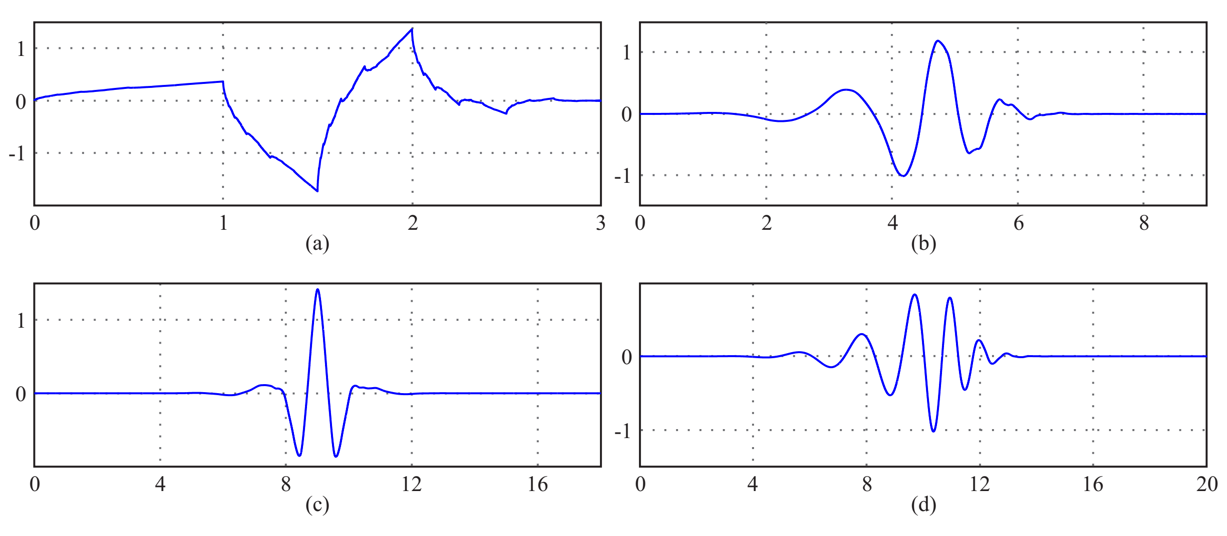

Fig. 2. Traditional mother wavelets: (a) — Symlet [2], (b) — Daubechies [5], (c) — Coiflet [3], (d) — Daubechies [10]

2.2 Transient studies using wavelets

Different wavelet families such as Daubechies, Symlet and Coiflet, that are shown in Fig. 2, have been used for transient studies in power systems. From these families, the most common in power system applications is the Daubechies one. For instance, according to [17], the mother wavelet that is mostly used to fault detection in transmission lines is the Daubechies 4 (db 4). Moreover, Symlet 1 (sym 1) has also been used for classifying transient phenomena in distribution systems [18] and the Coiflet family has been used in harmonic analysis under normal and fault conditions [19].

The variety of wavelets has generated a great discussion related to the selection of the best mother wavelet for analyzing electromagnetic transients in power systems. In the case of faults detection, Megahed [20] concluded that the Daubechies wavelets are more adequate for the application at hand. In order to contribute to the solution of the discussion, this paper proposes a methodology for developing a new mother wavelet using the high frequency information produced by different transient phenomena, with the aim of identifying different types of transients in power systems.

3 WAVELET TRANSFORM

Wavelet transform can be used for signal processing in continuous or discrete time. For instance, a continuous signal $x(t)$ can be analyzed if $x(t)$ is correlated with a wavelet function $\psi(t)$, giving as a result wavelet coefficients defined by [21]

$$WT(b,a) = |a|^{-1/2} \int_{-\infty}^{\infty} x(t)\psi^*\left(\tfrac{t-b}{a}\right) \mathrm{d}t \tag{1}$$

where a is the scale parameter, which is related to the frequency, b is the dilation parameter in time for the signal and $\psi^*(t)$ is the conjugate wavelet function, commonly called mother wavelet. More details about the wavelet transform can be found in [22]. For discrete signals, wavelet transform takes discrete values for the scale and dilation parameters respectively, which are defined by $a = 2^j$ and $b = k2^j$. Hence, discrete wavelet transform is described by

$$DWT(j,k) = 2^{-j/2} \sum_n x(n)\psi(2^{-j}n - k) \tag{2}$$

In this paper, a new mother wavelet $\psi^{\mathrm{new}}(t)$ is developed based on adaptive wavelets, that can be used for analyzing electromagnetic transients in power systems. The function $\psi^{\mathrm{new}}(t)$ is obtained with a filter bank that has general restrictions imposed by multiresolution analysis (MRA). Nevertheless, first, it is necessary to define the filter bank restrictions to obtain the filter bank coefficients in order to compute the DWT.

3.1 Filter bank restrictions

The mother wavelet $\psi^{\mathrm{new}}(t)$ is derived using a filter bank A, which has a low pass filter h_0 (first row of A) and a high pass filter h_1 (second row of A). Both filters must have the same number of coefficients N_f. Then, filter bank dimensions are equal to $(2, N_f)$ and its imposed restrictions, defined by MRA theory [23], are formulated as follows:

a) Orthogonality condition

$$\sum_{k=0}^{q} A_k A_{k+i}^{\top} = \delta(i) I \tag{3}$$

where $\delta(i) = 1$ if $i = 0$, and zero otherwise, I is the identity matrix, A_k is a square block and q is dependent on the number filter coefficients N_f.

b) Regularity condition

$$\sum_{k=0}^{N_f-1} h_0(k) = \sqrt{2}\,. \tag{4}$$

c) Lawton matrix condition

$$M_{i,j} = \sum_{k=0}^{N_f-1} h_0(k)h_0(k+j-2i)\,. \tag{5}$$

This matrix must have a unique eigenvalue equal to 1, which has dimension of $(2N_f - 3)$.

Using these described conditions, the filter bank A is parameterized. For more details about the parametrization process, see [24]. Then, the decomposition level is defined to compute the DWT, and wavelet coefficients are used to optimize the discriminant criterion.

3.2 Computing the DWT

DWT is divided into approximation and wavelet coefficients cA and cW respectively. These coefficients can be computed using the following filtering operations [25]

$$cA_{j+1,k} = \sum_{i=0}^{n} cA_j(i)h_0(2k-i)\,, \tag{6}$$

$$cW_{j+1,k} = \sum_{i=0}^{n} cA_j(i)h_1(2k-i) \tag{7}$$

where $j = 0, 1, 2, \ldots, L-1$ and L represents the decomposition level. If $j = 0$, $4cA_0 = x(n)$, where n is the number of samples. Moreover, the DWT reduces the output size by half in each band, when moving from one level to the next level. Then, the computed wavelet coefficients cW are used to optimize the proposed discriminant criterion, which is described in the following section.

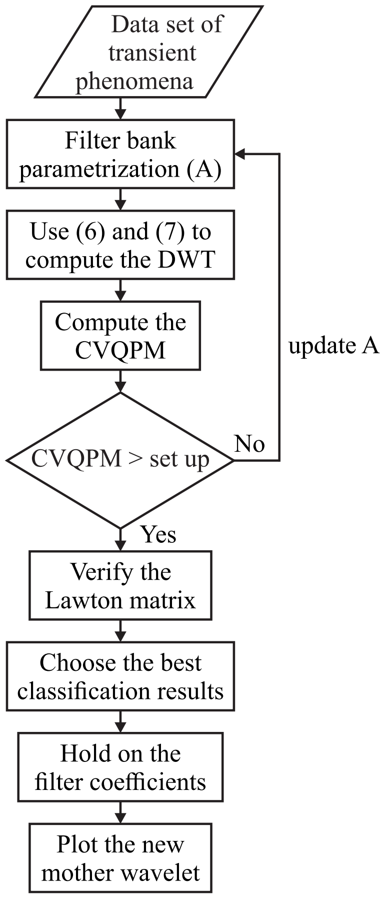

Fig. 3. Adaptive wavelet algorithm

4 DISCRIMINANT CRITERION

Based on the high frequency information produced by different transient conditions in power systems, the discriminant criterion is used to optimize the wavelet coefficients cW produced by the DWT. In this way, filter bank A is adapted gradually until the discriminant criterion is reached. According to the adaptive wavelet algorithm, the chosen discriminant criterion is the cross-validated quadratic probability measure (CVQPM), which is a cross validation criterion based on posterior probabilities [26]. It can be described by the following expression

$$CVQPM(cW(L)) = \frac{1}{n}\sum_{i=1}^{n} a_{Q/i} \tag{8}$$

where $a_{Q/i}$ is the appreciation score for cW of each transient transient phenomenon. The appreciation score is quadratic and it is defined as

$$a_{Q/i} = \frac{1}{2} + P\big(r|cW_{i(r)}(L)\big) - \frac{1}{2}\sum_{r=1}^{R} P_{/i}\big(r|cW_i(L)\big)^2 \tag{9}$$

where $P\big(r|cW_{i(r)}(L)\big)$ is the posterior probability of $cW_i(L)$ belonging to the true transient conditions (true class r) and $P_{/i}\big(r|cW_i(L)\big)$ is the posterior probability of $cW_i(L)$ belonging to other transient conditions (class r).

CVQPM takes values from zero up to one. Higher values are preferred, since in this way electromagnetic transients can be identified with high precision.

5 ADAPTIVE WAVELET ALGORITHM

The proposed methodology to obtain the new mother wavelet is based on the adaptive wavelet algorithm, which is shown in Fig. 3. The process begins when a data set of transient phenomena is loaded. After this, the filter bank A is parameterized using Pollen product factorization and orthogonal vectors; for this, the number of filter coefficients N_f must be defined. Then, using expressions (6) and (7), the DWT is computed up to a defined decomposition level. Moreover, the produced wavelet coefficients by each transient phenomenon are used to compute the discriminant criterion CVQPM, which is defined by posterior probabilities according to Bayes rule [27].

The algorithm is optimized until the CVQPM value is higher than a set up value, and then the Lawton Matrix condition must be verified. Otherwise, the filter bank parameters must be updated to compute again the DWT until the CVQPM is optimized. Hence, classification results in training and validation process are taken into account for developing the mother wavelet $\psi^{\text{new}}(t)$ based on the filter bank parameters. Because wavelets are derived from their respective filter bank coefficients, the scaling function $\phi^{\text{new}}(t)$ and the wavelet $\psi^{\text{new}}(t)$ can be visualized using an iterative method, spectral method or eigenvalue method [28].

6 ADAPTIVE WAVELET ALGORITHM FOR TRANSIENT SIGNALS

Adaptive wavelet algorithm is designed to identify and distinguish the high frequency information produced by different transient phenomena. DWT was used to feature extraction for all transient signals and they were classified based on the discriminant criterion described in Section 4. Data set of transient signals and its results are presented in the following subsection.

6.1 Data set of transients

Electromagnetic transients in power systems are characterized for having a wide frequency spectrum. Furthermore, each type of transient phenomenon has similar waveforms, which change in magnitude, phase or duration. This is a great advantage since it does not need to have a large data set of transient signals in order to implement the methodology.

In this work, only three types of transients in power systems are considered to obtain the function $\psi^{new}(t)$ and these are shown in Tab. 1. Each type of transient is

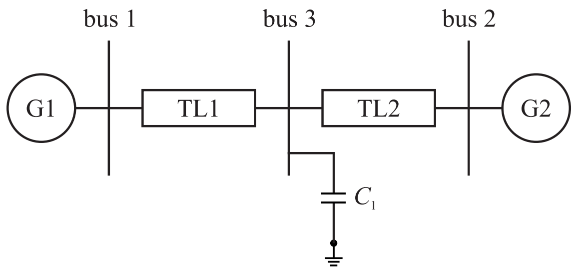

Fig. 4. Equivalent power system

Table 1. Data set for transient signals

Type of transients	class	Training data	Validation data
Arcing faults	1	50	16
Transmission lines energization	2	50	16
Capacitor switching	3	50	16
Total	3	150	48

considered as a class into the data set, *eg*, all arcing faults correspond to the class 1.

For all classes, it is used a sample frequency of 122.88 kHz and their simulation are carried out in the equivalent power system shown in Fig. 4, which has a fundamental frequency of 60 Hz. Furthermore, all transient signals are handled in per unit system and were simulated using the software *Alternative Transient Program* (ATP-EMTP). In this way, arcing faults are simulated along the transmission line $TL1$ using *Kizilcay's time dependent model* [29], in which different lengths of the line and different times of occurrence were considered. Lines energization is carried out in the transmission line $TL2$, which is energized by the side of bus 2 at different times and using tripolar and unipolar switching. Finally, to obtain the data set corresponding to capacitor switching, $C1$ is energized at different time instants and using different values of capacitance.

The transient phenomena described above are shown in Fig. 5, including a window of 16 ms (after the transient is occurred) for each case of the transient phenomena. Moreover, a window length equal to 2.0833 ms was chosen, since all samples in each decomposition level must be multiple of $2(\text{samples}/2^j)$. Furthermore, in this application, the maximum frequency observed is 61.44 kHz according to the Nyquist theorem. Therefore, the vector has 256 samples for each voltage signal, according to the chosen window.

6.2 Classification results

An adaptive wavelet algorithm was implemented for classifying transient signals using the high frequency information produced by them. In order to implement the adaptive wavelet algorithm, two things must be defined. First, the number of decomposition levels of the wavelet transform, *ie* for all transients the DWT is computed and their approximation coefficients are used to identify and classify each type of transient. Second, two data sets of transient phenomena must be available, one for training process and the other for validating the results.

In order to choose the best decomposition level for electromagnetic transient classification in electrical power systems, a variety of tests was implemented. In the fist decomposition level, the frequency range to identify transient phenomena is from 33.22 kHz up to 66.44 kHz. In the second decomposition level, the frequency range is around 16.61 kHz to 33.22 kHz; and each decomposition

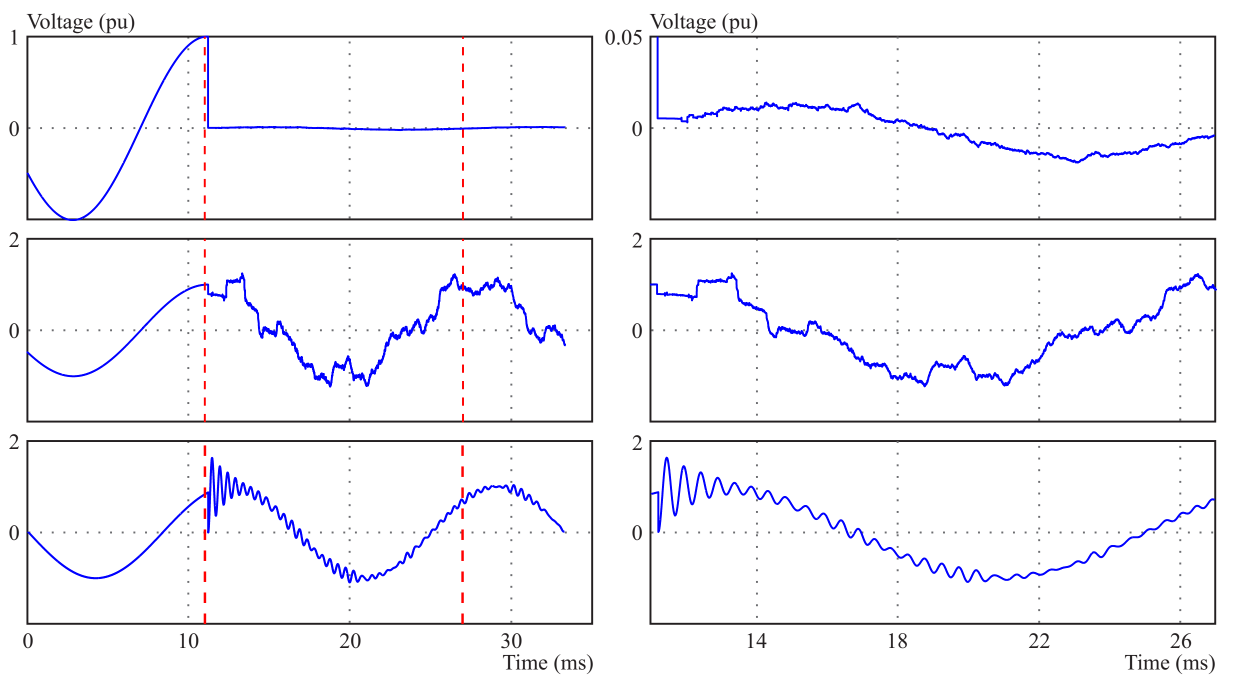

Fig. 5. Transient voltage signals: (a) — arcing faults, (b) — lines energization and (c) — capacitor switching

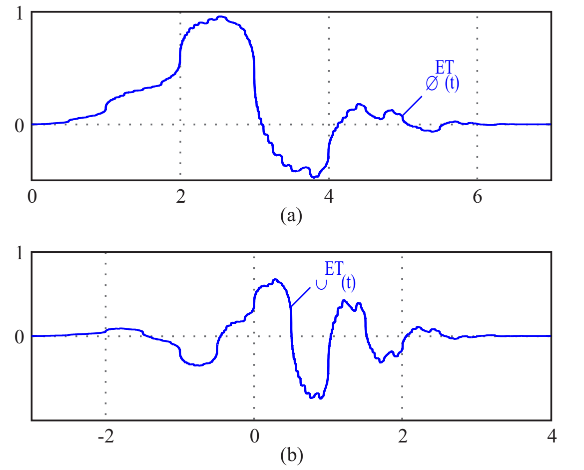

Fig. 6. (a) — Scaling function and (b) — Wavelet function

Table 2. Classification results obtained with adaptive wavelets

Adaptive wavelet					% Classification	
Wavelet	q	N_f	$N_{\rm coef}$	CVQPM	Training	Validation
A	3	8	16	0.8922	87.33	87.50
B	4	10	16	0.8943	86.00	85.41
C	5	12	16	0.8926	85.33	83.33
D	6	14	16	0.8917	86.00	75.00

level has its corresponding frequency range. The best results are obtained at the level 4, which corresponds to the frequency range from 4.1525 kHz up to 8.305 kHz, where 0.89 is the higher value reached by the CVQPM.

Moreover, different number of filter coefficients N_f were used in the optimization process. Table 2 shows the obtained results, which optimize the CVQPM discriminant. These results correspond to four new wavelets, which are called wavelet A, wavelet B, wavelet C and wavelet D. According to the results, the best wavelet is the called wavelet A, where the classification percent is almost equal in both training and validation processes. In this case, the number of filter coefficients was equal to 8, because for higher number of filter coefficients the results are affected in the validation process. Hence, this results will be used to obtain the mother wavelet for analyzing transient signals, which is renamed as mother wavelet ET($\psi^{ET}(t)$).

7 NEW MOTHER WAVELET FOR ANALYZING TRANSIENT SIGNALS

Mother wavelet $\psi^{ET}(t)$ is able to identify and classify the high frequency information produced by the studied transient signals, as it was shown in Tab. 2. In general, all wavelets can be obtained from their respective filter bank coefficients. The filter bank for the wavelet $\psi^{ET}(t)$ was obtained in the optimization process and it is presented in Tab. 3. These coefficients can be used to display the new mother wavelet graphic, using the method of the following subsection.

Table 3. Filter bank of the new mother wavelet ET

k	$h_0(k)$	$h_3(k)$
0	0.1346	0.0727
1	0.1552	0.0839
2	0.4502	−0.3015
3	0.7806	−0.2061
4	0.2061	0.7806
5	−0.3015	−0.4502
6	−0.0839	0.1552
7	0.0727	−0.1346

7.1 Graphic for the new wavelet ET

The new function $\psi^{ET}(t)$ is linked with a scaling function $\phi^{ET}(t)$ defined by low pass filter coefficients, and because of this reason the wavelet $\psi^{ET}(t)$ will be defined by its scaling function. Furthermore, it is not possible to describe many wavelets by mathematical functions, such as the case of the Daubechies wavelets family. Then, it is appealed to an iterative method to display the graphic for both functions $\phi^{ET}(t)$ and $\psi^{ET}(t)$; for more details to display a wavelet function see [28]. The scaling and wavelet function must be orthogonal according with the filter bank conditions imposed by MRA theory; this is proved in the following subsection. The results obtained for the scaling and wavelet function can be seen in Fig. 6. These graphics represent the new mother wavelet for analyzing electromagnetic transients and can be used in different applications of power systems.

Table 4. Eigenvalues for Lawton matrix

k	Eigen value
1	1
2	0.5
3	0.3209
4	−0.1600
5	−0.1233
6	$0.1020 + j0.0993$
7	$0.1020 - j0.0933$
8	0.1207
9	$0.0511 + j0.0391$
10	$0.0511 - j0.0391$
11	0.0592
12	−0.0198
13	0.0235

7.2 Filter bank validation

To validate the new wavelet $\psi^{ET}(t)$, this section shows how the proposed wavelet fulfills the basic conditions imposed by the MRA theory(listed in Section 3). In first place, the orthogonality condition must be validated using the obtained filter bank A, which is shown in Table 3. The orthogonality condition is validated using the expression (3), for which the filter bank A is divided in submatrices A_j of $(2,2)$, where j takes values from 0 up to 3. Therefore, substituting submatrices A_j into (3) gives as a result the following expression:

$$A_0A_0^\top + A_1A_1^\top + A_2A_2^\top + A_3A_3^\top . \tag{10}$$

Using the parameters of A, the result is an identity matrix and the orthogonality condition is satisfied. Moreover, the regularity condition is fulfilled since the sum of the low pass filter coefficients shown in Tab. 3 is equal to $\sqrt{2}$.

Finally, the last condition is checked using the Lawton matrix, where its corresponding eigenvalues are shown in Tab. 4; it can be seen that there exists a unique eigenvalue equal to one. Hence, the conditions imposed by the MRA theory are fulfilled for the new mother wavelet and it may be considered as an extension of the Daubechies family. As a consequence, in fact it can be used in other applications.

8 DAUBECHIES WAVELETS FAMILY AND WAVELET ET

As it was mentioned before, wavelets have been used in different applications of power systems, being the Daubechies family the most used. For instance, Daubechies wavelet 4 (db4) has been applied to fault detection and classification [17] and it is considered the most adequate wavelet for analyzing transient voltage signals, as well as Daubechies 5 (db5) for current signals [20]. Due to this reason, a comparison of both Daubechies wavelets and the proposed one was carried out, and the results are shown in Tab. 5. Moreover, this comparison allow to evaluate the performance of the new wavelet with respect to the more used Daubechies wavelets.

Table 5. CVQPM for Daubechies and ET wavelets

Classification before optimization			
Wavelet	Process	CVQPM	%
Initiation	Training	0.8387	78.67
	Validation	0.8656	70.83
Classification after optimization			
Wavelet	Process	CVQPM	%
ET	Training	0.8922	87.33
	Validation	0.9309	87.50
Classification using Daubechies wavelets family			
Wavelet	Process	CVQPM	%
db4	Training	0.8428	78.00
Validation	0.7914	68.75	
db5	Training	0.8757	84.67
	Validation	0.9265	87.50

Table 5 presents the CVQPM values for training and validation process, as well as the correct classification percent for Daubechies wavelets and wavelet ET (before and after the optimization process). For instance, the greatest CVQPM value is obtained in the validation process and is equal to 0.9309, which corresponds to the new wavelet $\psi^{ET}(t)$. Nevertheless, the classification percent for $\psi^{ET}(t)$ is equal to 87 % and it is the same in both training and validation process. Based on the presented discriminant criterion, it is concluded that db5 is the most suitable Daubechies wavelet for analyzing transient signals because its CVQPM values are greater than the wavelet db4 ones, where the CVQPM values are equal to 0.8757 and 0.9265 in training and validation process, respectively. However, the best results are obtained with the new wavelet $\psi^{ET}(t)$ and is concluded that the wavelet ET has a more successful performance, in comparison with the Daubechies wavelets.

9 CONCLUSION

In this paper, an adaptive wavelet algorithm was applied to design a new mother wavelet for analyzing electromagnetic transients in power systems, particularly capacitor switching, transmission lines energization and arcing faults. The new mother wavelet was obtained based on the best classification results produced by the adaptive wavelet algorithm, where a discriminant criterion (CVQPM) was used to gradually adapt the high frequency information for all transient signals used in this application. Once the discriminant criterion is satisfied, their respective filter bank coefficients are used to display the graphic of the new mother wavelet using an iterative method. The new mother wavelet is called wavelet ET and can be used in other applications of power systems. Moreover, it is concluded that the best Daubechies wavelet for analyzing transients in power systems is wavelet db5.

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Daniel Guillén was born in Michoacan, Mexico in 1984. He received the BSc degree from Instituto Tecnológico de Morelia, Mexico, in 2007, the MSc degree from Universidad Autónoma de Nuevo León, Mexico in 2010, and currently is pursuing his PhD degree at Universidad Autónoma de Nuevo León. His main research interests are fault detection in power systems, monitoring and diagnostic of partial discharges in power transformers and power system analysis under transient conditions.

Gina Idárraga-Ospina (Assoc Prof, Ing, PhD) received her Electrical Engineer degree in the Universidad Nacional de Colombia, Sede Medellín , Colombia, in 2002, the PhD degree (Magna Cum Laude) in Electrical Engineering from the Universidad Nacional de San Juan, Argentina, in 2007, financed by the German Academic Exchange Service (DAAD) scholarship. Since January 2008 she joined the Electrical and Mechanical Engineering Faculty (FIME) of the Universidad Autónoma de Nuevo León, Monterrey, México, as a Full-time Professor. Her fields of interest include the simulation and modelling of transients, signal processing.

Camilo A. Cortes (Assoc Prof, Ing, PhD) received the BEng degree in Electrical Engineering from the Universidad Nacional de Colombia in 2000, and the PhD degree (with honors) in Electrical Engineering from the Universidad Nacional de San Juan, Argentina, in 2005, financed by a German Academic Exchange Service (DAAD) scholarship. Since 2008, he has been with the Universidad Nacional de Colombia, Bogotá Campus, where he is currently an Associate Professor and Head of the Ph.D. and Master in Electrical Engineering. His current research interests include the design and analysis of electric vehicles components, signal processing, energy storage applications, and electromagnetic modeling.