The Compression of Electric Signal Waveforms for Smart Grids: State of the Art and Future Trends

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***Abstract*—In this paper, we discuss the compression of waveforms obtained from measurements of power system quantities and analyze the reasons why its importance is growing with the advent of smart grid systems. While generation and transmission networks already use a considerable number of automation and measurement devices, a large number of smart monitors and meters are to be deployed in the distribution network to allow broad observability and real-time monitoring. This situation creates new requirements concerning the communication interface, computational intelligence and the ability to process data or signals and also to share information. Therefore, a considerable increase in data exchange and in storage is likely to occur. In this context, one must achieve an efficient use of channel communication bandwidth and a reduced need of storage space for power system data. Here, we review the main compression techniques devised for electric signal waveforms providing an overview of the achievements obtained in the past decades. Additionally, we envision some smart grid scenarios emphasizing open research issues regarding compression of electric signal waveforms. We expect that this paper will contribute to motivate joint research efforts between electrical power system and signal processing communities in the area of signal waveform compression.**

***Index Terms*—electric power systems, signal compression, smart grid, data compression.**

I. Introduction

There has been a growing need to correctly characterize the behavior of electric power systems [1]–[4]. Around two decades ago, due to worldwide electric power energy sector deregulation, end users and utility companies started being concerned with the impacts caused by power quality problems. These problems also arise due to the massive use of non-linear loads and electronic-based equipment in residences, commercial centers, and industrial plants. In addition, it was perceived that those impairments could escalate if not correctly tackled. Therefore, the monitoring of electric power systems in real-time, along with off-line analysis using both centralized and decentralized schemes, has grown in importance. Several technologies have arisen aiming at monitoring the behavior of electric power systems in different levels: high voltage (HV), medium voltage (MV) and low-voltage (LV) [5].

Those factors pushed forward the development of mathematical tools, which are often based on digital signal processing techniques, for analyzing electric power system applications [1]–[4], [6]. These techniques have been used to extract relevant features, characteristics and information from measured quantities and their waveforms in order to feed high-level monitoring, diagnosis, metering and modeling, as well as prediction solutions [2]–[4], [6]–[8].

Currently, the electric energy sector is facing a new revolution with the purpose of making the electrical grid more flexible, reliable, reconfigurable, efficient, secure, green, sustainable, intelligent, adaptable, and observable at all voltage levels. Therefore, smart(er) grids are being investigated and deployed to change the way electric power systems are planned, designed, managed, monitored, and operated. Smart grids congregate the use of information and communication technologies, sensing, measurement, monitoring and control technologies to deal with the complex system that constitutes the electric power systems [9]–[14]. Anticipating this tendency, nations around the world, standardization forums, regulatory authorities as well as companies and Research, Development and Innovation institutes have started to work on this challenging and promising field.

According to the smart grid concepts [9]–[14], devices connected to power grids have a communication interface, some intelligence and ability to process data or signals and also to share information. Therefore, a considerable increase in data exchange and storage is likely to occur. In this context, one must seek an efficient use of channel communication bandwidth and a reduced storage requirement for power system data with for both immediate and long availabilities. Data compression encompasses techniques capable of representing information in a compact form. These compact representations are obtained by identifying and using structures that exist in the data. When digitizing a constant envelope sinusoid, we would spend a great amount of bits to encode its samples. However, we could represent this signal in a compact form with respect to amplitude, frequency and phase. Instead of encoding a large amount of samples, we could encode only three parameters. Therefore, the development of efficient algorithms for the compression of signal waveforms and ancillary data is of paramount importance for devising smart and powerful monitoring, diagnosis, and metering equipments that will contribute to successful smart grid deployments [9]–[22].

Although one notes that a considerable amount of effort was spent in this field in the past two decades [16]–[20], [23]–[56], an analysis of the main contributions reveals that the compression of signal waveforms from power systems (that we will refer to as "electric signals" for simplicity and for being in accordance with the literature) is far from being as mature as for speech, image, and video compression. Therefore, there is room for research, development and improvements in this field. In fact, smart grids will demand electric signal and ancillary data compression techniques that are suitable for distinct applications, such as protection, monitoring, metering, synchrophasor measurements, and diagnosis, just to mention a few. Most electric signals compression techniques try to address the needs related to power quality analysis, which depend upon the characterization of electric signals (voltage and current).

There are a few works that analyze the role of lossless compression techniques applied to data gathered in a power monitor or power meter [7], [17], [44], [46], [57], [58]. One of the leading power quality storage formats for electric power system waveforms is the PQDIF (Power Quality Data Interchange Format) which is defined by the IEEE1159 Working Group and also provides a lossless compression option [59]. From a signal processing point of view, the lossy compression algorithms proposed so far for electric signals can be grouped into three main classes: (i) transform-based coding [20], [23]–[26], [29]–[47], [60]; (ii) parametric coding [48]–[50] and (iii) mixed parametric and transform coding [51]–[55], [61].

This paper is organized as follows: Section II gives a general overview of the power system infrastructure and outlines the intrinsic phenomena normally recorded or measured in electric signals. Being aware of these phenomena allows compact signal representations, which is a important feature for the design of efficient compression frameworks; Section III presents the methods found in literature so far applied for compressing electric signals and reports their compression performance; Section IV indicates the future trends and open issues for research and development of compression techniques for smart grid applications; finally, Section V presents the concluding remarks.

II. Characteristics of electric signals

Electric power systems may be modeled as consisting of four main components: i) production or generation and cogeneration; ii) transmission; iii) distribution; iv) consumption. A simplified diagram for an electric power system is depicted in Fig. 1. Generally, the generator delivers energy at 13.8 kV level and this voltage is stepped up in the generation substation so that the energy is transmitted by using high voltage transmission lines, ranging from 138 kV up to 1000 kV, referred to as high voltage (HV) and ultra-high voltage (UHV), respectively. When the energy reaches the distribution substation, the voltage is stepped down to the medium voltage (MV) level again, characterizing the distribution network in grids. Usually, the primary distribution feeders leave from this substation at 13.8 kV level (MV) and are less than 10 km in length, except for rural sections where they may be longer, as demands for electricity are relatively scarce and scattered. Distribution transformers are connected to the primary feeders, in many points, to reduce the voltage level from 13.8 kV to 127 V, 220 V or 380 V (approximately) to energize distribution secondary feeders reaching the end users. Then secondary electric distribution system corresponds to the low voltage (LV) feeders.

A. Characteristics of Electric Disturbance Signals

The aim of power system monitoring is to access the evolution in time of disturbance phenomena, regardless of the quantities measured. These phenomena consist, in general, of sinusoidal oscillations of increasing or decreasing amplitudes, and are highly influenced by circuit switching, as well as by non-linear equipments. In order to analyze and compress signals from power systems it is important to use models that are capable of precisely representing signal components consistent with these phenomena, which can be classified as:

- Harmonics – steady-state low-frequency phenomena ranging from 50/60 Hz (the system fundamental frequency) to 3000 Hz. Their main sources are semiconductor apparatuses (power electronic devices), arc furnaces, transformers (due to their non-linear flux-current characteristics), rotational machines, and aggregate loads (a group of loads treated as a single component) [62].
- Transients – impulses or high frequency oscillations. Oscillations are observed superimposed to the voltages or currents of fundamental frequency (50/60 Hz) or to exponential DC and exponentially modulated components. They can be classified as normal and abnormal. The normal ones correspond to common operation events of the system, involving switched capacitor based AC/DC devices, tap changing and load switching. On the other hand, the abnormal correspond to those that are not common operation events and are somehow random, such as lightning, voltage dips, and other faults in the system [6], [63]. The frequency range of transients may span up to hundreds of thousands of Hz, although the measurement system (and the power line itself) usually filters components above few thousands of Hz.
- Inter-harmonics – sinusoidal components of frequencies that are not in multiples of the fundamental one [64]. They tend to have much shorter duration and lower power than the fundamental and harmonic components. They appear due to the high availability of power converters and loads not pulsating synchronously with the fundamental power system frequency.
- Swells and Sags – increase or decrease, respectively, in the RMS voltage of duration from half cycle to 1 minute (approximately) [62]. Usually, the variations are divided into small (voltage variations or voltage fluctuations) and large (voltage dips or sags, over-voltages or swells and interruptions) [3].

A sample of an MV electric signal showing the occurrence of an event is depicted in Fig. 2. The underlying phenomena found in such waveforms are heavily dependent on the voltage level of the electric grid as well as on the magnitude and linearity of the load connected to it [6], [63].

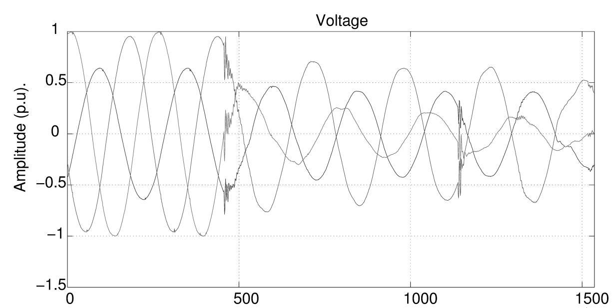

Fig. 2. A disturbance detected in a voltage signal measured in an MV electric circuit [65], showing transients and sags.

B. Modeling Electric Disturbance Signals

When analyzing disturbance signals, it is interesting to be capable of detecting, segmenting, modeling and identifying the relevant phenomena [3]. Some techniques commonly employed for modeling and analyzing disturbance in electric signals are: Fourier filtering [66], [67]; Prony analysis [68], [69]; auto regressive moving average models [70]; state space tracking methods [70] and Wavelets [68], [71]–[77]. In some cases, these methods are used along with artificial intelligence strategies [69], [78]–[81].

The components of electric signals can considerably vary regarding their origins (HV, MV, and LV electric grids) as well as the kinds of connected loads. Despite that, several

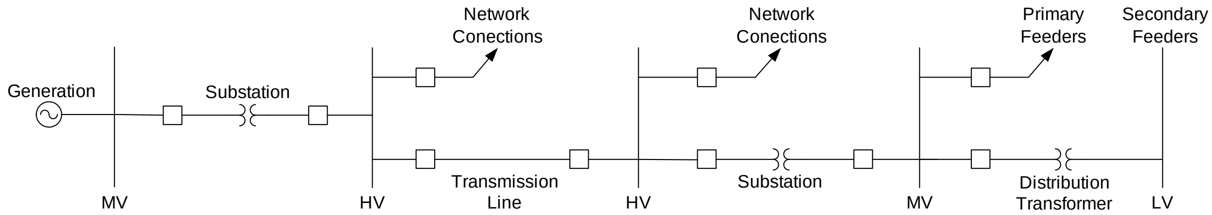

Fig. 1. A typical power system scheme (LV – low voltage, MV – medium voltage and HV – high voltage).

contributions, aiming at modeling transmission and distribution electric systems, have pointed out that a general model for the observed voltage and current signals can be expressed in the discrete time domain as [5], [6], [48], [63], [82]

$$x[n] = x(t)|_{t=nT_s} := f[n] + h[n] + i[n] + t[n] + v[n] \quad (1)$$

where $n = \{0, \cdots, N-1\}$, $T_s = \frac{1}{f_s}$ is the sampling period, the signals $f[n]$, $h[n]$, $i[n]$, $t[n]$, and $v[n]$ denote the power supply signal (or fundamental component), harmonics, inter-harmonics, transient, and background noise, respectively. The power supply signal can be expressed as

$$f[n] = A_0 \cos\left(2\pi \frac{f_0}{f_s} n + \theta_0\right), \quad (2)$$

in which A_0, f_0, and θ_0 denote its magnitude, fundamental frequency, and phase, respectively. Harmonics are given by

$$h[n] = \sum_{m=1}^{M} h_m[n], \quad (3)$$

where $h_m[n]$ refers to the m-th harmonic, expressed as

$$h_m[n] = A_{h,m} \cos\left(2\pi m \frac{f_0}{f_s} n + \phi_{h,m}\right) \text{rect}\left(n, n_{h,s_m}, n_{h,e_m}\right) \quad (4)$$

where $A_{h,m}$ is its magnitude, $\phi_{h,m}$ is its phase, n_{h,s_m} and n_{h,e_m} define its time support region, that is $\text{rect}\left(n, n_{h,s_m}, n_{h,e_m}\right) = u(n - n_{h,s_m}) - u(n - n_{h,e_m})$ – $u(\cdot)$ corresponds to the step function. Inter-harmonics are

$$i[n] = \sum_{j=1}^{J} i_j[n], \quad (5)$$

where $i_j[n]$, the j-th inter-harmonic, is given by

$$i_j[n] = A_{I,j} \cos\left(2\pi \frac{f_{I,j}}{f_s} n + \phi_{I,j}\right) \text{rect}\left(n, n_{i,s_j}, n_{i,e_j}\right) \quad (6)$$

$A_{I,j}$, $f_{I,j}$, and $\phi_{I,j}$ are its magnitude, frequency and phase, respectively, and $n_{i_{s_j}}$ and $n_{i_{e_j}}$ define its time support region. Transient components can be decomposed as

$$t[n] = t_{\text{spi}}[n] + t_{\text{not}}[n] + t_{\text{dec}}[n] + t_{\text{dam}}[n], \quad (7)$$

where $t_{\text{spi}}[n]$ denotes spikes, $t_{\text{not}}[n]$ denotes notches, $t_{\text{dec}}[n]$ denotes decaying oscillations and $t_{\text{dam}}[n]$ represents damped exponentials. These transients can be expressed as

$$t_{\text{spi}}[n] = \sum_{l=1}^{N_{\text{spi}}} t_{\text{spi},l}[n] \text{rect}\left(n, n_{\text{spi},s_l}, n_{\text{spi},e_l}\right), \quad (8)$$

$$t_{\text{not}}[n] = \sum_{l=1}^{N_{\text{not}}} t_{\text{not},l}[n] \text{rect}\left(n, n_{\text{not},s_l}, n_{\text{not},e_l}\right), \quad (9)$$

$$t_{\text{dec}}[n] = \sum_{l=1}^{N_{\text{dec}}} A_{\text{dec},l} \cos\left(2\pi \frac{f_{\text{dec},l}}{f_s} n + \phi_{\text{dec},l}\right) e^{-\alpha_{\text{dec},l}(n - n_{\text{dec},l})} \text{rect}\left(n, n_{\text{dec},s_l}, n_{\text{dec},e_l}\right), \quad (10)$$

and

$$t_{\text{dam}}[n] = \sum_{l=1}^{N_{\text{dam}}} A_{\text{dam},l} e^{-\alpha_{\text{dam},l}(n - n_{\text{dam},l})} \text{rect}\left(n, n_{\text{dam},s_l}, n_{\text{dam},e_l}\right). \quad (11)$$

Note that $t_{\text{spi},l}[n]$ and $t_{\text{not},l}[n]$ are the *n*-th samples of the *l*-th spike and notch transients, for instance. Also, the pairs $(n_{\text{spi},s_l}; n_{\text{spi},e_l})$, $(n_{\text{not},s_l}; n_{\text{not},e_l})$, $(n_{\text{dec},s_l}; n_{\text{dec},e_l})$, and $(n_{\text{dam},s_l}; n_{\text{dam},e_l})$ define the duration of these components.

It should be highlighted that noise encompasses different contributions. For example, the noise that is actually present in the power system (real noise) and the noise that is introduced by the signal conditioning and analog-to-digital conversion processes (electronic noise). The electronic noise may not to be random white noise, but rather be somehow predictable based on the oscillatory frequencies of the electronic circuitry used to capture the waveforms from the power system. However, in general, noise ($v[n]$) is assumed to be independent and identically distributed (*i.i.d.*) and usually modeled as normal $\mathcal{N}(0, \sigma_v^2)$, and also as independent of $f[n]$, $h[n]$, $i[n]$, and $t[n]$.

The discussed model is effective in representing several disturbances that appear in electric signals because the estimation of its parameters may provide valuable information regarding monitoring and diagnosis. Note that equation (10) may model capacitor switchings as well as signals resulting from power system faults. Equation (11) defines the decaying exponential as well as *direct current* (DC) components ($\alpha_{\text{dam}} = 0$), which may result from Geo-magnetic disturbances, for instance.

III. Main compression techniques for electric signals

Data compression schemes can be divided in two broad classes: lossless and lossy compression schemes [83]. In lossless compression, the reconstructed signal is identical to the original signal and the performance is measured by compression ratio. On the other hand, in lossy compression the reconstructed signal may differ from the original one and the performance must now be measured by the compromise between compression ratio and distortion. When one controllably introduces distortion in the signal without compromising its use or application, it is possible to achieve higher compression ratios than lossless compression approaches. In the following, we describe some of the techniques that have been presented for the compression of electric signals.

A. Lossless Coding

Lossless methods have been employed for coding power quality data [7], [17], [44], [46], [57]. Lempel-Ziv, Huffman and arithmetic coding methods [83], [84] are used to compress electric power signals in [44]. Lossless coding techniques were employed in electric signals comprising events such as flicker, sag, swell, impulse and harmonics [7], [17], [44], [46], [57].

In [46], one presents compression results for electric signals when using lossless off-the-shelf CODECs developed for audio and image signals, as well as entropy coders such as LZP2, FLAC, TTAEnc, MP3, ZIP (Lempel-Ziv variant), JPEG-LS, SPIHT-lossless and JPEG2000-lossless. Besides, the PQDIF file format comprises a lossless compression option that also consists of a Lempel-Ziv variant [59]. When using the PQDIF compression option, we can expect the same compression performance seen in [46] referring to the ZIP method.

Often one attempts to encode electric power system signals using image encoders [46], [47]. In order to use image coders, it is necessary to convert the electric power signal into a matrix representation where the rows correspond to non-overlapping segments of the signal. It is important to note that 2D coders enable the exploitation of redundancy across vertical samples providing more compact signal representations than one-dimensional coders [46]. Different 1D and 2D lossless coders were employed to compress a dataset of voltage waveforms with 800,000 samples captured at 20 kHz. It could be verified that among 1D coders a Lempel-Ziv variant technique achieves the highest compression performance with a compression ratio of 5:1 on the average. Among 2D coders, the JPEG2000 in lossless mode accomplishes the highest compression ratio on average, of around 9:1. Another 2D coder based on DCT was presented in [85].

In [17], it is proposed a lossless compression algorithm using high-order delta modulation along with Huffman coding. It carries out multiple differential operations over the signals to reduce their magnitudes so that fewer bits are required for coding. This compression approach is tested in distinct types of power quality events achieving a compression ratio of 2:1.

B. Transform Coding

In order to achieve higher compression levels, one would need to make use of lossy coding schemes which lead to signal degradation. However, the signal degradation must be such that the signal is still useful for analysis or diagnosis [86]. Aiming at this, coding techniques must accomplish a tradeoff between compression ratio and measured distortion such that compressed signals remain useful and effective for the analysis and diagnosis of electric disturbances.

Transform coding is a commonly used lossy compression framework. In this case, the encoding process is essentially composed by three steps: **i.** transformation of the input signal producing uncorrelated coefficients, **ii.** quantization of each coefficient (usually scalar quantization and eventually vector quantization), and **iii.** entropy coding.

Many transform-based compression techniques have been developed with the purpose of reducing the size of electric signals. Some techniques employ linear transformation such as the *Hartley Transform*, *Lapped Orthogonal Transform* (LOT) and the *Discrete Cosine Transform* (DCT) [47], [87]. However, a significant number of compression systems applied to electric signals use the *Discrete Wavelet Transform* (DWT) and the *Wavelet Packet Transform* (WPT) [20], [24], [30]–[33], [35]–[46], which we highlight here.

The transform approach whose basic components are formed by sine and cosine functions such as DFT (discrete Fourier transform) and DCT are effective for the analysis of predominantly sinusoidal, periodic and stationary signals, since they provide good localization in the frequency domain. Since disturbances in electric signals are normally subjected to non-periodic and transient components and to power frequency variations, the DFT alone can be inadequate to provide compact representations. This is the reason why wavelet-based transforms are so broadly used for compressing electric disturbance signals. They provide good localization in both frequency and time domains [88], and have the ability of concentrating a great portion of the signal energy in a few coefficients even when its underlying patterns comprise transient and non-periodic components. In what follows we analyze wavelet and wavelet packet transforms in more depth.

1) Discrete Wavelet Transform: The wavelet transform of a discrete signal $\mathbf{x} = [x_1\, x_2\, \ldots\, x_N]^T$, where N is the signal length, can be written as [30], [36], [38], [41]:

$$\boldsymbol{\alpha} = \mathbf{W}\,\mathbf{x} \qquad (12)$$

where $\boldsymbol{\alpha}$ denotes the coefficients vector, $\mathbf{W}$ is an $N \times N$ matrix consisting of row basis vectors. Thus the signal is represented as a linear combination of the row basis weighted by the coefficients in $\boldsymbol{\alpha}$. This signal representation can be obtained through a hierarchical filter bank which is implemented using a recursive algorithm known as multi-resolution pyramid decomposition [88].

Initially, the signal $\mathbf{x}$ is decomposed into coarse and detail signals, $\mathbf{a}_1$ and $\mathbf{d}_1$, using a low-pass and high-pass filters and followed by decimation by two. The same process is applied to the coarse signals. This process is repeated in N stages, (where each stage is associated to a scale or level of resolution. As result one obtains the approximation/scaling coefficients vector $\mathbf{a}_3$ and the details/wavelet coefficients vectors $\mathbf{d}_1$, $\mathbf{d}_2$ and $\mathbf{d}_3$. Note that as the signals are decimated by two at each resolution level, the number of wavelet transform coefficients remains the same as the number of samples of the original signal. There are different types of wavelet filters that can be employed, such as Daubechies, Symlets, Coiflets, among others [88], [89]. Fig. 3 shows the detail bands and the approximation band of the coarsest scale of a voltage dip signal obtained by using the DWT with Daubechies four coefficients filters. Note that the wavelet transform is able to capture the several occurrences on the signal, especially the transients.

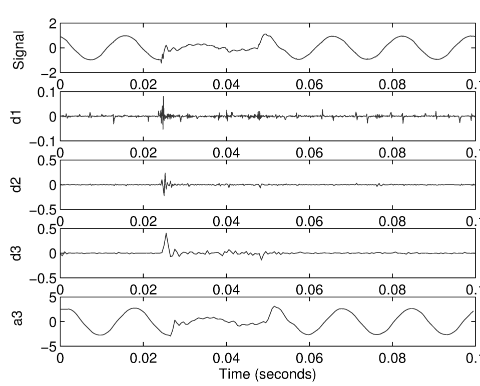

Fig. 3. Detail and approximation bands for a voltage dip signal taken from IEEE project group 1159.2, where the sampling rate is 15,360 Hz. The top plot corresponds to the original signal, and the detail bands are shown, from top to bottom, in increasing scale (decreasing frequency) order. The bottom plot corresponds to the approximation band of the coarsest scale.

The compression techniques proposed in [30], [36], [38], [41] essentially employ the discrete wavelet transform, with the coefficients below some pre-determined threshold value being discarded and the remaining coefficients being coded. In [30], one uses a Daubechies' wavelet with a four-coefficient filter along with a threshold of 10% of the maximum absolute value at each resolution level. This compression technique is employed to encode signals with 1500 samples, yielding compression ratios between 6:1 to 3:1 and *Normalized Mean Square Error* (NMSE) of 10^{-5} to 10^{-6}. In [37], the authors also utilize the DWT with Daubechies' four-coefficient filter, in conjunction with the Huffman coding technique. The thresholding process is chosen so that the NMSE remains in the order of 10^{-4}. In this case, the proposed compression method could achieve a compression ratio of 3.43:1. In [36], one uses the *Slantlet Transform* (SLT) which is an orthogonal discrete wavelet transform with two zero moments and with improved time localization. The simulation results presented in [36] show that the SLT-based compression technique can achieve a compression ratio of 10:1 with a *Mean Square Error* (MSE) of -19 dB at least. In [38], [41], a DWT with *B*-spline filters is employed. In addition, in [41] a neural-network based bit allocation procedure is used, achieving a compression ratio of 15:1 with MSE of at least -25 dB.

2) Wavelet Packet Transform: The WPT is a direct structure expansion of the DWT tree algorithm to a complete binary tree. Differently from the DWT where only the low-pass output signals passes through the two-band analysis process repeatedly, in the WPT both coarse and detail signals can be further decomposed to generate the next resolution level. The main advantage of WPT over the DWT is that, starting from the complete tree, one can prune subtrees of it, enabling the search for a better signal representation. This is equivalent to selecting the best basis for the signal expansion where each subtree denotes a subspace formed by the scaling and wavelet functions [43].

In [33], [43], a WPT is employed in the signal transformation stage. The work in [33] also applies the lossless LZW(Lempel-Ziv-Welch) technique [83] reaching a compression ratio of 10:1 with *Percentage Root Mean Square Difference* (PRD) below 10%. In [43], the WPT is used along with the arithmetic coding as the entropy coding technique. It was able to achieve a compression ratio of 6.9:1 with NMSE in the order of 10^{-5} .

3) Embedded Zero-tree Wavelet: The Embedded Zero-tree Wavelet (EZW) algorithm is a wavelet-based progressive compression method that encodes a signal into a bitstream with increasing accuracy. This method has the ability of compressing the signal at different bitrates according to the available bandwidth of the transmission channel.

First, one performs a discrete wavelet transform obtaining the coefficients for a number of scales. These coefficients are organized in a data structure called the *zerotree*. Each coefficient at a given scale is parent of all coefficients in the same spatial location at the next finer scale. The coefficients are encoded in decreasing order of scale in several passes using a simple uniform quantizer. Initially, the quantization threshold is defined at half the absolute value of the maximum wavelet coefficient. Then, for the consecutive passes the threshold is progressively divided by two. In summary, if the coefficient is larger than a threshold it is encoded and subtracted from the signal, otherwise, it is left for the next pass.

In [32], [44], the EZW coding technique, introduced in [90] originally for images, is used for the compression of power system electric signals. It provides compression ratios from 10:1 to 16:1 with low distortion (NMSE in the order of 10^{-5}).

C. Mixed Parametric and Transform Coding

As the electric power system signals of interest are formed by both transient (non-stationary) and sinusoidal (stationary) components, wavelet-based transform coding schemes do not completely exploit the signal's sparsity. In fact, wavelets are suitable for processing transient or short-time events, the ones produced by fast load transients or generation disconnection, faults, dips, lightning strokes, and disturbances of other kinds covering a broad frequency spectrum from kilohertz up to megahertz. In addition, the wavelet transform basis functions, when well localized in frequency are poorly localized in time, and when well localized in time are poorly localized in frequency. Therefore the short bandwidth and arbitrary frequency of sinusoidal signals make them unsuitable for an efficient representation in the wavelet transform domain. On the other hand, it has the ability to capture transient components as seen in Fig. 3. This motivated the research on hybrid coding techniques.

In [51]–[55], a compression framework using a mixed parametric and transform coding approach is proposed. The technique starts from an estimation of the fundamental and harmonics components of the signal under analysis, so that these components can be subtracted from the electric signal yielding a residue consisting predominantly of transient (non-stationary) components. After that, a wavelet transform is applied to this residue. This is exemplified in Fig. 4 that shows a voltage signal and the residue that results after the subtraction of the fundamental component. Since the fundamental component (sinusoidal one) can be thoroughly specified with five parameters (starting and ending samples, amplitude, frequency and phase), then improved performance can be reached. Usage of such approach is discussed in [61].

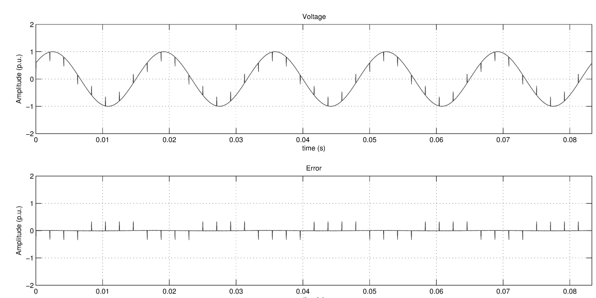

Fig. 4. Voltage signal corrupted by periodic transient events and residue obtained by subtracting the sinusoidal component.

In [51]–[54], one proposes a divide and conquer approach for compressing electric disturbance signals, the so-called *Enhanced Disturbance Compression Method* (EDCM). In principle, one performs the estimation of the amplitude and phase parameters by a Kalman filter algorithm [91] and the frequency parameter is estimated through an adaptive notch filter [92], [93]. Then a fundamental component waveform is generated based on the previously estimated parameters. This can be done adopting a simple solution using a second-order infinite impulse response (IIR) digital filter [94]. The acquired signal is synchronized with the generated fundamental component waveform. Then, it is subtracted from the delayed acquired signal frame, producing a residue that is subsequently processed through DWT. The transform coefficients are compared to a threshold and are lossless encoded along with the fundamental component parameters by using the LZW technique. The selection block is responsible for selecting the amplitude, phase and frequency estimated according to the time information generated by the timer block that provides the information about the corresponding time instant of the signal frame.

In [55], some improvements were introduced in the EDCM compression method generating the so called *Fundamental, Harmonic and Transient Coding Method* (FHTCM). Actually, this is a generalization of the EDCM with two fundamental differences. The FHTCM generates the estimation of the amplitude, phase and frequency of the fundamental and harmonics components by employing the *Notch Filtering-Warped Discrete Fourier Transform* (NF-WDFT) technique, instead of using the Kalman filter algorithm along with the adaptive notch filtering.

The second difference between EDCM and FHTCM is related to the transformation stage and the lossy compression of the transform coefficients. For an effective removal of signal redundancy, we need to obtain the appropriate basis for signal decomposition to provide compact representations. In [95]–[99], this subject had been addressed by considering a statistical model for the distribution of wavelet coefficients and by using the *Minimum Description Length* (MDL) criterion introduced by Rissanen [100], [101]. In [35], one has applied the Saito's MDL criterion [95] to power disturbance event compression in order to select both the optimal bases (DWT or WPT) and number of retained wavelet coefficients. However, the MDL criterion used in [35] does not consider quantization in its formulation. In [99], the authors have used the MDL criterion taking into account the quantization for the compression of image signals. By merging the ideas introduced in [35] and [99], it is possible to employ in FHTCM an MDL criterion that considers simultaneously a dictionary comprising several wavelet bases, an adaptive tree-structured decomposition and the quantization level of transform coefficients. Originally, the EDCM only employed a hard threshold over the the coefficients obtained through pyramid-structure decomposition. With these improvements, the FHTCM could achieve 1 bit/sample with MSE around -30 dB. A new technique that explores the mixed parametric and transform coding concept was introduced in [61].

D. Parametric Coding

Roughly, we can consider that electric signals are basically formed by sources, loads, and transmission lines, i.e., RLC circuits, whose transient behavior can be modeled by damped sinusoids. There are also discontinuities in these signals due to switching. Following these premises, a discrete-time version of an electric signal can be approximated via [48]:

$$x[n] = \sum_{i=0}^{M-1} \alpha_i e^{-\rho_i (n-n_{s_i})} \cos\left(2\pi \frac{k_i f_0}{f_s} n + \phi_i\right) \cdot \\ \cdot \mathrm{rect}\left(n, n_{s_i}, n_{e_i}\right), \qquad (13)$$

where M is the number of expansion elements, f_0 is the power frequency (50/60 Hz) and each element is represented by a 6-tuple $(\alpha_i, k_i, \rho_i, \phi_i, n_{s_i}, n_{e_i})$, where α_i is the amplitude, k_i is an integer multiple of the fundamental frequency, ρ_i is the decaying factor, ϕ_i is the phase, n_{s_i} and n_{e_i} are the starting and ending samples, and $u(\cdot)$ corresponds to the unit step function. One should note that using this model the signal is represented as a sequence of parameter sets $\{\gamma(k)\}_{k\in\mathcal{K}}$, being each $\gamma(i) = (\alpha_i, k_i, \rho_i, \phi_i, n_{s_i}, n_{e_i})$.

As the reader may observe, the idea behind parametric coding (as presented here) is to employ parameterized functions or signals called atoms to model the signal to be coded. Signal coding thus resides in analyzing the signal and choosing a set of parameter sets to model the signal. The different parameter sets correspond to different atoms that summed up approximate the signal. Fig. 5 shows examples of different parameterized functions and their modeling parameters.

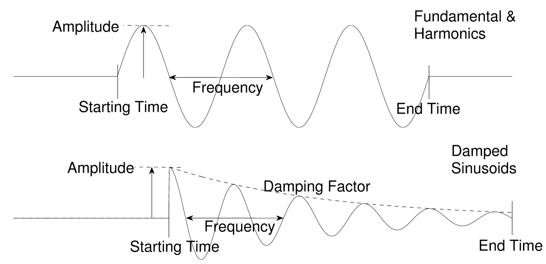

Fig. 5. Examples of parameterized atoms.

Based on the signal model given by equation (13), in [48] is proposed a compression technique of electric signals that employs parameterized dictionaries of damped sinusoids. The dictionary choice (parameter quantizer used) must be informed to the decoder as side information. An atomic decomposition using a parameterized dictionary of damped sinusoids with continuous parameters through the matching pursuit (MP) algorithm [48] is employed. After finding the parameterized model for an electric signal, the parameters of the atoms are quantized along with the coefficients. Details are as follows.

1) Decomposition Algorithm: Atomic decompositions represent signals using linear combinations of elementary functions, called atoms, drawn from a dictionary. In equation (13), each atom is given by $g_{\gamma(i)} = e^{-\rho_i (n-n_{s_i})} \cos\left(2\pi \frac{k_i f_0}{f_s} n + \phi_i\right)$ being defined by $\gamma(i) = (k_i, \rho_i, \phi_i, n_{s_i}, n_{e_i})$ and weighted by α_i. When based on a redundant dictionary – a collection of signals spanning the signal space – atomic decompositions can provide good adaptive signal approximations. The approximation is adaptive since the atoms are selected from the dictionary according to the signal being decomposed. The use of highly redundant dictionaries enables efficient decompositions of a wide range of signals. Several methods have been used to obtain these representations [88]. A popular one is the MP algorithm [102]. It performs successive approximations of signals iteratively employing the dictionary elements. At the first iteration, the MP algorithm chooses the atom with the highest correlation with the signal. The chosen atom is then scaled and subtracted from the signal obtaining a residue. The process is iterated with the residue until its energy becomes sufficiently small or until another stopping criterion is met [88], [102]. In more precise terms, a signal $x[n]$ can be approximated by an atomic decomposition as:

$$x[n] = \sum_{i=0}^{M-1} \alpha_i g_{\gamma(i)}[n], \qquad (14)$$

TABLE I
COMPARISON OF SOME TECHNIQUES EMPLOYED FOR THE COMPRESSION OF ELECTRIC SIGNALS.

Group	Category	Basic Technique	Compression Ratio	Distortion Metric	Distortion Value	Reference
Lossless	1D	Lempel-Ziv	5:1	–	–	[46]
		Delta-modulation Huffman Coding	2:1	–	–	[17]
	2D	JPEG2000	9:1	–	–	[46]
Lossy	Wavelet Transform	Daubechies DWT	6:1 to 3:1	NMSE	10^{-5} to 10^{-6}	[30]
		Daubechies DWT	3.43:1	NMSE	10^{-4}	[37]
		Slantlet DWT	10:1	MSE	-19 dB	[36]
		B-spline DWT	15:1	MSE	-25 dB	[41]
	Wavelet Packet	WPT and LZW	10:1	PRD	10%	[33]
		WPT and Arithmetic Coding	6.9:1	NMSE	10^{-5}	[43]
		EZW	10:1 to 16:1	NMSE	10^{-5}	[32], [44]
	Mixed Transform and Parametric	Fundamental, Harmonic and Transient Coding	16:1	MSE	-30 dB	[55]
	Parametric Coding	Damped Sinusoids Modeling	> 16:1	SNR	> 31 dB	[49]

in which the atoms $g_{\gamma(i)}[n]$ are selected from a redundant dictionary D, being indexed by the mapping $\gamma(i)$. If C_D is the dictionary cardinality, this mapping is defined as $\gamma : \mathbb{Z}^+ \rightarrow \{1, \ldots, C_D\}$. In compression applications, one encodes the number of terms M, the coefficients α_i and atom indexes $\gamma(i)$.

2) Improving Signal Model Coherence: The use of the greedy algorithm to search for the parameters of the damped sinusoidal signals that model a given electric signal according to equation (13) may lead to largely mismatched damped sinusoids with respect to the signal structures [50]. As a consequence, the signal model may not be coherent with the physical phenomena represented in the electric signal. The coherence between the electric signal and the signal representation is improved by introducing some heuristics in the greedy MP loop [48]. These heuristics lead to more physically interpretable representations of the electric signals corrupted by disturbances.

3) Achieving Compression: At the end of the decomposition, one obtains the signal approximation in equation (14) represented by the sequence of pairs $(\alpha_i, \gamma(i))$, $i = 0, \ldots, M-1$, where $\alpha(i)$ is the atom coefficient and $\gamma(i) = (\rho_i, \xi_i, \phi_i, n_{s_i}, n_{e_i})$ is the atom parameter as in equation (13). For compression, the coefficients and atoms parameters have to be quantized after the decomposition [48].

In [49], the quantization of the parameter vector $\gamma(i)$ is interpreted as the generation of a set of redundant dictionaries described as $\mathcal{D} = \{D_k\}_{k=1,\ldots,K}$, in which K is the number of dictionaries included in $\mathcal{D}$. In this case, the dictionary used must be indicated to the decoder as side information. The optimum rate-distortion (R-D) performance corresponds to the trade-off among the bits spent on side information (that corresponds to the atom indexes), and coefficients leading to the minimum distortion. The solution to this trade-off usually involves high computational demands, that increase with the number of distinct dictionaries in $\mathcal{D}$. In [49], two signals were compressed using this paradigm achieving an SNR of 31.65 dB at 0.95 bits/sample and an SNR of 31.12 dB at 0.584 bits/sample, respectively.

E. Summary of Electric Signal Compression Results

We have reviewed some of the techniques employed so far for the compression of electrical signals. Table I summarizes the results (as presented by their authors) collected in the literature for the techniques here discussed. As we have observed very different approaches for compressing electric signals have been proposed. They range from lossless to lossy compression schemes using different although promising approaches. In Table I we kept the evaluation metrics as employed by the authors of the different techniques in their works. As can be observed, an important issue for the development of techniques for compressing electric signals is an agreement on which metric shall be employed for evaluating the different lossy compression schemes.

IV. SMART GRIDS: NEW SCENARIO AND DEMANDS FOR THE COMPRESSION OF ELECTRIC SIGNALS

The scenario of modern power systems has a number of new challenges that can not be faced by the technology used to date in the field. The growing complexity in system operation due to the introduction of distributed and renewable generation, environmental restrictions to the construction of large power plants and transmission lines increase demand for electricity with acceptable quality, regulatory and economic issues, etc. Automation strategies have been widely applied in the generation and transmission side of the power system since the 1980's, while, due to the high costs involved fewer applications in the distribution side were implemented since. The Smart Grid concept emerges to congregate all these technologies already in use, taking advantage of the new and cheap information, communication, sensing, measurement, monitoring and control technologies. Particularly, most of the focus of Smart Grids are on the distribution, or demand side. In smart grids, each load connected to the electric power systems will have an interface to share information and to update its firmware, and also an affordable hardware to process information. Therefore, telecommunications infrastructure with quality of service (QoS) related to the power system requirements is sparking a huge research effort for introducing a new generation of equipment that enables to fulfill the demands and needs associated with the smart grid concept [103]–[105].

A. Communication Infrastructure

A large number of smart monitors and meters will be deployed and distributed in the power systems to allow broad observability and real-time monitoring [3], [106], [107]. Therefore, it is fundamental to verify the bulk of waveform data produced by these equipments and its impact on the communication infrastructure. For instance, power quality monitoring equipment can acquire voltage and current signals with sampling frequency as high as 1 Msps and 250 ksps, respectively [108]. If a 16-bit analog-to-digital converter is employed and four channels are considered for current and voltage recording, then one second of waveforms requires 10 MB for storage. Besides voltage and current waveforms, monitoring equipment may keep parameters associated with Power Quality standards, increasing the demand for storage space, channel bandwidth for data communication and lower communication delay. For time-constraint applications in smart grids, not satisfying those demands can result in efficiency losses, misoperation and eventually damages to power equipment.

B. Demand Side and Integration to the Grid

In a smart grid scenario, there will be the inclusion of prosumer, which stands for the consumer that produces energy. Along with it, vehicles and residential solar energy generators, as well as other forms of small generation and distribution of electric energy systems will demand reliable, low-cost, affordable and powerful monitoring systems to provide a complete diagnosis about the quality of bidirectional power flow. Also, the use of smart metering technology will allow consumers to monitor their energy consumption and control it. Given the current tendency, one may expect that equipment and devices to be connected to the electric power systems will be cognitive and cooperative. For instance, a set of monitoring and control technologies (like SCADA, power quality monitors, fault recorders and synchrophasors from one side and smart meters from the other) will work together, without human intervention, to provide precise diagnoses of the power system state at all levels, yielding an increased system awareness. Also, they will be updated or reconfigured with new functionalities for offering a suitable analysis. Based on the current stage of development, it is expected that smart grids will emphasize cognitive and cooperative aspects. In this challenging scenarios, the amount of information that is shared and stored increases considerably and, as a consequence, compression techniques become an important issue to be addressed.

C. Protection and Self-Healing

To date most research concerns applications to the transmission power system. An interesting application is the compression of waveforms recorded on digital fault recorders (DFR) that monitor the response of protection systems due to any power system disturbance. Considering large power systems, as those found in USA, China or Brazil, for example, the maintenance of faulty sections of transmission lines or manual intervention in unassisted power substations are very critical activities. During important disturbances, operational centers receive a large quantity of data providing information from many sources and have to actuate fast to ensure power flow continuity or system recovery after a blackout.

Operators need concise data as there is no time to go through elaborated fault analysis. Automated fault analysis systems have been developed aiming at preparing concise information for these situations. In [86] one presents algorithms to be used in an automated fault analysis system, capable, among other features, of processing files from DFR and calculating the distance of the fault event from the line terminals. Such applications enable to save precious time of maintenance teams when localizing and fixing faulty transmission lines. Signal compression techniques are suitable when the communication infrastructure for the DFR is poor or shared with other appliances [103], [105]. In this situation, precise fault location, which requires information from both line terminals, could become unavailable or take too long to be calculated, due to transmission delays.

Smart grids have also the ability of self-healing, that is, in principle, they rapidly detect, analyze, respond and restore from perturbations. For these purposes, they must make massive use of automated fault analysis tools, DFR and synchrophasor measurements, and depending on the application large phasor frame rates may be required. In the distribution side of power systems, research and applications of self-healing algorithms call for better fault understanding, which can be improved when fault recording files can be rapidly transmitted over bandwidth limited communication channels.

D. Compression Performance Evaluation

One must be aware that the aims for compression of electric signals are very different than those for other signal types. On one hand, when evaluating the performance of sound and image lossy compression schemes, one is interested in the amount of information that can be eliminated from the original signal such that the human auditory or visual system does not perceive the missing information [109], [110]. On the other hand, when compressing waveforms of electric signals, one has to verify if the distortion introduced by the compression technique leads to fault/disturbance misinterpretation by expert engineers or automated fault analysis systems. Usually, the analysis of fault recordings of electric signals encompasses detection, classification, event analysis, identification of underlying sources, source location, and operation analysis of the protection system and circuit breakers [3], [5], [6], [111].

E. Future Work

From the analysis of compression techniques for electric signals, it is clear that there is room for performance improvements. If we consider the demands related to smart grids, then the list of issues requiring research efforts increases considerably. Below we list interesting topics suitable for effort and investigation in the near future:

- The establishment a complete waveform database for fair comparison of compression techniques, considering each distinct application (like fault recording, power quality, synchrophasor), as well as distinct disturbance phenomena (like equipment fault behavior, power system fault behavior or power quality phenomena).
- The development of a set of evaluation parameters for the compression of electric signals that takes into account the analysis based on the reconstructed information.
- The definition of specifications and requirements for compression techniques applied to electric signals.
- The definition of applications and environments in which compression techniques should be applied.

Finally, by considering the smart grid paradigm as well as the future tendencies presented, the investigation of cognitive compression techniques seems to be a very promising issue to be addressed. Cognitive compression techniques are updated or reconfigured to each group of electric signals under analysis, which might result in improved compression ratio and reduced distortion. Cooperative compression techniques share information from signals acquired in different locations in order to generate more concise collective representations. A technique that unconsciously addresses this is presented in [112].

V. Conclusion

The main goal of this paper was to bring the attention to a challenging, thought-provoking, and timely research problem for automation, measurement and control of power systems in the near future. Special attention was given to the development attained so far regarding compression techniques for electric signals. The need for the introduction of powerful compression techniques for smart grid applications as well as some of the most important research challenges were addressed. Work on such challenges will contribute to the advent of novel, and low-cost devices for the widespread and successful introduction and adoption of smart sensing, monitoring, metering, diagnosis, and protection in the next generation of electric power systems, that is, for smart(er) grids.

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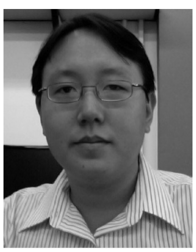

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