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Compression of electrical power signals from waveform records using genetic algorithm and artificial neural network

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ABSTRACT

This paper proposes a methodology for compression of electrical power signals from waveform records in electric systems, using genetic algorithm (GA) and artificial neural network (ANN). The genetic algorithm is used to select and preserve the points that better characterize the waveform contours; and the artificial neural network is used in the compression of other points as well as on the signal reconstruction process. Thus, the data resulting from the proposed methodology are formed by a part of the original signal and by a compressed complementary part in the form of synaptic weights. The proposed methodology selects and preserves a percentage of the original signal samples, which are aspects not explored in the literature. The method was tested using field data obtained from an oscillographic recorder installed in a 230 kV electrical power system. The results presented compression rates ranging from 8.59:1.00 to 24.16:1.00 for preservation rates ranging from 2.5% to 10%, respectively.

1. Introduction

Digital Fault Recorders (DFRs) and Digital Protection Units (DPUs) are widely used in electrical power systems to record voltage and current waveforms and digital signals (from protection functions, circuit breakers, and others) during disturbance occurrences in electrical power systems. The samples are acquired with a good time resolution for most disturbances detection and analysis applications [1]. In many applications, the information from oscillographic data can be used to detect faults occurrences in the electric system, providing information about their duration, severity and type (one-phase, two-phase, three-phase faults), their location, and even relays and circuit breakers functioning performances [1]. These applications make oscillographic data records very important to power systems operation, especially in post-mortem analysis.

Since 1980, the number of waveform records has increased due to expansion of the electrical power systems and to investments in the installation of DFRs and DPUs. In this scenario, the use of data compression techniques is very timely. Ref. [2] presented in 2014 a review of the main compression techniques devised for electric power signal waveforms providing an overview of the achievements obtained in the past decades. The methodologies for compression of electrical power signals, discussed in Ref. [2] are based on: LZW technique (Lempel-Ziv-Welch) [3,4]; Discrete Cosine Transform [5]; Transform Coding [6–12]; Approach Huffman Coding [4,13,14]; EZW (Embedded Zero-tree Wavelet) [15,16]; Matching Pursuits Algorithm [17,18]; Discrete Cosine Transform [19]; Wavelet Packet Transform [20–30]; DWT (Discrete Wavelet Transform) [31]; Wavelet Transform and Spline Interpolation and neural networks based bit allocation procedure [32–34]; and MDL (Minimum Description Length) [35] for the compression of image signals.

The lossy compression methodologies cited previously do not have the ability to select and preserve the points that better characterize the original signal contours. Preserving these points means preserving the information that characterizes the original signal, that is, for these points there is no loss of information. Considering this aspect, this paper proposes an innovative strategy that employs genetic algorithm (GA) and artificial neural network (ANN) for lossy compression of electrical power signals. This method uses GA to select a percentage of the samples (points) that better

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characterizes the original signal contours, and an ANN to compress and decompress the other points. Selecting samples (points) that better characterize the original signal contours and preserving a percentage of the original signal are aspects not explored in the examined literature. Additionally, as can be seen in references cited previously, lossy compression methodologies do not use GA, and neither GA and ANN, in conjunction, as compression and decompression tools.

2. Material and methods

2.1. Data compression using genetic algorithm and artificial neural network

The motivation for using genetic algorithm and artificial neural network for compression and decompression of electrical power signals is due to the fact that genetic algorithm is an efficient search technique in exploring the solutions space to obtain solutions close to the optimal one [36], in addition to artificial neural network ability to learn and generalize, as well as by its failure tolerance and flexibility characteristics [37]. In addition, neural networks have been applied successfully in several other problems such as presented in Refs. [38–41].

In the proposed methodology GA is used to select which are the points that better characterize the waveform contours, and the ANN acts as an interpolator for the points selected by the GA.

The method is divided into two modules: the first one, presented in Fig. 1, is responsible for data compression, and the second one, presented in Fig. 2, is responsible for data decompression.

Block (a) (Fig. 1) decodes the points stored in the COMTRADE file that contains voltage or current waveforms recorded during the event. These points, represented in Fig. 1b, form the search space, or universal set ***U***, of the GA. The GA (Fig. 1c) aims to select a set ***S*** of points that better characterizes the contours of the current or voltage signals. Therefore, each chromosome must represent a set of points, as a possible candidate for the solution. A Multilayer Perceptron ANN is trained to perform interpolation between the points selected by the GA. The training process uses the points of set ***S*** (Fig. 1d) and the points of set ***T*** (Fig. 1e), complement of set ***S*** in ***U***. The artificial neural network training (Fig. 1f) produces synaptic weights values (Fig. 1g) that contain information about the points not chosen by the GA, so as to allow the reconstruction of voltage or current signals by interpolation. Finally, the points selected by the GA and the neural network synaptic weights form the compressed signal (Fig. 1h).

The second module decompresses voltage or current signals. To rebuild the signals, the second module uses the synaptic weights (Fig. 2a) adjusted in the first module, and the points in set ***S*** (Fig. 2b), that were selected by the GA. The ANN uses the synaptic weights adjusted in its structure and the points of set ***S*** as input signals. The ANN (Fig. 2c) determines, by interpolation, an approximation of the complementary set (set ***T***) of ***S***, called ***T'*** (Fig. 2d). At the end of the process, it is accomplished a union operation (Fig. 2e) between sets ***T'*** and ***S*** (Fig. 2b), resulting in set ***U'*** whose points form the decompressed signal (Fig. 2f).

2.2. Chromosome representation

The chromosome representation in this work consists of a way to represent the points to be selected by the GA. The ordinates of the points are the values of voltage or current signals. The abscissas are values that represent the time when each ordinate was sampled. As voltage and current signals are sampled sequentially over time and with fixed sampling frequency (f), the abscissa values form an arithmetic progression with ratio equal to $\Delta t = 1/f$. Therefore, the abscissa value of each point is a function of the sample position, defined by the sampling sequence, as represented in Eq. (1).

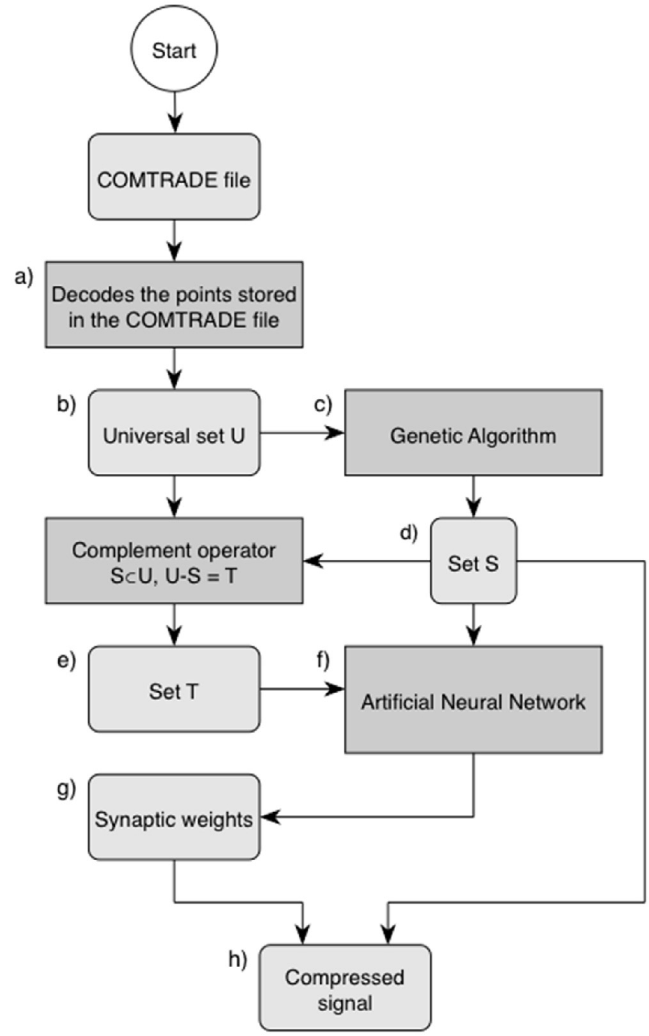

Fig. 1. Block diagram of the methodology for compression of electrical power signals from COMTRADE file.

$$t(n) = t(1) + (n-1) \cdot \Delta t \quad (1)$$

Where:

n: abscissa position in the sampling sequence;

$t(n)$: abscissa corresponding to position n in the sampling sequence;

$t(1)$: abscissa corresponding to position $n = 1$ in the sampling sequence; and

Δt: sampling period.

The sampled signal meets the concepts of function given in Ref. [42], and there is a two-way relationship, given in Eq. (1), between the abscissas and their positions in the sampling sequence. Thus, the points selected by the GA can be represented in the chromosome by their positions n in the sampling sequence. So, the chromosome is divided into genes (Fig. 3), where each gene encodes the abscissa position by 0 s and 1 s.

The number of bits in each gene is defined in Eq. (2) as:

$$Q_{bits} = log_2 \left[\left(V_{upper} - V_{lower} \right) \cdot 10^{ps} + 1 \right] \quad (2)$$

Where:

Q_{bits}: number of bits of the gene;

V_{lower}: lower value of the range $[V_{lower}, V_{upper}]$, and it is equal to 1 because it is the first sample;