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Non-linear transducers I/O modeling by ANN based on Harmonic Domain

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Abstract. Modeling the non-linearity of transducers such as inductive voltage transformers is challenging for metrologists. This paper presents a methodology to model non-linear transducers through a black-box approach. First, input and output signals are decomposed into harmonic components, to be mapped by an appropriate Artificial Neural Network (ANN). To support the choice of the ANN general features, we perform simulations in the Harmonic Domain (HD). That way, harmonic interactions due to non-linearity effects are considered by the procedure, which can be used in either single or multi-tone approaches. The proposed methodology is then used to characterize the metrological performance of one voltage transformer submitted to multi-harmonic signals.

1. Introduction

The rise of distributed generation and the increase of non-linear loads in power systems progressively introduce considerable harmonic distortion in the grid [1]. Meanwhile, voltage and current transducers, originally designed to operate in a typical sinusoidal scenario, are still commonly used in measurement systems, for high voltage (instrument transformers) and low voltage (voltage dividers, shunts, transformers, inductive dividers) circuits. However, in most cases, transducers are characterized only at the fundamental frequency, and in a wider frequency range only with a single-tone approach [2], which is not able to take into account harmonic interactions. Those interactions may occur if the transducer under test has significant non-linearity, and they are particularly observed when one deals with multi-harmonic signals.

In this work, we present a method for modeling a transducer from its input and output signals decomposed into harmonic components and mapped by Artificial Neural Network (ANN). The procedure is capable of considering typical nonlinear effects of transducers, as well as the uncertainty of measurements with different harmonic compositions. First, to define the main features of the ANN (such as network architecture and training algorithm), we perform computer simulations considering a hypothetical transducer with known typical nonlinearities, with its input and output signals represented in the Harmonic Domain (HD). Also, we can check the ANN's ability to map nonlinear relationships in a typical multi-harmonic signal scenario. Finally, the method is used to obtain a voltage transformer (VT) model from real input and output measurements of distorted signals.

2. Non-linearity representation in Harmonic Domain

For a mathematical representation of nonlinear systems, the typical analysis performed with Fourier Series components ignores an important characteristic resulting from the non-linearity of some electrical equipment: the coupling of distinct frequency components. Alternatively, one can perform nonlinear modeling in the HD, which is considered an extension of the Fourier-based frequency domain, widely used in power system modeling [3]. Aiming at demonstrating the capability of our proposed methodology to map harmonic couplings, we implemented an algorithm for calculating, in the HD, the output signals of a known transducer, from its input signal, also represented in the HD.

Let the harmonic function in equation (1) represent the input signal of a nonlinear transducer.

$$x(t) = \sum_{i=-h}^{h} X_h e^{jh\omega_0 t} \Rightarrow \mathbf{X} \quad . \tag{1}$$

The HD vector form of *x(t)* is represented by **X**, composed by its respective coefficients of the complex exponential series. Each coefficient is related to the order of the associated harmonic component. In the same way, *y(t)* represents the output signal, and its HD vector form is represented by **Y**.

The transducer is modeled by a nonlinear polynomial function in equation (2) where q is the polynomial order, and b_q is the respective coefficient.

$$y(t) = \sum_{q=0}^{n} b_q x^q(t) \quad , \tag{2}$$

As input data, we consider the harmonic components of the transducer input signals. The output data is given by the HD calculation algorithm. According to [3], the polynomial evaluation via repeated convolutions, given by

$$\mathbf{X}^q = \mathbf{X}^{q-2} \circledast \mathbf{X}^{q-1} \quad , \tag{3}$$

is an appropriate tool to represent non-linearities in HD, being able to take into account harmonic interactions between components.

3. I/O non-linear mapping investigation using HD

In order to find a suitable network architecture and training algorithm to perform the non-linear mapping of the transducer, we carried out a set of simulations using the HD algorithm. To simulate real measurements, a set of input vectors **X** was generated for each applied waveform, considering the magnitude of each harmonic component as a random variable, with a range of a few units at 10^{-6}. The transducer under test was modelled by equation (2), considering its non-linearity as known (with q = 3). The respective output vectors **Y** were calculated by the HD algorithm (Flux 1). It should be noted that this stage aims to generically assess the ANN ability to map a non-linear relationship generated in the Hd. These are non-specific tests carried out to evaluate the adherence of different architectures, using only simulated data in HD.

The ANN was implemented by the *Matlab Neural Network Toolbox*, due to its versatility to evaluate different network configurations [4]. A preliminary investigation showed that the *feedforward backpropagation* type ANN is a suitable alternative for performing the nonlinear I/O mapping. For layer composition, neurons with *sigmoid* activation functions were used, as shown in the schematic diagram presented in figure 1 (Flux 1). First, part of the *dataset* is used to perform the supervised training. Several training algorithms were evaluated, and the Levenberg-Marquardt (LM) presented the most suitable results for the evaluated set of waveforms. A comparison of the ANN and the HD model outputs showed differences between the ratio of each harmonic components lower than few parts-per-million.

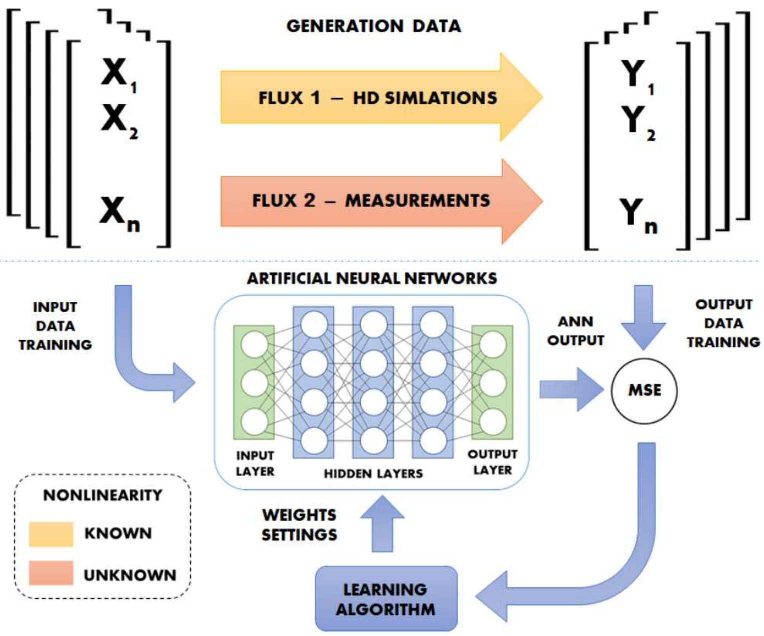

Figure 1. Schematic diagram presenting the two ANN training processes.

4. ANN implementation for real measurements

After carrying out the general investigation on the architecture of the ANNs in the previous section, we implemented the method using real measurements of a low voltage transformer (VT) with unknown nonlinearity. The measurement setup is presented in figure 2. The metrological characterization of the VT was performed at the 240:120 ratio. Waveforms with different harmonic compositions were applied by an Arbitrary Waveform Generator (AWG) and an amplifier. Two resistive voltage dividers (RVD) previously characterized at the investigated frequencies and two synchronized digital multimeter 3458A (DMM) were connected to the RVD to sample the input and signals. Data acquisition was carried out using the *TWM software* - *TracePQM* [5] and a FFT algorithm implemented in Matlab. The measurement system uncertainty does not exceed 10 ppm.

Hundreds of measurements were performed and stored in the input and output vectors, as can be seen in figure 1 (Flux 2). The ANN was trained by the same procedure described in section 3. Figure 3 presents a comparison of fundamental frequency VT ratio under different multi-tone input signals, where relative deviations of up to almost 500 ppm show evidence of the nonlinear effect of other harmonic components on the fundamental. Meanwhile, the ANN adherence proved to be an adequate model, showing deviations from the measurements not greater than a few parts-per-million.

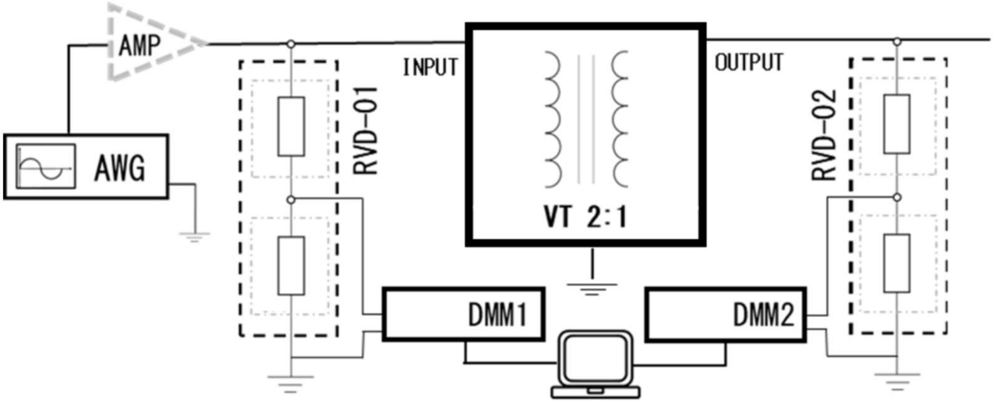

Fig. 2. Measurement setup squematic diagram

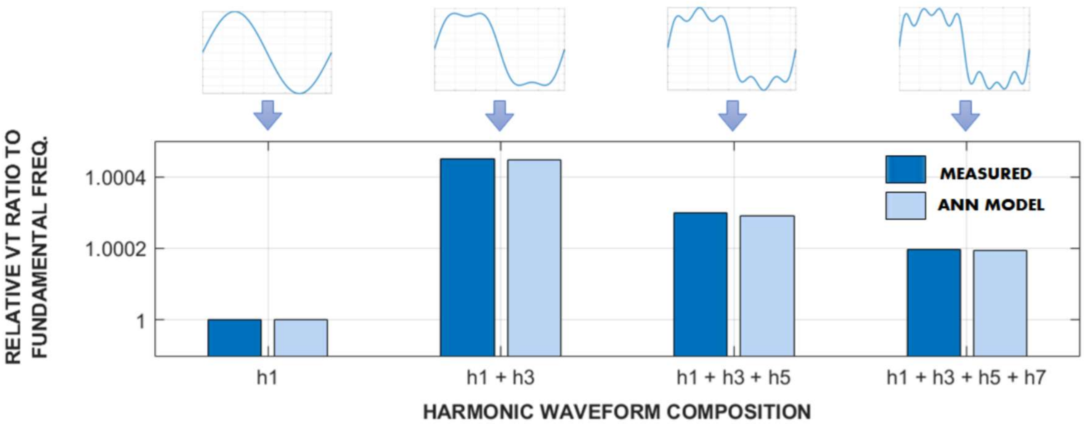

Fig. 3. Relative ratio comparison for the fundamental component measured under different harmonic waveforms composition.

5. Conclusions

The obtained results suggest that the proposed method is a promising alternative to deal with multi-harmonic signals in a metrological scenario. The simulations performed in HD can give a mathematical support for the ANN implementation strategy, since the nonlinearity is known. For real measurements, the ANN was able to perform an accurate I/O mapping in the analyzed frequency range, with deviations from the measured fundamental ratio not exceeding a few parts-per-million, compatible with the measurement uncertainty. Besides, for the modeling of the VT displacement, preliminary results indicated a very similar behavior of the proposed method, especially regarding to ANN adherence. However, some issues regarding synchronized I/O measurements in higher frequency ranges demand further investigation. It is also worth evaluating cases with more complex waveforms in wider frequency ranges. Finally, a thorough evaluation of the method's performance is necessary, as far as an estimation of the ANN model´s contribution to the overall uncertainty.

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