Neuro-fuzzy modeling and prediction of current total harmonic distortion for high power nonlinear loads

Manuela Panoiu, Caius Panoiu, Loredana Ghiormez
Electrical Engineering and Industrial Informatics Department
Polytechnic University of Timisoara
Romania
manuela.panoiu@fih.upt.ro, caius.panoiu@fih.upt.ro, loredana.ghiormez@fih.upt.ro

Abstract—The paper presents the results of the modeling and the prediction of the total harmonic distortion (THD) of the current and the voltage for a nonlinear high power load. Modeling was performed using intelligent techniques based on neural networks and fuzzy inference. To achieve this, data were measured in the electrical installation of a non-linear electrical load, in this case a high-power electric arc furnace. These data were measured over the entire duration of a steel charge. The measured data was used to train a neuro fuzzy adaptive system. Following training, tests with different architectures have been performed with the neuro fuzzy adaptive system. The modeling and prediction results are useful in designing harmonic current filters. The presence of these harmonic currents decreases productivity and affects the quality of power.

Keywords—modeling and prediction; total harmonic distortion; ANFIS; fuzzy

I. INTRODUCTION

Nonlinear loads, especially high power, reduce the quality of electricity in the power supply network. Thus the following effects occur: high reactive power, low power factor, high values of harmonic currents and harmonic voltages, sometimes even unbalance between phases in high power loads [1-5]. Such a high power nonlinear load is an Electric Arc Furnace (EAF). Therefore, some actions are needed to limit these negative effects. These actions include power factor compensation, harmonic current filtering, load balancing, flicker effect, and others [6], [7], [8]. All these actions require design of equipment, design that will ensure at least partial elimination of undesirable effects. For example, harmonic current filtering requires the design of harmonic current filters. In the case of high power loads, it is difficult to design without being able to test the projected filters. A test on the real system is difficult to do in the case of high power loads. That is why it would be useful to be able to do a simulation based on a model of the system. For this purpose, a neuro fuzzy modeling of the harmonic distortion of the current and the voltage followed by a prediction of the variation of these values was made. This approach has been made by other researchers and the results are presented in other scientific articles [9-13]. To perform this modeling, measurements were made in the installation of an electric arc furnace [12], [16], [17], and [18]. As a result of these measurements, curves of variation of total harmonic distortion for current and voltage were obtained. These data were used to train a neuro fuzzy system.

II. PERIODIC NON-SINUSOIDAL SIGNALS

A periodic function with the T period is defined by

\[ f(t) = f(t + T) \] (1)

The periodic function represented by the Fourier series:

\[ f(t) = \sum_{k=1}^{\infty} c_k \cdot \sin(k \omega t + \phi_k) \] (2)

where:

\[ c_k = b_k + j a_k = c_k \cdot e^{j \phi_k} \] (3)

and

\[ \phi_k = \arctg \frac{a_k}{b_k} \] (4)

The criteria of quantitative analysis of the harmonics composition in the structure of a signal are [9]:

Harmonic level - is the ratio expressed as a percentage of the effective value of the considered harmonics \((F_k)\) and the effective value of the \(F_1\):

\[ \gamma_K = \frac{F_k}{F_1} \cdot 100 \% \] (4)

The Total Harmonic Distortion coefficient is defined as the ratio of the RMS of all the harmonic frequencies (from the 2nd harmonic on) over the RMS voltage of the fundamental frequency:

\[ THD = \sqrt{\sum_{k=2}^{40} \left( \frac{F_k}{F_1} \right)^2} \cdot 100 \% \] (5)
III. RESULTS OF TOTAL HARMONIC DISTORTION MEASUREMENTS OF AN ELECTRIC ARC FURNACE

The measurements were made in the electrical installation of an EAF with the capacity of 120 tons and the power of 105 MVA. The furnace feeds from a 230 kV / 33 kV transformer. The EAF is powered from the 33 kV line. The currents and voltages were measured on the 33 kV line using a DAQ board as can be seen in figure 1. The acquisition was made during the duration of an entire charge of steel. The values of THD for voltages and currents are calculated using the relation (5), where \( F \) represent current or voltage. Figure 2 shows the variations in total harmonic distortion of current and voltage on the medium voltage line for 1200 samples.

System modeling using conventional mathematical methods (such as differential equations) is not possible if the modeling system is affected by uncertainties or nonlinearities. For such cases a neuro-fuzzy inference system using fuzzy rules can model the qualitative aspects of human reasoning without using quantitative analysis [10], [11], [12], [15], and [16].

![Data acquisition diagram](image1)

**Fig. 1.** Data acquisition diagram

To perform the prediction with a neuro fuzzy system, the Neural Networks Toolbox in Matlab was used [19]. This package contains a number of functions for training and simulating neural and fuzzy systems. Thus, an application was implemented that allows the modeling of the variation of the total harmonic distortion of the current and the voltage using ANFIS.

![Graph showing variations in THD for current and voltage](image2)

**Fig. 2.** The variation of THD for current and voltages for 1200 samples

IV. MODELING AND PREDICTION RESULTS WITH ANFIS

ANFIS is a type of artificial neural network based on the Takagi-Sugeno fuzzy inference system. ANFIS integrates both neural networks and fuzzy logic principles and therefore has the potential to capture the benefits of both in a single system. [19] ANFIS is an adaptive network that uses supervised learning, which has a function similar to the model of Takagi–Sugeno fuzzy inference system [19]. The ANFIS architecture is shown in Figure 3.

The values of the current and voltage total harmonic distortions measured in the installation of an electric furnace from an industrial plant were used as data for the ANFIS system. To obtain results close to reality, a number of samples were chosen to train as much as possible so that the system could learn the characteristics of the modeling system, i.e. the variation of total harmonic distortions.
Figure 2 also shows how training data is selected for prediction. As can be seen, the number of samples is 1200. From these samples, the first 800 were used for training and learning of the system characteristics, and for the testing and prediction the last 400 samples were used. The Matlab application that models the total harmonic distortion for current and voltage is implemented as follows: In the first step, the number of samples used for training and the number of samples used in the prediction were selected. To do this, we chose the ratio of 2/3 data used for training and 1/3 data used for prediction. This report can be changed later. Then the vectors with data indices used for training and testing were built. These vectors are then used for the selection of test and training samples.

To make a prediction with ANFIS, it is necessary to know the values of the time series until time \( t \) to be able to predict the value at a time \( t + p \). The standard prediction method is to create a mapping from \( N \) samples sampled at \( d \) time units \((t-(N-1)d), x(td), x(t)\) to predict a future value \( x(t+p) \).

For example, in the case presented in the paper, for \( N = 5 \), \( d = 4 \), \( p = 4 \) will be created the vector with data to drive a vector with 5 columns:

\[
[x(t-16) x(t-12) x(t-8) x(t-4) x(t)]
\]

To predict \( x(t+4) \).

In our paper \( x \) represent THD for current or voltage.

Matlab has been used to implement modeling and prediction because it provides a powerful toolbox for neural networks and fuzzy inference [20]. A number of \( N = 5 \) previous samples and \( d = 2 \) was chosen to predict a value at time \( p = 2 \).

The fuzzy inference system was implemented using 3 methods: a default method - "grid partition" - the second method - "Subtractive clustering" - and the third method of center selection "FCM".

In the paper are presented the results of modeling and prediction using these three methods for a number of \( N = 5 \) previous samples and for \( d = 2 \).

An error analysis for values of \( N = 3, 4, 5 \) and for \( d = 1, 2, 3, 4, 5 \) is also presented.

A. ANFIS based on grid partition

This is the default method used by Matlab ANFIS to generate the Sugeno – type fuzzy inference system (FIS). To generate the inference system it must be choose first the number of membership functions, then the type of input and output membership functions (constant or linear). Two fuzzy sets were chosen for each input. Figure 4 shows the ANFIS structure. The number of rules used by this method is 32. It can be seen from Figure 4 that the system architecture includes a large number of neurons on the rule layer. This may be a reason to slow down the training process.

Figure 5 shows modeling and prediction results for a number \( N = 5 \) and \( d = 2 \) using the grid partition generation method for FIS. Also in Figure 5 we can see the error variation and the standard deviation. It can be noticed that the errors are higher in the test region. The system with 3 fuzzy sets was tested on each input, but the training process takes too long.

B. ANFIS based on subtractive clustering

The technique "Clustering" of numerical data is the basis of several algorithms for classification and system modeling. The purpose of the data grouping is to identify the natural clustering of the data belonging to a large set of data and to produce a concise representation of the behavior of the system [20], [21], and [22]. The ANFIS training parameters are: influence radius \(= 0.3 \), maximum epochs \( = 100 \). The ANFIS structure are show in figure 6.

It can be seen that the ANFIS architecture has 6 neurons in the rule layer, and 6 fuzzy sets on each input. The architecture is derived from the radius influence parameter. The smaller this is, the higher the number of fuzzy sets.

Figure 7 shows modeling and prediction results for a number \( N = 5 \) and \( d = 2 \) using the subtractive clustering generation method for FIS. Also in Figure 7 we can see the error variation and the standard deviation.

It can be noticed that the errors in the test region are higher than in the train region but not as high as the grid partition method.
The influence radius parameter influences the network architecture. For example, for radius influence = 0.8 the network architecture will have two fuzzy sets for each input and two neurons in the rule layer.

C. ANFIS based on Fuzzy C-Means Clustering

It is a method that shows how to group objects that populate a multidimensional space into a specified number of different classes. It starts with an initial estimate of the group centers and is assigned randomly to each object a degree of belonging to each group. Finally, iterative updating of group centers and membership levels results in a number of groups whose centers do not necessarily coincide with clustering objects.

We chose 10 clusters for training ANFIS. Thus, in ANFIS architecture there will be 10 neurons on the rule layer and 10 fuzzy sets for each input like can be seen in figure 8.

Figure 9 shows modeling and prediction results for a number N = 5 and d = 2 using the subtractive clustering generation method for FIS. Also in Figure 9 we can see the error variation and the standard deviation.

Analyzing these results we can see that the errors are comparable to those obtained with the subtractive clustering method.
The initial cluster number influences the network architecture. But if it starts with too many clusters, the training process takes too long.

Table 1 compares the results obtained with the three methods of generating FIS. Comparisons were made in terms of RMS error for training and testing for different architectures of ANFIS. ANFIS architectures that generate FIS were used using the three methods and with the N and d parameters resulting from the table.

V. CONCLUSIONS

The paper presents a study regarding the modeling and prediction of the total harmonic distortion of the current appearing in the medium voltage installation of an electric arc furnace. Modeling is done with ANFIS in Matlab. From the study we found that ANFIS learned very well how to modify THD. Thus, following a training with 800 samples, the system manages to supply THD variation for another 400 samples with very low errors.

It was also attempted to train with different values of the number of samples from all the samples. It has been found that if the number of samples used in training is lower than the one used in testing, the system fails to model correctly.
<table>
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<th>d</th>
<th>Grid partition</th>
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Fig. 9. Modeling and prediction results for ANFIS training using Fuzzy C-Means Clustering
REFERENCES


