Artificial neural networks in predicting current in electric arc furnaces

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Abstract. The paper presents a study of the possibility of using artificial neural networks for the prediction of the current and the voltage of Electric Arc Furnaces. Multi-layer perceptron and radial based functions Artificial Neural Networks implemented in Matlab were used. The study is based on measured data items from an Electric Arc Furnace in an industrial plant in Romania.

1. Introduction
The Electric Arc Furnace (EAF) is used in the melting process of the scraps which are loaded in the furnace tank. The EAF is one of the modern ways of making steel, but having very large power input ratings. It also behaves like a nonlinear load and can cause large power quality problems, mainly harmonics, interharmonics, the flicker phenomenon and voltage unbalances. Because of these, solutions must be identified through which these disturbances should not be injected in the power supply network. So, the prediction of the future values of the current arc and voltage is need. Based on these values actions can be taken to mitigate (lessen) the disturbances.

2. The AC Electric Arc
The power supply equivalent diagram for a single phase is show in figure 1, where r and L being the resistance, respectively the equivalent inductance of the supplying circuit, and Rₐ and vₐ the resistance of the electric arc, respectively the arc voltage [1]. The waveforms of the electrical issues (current arc, voltage arc and voltage supply) are also show in figure 1.

3. Modelling the AC Electric Arc
EAFs are used in the production of steel and other metals. EAFs are very large, dynamic and time varying loads due to the nonlinearity of the electric arc. Electric-arc steelmaking generally has two successive stages, a melting stage and a refining stage. For these reasons it is very difficult to find an accurate model for the electric arc. In the reference literature many modeling methods can be found: nonlinear resistive models [3], [4] voltage source models [5], [6] models based on V-I characteristics of the EAF [7], models based on relations between the length of the arc, the voltage and the current of the arc [2], model that used chaos theory [8] and advanced models that use neural networks and fuzzy logic [8-12].
In this paper, in order to model the electric arc, two types of Artificial Neural Networks (ANN) were used: multi-layer perceptron ANN and radial based functions ANN. In order to develop a model based on ANN, actual recorded data from the electrical installation of an EAF are necessary. These data are obtained by measuring the voltages and currents in the secondary side of furnace transformer of an EAF with the capacity of 100 tones [1]. The frequency of acquisition was 5 kHz. The measured data, both from the melting stage and from the refining stage, has been used for ANN training.

3.1. Model based multi-layer-perceptron ANN
A multi-layer-perceptron ANN is a feedforward artificial neural network with one input layer, one output layer and one hidden layer. In figure 2 a multi-layer-perceptron ANN is shown.

ANN architecture affects the performance of electric arc modelling. In [13] a study regarding the influence of the ANN architecture to the electric arc model in Matlab was performed. The best results were obtained for a number of neurons in the hidden layer greater than 100. But by over-increasing the number of neurons, the validation and the testing performance of the neural network begin to decrease because the network loses its ability to generalize (overtraining phenomenon).

Based on this study, the architecture of the multi-layer-perceptron was chosen with 80 hidden neurons and a learning rate of 0.8. Other training parameters are: the training function was trainlm, from the Matlab Neural Networks toolbox, trainParam.max_fail = 6, trainParam.epochs = 500. For these values the simulations results for the melting stage are presented in fig. 3 and the ones for the refining stage in figure 4. Figure 3a presents the variation for the measured and simulated voltages, figure 3b presents the variation for the measured and simulated currents and figure 3c presents the voltage – current characteristics of the electric arc for both measured and simulated values (for melting
stage). In figures 4a, 4b and 4c similar results are shown but for the refining stage. The results are shown for a single phase in order to obtain a clearer image. By analysing the results, it can be concluded that, in the case of the currents, both for the melting and the refining stage, the prediction is better.

![Figure 4a](image1.png)

![Figure 4b](image2.png)

![Figure 4c](image3.png)

**Figure 3.** Comparisons between measured and simulated items for the melting stage
a) Variation of measured and simulated voltages  b) Variation of measured and simulated currents  
c) The current – voltage characteristics (measured and simulated)

**Table 1.** The Total Harmonics distortion and the pondered Total Harmonic Distortion for measured and simulated data set (from figure 3).

| Electric parameter | Measured values | Simulated values |
|--------------------|----------------|-----------------|
| Thdi               | Phase 1 3.03%  | 9.70%           |
|                    | Phase 2 2.04%  | 6.46%           |
|                    | Phase 3 2.18%  | 14.50%          |
| Thdu               | Phase 1 8.36%  | 6.27%           |
|                    | Phase 2 7.92%  | 10.54%          |
|                    | Phase 3 9.04%  | 8.72%           |
| Thdpi              | Phase 1 7.08%  | 20.05%          |
|                    | Phase 2 4.59%  | 13.98%          |
|                    | Phase 3 5.22%  | 31.24%          |
| Thdpu              | Phase 1 20.59% | 13.74%          |
|                    | Phase 2 20.02% | 22.22%          |
|                    | Phase 3 26.55% | 20.20%          |
For the analysed data, the main electrical parameters of the power quality are also determined and presented in table 1. Hence, the total harmonic distortions of the current and the voltage for all three phases are determined.

![Figure 4](image.png)

**Figure 4.** Comparisons between measured and simulated items for refining stage
a) Variation of measured and simulated voltages  
 b) Variation of measured and simulated currents  
 c) The current – voltage characteristics (measured and simulated)

### 3.2. Model based on radial bases functions ANN

The radial-basis function artificial neural network (RBF-ANN) is an alternative to the multi-layer perceptron and has gained attention in many applications in recent years due to its simpler structure [12], [14].

RBF-ANN is a feedforward neural network with a much simpler structure than MLP-ANN. A typical structure of RBF-ANN is shown in Figure 5, including the input layer, the hidden layer, and the output layer [14]. The input-output connection consists of two transformations: a nonlinear transformation from the input layer to the hidden layer and linear transformation between hidden and output layers. The RBF networks learn supervised with increasing rates, being designed as functional approximation methods ("curve fitting").

RBF-ANN generally are used for the approximation of curves in multidimensional space. Learning is equivalent to finding a surface in a multidimensional space to match (fit) as described by the input data.
Compared with the multi-layer perceptron networks (RNA MLP) RBF ANN may require more neurons but their training requires less time. This is because the output neurons of the hidden layer MLP are significant for large regions of the input space while the radial functions based on neurons respond only to relatively small regions of the input space. RNA RBF responds better when more vectors are available.

The most common radial basis function used in RBF-ANN is given by

\[
\phi_k(x) = \exp\left(-\frac{(x - wc_k)^T(x - wc_k)}{2\sigma_k^2}\right)
\]

Where \(x\) is the input vector data, \(wc_k\) is central vector for a hidden neuron, \(\sigma_k\) is the normalization factor.

By using the measured values of the current and of the voltage at the RBF-ANN input as input vectors, respectively estimated values, an approximation for the current voltage characteristic \(V-I\) can be obtained.

The training parameters used by newrb function from the Matlab Neural Network Toolbox were \(eg=0.1\) (Mean squared error goal) and \(spread = 2\) (Spread of radial basis functions).

In figures 6 and 7 the results of the simulation are shown.

4. Conclusions

In this paper two ANN architectures for the modelling of the electric arc were studied: the multi-layer perceptron ANN (MLP-ANN) and the radial based functions ANN (RBF-ANN). The ANN models were implemented in Matlab 2012 environment. The training and testing results obtained were used to implement an ANN model that can estimate the voltage – current characteristic for both stages of an EAF process: the meltdown stage and the refining stage. The reliability of the predicted currents not only depends on the ANN architecture but also on the input data. Both qualitative and quantitative comparisons were made for the electrical parameters between the simulation results and the performed measurements. By observing the results, it is noticeable that the current waveforms are closely matched by using these advanced models (based on ANN) due to the direct usage of currents as the inputs of the models.
**Figure 6.** Comparisons between measured and simulated items for the melting stage

**Figure 7.** Comparisons between measured and simulated items for the refining stage
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