APPLYING ARTIFICIAL NEURAL NETWORKS TO ENERGY QUALITY MEASUREMENT

Fernando Soares dos Reis
Fernando César Comparsi de Castro
Maria Cristina Felippetto de Castro
Uiraçaba Abaetê Solano Sarmanho
Luciano Chedid Lorenzoni
Pontifícia Universidade Católica do Rio Grande do Sul
Avenida Ipiranga, 6681 – Porto Alegre, RS – Brasil CEP: 90619-900
f.dosreis@ieee.org

Abstract – **This work applies an Artificial Neural Network for noisy sinusoidal signals filtering which stem from the electric power network. An eigenfilter is implemented by means of a linear neural network trained by the Hebbian Learning Algorithm. The obtained results show that the noise component is minimized with no phase lag.**

KEYWORDS

RNA, Filtering, Power, Hebbian.

I. INTRODUCTION

Market-optimized solution for electric power distribution involves energy quality control. In recent years the consumer market has demanded higher quality standards, aiming efficiency improvement in the domestic as well industrial uses of the electric power. Electric power quality can be assessed by a set of parameters which includes Total Harmonic Distortion (THD), Displacement Factor, Power Factor, among others. These parameters are obtained by measuring the voltage and current in the electric bus for which is desired to perform the quality assessment. Most measurement systems employ some filtering in order to improve the measured parameters. However, it is crucial for the measurement performance that the filter does not introduce any phase lag in the measured voltage or current. In this work, a linear Artificial Network (ANN) trained by the Generalized Hebbian Algorithm (GHA) is used as an engenfilter [1], so that a measured noisy sinusoidal signal is cleaned, improving the measurement precision.

A linear ANN which uses the GHA as learning rule performs the Subspace Decomposition of the training vector set [1]. Each subspace, into which the training set is decomposed, contains highly correlated information. Therefore, since the auto-correlation of the noise component is nearly zero, upon reconstructing the original vector set from its subspaces, the noise component is implicitly filtered out.

II. HEBBIAN RULE

The older rule of learning is the postulate of Hebb´s learning. Hebb based it on the following observation of experiments neurobiological: If neurons on both sides of a synapse are activated synchronous and repeatedly, the force of the synapse is increased selectivity.

Analytically the Hebb´s rule can be described according to the Equation 1:

$$w_{ij}(t+1) = w_{ij}(t) + \eta y_j(t) x_i(t) \qquad (1)$$

Where x_i and y_j are, respectively, the values of exit of the neurons i and j which are connected by the synapse w_{ij}.η is the learning tax. Observe that x_i is the entrance of the synapse.

An important property of this rule is that the learning happens locally, that is, the alteration in the weight of the synapse only depends on the activity of the two neurons by the synapse connected. This simplifies in a significant way the complexity of the learning circuit.

A single trained neuron using the Hebb´s rule presents orientation selectivity. The Figure 1 demonstrates this property. The indicated points are drawn starting from a distribution two-dimensional Gaussian and they are used to train a neuron. The vector of weights of the neurons is initialized as indicated. As the training continues the vector of weights moves progressively closer of the direction w of maximum variance in the data. In fact, w is the eigenvector of the data covariance matrix that corresponds to the largest eigenvalue.

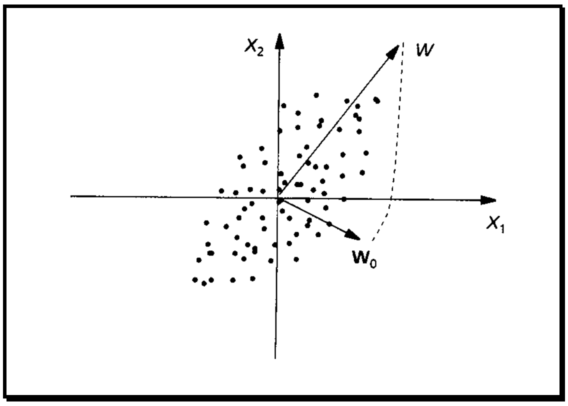

Figure 1. Only trained neuron using the Generalized Hebbian Algorithm (GHA) presents an orientation selectivity.

III. GENERATION OF THE ENTRANCE VECTOR

Through the simulation in MathCAD software sinusoidal signs of noisy positive semi cycle (with harmonic components) were generated, divided in one hundred sixty seven points each one of the ten samples, according to display the Figure 2.

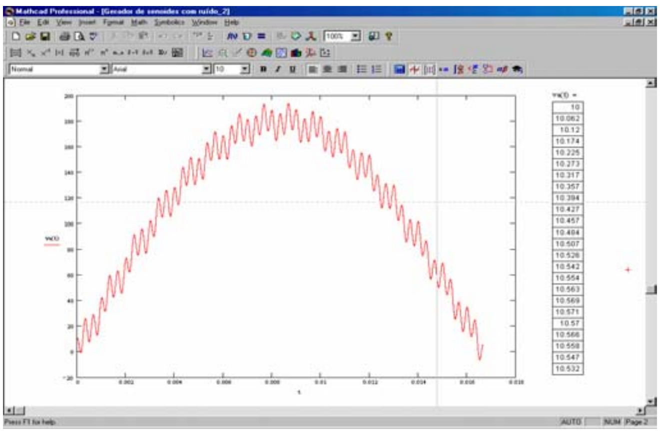

Figure 2. Environment of data generation.

IV. PARAMETERS OF THE NEURAL NETWORK (NN)

The subject was treated through an input-output mapping associating data and results obtained with the model developed in MathCAD software, as already described, using the associated data and results as inputs of the NN. The net was parameterized considering only three sub-spaces of the initially presented one hundred sixty seven. The core of the problem was that the eigenvalues were adjusted in the direction of the eigenvectors in order to be considered just the fundamental components of the sinusoidal waves, disrespecting the other noise signs.

Those are the parameters of the net:

A. The Entrance Vector

The size of the entrance vector is ten samples (ten positive semi cycles with different noises) in R^{167} (hundred sixty seventh order), due to the one hundred sixty seven points belonging of the sampled sinusoidal waves.

B. Sub-spaces

The number of considered sub-spaces was three, because in this application the objective was to extract the fundamental sinusoidal wave.

C. Initial Learning Tax

The learning tax (the speed in which the neural network learns) used was $1x\ 10^{-20}$, what is considered a slow tax, due to the dimension of the entrance vector.

D. Training Window

The training window size used was sixty, what represents the number of neurons simultaneously trained.

E. Alpha Tax

The alpha tax (parameter that adjusts the speed of net convergence) used was of 1500, providing a slow convergence, due to the dimension of the entrance vector.

F. *Training Season*

The maximum number of training seasons (in which the entrance vector was presented to the neural network) was one thousand.

G. *Initial Synapses Interval (R)*

The used interval was [–7.5; 7.5], where R is calculated starting from the average of the synapses number by neuron (the entrance and exit connections that allow a neuron to interact with the others).

V. RESULTS ANALYSIS

The results were shown satisfactory, because the Neural Network got to filter the signs with harmonic content. In some cases the filtering was not of extreme effectiveness, but it presented purest waveforms than the originally presented to the net.

Some of the obtained results are presented in the figures below. In the graphs are indicated the *Entrance (E),* the *Exit (S)* and the *Difference (D)* that consists of the *Noise (D = E-S)*. For the best visualization the *Entrances (E)* curves were moved, not representing a DC gain.

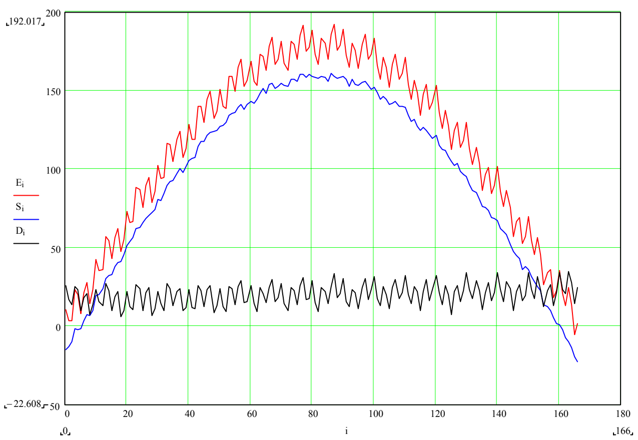

Figure 3. Graph of the 1st sample with the positive semi cycles of the *Entrance (E) and Exit (S)* sinusoids and the *Difference (D)*-that represents the Noise.

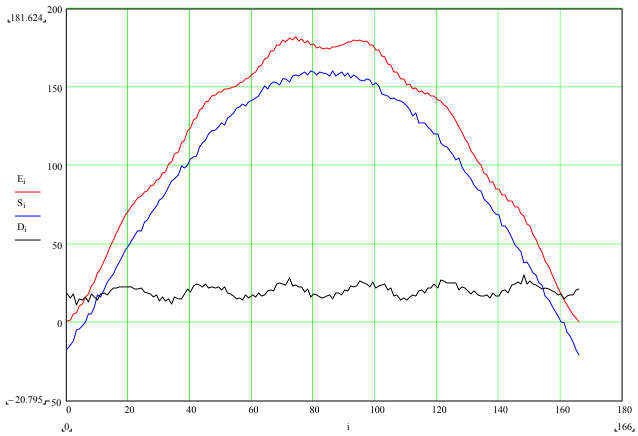

Figure 4. Graph of the 5th sample with the positive semi cycles of the *Entrance (E) and Exit (S)* sinusoids and the *Difference (D)*-that represents the Noise.

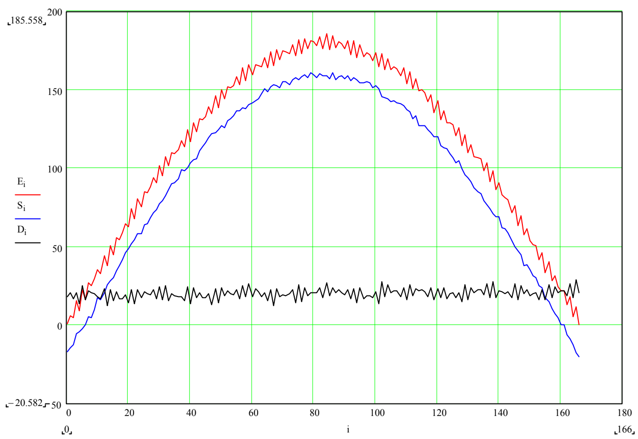

Figure 5. Graph of the 6th sample with the positive semi cycles of the *Entrance (E) and Exit (S)* sinusoids and the *Difference (D)*-that represents the Noise.

VI. CONCLUSIONS

The results obtained in this work demonstrate the capacity of NNs through the Hebbian Algorithm in accomplishing with success the filtering of harmonic content and noise in the power line. With the obtained good results, it fits to propose new studies of the NN in order to optimize such results. The practical implementation of the same would be the object of a next stage.

REFERENCES

[1] Haykin, S.; Neural Networks: A Comprehensive Foundation. EUA: Prentice Hall, 1999.

[2] Bishop, C. M.; Neural Networks for Pattern Recognition; Oxford University Press; 1995.

[3] Braga, A. P., Carvalho, A. P. L. F., Ludemir, T. B.; Fundamentos de Redes Neurais Artificiais, 11ª Escola de Computação; Rio de Janeiro, de 20 a 24 de julho de 1998.

[4] Zurada, J. M.; Introduction to Artificial Neural Systems; PWS Publishing; 1992.

[5] John Hertz, Andres Krogh e R. G. Palmer, Introduction to the Theory of Neural Computing, Lecture Notes Vol. 1, Santa Fe Intitute, Studies in The Sciences of Complexity, Addison-Wesley Publishing Company, 1991.

[7] Jacek M. Zurada, Introduction to Artificial Neural Networks, West Publishing Company, 1992.

[8] Philip D. Wasserman, Advanced Methods in Neural Computing, Van Nostrand Reinhold - NY, 1993