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Neural Networks for Estimation of Iron Losses in Ferromagnetic Cores

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Abstract: - A Neural networks (NNs) approach is presented for evaluating the frequency dependent iron losses in ferromagnetic cores. The architecture of the implemented neural network is a feed-forward net, but, instead of the usual classical gradient descendent algorithm, the present approach is based on a genetic algorithm training. The use of the genetic algorithms avoids local minima in the optimization of the synaptic weight space (NN training). The implemented NN has a single input (the frequency of the imposed field source), and a single output (the iron loss). Validation versus experimental data is presented.

Key-Words: - Neural Networks, Genetic Algorithms, Hysteresis, Fourier Analysis, Iron Losses

1 Introduction

The prediction of the frequency dependent iron losses is a fundamental task in magnetic machines and sensors design. The computation of losses is classically performed by approaches involving the implementation of static hysteresis models (i.e. Jiles or Preisach) added with eddy currents and anomalous losses computation methods (e.g. FEM). These approaches are further complicated in presence of non sinusoidal excitations: the determination of suitable model parameters and adequate meshing in FEM application is strongly required. The aim of the present paper is to describe an alternative approach for the prediction of dynamic hysteresis losses under pure sinusoidal excitations by using Neural Networks (NNs). In many cases the data sheets of a particular material furnishes the hysteresis loops for a generic number of frequencies. Thus, it is possible to determine the iron losses per unit of volume at each experimental frequency by evaluating the loop area. By means of the Fourier Descriptor [1] the loop area evaluation can be performed in all cases in which the hysteresis loop shape is assigned. Several computed (or measured) losses for a set of frequency have been used to train Neural Networks. In particular a NN having a single input neuron (the frequency) and a single output neuron (the corresponding loss) has been designed. After training the NN is able to predict any loss referred to an out-of-training frequency. It is evident the utility of this tool for designers. The training algorithm of the implemented NN has been designed by exploiting Genetic Algorithms (GAs) instead of the usual gradient descendent algorithm used for classical back-propagation networks. In this way it has been possible to avoid to stop the training in a local minimum in the synaptic weight space. The present approach has been validated comparing results with experimental tests on a commercial ferromagnetic toroid.

2 Problem Formulation

Back propagation multilayer NNs have been already used for dynamic loop shape prediction under sinusoidal exciting field [1] [2]. The aim of papers [1] and [2] was to predict the shape of hysteresis loops by varying the frequency of the sinusoidal imposed magnetic field. Thus, in [1] the NNs are used to predict the Fourier Series (FS) coefficients of the flux density, B(t), in presence of a sinusoidal excitation H(t) at a generic frequency. In this case, two equal NNs working in parallel, one dedicated to the first n sinusoidal coefficients, and one dedicated to the first n cosinusoidal coefficients of the B(t) FS was implemented. Each NN had 2 hidden layer with 15 neurons, 2 input neurons managing the H(t) fundamental frequency, f, and the peek amplitude, Hm; k (k = 1.. 50) output neurons each returns the k-th harmonic term of B(t) FS. On the other hand, in the present paper, the aim is to evaluate only the dependence of the iron losses from the magnetic field frequency. Thus, the NN approach can be now strongly simplified. In this kind of analysis, it is enough to use a single NN having one input neuron (representative of the frequency) and one output neuron (representative of the power loss). The pattern for NN training (a list of frequency and corresponding power) can be obtained: 1) from the knowledge of several hysteresis loops from data sheets; 2) from the knowledge of the power loss directly from a wattmeter in a experimental context.

2 NN Training patterns

For creating suitable patterns for NN training, a numerical evaluation of iron losses is necessary. In the present paper, the approach proposed in [2] has been followed. As it is known, the static hysteresis loop area, on the B-H plane, corresponds to the magnetic energy density. In dynamic regime, it represents the global energy density including eddy currents, hysteresis and anomalous losses per unit of volume and frequency. In fact, the electrical power supplied to the exciting coil of the ferromagnetic nucleus is expressed by the following product:

$$p(t) = v(t)i(t) = \int_S \frac{\partial \vec{B}}{\partial t} \cdot \hat{n} dS \cdot \oint_{\lambda_m} \vec{H} \cdot d\hat{l} \tag{1}$$

where

$$v(t) = -N \int_S \left(-\frac{\partial \vec{B}}{\partial t} \right) \cdot \hat{n} dS$$

is the exciting coil electromotive force measured on N turns;

$$i(t) = \frac{1}{N} \oint_{\lambda_m} \vec{H} \cdot d\hat{l}$$

is the current flowing into the coil and generating the magnetic field H(t); S is the nucleus cross section area; m is the nucleus magnetic path. The mean value of the power is equal to the losses, P:

$$P = f \int_0^{1/f} p(t) dt \tag{2}$$

where f is the H(t) fundamental frequency. Equation (2) returns also the B-H loop area (energy density) multiplied by the core volume and by the fundamental frequency and we can write:

$$A_{loop} = \frac{P}{S \lambda_m f} \tag{3}$$

In fact, by applying the Parseval Theorem to the mean value of the product between B(t) FS and H(t) FS, and by manipulating equations (1) and (2), we have:

$$P = \sum_{r=1}^{n} S \lambda_m \pi k f H_r B_r \cos(\beta_r - \alpha_r + \frac{\pi}{2}) \tag{4}$$

where βr and αr are the phases of the r-th harmonic of flux density and magnetic field respectively, as well as Br and Hr are the peek amplitudes;

$$\cos(\beta_r - \alpha_r + \frac{\pi}{2})$$

is the power factor. Equation (4), also indicates that only the H(t) and B(t) harmonics with same r-th order give a contribution to power losses. All other B(t) harmonics, which do not appear in the H(t) FS, play a deformation role but do not generate losses. Moreover, it must be observed, that equation (6) can not be directly used to predict the loop area value in the present approach. In fact, as previously said, the loop prediction is graphic and it has been performed on the B-H plane where the time does not explicitly appear; consequently, B(t) is not still known. For this task, the Fourier Descriptor approach proposed in [1] has been applied.

3 Implemented Neural Network

The implemented NN architecture is shown in Figure 1. It consists of a three-layer perceptron made of a single input, single hidden and a single output layer. The NN input is the frequency (Hz) of the magnetic field, while the output is the power loss (W). The NN learning is based on the early stopping criterion. Moreover, the NN training is based on Genetic Algorithms (GAs) [3] instead of the usual gradient descendent algorithm used for classical back-propagation networks. In this way it is possible to avoid the inconvenient of local minimum in the synaptic weight space [3]. The GAs are evolutionary algorithms which find inspiration from natural evolution. A detailed description of GAs and applicative examples are available in literature [4] – [6].

The NN training uses a data pattern which is iteratively presented to the NN (see Table 1: Training Set). For each iteration (a presentation of the whole training set to the NN) the GAs operates an optimization of the NN synaptic weights. Then a new out-of-training pattern: the Test Set (see Table 2) is used to evaluate the error of the NN response. When the error on the test set becomes lower of an assigned value the training is over.

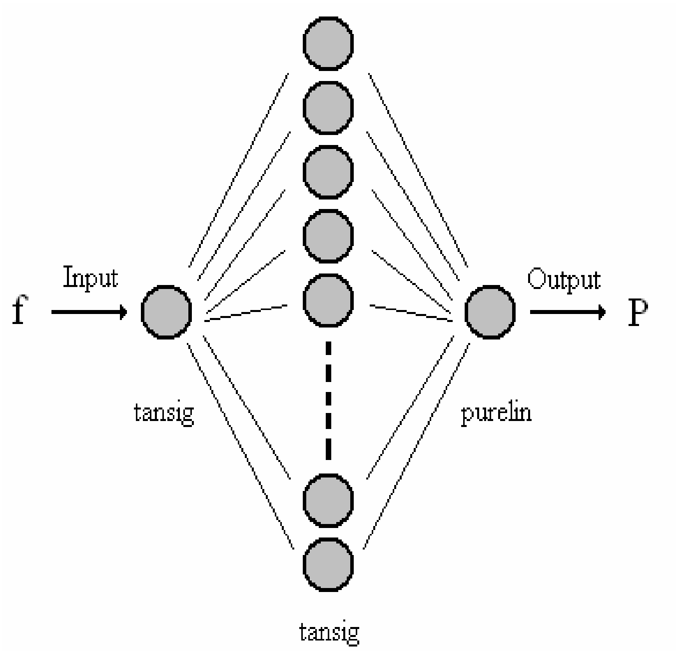

Figure. 1: Implemented Neural Network

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The present approach has been validated comparing results with experimental tests on a ferromagnetic core made of Alnico 2 material with

nucleus resistivity $\rho = 0.57 \cdot 10^{-6}$ Ωm,

height of lamination $d = 30 \cdot 10^{-2}$ mm

width w = 5 mm.

In Figure 2. is reproduced the frequency dependent loops for some used in NN training frequencies.

2.1 NN Performance

Figures 3 and 4, show the trend of the Mean Square Error performed by the Genetic Algorithm used to update the synaptic weights.

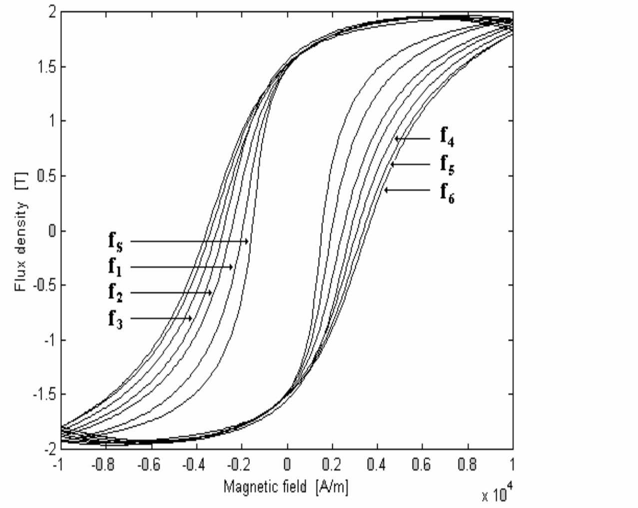

Figure. 2: Frequency dependent hysteresis loops under analysis

Table 1: Training Set

Frequency Hz	Actual kW	Estimated kW
1515	0.4910	0.5448
4515	1.6710	1.6100
6015	2.3450	2.3503
7515	3.0670	3.0700
1.052e+004	4.6340	4.6333
1.202e+004	5.4730	5.4607
1.352e+004	6.3450	6.3485
1.502e+004	7.2490	7.2479
1.802e+004	9.1410	9.1419
1.952e+004	10.1300	10.1390
2.102e+004	11.1300	11.1348
2.402e+004	13.2200	13.2271
2.552e+004	14.2900	14.2896
2.702e+004	15.3800	15.3721
3.002e+004	17.6200	17.6738
3.152e+004	18.7600	18.7369
3.302e+004	19.9200	19.9734
3.452e+004	21.1000	21.0704

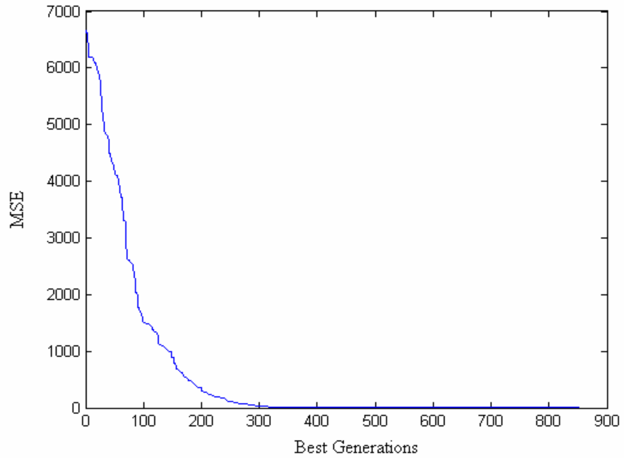

Figure 3: Mean Square Error performed by the Genetic Algorithm for the Training Set.

Table2: Test Set

Frequency Hz	Actual kW	Estimated kW
3015	1.0510	1.0052
9015	3.8310	4.1173
1.652e+004	8.1820	7.5932
2.252e+004	12.1700	12.4446
2.852e+004	16.4900	17.4945
3.602e+004	22.2900	21.2819

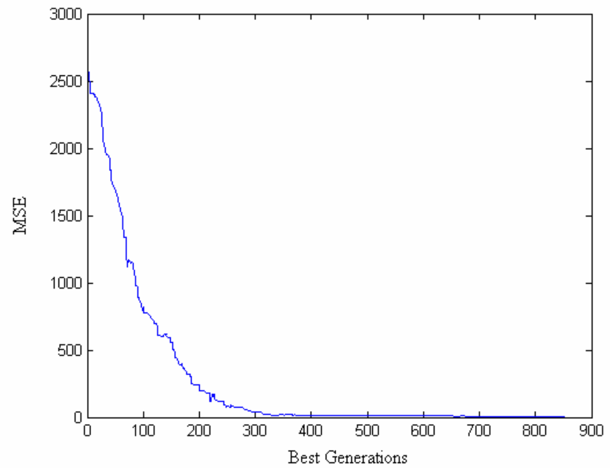

Figure 4: Mean Square Error performed by the Genetic Algorithm for the Test Set.

4 Conclusion

A Neural network approach has been used for evaluating the frequency dependent iron losses in ferromagnetic cores. The neural network architecture is a multilayer feed-forward net. Instead of the usual gradient descendent algorithm classically used to train back-propagation networks, the present approach is based on a genetic training. The validation demonstrates that the present approach shows adequate accuracy and it can be used as a tool for designers.

References:

[1] P. Del Vecchio, A. Salvini, "Neural networks and Fourier descriptor macromodeling dynamic hysteresis", IEEE Trans. on Mag., vol. 36 n. 4, pp. 1246-1249, July 2000.

[2] F. Riganti Fulginei, R. Russo, A. Salvini, Evaluation of Dynamic Hysteresis Losses by a Fourier Descriptor Approach, *Proceedings of PIERS'04*, Pisa 28-31 March 2004, pp.521-524.

[3] Amit Konar, *Computational Intelligence : Principles, Techniques and Applications,* Computational intelligence, Springer, May 31, 2005.

[4] D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, MA, 1989.

[5] F. Riganti Fulginei, A. Salvini, Genetic Algorithms and Neural Networks Generalizing the Jiles-Atherton Model of Static Hysteresis for Dynamic Loops, IEEE Transactions on Magnetics, March 2002.

[6] G. Pucacco, F. R. Fulginei, A. Salvini, Generalization of the Static Preisach Model for Dynamic Hysteresis by a Genetic Approach, IEEE Transactions on Magnetics, May 2003, Vol. 39, No.3, pp. 1353-1356.