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Mathematical Model and Neural Networks for the Dynamic Hysteresis Losses Calculation

Nouicer A[1]* and Feliachi M[2]

[1]Electrical Engineering Department, University of Oumelbouaghi, Algeria

[2]IREENA-IUT Laboratory, Saint Nazaire, France

ABSTRACT

In this paper, the dynamic hysteresis energy losses of the FeBSiC amorphous alloy sample were determined by means of mathematical model and neural networks. The changes in magnetic hysteresis curves as a function of frequency are introduced via the variation of the coercive magnetic field. So, a neural network (NN) has been trained to learn this function and used in the modelling of frequency-dependent hysteresis with a mathematical model. The model can calculate core losses based on the input parameters obtained from experimental measurements. This study is especially aimed at giving improved issue to avoid the empirical functions that require the identification of several parameters.

***Corresponding author**

Nouicer A, Electrical Engineering Department, University of Oumelbouaghi, Algeria.

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Introduction

Magnetic hysteresis is a complex phenomenon, which is important both from theoretical and practical points of view. It affects the dynamic behaviour of ferromagnetic materials; thus, it should be taken into account in engineering calculations.

A realistic hysteresis model must be able to take into account the diversity of the operating conditions of the systems such the variation of the excitation field frequency and the temperature.

Several models are existing in the literature and can describe all facets of the magnetic hysteresis. The two most common ones are the Jiles- Atherton and Preisach models. The first one is of considerable interest due to its relative simplicity and the physical meaning of its parameters. Recently, some improvements have been introduced to this model in order to describe the magnetization processes in ferromagnetic materials in dependence of the temperature and the frequency [1]. However, its numerical implementation is quite complex, especially the modified models, and requires the identification of four parameters. Among the phenomenological hysteresis models, the Preisach model is the most common approach as well as its numerous extensions which are often summarized as Preisach-like hysteresis models. The Preisach model rests upon the weighted elementary hysteresis operators whose superposition determines the whole hysteresis behaviour. Numerous reformulations of the scalar Preisach model have been further elaborated in order to obtain the Preisach operator in a general vectorial form [2]. The numeric implementation of this model is also quite complex and requires more CPU times.

The design of highly efficient electromagnetic devices requires an optimization procedure for minimizing the core losses due to time-varying electromagnetic fields. In order to achieve the optimum design, accurate core loss calculations have to be performed for each candidate design. Therefore, it is essential to have an accurate and fast hysteresis model to calculate core loss in order to optimize the device within a convenient computation time.

Recently, a new mathematical model of frequency dependent hysteresis (based on the model presented in) is proposed [3,4]. Variation of only one model parameter with the frequency is suggested. This model is closely related to the Bergqvist hysteresis model with the dry friction-like hysteresis mechanism, but it has a simplified mathematical form and method of computation [3,5]. The variation of the coercivity with frequency is fitted with empirical functions containing tree fitting parameters. Those parameters need to be identified from the measured cycle.

In this paper, an artificial neural network has been used to learn directly the relation between coercivity and frequency. The obtained neuronal model is introduced in mathematical hysteresis model to achieve accurate and computationally efficient hysteresis loss prediction.

The frequency dependent hysteresis and its influence on the core loss in $Fe_{81}B_{13}Si_{14}C_2$ amorphous alloy sample at frequencies in the range of 50–1000Hz has also been presented and discussed. The simulation results are compared with the experimental data published in [3].

Employed Frequency-Dependent Hysteresis Mathematical Model

A new arctangent mathematical model of the frequency-dependent hysteresis loop is proposed in [4]. The major hysteresis loop can be represented by the following expression [3,4]:

B=±a.arctan[b (±H+d)]+c.H (1)
B=±a.arctan[b (±H-d)]+c.H (2)

The positive sign in (1) and (2) should be used in modelling of the positive parts of the descending (ascending) curve and the negative sign should be used in modelling of the negative part of the descending (ascending) curve.

Parameters model can be calculated using simple expressions using the measured values of the coercive magnetic field H_c, the saturation magnetic field H_s, the remanent magnetic induction Br and the magnetic induction at saturation Bs. Parameter d can be set to the value of the coercive magnetic field H_c. The Parameter a can be calculated as 2Bs/π. The descending curve of the major loop must pass through the points (0, Br) and (Hs, Bs). Therefore, parameters b and c can be calculated using Eq. (3) and Eq (4) [4]:

$$b = \frac{\tan(\pi.\frac{B_r}{2B_s})}{H_c} \quad (3)$$

$$c = \frac{B_s - \frac{2}{\pi}B_s \arctan[b(H_s+H_c)]}{H_s} \quad (4)$$

Each parameter has influence on the shape of the constructed major hysteresis loop.

The model is generalized to calculate initial magnetization curve, first-order and higher-order reversal curves.

Generally, the hysteresis loop evolves with the change of the frequency and the two representative parameters of the loop, Hc and Br, depend on the frequency. In the case of the FeBSiC amorphous alloy presented in, the most important visible change in the hysteresis loop with the increase of the frequency is the increase of the coercivity [3]. The variation of Br is negligible and can be considered constant.

The frequency dependence of hysteresis curves is incorporated in the mathematical model by setting parameter d equal to Hc. The variation of the coercivity with frequency can be fitted with the following function [3,6]:

$$H_c(f) = \alpha + \beta\sqrt{f} + \gamma f \quad (5)$$

where α, β, and γ are fitting parameters that need to be calculated from experimental data.
Parameters α correspond to the coercivity at zero frequency. Parameters β and γ correspond to the anomalous eddy currents and normal eddy currents, respectively [3].

In those parameters are fitted from some measurements of the variation of the coercivity with frequency and using Wolfram Mathematica software [3]. The obtained results are: α=17.336, β=0.1983 and γ=0.0073.

In this paper, we propose a neural network model for fitting the observed dependence of the coercivity on the frequency directly from measurements. The generalisation characteristic of this model offers an accurate predictive approach to calculate the coercivity over a wide range of frequencies and its use in the mathematical hysteresis model gives an accurate and computationally efficient hysteresis loss prediction. It can extrapolate the coercivity for zero frequency and so the static-hysteresis loss with an acceptable precision.

A Neural Network Model for Fitting the Frequency Dependence of the Coercivity
In previous works, ANN has been successfully used for modelling the magnetic hysteresis of different materials. For example, In an ANN is used for modelling the mechanical stress influence on magnetic hysteresis of magnetostrictive materials [7]. In, the temperature dependency of the 3F3 magnetic hysteresis is presented using an ANN [8].

The aim of this paper is to improve the presented mathematical model by seeking a simple relation to represent the frequency dependence of the coercivity. It is especially aimed at giving improved issue to avoid the empirical functions that require the identification of several parameters. In addition to its simplicity and accuracy, the seeking model must overcome the problems of identification. To do, it was thought to neural networks. It is well-known that neural network technique can implement all sorts of nonlinear mappings, it has always been regarded as one of the best approaches to modelling nonlinearities. In our work, a single-input-single-output three layers NN is adopted. It has the task of predicting the frequency dependence of the coercivity. The implemented NN architecture consists of three-layers perceptron made of an input layer, a single hidden layer and an output layer. The NN input is the frequency (Hz) of the magnetic field, while the output is the coercivity (A/m).

Several tests were carried out to determine the optimal architecture of the neural network, and more exactly the number of neurons in the hidden layer. The optimal configuration consists of a neural network with one neuron in the input layer with a linear transfer function, four neurons in the hidden layer with a sigmoid transfer function and one neuron in the output layer with a linear transfer function. The pattern for NN training (a list of frequency and corresponding coercivity) are created from the experimental data published in [3]. The authors have measured the hysteresis loops with a toroidal core sample made of $F_{e81}B_{13}Si_{14}C_2$ amorphous alloy [3]. Measurements have been made under sinusoidal excitation of the variable frequency in the range from 50 to 1000Hz and a maximum of the excitation magnetic field amounted to 100A/m. The coercive magnetic field values Hc, are obtained from the experimental hysteresis loops and their variation with the frequency f is presented in Table 1 [3].

Table1: Variation of Coercivity with Frequency [3].

Frequency f [Hz]	Corcivity Hc [A/m]
50	19.16
200	21.38
400	24.57
600	26.26
800	28.98
1000	30.84

The frequency values are normalized to avoid injecting large values in the neural network and thus improving the process of convergence.

NN Performance

Figure 1 shows the trend of the mean square error performed by Levenberg-Marquard algorithm. We notice the fast convergence of the NN

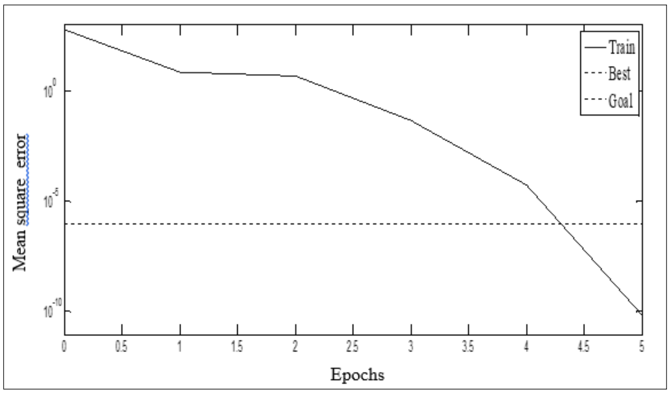

Figure 1: Mean Square Error Performed by Levenberg-Marquard Algorithm for the Training Set

In order to test the NN training, the NN thus prepared is used to predict the coercivity for the training data base frequencies. The convergence test results are listed in the Table 2

Table 2: Results of the Convergence Test

Frequency f [Hz]	Experimental Value of Hc [A/m]	NN Predicted Value of Hc [A/m]
50	19.16	19.16
200	21.38	21.38
400	24.57	24.57
600	26.26	26.26
800	28.98	28.98
1000	30.84	30.84

Through simulation, the results prove that the approximation precision is very high and the error prediction for the whole tests is zero. This is justified by the simple nonlinear mapping.The obtained predicted results are used for modelling the frequency-dependent of the hysteresis loops of the $F_{e81}B_{13}Si_{14}C_2$ amorphous alloy, using the mathematical model described above. The model parameters are: a=0.35395, b=0.875, c=0.000015 and d is equal to the value of the coercivity Hc. Figure 2 shows the simulation results.

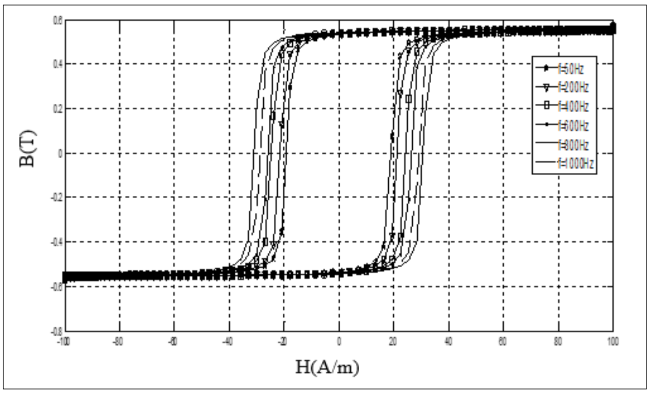

Figure 2: Modelling Hysteresis Loops using the Predicted Values of the Coercivity of the Table 2

Generalization Test of the NN

The generalization test consists of using the NN to predict the frequency dependence of the coercivity for the values of the frequency out of the training database. Due to the lack of experimental data, the obtained results are compared with those obtained using eqt (5) with parameters α =17.336, β=0.1983 and γ =0.0073 [3]. The generalization test results are listed in the Table 3

We can notice a slight difference between the predicted values and those calculated. This difference occurs because the small size of the training database. So, the generalization ability can be improved by using a large database of the pattern for NN training.

Table 3: Results of the Generalization Test

Frequency f [Hz]	NN Predicted Value of Hc [A/m]	Calculated Value of Hc [A/m]
100	19.3659	20.0490
300	24.5065	22.9607
500	25.9681	25.4201
700	26.8664	27.6925
900	30.5419	29.8550
950	30.7608	30.3830

Figure 3 Presents the Modelling Frequency-Dependent of the Hysteresis Loops of the Fe81B13Si14C2 Amorphous alloy using the Predicted Values of Hc listed in table 3

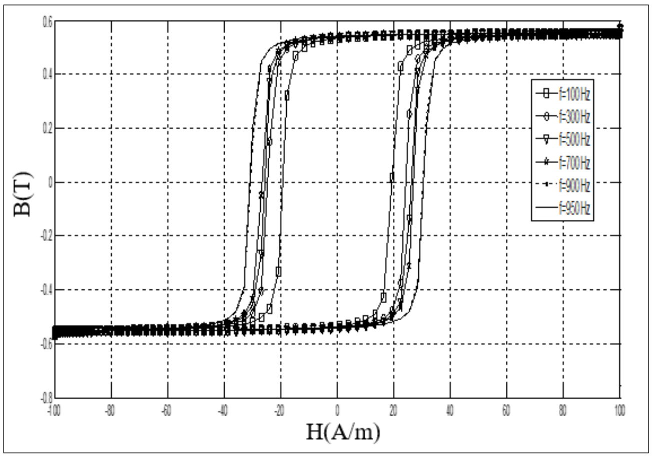

Figure 3: Modelling Hysteresis Loops using the Predicted Values of the Coercivity of the table3

Calculation of the Dynamic Hysteresis Energy Loss

The described approach has been applied to compute the dynamic hysteresis energy loss of the $F_{e81}B_{13}Si_{14}C_2$ amorphous alloy sample at frequencies in the range of 50–1000Hz. The hysteresis loops are calculated using equations (1) and (2) and the frequency dependence of hysteresis curves is incorporated by NN model. The variation of the energy loss per unit volume (areas of loop) with the frequency W(f) is presented in figure. 4, where the measured values are those published in [3].

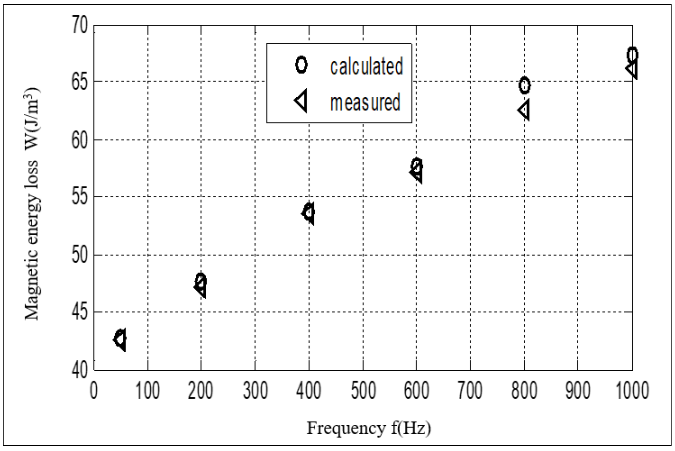

Figure 4: Comparison between Measured and Calculated Loop Hysteresis Energy losses [3].

One can notice the good agreement between measurements and calculated loop hysteresis energy losses with a slight difference for the two last frequencies.

The NN model is used to extrapolate the value of the coercivity at zero frequency Hc(0)=19.0928. According to this, the static hysteresis loss amounts to W=42.67 W/m^3.

Conclusion

In this paper, a mathematical model and neural networks combined technique has been presented to simulate the BH curves and magnetic power losses. The frequency dependence of the coercivity is introduced to the mathematical model via a neural network. The aim of using the neuronal model is to avoid the problem of the identification that requires the empirical functions. The generalisation characteristic of the NN offers an accurate predictive approach to calculate the coercivity over a wide range of frequencies. Another main advantage of the NN is the ability to implement multiple nonlinear mappings simultaneously, such the effect of the frequency and temperature on the hysteresis loop. However, the model precision depends essentially on the size of the database of the pattern for NN training. The proposed approach is then applied to calculate the hysteresis losses in an $F_{e81}B_{13}Si_{14}C_2$ amorphous alloy at frequencies in the range of 50–1000Hz. The experimental results approve the proposed approach.

References

1. Nouicer A, Nouicer E, Feliachi M (2015) A Neural Network for Incorporating the Thermal Effect on the Magnetic Hysteresis of the 3F3 Material using the Jiles–therton Model. Journal of Magnetism and Magnetic Materials 373: 240-243.
2. Sören Rosenbaum, Michael Ruderman, Tom Strohla, Torsten Bertram (2010) Use of Jiles–Atherton and Preisach hysteresis models for inverse feed-forward control. IEEE transactions on magnetics 46: 3984-3989.
3. Branko Koprivicaand, Alenka Milovanovic, Nebojsa Mitrovic (2017) Mathematical modelling of frequency-dependent hysteresis and energy loss of FeBSiC amorphous alloy. Journal of Magnetism and Magnetic Materials 422: 37-42.
4. Milovanovic AM, Branko Koprivica M (2015) Mathematical model of major hysteresis loop and transient magnetizations. Electromagnetics 35: 155-166.
5. Bergqvist A (1997) Magnetic vector hysteresis model with dry friction-like pinning. Physica B 233: 342-347.
6. N Mehboob (2012) Hysteresis Properties of Soft Magnetic Materials Ph.D thesis, Technical University of Wien, Wien Austria.
7. Nouicer A, Nouicer E, Feliachi M (2013) Neural network-DFT based model for magnetostrictive hysteresis. International Journal of Applied Electromagnetics and Mechanics 42: 343-348.
8. Nouicer A, Nouicer E, Mahtali M, Feliachi M (2013) A Neural Network Modeling of Stress Behavior in Nonlinear Magneto strictive Materials. Journal of Superconductivity and Novel Magnetism 26: 1489-1493.