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# Identification of Parameters of JILES ATHERTON model by Neural Networks.

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*Abstract*— In this paper a procedure for the identification of the parameters of Jiles-Atherton (JA) model is presented. The parameters of JA model of a material are found by using a neural network trained by a collection of hysteresis curves, whose parameters are known. After a presentation of Jiles-Atherton model, the neural network and the training procedure are described and the method is validated by using some numerical as well as experimental data

*Index Terms*—Hysteresis modelling, magnetic materials, electric machines.

## INTRODUCTION

A general problem for every hysteresis model is its identification. The identification of a model consists in guessing the right parameters to be used in the model in order to describe the hysteresis curve of a given material. As a result, in the Jiles Atherton (JA) model (1-3) of a given material, as well as in any analytical model of hysteresis, the parameters of the model are assumed to be known. However, this could not always be true and especially for new materials can be difficult to guess the right parameters.

In this paper, I present an approach that allows to identify the parameters of JA model on the basis of some known magnetic behavior. The fundamental idea of this method is to identify the parameters of a material by using a neural network trained by a collection of hysteresis curves, whose JA model is known.

Artificial Intelligence techniques have been largely used in many technical fields: such as control technology, diagnostics, pattern recognition etc., see (4) for references. Approaches that use neural networks to obtain the numerical parameters of given distribution function in classical, dynamic and vectorial Preisach model are known in literature (5-7), on the contrary the identification of JA model has been based mainly on least squares methods, genetic algorithms as well as fuzzy logic technique (7). In this paper Neural Networks are used to identify JA model for various types of materials.

The proposed identification procedure can be divided into three steps: A) network training; B) submission of test set ; C) output of the results.

A suitable network is used on the basis of physical consideration.

The network is trained by some hysteresis data, which are generated from a set of well identified JA models. The set of training data consists of the magnetization values and the used parameters in JA model. The output of this process is a trained neural network able to identify a JA model, this network uses as input an hysteresis curve and yelds the parameters of JA model which best describe the submitted curve.

In order to validate the approach, a comparison between numerical loops and experimental data is reported. is shown

The trained network showed that it was able to identify the parameters of JA model of the experimental curves used.

## THE JILES-ATHERTON MODEL

The J-A model has the following form:

$$\frac{dM}{dH}=\frac{(1-c)\frac{dM_{irr}}{dH_e}+c\frac{dM_{an}}{dH_e}}{1-\alpha c\frac{dM_{an}}{dH_e}-\alpha(1-c)\frac{dM_{irr}}{dH_e}} \quad (1)$$

Where: $M$ is the magnetization, $H$ is the applied magnetic field, c is the coefficient of reversibility of the movement of the walls, $M_{irr}$ is the irreversibile magnetization, $H_e$ is the effective field ($H_e=H+\alpha M$ ), $M_{an}$ is the anhysteretic magnetization, $\alpha$ is linked to hysteresis losses.

$M_{an}$ can be calculated through the Langevin's equation:

$$M_{an}(H_e)=M_s\left(\coth\left(\frac{H_e}{a}-\frac{a}{H_e}\right)\right) \quad (2)$$

where $M_s$ is the saturation Magnetization, $a$ is a form factor and $M_{irr}$ is defined as follows:

$$\frac{dM_{irr}}{dH_e}=sign\left(\frac{dH}{dt}\right)\frac{M_{an}-M_{irr}}{k} \quad (3)$$

where $t$ is time and $k$ describes interactions between Weiss' domains. As a result, J-A model is a five-parameter model

## IDENTIFICATION

The identification procedure consists of three steps: A) training; B) submission of data ; C) output. The step A is executed separately from steps B and C.

### Training

Training phase aims to build a network, whose input is the hysteresis curve and the output consists of the parameters of J-A Model that better reproduces the hysteresis cycle loop which had been submitted to the network.

The neural network used consists of a three layer neural network: the first layer consists of 25 linear neurons, the second layer of 40 neurons with hyperbolic tangent sigmoid function, and the output layer of 5 linear neurons. The input is made up of a 32-component vector. The first layer makes a linear reduction from the high dimension input space to a slightly lower 25-dimension space. The output of the first layer is therefore the feature vector that sums up the most relevant characteristics of the input space and is strictly connected to five relevant properties of the hysteresis loop. The 40 neurons of the second layer neurons allows to store a number of parametric curves equal at least equal to 1000. The output layer is made up of 5 neurons which are the free parameters of J-A model that most suitably permits to produce the inputs. In Fig.1 it is shown shows how the network works.

The training set is made of 243 vectors. Each input vector has 32 coordinates, while the target vectors are defined on a 5D space. The 32 coordinates are the ordinates of a first order reversal hysteresis curve obtained under sinusoidal excitation. The excitation amplitude is the same in all cases and all the transients have died out. Each input vector was computed by inserting in eqs 1, 2 and 3 a unique set of parameters.

In the end The the Levenberg-Marquadt algorithm has been used for the training phase.

Submission of data.

Each input vector belongs to a 32D space and is made up of the the ordinates of a hysteresis loop. Hysteresis loop data must spans the same interval spanned from the vectors used in the training phase.

Output of the results

The output of the network consists of five parameters. They represent the parameters of the J-A model that is associated to the presented loop. These numbers are the interpolation of the network to the best value that it is able to output to describe the presented hysteresis loop.

Validation and experimental verification .

In order to validate the approach here presented two types of numerical tests were performed: the first one aimed to verify the ability of the method to obtain the correct numerical parameters used in JA model to build a numerical hysteresis loop, the second one verified the capability of the approach to identify the numerical parameter of an experimental hysteresis loop.

In order to verify the reliability of the model, the 2-norm of the difference between the input and the output curve was chosen as test index of the tests above presented. The mathematical expression of the index reads as follows:

$$i = \sum_{t=1}^{t=32} [\Phi(t) - \phi(t)]^2 \Big/ (\phi_{av}(t) \cdot 100) \quad (1)$$

where i is the index, t labels the points of the hysteresis loops, $\Phi(t)$ is the ordinate of t-th point of the output loop and $\phi(t)$ is the ordinate of t-th point of the input loop, $\phi_{av}$ is the average between $\Phi(t)$ and $\phi(t)$ .

As far as the tests aimed to verify the ability to re-obtain the numerical parameters used to build a numerical hysteresis loop is concerned, several numerical curves were elaborated by the trained network. All the curves were different from the ones used in the training phase. In table 1 is reported the error recorded on the parameters and the test index used. Fig. 2 compares the experimental curve to the reconstructed one.

Table 1

Error on recorder on the curve of fig. 2

| *Parameter* | Input | Output |
|---|---|---|
| $\alpha$ | 0.0001 | 0.000107 |
| $a$ | 34 | 34.1 |
| $c$ | 0.11 | 0.12 |
| $k$ | 50 | 50.5 |
| $M_s$ | 1.5 | 1.51 |
| $i$ | 0.03 | |

A comprehensive analysis was performed by submitting several numerical curves to the network. These curves had a saturation field between 0.5 and 1.5 T, a coercive field between 5 and 1000 A/m, a remanent field between 0.1 and 1.1 T. In table 2 the maximum errors recorded are shown.

Table 2

Maximum errors

| *Parameter* | Errors |
|---|---|
| $\alpha$ | 10% |
| $a$ | 11% |
| $c$ | 13% |

| | |
|---|---|
| $k$ | 8% |
| $M_s$ | 5 % |

As far as the experimental verification is concerned, the hysteresis curves of NiFe 20-80 and the virgin curve of the hard axis of 3.2% Wg FE-Si Magnetic steel samples were used.

As far as NIFe 20-80 is concerned, the curve used for the test had a saturation flux density $B_{max}$=0.81 T, a saturation magnetic field $H_{max}$= 20A/m, a coercive field $H_c$=0.91 A/m and a remanent induction $Br$=0.35 T. In table 3 these parameters are confronted with the parameters obtained by the neural networks. It can be seen as the error as well as the test index are quite low.

Table 3

Error on an experimental hysteresis curve

| *Parameter* | Error |
|---|---|
| $B_{sat}$ | 0.8% |
| $H_{max}$ | 3.0% |
| $H_c$ | 3.5% |
| $Br$ | 0.6% |
| $i$ | 1.8 |

As far as the virgin curve of the hard axis of 3.2% Wg FE-Si Magnetic steel samples is concerned, fig.3 shows how it can be reconstructed by a trained network.

## CONCLUSIONS

This paper presents a novel method for the determination of J-A model.

The proposed method uses neural networks and is able to identify models that were non presented to the network. The neural network used consists of a three layer network and the input vector belongs to a 32D space. The method has been applied to identify experimental hysteresis curve and it has shown a good numerical accuracy.

AKNOWLDGMENTS

This work was supported by MIUR (project “Finanziamenti Ricerca Scientifica di Ateneo 2009” ex quota 60%).

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LIST OF FIGURE CAPTIONS

Fig. 1 Schematic representation of the proposed identification method. From a hysteresis loop an one 32 component vector is built. This vector is the input of a previously trained neural network. The outputs are the parameters of the J-A model.

Fig. 2 Comparison between a numerical hysteresis curve. Continuous line is the input curve, diamond the output line. The parameters used to obtain the output curve were those obtained from then network when the input was the input curve. Input and output curve are almost indistinguishable.

Fig.3 Plot of the virgin curve of hard axis of 3.2% Wg FE-Si Magnetic steel samples. The squares are the measured points, the continuous line is the fitting curve