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Two-dimensional magnetic modeling of ferromagnetic materials by using a neural networks based hybrid approach

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ABSTRACT

This paper presents a hybrid neural network approach to model magnetic hysteresis at macro-magnetic scale. That approach aims to be coupled together with numerical treatments of magnetic hysteresis such as FEM numerical solvers of the Maxwell's equations in time domain, as in case of the non-linear dynamic analysis of electrical machines, and other similar devices, allowing a complete computer simulation with acceptable run times. The proposed Hybrid Neural System consists of four inputs representing the magnetic induction and magnetic field components at each time step and it is trained by 2D and scalar measurements performed on the magnetic material to be modeled. The magnetic induction B is assumed as entry point and the output of the Hybrid Neural System returns the predicted value of the field H at the same time step. Within the Hybrid Neural System, a suitably trained neural network is used for predicting the hysteretic behavior of the material to be modeled. Validations with experimental tests and simulations for symmetric, non-symmetric and minor loops are presented.

1. Introduction

One of the most challenging topics in the field of computational magnetism is the Vector hysteresis modeling. Many authors presented different models in literature representing the vector nature of magnetic materials [1–17]. In several applications these models must be suitably corrected according with experimental data previously measured with the aim to get a good accuracy, and their implementation can become critical or even impossible from the computation point of view. To overcome these problems, a possible solution could be the use of "black box" approaches: fully numerical methods without any physical interpretation of the phenomena, but usually fast and reliable algorithms for a quite accurate numerical reconstruction of data. Among these approaches [18–29], we present in this paper a suitably trained Hybrid Neural System (HNS) composed by more than one Feed-Forward Neural Network (FFNN) for the modeling of two-dimensional and scalar magnetic hysteresis. The HNS can be utilized as constitutive law of the magnetic materials together with a FEM solver for a complete computer simulation using acceptable computing times. The HNS consists of two input neurons representing the magnetic inductions components at the k-th simulation step and it is trained by measurements performed on the magnetic material to be modeled. The magnetic induction is assumed as exciting field, consequently its trend is a priori known. The output returns the predicted values of the magnetic field H at k-th simulation step, referred to the input pattern. The high speed of calculation of FFNNs allows the HNS to be used to reproduce the magnetic behavior in time domain of complex devices, such as electrical machines or magnetic sensors. The complete description of the HNS is presented in the next sections. In this paper we will make use of the HNS approach to the prediction of the components of the magnetic field both on a Not Oriented Grain (NOG) and an Oriented Grain (OG) electric steel core, in order to get circular (as in several rotating electrical machines) and unidirectional (as in static electrical machines) polarization of the magnetic induction. The predicted data of the magnetic field components are compared to the measured data related to the same values of the amplitude and phase of the magnetic induction. The detailed description of the proposed examples and the obtained results are presented in the final section.

2. Neural networks applied to the prediction of circular polarizations of the magnetic induction

In this paragraph, the neural approach for modeling 2D magnetic without hysteresis is described. A suitable system of feed-forward neural networks, that we call neural system (NS), is used with the aim of building the curves of magnetic field H starting from the magnetic induction B ones without taking into account any hysteresis phenomena. The NS performs a non linear transformation from the plan Bx–By to the plan $\hat{H}$x–$\hat{H}$y for the case of circuital excitations of the magnetic induction. In Fig. 1, the curve *1*

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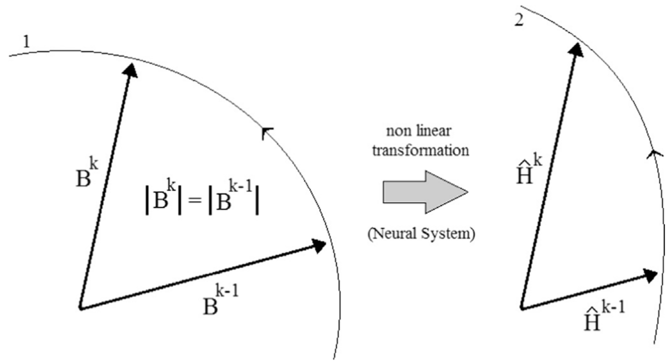

Fig. 1. Non linear transformation from the plan Bx–By to the plan Ĥx–Ĥy performed by neural system for circular polarizations of B.

represents a circular path of B on the plain Bx–By and the curve *2* is the transformed path of Ĥ on the plan Ĥx–Ĥy. The hat over the components of *H* indicates that they are computed without taking into account any hysteresis phenomena. In order to do that, the NS is trained on a specific set of experimental data, measured on the magnetic sample to be modeled. The herein presented NS is an optimized version of the one proposed in [30], having just two inputs instead of four. The curves of the field *H* simulated by NS are obtained step by step, taking into account the values of the components of *B* at each step. The measurements on which the NS has to be trained are generated by using circular polarizations of *B* like those shown in the left part of Fig. 2. The prediction of the Ĥ components at the *k*-th step starting from the *B* components at the same step is a typical Multi-Input-Multi-Output (MIMO) problem [31]: in particular, for this case, it is a 2-input-2-output problem. However, it can be theoretically split in two 2-Input-Single-Output problem by applying the procedure described in [32].

In this way two different NNs can predict the values of components of Ĥ, one for Ĥx and one for Ĥy. Nevertheless, even after dividing the original problem in two neural networks, however it is expected that they have a complex structure and require a complicated learning process due to the high amount of data to be handled. In order to further decrease the degree of complexity, we have considered a suitable NS composed by 2*n* neural networks, where *n* is the number of zones (different annular rings) partitioning the Bx–By plane. On each ring, a different couple of NNs is trained and used to reproduce the components of the magnetic field Ĥ. In this way, the amount of data to be handled for each annular ring becomes smaller and the training process of each singular NN is acceptable in terms of computational cost and run time. Indeed, since the adopted NNs have just one hidden layer (see Fig. 3a), they are very easy to train and require a typical learning time of a few minutes on a standard Intel Core i5-480M notebook based PC. Fig. 3b shows the scheme of neural system for a generic case. The *n* blocks of the couples of neural networks, NNx and NNy of Fig. 3b are used to predict Ĥx and Ĥy respectively, for each annular ring. The block selector allows choosing the correct couple of NNs simply by verifying the current position of the point (Bx,By) at the *k*-th step in the Bx–By plane. Finally, it is important emphasizing that NS cannot be applied on the cases of non circular polarizations of *B* because when the amplitude of *B* changes, it is needed to take into account the hysteresis effects of the material to be modeled. In the next paragraph a suitably trained neural network will be presented to face that issue.

3. Neural networks applied to the prediction of unidirectional polarizations of the magnetic induction

In this section a NN approach to provide a simpler way to take into account hysteresis for unidirectional polarizations avoiding both the identification of models and their inversion is presented. The proposed hysteresis neural network (HNN) is able to predict the magnetic hysteretic behavior of a ferromagnetic material by using few simple measurements. The NN consists of three input neurons, representing the magnetic field, H, the flux density, B, and the angle α_B, at $(k-1)$-th step, one hidden layer with 30 neurons and one output neuron that gives as result the value $\frac{1}{\mu} = \frac{dH}{dB}$, where μ is the differential magnetic permeability at $(k-1)$-th step (see Fig. 4a). Thus, the predicted change value of magnetic field at *k*-th step is obtained as follows:

$$\left|H^k_{hys}\right| = \left|H^k\right| - \left|H^{k-1}\right| = \frac{\left|B^k\right| - \left|B^{k-1}\right|}{\mu^{k-1}} \tag{1}$$

whereas the quantity $\left|B^k\right| - \left|B^{k-1}\right|$ is a priori known. The difference $\left|H^k\right| - \left|H^{k-1}\right|$obtained by the output $\frac{1}{\mu^{k-1}}$ of the HNN is named by the authors, $\left|H^k_{hys}\right|$, because it is the amplitude of the hysteresis vector H^k_{hys} applied to the output vector Ĥ given by NS, as described in the next paragraph. The experimental loops used for carrying out data for the HNN training are suitable asymmetric loops measured at different angles α_B on the *H–B* plain. In Fig. 4b an example of asymmetric loops at α_B=0 rad is shown, measured on

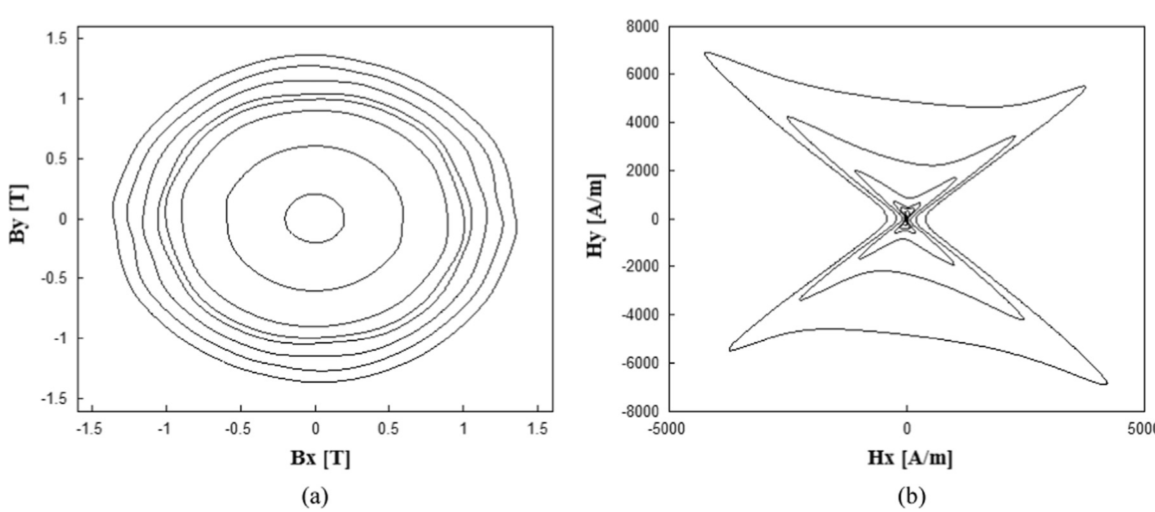

Fig. 2. Oriented Grain (OG) Si–Fe electric steel – measured data of the loops of the field *H* (b) for circular polarizations of *B* (a).