Neural Network approach for modelling hysteretic magnetic materials under distorted excitations

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Abstract — A Neural Network (NN) approach for modelling ferromagnetic materials is presented. The macroscopic hysteretic nature of the material is taken into account together with iron losses by a ad-hoc NN which can be trained for modelling any kind of quasi-static dynamic loop (saturated and non-saturated, symmetric or asymmetric) generated by assigned distorted excitations. The main important advantages of this approach are: 1) easy NN implementation and training (just simple dynamic hysteresis measurements are required); 2) independence from the nature of excitation: the NN can indifferently perform the direct problem (prediction of B from a known waveform of H) or the inverse problem (prediction of H from a known waveform of B).

I. INTRODUCTION

The modelling of magnetic material has been the subject of many studies, above all to take into account the hysteresis phenomenon and to model it in an efficient and accurate way, since magnetic materials have a lot of useful technical applications (magnetic recording device, motors, etc). Consequently the research and the development of new approaches of analysis and treatment remains a central issue. The possibility of using Neural Networks to model magnetic hysteresis has been verified in literature [1], and represents a good solution if a dedicated model for the training of the network is implemented. By starting from a small set of measured quasi-static loops, the NN manages the values of the magnetic field, H, and the flux density, B, as inputs while the differential permeability is the output. In particular, the proposed NN is able to perform the modelling of saturated and non-saturated, symmetric or asymmetric quasi-static hysteresis loops. Moreover, by adding a further input (the frequency *f*) to the previous NN, it is possible to take in account the effects of hysteresis losses on all of those cases in which distorted dynamic excitations are applied. In particular, the time-window [2] and Prony sinusoidal regression [3] techniques for non-static hysteresis paths have been implemented.

II. NEURAL NETWORK MODEL FOR QUASI-STATIC HYSTERESIS LOOPS

The Neural Networks approach for modelling magnetic hysteresis is a valid alternative to the use of classical models such as the Preisach or Jiles-Atherton ones [4]. In fact, any hysteresis model requires the experimental characterization of the material by using measured loops. Moreover, as shown in [5], the characterization performed by using the saturated major loop is often not suitable for simulating minor loops with accuracy. In addition the optimal identification of the classical hysteresis models is still an open problem (see for example [6-7] and the references within), and the most used hysteresis models, such as Preisach or Jiles Atherton, have to be inverted if the flux density is the independent variable. In fact, the direct models allow faster computation when the external magnetic field H can play the role of the independent variable [8-9]. Thus, the aim of the presented NN approach is to provide a simpler way to take into account hysteresis avoiding both the identification of models and their inversion. The proposed NN approach is able to predict the quasi-static magnetic hysteretic behaviour of a ferromagnetic material by using few simple measurements (see Fig. 1).

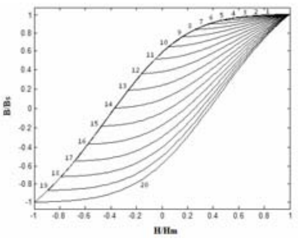

Fig. 1. Example of the asymmetric saturated loop used for NN training.

The implemented NN is made by means simple feedforward architecture and trained by using the Levenberg-Marquardt backpropagation algorithm. The NN consists of two input neurons, representing the magnetic field, *H*, and the flux density, *B*, one hidden layer with 9 neurons and one output neuron that gives as a result the value of the differential permeability, $\mu_d(H,B) = dB/dH$.

The experimental loops used for carrying out data for the NN training are suitable asymmetric loops. Each loop is generated by following a path in the B-H plane that always involves a portion of the descending major-saturated-loop branch and a different ascending non-symmetric branch. Then, each experimental asymmetric loop is sampled using *n* points. The couple of co-ordinates [*H*(k),*B*(k)] of each *k*-th sampled point ($k = 1 \ldots n$) is fed to the input of the NN. The corresponding differential magnetic permeability, $\mu_d(H(k),B(k)) = dB(k)/dH(k)$, is used as output. It is important to note that, by means the $\mu_d(H(k),B(k))$ value is possible to obtain both the value of $B(k+1) = \mu_d(H(k),B(k)) \cdot dH(k)$ (direct problem) and the value of $H(k+1) = \mu_d(H(k),B(k))^{-1} \cdot dB(k)$ (inverse problem) with the same trained NN.

Thus, the requested measurements for assembling the input and the output training patterns are the values of external magnetic field H, the flux density B and the differential permeability, μ_d . In particular, the training set was made of 100 *H-B* sampled points for each experimental hysteresis loop (see Fig.1). Altogether, 20 measured loops have been used during the training phase. In Fig. 2 the performance of NN model and experimental data are compared for the case of quasi-static hysteresis loops obtained by Praisach model.

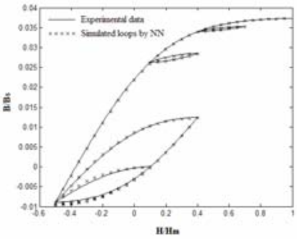

Fig. 2. Example of NN approach validation for quasi-static case.

III. NEURAL NETWORK MODEL FOR DYNAMIC HYSTERESIS LOOPS

The change of hysteresis loop shape due to hysteretic material losses that occurs for all the dynamic cases, is taken in account by using the frequency parameter, *f*, as a further NN input. (see Fig. 3). This new NN can be regarded as a generalization of that of the previous case. Thus, the further input parameter, *f*, is used to training the NN on asymmetric hysteresis loops at different frequencies of excitation field. Once the NN was trained for asymmetric hysteresis loops at different frequencies, it is able to reconstruct any hysteretic path due to a distorted excitation by using the time-window and the time-frequency approach described in [2].

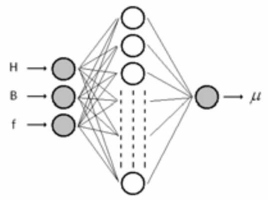

Fig. 2. Feedforward NN for dynamic hysteresis loops.

IV. VALIDATION EXAMPLE OF NN APPROACH FOR MAGNETIC MODELLING UNDER DISTORTED EXCITATION

A validation of presented NN approach has been made by a comparison with the results shown in [2] where the time-frequency approach was applied together with a dynamic version of the Jiles-Atherton (JA) model. A distorted magnetic filed H divided in a series of suitable time windows has been fixed (Fig. 4 (a)). By means of a time-frequency approach [2], different frequencies values for each time window have been founded. In Fig. 4 (b) the whole path of hysteresis has been reconstructed by using the previous trained NN with a specific input frequency value for each time window. It is clear that the present approach fits the experimental loops as well as the windowed dynamic JA models [2].

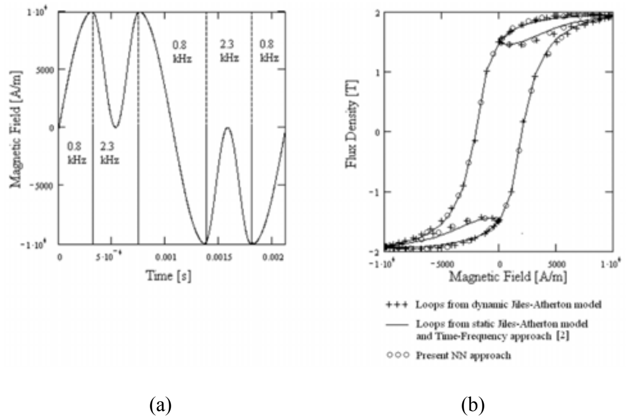

Fig. 4. A validation example of presented NN approach (b) under a distorted excitation H (a) compared with the appraoach proposed in [2].

V. CONCLUSIONS

A NN approach for analyzing magnetic field problems involving ferromagnetic materials has been presented. In particular the proposed neural approach can perform any dynamic hysteresis path generated by a fixed distorted excitation taking in the account the iron losses. The main important advantages of this approach are: 1) its easy to be implemented, since just simple hysteresis measurements are required for NN training, 2) the present approach is independent from the nature of the excitation: i.e. the NN can indifferently perform the direct problem (prediction of B from a known waveform of H) or the inverse problem (prediction of H from a known waveform of B). This last point allow us to overcome the numerical problems that arises for describing the inverse JA model.

VI. REFERENCES

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