A New Neural-Network-Based Scalar Hysteresis Model

M. Kuczmann and A. Iványi

***Abstract*—A neural network (NN)-based model of scalar hysteresis characteristics has been developed for modeling the behavior of magnetic materials. The virgin curve and a set of the first-order reversal branches can be stored preliminary in a system of three NNs. Different properties of magnetic materials can be simulated by a simple if–then type knowledge-based algorithm. Hysteresis characteristics of different materials predicted by the introduced model are compared with the results of the classical Preisach simulation technique. Comparisons are plotted in figures.**

***Index Terms*—Feedforward-type neural networks, Preisach model, scalar hysteresis model.**

I. INTRODUCTION

SIMULATION of hysteresis characteristics of magnetic materials must be included in computer-aided design software as a tool to predict the behavior of different electrical equipments. The industrial sector has increasing demand for hysteresis models to simulate electromagnetic field quantities in many kind of arrangement. Mathematically, hysteresis characteristics of magnetic materials can be described by a hysteresis operator, which is a nonlinear, multivalued relation between the magnetic field intensity $H(t)$ and the magnetization $M(t)$. Many available approaches and hypothesis have been developed since the last period of magnetic research, as the classical Preisach model and its generalizations, the Jiles–Atherton model, the Stoner–Wohlfarth model and some new approach constructed on the theory of neural networks (NNs) [1]–[6].

A hysteresis operator based on the well-known function approximation capability of feedforward type NNs is introduced in this paper [7]–[8]. The virgin curve and a set of the first-order ascending and descending reversal branches after some preprocessing can be predicted by NNs. General properties of hysteresis phenomena can be developed as if–then type rules of the knowledge-base of the model. Two kinds of training data sets have been generated by the classical Preisach model and the good agreement between the two simulation techniques is illustrated in figures.

II. NEURAL NETWORK MODEL OF HYSTERESIS

The developed model consists of a system of three feedforward-type NNs with bipolar sigmoid transfer functions and an if–then type knowledge-base about the hysteresis phenomena [7], [8].

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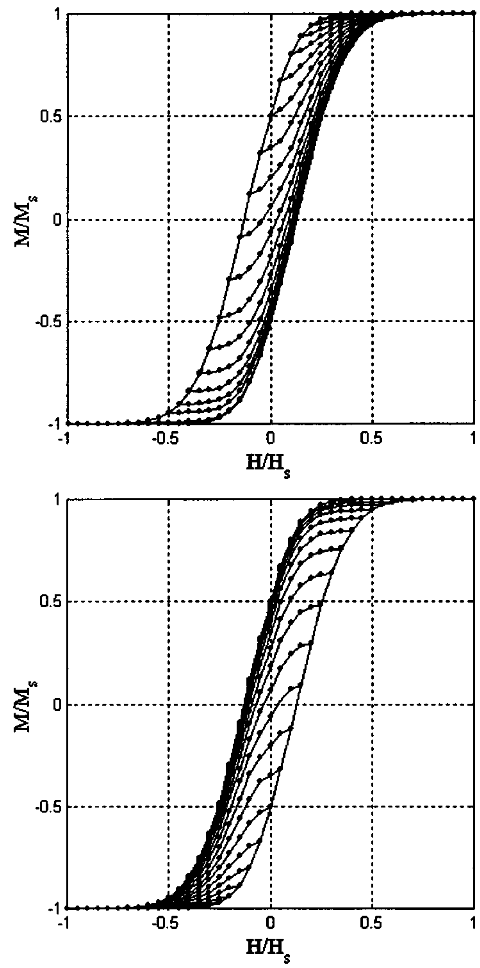

Fig. 1. First-order reversal curves.

The classical scalar Preisach model [1] has been used to generate different types of training data sets to find the appropriate one. Consequently, the anhysteretic curve and two sets of the first-order transition branches (Fig. 1) have been measured. Systematically generated ascending and descending external magnetic field must be excitated to measure transition curves. The required first-order reversal curves are obtained with the input function

$$H(t) = H_s \cdot \left[\frac{\alpha - 1}{2} + \frac{\alpha + 1}{2} \cdot \sin(\omega \cdot t + \pi/2)\right] \quad (1)$$

where H_s is the magnetic field intensity in saturation state, ω is the frequency of excitation, $\alpha = k/n$ and $k \in [-n, n]$ is an integer, and n denotes the number of reversal curves.

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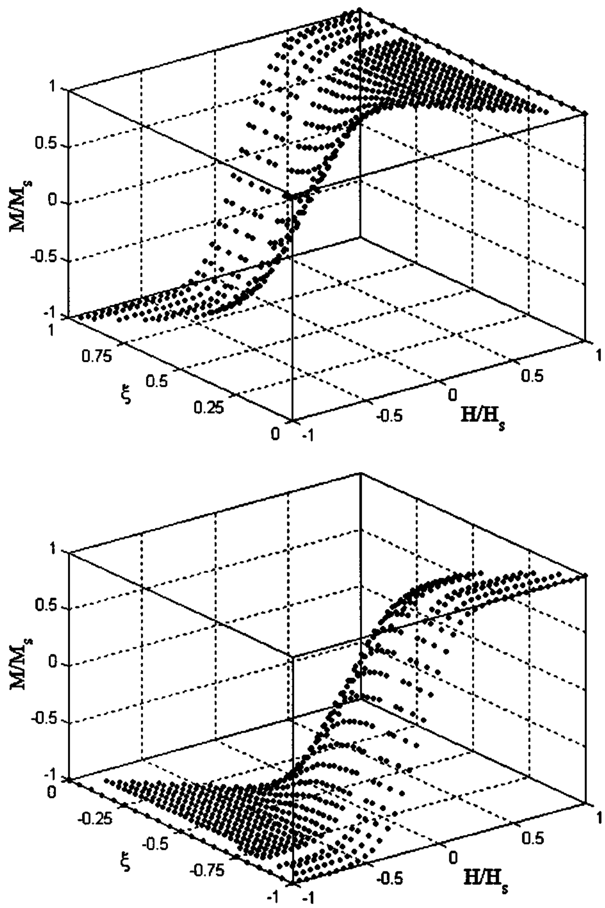

Fig. 2. First-order reversal curves after preprocessing.

Introducing a new dimension, measured and normalized ascending and descending data sets, which are multivalued functions can be described by a set of single-valued and three-dimensional (3-D) surfaces. The upgrade part of hysteresis characteristics can be described with a positive real parameter ξ and the descending curves can be approached with negative value of the same parameter ξ. The value of this parameter for a first-order transition branch can be calculated at turning points of normalized magnetic field intensity, as

$$\xi^{(\mathrm{asc})} = 1 - \frac{1 + H_{\mathrm{tp}}}{2} \tag{2}$$

for ascending and

$$\xi^{(\mathrm{desc})} = -\frac{1 + H_{\mathrm{tp}}}{2} \tag{3}$$

for descending curves. The effect of this preprocessing technique can be seen in Fig. 2 for ascending and descending branches. These are surfaces on the plane of the normalized magnetic field intensity and the additional parameter ξ. Hysteresis curves for different values of the parameter ξ can be seen in Fig. 3.

After preprocessing of the first-order reversal curves, function approximation is worked out by the well-known feedforward type NNs, trained by the Levenberg–Marquardt backpropagation method. The developed hysteresis model

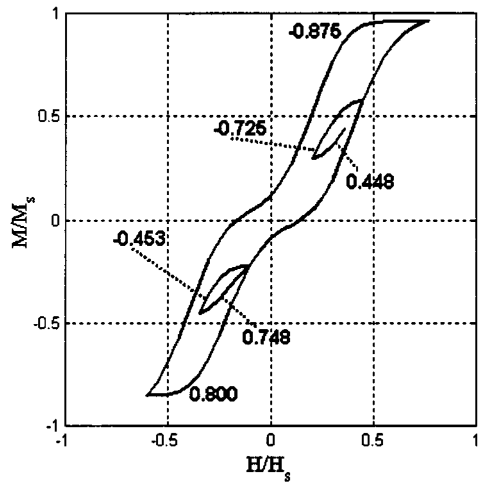

Fig. 3. Illustration for parameter ξ.

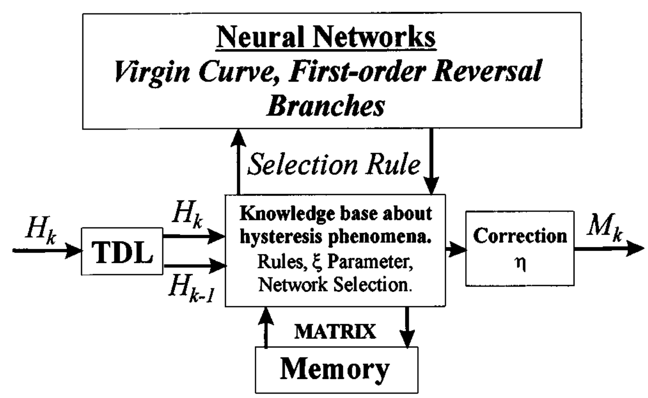

Fig. 4. Block diagram of the scalar model.

consists of three trained NNs, so anhysteretic magnetization curve and the first-order reversal curves are stored, but memory mechanism should be realized by an additional algorithm. It is the knowledge-base about the properties of hysteresis phenomena. In general, the normalized magnetization at a simulation step responsed by the neural model is constructed on the actual value of the relative magnetic field intensity, the appropriate value of parameter ξ and a set of turning points stored in the memory of the model. The knowledge-base is the main part of the implemented neural model. It contains if–then type rules about hysteresis phenomena and controls the other blocks of the model. The block representation of the model can be seen in Fig. 4.

The operation of the model is built on a set of turning points in the ascending and descending branches, saved in the memory, which is a matrix with the division $\mathbf{MATRIX} = [H_{\mathrm{tp}}, M_{\mathrm{tp}}, \xi]^T$.

Turning points can be detected by the evaluation of a sequence of $\{H_{k-1}, H_k\}$, generated by a tapped delay line. After detecting a turning point $H_{\mathrm{tp}} = H_{k-1}$ and storing it in the memory, the aim is to select an appropriate transition curve for the detected turning point $(H_{\mathrm{tp}}, M_{\mathrm{tp}})$. Conditions are collected in the selection rules, to choose the suitable NN, as follows.

Starting from demagnetized state, or reversible magnetization process is simulated, NN that approximates the anhysteretic

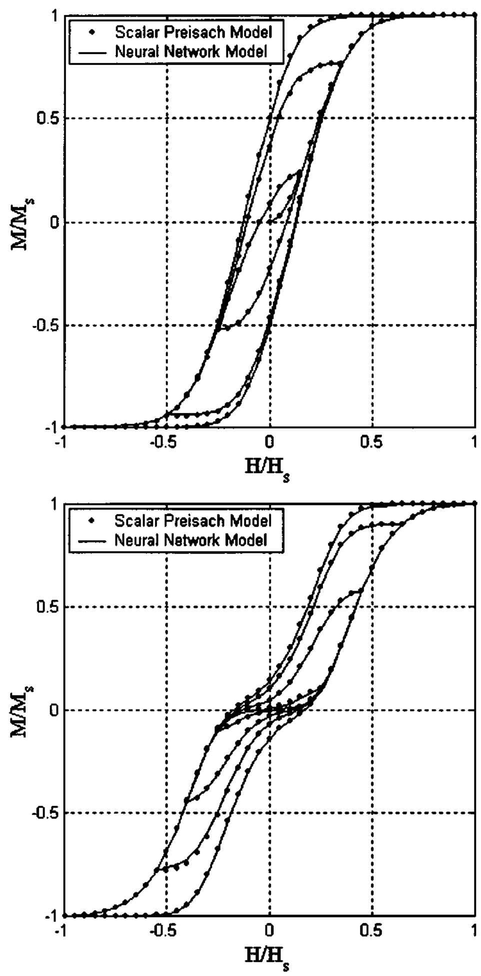

Fig. 5. Alternating magnetic field intensity.

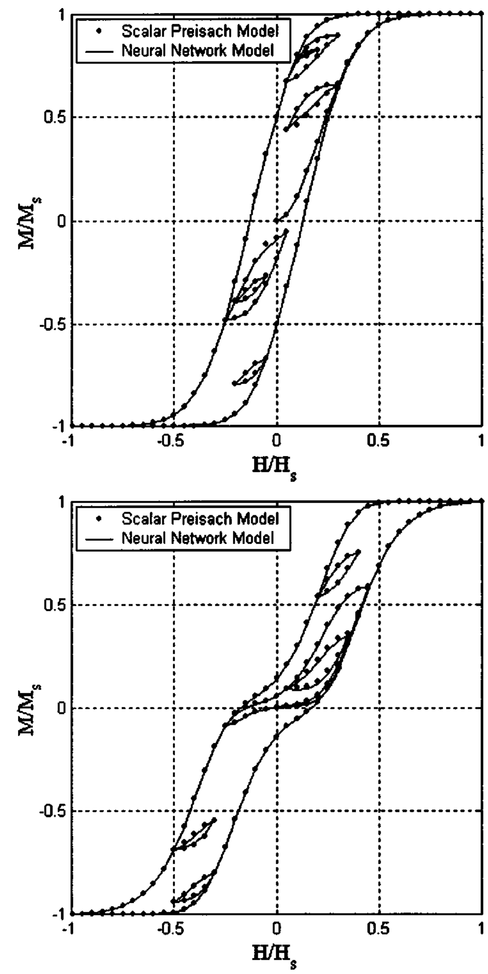

Fig. 6. Minor loops.

curve must be operated either increasing or decreasing excitation.

NN, which simulates descending branches, must be used detecting a turning point with the following settings: $H_{k-1} > H_{k-2}$ and $H_k < H_{k-1}$.

NN that models ascending curves must be turn on, when a turning point is shaped with settings $H_{k-1} < H_{k-2}$ and $H_k > H_{k-1}$.

The network simulating the virgin curve must be applied if $\mathbf{MATRIX}^{(\mathrm{desc})}$ ($\mathbf{MATRIX}^{(\mathrm{asc})}$) has only one column or a minor loop in the anhysteretic curve is just closed.

The same NN is selected at step k than applied at simulation step $k-1$, when turning point has not detected.

If $\mathbf{MATRIX}^{(\mathrm{desc})}$ ($\mathbf{MATRIX}^{(\mathrm{asc})}$) has more columns and magnetic field intensity is increasing (decreasing), the actual minor loop must be closed at the minimum value of $H_{\mathrm{tp}}^{(\mathrm{desc})}$ (maximum value of $H_{\mathrm{tp}}^{(\mathrm{asc})}$). This is the condition of closing minor loops. After closing a minor loop, the appropriate columns must be erased.

The results of simulation have showed that the value of normalized magnetization responsed by the according NN and the adequate value of normalized magnetization, chosen from the appropriate column of the memory at the value of H_{GOAL} are not equal. So some corrections η must be used to eliminate this deviation to close a minor loop. The value of parameter η can be calculated as the difference between the required value of magnetization and the response of the actual NN at the value of magnetic field intensity H_{GOAL} $(M^{(\mathrm{NN})}(H_{\mathrm{GOAL}}, \xi_{\mathrm{START}}))$, when an actual minor loop is closed,

$$\eta = M_{\mathrm{tp}} - M^{(\mathrm{NN})}(H_{\mathrm{GOAL}}, \xi_{\mathrm{START}}). \tag{4}$$

This parameter must be calculated ahead, when opening a minor loop. ξ_{START} is the value of parameter ξ at the actual H_{START}.

The parameter η must be taken into consideration while closing a minor loop at the value H_{GOAL}, so an additive correction must be summed with the response of the actual NN. The value of magnetization (M_{tp}) and the response of the selected NN $(M^{(\mathrm{NN})}(H_{\mathrm{START}}, \xi_{\mathrm{START}}))$ are corresponding at the turning point, where the minor loop opens, so that an appropriate curve is joined at H_{START} by the calculated parameter ξ_{START}. The value of correction η must be summed with the response of the actual NN $\boldsymbol{Net}_k$, increasing linearly at the kth step

$$M_k = \boldsymbol{Net}_k + \eta \cdot \frac{H_k - H_{\mathrm{START}}}{H_{\mathrm{GOAL}} - H_{\mathrm{START}}} \tag{5}$$

at ascending branches if the $\mathbf{MATRIX}^{(\mathrm{desc})}$ has more columns and

$$M_k = \boldsymbol{Net}_k + \eta \cdot \frac{H_{\mathrm{START}} - H_k}{H_{\mathrm{START}} - H_{\mathrm{GOAL}}} \tag{6}$$

at descending curves if the $\mathbf{MATRIX}^{(\mathrm{asc})}$ is not a vector.

There are reversible and irreversible parts on the virgin curve. A normalized parameter H_{rev} must be given to determine the limit of reversible magnetization process.

III. Comparisons With the Preisach Model

The experimented NN model of hysteresis can be used as a scalar model with continuous output to simulate the behavior of isotropic magnetic materials. Two kind of hysteresis characteristics predicted by the developed model have been compared with the results of the Preisach model to show the good applicability. The response of magnetic material for alternating magnetic field intensity can be seen in Fig. 5. Noncongruent minor loops are plotted in Fig. 6. Approach of NN model is denoted by solid line, approximation with Preisach model is plotted by points.

As it can be seen from the figures, hysteresis characteristics measured in the rolling and in the transverse direction on an anisotropic magnetic material can be simulated as well. Noncongruent minor loops are also can be predicted by the NN hysteresis model.

IV. Conclusion

A NN model for magnetic hysteresis based on the function approximation capability of NNs has been experimented. The anhysteretic magnetization curve and a set of the ascending and a set of the descending first-order reversal branches must be measured on a real magnetic material. Introducing an additional parameter ξ solves a fundamental problem of simulating hysteresis characteristics, that is the multivalued property. The magnetization becomes a single-valued function of two variables and an if–then type knowledge-base can be used for simulating different phenomena of magnetic materials.

Aim of further investigations is to compare the hysteresis characteristics simulated by the developed model and measurements and introducing different properties of magnetization phenomena as temperature dependence, frequency dependence and accommodation. A 3-D vector hysteresis model can be developed constructed on the anisotropy energy.

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