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A neuro-fuzzy-based Preisach approach on hysteresis modeling

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Abstract

Most of the present identification techniques of the Preisach model rely on a fairly large amount of experimental data. This paper proposes a method that utilizes the available data in the major loop and omits the need of measuring the first-order reversal curves. The method models hysteresis by applying the classical Preisach model whose identification procedure is performed by the utility of neuro-fuzzy approximators. The method is applied to the prediction of cyclic minor loops of a soft magnetic composite. The simulation and measurement results show the good accuracy of the method and validate the proposed approach.

Keywords: Preisach model; Everett function; Ferromagnetic hysteresis; Neuro-fuzzy approximators

1. Introduction

The phenomenon of hysteresis is naturally encountered in the study of ferromagnetic materials. The Preisach model is a mathematical tool that has been successfully used to model this phenomenon for many years. From several Preisach-type models [1], the Classical Preisach Model (CPM) in its scalar form has prompted many researchers to improve its accuracy and applicability. It is often expressed by

$$y(t) = \Gamma[u](t) = \iint_{\alpha \geqslant \beta} \mu(\alpha, \beta)[\gamma_{\alpha\beta} u](t)\, \mathrm{d}\alpha\, \mathrm{d}\beta, \tag{1}$$

where u corresponds to the input and $y(t)$ to the output of the Preisach model. $[\gamma_{\alpha\beta}u](t)$ is an operator sometimes referred to as an elementary Preisach hysteron since it is a basic block from which the Preisach operator $\Gamma[u]$ will be constructed; and $\mu(\alpha, \beta)$ is a density function.

The well-known method to identify the density function using first-order reversal curves proposed by Mayergoyz [1] has received a wide success to represent hysteresis in diverse applications. In the context of this work, we assume that, only the data of the major loop are available. For this instance, in this paper, an attempt to improve the accuracy of hysteresis modeling will be achieved by the use of *neuro-fuzzy* approximators. The proposed approach based on neuro-fuzzy systems will be applied to identify the Preisach density function by means of approximating the Everett function

$$E(\alpha, \beta) = \iint_{\Omega} \mu(\alpha, \beta)\, \mathrm{d}\alpha\, \mathrm{d}\beta. \tag{2}$$

In case we would like to find the density function $\mu(\alpha, \beta)$ we can take the double derivative with respect to α and β on both sides of Eq. (2). In fact, the density function does not have to be reconstructed, since the output can be efficiently computed by combinations of integrals, over suitable triangles (Ω) in the Preisach plane [1,2]. Such an approach permits to reconstruct the Everett function in a finite number of points corresponding to the measured values on the first-order reversal curves.

In the absence of the measured first-order curves, a phenomenological approach introduced in Ref. [3] will be used to generate an approximated family of first-order reversal curves. This allows one to form any reversal curve by means of conjugation of the portions which are transplanted from the major loop branches. The procedure is briefly described in the appendix.

The conventional mathematical methods based on hard computing such as polynomial or cubic spline interpolators can be in many cases satisfactory and the search of methods based on soft computing such as neural networks or fuzzy logic may hence seem unsound. Our experience

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with hysteresis modeling, however, showed that linear and polynomial or cubic spline interpolations require a lot of measured (or constructed) data in order to have smooth accurate modeling. Recently, neural networks have been plausibly applied to supplant conventional mathematical methods in order to enhance the modeling accuracy of hysteresis [4,5]. From other aspect, the trend of using fuzzy modeling becomes justified in situations where information about the system can be inferred from a limited amount of data. Fuzzy logic provides a simple way to arrive at a definite conclusion based upon partial, imprecise, noisy, or missing information [6]. Therefore, in the availability only of the major loop, conceptually, fuzzy modeling brings a potential to satisfactorily model the nonlinear hysteretic behavior.

Smoothing the measured data, without any extra effort for using filters, is the main advantage of using neuro-fuzzy in hysteresis modeling whereas the neuro-fuzzy models work as predictors and filters. This makes this approach distinctly useful to model magnetic hysteresis.

2. Neuro-fuzzy modeling

Neuro-fuzzy refers to the combination of fuzzy set theory and neural networks with the advantages of both [7]. In 1993, Jyh-Shing Roger Jang proposed a novel architecture called *Adaptive-Network-Based Fuzzy Inference System*, or simply ANFIS [8], which can serve as a basis for constructing a set of fuzzy if–then rules with appropriate membership functions to generate the stipulated input–output pairs. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input–output data. This learning method works similarly to that of neural networks.

The important contribution of ANFIS is the idea of expressing, as net architecture, the main components of a fuzzy inference system: fuzzification, implication and defuzzification. The utility of ANFIS illustrated in Fig. 1 can be devised to identify a Preisach density function $\mu(\alpha,\beta)$ by taking advantage of the Everett function $E(\alpha,\beta)$. The rule base which contains fuzzy if–then rules of Takagi and Sugeno's type can be written in case of using 2 nodes as

if α is A_1 and β is B_1, then $\bar{E}_1 = f_1(\alpha,\beta)$,

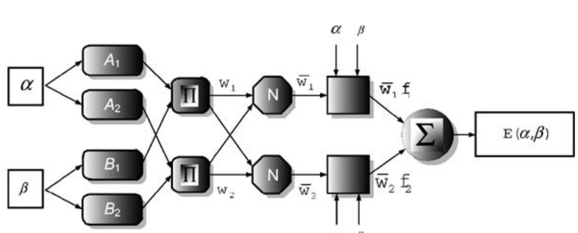

Fig. 1. ANFIS net architecture for the realization of the Everett function.

if α is A_2 and β is B_2 then $\bar{E}_2 = f_2(\alpha,\beta)$,

where A_i and B_i, $(i = 1,2)$, are fuzzy sets in the antecedent, while $\bar{E}_i = f_i(\alpha,\beta)$ is a crisp function in the consequent usually expressed by a polynomial

$$\bar{E}_i = f_i(\alpha,\beta) = p_i\alpha + q_i\beta + r_i, \quad i = 1,2,$$

where $\{p_i, q_i, r_i\}$ is a set of the consequent parameters. Let the membership functions of the fuzzy sets A_i, B_i be $\mu_{A_i}(\alpha), \mu_{B_i}(\beta)$, respectively. Usually they are chosen to be bell-shaped, with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i}(\alpha) = \frac{1}{1 + [((\alpha - c_i)/a_i)^2]^{b_i}}, \quad i = 1,2, \tag{3}$$

where $\{a_i, b_i, c_i\}$ is a set of the premise parameters. It is worth mentioning that by changing the value of each parameter in the membership functions, one can obtain distinct similarity to several shapes of hysteresis curves. This will support our approach to flexibly apply a neuro-fuzzy system to various magnetic materials which exhibit different hysteresis shapes.

Evaluating the rule premise results in

$$w_i = \mu_{A_i}(\alpha)\mu_{B_i}(\beta), \quad i = 1,2$$

and evaluating the implication and rules consequences gives

$$E(\alpha,\beta) = \frac{w_1(\alpha,\beta)f_1(\alpha,\beta) + w_2(\alpha,\beta)f_2(\alpha,\beta)}{w_1(\alpha,\beta) + w_2(\alpha,\beta)}. \tag{4}$$

This can be separated to phases by first defining

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2.$$

Then $E(\alpha,\beta)$ can be written as

$$E(\alpha,\beta) = \bar{w}_1 f_1 + \bar{w}_2 f_2. \tag{5}$$

ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs backpropagation gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equation, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning method since it combines the gradient descent and the least-squares method.

The training data to ANFIS will be supported by recomposing first-order reversal curves from the major loop using Zirka's method [3] described briefly in the appendix. The training data are computed from the recomposed-first-order curves by using the Everett measure

$$E(\alpha,\beta) = \tfrac{1}{2}(y_{\alpha\beta} - y_\alpha). \tag{6}$$

After training ANFIS, ultimately, an Everett surface can be established according to the procedure reported above. The parameters $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$ are adjusted by employing a hybrid learning according to the input–output experimental data such that an Everett function for any hysteretic behavior can be approximated.

The implementation of the Preisach model (1) will be made following the procedure described in Ref. [2, pp. 45–58] and expressed by

$$y(t) = 2\sum_{k=1}^{n}(E(\alpha_k, \beta_{k-1}) - E(\alpha_k, \beta_k)) - E(\alpha_0, \beta_0), \tag{7}$$

where the function $E(\alpha_k, \beta_k)$ is computed from the ANFIS inference system defined by Eq. (4); α_k, β_k represent the sequence of local extrema and they are decreasing and increasing sequences of α, β coordinates of interface vertices, respectively; n is the number of horizontal links made in the Preisach plane.

3. Implementations and results

The major loop data of a soft magnetic composite (SMC Somaloy 550) were experimentally obtained at the Laboratory of Electromechanics. To test the sensitivity of ANFIS to the amount of the training data, we recomposed two sets of first-order curves following the approach described in the appendix. Including the ascending branch of the major loop, the first set contained 5 curves whereas the second set contained only 3 curves. The number of the input–output pairs of the sample data was 189 in the first set and 116 in the second set. These samples were submitted to train the ANFIS system according to a chosen error criterion.

In each input, α and β, the number of membership functions was fixed to 3 for both cases and their type was defined by Eq. (3). After ANFIS was trained, its premise and consequent parameters were tuned to the optimum values through the learning process. The computation of these parameters was facilitated by a gradient vector, which provided a measure of how well the fuzzy inference system was modeling the input–output data for a given set of parameters. For both cases, the ANFIS contained 8 rules. The initial shapes and positions of the membership functions were symmetric. An example for the training case with 5 curves illustrating the final shapes of the membership functions of the input α is shown in Fig. 2.

A procedure was performed in a Matlab environment to implement the numerical Preisach model expressed by Eq. (7). To verify the accuracy of the model, we carried out experimental measurements of minor loops caused by applying a cyclic external field on the SMC measuring sample. The simulated results in Fig. 3 refer to the case in which the number of the input–output pairs of the sample data was 189 (5 curves). Comparing with the experimental results, it is evident that the modeling accuracy is highly satisfactory in spite of the limited original data measured on the sample of SMC. This gives an advantage to ANFIS for the great capability of predicting the output $E(\alpha, \beta)$ with the appreciated help of the training data endorsed by the recomposed-first-order curves based on Zirka's approach.

Fig. 4 indicates the case at which the number of the input–output pairs of the sample data was 116 (3 curves). It is still seen that ANFIS was able to approximate $E(\alpha, \beta)$

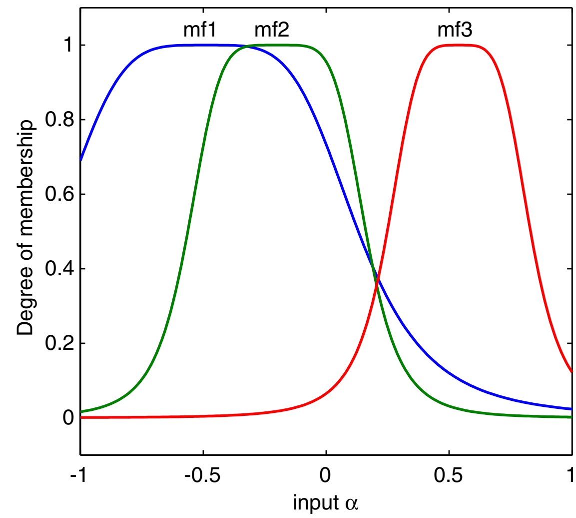

Fig. 2. Final adjusted membership functions of the input α.

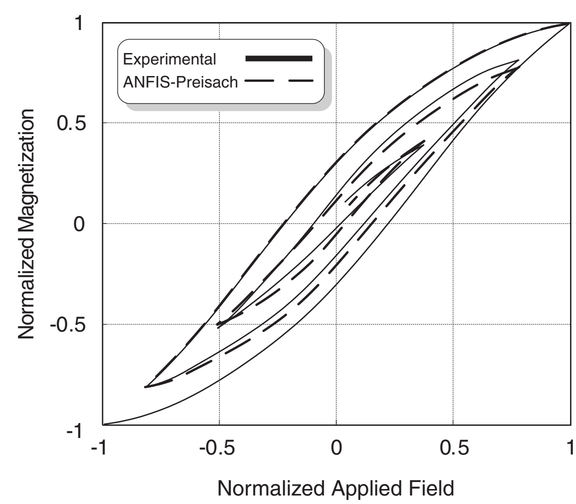

Fig. 3. Predictions of the neuro-fuzzy-based Preisach approach in case of using 189 pairs of samples.

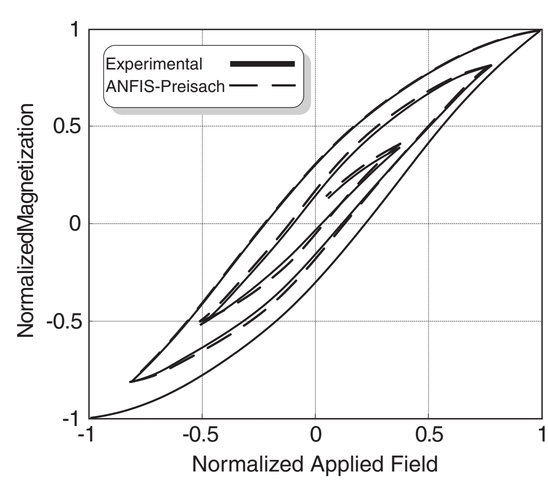

Fig. 4. Predictions of the neuro-fuzzy-based Preisach approach in case of using 116 pairs of samples.

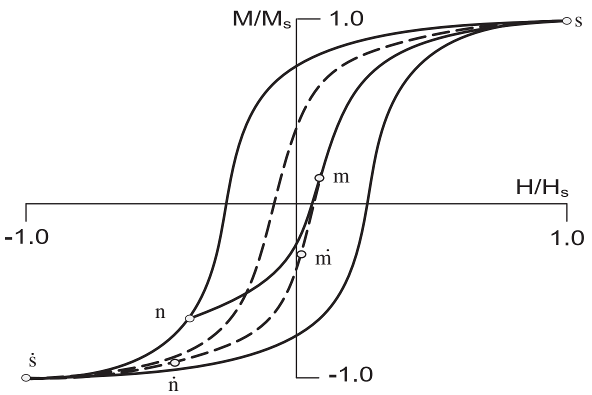

Fig. A.1. Construction of the first-order curves.

with reasonably accurate predictions thanks to the smoothing and interpolating capabilities of ANFIS. This type of modeling in which only limited data were available worked well because the limited data presented to ANFIS for training (or estimating) the membership function parameters were representative of the main features of the Everett function that the trained ANFIS was intended to model.

4. Conclusion

The significance of this work lies in the application of neuro-fuzzy systems to model magnetic hysteresis. The replacement of the measured first-order reversal curves by means of approximating the Everett function on the basis of the information provided only by the major loop was successfully implemented.

Appendix

Zirka's method can be summarized in Fig. A.1 in which the dashed curves are constructed using

$$H(M) = H_a(M) - K[H_a(M) - H_d(M)], \tag{A.1}$$

where $H_a(M)$ and $H_d(M)$ denote the values of the magnetic field on ascending and descending branches of a major loop, respectively, corresponding to the magnetization M; K is a constant that can take the values from 1 to 0. The particular cases for which $K = 0$ and 1 represent the ascending and descending branches of the major loop, respectively. The dashed lines were the result of $K = 0.3$ and 0.7.

A first-order curve s–m–n is composed of two segments. The upper segment s–m is the part of the curve s–$\dot{m}$–$\dot{s}$, and the lower segment m–n has been transplanted (copied) from the lower part of this curve where $\dot{m}$–$\dot{n}$ represents its segment which is displaced along the H and M axes by values ΔH and ΔM, respectively. Boundaries $\dot{m}$ and $\dot{n}$ of the transplantate and its displacements ΔH and ΔM are chosen to ensure continuity of the derivative dM/dH at the junction m.

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