Application of the Preisach model with a neural weighting function approximator to modeling of selected branched characteristics

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The article presents modeling of ramified characteristics and lossy processes in hysteresis loops by means of a hybrid model. The modeling system of closed loops of elementary characteristics – the classical Preisach model – is used as the basis for the discussion. The model was developed by including a neural density function approximator.

The work concentrates on lossy branched characteristics in a non-symmetrical circulation of the coordinate system, as well as on clear extrema in the range of accumulation of discrete values. These factors affect the density function shape and the neural network structure used for the approximation.

The authors give three typical examples of modeling of ramified characteristics. The first example is a retrogressive characteristic of the second generation of superconducting material; the second one deals with the typical hysteresis in ferromagnetic materials, whereas the third one includes magnetic hysteresis in high-temperature superconductors.

I. INTRODUCTION

Modeling of nonlinear environments, with lossy dynamic characteristics, requires the determination of the ramified characteristics of changes from the baseline. The essence of the difference is in the outline diagram according to the case of incremental changes in terms of decreasing, or for the case of monotonic change along with other values of the previous extrema. It is not possible to describe such change with a mathematical model defined by functional mapping of the input relative to output values [1], [4], [6].

Reliable description of phenomena or physical properties of the dynamic processes often requires the determination of many complex causal relationships. There are reports of lack of significant correlations of the initial input values to output values. In such cases, the modeling focuses on the use of fuzzy logic and neural network models [3], [6].

II. HYBRID MODEL

Mapping the ramified characteristics of nonlinear lossy environments requires the development of a hybrid numerical model.

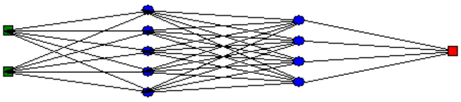

Fig. 1. Diagram of the used multilayer structure

The model uses the basic properties of the Preisach mathematical model developed for constructing a phenomenological hysteresis, and the characteristics of the approximation multilayer neural network structure (Fig. 1).

The mathematical Preisach model was defined as a projection in a limited field of two-dimensional set of real numbers. It is a summation of each of the hysteresis operators $\gamma_{\alpha\beta}$ at any point R^2. The value of each operator is determined by assigning coordinates (α, β) of temporary input values with respect to monotonicity and the selection of the density function $\mu(\alpha, \beta)$ value.

$$\mathrm{R_s}(i) = \sum_{N_n} \mu(\alpha,\beta)\gamma_{\alpha\beta}\,\mathrm{d}\alpha\mathrm{d}\beta \tag{1}$$

Equation (1) of the density function values takes into consideration the areas with positive or negative factor $\gamma_{\alpha\beta}$ which allows for the calculation of the temporary value of the modeled static parameter. Such an understanding of the relationship (1) in the continuous domain makes it possible to define a Preisach model (2) for the continuous density function $\mu(\alpha, \beta)$.

$$\mathrm{R_s}(i) = \iint_{\mathrm{P}} \mu(\alpha,\beta)\gamma_{\alpha\beta}(i(t))\,\mathrm{d}\alpha\mathrm{d}\beta \tag{2}$$

Every elementary operator reacts to the value of the response in accordance with the input value. The weighted sum of all output values of elementary operators, multiplied by the total density function sets the output of the system. The set of weights $\mu(\alpha, \beta)$ shapes the weighting function, which is defined as a description of the relative share of the operator in the total elementary hysteresis [1].

In this article the authors propose a new way of approximating the density function $\mu(\alpha, \beta)$ of the Preisach model by using algorithms of artificial neural networks.

The presented research is based on the comparison of the results of modeling using classical approximation and algorithms that use artificial neural networks [2], [3], [6].

$$\mu(\alpha,\beta) = \mathrm{R_s} e^{-\frac{1}{2}\left[\left(\frac{\alpha-\delta_\alpha}{\sigma_\alpha}\right)^2 + \left(\frac{\beta-\delta_\beta}{\sigma_\beta}\right)^2\right]} \tag{3}$$

Function (3) was used to determine the reverse (Fig. 3) characteristics of strips of the second generation superconducting material. R_s sets the value of the resistance in the resistive state, the parameters δ_α, δ_β – are constants defining the limit of the critical temperature, σ_α, σ_β are constants assigned to the heat capacity. The equation (3) defines the desired approximating function in the classical model calibrated with experimental data (Fig. 2).

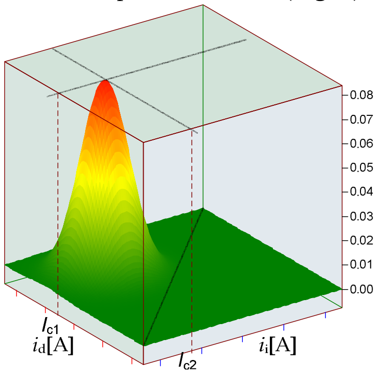

Fig. 2. Density function of the superconducting material (the function's domain represents the increasing current values and decreasing ones)

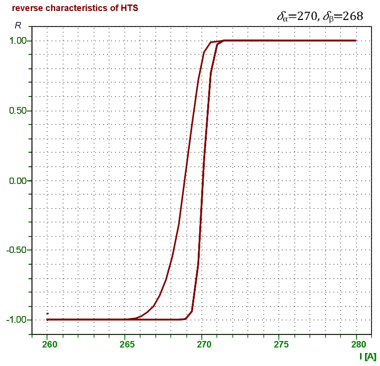

Fig. 3. The graphical representation of the HTS reverse characteristics

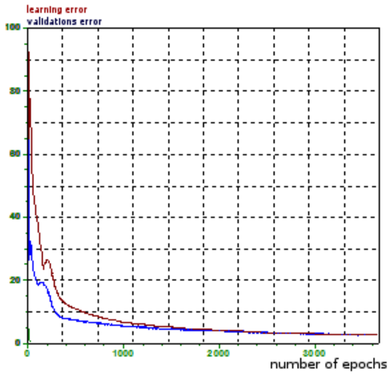

Fig. 4. Results of approximation - learning and validation errors of the artificial neural network

The authors also present two cases of modeling magnetic hysteresis loops. The first selected object is a current limiter with a collapsible cut core. The density function of such object is based on the calibration of the measurement data of the elemental metal bar in the Hopkinson yoke.

The second case is a superconducting material hysteresis [5]. In all the cases, the basis for the analysis are the validation and learning errors (Fig. 4).

The described examples show the benefits of the hybrid model – a combination of the classical Preisach model and artificial neural network algorithms. The benefits consist of replacing the analytical model of the density function by a fuzzy model – the weight values of neural structures. The evaluation of the selected model was based on the results of the learning process. The convergence of graphical representations of the validations errors and the learning errors values have been examined (Fig. 4). The surface shapes of the density function for a ferromagnetic material (Fig. 5), and HTS (Fig. 6) are presented as approximation results. The applied model is characterized through all the properties of the algorithms of artificial neural networks.

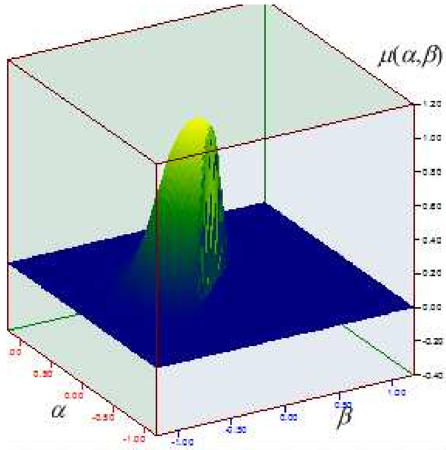

Fig. 5. Results of approximation - weighting function values (ferromagnetic materials)

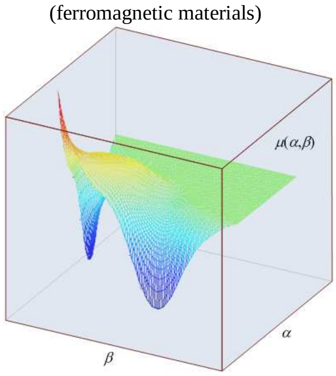

Fig. 6. Results of approximation of HTS hysteresis density function

The authors demonstrated that the proposed hybrid model is a useful tool for basic modeling of ramified magnetic characteristics (Fig. 3).

III. REFERENCES

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