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Real Coded Genetic Algorithm for Jiles–Atherton Model Parameters Identification

J. V. Leite, S. L. Avila, N. J. Batistela, W. P. Carpes, Jr., N. Sadowski, P. Kuo-Peng, and J. P. A. Bastos

Abstract—The parameters set of the Jiles–Atherton hysteresis model is identified by using a real coded genetic algorithm. The parameters identification is performed by minimizing the mean squared error between experimental and simulated magnetic field curves. The procedure is validated by comparing experimental and simulated results.

Index Terms—Magnetic hysteresis modeling, magnetic materials, parameters identification.

I. INTRODUCTION

AMONG the hysteresis models proposed in recent years for representing nonlinear characteristics of magnetic materials, the Jiles–Atherton (JA) model has been one of the most investigated. Compared to other models, the JA model has some advantages: it is formulated in terms of a differential equation and it uses only five parameters whose identification is performed from a single measured hysteresis loop [1].

The mathematical hysteresis model presented by Jiles and Atherton is based on physical considerations about the materials magnetic behavior [1]. Consequently, the five parameters of the JA model have a physical significance and a way to obtain the suitable parameters set is based on the physics concepts of the parameters. In this way, Jiles and Thoelke [2] proposed the first methodology for JA parameters identification from an experimental B-H loop.

Several others methods have been developed to achieve the best parameters set for the JA hysteresis model. Among them, some authors have proposed the use of optimization techniques to obtain a good representation of hysteresis loops. For instance, [3] uses an optimization technique based on simulated annealing and [4] uses a genetic algorithm with binary codification.

As an original contribution, we present here an optimization methodology based on a real coded genetic algorithm. The model parameters are obtained by fitting the simulated curve with the experimental one.

This method is less time consuming compared to trial-and-error adjustment (as given in a previous work [5]) and, as it will be shown, the obtained parameters allow a good agreement between simulated and measured curves even for inner loops.

II. INVERSE JA MODEL

In the original JA model, the total magnetization M is calculated from the magnetic field H. M is decomposed into reversible and irreversible components.

A modified JA model using the magnetic induction B as an independent variable was proposed in [6]. This inverse model keeps the original advantages of the direct model and can be directly used in time-stepping finite element calculations using a formulation based on the magnetic vector potential.

The main equation of this model is

$$\frac{dM}{dB} = \frac{(1-c)\dfrac{dM_{\text{irr}}}{dB_e} + \dfrac{c}{\mu_0}\dfrac{dM_{\text{an}}}{dH_e}}{1 + \mu_0(1-c)(1-\alpha)\dfrac{dM_{\text{irr}}}{dB_e} + c(1-\alpha)\dfrac{dM_{\text{an}}}{dH_e}}. \quad (1)$$

Both original and modified models belong to the Langevin type hysteresis models. If there is no hysteresis loss, the magnetization follows the anhysteretic curve M_{an} given by

$$M_{\text{an}} = M_s \left[\coth \frac{H_e}{a} - \frac{a}{H_e} \right]. \quad (2)$$

Its derivative with respect to the effective magnetic field H_e is

$$\frac{dM_{\text{an}}}{dH_e} = \frac{M_s}{a} \left[1 - \coth^2 \frac{H_e}{a} + \left(\frac{a}{H_e} \right)^2 \right] \quad (3)$$

where the effective magnetic field H_e is given by

$$H_e = H + \alpha M. \quad (4)$$

The following complementary relationships are also needed:

$$\frac{dM_{\text{irr}}}{dB_e} = \frac{M_{\text{an}} - M_{\text{irr}}}{\mu_0 k \delta} \quad (5)$$

where M_{irr} is the irreversible component of magnetization, and δ is a directional parameter and takes the value $+1$ for $dH/dt > 0$ and -1 for $dH/dt < 0$. The effective magnetic density B_e and the magnetic induction B are given, respectively, by

$$B_e = \mu_0 H_e \quad (6)$$

$$B = \mu_0 (H + M). \quad (7)$$

Parameters $a, \alpha, c, k,$ and M_S must be determined from a measured hysteresis loop [2], [3].

In this work, an alternative solution uses a mean squared error (MSE) definition based on the fitting between the measured and the calculated curves. The objective is to find the JA model parameters that minimize this MSE. The search for the global minimum is performed by an optimization method based on genetic algorithms (GAs) [7].

III. Genetic Algorithms

GAs optimizers are well-known tools in the electromagnetic community [8], [9]. GAs are stochastic optimization techniques founded on the concepts of natural selection and genetics. The algorithm starts with a set of solutions called *population*. Solutions from a population are used to form a new population. This is motivated by the hope that the new population will be better than the old one. Solutions that will form new solutions are selected according to their fitness: the more suitable they are, the more chances they have to reproduce. This is repeated until some condition (for example, number of generations or improvement of the best solution) is satisfied.

Among the advantages of GAs, we can quote that they can optimize with continuous or discrete parameters and do not require information about gradients; the possible discontinuities present on the fitness function have little effect on the overall optimization performance; GAs are resistant to becoming trapped in local optima; they can handle numerically generated data, experimental data, or analytical functions; and they can be employed for a wide variety of problems.

Real coding is well suited to a large class of programming languages and to problems with a great number of variables. For this reason, modified genetic operators are being developed for a real coded GA aiming an effective exploration of the search space [10]. These modified genetic operators are used in this paper as well as the improvement tools presented in [11].

A. Parameters Identification Procedure

Fig. 1 is a schematic representation of the parameters identification procedure presented here. The first step is the characterization of the individuals that will form the population.

The individuals are composed by the five parameters of the JA model (in real coding, it is not necessary to code the variables in binary representation). We consider the case where the population is given by

$$\mathrm{Pop}^n = \begin{bmatrix} M_s^{n,1} & k^{n,1} & c^{n,1} & a^{n,1} & \alpha^{n,1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ M_s^{n,np} & k^{n,np} & c^{n,np} & a^{n,np} & \alpha^{n,np} \end{bmatrix} \quad (8)$$

where each line represents an individual (a point in the optimization space), n is the generation, and np is the population size.

The initial values assigned to the population are random values in the allowable range, as shown in Tables I and II.

Each individual of this population is evaluated using the fitness between calculated and experimental results.

The convergence criterion is based on the achievement of an acceptable (fixed) MSE:

$$X = \min(\mathrm{MSE}) \quad (9)$$

and also on a maximum allowed number of generations.

If convergence is not attained, genetic operators (selection, crossover, mutation, and improvements techniques) are applied. The selection procedure is responsible for forming the pairs that will be submitted to the other genetic operators. Selection is a mechanism related to individual fitness. The "roulette wheel" method was used as the selection procedure [7]. Crossover and
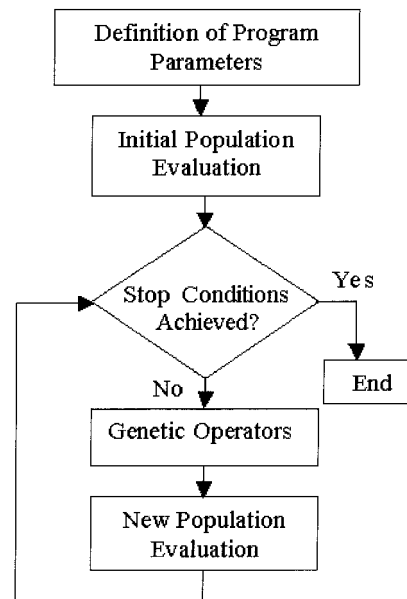

Fig. 1. Optimization procedure.

TABLE I
MATERIAL A PARAMETERS

Parameter	Design Variable Range	Optimized Values
Ms	1×10^6 - 2×10^6	1.453×10^6
k	25 - 100	72.352
c	100×10^{-3} - 500×10^{-3}	350.25×10^{-3}
a	25 - 100	88.424
α	50×10^{-6} - 300×10^{-6}	177.03×10^{-6}

TABLE II
MATERIAL B PARAMETERS

Parameter	Design Variable Range	Optimized Values
Ms	1×10^6 - 2×10^6	1.589×10^6
k	150 - 750	289.76
c	100×10^{-3} - 500×10^{-3}	417.75×10^{-3}
a	150 - 750	584.07
α	$0,5 \times 10^{-3}$ - 2×10^{-3}	1.001×10^{-3}

mutation are mechanisms used to change the genetic materials of the individuals. They are the main tools for the success of the optimization process and must be implemented in order to allow an effective exploration of the search space. We use an efficient scheme for crossover and mutation for a real coded GA, proposed in [10]. The improvement techniques presented in [11] are also used here: global elitism (which avoids loss of good solutions during the process), dynamic adaptation of crossover and mutation probabilities (variation of the probabilities values according to the population behavior), and reduction of the variables spaces (reduction of the variables ranges to increase the results precision and to facilitate the search toward the global minimum). The new individuals created by the genetic operators described above will be evaluated and the iterative process will be repeated until one convergence criterion is reached.

B. Program Data

The GA was implemented with 30 individuals (each with five variables corresponding to the parameters of the JA hysteresis model). The maximum number of generations was set to 50. The initial crossover and mutation probabilities were set in 90% and 5%, respectively. The allowable ranges for each variable are shown in Tables I and II.

The objective function to be minimized corresponds to the total MSE between experimental and simulated magnetic field curves.

The suitable ranges for the variables must be provided to the program. These ranges can be obtained by a trial-and-error procedure: we perform repeated calculations using a small number of individuals with few generations and we observe the error behavior for each chosen range.

The optimization procedure was executed several times. In the great majority of the cases, the algorithm found practically the same best individual. This demonstrates the convergence of the applied methodology. For a stochastic optimization method, the final solution can only be considered optimal by repetition of the results [7]. In the next section, the best solution found for the proposed examples is presented.

IV. RESULTS

A. Measured Curves

The experimental curves shown in this paper were obtained in a workbench presented in [5]. The magnetic device used was an Epstein's frame 0.28-m long with 0.03-m-width iron sheets. The primary and secondary windings have 700 turns ($N_p = N_s = 700$). The magnetic mean path ℓ_m is 0.94 m. The electric resistance of primary winding is 0.691 Ω. The secondary voltage $v_s(t)$ and the primary current $i_p(t)$ are measured simultaneously with an oscilloscope. The magnetic field is related to the $i_p(t)$ current by

$$H_{\exp}(t) = \frac{N_p}{\ell_m} i_p(t). \tag{10}$$

The magnetic induction is obtained by time integration of the $v_s(t)$ voltage in the secondary coil:

$$B_{\exp}(t) = \frac{1}{N_s S} \int v_s(t) dt \tag{11}$$

where S is the cross section of the Epstein's frame.

It is important to remark that the use of the inverse JA model for the parameters identification has an additional advantage compared with the original model: the input of the inverse model is the magnetic induction waveform. Since the magnetic induction is obtained from integration, it is naturally filtered, with fewer oscillations than those of the magnetic field waveform. The noise present in the field waveform brings additional difficulties to the parameters identification procedure.

The obtained set of parameters is valid for both models, original and inverse, allowing good agreement between measured and calculated data.
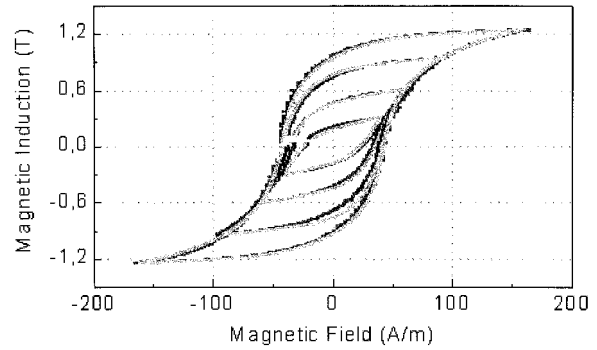

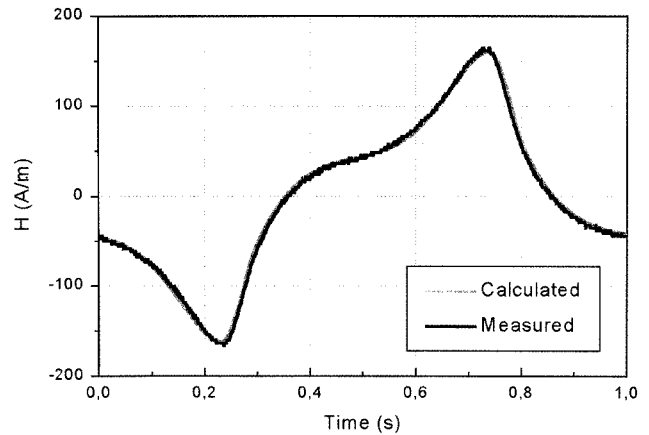Fig. 2.   Hysteresis loops: measured and modeled for material A.

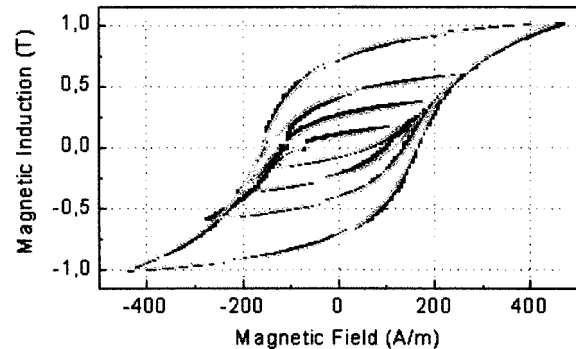Fig. 3.   Field: measured and modeled for material A.

Fig. 4.   Hysteresis loops: measured and modeled for material B.

B. Comparison With Simulation

Fig. 2 shows the experimental and simulated hysteresis curves for a material A modeled with the set of parameters obtained with the methodology proposed here. Table I shows the search ranges and the optimized parameters set for material A. Fig. 3 shows the experimental and simulated field curves of this material when submitted to a 1.24 T peak value sinusoidal induction.

Calculated and measured hysteresis loops for a different material B are shown in Fig. 4; the corresponding field curves are presented in Fig. 5. The search ranges and the optimized parameters set are shown in Table II. The comparison between these results shows a good agreement.

Fig. 6 and 7 show, respectively, the evolution of the MSE for materials A and B. We observe that the error decreases quickly
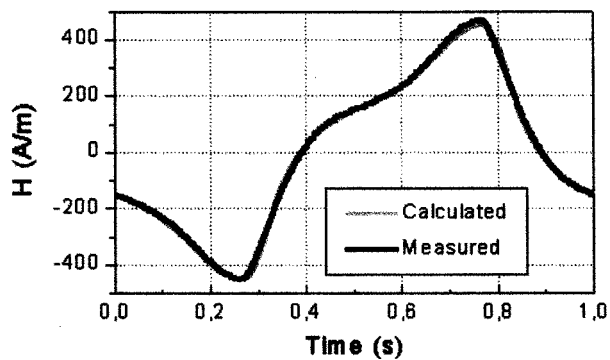
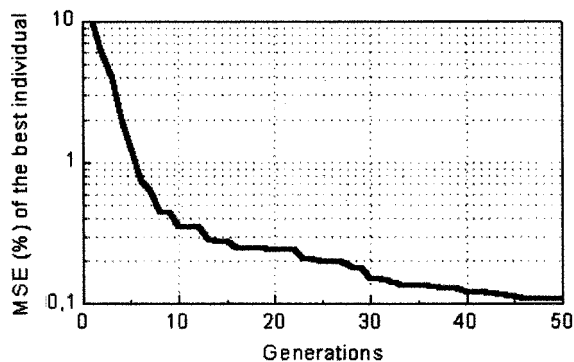Fig. 5. Field: measured and modeled for material B.
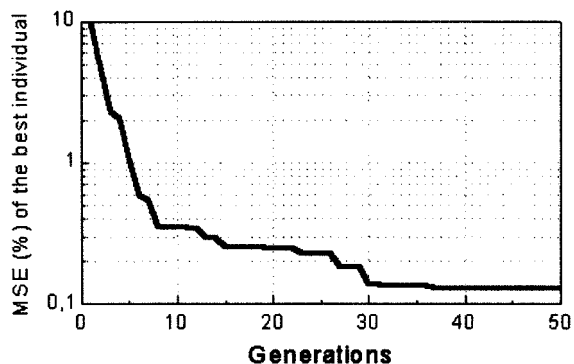

Fig. 6. Evolution of the total error for material A.

Fig. 7. Evolution of the total error for material B.

and the algorithm reaches an optimized set of parameters with little computational effort.

V. CONCLUSION

A Jiles–Atherton parameters identification program was implemented using genetic algorithms and tested with measured curves.

The GA methodology used in this work allows results to be obtained with good precision. Real coding has advantages related to the convergence time (few generations) and simplicity to assemble the individuals (it is not necessary to code them in binary representation). The computational effort and calculation time are lower compared to trial-and-error adjustment.

The good agreement between calculated and measured hysteresis curves, for the complete set of magnetic induction amplitudes, validates the proposed procedure.

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