Identification of Jiles-Atherton model parameters using Particle Swarm Optimization

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***Abstract*— This paper presents the use of the Particle Swarm Optimization for the identification of Jiles-Atherton model parameters. This approach is tested on two magnetic materials : NO 3% SiFe and NiFe 20-80. Results are compared with those obtained with a direct search method. Experimental validations are also presented.**

I. Introduction

The modelling of some electromagnetic devices requires to take into account an accurate behavior representation of the magnetic materials (static hysteresis law). The desciption of magnetization process based on Jiles-Atherton (J-A) theory [1] is usualy used because it can be easily implemented. Moreover the J-A model requires few memory storage and its implementation uses only five parameters. However, the identification of these parameters is based on an iterative procedure [2] which may introduce convergence problems. Indeed this classic procedure is very sensitive to initial values of parameters chosen as starting point for the optimization. Therefore new methods such as Simulated Annealing Method [3] or Genetic Algorithm [4] have been recently introduced. This paper presents another heuristic method, the Particle Swarm Optimization (PSO), in the aim to bring another solution. This method is based on a socio-cognitive theory contrary to the genetic algorithm method based on a natural selection : there is no elimination of individual of the population so there is less risk to exclude a good solution.

II. Implementation

A. J-A Model

The following form of J-A equations are considered : [5]

$$\frac{dM}{dH} = \frac{(1-c)\frac{dM_{irr}}{dH_e} + c\frac{dM_{an}}{dH_e}}{1 - \alpha c\frac{dM_{an}}{dH_e} - \alpha(1-c)\frac{dM_{irr}}{dH_e}} \quad (1)$$

where :

- M_{an} is the anhysteretic magnetization provided by the Langevin's equation

$$M_{an}(H_e) = M_s(coth(\frac{H_e}{a}) - \frac{a}{H_e}) \quad (2)$$

- H_e is the Weiss' effective field : $H_e = H + \alpha M$
- M_{irr} is the irreversible magnetization component defined by :

$$\frac{dM_{irr}}{dH_e} = \frac{M_{an} - M_{irr}}{k\delta} \; with \; \delta = sign(\frac{dH}{dt}) \quad (3)$$

$\alpha, a, c, k \; and \; M_s$ are the parameters of the model where a is a form factor, c the coefficient of reversibility of the movement of the walls, M_s the saturation magnetization, k and α represent the hysteresis losses and the interaction between the domains respectively.

B. PSO Process

The PSO is an adaptative algorithm based on a social-psychological analogy [6]. Each particle i of the swarm is defined as a potential solution to a problem in a five dimensional space. This particle i is associated to its position $x_i = (\alpha_i, a_i, c_i, ki, M_{Si})$. Each particle has a position (5) and a velocity (4) (their values are randomized initially).

The Fitness function for a particle i is defined as the squared error between the measured values and the calculated ones (obtained by considering the parameters associated to the particle i) of a static hysteresis loop.

The position with the lowest fitness score in each iteration is defined to be the entire swarm's global best (gbest) position. In addition, each particle keeps its best position that it has visited, known as the particle's personal best (pbest).

The particle motions are governed by the following rules which update particle positions x_i with variation's step for each parameters $v_i = (v_{\alpha_i}, v_{a_i}, v_{c_i}, v_{ki}, v_{M_{Si}})$:

$$v_i^{t+1} = \omega v_i^t + p_1 rd_1 \times (pbest - x_i) + p_2 rd_2 \times (gbest - x_i) \quad (4)$$

$$x_i^{t+1} = x_i^t + v_i^t \quad (5)$$

where x_i is the current position of particle i, $pbest$ is the best position obtained by particle i, $gbest$ is the swarm's global best position, v_i is the velocity of particle i, ω is an inertia weight, p_1 and p_2 are social and cognitive parameters, rd_1 and rd_2 are two random numbers between 0-1 and t is the current iteration.

A variable neighbourhood operator is also introduced [7] in order to improve the convergence of this method. During the

initial step of the optimisation, the neighbourhood of the particle is reduced to itself. As the number of iterations increases, the neighbourhood will be gradually extended to include all particles. In other words, the variable $gbest$ in the classical PSO algorithm is replaced by $lbest$ (i.e. local best solution) where a local neighbourhood size is gradually increased. The neighbourhood of a particle is defined by the minimum of Euclidian norm for the five normalized parameters

In addition, the value of the inertia weight ω in the PSO is also gradually fitted (6) in order to improve the accuracy during the final steps of optimisation.

$$\omega = \frac{(\omega_{start} - \omega_{end}) \times (Max_{iter} - Iter)}{Max_{iter}} + \omega_{end} \qquad (6)$$

where ω_{start} and ω_{end} are initial and final values for the random inertia weight.

III. Results

This method is used to obtain the five parameters of J-A model for the magnetization representation of two different magnetic materials.

A. NO 3% SiFe material

The table I compares the different parameter values obtained by considering the PSO algorithm and a Direct Search Method (DSM) : the fminsearch function of MATLAB.

TABLE I

Optimization results

Parameters	PSO	Direct Search
α	8.8448e-5	7.755e-5
a	38.3704	35.483
c	0.13568	0.22365
k	50.7865	56.968
M_s	1.1163e6	1.112e6

In the table II, the error is calculated in several characteristic points : $B_{\frac{1}{2}}$ (respectively $B_{-\frac{1}{2}}$) is a point on the descending part of the B-H major loop, whose H-coordinate is equal to $0.5H_{max}$ (respectively $-0.5H_{max}$) and B_{1M} is a point on the first magnetization B-H curve, whose H-coordinate is equal to $0.25H_{max}$.

TABLE II

Estimation errors for a major hysteresis loop

Characteristic point	PSO error	Direct Search error
Hc	0.3%	0.8%
B_r	0.6%	6.2%
$B_{\frac{1}{2}}$	0.1%	0.52%
$B_{-\frac{1}{2}}$	0.3%	1.8%
B_{1M}	4.1%	42%

The PSO allows to obtain accurate results concerning the determination of the first magnetization (B_{1M}) contrary to a DSM.

B. NiFe 20-80 material

The DSM for this material leads to negative values of α and c (not physical). However the PSO suits. Results are reported in table III

TABLE III

Optimization results and estimation errors for major hysteresis loop

Parameters	PSO	Points	PSO error
α	5.1508e-5	Hc	33%
a	15.7511	B_r	0.6%
c	0.82557	$B_{\frac{1}{2}}$	1.2%
k	5.3407	$B_{-\frac{1}{2}}$	0.8%
M_s	9.192489e5	B_{1M}	8.3%

The 33% error obtained for H_c is not significant of the accuracy of the method because the material has a very small coercivity field (less than 1 A/m).

IV. Conclusion

PSO has been applied with success to estimate the J-A model parameters.Two tests have been presented here ; all other tests we did show that this method is not influenced by initial random values, doesn't have any convergence problem, and is anyway more accurate than DSM.

In the near future, we will go further into the notion of neighbourhood, and give comparisons with the genetic algorithms in terms of accuracy, calculation time and easiness of implementation.

In some cases, it may be more important to have a good accuracy for minor loops than for the first magnetisation curve : we plan to modify the fitness function to allow to give more weigh to the shape of minor loops on the JA coefficients.

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