APPLICATION OF A PSO ALGORITHM FOR IDENTIFICATION OF THE PARAMETERS OF JILES-ATHERTON HYSTERESIS MODEL

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Abstract

In the paper an algorithm and computer code for the identification of the hysteresis parameters of the Jiles-Atherton model has been presented. For the identification the Particle Swarm Optimization method (PSO) has been applied. The computer code has been elaborated using Delphi environment. The results of optimization have been compared to experimental ones. Selected results of the calculation are presented and discussed.

1 Jiles-Atherton hysteresis model

The model presented by D. Jiles and D. Atherton is a full physical model describing magnetic hysteresis. The application of this model makes it possible to illustrate the magnetization vector and the ferromagnetic loss of a specific magnetic material.

In the Jiles-Atherton model [2, 3], it is assumed that the magnetization M of a material is caused by the factors representing reversible M_{rev} and irreversible M_{irr} processes during the magnetization of the core

$$M = M_{rev} + M_{irr} \tag{1}$$

The irreversible process occurring in the course of magnetization is described by a differential equation

$$\frac{\mathrm{d}M_{irr}}{\mathrm{d}H} = \frac{M_{an} - M_{irr}}{k_h \delta - \alpha(M_{an} - M_{irr})} \tag{2}$$

where $\delta = \mathrm{sgn}\,\mathrm{d}H/\mathrm{d}t$, M_{an} is a non-hysteresis curve described by

$$M_{an} = M_{sat}\left(\coth\frac{H+\alpha M}{a} - \frac{a}{H+\alpha M}\right) \tag{3}$$

Here, k_h and α are the factors depending on material parameters[3], a is the shape factor, M_{sat} is the saturation magnetization. In the elaborated model, it is assumed that the reversible process inside is described by the equation

$$M_{rev} = c(M_{an} - M_{irr}) \tag{4}$$

where c is the factor depending on the type of material.

Substituting (4) into (1), after differentiation the following expression it is obtained

$$\frac{\mathrm{d}M}{\mathrm{d}H} = \frac{(1-c)(M_{an} - M_{irr})}{k_h \delta - \alpha(M_{an} - M_{irr})} + c\frac{\mathrm{d}M_{an}}{\mathrm{d}H} \tag{5}$$

When modeling the voltage forced magnetic field, it is necessary to calculate the field intensity on the basis of magnetic flux density. Such situation occurs in the FEM algorithms using vector magnetic potential. Then, instead of the derivative of M with respect to the field intensity (5), its derivative with respect to the magnetic flux density is determined

$$\frac{\mathrm{d}M}{\mathrm{d}B} = \frac{(1-c)\dfrac{\mathrm{d}M_{an}}{\mathrm{d}B_e} + \dfrac{c}{\mu_0}\dfrac{\mathrm{d}M_{an}}{\mathrm{d}H_e}}{1 + (1-\alpha)\left(\mu_0(1-c)\dfrac{\mathrm{d}M_{irr}}{\mathrm{d}B_e} + c\dfrac{\mathrm{d}M_{an}}{\mathrm{d}H_e}\right)} \tag{6}$$

where μ_0 is the air permeability, H_e is the effective magnetic field intensity, $B_e = \mu_0 H_e$, and magnetic flux density $B = B_e - \mu_0 \alpha M + \mu M$.

In order to solve equations (5) and (6), i.e. to determine the magnetization M, numerical Runge-Kutta method for solving differential equations has been used.

2 The Particle Swarm Optimization Method

The PSO method is based on the observation of the social behavior of animals such as bird flock and fish shoal [1]. The swarm consists of individuals which are called particles. Each particle has a position and velocity. The particles learn from own past experience. This is because each particle remembers his best individual position $\mathbf{p}_i$ (with optimal value of the objective function) in previous time steps. Furthermore, in each step, the particles know the position of the leader, i.e. the position $\mathbf{p}_b$ of the best particle in the swarm. The first procedure of the PSO algorithm is initiation. In this procedure the vectors of positions $\mathbf{x}_0^i$ and velocities $\mathbf{v}_0^i$ of each particle (i is the particle number) are assumed. In next step the evaluation of each particle according the objective function (called the fitness function) is carried out. Then, the best particle position $\mathbf{p}_b$ can be founded. For each individual the objective function is compared with objective function in previous step. If current value is better than previous one then the value of $\mathbf{p}_i$ is updated.

In the next stage the vectors of velocity $\mathbf{v}_k^i$ and new position $\mathbf{x}_k^i$ are updated. In order to calculate velocity for the *j*-th search direction following formula is used

$$v_k^i(j) = w_1 v_{k-1}^i(j) + c_1 r_1 \left(p_i - x_{k-1}^i(j)\right) + c_2 r_2 \left(p_b - x_{k-1}^i(j)\right) \quad (7)$$

where k is the number of time step, w_1 is the weight of inertia, $v_{k-1}^i(j)$, $x_{k-1}^i(j)$ are the components of velocity and position of particle, respectively, c_1, c_2 are the learning factors [1], r_1, r_2 are the random numbers; usually r_1, $r_2 \in$ (0, 1).

Finally, the new particle positions is calculated

$$x_k^i(j) = x_{k-1}^i(j) + v_k^i(j) \quad (8)$$

3 The optimization procedure

The algorithm and computer code for identification of the hysteresis parameters of the Jiles-Atherton model has been elaborated. In order to optimize these parameters, the PSO algorithm has been applied. The aim of the optimization was defined as following: for the known hysteresis loop (derived from measurement) the parameters shall be assigned which enable to best illustrate the hysteresis using the Jiles-Atherton model.

The hysteresis loop was described by five variables $(j = 1,2...5)$: $z_1 = M_{sat}$, $z_2 = a$, $z_3 = k_h$, $z_4 = c$, $z_5 = \alpha$. These design variables determine the vector $\mathbf{z} = [M_{\text{sat}} \;\; a \;\; k \;\; c \;\; \alpha]^T$.

All the variables have been transformed into dimensionless quantities as follows

$$s_i(j) = \frac{\left(z_i(j) - z_{i\min}(j)\right)}{\left(z_{i\max}(j) - z_{i\min}(j)\right)}, \quad j = 1,2...5 \quad (9)$$

where $z_{i\min}(j)$ and $z_{i\max}(j)$ are the lower and upper limits of expected of intervals each variable $z_i(j)$, respectively. If $z_i(j) \in \langle z_{i\min}(j), z_{i\max}(j) \rangle$ then $s_i(j) \in \langle 0,1 \rangle$.

The dimensionless objective function for *i*-th particle has the form

$$f_i(\mathbf{s}) = \lambda_1 g_1(\mathbf{s}) + \lambda_2 g_2(\mathbf{s}) + \lambda_3 g_3(\mathbf{s}) \quad (10)$$

$$g_1(\mathbf{s}) = \frac{1}{N} \sum_{n=1}^{N} \left(H^{(m)}[n] - H^{(s)}[n]\right)^2 \quad (11)$$

$$g_2(\mathbf{s}) = \left(\frac{S^{(m)} - S^{(s)}}{S^{(m)}} \right), \; g_3(\mathbf{s}) = \left(\frac{H_m^{(m)} - H_m^{(s)}}{H_m^{(m)}} \right) \quad (12)$$

where $\mathbf{s}$ is the vector composed of five variables $s(j)$, $\lambda_1, \lambda_2, \lambda_3$ are the weighting factors, N is the number of measurement samples, (m) and (s) superscript denotes the measured and simulated values, respectively, $H^{(m)}[n]$, $H^{(s)}[n]$ are the values of magnetic field intensity for n-th measured and simulated sample, $S^{(m)}$, $S^{(s)}$ are the areas of measured and simulated loop areas, $H_m^{(m)}$, $H_m^{(s)}$ are the maximum values of magnetic field intensity for measured and simulated hysteresis loop, respectively.

4 Results

The calculations on the swarm with 1500 particles have been performed. The number of time step was 100. The following parameters of the optimization procedure have been assumed: $\lambda_1 = 0.1$, $\lambda_2 = \lambda_3 = 0.45$, $w_1 = 0.5$, $c_1 = 1.1$ and $c_2 = 1.3$. The authors developed computer code for hysteresis loop parameters identification. The computer code has been elaborated on the basis of Delphi environment. The measured and optimized hysteresis loops for ferrite K 2004 [4] are presented in Figure 1.

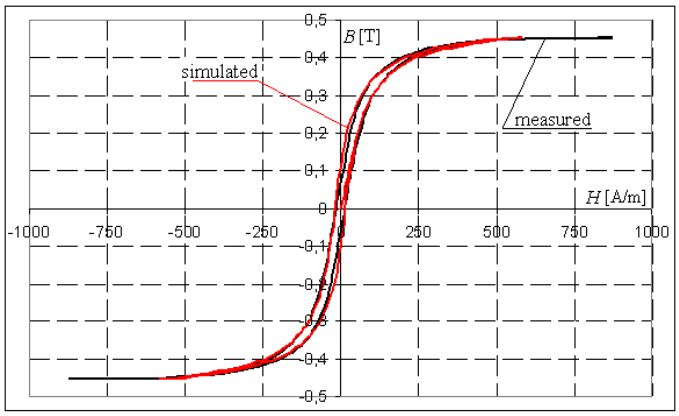

Fig. 2. Comparison of measured and simulated hysteresis loops for ferrite K 2004

Regarding the specifics of the problem, in case of using the PSO method to identify the hysteresis parameters it is essential to apply the objective function, which consists of three components. Otherwise the hysteresis loops derived from simulating calculations would differ from the experimental loop. The elaborated algorithm and software make it possible to assign hysteresis parameters with good accuracy.

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