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ABC method for Hysteresis Model Parameters Identification

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The paper deals with the application of the artificial bee colony (ABC) method for hysteresis parameters identification. For the first time, the ABC method will be applied on hysteresis model optimization. For this purpose, two hysteresis models are tested: the first is based on a physical magnetic material behavior, which is Jiles-Atherton and the second is simpler, Fröhlich hysteresis model built on mathematical considerations.

This method's robustness will be assessed, by comparing the experimental signals to model results.

I. INTRODUCTION

Electrical engines and electromagnetic machines are designed according to the customer requests and safety norms. Furthermore, the advanced technologies have to target the optimized operating conditions. For this purpose, it is necessary to build robust numerical modeling based on the magnetic material behavior. In literature, several models have been proposed and studied in large material application. It can be splitted into families: analytical ones: such as Rayleigh [1], Potter [2] or Fröhlich [3][4][5], which offer comfortable implementation in finite element code, but still limited to low or high magnetization behavior description. The second family is based on physical considerations such as the Preisach model [6] and the Jiles-Atherton model [7]. These are considered as the most robust and reliable models can be applied on soft and hard magnetic materials by parameter identification process. This task remains complex due to the inter dependency of each parameter to the other. The first investigation realized in this topic is based on iterative procedure [8]. It leads to good approximation of parameter's values but often presents convergence problems and can engender numerical instability. Other authors have proposed deterministic optimization methods [9][10], where the results were successful but request a great time calculation. Since two decades, stochastic optimization methods like generic algorithms and neural network [11][12][13] have been investigated. Other works combined between generic algorithms and simulated annealing [14]. It results accurate solution in a very short time.

Recently, swarm intelligence method is used in electromagnetic applications. The most famous one is the particle swarm optimization (PSO) [15], inspired by the collective behavior of birds and fishes. Many experts have investigated this method

in Jiles -Atherton parameters and have assessed the ability of this technique to solve optimization problems [16][17]. In the same class a new method, so called “artificial bee colony method (ABC)”, is introduced by D.Karaboga [18], based on the foraging behavior of honey bees. The algorithm offers a global optimization in constrained and unconstrained optimization problems. This algorithm proved its performance compared to other algorithms like GA and PSO [19][20].

During the last decade several studies focused on improving the convergence speed [21][22][23] and it is also used to solve the dynamic optimization problems in[24].

For the first time, this method will be tested and applied for hysteresis model identification. This paper deals with the application of ABC method to estimate the parameter set of the Jiles-Atherton model. The validation of the proposed procedure is firstly verified in the simple case of Fröhlich model, where the parameters can be derived analytically and then the optimization algorithm will be tested in the most complex case of Jiles-Atherton model. The calculated curves will be compared to the measured ones.

II. JILES-ATHERTON MODEL

In the original Jiles-Atherton model [7], the magnetization M is decomposed into its reversible components M_{rev} and its irreversible components M_{irr} as follows:

$$M = M_{irr} + M_{rev} \quad (1)$$

The relationship between these two components M_{rev} , M_{irr} and the anhysteretic magnetization is obtained from physical considerations of the magnetization process and are given by:

$$M_{rev} = c(M_{an} - M_{irr}) \quad (2)$$

$$\frac{dM_{irr}}{dH} = \frac{M_{an} - M_{irr}}{k\delta - \alpha(M_{an} - M_{irr})} \quad (3)$$

The anhysteretic magnetization M_{an} in (2) and (3) follows the Langevin function, which is a nonlinear function of the effective field, $H_e = H + \alpha M$:

$$M_{an} = M_s \left(\coth\left(\frac{H_e}{a}\right) - \frac{a}{H_e} \right) \quad (4)$$

With α is a factor that takes account for interdomain coupling; c is the proportionality constant that accounts for reversible motion; k is a coefficient accounting for the pinning energy; δ is a directional parameter it takes the value +1 for $dH/dt > 0$ and -1 for $dH/dt < 0$; M_s is the saturation magnetization; a is a normalization constant of the H field.

Combining the irreversible and the reversible components of magnetization, the differential equation for the rate of change of the total magnetization is given by:

$$\frac{dM}{dH} = (1 - c) \frac{M_{an} - M_{irr}}{k\delta - \alpha(M_{an} - M_{irr})} + c \frac{dM_{an}}{dH} \quad (5)$$

III. FRÖHLICH HYSTERESIS MODEL

The Fröhlich model gives an approximation of the relation between the magnetic induction B and the excitation field H . The following relations allow the representation of the hysteresis curve.

For initial magnetization

$$B(H) = \frac{H}{(\alpha + \beta|H|)} \quad (6)$$

For upward curve

$$B(H) = \frac{H - H_c}{(\alpha + \beta|H - H_c|)} \quad (7)$$

For downward curve

$$B(H) = \frac{H + H_c}{(\alpha + \beta|H + H_c|)} \quad (8)$$

Where α and β are defined from the characteristic points of an experimental hysteresis curve given in Fig. I:

$$\alpha = H_c \left(\frac{1}{B_r} - \frac{1}{B_s} \right) \quad (9)$$

$$\beta = \frac{1}{B_s} \quad (10)$$

Where H_c is the coercitive magnetic field, H_s the saturation magnetic field, B_r the remanent flux density and B_s the saturation flux density.

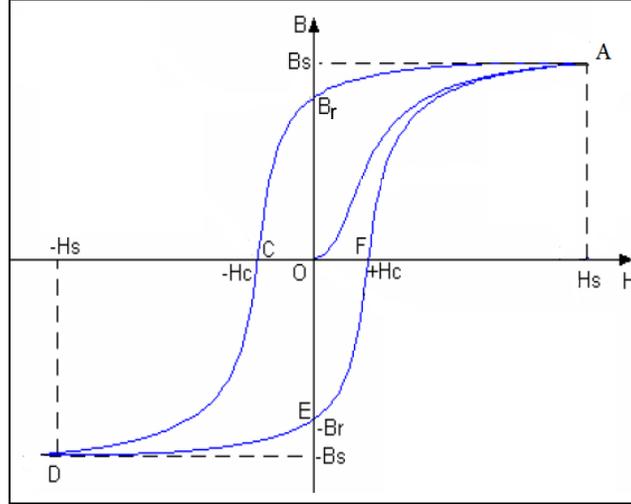


Fig. 1. Characteristic points of hysteresis loop

IV. ARTIFICIAL BEE COLONY ALGORITHM

A. Principles

The first study of the ABC method is from Karaboga [18] in optimization of mathematical problems. The machine-learning algorithm is based on the bees' behavior during the nectar collection. The bees are divided in three groups: employed bees, onlookers and the scouts.

The first group, called the "employed bees" is associated to food sources they are exploiting. They carry information like the distance from the hive to their food source and the profitability of it. Coming back to the hive, they indicate the qualitative and quantitative food sources position, by accomplishing a specific dance. The onlooker bees collect the given information and choose the most interesting sources for the exploitation. If a source is exhausted, the employed bee assigned to it becomes a scout looking for other sources. The number of the employed bees is the same as the number of food sources and is about half the swarm size.

B. Algorithm

In the optimization algorithm, the potential optima represent the food sources and the quality of the nectar is the fitness cost. The onlooker bees chose food sources according to a selection probability. If an employed bee is unable to improve its

solution in a given number N_{max} of time steps, a new solution is randomly assigned. The definition of this iteration control parameter N_{max} is very important in the optimization process.

The general algorithm of ABC method is given by [25]:

1. Initialize
2. Repeat
 1. Execute employed bees working step
 2. Execute onlookers working step
 3. Execute scouts working step
 4. Save best solution achieved so far as approximation for global optimum
3. Until maximum number of iterations is reached

In practical, four steps are required in order to apply ABC method optimization. The inputs are the swarm size m , the number D of parameters to optimize over, the total iteration number N_{total} and the number of iterations N_{max} for every employed bee it abandons its actual food source if its solution hasn't improved.

Step 1: An initial solution is obtained randomly for the employed bees by:

$$X_{i,j} = X_{min,j} + \epsilon \cdot (X_{max,j} - X_{min,j}) \quad (11)$$

where $i \in \{1, 2, \dots, m/2\}$, $j \in \{1, 2, \dots, D\}$, $X_{min,j}$ and $X_{max,j}$ are the lower and upper limit values for the parameter indexed by j and ϵ is a random number uniformly distributed in the interval $[0, 1]$.

For each solution, a fitness value is calculated according to:

$$fit_i = \begin{cases} \frac{1}{1 + f(X_i)}, & f(X_i) \geq 0 \\ 1 + |f(X_i)|, & f(X_i) < 0 \end{cases} \quad (12)$$

where f is the function to optimize.

Step 2.1: For each employed bee, an additional solution is calculated:

$$V_{ij} = X_{ij} + \varphi_{ij}(X_{ij} - X_{kj}) \quad (13)$$

Where the index j is chosen randomly from $\{1, 2, \dots, D\}$, the index k is chosen randomly from $\{1, 2, \dots, m/2\}$ and φ_{ij} is a random number uniformly distributed in the interval $[-1, 1]$. The best solution is selected between V_{ij} and X_{ij} based on their fitness values.

Step 2.2: For each onlooker bee a new solution X_i from the employed bees is selected with probability:

$$P_i = \frac{fit_i}{\sum_{n=1}^{m/2} fit_n} \quad (14)$$

Again, a neighbor solution V_{ij} is build according to equation (13). In the same way as for the employed bees, the best solution is selected and saved.

Step 2.3: If a solution of an employed bee is not improved until the limit of iterations is reached, the corresponding solution is then replaced by a new one obtained via equation (11).

Step 2.4: Save best solution found so far for output.

The process is completed when the total number of iterations N_{total} is reached hence the optimal solution can be recovered.

V. ARTIFICIAL BEE COLONY ALGORITHM FOR MAGNETIC HYSTERESIS PARAMETER IDENTIFICATION

The aim is to find the optimal parameters for accurate hysteresis description. The ABC method is tested on two different hysteresis models; simpler Fröhlich model and more complex Jiles-Atherton model.

The objective function is defined for one loop identification as:

$$f = \frac{1}{N} \sqrt{\sum_{i=1}^N \left(\frac{B_{i,meas} - B_{i,sim}}{\max(B_{meas})} \right)^2} \quad (15)$$

Where N is the number of measured points of the hysteresis loop, $B_{i,meas}$ denotes the i^{th} measured value of the magnetic flux density and $B_{i,sim}$ corresponds to the i^{th} value of magnetic flux density predicted by the magnetic hysteresis model.

For several loops identification the area per cycle between measurements and simulation is also taken into account [16]. In

this case the total objective function is given by:

$$f = \sum_{k=1}^s f_k \quad (16)$$

Where f_k is the objective function corresponding to each hysteresis loop and s is the number of used loops.

VI. Results

For this first step in ABC method investigation, we will focus on Fröhlich model. For this model the solution can be computed analytically too. Finally, Jiles-Atherton with 5 parameters will be tested. The comparison will be made on numerical signal and then measured ones.

A. Fröhlich Model

For this calculation the swarm size: $m = 300$ and the maximum number of iterations is set at 40. The analytical solution of both parameters: α and β are obtained using Eq. 9 and Eq.10. From measured signal $B_s=1.65$ Tesla, $H_s=3414$ A/m, $B_r= 0.93$ tesla and $H_c= 417.8$ A/m. This solution is also used to define the interval variation of the both parameters in the initialization state of the ABC algorithms.

Fig.2 denotes the comparison between experimental hysteresis loop and modeled curves obtained respectively via ABC method and the analytical calculation. It is noticed that ABC method, shows lower error with 1.75%.

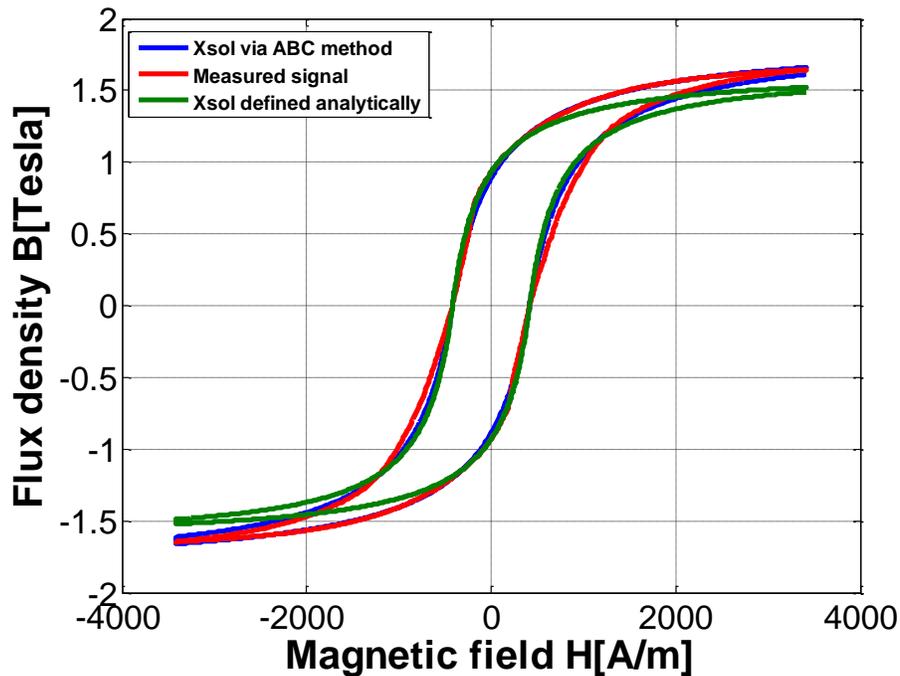


Fig. 2. Measured and simulated hysteresis curves generated with Fröhlich model

The optimized parameters are detailed in TABLE.I.

TABLE I. Fröhlich parameters obtained by ABC method
using experimental hysteresis loop

Fröhlich parameters	Variable range	Analytical method	ABC method
α	0-400	195.55	244.42
β	0-1	0.60	0.53

The Fig.3 shows the error evolution f with the iteration number. The algorithms converged quickly and the error is decreasing in the first iteration steps.

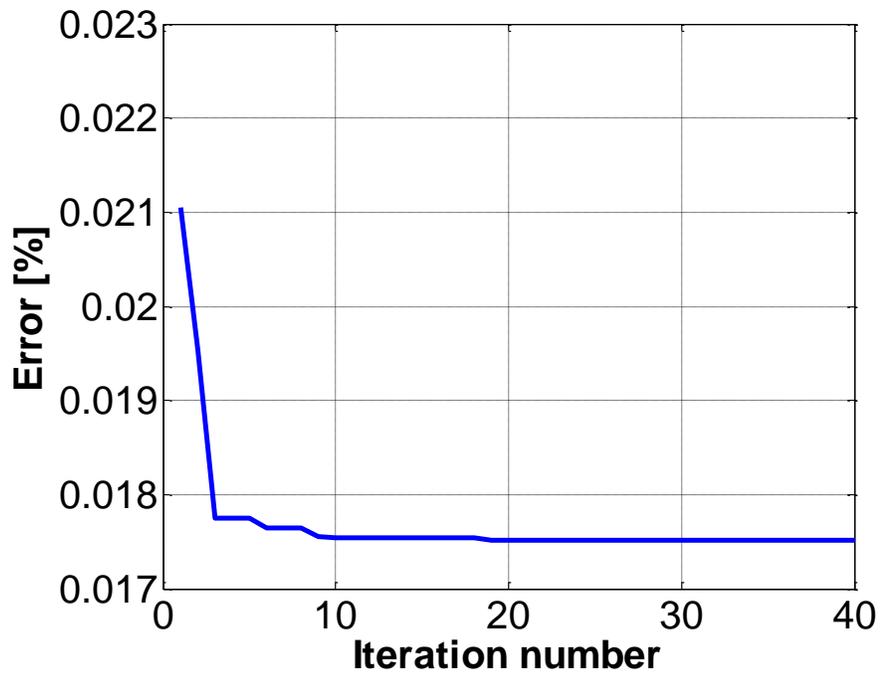


Fig. 3. Error evolution with iteration number for Fröhlich parameters identification

A good estimation of Fröhlich parameters allows using it in applications which require a very expensive computing time such as finite element method integration.

B. Jiles- Atherton Model

At the beginning, the optimization is carried out on the generated hysteresis loop via parameters from literature [8] (M_s , a , α , k , c). The swarm size $m=300$ and the number of iteration is set at 200. Fig.4 shows the simulated hysteresis curves built via values of reference [8] and via optimized parameters (ABC method). The results are quite good and offer a total mean error of 1.3%.

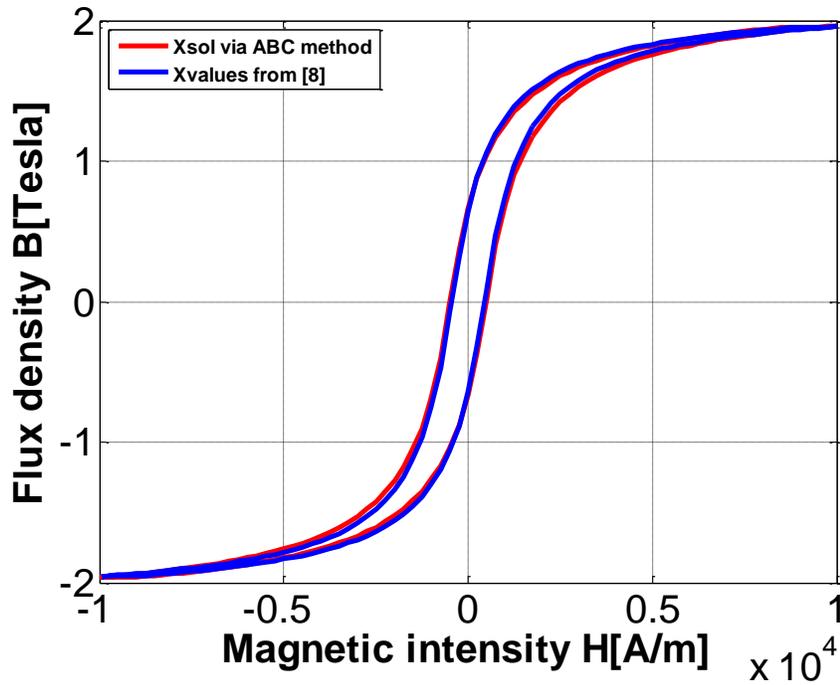


Fig. 4. Calculated and theoretical hysteresis curves generated by the Jiles- Atherton model

The values of calculated parameters are detailed in Table II.

TABLE II. Jiles Atherton parameters obtained by ABC method

JA parameters	Variable range	Values of literature [8]	ABC method
M_s	$1.6 \times 10^6 - 1.8 \times 10^6$	1.7×10^6	1.75×10^6
a	800 - 1500	1000	1337
α	$1 \times 10^{-3} - 1.5 \times 10^{-3}$	1×10^{-3}	1.5×10^{-3}
k	400 - 800	500	490
c	0.05 - 0.5	0.1	0.08

At last, the

first

validation of the proposed method with experimental data is illustrated in Fig.5. The measured hysteresis loop is the same as that presented in Fröhlich model. The number of bees is taken 300 and the iteration number is 200. The range of parameters is chosen after several trials. The number of bees plays a very important role in the optimization process.

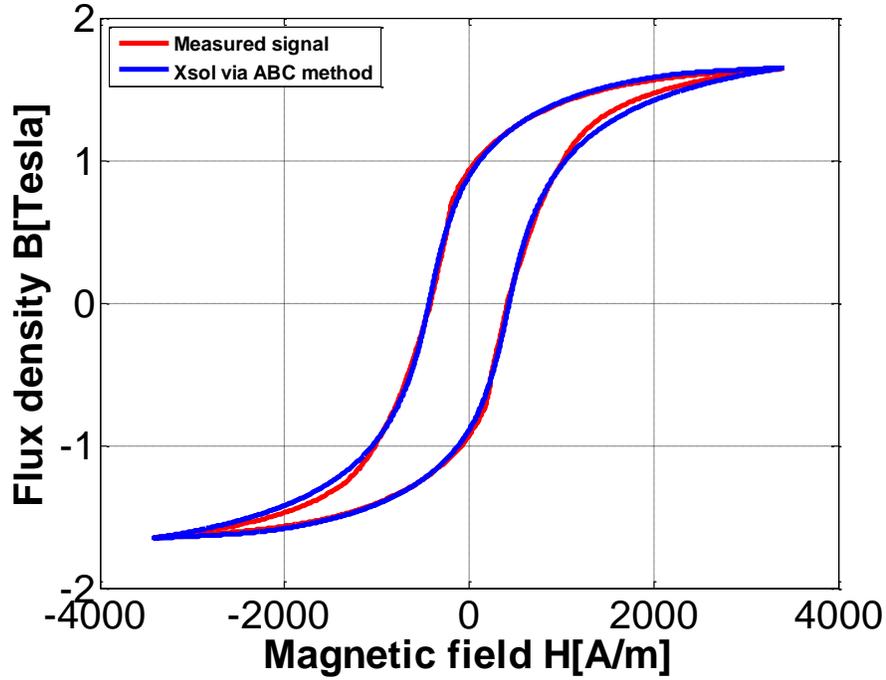


Fig. 5. Measured and hysteresis curves generated by the Jiles- Atherton model for the first experimental loop

The obtained parameters are presented in Table III.

TABLE III. Jiles Atherton parameters obtained by ABC method using first experimental loop

JA parameters	Variable range	ABC method
M_s	$1.6 \times 10^6 - 1.7 \times 10^6$	1.61×10^6
a	200 - 1500	882.55
α	$1 \times 10^{-3} - 8 \times 10^{-3}$	1.34×10^{-3}
k	200 - 800	742.64
c	0.1 - 0.9	0.373

A good representation of hysteresis loop is run via ABC optimization method. The error evolution is presented in Fig.6, the convergence is slower in this case because of the large number of parameters to identify.

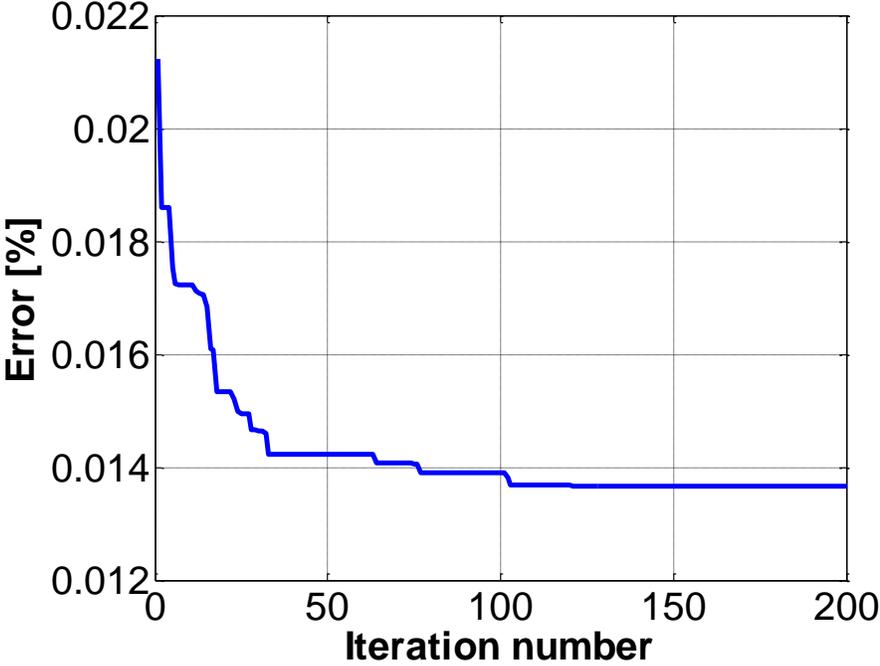


Fig. 6. Error evolution with iteration number for Jiles-Atherton parameter identification for the first experimental loop

To see the efficiency of the ABC method, it is applied for the identification of six loops with different maximum flux densities. Fig.7 shows comparison between three measured loops and modeled ones. The corresponding parameters are given in TableIV.

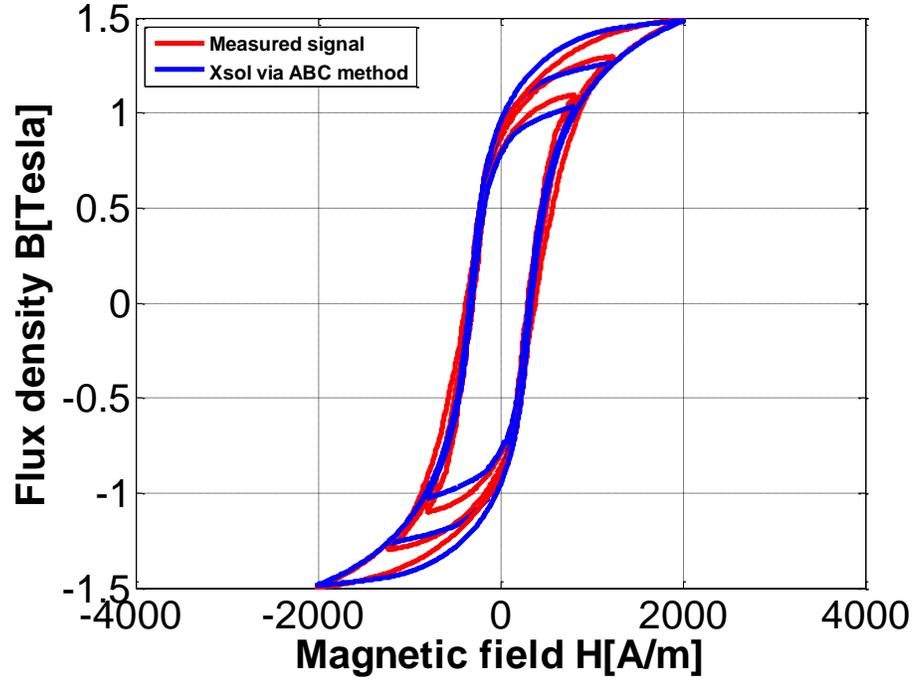


Fig. 7. Measured and hysteresis curves generated by the Jiles- Atherton model for different maximum flux densities for the first experimental loop

The application of the ABC method for the identification of several measured loops gives correct results, accuracy can be improved by adding the number of measured loops.

TABLE IV. Jiles Atherton parameters obtained by ABC method

using several measured loops with different maximum flux densities for first experimental loops

JA parameters	Variable range	ABC method
M_s	$1.5 \times 10^6 - 1.7 \times 10^6$	1.54×10^6
a	200 - 1500	658.55
α	$1 \times 10^{-3} - 8 \times 10^{-3}$	1.1×10^{-3}
k	500 - 800	613.152
c	0.1 - 0.9	0.35

In Fig.8 the procedure is also validated by comparing experimental and simulated hysteresis loop for Fe-Si material.

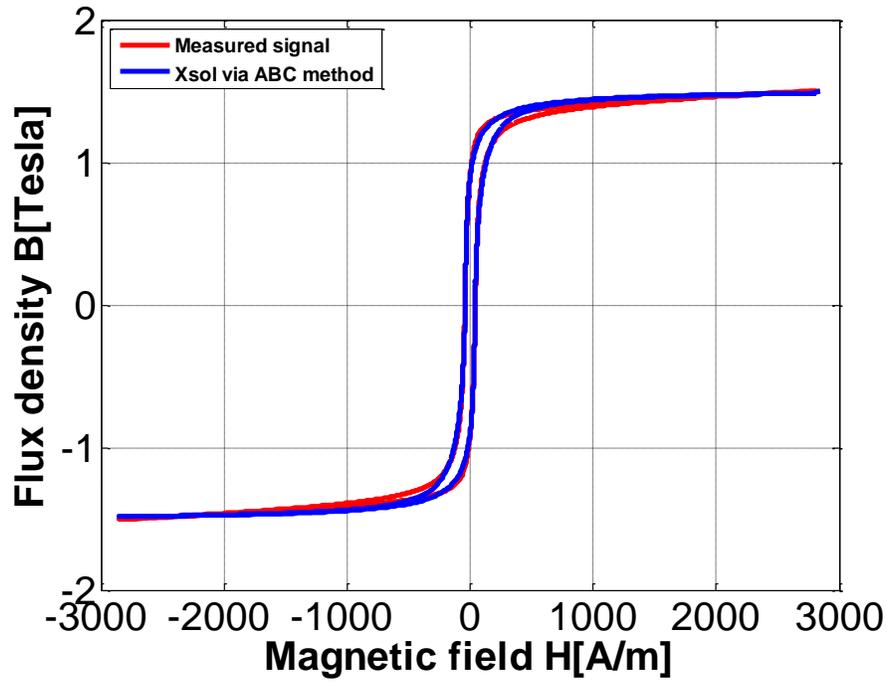


Fig. 8. Measured and hysteresis curves generated by the Jiles- Atherton model for Fe-Si material

The obtained parameters are presented in Table V.

TABLE V. Jiles Atherton parameters obtained by ABC method using Fe-Si experimental loop

JA parameters	Variable range	ABC method
M_s	$1 \times 10^6 - 1.7 \times 10^6$	1.2×10^6
a	30 - 200	49.7
α	$1 \times 10^{-5} - 1 \times 10^{-3}$	1.12×10^{-4}
k	30 - 200	71
c	0.01 - 0.9	0.24

To obtain a good approximation of hysteresis for Fe-Si, the program is executed for a number of iterations equal to 200 and $m=400$. The error evolution is presented in Fig.9.

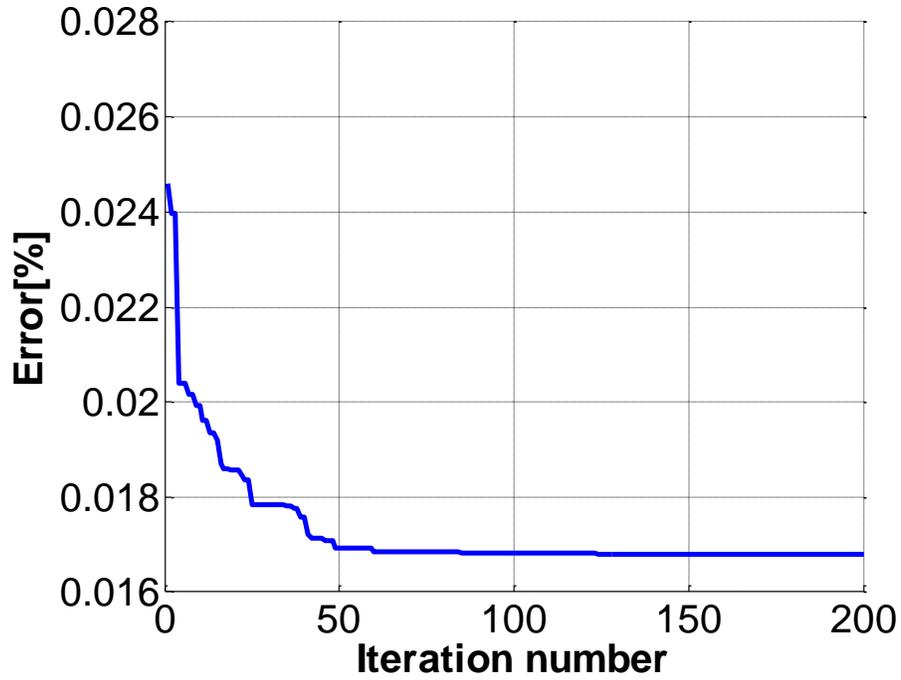


Fig. 9. Error evolution with iteration number for Jiles-Atherton parameter identification for Fe-Si material

In the same way Fig.10 gives the results of the identification done on several hysteresis curves at different maximum flux densities of Fe-Si material. The obtained parameters shown in Table VI allow a very good representation of hysteresis loops.

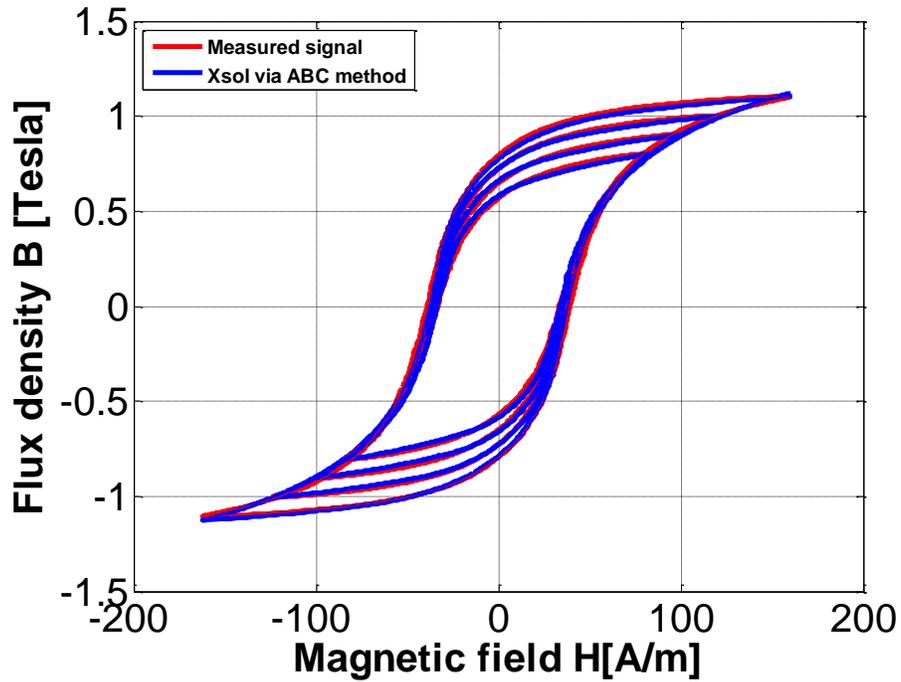


Fig. 10. Measured and hysteresis curves generated by Jiles- Atherton model for different maximum flux densities for Fe-Si material

TABLE VI. Jiles Atherton parameters obtained by ABC method

using several measured loops with different maximum flux densities for Fe-Si experimental loops

JA parameters	Variable range	ABC method
M_s	$1 \times 10^6 - 1.5 \times 10^6$	1.33×10^6
a	60 - 150	85.7
α	$1 \times 10^{-5} - 1 \times 10^{-3}$	1.8×10^{-4}
k	60 - 150	81.75
c	0.01 - 0.9	0.44

VII. Conclusion

For the first time the ABC, BEE principal algorithms is applied on hysteresis identification problem. The advantage of this algorithm is that it requires only few parameters. The robustness of this method is assessed on comparison between measured and calculated signal on Fröhlich and JA model, the first with 2 independent parameters and the second with 5 dependent parameters, the ABC method can accurately describe measured hysteresis loops. The algorithm converges in a short time and offers high accurate results. The rate of convergence depends on the number of parameters to be identified. For both models the program gives good results from a number of bees equal to 300. For both tested materials, the characteristic points and the surface of the loops which represent the hysteresis losses agree very well with those of measured ones. This method shows the ability to give good results for the identification of several loops with different maximum flux densities too.

As a perspective, complex hysteresis loops will be tested such as: minor asymmetric curves, reversal loops...

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