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Parameters Optimization of the Chemical Reaction Hysteresis Model Using Genetic Algorithms and the Artificial Bee Colony Method

Yasmine Gabi[1, 2, *], Kevin Jacob[2], and Klaus Szielasko[1]

[1] *Fraunhofer Institute for Nondestructive Testing IZFP, Campus E3 1, 66123 Saarbrücken, Germany*
[2] *Chair of Cognitive Sensor Systems, Saarland University, Campus E3 1, 66123 Saarbrücken, Germany*

ABSTRACT: This paper presents the application of both genetic algorithm (GA) and artificial bee colony (ABC) method for parameter identification for the chemical hysteresis model. This model is known to be based on physics approaches, and it is characterized by nine parameters, which describe the reversible and irreversible magnetization mechanisms. Splitting the parameter optimization in two parts using hysteresis curves at various amplitudes offers a more efficient way of solving the optimization problem. Based on the root mean squared error between modeled and experimental B-H loops, it has been shown that GA delivers lower errors in shorter time.

1. INTRODUCTION

The challenge nowadays for manufacturers of technological products is to optimize a design in competitive time, ensuring good quality performance according to customer specifications. Therefore, it is necessary to use robust tools in each step of the design. For a few decades, experts have focused on the development of simulation tools, models, and optimization algorithms, with the aim to reduce experimental prototyping costs. In this light, the present paper regards the ferromagnetic properties of steel as a key parameter to be optimized. The modelling of magnetic hysteresis is still a challenging issue, in terms of time and accuracy in parameter estimation/identification. Furthermore, some aspects such as the implementation in the finite element or finite volume code and management of convergence have to be taken into account. In literature, a broad range of hysteresis models can be found, and some of them are morphological like Rayleigh [1], Mel'gui [2], Fröhlich [3] etc., while others are physically motivated like the Jiles-Atherton model [4] and chemical model [5]. Given measured hysteresis curves, the challenge consists of estimating the model parameters such that the model fits the measured data. The modelling of some electromagnetic devices like, for example, the 3MA sensor [6], requires a robust hysteresis model, which is capable of reproducing the measured signals at various amplitudes. Furthermore, the model must be able to reproduce minor asymmetric curves and to take into account the impact of frequencies [7]. The most popular is the Preisach model [8], but the parameter estimation and numerical calculation when it is implemented in finite element method (FEM) code is quite time-consuming. Leite et al. [9] have extended the Jiles-Atherton model for minor asymmetric curves, while being limited to one operating point. The model of Artangent is tested in the framework of electrical steel; the authors have shown the capability of the model to reproduce minor asymmetric curves [10]. Nevertheless, the implementation of this model in FEM code requests further developments. The chemical hysteresis model is more attractive, as it is able to describe the nonlinear behavior of the material in scalar and in vector forms. Furthermore, the impact of frequency and waveform of the signal are taken into account. The chemical model has been tested for various soft steels such as SiFe material and textured NiFe material [11]. A lot of experts have been attracted by the chemical model capabilities in perspective of implementation in numerical simulation tools such as Flux software and Reluctool, aiming at an easy design of electrical engineering machines. Do et al. have investigated the performance of the model on soft ferromagnetic materials such as nanocrystalline FeNi [12]. Later, Chailloux et al. [13] tested the impact of temperature on the magnetic behavior via the chemical model. A correlation between hysteresis model parameters and temperature is established [14]. In addition, the chemical hysteresis model is presented as an analytical model, so the calculation in 3D FEM code is faster. Nevertheless, the identification of the model parameters remains complex since there are nine parameters to be defined.

In this work, chemical model parameters are investigated via two optimization methods: genetic algorithm [15] and artificial bee colony (ABC) technique [16]. For this purpose, 22MnB5 steel is characterized under quasi-static magnetization through minor symmetric and asymmetric hysteresis loops. The accuracy and computation time of both optimization methods are highlighted, by the comparison of simulated B-H loops to experiments.

* Corresponding author: Yasmine Gabi (yasmine.gabi@izfp.fraunhofer.de).

2. CHEMICAL HYSTERESIS MODEL

The chemical hysteresis model is original in terms of the physical insight. In fact, it is based on an analogy between transformations of magnetic states and chemical reactions. Usually in each chemical reaction, atoms and molecules interact with each other. Let's take the example of Acid and Base reaction:

$$\text{Base} + \text{Proton} \rightarrow \text{Acid}$$

At the thermodynamic balance, we can write

$$\text{K} = [\text{Base}] \cdot [\text{Proton}]/[\text{Acid}]$$

where $1/K$ is defined as reaction constant. $[X]$ is defined as quantity of X.

Similarly, ferromagnetic material is also composed by positive and negative spin moments atoms S^+ and S^-. Under external magnetic field H, the induction variation can be described as irreversible reactions. When magnetic field is increasing:

$$S^- + h = S^+$$

where h is the part of external magnetic field needed for the reaction. It is also called the active part of H and can be associated with the external field undergone by each atom S^-. The magnetization is then the result of a thermodynamic equilibrium obtained by transferring the results of chemistry to the physics of materials. After the development of equations (detailed in [17]), the results lead to Equation (2).

Furthermore, the chemical model is described in two parts, where the total induction is computed by taking into account the participation of the irreversible magnetization, J_{irrev}, which corresponds to the domain wall movement during the magnetization process and to the reversible part J_{rev}, which represents the contribution of the magnetization rotation process (Equation (1)):

$$B_{\text{tot}} = (J_{\text{irrev}} + J_{\text{rev}}) + \mu_0 H \tag{1}$$

The algorithm for the irreversible contribution J_{irrev} progresses as follows:

- Initialization step

$$\begin{aligned} J_0 &= 0 \\ \gamma_0 &= 2 \cdot 10^{-3} \\ K &= \exp(\beta \cdot H_c) \\ b_0 &= K \cdot \exp\left(\frac{\gamma_0}{\beta}\right) \\ J_1 &= J_{\text{irrevSat}} \cdot \tanh\left(\frac{\beta}{2\gamma_0} \ln\left(\exp(2\gamma_0 + b_0) - \frac{\beta H_c}{2}\right)\right) \end{aligned}$$

- For $i = 1, \ldots, N-1$, where N is the length of the measured signal:

$$\begin{aligned} A_i &= K \cdot \frac{J_{\text{irrevSat}} - J_i}{J_{\text{irrevSat}} + J_i} \\ \gamma_i &= \frac{\beta \ln(c_0)}{\ln(A_i \cdot \exp(\beta \cdot H_i))} \\ b_i &= K \cdot \exp\left(\frac{\gamma_i}{\beta}\right) \\ \phi_i &= \frac{\beta}{2\gamma_i} \ln(\exp(\gamma_i H_i) + b_i) \\ J_i &= J_{\text{irrevSat}} \cdot \tanh\left(\frac{\beta}{2\gamma_i} \ln\left(\exp(2\gamma_i H_i + b_i) - \frac{\beta H_c}{2}\right)\right) \\ J_{\text{irrev},i} &= J_{\text{irrevSat}} \cdot \tanh\left(\phi_i - \frac{\beta \cdot H_c}{2}\right) \\ J_i &= J_{\text{irrev},i} \end{aligned} \tag{2}$$

Parameters J_{irrevSat}, H_c, β, and c_0 are inputs for the irreversible part of the model. They can be defined using various hysteresis loops between 0.3 T and 1.2 T.

- Initialization step

$$\begin{aligned} \theta_0 &= \frac{\pi}{2} \\ \theta_1 &= \frac{\pi}{2} \end{aligned}$$

- For $i = 2, \ldots, N-1$, where N is the length of the measured signal:

$$\begin{aligned} D_i &= k_1 \cdot \sinh(k_2 \cdot (\theta_i - \theta_0)) \\ \alpha_i &= \frac{\ln(c_1)}{\frac{(a - D_i)}{\sin(\theta_i)} - H_i} \\ h &= \frac{1}{\alpha_i} \cdot (\ln(c_1) + \alpha_i \cdot H_i) \\ & k_1 \cdot \sinh(k_2 \cdot (\theta_i - \theta_0)) + h \cdot \sin(\theta_i) - a = 0 \end{aligned} \tag{3}$$

Nourdine [18] have chosen an energy minimization approach for the description of magnetic rotation phenomena (Equation (3)).

Then, the magnetization of the reversible part is defined as:

$$J_{\text{rev},i} = J_{\text{revSat}} \cdot \cos(\theta_i) \tag{4}$$

k_1, k_2, a, c_1, and J_{revSat} are five input parameters, belonging to the reversible part of the magnetization formula. These parameters can be determined using minor centered hysteresis loops from 1.5 T to 1.8 T.

3. MATERIAL HYSTERESIS CHARACTERIZATION

In order to estimate those parameters, it is first necessary to collect hysteresis loops under various amplitudes. For this purpose, the material grade 22MnB5 is investigated. Different specimens were laser-cut in order to fit the Fraunhofer IZFP hysteresis frame with 120 mm length, 10 mm width, and 1.6 mm thickness. The B-H frame consists of a U-shaped yoke made of ferrite steel as shown in Figure 1. The yoke is surrounded by the magnetization coil. A current AC excitation generates magnetic field in the yoke and canalized through the sample.

The sample is positioned in the center area of the yoke and maintained via two poles. The tangential magnetic field strength at the sample surface is measured using a Hall effect sensor located in the center of the sample.

The mean flux density is measured by integration of the voltage induced in a circumferential coil. The B-H signals are collected at lower magnetization frequency, $f = 2$ Hz.

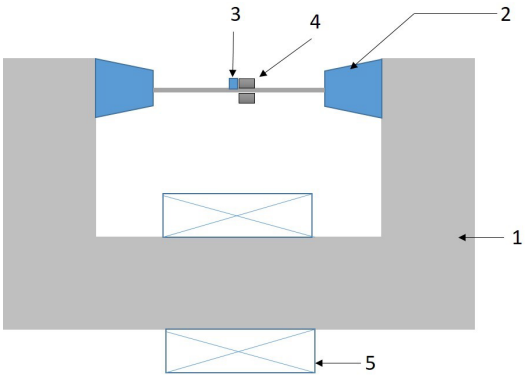

FIGURE 1. Hysteresis measurement frame with 1) ferrite yoke, 2) steel poles, 3) Hall sensor, 4) receiver coil, and 5) magnetization coil.

4. EVALUATION PROCESS

The determination of the chemical hysteresis parameters turns out to be difficult. Some of these parameters depend on the intrinsic properties of ferromagnetic material such as coercive field strength H_c and the ratio of maximum magnetization of the domain wall displacement J_{irrevSat} and the rotation magnetization J_{revSat}. Shikazumi [19] have discussed the ratio between the reversible part and the total magnetization. For such a family of materials, it is indicated that the maximum irreversible part contributes 50% of the total induction at saturation. The rest is devoted to reversible magnetization. The remaining six parameters: β, c_0, k_1, k_2, a, and c_1 have no link to directly measurable quantities and then should be selected randomly. Several optimization algorithms are tested in order to validate the physical concept of the magnetic material behavior. Other authors have proposed deterministic methods [20], simulated annealing method [21], particle swarm optimization (PSO) [22], and many more. In this work, two methods, namely genetic algorithm (GA) [23] and artificial bee colony (ABC) method [24], are tested for parameter estimation of the chemical model. For each hysteresis curve step (i), the criteria error function ε is defined as the root mean squared error between measured B_{meas} and computed B_{simul} flux density, Equation (5). The objective function (6) is defined as the sum of the errors for various hysteresis loops, which varies from 0.2 T to 1.8 T.

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(B_{\text{meas},i} - B_{\text{simul},i}\right)^2} \tag{5}$$

In Equation (5), N denotes the number of samples of the measurement of the magnetic flux density. In Equation (6), M denotes the number of hysteresis curves used for the identification, with ε_j being the error for the jth curve.

$$\varepsilon_{\text{tot}} = \frac{1}{M}\sum_{j=1}^{M}\varepsilon_j \tag{6}$$

5. OPTIMIZATION METHODS

According to the number of parameters, it is necessary to perform stochastic optimization methods. Both GA and ABC method are carried out in Matlab environment.

5.1. Artificial Bee Colony (ABC)

The first authors reporting ABC method in hysteresis optimization are Sedira et al. [25]. In the optimization algorithm, the solution represents the food sources, and the quality of the nectar is the fitness cost. As it is the case in the nature, various bees are involved: onlooker bees, employed bees, and scouts. The employed bees target zones of food sources. The information (position and food quality) is shared with onlooker bees, which focuse on better quality food sources. If these sources are exhausted, the scouts randomly look in the environment to find out new food zones. The solution is defined randomly if the onlooker bees are not able to improve the food quality in a given number of time steps N_{max}.

The ABC algorithm, is given by Karaboga and Akay in [26]:

- Initialization
- Iteration
    - Run employed bees working step
    - Run onlookers working step
    - Run scouts working step
    - Save best solution achieved so far as approximation for global optimum
- Until maximum number of iterations is reached

The inputs are the swarm size m, the 9 parameters to optimize over, the total iteration number $N_{\text{total}} = 100$, and the number of iterations $N_{\text{max}} = 5$ for every employed bee before it abandons its actual food source if its solution is not improved. The number of employed and onlooker bees are fixed to 150 and 150, respectively.

5.2. Genetic Algorithm (GA)

Genetic algorithms are mostly used for solving conventional problems. This method is inspired by biological law, as it is the case for ABC technique. It is guided by two processes: crossover and mutation, which lead to optimal solutions. Crossover combines genetic data from two parent genotypes to produce descendants, developing inheritance with good traits. In mutation operation, random changes in genes are introduced, and then the diversity of genetic is maintained. The solution is defined after repeated operation of crossover and mutation, and by selecting the fittest individuals, the population is then progressing over generations. The basic GA procedure is as follows:

- Initialization
- Iteration
    - Parent selection from population
    - Create Children by crossover population
    - Realize mutation on the new population

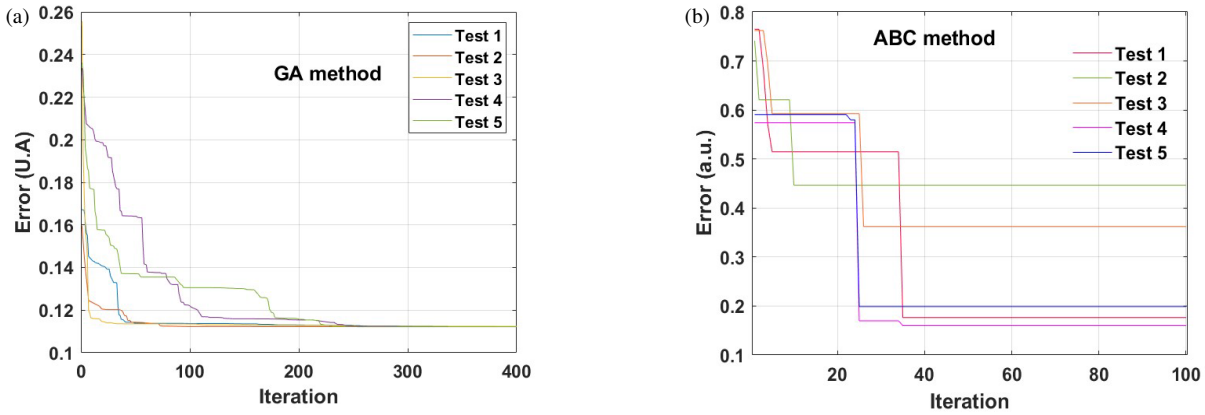

FIGURE 2. Error evolution with iteration number of (a) GA algorithm and (b) ABC algorithm.

- Save best solution achieved so far as approximation for global optimum

• Until maximum number of iterations is reached

In this work, the Matlab GA toolbox is used. The inputs of the algorithm are [27]: population size, maximum iteration number, and stop criteria as well as lower and higher bounds of the parameter variation. These quantities have been topic of studies and investigation on various applications. One of the first who tested GA for Jiles-Atherton hysteresis parameter identification was Chwastek and Szczyglowski [28], where he stated the number of individuals to 10, and the criteria of computation finalization to 250 generations. Besides this, Hergli et al. have applied GA for two well-known hysteresis models, Jiles-Atherton [29] and Preisach [30]. The authors proposed an initial population of 20 individuals and 200 iterations. Various studies have been performed in order to define best-optimized GA parameters (mutation P_m and cross over population P_c). Some of them are purely experimental trial and error approach, based on tuning parameters by hands and test different values by selecting the ones which offer the best results [31], while others drive theoretical studies [32–34] and suggest dynamic set of parameters, by changing these values in a given interval during the GA runs. De Jong [35] expresses some doubts on the consistence of an adaptive implementation of the GA operators to be optimized during the run.

In this work, the study is carried out using GA input parameters, which were already defined in previous works of optimization of magnetic hysteresis models parameters like Jiles-Atherton and Praisach models [29]. Worden and Manson [36] have also used similar inputs in the investigation of mechanical optimization system, where P_c and P_m were fixed to 0.2 and 0.8. The objective function is the same as that for the ABC approach (Equation (5)), with negative sign, since the Matlab toolbox solves maximization problems. The input parameters for GA in this study will be extended to 60 individuals and 400 generations. The crossover probability P_c and mutation probability P_m are respectively equal to 0.2 and 0.8. P_m and P_c are kept constant.

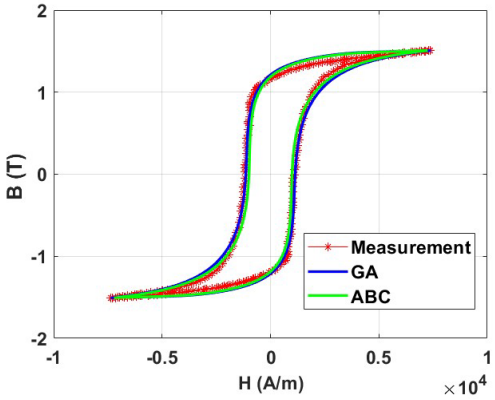

FIGURE 3. Simulated hysteresis loops obtained via ABC method and GA, compared to measurement.

6. RESULTS AND DISCUSSION

The current development of the chemical model provides an easier dissociation of the algorithms. As indicated in the previous paragraphs, the decoupling of both contributions linked to irreversible process, and the reversible rotation is useful in terms of computation time. The selection of the bounds is very important, since a too large search space will generally result in very long computation time until a feasible solution is found, especially for higher dimensionality.

First, trial consists in identification on one hysteresis loop at 0.8 T. Then, the first part of the model is requested. The parameter ranges are summarized in Table 1. Once the first four parameters are calculated from Equation (2), it rests only those from irreversible contribution. The contribution J_{rev} is subtracted from B_{tot} according to Equation (1).

TABLE 1. Parameter bounds, best result obtained via ABC and GA method, for irreversible part of the chemical model over 5 runs.

Parameters	Bounds	Results from	
		ABC method	GA method
J_{revSat}	[0.1, 1.3] T	1.07 T	1.05 T
H_c	[8, 12] A/cm	11.12 A/cm	11.35 A/cm
β	$[10^{-3}, 10^{-1}]$	$5.52 \cdot 10^{-3}$	$6.06 \cdot 10^{-3}$
c_0	[50, 300]	160.65	154.77

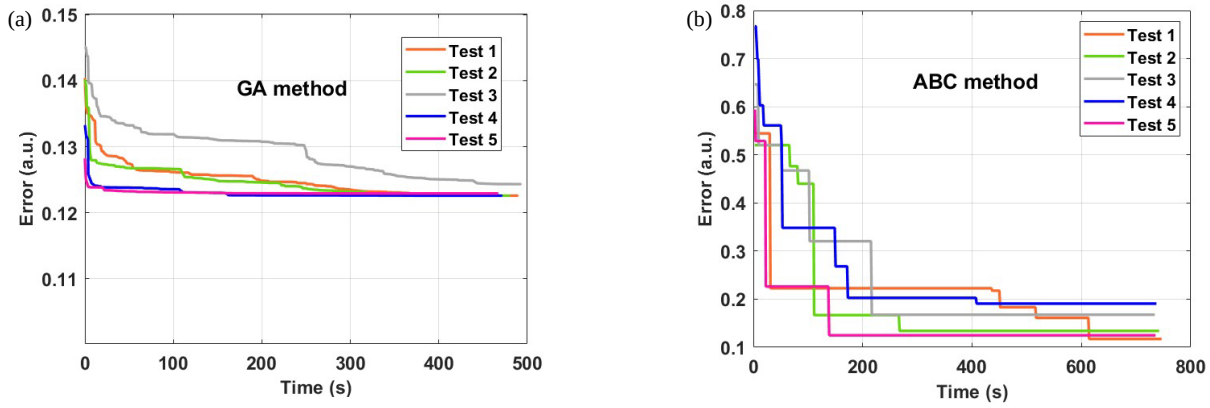

FIGURE 4. Error versus calculation time for both (a) GA and (b) ABC optimization methods.

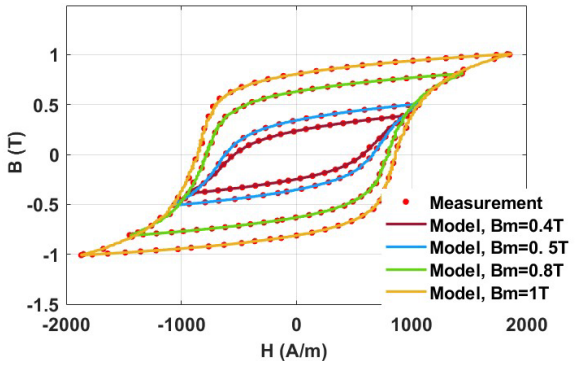

FIGURE 5. Results from GA methods and measured data at $f = 2$ Hz, for various amplitudes $B_m = [0.4\text{–}1]$ T.

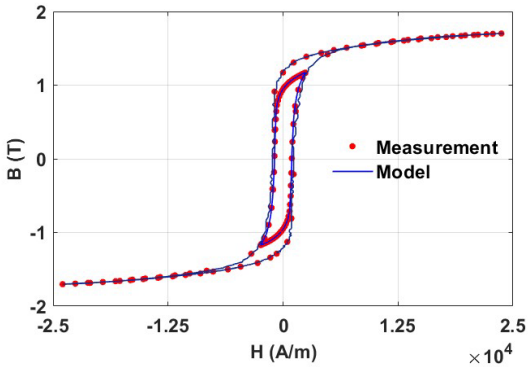

FIGURE 6. Results from GA methods and measured data at $f = 2$ Hz for $B_m = 1.2$ T and $B_m = 1.7$ T.

Table 2 summarizes the chosen bounds of the other five parameters. For both optimization methods, the set of parameters which results in the lowest error over five runs is retained. Figure 2 shows the error (Equation (5)) over iterations for both optimization methods for five runs.

TABLE 2. Parameter bounds, best result obtained via ABC and GA method, for reversible part of the chemical model over 5 runs.

Parameters	Bounds	Results from	
		ABC method	GA method
J_{irrevSat}	[0.8, 1.3] T	1.02 T	1.05 T
a	$[10^3, 5 \cdot 10^3]$	3000.5	2979.55
c_1	$[2 \cdot 10^{-3}, 10^{-1}]$	$1.12 \cdot 10^{-2}$	$1.06 \cdot 10^{-2}$
k_1	$[10^{-2}, 10]$	2.12	1.89
k_2	[500, 4000]	2510	2489.56

It is observed that the GA achieves lower error values than the ABC method, for similar population size and ABC swarm size.

Figure 3 illustrates modeled and simulated hysteresis curves from ABC and GA. In order to visualize the error versus time for both methods, the size of magnetic field data is reduced to 100 measurement points.

After several tests, the error for GA was about 0.123 with time calculation of 500 s. The error obtained via ABC method after 780 s was varied by run, and the lowest error observed was about 0.124 (Figure 4).

The optimization was also performed for minor hysteresis loops at various operation points. Figure 5 and Figure 6 show comparisons between measurement and modeled hysteresis curves for the irreversible and rotation contribution. The parameters are identified via GA methods. The chemical model reproduces minor hysteresis loops with high accuracy.

In the following, the chemical model is also assessed for minor asymmetric loops. Figure 7 shows the magnetic response of the combination of both signals [37]:

- Low-frequency signal: 10 Hz, at high amplitude ($B_m = 0.6$ T and $B_m = 1.6$ T)
- High-frequency signal: 20 kHz, at low amplitude (Rayleigh domain)

The low frequency signal establishes an operating point of the ferromagnetic material $B_m = 0.6$ T and $B_m = 1.6$ T. The resulting signal from superimposed signals is composed by minor asymmetric loops distributed around the parent centered hysteresis curve (operating point). Since the amplitude excitation of the high frequency signal is in the range of Rayleigh domain, the dynamic effect is neglected. The chemical model is able to reproduce minor asymmetric curve signals at low and high operating points, with quite good accuracy.

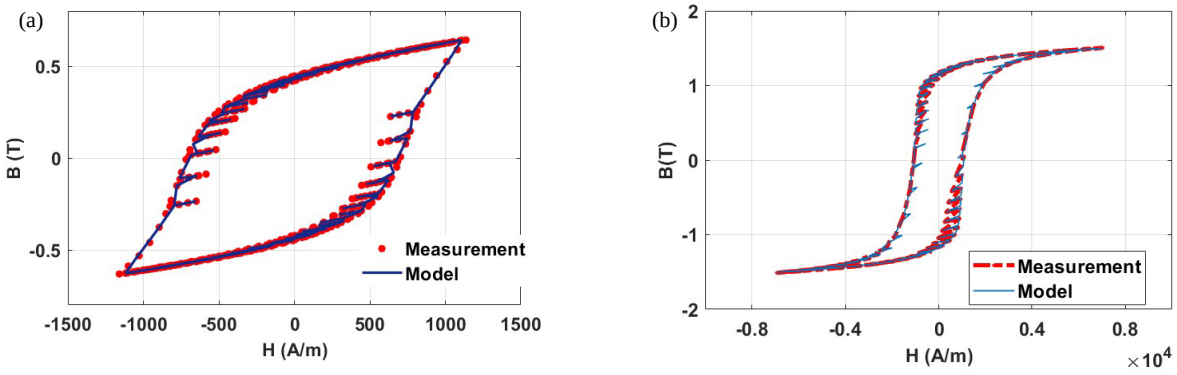

FIGURE 7. Simulated and measured signals for (a) $B_m = 0.6$ T and (b) $B_m = 1.6$ T.

7. CONCLUSION

The main goal of this study was to explore the capacity of both genetic algorithm (GA) and artificial bee colony (ABC) method in the estimation of chemical hysteresis model. The models were optimized with both ABC method and genetic algorithms which are quite good. Both reproduce hysteresis loops close to the experimental data with high accuracy. The GA method clearly outperforms the ABC method in terms of computation time and final error reached after reasonable time.

REFERENCES

[1] Rayleigh, L., "XXV. Notes on electricity and magnetism. III. On the behaviour of iron and steel under the operation of feeble magnetic forces," *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, Vol. 23, No. 142, 225–245, 1887.

[2] Mel'gui, M., "Formulas for describing non-linear and hysteresis properties of ferromagnetic materials," *Defektoskopiya*, Vol. 11, 3–10, 1987.

[3] Fröhlich, O., "Investigations of dynamoelectric machines and electric power transmission and theoretical conclusions therefrom," *Elektrotech Z*, Vol. 2, 134–141, 1881.

[4] Jiles, D. C. and D. L. Atherton, "Theory of ferromagnetic hysteresis," *Journal of Magnetism and Magnetic Materials*, Vol. 61, No. 1-2, 48–60, 1986.

[5] Nourdine, A., A. Kedous-Lebouc, G. Meunier, and T. Chevalier, "A chemical reaction hysteresis model for magnetic materials," *IEEE Transactions on Magnetics*, Vol. 36, No. 4, 1230–1233, Jul. 2000.

[6] Gabi, Y., K. Jacob, B. Wolter, C. Conrad, B. Strass, and J. Grimm, "Analysis of incremental and differential permeability in NDT via 3D-simulation and experiment," *Journal of Magnetism and Magnetic Materials*, Vol. 505, 166695, 2020.

[7] Hamel, M., A. N. Ouslimane, and F. Hocini, "A study of Jiles-Atherton and the modified arctangent models for the description of dynamic hysteresis curves," *Physica B: Condensed Matter*, Vol. 638, 413930, 2022.

[8] Preisach, F., "Über die magnetische Nachwirkung," *Zeitschrift für Physik*, Vol. 94, No. 5, 277–302, 1935.

[9] Leite, J. V., A. Benabou, and N. Sadowski, "Accurate minor loops calculation with a modified Jiles-Atherton hysteresis model," *COMPEL — The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, Vol. 28, No. 3, 741–749, 2009.

[10] Birouche, C., M. Hamel, A. N. Ouslimane, R. Fellag, and M. Zaouia, "Accurate asymmetrical minor loops modeling with the modified arctangent hysteresis model," *Physica B: Condensed Matter*, Vol. 679, 415796, 2024.

[11] Nourdine, A., A. Kedous-Lebouc, and G. Meunier, "A new vectorial hysteresis model for cube textured NiFe sheet based on a chemical reaction analogy," in *2002 IEEE International Magnetics Conference (INTERMAG)*, Amsterdam, Netherlands, Apr.-May 2002.

[12] Do, T. P., F. Sixdenier, L. Morel, E. Morin, L. Gerbaud, and F. Wurtz, "Qualification protocol for hysteresis model of magnetic materials in static and dynamic modes. Application in design software," in *19th Soft Magnetic Materials Conference*, Turin, Italy, Sep. 2009.

[13] Chailloux, T., C. Martin, M.-A. Raulet, C. Joubert, F. Sixdenier, and L. Morel, "Homogenised magnetic diffusion. Dependence of static hysteresis," *European Journal of Electrical Engineering*, Vol. 15, No. 2-3, 225–239, 2012.

[14] Chailloux, T., "Caractérisation et modélisation de matériaux magnétiques en hautes températures en vue d'une application au filtrage CEM," Ph.D. dissertation, Universite Claude Bernard-Lyon I, Villeurbanne, France, 2011.

[15] Leite, J. V., S. L. Avila, N. J. Batistela, W. P. Carpes, N. Sadowski, P. Kuo-Peng, and J. P. A. Bastos, "Real coded genetic algorithm for Jiles-Atherton model parameters identification," *IEEE Transactions on Magnetics*, Vol. 40, No. 2, 888–891, Mar. 2004.

[16] Karaboga, D. and B. Akay, "A comparative study of artificial bee colony algorithm," *Applied Mathematics and Computation*, Vol. 214, No. 1, 108–132, 2009.

[17] Nourdine, A., A. Kedous-Lebouc, G. Meunier, and T. Chevalier, "A new hysteresis model generation — Application to the transverse axis of GO SiFe sheet," *IEEE Transactions on Magnetics*, Vol. 37, No. 5, 3340–3344, 2002.

[18] Nourdine, A., "Modélisation de l'hystérésis dans les matériaux magnétiques et Introduction de modèles dans le logiciel de simulation aux éléments finis Flux3D," Ph.D. dissertation, Dept. Elect. Eng., Institute Polytechnical, Grenoble, France, 2002.

[19] Chikazum, S., *Physics of Magnetism*, Wiley, New York, 1964.

[20] Hernandez, E. D. M., C. S. Muranaka, and J. R. Cardoso, "Identification of the Jiles-Atherton model parameters using random and deterministic searches," *Physica B: Condensed Matter*, Vol. 275, No. 1-3, 212–215, 2000.

[21] Bai, B., J. Wang, and K. Zhu, "Identification of the Jiles-Atherton model parameters using simulated annealing method," in *2011*

International Conference on Electrical Machines and Systems, 1–4, Beijing, China, Aug. 2011.

[22] Marion, R., R. Scorretti, N. Siauve, M.-A. Raulet, and L. Krahenbuhl, "Identification of Jiles-Atherton model parameters using particle swarm optimization," *IEEE Transactions on Magnetics*, Vol. 44, No. 6, 894–897, Jun. 2008.

[23] Glover, F., J. P. Kelly, and M. Laguna, "Genetic algorithms and Tabu search: Hybrids for optimization," *Computers & Operations Research*, Vol. 22, No. 1, 111–134, Jan. 1995.

[24] Karaboga, D. and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Applied Soft Computing*, Vol. 8, No. 1, 687–697, 2008.

[25] Sedira, D., Y. Gabi, A. Kedous-Lebouc, K. Jacob, B. Wolter, and B. Straß, "ABC method for hysteresis model parameters identification," *Journal of Magnetism and Magnetic Materials*, Vol. 505, 166724, Jul. 2020.

[26] Karaboga, D. and B. Akay, "A comparative study of artificial bee colony algorithm," *Applied Mathematics and Computation*, Vol. 214, No. 1, 108–132, 2009.

[27] Houck, C. R., J. Joines, and M. G. Kay, "A genetic algorithm for function optimization: A Matlab implementation," *NCSU-IE TR 95-09*, 1995.

[28] Chwastek, K. and J. Szczyglowski, "Identification of a hysteresis model parameters with genetic algorithms," *Mathematics and Computers in Simulation*, Vol. 71, No. 3, 206–211, 2006.

[29] Hergli, K., H. Marouani, M. Zidi, Y. Fouad, and M. Elshazly, "Identification of Preisach hysteresis model parameters using genetic algorithms," *Journal of King Saud University — Science*, Vol. 31, No. 4, 746–752, 2019.

[30] Hergli, K., H. Marouani, and M. Zidi, "Numerical determination of Jiles-Atherton hysteresis parameters: Magnetic behavior under mechanical deformation," *Physica B: Condensed Matter*, Vol. 549, 74–81, 2018.

[31] Cicirello, V. A. and S. F. Smith, "Modeling GA performance for control parameter optimization," in *GECCO-2000: Proceedings of the Genetic and Evolutionary Computation Conference*, 235–242, Morgan Kaufmann Publishers, Las Vegas, 2000.

[32] Bramlette, M. F., "Initialization, mutation and selection methods in genetic algorithms for function optimization," in *Proc. of the 4th International Conference on Genetic Algorithms*, 100–107, San Mateo, CA, USA, 1991.

[33] Srinivas, M. and L. M. Patnaik, "Adaptive probabilities of crossover and mutation in genetic algorithms," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 24, No. 4, 656–667, 1994.

[34] Fernandez-Prieto, J. A., J. Canada-Bago, M. A. Gadeo-Martos, and J. R. Velasco, "Optimisation of control parameters for genetic algorithms to test computer networks under realistic traffic loads," *Applied Soft Computing*, Vol. 11, No. 4, 3744–3752, 2011.

[35] De Jong, K., "Parameter setting in EAs: A 30 year perspective," in *Parameter Setting in Evolutionary Algorithms*, 1–18, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007.

[36] Worden, K. and G. Manson, "On the identification of hysteretic systems. Part I: Fitness landscapes and evolutionary identification," *Mechanical Systems and Signal Processing*, Vol. 29, 201–212, 2012.

[37] Gabi, Y., "Modélisation FEM du système de contrôle non destructif 3MA en ligne de production des aciers dual phase," Ph.D. dissertation, G2ELab — Laboratoire de Genie Electrique de Grenoble, France, 2012.