A robust method to estimate the parameters of Chemical Hysteresis Model

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Abstract —The paper presents the application of genetic algorithms to the estimation of chemical hysteresis model parameters [1]. The model uses nine parameters which should have meaningful sets. A new strategy based on dividing the optimization in two parts allows obtaining a good precision. This approach has been tested on two magnetic materials FeSi3% and dual phase. The error between the model and the experimental data points on B_H plan has been determined. It has been proved that the new method is robust and can generate meaningful sets of model parameters in both cases.

I. INTRODUCTION

The Chemical hysteresis model [1] is original in term of the physical insight. In fact, it is based on analogy between the electronic transformation of the material and chemical reaction. As other classical models, the chemical one has advantages and drawbacks.

Its advantages are:

- Formulation in terms of an argument hyperbolic tangential, easy for computation.
- Parameter identification is possible using two hysteresis loops.
- Some parameters are the physical characteristics of the material like coercitive field .

Its drawbacks are:

- Nine parameters, which make the identification process difficult.
- Unphysical meaning of certain parameters.

This model is formulated in term of equations having 9 parameters description of magnetization process [1]. The aim of this paper is to provide a robust estimation process, based on combining the new strategy with genetic algorithm optimization. The results of estimation of Chemical hysteresis model parameters using an implementation of genetic algorithm toolbox for Matlab environment [2]. All modeled characteristics are compared with the measured ones in order to assess their accuracy.

II. CHEMICAL MODEL FORMULATION

The main property of the chemical model is the decomposition of the magnetization J into its reversal component J_{rev}, which corresponds to domain wall bending during the magnetization process, and its irreversal part J_{irr} which corresponds to the rotation of the magnetization. The formulation is:

$$J_{rev} = J_{revSat}.\tanh\left(\left(\frac{\beta}{2\gamma}\right).\ln\left(c_0\ \exp(\gamma.H)\right) - \frac{\beta.H_c}{2}\right) \quad (1)$$

$$\gamma = \frac{\beta.\ln(c_0)}{\ln\left(A.\exp(\beta.H)\right)} \quad (2)$$

$J_{revSat}, \beta, H_c, c_0$ are the first four parameters which describe the reversal part. An energy approach is then used to describe the phenomenon of the magnetic moments rotation. A thermodynamic equilibrium equation is developed in order to have the angle θ evolution according to five constant parameters to identify. The system to be solved is written:

$$k_1.sh\left(k_2\left(\theta - \frac{\pi}{2}\right)\right) + h.\sin\vartheta - a = 0 \quad (3)$$

$$\alpha = \frac{\ln(c_1)}{\ln\left(A.\exp(\alpha.H)\right)} \quad (4)$$

$$\exp(\alpha.h) = c_1.\exp(\alpha.H) \quad (5)$$

The magnetization of the irreversible part is defined:

$$J_{irrev} = J_{IrrevSat}.\cos(\theta) \quad (6)$$

k_1, k_2 ,a,c_1 and J_{irrSat} are the parameters of the irreversal part. The total induction is computed by taking in to account of the participation of the revesal magnetization part and rotations of the magnetic moments:

$$B_{tot} = \left(J_{rev} + J_{irrev}\right) + \mu_0 H \quad (7)$$

The identification of the nine parameters for the chemical hysteresis model turns out to be a difficult process. Some of these parameters depend on the intern characteristics of the material. For example H_c corresponds to the coercitive field of the material; J_{revSat} and $J_{irrevSat}$ represent respectively the maximum induction of the wall displacement contribution and the rotation magnetization one.

We have tested a deterministic method to optimize the parameters; this method imposes an initial set of parameters, which makes the identification difficult. To overcome this problem, a Genetic Algorithm is used [3-5]. This identification process is automatic.

III. IDENTIFICATION PROCESS

The objective function is defined as a root mean square erreur epsilon, in such a way to achieve the best agreement between measured B_{imeas} and the computed magnetic flux densities B_{isimul}. The optimization is achieved when the

global minimum of the objective function (8) is found for the model parameters.

$$\varepsilon(\%) = \sqrt{\sum_{i=1}^{N} \frac{(B_{imeas} - B_{isimul})^2}{N}} \times 100 \qquad (8)$$

In (10), N denotes the number of points of measured magnetic flux density.

A. *Conventional process of identification:*

A direct research of the minimum global of the objective function gives these parameters:
J_{revSat} = 0.5 T, Hc = 7, β = 0.26, c_0 = 10.
$J_{irrevSat}$ =1.5 T, a = 10, c_1 = 5.4, k_1= 20, k_2 =10
The application of the nine parameters gives the computed B-H hysteresis loops, which are shown in Fig.1.

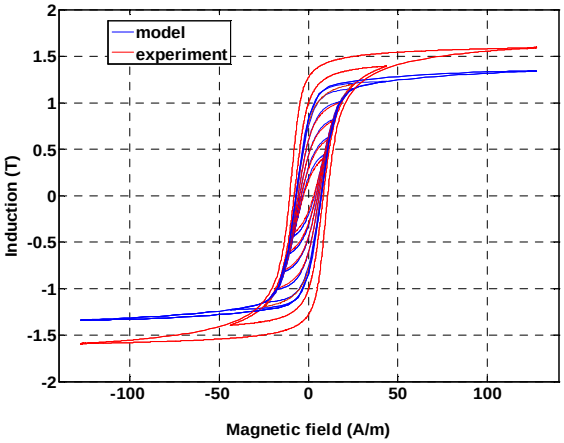

Fig. 1. The simulated and measured hysteresis loops at f = 10 Hz

The results are not suitable especially above Bmax > 1.1T, the error is estimated at 30%.The value of the Jrev and Jirr has not a meaningful set. It is important to evaluate the proportion of the wall displacement and the rotation magnetization. A lot of specialists as Schikazumi [6] have discussed this topic. The microstructure and different energy indicate the ratio of the reversal part and the irreversible one. In order to target the optimization and to have a best control of the parameters, a new strategy is proposed.

B. *Identication strategy:*

The strategy consists to divide the identification of the hysteresis model parameters in two steps: reversal part with only four parameters using the measured hysteresis loops at the operating point Bmax lower than 1.2T. After, this first identification, the four parameters are known. Then, two measured hysteresis at the operating point above 1.4T are chosen in order to extract the five parameters.
For this optimization, we have the same objective function but in this case we evaluate the error between measured induction and B_{rev} and B_{irrev}. The identified parameters are:
Part I: J_{revSat} = 1 T, Hc = 8, β = 0.25, c_0 = 10.
Part II :$J_{irrevSat}$ =1.1 T, a = 25, c_1 = 10.8, k_1= 8, k_2 =5.54.
The comparison between measurement and computation in the different contribution of the magnetization process is shown Fig. 2.

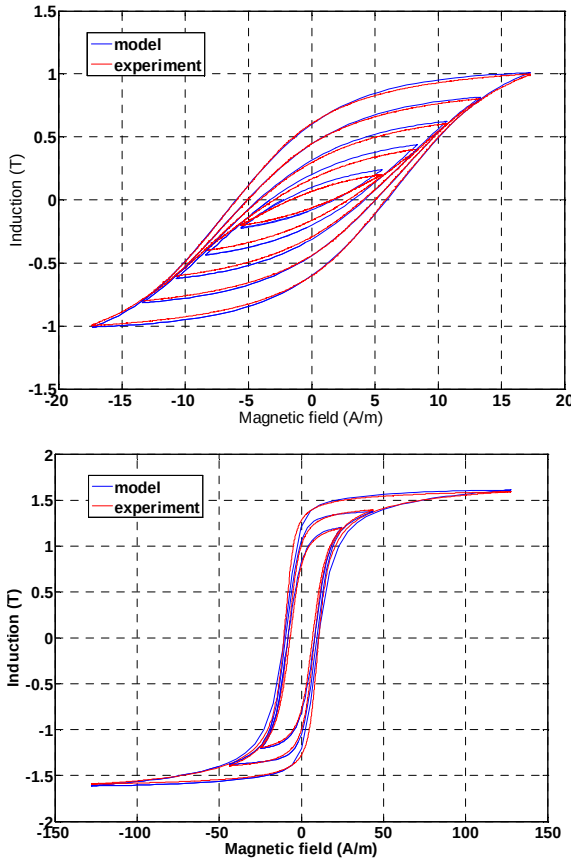

Fig. 2. The results of comparison between measurements and simulation at different state of magnetization.

There was a good agrement between measurement and computation. The error is lower than 3% for the reversal part identification and 5% for the irreversible one.

IV. CONCLUSION

In this paper the application of a genetic algorithm based method for estimation of Chemical hysteresis model parameters has been discussed. It has been proved that the strategy optimization gives meaningful set parameters, and the comparison between the measured and the simulated hysteresis loops gives the best results.

V. REFERENCES

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