An Improved Jiles-Atherton Model for Least Square Identification using Sensitivity Function Normalization

Erik Etien, *Member, IEEE*, Damien Halbert, Thierry Poinot

Abstract—In this article, an improved version of Jiles-Atherton model for least square identification is presented. First, a simplified anhysteretic magnetization model is used in order to provide simple estimates of the initial parameters. Then, a normalization of sensitivity functions is performed to improve the convergence of the Levenberg-Marquardt algorithm, leading to the emergence of optimal parameters. Experimental trials validate the proposed method.

Index Terms—Magnetic hysteresis, Jiles-Atherton model, nonlinear least square algorithm.

I. INTRODUCTION

Among the most studied nonlinear phenomena, hysteresis has always attracted the attention of researchers from a range of communities, including mathematics, electrical engineering and mechanics. In the domain of magnetism, the Jiles-Atherton (JA) model, based on physical considerations, has been particulary successful [1] and is widely used in finite element-based software and in the simulation of electronic design tools. Its relative simplicity and the limited number of parameters make the JA model a powerful tool and one which is well-positioned compared to its competitors [2].

In terms of parameters-identification, the J.A model possesses two main disadvantages:

- The procedure calls for complex experimental trials in order to obtain the initial parameters. As shown in [3] essential trials are needed before starting the identification algorithm. These consist of the original magnetization curve, the major loop and the anhysteretic curve. The last-mentioned curve is particularly difficult to obtain, and although some original procedures have been proposed [4], this method has disappeared in recent years.
- Due to the nonlinearities in the JA model, some convergence problems may exist if the initial parameters are not chosen correctly.

From the methodological point of view, the iterative method proposed by Jiles in 1986 was quickly replaced by the nonlinear optimization process of least squares [5], [6] or simulated annealing techniques [7], [8]. It is well known that these methods are very sensitive to the initial parameters and a gap between the values of these parameters can lead to the convergence towards a local minimum. In order to circumvent this problem, genetic algorithms were proposed recently [9], [10].

In this paper, it is demonstrated that good results may be obtained with least square algorithms, with convergence being improved. This comes about in two ways: through the improvement in the estimation of the initial parameters and through the modification of the nonlinear least square algorithm. A discrete form of the J.A model is proposed in section II, allowing calculations to be simplified over the different steps of the procedure. Section III describes how the improvement in the estimation of initial parameters is accomplished. In section IV, a modification of the least square algorithm, based on a normalization technique, is applied and validated through a simulation. In addition the simulation data is compared with the experimental data generated in section V.

II. DISCRETIZATION OF THE JILES ATHERTON MODEL

The differential equation describing the Jiles Atherton model is given by [3]

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

Where M is the total magnetization, H is the applied magnetic field, μ_o is the magnetic permeability of free space, k determines the hysteresis losses, c represents reversible wall motion, α is the effective field and δ is a directional parameter having the value $+1$ for $\frac{dH}{dt} > 0$ and -1 for $\frac{dH}{dt} < 0$.

The anhysteretic magnetization M_{an} is given by Eq. (2) using the Langevin function [11]

$$M_{an}(H) = M_s(\coth(\frac{H + \alpha M}{a}) - \frac{a}{H + \alpha M}). \quad (2)$$

With M_s being the saturation magnetization and a the parameter which represents the anhysteretic behavior. A more convenient form of (1), for the purpose of simulation, is given by the following relationship

$$\frac{dM}{dt} = (1-c)\frac{dH}{dt}\frac{M_{an} - M}{\frac{\delta k}{\mu_o} - \alpha(M_{an} - M)} + c\frac{dM_{an}}{dt}. \quad (3)$$

The five parameters to be estimated are $\widehat{\underline{\theta}}^T = [\widehat{M_s}\ \widehat{a}\ \widehat{c}\ \widehat{\alpha}\ \widehat{k}]$ (notation ˆ denotes estimated values). The identification procedure developed in section IV needs derivatives of the estimated

Fig. 1. Comparison of the true curve M_{an} (Eq. (6) with $\widehat{M}_{l-1} = \widehat{M}_{an_{l-1}}$) and pseudo M_{an} curve (displacement of the upper branch around 0).

magnetic field $\widehat{M}$ with respect to the five parameters. Analytic expressions of these derivatives are difficult to obtain because of the implicit character of Eq. (3). Consequently, the Jiles Atherton model is easier to handle in its discrete form. Derivatives are estimated using the classical Euler approximation

$$\frac{dy}{dt} = \frac{y_l - y_{l-1}}{T_s}. \tag{4}$$

with T_s the sample period and l the sample index. The discrete model is given by

$$\widehat{M}_l = \widehat{M}_{l-1} +$$

$$\frac{(1-\widehat{c})(H_l - H_{l-1})(\widehat{M}_{an_{l-1}} - \widehat{M}_{l-1})}{\frac{\delta.\widehat{k}}{\mu_o} - \widehat{\alpha}(\widehat{M}_{an_{l-1}} - \widehat{M}_{l-1})} + \widehat{c}(\widehat{M}_{an_l} - \widehat{M}_{an_{l-1}}), \tag{5}$$

with

$$\widehat{M}_{an_l} = \widehat{M}_s[\coth\frac{H_l + \widehat{\alpha}\widehat{M}_{l-1}}{\widehat{a}} - \frac{\widehat{a}}{H_l + \widehat{\alpha}\widehat{M}_{l-1}}]. \tag{6}$$

III. IMPROVING THE ESTIMATION OF INITIAL PARAMETERS

A. Anhysteretic parameters initialization

Nonlinear least square algorithms start with initial vector parameters $\widehat{\theta}_o^T = [\widehat{M}_{s_o}\ \widehat{a}_o\ \widehat{c}_o\ \widehat{\alpha}_o\ \widehat{k}_o]$ and, according to reference [3], the relationships between these parameters may be derived from the original magnetization curve, the major loop and the anhysteretic curve. Theoretically, the anhysteretic curve is obtained by imposing a given constant magnetic field H_o, and by adding to it an oscillating field of slowly decreasing amplitude. In Practice, the magnetization M is obtained by integrating an induced voltage generated by a measurement winding. The integration of the mean value H_o leads to a drift which prevents the use of this method. Accordingly, the autors decided to replace it with a pseudo-curve obtained by centering the upper branch of the major cycle around zero.

In figure 1, a set of parameters resulting from ref. [3] (material Fe $0.8wt\%C$, parameters in table I, first column) is used to simulate, on the one hand, the major loop using Eq. (5) and (6). On the other hand, the anhysteretic curve is obtained using Eq. (6) where only anhysteretic magnetization is considered ($\widehat{M}_{l-1} = \widehat{M}_{an_{l-1}}$). This curve may be compared with the pseudo-curve in figure 1, which shows a good approximation of M_{an} curve.

The initial parameters $\widehat{M}_{s_o}$, $\widehat{a}_o$ and $\widehat{\alpha}_o$, characterizing the anhysteretic magnetization, are derived from the following equations [3]:

$$\widehat{a}_o = \frac{\widehat{M}_{s_o}}{3}(\frac{1}{\chi'_{an}} + \widehat{\alpha}_o), \tag{7}$$

Fig. 2. $\Delta_f = |f_1(x) - f_2(x,\gamma)|$ Vs x and γ

Fig. 3. $\Delta_f = |f_1(x) - f_2(x,\gamma)|$ Vs x for different values of parameter γ

with

$$\chi'_{an} = \lim_{H\to 0 M\to 0}\{\frac{d}{dH}M_{an}(H)\} \tag{8}$$

It is possible to propose a simpler solution to determine these three initial parameters. Accordingly, we use the more convenient expression

$$M_{an}(H) = \frac{2}{\pi}M_s tan^{-1}[\frac{(H + \alpha M)}{a'}] \tag{9}$$

with $a' = \gamma.a$

This function is interesting because it is a linear in the parameters function. Consequently its parameters may be estimated using a simple least square method, as will be shown below. We are able now to verify that Eq. (2) may be advantageously replaced by Eq. (9), considering the two functions

$$f_1 = \coth(x) - \frac{1}{x} \tag{10}$$

and

$$f_2 = tan^{-1}(x') \tag{11}$$

used in models (2) and (9) with $x = H + \alpha M$ and $x' = \frac{x}{\gamma}$

The error $\Delta_f = |f_1(x) - f_2(x,\gamma)|$ is shown in figure 2. The value γ leading to the minimal error is determined numerically : $\gamma = 1.5708 = \frac{\pi}{2}$. In figure 3, the error Δ_f is plotted for different values of parameter γ, thus confirming the optimal value derived above.

Consequently, whatever the parameters a and α, the model (2) may be replaced by (9) by $a' = \frac{\pi}{2}a$.

Now, the simplest model (9) may be used in order to obtain the initial parameters $(\widehat{M}_{s_o}, \widehat{a'_o}, \widehat{\alpha_o})$ using linear least square technique shown later, below.

Considering only anhysteretic magnetization , M is replaced by M_{an} in (9). For the purpose of allowing this equation to be simulated, the following discrete form is proposed:

$$M_{an_l} = \frac{2}{\pi}\widehat{M}_{s_o}.tan^{-1}\left[\frac{1}{\widehat{a'_o}}H_l + \frac{\widehat{\alpha_o}}{\widehat{a'_o}}M_{an_{l-1}}\right] \tag{12}$$

Considering $\widehat{M}_{s_o}$ as a known parameter. We form the intermediary variable M'_{an_l} defined by :

$$M'_{an_l} = tan\left(\frac{\pi}{2}\frac{M_{an_l}}{\widehat{M}_{s_o}}\right) \tag{13}$$

The estimated value of M'_{an_l} can be written :

$$\widehat{M}'_{an_l} = \frac{1}{\widehat{a}'_o} H_l + \frac{\widehat{\alpha_o}}{\widehat{a}'_o} \widehat{M}_{an_{l-1}} \tag{14}$$

or equivalently:

$$\widehat{M}'_{an_l} = \begin{bmatrix} H_l & \widehat{M}_{an_{l-1}} \end{bmatrix} \cdot \begin{bmatrix} \dfrac{1}{\widehat{a}'_o} \\ \dfrac{\widehat{\alpha_o}}{\widehat{a}'_o} \end{bmatrix} = \underline{\varphi}^T . \hat{\underline{\theta}}' \tag{15}$$

Equation (15) can be generalized as a vector, e.g. :

$$\widehat{\underline{M}}'_{an} = P . \hat{\underline{\theta}}' \tag{16}$$

$\widehat{\underline{M}}'_{an}$ is the vector containing the N samples of the estimated output, $\hat{\underline{\theta}}'^T = \begin{bmatrix} \dfrac{1}{\widehat{a}'_o} & \dfrac{\widehat{\alpha_o}}{\widehat{a}'_o} \end{bmatrix}$, is the vector containing the parameters to be determined.

$P \in \Re^{N \times 2}$ is a matrix equal to $P = \begin{bmatrix} \underline{H} & \underline{M}_{an_{-1}} \end{bmatrix}$ where $\underline{H} \in \Re^{N-1}$ and $\underline{M}_{an_{-1}} \in \Re^{N-1}$ are vectors defined by :

$$\underline{H} = \begin{bmatrix} H_2 \\ . \\ . \\ . \\ H_N \end{bmatrix} \text{ and } \underline{M}_{an_{-1}} = \begin{bmatrix} \widehat{M}_{an_1} \\ . \\ . \\ . \\ \widehat{M}_{an_{N-1}} \end{bmatrix} \tag{17}$$

$\hat{\theta}'^T$ is obtained by the Least Square solution :

$$\hat{\underline{\theta}}^T_{LS} = \left(P^T P\right)^{-1} P^T \underline{M}'_{an} \tag{18}$$

With

$$\underline{M}'^T_{an} = \begin{bmatrix} M'_{an_2} & .... & M'_{an_N} \end{bmatrix} \tag{19}$$

B. Validating the simulation

In order to validate the above initialization procedure, we have again used again the major loop and the pseudo anhysteretic curve shown in figure 1 (parameters from ref. [3]). The modified model (12) is used to initialize the parameters $\widehat{M}_{s_o}, \widehat{a}_o$ and $\widehat{\alpha_o}$ using least square solution (18). The fourth parameter $\widehat{c}_o$ was then calculated using the following relationship [3]:

$$\widehat{c}_o = \frac{3\widehat{a}_o \chi'_{in}}{\widehat{M}_{so}} \tag{20}$$

with

$$\chi'_{in} = \lim_{M \to 0 H \to 0} \frac{dM}{dH} \tag{21}$$

The last parameter $\widehat{k}_o$ may be obtained from Eq. (1) and Eq. (21)

$$\widehat{k}_o = \mu_o \frac{M_{an}(H_c)}{1 - \widehat{c}_o} . \{\widehat{\alpha}_o + \frac{1}{(\frac{1}{1-\widehat{c}_o})\chi'_{max} - (\frac{\widehat{c}_o}{1-\widehat{c}_o})\frac{dM_{an}(H_c)}{dH}}\} \tag{22}$$

with $\chi'_{max} = \chi'_{H_c}$, the differential susceptibility at the coercive point. Using the three initial parameters $\widehat{M}_{s_o}, \widehat{a}_o$ and $\widehat{\alpha}_o, \dfrac{dM_{an}(H_c)}{dH}$ in Eq. (2) is then calculated.

The results are summarized in table I.

	Material parameters	Estimated initial parameters
$M_s(A.m^{-1})$	1.6×10^6	1.59×10^6
$a(A.m^{-1})$	1000	995.5
$k(A.m^{-1})$	700	697.43
α	1.4×10^{-3}	9.31×10^{-4}
c	0.22	0.28

TABLE I
ESTIMATED INITIAL PARAMETERS

The original magnetization curve and major cycle are sufficient to obtain initial parameters close to real ones. The curves are shown in figure 4. The two cycles are not identical, confirming that the initializing procedure cannot provide the true parameters directly. The initial parameters are thus used to initiate a nonlinear least-squares algorithm, which is described in the following section.

IV. IMPROVED NONLINEAR LEAST SQUARE ESTIMATION

A. Conventional nonlinear least square estimation

The parameter vector $\hat{\underline{\theta}}$ is estimated minimizing the following criterion

$$J = \underline{\epsilon}^T \underline{\epsilon}, \tag{23}$$

with $\underline{\epsilon}$ the residual vector $\in \Re^{K \times 1}$ (with K the number of samples) defined by :

$$\underline{\epsilon} = \underline{M}^\star - \hat{\underline{M}}(\hat{\theta}), \tag{24}$$

$\underline{M}^\star$ and $\hat{\underline{M}}$ are, respectively, vectors containing measured and estimated samples of magnetic fields.

The criterion J is a scalar that represents the sum of the quadratic errors between measured and estimated outputs [12]. Optimal values are obtained using the iterative Levenberg-Marquardt algorithm [13] which achieves a harmonious compromise between the stability of the Gradient method and the rapid convergence rate of the Gauss-Newton method

$$\hat{\underline{\theta}}_{j+1} = \hat{\underline{\theta}}_j - [(J'' + \lambda I)^{-1} J']_{\hat{\underline{\theta}}=\hat{\underline{\theta}}_j}. \tag{25}$$

The parameter λ is tuned during the procedure. Thus, this algorithm oscillates between the gradient ($\lambda \gg 1$) and the

Newton ($\lambda << 1$) methods.

The pseudo-Hessian J'' and the gradient J' can be written as [14]

$$J' = \frac{\partial J}{\partial \hat{\underline{\theta}}} = -2\underline{\epsilon}^T \sigma_{\hat{\underline{\theta}}}, \tag{26}$$

$$J'' = \frac{\partial^2 J}{\partial \hat{\underline{\theta}}^2} \cong 2\sigma_{\hat{\underline{\theta}}}^T \sigma_{\hat{\underline{\theta}}}, \tag{27}$$

where $\sigma_{\hat{\underline{\theta}}} \in \Re^{K \times 5}$ is the sensitivity function matrix defined by

$$\sigma_{\hat{\underline{\theta}}} = \frac{\partial \hat{\underline{M}}}{\partial \hat{\underline{\theta}}} = \left[\begin{array}{ccccc} \frac{\partial \hat{M}}{\partial \hat{M}_s} & \frac{\partial \hat{M}}{\partial \hat{a}} & \frac{\partial \hat{M}}{\partial \hat{c}} & \frac{\partial \hat{M}}{\partial \hat{\alpha}} & \frac{\partial \hat{M}}{\partial \hat{k}} \end{array} \right] \tag{28}$$

The sensitivity functions quantify the dependence of the model predictions with respect to the parameters. The Euler approximation may be used again to calculate these derivatives, considering small variations $\epsilon \hat{\underline{\theta}}$ around the parameter vector $\hat{\underline{\theta}}$:

$$\sigma_{\hat{\underline{\theta}}} = \frac{\hat{M}(\hat{\theta}(1+\epsilon)) - \hat{M}(\hat{\theta})}{\epsilon.\hat{\underline{\theta}}}. \tag{29}$$

B. Rate of improvement in convergence using normalization

In the case of the JA model, parameters may have very distant values ($M_s \approx 10^6$ et $\alpha \approx 10^{-3}$). Consequently the algorithm can converge too slowly or may be, in the worst case, simply aborted. Indeed, in Eq. (25), the matrix ($J'' + \lambda I$) must be inverted at each iteration. Values that are too distant, particularly in diagonal terms, lead to conditioning problems. Let us consider the example used in section III-B. With this set of parameters (table I), the matrix ($J'' + \lambda I$) is calculated using Eq. (5), (6) and approximations (29), (27). The condition number of the matrix ($J'' + \lambda I$) is calculated to give an indication of the accuracy of the results of matrix inversion. A value near 1 indicates a well-conditioned matrix. Results are shown in table II for different choices of parameter λ.

λ	condition number
1	3×10^{17}
10^6	45×10^{12}
10^{21}	1.04

TABLE II
CONDITION NUMBER OF THE MATRIX ($J'' + \lambda I$)

A correct conditioning may be obtained using a very large λ. However, maintaining λ at a constant value leads to a gradient algorithm with a very slow convergence. The parameter λ must be tuned at each iteration in the optimization process. Another solution consists in modifying the sensitivity functions. Let us consider the two sensitivity functions $\frac{\partial \hat{M}}{\partial \hat{M}_s}$ and $\frac{\partial \hat{M}}{\partial \hat{\alpha}}$ shown on figure 5. The magnitude of the curve $\frac{\partial \hat{M}}{\partial \hat{M}_s}$ appears much larger than the other and this leads to the conditioning problems described above.

Fig. 5. Sensitivity functions $\frac{\partial \hat{M}}{\partial \hat{M}_s}$ and $\frac{\partial \hat{M}}{\partial \hat{\alpha}}$ without normalization.

To circumvent this problem, the sensitivity functions are normalized [14]. Let us consider the estimated parameters vector $\hat{\underline{\theta}}$ with its initial value $\hat{\underline{\theta}}_o$

$$\hat{\underline{\theta}} = \hat{\underline{\theta}}_o + \Delta \hat{\underline{\theta}} \tag{30}$$

Vector $\Delta \hat{\underline{\theta}}$ is defined by $\Delta \hat{\underline{\theta}} = \hat{\underline{\eta}}^T \hat{\underline{\theta}}_o$ with

$$\hat{\underline{\eta}}^T = \left[\begin{array}{ccccc} \hat{\eta}_{M_s} & \hat{\eta}_a & \hat{\eta}_c & \hat{\eta}_\alpha & \hat{\eta}_k \end{array} \right] \tag{31}$$

The sensitivity functions matrix $\sigma_{\hat{\underline{\theta}}}$ can be written as

$$\frac{\partial \hat{\underline{M}}}{\partial \hat{\underline{\theta}}} = \frac{1}{\hat{\underline{\theta}}_o} \frac{\partial \hat{M}}{\partial \hat{\underline{\eta}}}, \tag{32}$$

where the sensitivity matrix $\underline{\sigma}_{\hat{\eta}} = \frac{\partial \hat{M}}{\partial \hat{\underline{\eta}}}$ is now normalized and with the same order of magnitude as the others. Marquardt algorithm [13] now estimates the vector $\hat{\underline{\eta}}$, thus parameter vector $\hat{\underline{\theta}}$ using Eq. (30). Thanks to this method, a better convergence may be achieved. According to this improvement, the new algorithm is

$$\hat{\underline{\eta}}_{j+1} = \hat{\underline{\eta}}_j - \{[J''_{\underline{\eta}\underline{\eta}} + \lambda I]^{-1} J'_{\underline{\eta}}\}_{\hat{\underline{\eta}}=\hat{\underline{\eta}}_j}, \tag{33}$$

with

$$J' = \frac{\partial J}{\partial \hat{\underline{\eta}}} = -2\underline{\epsilon}^T \underline{\sigma}_{\hat{\eta}}, \tag{34}$$

$$J'' = \frac{\partial^2 J}{\partial \hat{\underline{\eta}}^2} = 2\underline{\sigma}_{\hat{\eta}}^T \underline{\sigma}_{\hat{\eta}}, \tag{35}$$

In order to illustrate the conditioning improvement, the modified sensitivity function matrix (32) is calculated with the parameters of table I. Figure 6 shows that the two functions $\frac{\partial \hat{M}}{\partial \hat{\eta}_{M_s}}$ and $\frac{\partial \hat{M}}{\partial \hat{\eta}_\alpha}$ have the same order of magnitude, which is desirable.

Fig. 6. Sensitivity functions $\frac{\partial \hat{M}}{\partial \eta_{M_s}}$ and $\frac{\partial \hat{M}}{\partial \eta_\alpha}$ with normalization.

Condition numbers are given in table III. The normalization technique leads to a better matrix conditioning.

λ	condition number
1	85153
10^6	85152
10^{21}	1

TABLE III
CONDITION NUMBER OF THE MATRIX ($J'' + \lambda I$) WITH NORMALIZATION

In order to illustrate the improvement in convergence, the initial parameters of table I (second column) are used to start, on the one hand, a standard Marquardt algorithm and, on the other, a normalized Marquardt algorithm. The two rates of convergence are shown in Fig. 7. We see that, using normalization, the algorithm provides estimated parameters after only 7 iterations. Without normalization, the estimation converges more slowly.

Fig. 7. Rate of convergence Vs iterations, non-normalized algorithm (dashed line), normalized algorithm (solid line).

V. EXPERIMENTAL RESULTS

The algorithm described above is now applied to a $FeNi80$ toroïdal core made of ribbon with $200\mu m$ thick, diameter: $8.5cm$ and an effective area of $1.28cm^2$).

A frequency generator associated with a 300 Watt integrated linear amplifier provides the necessary current to obtain the nominal functioning. Primary current $i_1(t)$ is measured with a Tektronix A6302 current probe associated with a probe amplifier TM502A (Fig.8). The primary current and the secondary voltage are obtained with a sample period $T_s = 0.1ms$ using a dSpace DS1102 Controller Board associated with the Matlab /Simulink environment. The magnetic field of the core is given by:

$$h(t) = \frac{i_1(t).N_p}{L_m}, \qquad (36)$$

with L_m the magnetic path length and N_p the number of primary turns.

The magnetic induction is obtained using

$$b(t) = \frac{1}{N_s.S} \int u_2(t)dt. \qquad (37)$$

with S the magnetic flux area and N_s the number of secondary turns. The magnetization M is calculated using Eq. (36) and (38):

$$M(t) = \frac{b(t)}{\mu_o} - h(t). \qquad (38)$$

The core is excited using a sinusoïdal voltage of $10Hz$ frequency . Based on the experimental data, the identification procedure is implemented:

- from the measured major loop (top of figure 9), initial parameter $\hat{M}_{so} = 7.510^6$ is determined and the pseudo-anhysteretic curve is obtained by centering the upper branch;
- initial parameters $\hat{\alpha}_o = 8,9710^{-6}$ and $\hat{a}_o = 4.86$ are estimated using the least squares solution (18);
- the last parameters $\hat{c}_o = 0.698$ and $\hat{k}_o = 0.178$ are determined using Eq. (20) and (22);
- these five initial parameters are used to start the normalized Levenberg-Marquardt algorithm (33).

	Estimated initial parameters	Optimized parameters
$M_s(A.m^{-1})$	7.5×10^5	7.72×10^5
$a(A.m^{-1})$	4.86	4.36
$k(A.m^{-1})$	0.18	2.44
α	8.97×10^{-6}	1.7×10^{-5}
c	0.7	0.49

TABLE IV
OPTIMIZED PARAMETERS

Fig. 8. Diagram of experimental set-up

The optimized parameters are shown in table IV.

Figure 9 demonstrates that there is excellent agreement between experimental and estimated data. Reversal and increasing cycles are shown in figures 10 and 11. The magnetization M is correctly estimated, except for the case of the low induction level. The problems encountered in the modeling of minor cycles modeling are well known and not treated in this work ([15], [16], [17]).

VI. CONCLUSION

Improvements in the Jiles Atherthon model identification procedure depend on the initial parameters and on the correct conditioning of the matrices to be inverted. An original intialization procedure was described allowing the five initial parameters of the model to be calculated just from the knowledge of the original magnetization curve and the major cycle only. On the other hand, the normalization technique described here allows the convergence of the model to be improved in terms of needing only a small number of iterations. Other improvements can be built in to the design in order to limit the initial parameters to optimal ones and to circumvent the problem of potential local minima.

REFERENCES

[1] D.C. Jiles D.L. Atherton *Theory of ferromagnetic hysteresis. Journal of Magnetism and Magnetic Material*,vol. 61, pp. 48-60, 1986.
[2] F. Liorzou B. Phelps D.L. Atherton *Macroscopic models of magnetization. IEEE Trans. Magn.*, vol. 36, pp. 418-428, 2000.
[3] D.C Jiles, J.B Thoelke, M.K Devine   *Numerical Determination of Hysteresis Parameters for the Modeling of Magnetic Properties Using the Theory of Ferromagnetic Hysteresis. IEEE Trans. Magn.*, vol. 28, pp. 27-35, Jan. 1992.
[4] O. Hubert L. Daniel R. Billardon *Experimental analysis of the magnetoelastic anisotropy of a non-oriented silicon iron alloy. Journal of Magnetism and Magnetic Materials*,vol. 254-255, pp. 352-354,January 2003.
[5] H.G.. Brachtendorf, C. Eck, R. Laur   *Macromodeling of hysteresis Phenomena with Spice. Trans. on Circuits And Systems*, vol. 44, pp. 378-388, 1997.
[6] P. Kis, A Ivanyi *Parameter Identification of JA Model with Nonlinear Least Square Method .* in Proc. HMM 2003, Salamanca, Spain, 28-30 May 2003.

Fig. 9. Comparison between experimental (solid line) and estimated (+) data. Top: major cycles, bottom: magnetization M.

Fig. 10.   Top: reversal cycles, bottom: comparison between experimental (solid line) and estimated (+) magnetization.

Fig. 11. Top: increasing cycles, bottom: comparison between experimental (solid line) and estimated (+) magnetization.

[7] D. Lederer, H. Igarashi, A. Kost, T. Honma *On the Parameter Identification and Application of the JA Hysteresis Model for Numerical Modelling of Measured Characteristics* . *IEEE Trans. Magn.*, vol. 35, pp. 1211-1214, 1999.

[8] E.D.M. Hernandez, C.S. Muranaka, J.R. Cardoso *Identification of the JA model parameters using random and deterministic searches*. *Physica B*, vol. 275, pp. 212-215, 2000.

[9] P.R Wilson, J.N Ross, A.D Brown *Optimizing the JA Model of Hysteresis by a Genetic Algorithm* . *IEEE Trans. Magn.*, vol. 37, pp. 989-993, 2001.

[10] A. Salvini F.R. Fulginei Genetic algorithms and neural networks generalizing the JA model of static hysteresis for dynamic loops. *IEEE Trans. Magn.*, vol.38, pp. 873-876, 2002.

[11] D.C. Jiles J.B. Thoelke *Theory of ferromagnetic hysteresis:determination of model parameters from experimental hysteresis loops. IEEE Trans. Magn.*,vol. 25, pp. 3928-3930, 1989.

[12] L. Ljung System identification - Theory for the user. *Prentice Hall*, 1987.

[13] W.D. Marquardt An algorithm for least squares estimation of nonlinear parameters. *Journ. Soc. Indust. Appl. Math.*, vol. 11, pp. 431-441, June 1963.

[14] J.C. Trigeassou T. Poinot S.Moreau, A methodology for estimation of physical parameters. System Analysis Modelling Simulation, vol. 43, pp. 925-943, 2003

[15] D.C Jiles A self consistent generalized model for the calculation of minor loop excursions in the theory of hysteresis. *IEEE Trans. Magn.*, vol. 28, pp. 2602-2604, Sept. 1992.

[16] K.H Carpenter Simples models for dynamic hysteresis which add frequency dependant losses to static models. *IEEE Trans. Magn.*, vol. 34(3), pp. 619-622, May 1998.

[17] A. Salvini F.R. Fulginei C. Coltelli Neuro-Genetic Time-Frequency Approach Macromodeling Dynamic Hysteresis in Harmonic Regime. *IEEE Trans. Magn.*, vol.39, pp. 1401-1404, May 2003.

Thierry Poinot received is Ph.D. degree in Automatic Control from Poitiers University, France, in 1996. From 1996, he is professor of Ecole Supérieure d'Ingénieurs de Poitiers. His research interests identification of linear and nonlinear continuous time systems, modelling and identification of fractional systems.

Erik Etien (M'04) was born in France in 1970. He received the Ph.D. degree from the University of Poitiers in Automatic in 1999. His research interests the development of soft-sensors in the field of electrical engineering.

Damien Halbert was born in France in 1978. He prepares for the PhD degree in the laboratory of Automatic of Poitiers. His research interests application of identification techniques for hysteresis modeling and characterization of magnetic cores for industrial applications.