Multiobjective Lightning Search Approach Applied to Jiles-Atherton Vector Hysteresis Model Parameters Estimation

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Hysteresis is a fundamental property commonly encountered in physical systems of a wide variety of engineering and science fields and the parameter identification of hysteresis models is an essential task for adequate hysteretic material simulation. In magnetic vector hysteresis models as the Jiles-Atherton (J-A) the work increases in complexity since one must solve a nonlinear system with a relative large number of variables. In these cases, fitting methods based on efficient optimization methods is an attractive solution. In this study, an improved multiobjective lightning search algorithm (IMLSA), a stochastic optimization metaheuristic algorithm, is introduced for solving J-A model identification. The proposed IMLSA based on mutation operator of the differential evolution is verified using data from a rotational single sheet tester in two-dimensional version. Numerical comparisons of IMLSA with results using a multiobjective lightning search demonstrated that the performance of the IMLSA is promising in parameters estimation of nonlinear hysteretic J-A models.

***Index Terms*— Hysteresis model, vector hysteresis, parameters identification, lightning search, multiobjective optimization.**

I. Introduction

THE complex behavior of rotating flux plus the anisotropic characteristic of magnetic material demand a vector hysteresis model in order to represent the phenomenon. One of the most popular nonlinear dynamical mathematical models is the Jiles-Atherton (J-A) [1] hysteresis model. The inverse J-A vector hysteresis [7] is well adapted for some applications as, for instance, the finite element method with vector potential formulation. The parameter identification of a J-A hysteris model is a hard task cause the nonlinear mathematical model behavior makes virtually impossible to obtain a system of analytic equations where a great number of parameters combination are expected. Therefore a fitting procedure combined with optimization metaheuristics [2] is an appropriate methodology for the parameters obtaining [3]-[5].

An optimization metaheuristic is an algorithm for solving approximately a wide range of hard optimization problems without previous knowledge about it. Many nature-inspired population-based metaheuristics [2,6] deal with a set (i.e. a population) of solutions rather than with a single solution.

In 2015, a new stochastic optimization metaheuristic algorithm inspired by the natural phenomenon of lightning and the mechanism of step leader propagation called lightning search algorithm (LSA) [7] was proposed. The current paper's main contribution is an improved multiobjective lightining search algorithm (IMLSA) inspired on mutation operator of the differential evolution (DE) paradigm [8] to parameters estimation of vector hysteresis J-A model. The optimization results using IMLSA are compared with another multiobjective LSA (MLSA). The presented approach is validated by comparison between simulated and experimental data.

The remainder of this digest is structured as follows. Section II explains the basic of mathematical formulation for the J-A model. Thereafter, Section III presents briefly the fundamentals of the different LS optimizers. Section IV reports the computational results and analysis while Section V signifies the end of the paper after providing the concluding remarks and possible paths for future research.

II. The Jiles-Atherton Vector Hysteresis Model

The main equations of J-A vector hysteresis model are the following:

$$d\boldsymbol{M} = \frac{1}{\mu_0}\left\{\mathbf{1} + F_\chi \cdot \left(1-\ddot{\alpha}\right) + \vec{c}\cdot\ddot{\xi}\cdot\left(1-\ddot{\alpha}\right)\right\}^{-1}\cdot\left\{F_\chi\cdot\vec{c}\cdot\ddot{\xi}\right\}d\boldsymbol{B} \quad (1)$$

$$F_\chi = \vec{\chi}_f \left|\vec{\chi}_f\right|^{-1}\cdot\vec{\chi}_f \quad (2)$$

$$\vec{\chi}_f = \ddot{k}^{-1}\cdot\left(\boldsymbol{M}_{an} - \boldsymbol{M}\right) \quad (3)$$

$$\boldsymbol{M}_{an} = \boldsymbol{M}_{an}\left(\left|\boldsymbol{H}_e\right|\right)\frac{\boldsymbol{H}_e}{\left|\boldsymbol{H}_e\right|} \quad (4)$$

where $\boldsymbol{M}$ is the vector total magnetization, $\boldsymbol{B}$ is the induction vector, $\mathbf{1}$ is the identity matrix, $\vec{\chi}_f$ is a auxiliary vector related to the irreversible magnetization, $\boldsymbol{M}_{an}$ is the anhystereric magnetization given by the vectored Langevin equation, $\boldsymbol{H}_e$ is the effective magnetic field given by $\boldsymbol{H}_e = \boldsymbol{H} + \ddot{\alpha}\cdot\boldsymbol{M}$, and $\ddot{\xi}$ is a matrix containing the derivatives of $\boldsymbol{M}_{an}$ with respect to $\boldsymbol{H}_e$ [9].

In the original J-A scalar hysteresis model there were five parameters to be determined: M_S, related to saturation magnetization; k, related to magnetic losses; a, related to anhysteretic magnetization; α, related to magnetic domains coupling and c related to reversible magnetization. In the vector version the differential equation of magnetization is a function of vector variables, and the five parameters of the original J-A model are now replaced by five tensors: $\overleftrightarrow{M}_S$, $\overleftrightarrow{k}$, $\overleftrightarrow{\alpha}$, $\overleftrightarrow{a}$ and the tensor $\overleftrightarrow{c}$.

In this work, the vector model was implemented in its 2D version, so it's necessary to obtain a set of ten parameters being five for the rolling direction (x) and five for the transverse direction (y). For validation, experimental data was obtained from a rotational single sheet tester (RSST).

III. Fundamentals of Lighting Search Optimizers

LS algorithm uses the concept of fast particles known as projectiles. Three projectile types are developed to represent the transition: the ones that create the first step leader population, the ones that attempt to become the leader and the lead ones that represent the projectile fired from the best positioned step leader [7]. The major exploration feature of the LSA is modeled using the exponential random behavior of space projectile and the concurrent formation of two leader tips at fork points using opposition-based learning (see details in [10]). The basic steps of the LSA are summarized and illustrated in Fig. 1.

```
Definition of objective function and control parameters
Generate population of step leaders (transition projectile)
Evaluate performance (projectiles energies)
Initialize the generation's counter, t = 1
While t < maximum of iterations
    Update leader tips energies, best and worst step leaders
    Update direction and kinetic energy
    Eject space and lead projectiles
    Evaluate performance (projectiles energies)
    Verify the channel and focking occurrence
    Update the generation's counter, t = t + 1
End while
Return a lightning strike point (best step leader)
Postprocess results
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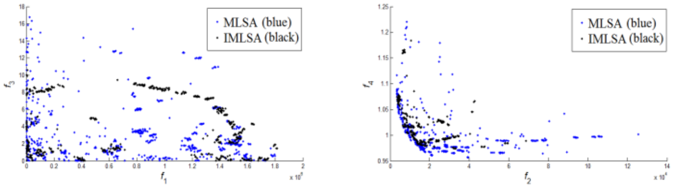
Fig. 1. Pseudo code of the LSA for single-objective problems.

When compared with its counterpart, the MLSA differs using a combination of the nondominated rank and the crowding distance computation for selecting the best and the worst step leaders. In addition, the channel update is based on the projectiles energies and it is performed by a direct comparison using the domination mechanism. On the other hand, the proposed IMLSA also contains a mutation operator inspired in DE to deal with the problem of maintaining diversity and promoting exploration during the optimization process.

IV. Optimization Results

The MLSA and IMLSA are employed to find a parameter set that minimize the mean squared error (MSE) and loss error (LE) between calculated and measured rolling (x) and transverse (y) curves. The MSEx, MSEy, LEx and LEy are the minimization objective functions f_1, f_2, f_3 and f_4, respectively. Results (30 runs) are illustrated in Fig. 2.

Fig. 3 plots the measured and calculated curves using the parameters set obtained by an IMLSA with best tradeoff between the four objectives (minor arithmetic mean of the normalized objective functions values). From the Fig. 3, we can observe that the IMLSA can find a good trade-off solution close to the measured and calculated *B-H* curves.



(a) f_1 versus f_3 (b) f_2 versus f_4

(c) f_1 versus f_2 (b) f_3 versus f_4

Fig. 2. Results of the solution space using MLSA and IMLSA.

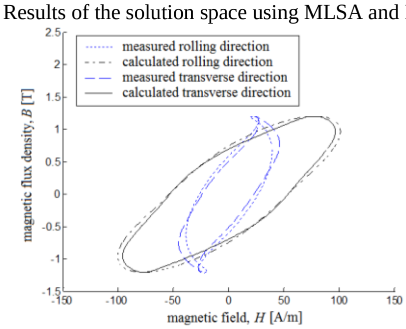


Fig. 3. *B-H* curves for the material under rotational excitation using IMLSA.

V. Conclusion

The proposed IMLSA is efficient for identification of the J-A vector hysteresis model. It is shown that IMLSA can produce competitive results compared with the MLSA in terms of the solution quality related to MSE minimization.

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