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The Parameters Identification of Magnetic Core Using Fruit Fly Optimization Algorithm

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This paper is concerned about the parameters identification of the Jiles-Atherton hysteresis loop model using Fruit Fly Optimization Algorithm (FOA). An improved Fruit Fly optimization algorithm (IFOA) is proposed to overcome the drawback of FOA, such as easily falling into local optimum, low precision, and poor stability. The IFOA has been applied to identify Jiles-Atherton model parameters of conventional non-oriented electrical steel. The simulation results are compared with those of FOA and Particle Swarm Optimization (PSO), which shows the modelled M - H curve obtained with IFOA is in good agreement with the measured M - H curve and IFOA method has the advantages of better global searching ability, higher precision and stability.

1. Introduction

Hysteresis phenomenon is a common nonlinear property in physical systems and electromagnetic devices. The accurate modelling of the hysteresis characteristics of magnetic materials is crucial to the safety of the equipment and the stable operation of the systems. Several models have been developed to describe hysteresis characteristics of magnetic materials, such as Preisach model (Preisach, 1935), Globus model (Globus, 1971) and Jiles-Atherton model (Jiles and Atherton, 1986). Preisach model is expressed by complex mathematical formulas without considering the origin of the hysteresis. Globus model does not take into account of the interaction between magnetic domains. Jiles-Atherton model is derived on the basis of physical mechanism, which truly describes the non-linear relation between magnetic field intensity and the magnetic induction intensity. Jiles-Atherton model is expressed by a first order differential equation with five parameters. Due to its simple expression and accuracy, Jiles-Atherton model is the most widely used in hysteresis modelling.

Many artificial intelligence optimization algorithms are proposed to identify the parameters of the Jiles-Atherton Model. Chwastek and Szczyglowski (2006) have reported to apply Genetic Algorithm (GA) to estimate the five parameters of Jiles-Atherton model. Marion (2008) has estimated the five parameters of Jiles-Atherton model using Particle Swarm Optimization(PSO), and Naghizadeh et al. (2012) have identified the parameters using Shuffled Frog Leaping Algorithm (SFLA). However, Genetic Algorithm has the drawbacks of slow convergence and premature. Although Particle Swarm Optimization is accuracy, it often falls into local optimum. Shuffled Frog Leaping Algorithm has the ability of escaping from local optimum, but it requires more computation and memory size. Thus, an effective method needs to be found with accuracy and convergence rate.

Fruit Fly Optimization Algorithm (FOA) is a new swarm intelligent optimization algorithm developed in recent years (Pan, 2012). Base on its high convergence rate and accuracy, less parameters and calculation amount, it is widely used to solve practical problems. Li et al. (2013) have used improved FOA in matching pursuit to increase the speed and accuracy of the signal sparse decomposition, Niu et al. (2015) have applied FOA to optimize the operation of a GE gasification process, which is to maximize the syngas yield with two decision variables. However in applications, FOA may fall into local optimum and face the dilemma of slow search

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speed, low efficiency and poor stability, when the actual system is complex or the optimization problem is with high dimensions.

An improved Fruit Fly Optimization Algorithm (IFOA) is proposed to solve the problems above. Dynamic search step is applied, which can expand the searching scope and increase the diversity of FOA. The algorithm can jump out of local minimum, and converge to the global minimum. The performance of IFOA is much better than FOA in converge rate and search precision.

In this paper, FOA and IFOA algorithms are used to identify the parameters of the Jiles-Atherton model. The simulation results of FOA and IFOA are compared with those obtained with PSO algorithm in fitness values with iterations, simulation time, and estimation errors in percentage. The contributions of this paper are:(1) First determining the parameters of Jiles-Atherton model with FOA; (2) Improving the performance of FOA by using dynamic search step; (3) Verifying the effectiveness of the algorithm by simulations.

2. Principle of FOA

FOA is a novel swarm intelligent optimization method proposed by Taiwan scholar Pan in 2012. This algorithm is put forward based on food finding behavior of fruit fly. Fruit fly is superior to other species, especially in the sense of smell and vision. Osphresis organ of fruit fly can collect all kinds of smell floating in the air.It can find the location of food and other fruit flies' flocking by its sensitive vision, and flies towards that location. According to the foraging process of fruit fly, the steps of FOA are described as follows:

Step 1: Determine the number of fruit flies and iterations, and initialize randomly fruit flies location (*X_axis, Y_axis*).

Step 2: Give a random flight direction and distance of an individual fruit fly.

$$\begin{cases} X_i = X\_axis + Random\ \ Value \\ Y_i = Y\_axis + Random\ \ Value \end{cases} \tag{1}$$

Step 3: Calculate the distance (D_1) between individual fruit fly (X_1, Y_1) and the origin, and then calculate the smell concentration judgment value (S_1).

$$D_i = \sqrt{X_i^2 + Y_i^2} \tag{2}$$

$$S_i = 1/D_i \tag{3}$$

Step 4: Calculate the smell concentration ($smell_1$) of the individual fruit fly by substituting the smell concentration judgment value (S_1) into the smell concentration judgment function (so-called Fitness function).

Step 5: Find out the individual fruit fly with minimum smell concentration value (for minimum problems).

$$[bestsmell, bestindex] = min(smell) \tag{4}$$

Step 6: Keep the minimum smell concentration value and its coordinate (X, Y), and the fruit flies fly towards the location with minimum smell concentration value using vision.

$$\begin{cases} Smellbest = bestsmell \\ X\_axis = X(bestindex) \\ Y\_axis = Y(bestindex) \end{cases} \tag{5}$$

Step 7: Enter iterative optimization to repeat the implementation of 2-5. When the smell concentration is superior to the previous iterative smell concentration, turn to step 6.

3. Parameter identification of Jiles-Atherton model

3.1 Jiles-Atherton model

Jiles-Atherton model is a widely used mathematical model which represents the nonlinear characteristics of magnetic core. The model is based on the physical process of hysteresis, which is described by a differential equation with five parameters:

$$\frac{dM}{dH} = \frac{(1-c)(M_{an} - M) + ck\delta \frac{dM_{an}}{dH}}{\delta k - a(1-c)(M_{an} - M)} \tag{6}$$

Here, M_{an} is the anhysteretic magnetization. c is reversible magnetization coefficient. k is pinning factor. α is coupling factor between magnetic domains. δ is direction parameter, which is defined as $\begin{cases} dH/dt > 0, \delta = 1 \\ dH/dt < 0, \delta = -1 \end{cases}$.

The anhysteretic magnetization M_{an} is provided by Eqs (7):

$$M_{an} = M_s \cdot \left\{ \coth\left[\frac{H_e}{a}\right] - \frac{a}{H_e} \right\} \tag{7}$$

Here, M_s is saturation magnetization. a is form factor. H_e is effective magnetic field which is given by:

$$H_e = H + \alpha M \tag{8}$$

Combined Eqs (6) - (8) can form a first order equation. The numerical solution of the differential equation can be obtained when the five parameters (M_s, α, a, c, k) and the initial value are determined. Thus M-H curve can be obtained. While the parameters identification of Jiles-Atherton model is to determined the five parameters according to the experimental data of hysteresis characteristics.

3.2 Fitness function

Using optimization algorithm to identify the parameters of the Jiles-Atherton model is an optimization question, so an appropriate fitness function must be defined. The fitness function is defined as:

$$fitness = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_{expi} - M_i)^2} \tag{9}$$

Here, M_1 is the calculated value from Jiles-Atherton model. M_{expi} is experimental magnetization at H_1. The process of parameter identification is the process of seeking the minimum value of the fitness function. The smaller the fitness value is, the more accurate the identification results are.

3.3 Improvement of FOA

The second step of FOA is giving a random flight direction and distance to an individual fruit fly, described in Eqs (1).

From Eqs (1), it is found that the step size is a random value which has certain blindness. It can influence the improvement of search efficiency and precision. At the same time, the fruit flies fling towards ($X_{\_axis}$, $Y_{\_axis}$) with different directions and distances will reduce the search scope, which is easy to cause premature convergence and falls into local optimum. So it is important to select the step size of FOA.

Thus dynamic search step is applied as step size which is shown in Eqs (10).

$$\begin{cases} X_k = X\_axis + Random\ \ Value * D_k * h^k \\ Y_k = Y\_axis + Random\ \ Value * D_k * h^k \end{cases} \tag{10}$$

Here, D_k is the distance between the location of the best fruit fly for the k-th iteration and the origin; h is variation factor which is determined by the optimization problem.

After the improvement, flies can search locations in a large scope, which can increase the diversity of the fruit flies position. The algorithm can jump out of local minimum values and find the global optimal solution. The optimization accuracy of IFOA will greatly increase especially for high dimensional parameters optimization.

4. Results and discussion

PSO is an intelligent optimization algorithm which has the merits of fast search speed, simple operation, and high efficiency. Due to its advantages, PSO is used widely in parameter optimization. Lin et al. (2006) have used PSO to identify Hammerstein model. Ma et al. (2012) have applied improved PSO in load optimal dispatch. Thus, in this paper, IFOA, FOA and PSO are used to identify the parameters of Jiles-Atherton model for non-oriented electrical steel (V3250-50A). The measured data and ranges of parameters are taken from Chwastek and Szczyglowski (2006).

The parameters of PSO algorithm are set as typical values. Swarm size is 40, inertial factor η=0.72, and acceleration constant C_1=2 and C_2=2.5. The swarm size of FOA and IFOA algorithms are both 40. The variation factor of IFOA is 0.9.

All the three algorithms are implemented in MATLABR2007b. The simulations are completed in a computer with Intel(R) Core(TM) i5-2500s, 2.70 GHz CPU, and 3062 MB RAM.

PSO, FOA and IFOA algorithms are run for 30 times respectively to assure the repetitiveness of convergence. The results in Table 1 (expect Best fitness and Worst fitness) and Figure 2 are averaged.

Table 1: Identification results

Parameter	PSO	FOA	IFOA
$M_s \times 10^6$(A/m)	1.246	1.213	1.231
$\alpha \times 10^{-5}$	3.091	8.934	11.46
a(A/m)	0.335	55.07	57.77
c	0.042	0.989	0.562
k(A/m)	96.29	51.29	67.44
Best Fitness$\times 10^4$	0.612	0.614	0.358
Worst Fitness$\times 10^4$	3.294	0.955	0.418
Average Fitness$\times 10^4$	2.961	0.729	0.377
Simulation time (s)	448.1	232.1	174.3

From Table 1, it can be observed that the fitness value achieved with IFOA is lower than the minimum fitness value of PSO and FOA. The simulation time of FOA and IFOA are much shorter than PSO, and the computation speed of IFOA is the best of the three methods. IFOA is proved to have high identification accuracy and fast calculation speed.

The difference between the best fitness value and the worst fitness value for IFOA is 600A/m which is 15.92 % of the average fitness value, while it is 90.58 % for PSO and 46.78 % for FOA. It is stated that the stability of IFOA is better than that of FOA and PSO. The best fitness, worst fitness and average fitness of IFOA are shown in Figure 1.

Figure 2 depicts the fitness values with iterations. It shows that IFOA has the best fitness value after convergence and IFOA requires least iterations to reach minimum fitness value. The accuracy of IFOA is better than that of FOA and PSO.

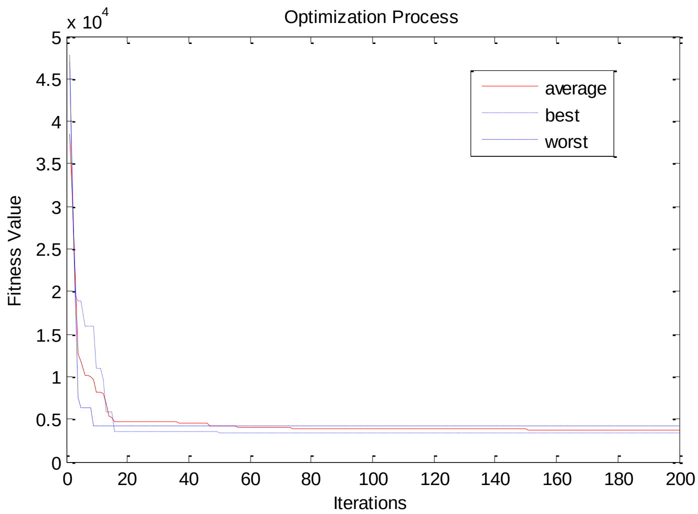

Figure 1: Optimization process of fitness function of IFOA

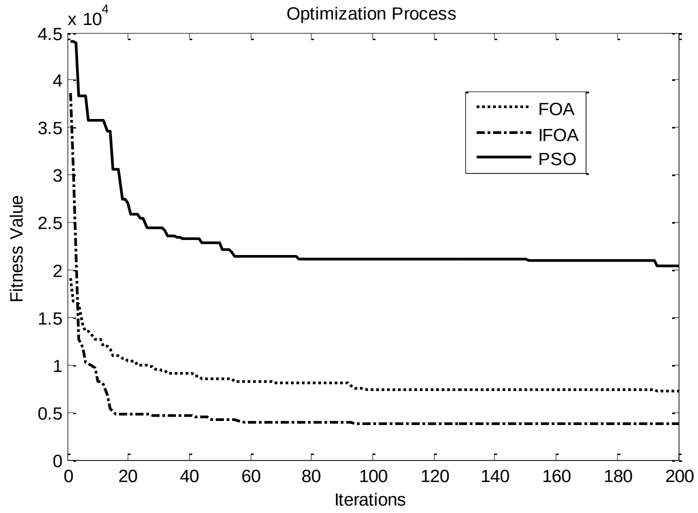

Figure 2: Optimization process of Fitness function

The modelled M - H curve compared with measured M-H curve is shown in Figure 3. The parameters of the Jiles-Atherton model are taken from Table 1 which are identified by IFOA. Jiles-Atherton model is built in Simulink/Matlab, and the excitation field is a 10 Hz sinusoidal wave which is the same as the experimental condition. From Figure 3, it is found that the modelled M-H curve is in good agreement with measured curve.

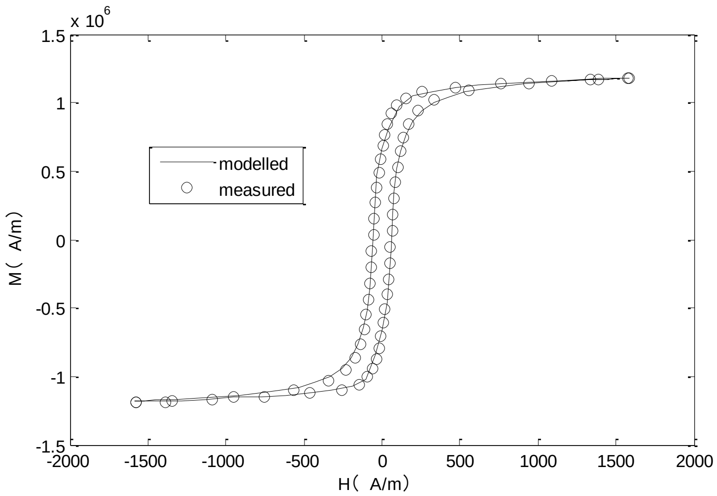

Figure 3: Modelled and measured M - H curve

Table 2 gives the estimation errors of four characteristic points on M-H plane. The estimation errors are evaluated from:

$$\varepsilon(\%) = \left| \frac{M_{model}(H) - M_{exp}(H)}{M_{exp}(H)} \right| \times 100 \tag{11}$$

In Table 2, H_c is coercivity, M_r is remanence, M_1 and M_2 are two points on the descending part of the *M-H* loop, whose *H*-coordinates are $0.5H_{max}$ and $-0.5H_{max}$ respectively.

From Table 2, the estimation errors at H_c obtained with PSO and FOA are much bigger than that of IFOA, and the errors at the other three points are almost the same. IFOA is found to be in lower percentage estimation errors.

Table 2: Estimation errors in percentage

Point on M-H plane	PSO	FOA	IFOA
H_c	11.7	19.2	0.13
M_r	5.13	4.54	4.98
M_1	0.31	0.10	0.35
M_2	1.23	1.10	0.74

5. Conclusion

This paper has demonstrated that it is possible to use FOA to optimize the parameters of Jiles-Atherton model. The FOA and IFOA have been used to identify the Jiles-Atherton model parameters of non-oriented electrical steel. The results are compared with those of PSO. It is stated that FOA is more precise and has better stability compared with PSO. IFOA has better performances than FOA in precision, converge rate, and stability. During the tests, it is noticed that FOA and IFOA are easier to implement than PSO.
In this paper, only the identification of the Jiles-Atherton model has been done. More work should be done on the application of the identified model in the analysis and design of the electromagnetic devices, such as transformer, inductor and fluxgate sensor.

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