Journal of Magnetism and Magnetic Materials 395 (2015) 229–233

Contents lists available at ScienceDirect

Journal of Magnetism and Magnetic Materials

journal homepage: www.elsevier.com/locate/jmmm

Bouc–Wen hysteresis model identification using Modified Firefly Algorithm

Mohammad Asif Zaman [a,*], Urmita Sikder [b]

[a] Department of Electrical Engineering, Stanford University, United States
[b] Department of Electrical Engineering and Computer Sciences, University of California, Berkeley, United States

ARTICLE INFO

Article history:
Received 8 May 2015
Received in revised form
7 July 2015
Accepted 25 July 2015
Available online 28 July 2015

Keywords:
Bouc–Wen model
Parameter identification
Modified Firefly Algorithm

ABSTRACT

The parameters of Bouc–Wen hysteresis model are identified using a Modified Firefly Algorithm. The proposed algorithm uses dynamic process control parameters to improve its performance. The algorithm is used to find the model parameter values that results in the least amount of error between a set of given data points and points obtained from the Bouc–Wen model. The performance of the algorithm is compared with the performance of conventional Firefly Algorithm, Genetic Algorithm and Differential Evolution algorithm in terms of convergence rate and accuracy. Compared to the other three optimization algorithms, the proposed algorithm is found to have good convergence rate with high degree of accuracy in identifying Bouc–Wen model parameters. Finally, the proposed method is used to find the Bouc–Wen model parameters from experimental data. The obtained model is found to be in good agreement with measured data.

1. Introduction

Hysteresis is a fundamental property which is found in a wide range of physical systems such as magnetism, piezo-electric materials, and mechanical vibration. For analysis of such systems, accurate measurement and modeling of hysteresis phenomenon is necessary [1,2]. Several mathematical models have been developed to describe the hysteresis process, such as Bouc–Wen model [3,4], Jiles–Atherton model [5], and Preisach model [6,7]. The Bouc–Wen model is a smooth endochronic model which can accurately model a variety of hysteresis patterns. As a result, it has become a very useful model for engineers. However, the highly nonlinear nature of the model along with a large number of model parameters has made the identification of the Bouc–Wen system a challenging problem [8].

The Bouc–Wen model requires seven parameters to describe the hysteresis phenomenon. Other models require less parameters (for example, Jiles–Atherton model only requires five parameters). The effect of the parameters on the shape of the hysteresis loop is highly nonlinear and difficult to relate [9]. For these reasons, the Bouc–Wen model has been comparatively less used in the field of magnetism [10]. It has been reported that Jiles–Atherton can predict the dynamic effects in ferroelectric material more accurately compared to Bouc–Wen model [11]. However, the model has been receiving more attention in recent times due to the development of efficient numerical algorithms that can be used to identify the model parameters more accurately [10,12]. The dynamic performance of the model is expected to improve and become comparable to Jiles–Atherton model if such accurate parameter values are used.

Bouc–Wen model is mostly used for inverse problems where a set of experimental data points are given and it is required to evaluate the model parameters that will produce a curve which follows the experimental data with least error [13]. Several methods have been discussed in the literature to accomplish this, including analytic approaches, Gauss–Newton, simplex, reduced gradient method, and extended Kalman filters [8,14]. Due to the nonlinear nature of the problem, stochastic optimization algorithms have been found to be well suited to solve it. Algorithms such as Genetic Algorithm (GA) [13], Particle Swarm Optimization (PSO) [15,16], and Differential Evolution (DE) [17,18] have been used to solve this problem. To improve the performance, hybrid algorithms [8] and multi-objective optimization [12] have been used. Recently, Laudani et al. have used Metric-Topological Evolutionary Optimization (MeTEO) to obtain the Bouc–Wen model parameters [10]. Such algorithms have been used in many electromagnetic optimization problems [19,20]. Although these methods have produced accurate results, newer and more robust algorithms are continuously being utilized to obtain faster convergence rate and higher accuracy. In this paper, a Modified Firefly Algorithm (MFA) is used to estimate the parameters of the Bouc–Wen model. The use of conventional or modified versions of FA for

* Corresponding author.
E-mail address: zaman@stanford.edu (M.A. Zaman).

http://dx.doi.org/10.1016/j.jmmm.2015.07.080
0304-8853/

this problem have not been reported in the literature so far.

Firefly Algorithm (FA) is a population based stochastic optimization algorithm which is well suited for nonlinear problems [21,22]. It has been successfully used in many engineering applications [23]. This paper proposes a modified version of FA (MFA) and uses it to estimate the model parameters. To the best of the authors' knowledge, modified versions of FA similar to the proposed MFA have not been reported in the literature yet. The purpose of this work is to show the effectiveness of MFA in solving the parameter identification problem. The performance of the MFA is compared with standard FA, GA and DE and it is found that MFA shows faster convergence rate with smaller percentage of error among the four algorithms. In addition to comparative analysis, the proposed MFA is also used to estimate Bouc–Wen model parameter values of an amorphous material (VITROVAC 6025 F). After the parameters are identified, the modeled hysteresis loop is compared with measured value. It is seen that the results are consistent with measured values, which verifies the effectiveness of the proposed method.

The paper is organized as follows: Section 2 describes the Bouc–Wen model equations. Section 3 presents overview of conventional FA and presents MFA. Section 4 describes how the algorithm was implemented and linked to the Bouc–Wen model parameters. Simulation and results are discussed in Section 5 and concluding remarks are given in Section 6.

2. Bouc–Wen model

The Bouc–Wen model is a system of nonlinear differential equations given by [10,15]

$$\begin{cases} \ddot{x} + 2\xi\omega_n\dot{x} + \alpha\omega_n^2 x + (1-\alpha)\omega_n^2 z = u(t) \\ \dot{z} = -\gamma|\dot{x}||z|^{n-1}z - \beta\dot{x}|z|^n + A\dot{x} \end{cases} \quad (1)$$

where $u(t) = B\cos(\omega t)$ is a normalized forcing function [24]. From (1), it can be seen that the Bouc–Wen model contains seven parameters. The parameters are the rigidity ratio, α $(0 \le \alpha \le 1)$, the linear elastic viscous damping ratio, ξ $(0 \le \xi \le 1)$, the pseudo-natural frequency of the system, ω_n (in rad/s), the hysteresis amplitude controlling parameter, A, and hysteresis loop shape controlling parameters β, γ and n $(n \ge 1)$. Through proper choice of these parameter values, a wide range of hysteresis loops can be described. A detailed description of how these parameters affect the hysteresis loop can be found in [9].

The variable z is a *fictitious* displacement related to the actual displacement, x [15]. Plotting the variables z against x gives the hysteresis loop. For a given set of values of the model parameters, the system of differential equations given in (1) can be solved to generate the loop. State space representations are found to be very useful in solving the Bouc–Wen model [10]. The state space representation of (1) is given by

$$\begin{cases} \dot{Y}_1 = Y_2 \\ \dot{Y}_2 = -2\xi\omega_n Y_2 - \alpha\omega_n^2 Y_1 - (1-\alpha)\omega_n^2 Y_3 + u(t) \\ \dot{Y}_3 = -\gamma|Y_2||Y_3|^{n-1}Y_3 - \beta Y_2|Y_3|^n + AY_2 \end{cases} \quad (2)$$

where $[Y_1\ Y_2\ Y_3]^T = [x\ \dot{x}\ z]^T$. The three first order differential equations can be simultaneously solved numerically to obtain the hysteresis loop [25].

3. Firefly Algorithm

FA is a population based metaheuristic global optimization algorithm [21,23]. It was inspired by the behavior of a group of fireflies. Along with DE and PSO, FA have found application in a wide range of engineering areas [23]. This section starts with the overview of FA. After that, the proposed MFA is discussed.

3.1. Overview of Firefly Algorithm

The FA starts the optimization process by defining the solution space. The dimension of the solution space, D, is equal to the number of parameters to be optimized. As optimizing the seven parameter of Bouc–Wen model is required here, $D=7$. Each dimension is bounded by the allowed range of values of the parameters. The ranges can be obtained from the mathematical model, physical considerations or trial-and-error based approaches. Next, a set of random vectors $\mathbf{u}_i$, $i = 1, 2...N$, each representing the position of a firefly in the D dimensional solution space is defined. Here, N=*population size*, which denotes the number of fireflies. Such set of N fireflies is called a *generation*. The position of each firefly is a D dimensional vector. The position of the ith firefly is given by

$$\mathbf{u}_i = [u_{i,1}\ u_{i,2}\ \dots\ u_{i,D}]^T \quad (3)$$

Each firefly represents a potential solution of the optimization algorithm. For the Bouc–Wen model parameter identification problem discussed in this paper, each dimension represents one of the model parameters. The parameters are mapped as

$$[u_{i,1}\ u_{i,2}\ \dots\ u_{i,7}]^T = [\alpha\ \beta\ \gamma\ \xi\ \omega_n\ A\ n]\nu^T \quad (4)$$

Here, ν^T is a scaling vector. The first generation of fireflies, $[\mathbf{u}_1^1\ \mathbf{u}_2^1\ \dots\ \mathbf{u}_N^1]$, is randomly selected from a uniform distribution over the solution space. Here, the superscript, $G=1$, denotes the generation number. The subsequent generations are obtained from the operations of FA.

The quality of each potential solution (firefly position) is defined by its *fitness* value. The *fitness function*, $f_{fit}(u_{i,1}\ u_{i,2}\ \dots\ u_{i,7})$, relates the optimization algorithm to the physical problem. It takes the parameters to be optimized as inputs (each firefly position, $\mathbf{u}_i$) and gives a single scalar output value. The better the potential solution is, the higher the fitness value will be. The fitness function for the current problem will be discussed in Section 4.

The fitness values of each of the N firefly, termed as the *brightness*, I, are assigned by evaluating the fitness function [26]. The higher the fitness value is of a firefly, the brighter it is. When the brightness of each firefly of the first generation is calculated, the firefly positions are updated to form the second generation. The motion of one firefly is influenced by the *attractiveness* of the other fireflies. Each firefly follows a path that brings it closer to other attractive fireflies. Relative attractiveness of firefly j to firefly i, Λ_{ij}, depends on the brightness of the fireflies as well as the distance between the fireflies. It is given by the equation

$$\Lambda_{ij} = \begin{cases} \Lambda_0 e^{-\sigma r_{ij}^2} & \text{if } I_j > I_i \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where Λ_0 is the attractiveness at zero distance, and

$$I_j = f_{fit}(\mathbf{u}_j) = f_{fit}(u_{j,1}\ u_{j,2}\ \dots\ u_{j,7}) \quad (6)$$

$$r_{ij} = \|\ \mathbf{u}_j^G - \mathbf{u}_i^G\ \| \quad (7)$$

Here, r_{ij} is the Euclidean distance between the two fireflies and σ is a FA process parameter denoting brightness gradient exponent. Eq. (5) suggests that the brighter a firefly is, the more attractive it is to other fireflies. However, brightness decreases with distance. So, the further a firefly is to another, the less attractive it becomes.