

Bouc-Wen Hysteresis Model Identification by the Metric-Topological–Evolutionary Optimization

A. Laudani, F. Riganti Fulginei and A. Salvini

Department of Engineering, Roma Tre University

Via Vito Volterra 62, 00146, Italy

alaudani@uniroma3.it

Abstract— The identification of Bouc-Wen hysteresis model by means of a new hybrid heuristic called Metric-Topological–Evolutionary Optimization (MeTEO) is presented. The present approach is based on the hybridization of three evolutionary heuristics: the Flock-of-Starlings Optimization (FSO), which shows high exploration capability but a lack of convergence; the Particle Swarm Optimization (PSO), which has a good convergence capability; 3) the Bacterial Chemotaxis Algorithm (BCA), which has no collective behavior, no exploration skill but high convergence capability. MeTEO is designed to use parallel architectures and exploits the fitness modification (FM) technique. Numerical validations are presented in comparison with the performances obtained by using other approaches available in literature.

Index Terms — Hysteresis models, Swarm Intelligence, Evolutionary Computation, Optimization, Inverse Problems .

I. INTRODUCTION

The identification of Bouc-Wen hysteresis model is an inverse problems that has been widely discussed by using many different approaches [1]-[4]. On the other hand, in the identification of hysteresis different models, such as Preisach or Jiles-Atherton, the use of modern heuristics such as Genetic Algorithms (GAs), Simulated Annealing (SA), Soft-Computing (SC), Hybrid Algorithms (HA) and so on [5]-[7], have been widely successfully tested.

In the present paper we propose the identification of the Bouc-Wen hysteresis model by means of a new hybrid heuristic inspired to artificial life: the Metric-Topological–Evolutionary Optimization (MeTEO) [8]. Exploration and convergence are two important requirements for the algorithms which are devoted to inverse-problems and/or optimization. For this reason MeTEO is based on the hybridization of two heuristics coming from swarm intelligence: 1) the Flock-of-Starlings Optimization (FSO) performing high exploration capability; 2) the standard Particle Swarm Optimization (PSO), showing a less exploration capability but a better convergence capability; and a third evolutionary heuristic called the Bacterial Chemotaxis Algorithm (BCA), which has no collective behavior and even it shows no exploration skill performs strong convergence to the final solution. Moreover, with the aim to speed up the algorithm, MeTEO has been implemented on a parallel architecture (cluster) and a special technique, called fitness modification (FM) [8], has been ideated for avoiding returning in already explored subspaces.

II. METRIC AND TOPOLOGICAL EVOLUTIONARY OPTIMIZATION

MeTEO algorithm is able to deal with a wide class of optimization problems (e.g. [9]-[10]) by simulating a natural habitat in which three different species live. They are simulated by three different heuristics: FSO, PSO and BCA. The strategy of MeTEO can be summarized as follows: a) FSO is permanently running; b) whenever FSO finds a possible solution in a subregion of the search space, PSO is launched for searching the minimum in that smaller area; c) afterwards, PSO mutes in BCA, for refining solution. To implement the above strategy, a parallel computing has been designed (cluster). The FSO is a heuristic that over-performs PSO and other heuristics in those problems where a high exploration capability is requested [11]. For this reason, the FSO plays a supervisor rule on the Master PC of a computer cluster, in Master-Slave configuration. The FSO not stops if the pre-fixed number of iterations is not completed. Whenever FSO finds a possible global minimum, MeTEO lunches PSO on one of the PC slaves. The PSO task is to approach as much as possible to a more restricted area containing the solution. Indeed, it has a convergence capability stronger than the one of FSO. However, since PSO is not sufficiently fast, MeTEO will substitute it by BCA as soon as the minimum to be detected is estimated to be very close [7]. Whenever the PSO-BCA process ends, the corresponding PC slave records the found best value in a shared folder located in the Master PC. At the end of the fixed number of iterations of FSO, MeTEO stops the whole process and detects the best solution among the ones listed in the shared folder (i.e. the global minimum). With the aim to speed up the FSO exploration process a further technique called fitness modification (FM) has been introduced. It consists of changing the value of the fitness function in the subregion in which MeTEO launches the PSO. The FM has the role of making a strong increment of the fitness values into the above subregion. In this way, in the neighborhood where the FSO detected a minimum, now detects a maximum, i.e. the FSO dynamic is forced to escape from this region.

III. THE BOUC-WEN MODEL

The hysteretic Bouc-Wen model [12] is a nonlinear system described by differential equation:

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

whereas the seven characteristic parameters to be found are: α rigidity ratio ($0 \leq \alpha \leq 1$), ξ linear elastic viscous damping ratio ($0 \leq \xi \leq 1$), ω_n pseudo-natural frequency of the system (rad/s), A parameter controlling hysteresis amplitude, β , γ , n parameters controlling hysteresis shape ($n \geq 1$).

The variable z takes in account the hysteretic phenomena through the second equation in (1). To solve the Bouc-Wen model it is very useful utilizing its state-space representation:

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

where $[Y_1 \ Y_2 \ Y_3]^T \equiv [x \ \dot{x} \ z]^T$.

IV. VALIDATION

Validation tests have been performed by comparing the results obtained by MeTEO with the ones presented in [1]. The figure 1 shows a comparison between the original loop and the one identified by MeTEO. Moreover, in the table I, the values of the best found parameters by different algorithms are listed with the related percentage errors compared to the original ones. The function $u(t)$ has been simulated as a sinusoidal function $u(t) = B \cos(\omega t)$ where $B = 2$ and $\omega = 2$.

It is important to emphasize that MeTEO is able to find optimal parameters (that are very accurate in comparison with the actual original parameters of the model) even if the used guess values of the algorithm are fixed into the search space in such way to be very distant with respect to the correct ones. Moreover, among all the results shown in table I, the parameters obtained by using the MeTEO approach have the highest accuracy in comparison with other techniques thanks to its qualities in exploration and in convergence due to the use of the global search algorithms, such as FSO and PSO, as well the local search algorithm BCA.

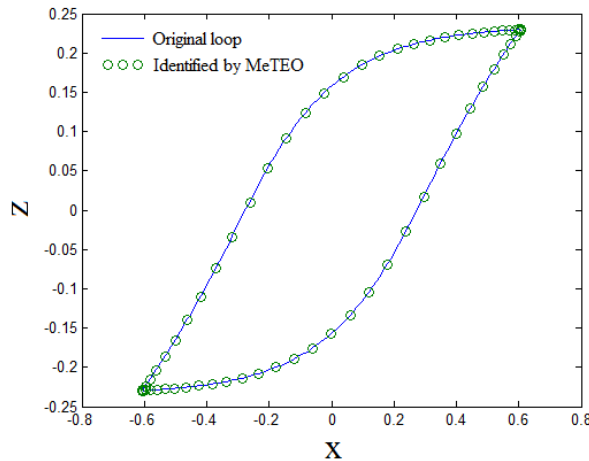


Fig. 1. Comparison between the original loop and the one identified by MeTEO

TABLE I
COMPARISON OF BEST PERFORMANCES

Parameter	α	β	γ	ξ	ω_n	A	n
Target values	0.4	4	2.1	0.15	3	0.8	1.4
GA [2]	0.244	2.728	1.945	0.325	1.555	2.207	1.903
IPSO [1]	0.400	3.892	1.998	0.150	2.999	0.804	1.376
MeTEO	0.400	4.000	2.100	0.150	2.999	0.799	1.399
GA error (%)	39.00	31.80	7.38	116.6	48.17	175.8	35.93
IPSO error (%)	0.15	3.43	0.09	0.07	0.01	0.51	1.71
MeTEO error (%)	0.150	0.020	0.010	0.006	0.033	0.001	0.015

REFERENCES

- [1] M. Ye and X. Wang, "Parameter Identification of Hysteresis Model with Improved Particle Swarm Optimization", *Control and Decision Conference, 2009. CCDC '09*, 17-19 June 2009, Guilin, China. pp. 415 - 419
- [2] K. H. Hornig and G. T. Flowers, "Nonlinear model of hysteresis of composite materials: An optimization approach using genetic algorithms", *Proceedings of 10th Int. Conf. on Sound and Vibration*, 2003, pp. 2317-2324
- [3] X. Xiaomin, Z. Ling and S. Qing "Parameter Identification and Simulation of the Noise-Involved Hysteretic Model Using Improved Genetic Algorithm", *International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, 13-14 March 2010, Changsha City, China, pp. 868 - 871
- [4] Y. Iskandarani, H. R. Karimi and M. Rygaard Hansen, "An iterative based approach for hysteresis parameters estimation in Magnetorheological dampers", *6th IEEE International Conference on Intelligent Systems (IS)*, 2012, pp. 439-444
- [5] F. Riganti Fulginei and A. Salvini, "Neural Network Approach for Modelling Hysteretic Magnetic Materials under Distorted Excitations", *IEEE Transactions On Magnetics*, vol. 48, p. 307 -310, 2012
- [6] F. Riganti Fulginei and A. Salvini, "Hysteresis model identification by the Flock-of-Starlings Optimization", *International Journal Of Applied Electromagnetics And Mechanics*, vol. 30, p. 321-331, 2009
- [7] F. Riganti Fulginei and A. Salvini, "Comparative Analysis between Modern Heuristics and Hybrid Algorithms", *COMPEL*, vol. 26, p. 259-268, 2007
- [8] F. Riganti Fulginei, A. Salvini and G. Pulcini, "Metric-Topological-Evolutionary Optimization", *Inverse Problems in Science & Engineering (IPSE)*, vol. 20, p. 41-58, 2012
- [9] S. Coco, A. Laudani, F. Riganti Fulginei, A. Salvini and G. Pulcini, "Shape Optimization of Multistage Depressed Collectors by Parallel Evolutionary Algorithm", *IEEE Transactions On Magnetics*, vol. 48, p. 435-438, 2012
- [10] A. Laudani, F. Riganti Fulginei, A. Salvini, S. Coco, G. Pollicino and G. Pulcini, "TWT magnetic focusing structure optimization by parallel evolutionary algorithm", *COMPEL*, vol. 31, pp. 1338-1346, 2012
- [11] F. Riganti Fulginei and A. Salvini, "The Flock of Starling Optimization: Influence of Topological Rules on the Collective Behavior of Swarm Intelligence", *Computational Methods for the Innovative Design of Electrical Devices*. vol. 327, p. 129-145, 2011
- [12] M. Ismail, F. Ikhouane and J. Rodellar, "The Hysteresis Bouc-Wen Model, a Survey", *Archives of Computational Methods in Engineering*, Volume 16, Issue 2, pp 161-188, June 2009