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# **Usage of Comprehensive Learning Particle Swarm Optimization for Parameter Identification of Structural System**

*Hesheng Tang, State Key Laboratory for Disaster Reduction in Civil Engineering, Tongji University, Shanghai, China*

*Lijun Xie, Research Institute of Structural Engineering and Disaster Reduction, Tongji University, Shanghai, China*

*Songtao Xue, Department of Architecture, Tohoku Institute of Technology, Tohoku, Japan*

### **ABSTRACT**

*This paper introduces a novel swarm intelligence based algorithm named comprehensive learning particle swarm optimization (CLPSO) to identify parameters of structural systems, which could be formulated as a multi-modal numerical optimization problem with high dimension. With the new strategy in this variant of particle swarm optimization (PSO), historical best information for all other particles is used to update a particle's velocity. This means that the particles have more exemplars to learn from, as well as have a larger potential space to fly, avoiding premature convergence. Simulation results for identifying the parameters of a five degree-of-freedom (DOF) structural system under conditions including limited output data, noise polluted signals, and no prior knowledge of mass, damping, or stiffness are presented to demonstrate improved estimation of these parameters by the CLPSO when compared with those obtained from standard PSO. In addition, the efficiency and applicability of the proposed method are experimentally examined by a twelvestory shear building shaking table model.*

*Keywords: CLPSO, Optimization, Parameter Identification, PSO, Structural System*

#### **INTRODUCTION**

Nowadays, system identification with good accuracy and general practicality is quite a significant tool for assessing the performance of structures in civil engineering. The goal of system identification is to estimate the "best" set of parameter values, which minimizes the error between the actual physically measured response of a system and the simulated response. This parameter estimation problem can be formulated as a non-convex, nonlinear optimiza-

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tion problem, and can therefore be solved using global optimization techniques. Recently, some researchers tried to use some sort of heuristic intelligent optimization algorithms to tackle system identification problems with limited and noise contaminated measurements. Simulated annealing (SA) and genetic algorithm (GA) have been implemented for model updating techniques that optimize a finite element model to accurately describe the dynamic behaviour of structures (Levin & Lieven, 1998) and to identify the elastic constants of composite materials (Cunha et al., 1999). Evolution strategy (ES) algorithms have been presented for the identification of multiple degree-of-freedom (DOF) systems (Franco et al., 2004). Tang et al.(2008) have applied a differential evolution (DE) strategy to parameters estimation of structural systems. Particularly, in the field of structural damage detection, GA has been used to identify damage severity of trusses (Chou & Ghaboussi, 2001) and to solve the global system identification problem in shear-type building structures. These references (Koh et al., 2003; Perry et al., 2006) have presented a modified GA based on migration and artificial selection strategies to improve the computational performance in terms of identification accuracy and computational speed. Although many GA versions have been developed, they are still time consuming. SA has proven to be thorough and reliable, but is generally too slow and inefficient to be of practical use with larger modelling problems (Mayer, 2002).

As a novel evolutionary computation technique, particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) has attracted much attention and has wide applications, owing to its simple concept, easy implementation and quick convergence. PSO has been successfully applied in many fields, such as function optimization, fuzzy system control, simulation and identification, automatic target detection, optimal design, parameters estimation and damage identification (Hassan et al., 2011; He & Wang, 2007; Kennedy et al., 2001; Liang et al., 2006; Perera et al., 2010; Shi, 2001; Xue et al., 2009).

The particle swarm optimizer shares the ability of the genetic algorithm to handle arbitrary nonlinear cost functions, but with a much simpler implementation. Boeringer & Werner (2003) have investigated the performance of GA and PSO for a phased array synthesis problem. The results show that some optimization scenarios are better suited to one method versus the other, which implies that the two methods traverse the problem hyperspace differently. In another publication (Mouser & Dunn, 2005), the authors compared the performance of GA and PSO for optimizing a structural dynamics model. The results show that the PSO significantly outperformed the GA. Also, the PSO is much easier to configure than the GA and is more likely to produce an acceptable model.

Although it has been shown that the PSO performs well on many optimization problems, it may easily get trapped in a local optimum when solving complex multimodal problems. In order to improve the performance on complex multimodal problems, a comprehensive learning PSO (CLPSO) has recently been proposed (Liang et al., 2004; Liang et al., 2006). Huang et al. (2006) presented a CLPSO based method to handle multiple objective optimization problems. In a recent article (Majhi & Panda, 2009) the CLSPO based algorithm has been applied to identify the feed-forward and feedback coefficients of IIR systems. It is reported that this method outperforms the existing standard recursive LMS (RLMS), GA and PSO based methods in terms of minimum MSE after convergence, execution time and product of population size and number of input samples used in training. Further, this method exhibits significant improvement in convergence behaviour under multimodal situation compared to those obtained by GA and PSO methods.

In the realm of structural engineering, identification of structural systems with unknown mass, stiffness and damping properties – is a challenging problem rarely considered due to the difficulty encountered in many identification methods. Thus, the main motive of this paper is to propose a new algorithm using a powerful PSO technique for identification of a structural

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