Chapter 2
Comprehensive Learning Particle Swarm Optimization for Structural System Identification

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ABSTRACT

This chapter introduces a novel swarm-intelligence-based algorithm named the comprehensive learning particle swarm optimization (CLPSO) to identify parameters of structural systems, which is formulated as a high-dimensional multi-modal numerical optimization problem. 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 and 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 CLPSO when compared with those obtained from PSO. In addition, the efficiency and applicability of the proposed method are experimentally examined by a 12-story shear building shaking table model.

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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 optimization 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) have been implemented for model updating techniques that optimize a finite element model to accurately describe the dynamic behaviour of structures (Levin & Lieven, 1998). Genetic algorithm (GA) have been successfully applied to the identification of the elastic constants of composite materials (Cunha et al., 1999) and the main properties of a base-isolated concrete bridge under static and dynamic loading conditions (Chisari et al., 2015). 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), to detect crack in structural elements (Buezas et al., 2011) 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. An approach based on GA combined with artificial neural networks has been employed for damage detection on a three-story steel frame (Betti et al., 2015). 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).

In the past decades, swarm intelligence algorithms have received a lot of attention in optimization problems (Piotrowski et al., 2017). 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 (Poli et al., 2007; Banks et al., 2008; Der Valle et al., 2008). PSO works to iteratively improve a swarm of candidate solutions, which are called particles, in the case of an objective function. PSO has been successfully applied in many fields, such as function optimization, fuzzy