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Hybridized optimization algorithms for design of trusses with multiple natural frequency constraints

A. Kaveh [*], M. Ilchi Ghazaan

Centre of Excellence for Fundamental Studies in Structural Engineering, Iran University of Science and Technology, Narmak, P.O. Box 16846-13114, Tehran, Iran

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ABSTRACT

In this paper, two optimization algorithms are applied for finding the optimal mass of truss structures with natural frequency constraints. The Particle Swarm Optimization with an Aging Leader and Challengers (ALC-PSO) algorithm is the first technique which applies the aging mechanism to particle swarm optimization (PSO) algorithm. The second method is HALC-PSO that transplants harmony search-based mechanism to ALC-PSO as a variable constraint handling approach. In these methods, the leader of the swarm ages and has a limited lifespan which is adaptively tuned according to the leader's leading power. If a leader shows a strong ability to lead the swarm toward better positions, its lifespan is increased, otherwise the leader gets aged quickly and when its lifespan is exhausted, a new particle emerges to challenge and claim the leadership. Therefore, premature convergence can be prevented in these methods. Five well-known truss mass optimization examples on Layout and size with frequency constraints are presented to demonstrate the viability of the algorithms. This type of problem is highly non-linear and non-convex dynamic optimization problems since mass reduction conflicts with the frequency constraints, especially when they are lower bounded. Numerical results show the robustness and high performance of the ALC-PSO and HALC-PSO algorithms for structural optimization problems with frequency constraints. It is found that the best results are obtained using HALC-PSO algorithm in most of the cases.

1. Introduction

Structural design optimization is a critical and challenging activity and its aims is to design a structure with minimum weight or minimize an objective function value corresponding to minimal cost of the structure while a system of given constraints are satisfied. The use of meta-heuristic search techniques in optimum design of structures is a relatively new field, and requires a significant amount of further research [1–6].

One of the principal parameters that affect the dynamic behavior of structures is their natural frequencies. In particular, some limitations should be imposed on the natural frequency ranges to improve the performance of the structure and avoid the resonance phenomenon. Mass reduction conflicts with frequency constraints especially when they are lower bounded. Furthermore, when optimizing for mass with frequency constraints, vibration modes can switch, for example, from a bending mode to a torsional or axial mode, and this can lead to substantial changes in frequencies, causing convergence difficulties; therefore, optimization on layout and sizing of truss structures with frequency constraints is a non-linear optimization problem [7].

Optimum design of structures considering natural frequency constraints has been studied since the 1980s [8] and approached with mathematical programming and meta-heuristic algorithms. Grandhi and Venkayya [9] utilized an optimality criterion based on uniform Lagrangian density for resizing and scaling procedure to locate the constraint boundary, Sedaghati [10] utilized a new approach using combined mathematical programming based on the sequential quadratic programming (SQP) technique and a finite element solver based on the integrated force method. Lingyun et al. [11] combined the simplex search method and the niche genetic hybrid algorithm (NGHA) for mass minimization of structures with frequency constraints. Gomes [7] used the particle swarm optimization (PSO) algorithm to study simultaneous layout and sizing optimization of truss structures with multiple frequency constraints. Miguel and Fadel Miguel [12] employed Harmony Search (HS) and Firefly Algorithm (FA), to solve this type of problems. Kaveh and Zolghadr [13] combined Charged-System Search and Big Bang with trap recognition capability (CSS–BBBC) to solve layout and sizing optimization problems of truss structures with natural frequency constraints.

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[*] Corresponding author. Tel.: +98 21 77240104; fax: +98 21 77240398.
E-mail address: alikaveh@iust.ac.ir (A. Kaveh).

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In this study, two methods based on the PSO algorithm are employed to find the optimal design of the truss structure subject to multiple natural frequency constraints. PSO is a population-based technique having some advantages such as few parameters to adjust, easiness of implementation, global search capability in some problems and, in general, fast convergence [14,15]. However, in this method all particles are led by the historically best position of the entire swarm, ***gBest***, and when it located at a local optimum may trap the whole swarm and lead to premature convergence. Therefore, Particle Swarm Optimization with an Aging Leader and Challengers (ALC-PSO) algorithm was introduced to keep the advantages of PSO and overcoming its shortcomings [16]. In this algorithm, the leader of the swarm ages and has a limited lifespan that is adaptively tuned according to the leader's leading power. When the lifespan is exhausted, the leader is challenged and replaced by newly generated particles [16]. The HALC-PSO algorithm which uses harmony search-based mechanism in ALC-PSO to return in the feasible space the particles violating optimization constraints is also introduced in this study.

The remainder of this paper is organized as follows: Statement of the optimization design problem with frequency constraints is formulated in Section 2. In Section 3, after a brief introduction to PSO, the ALC-PSO and HALC-PSO algorithms are described. Section 4 includes five classical benchmark problems from literature which are investigated in order to show the robustness and effectiveness of the algorithms. Finally, conclusions are derived in Section 5.

2. Statement of the optimization problem

In structural optimization problems with frequency constraints, the objective is to minimize the mass of the structure while satisfying some constraints on natural frequencies. The design variables may be the cross-sectional areas of bars (sizing optimization) or/and the nodal coordinates (layout optimization). The connectivity information of the structure is predefined and kept fixed in the optimization process. In addition, each variable should be chosen within a permissible range. Thus, the optimal design problem can be expressed as follows:

$$\begin{array}{ll} \text{Find} & \{X\} = [x_1, x_2, \ldots, x_{ng}] \\ \text{to minimize} & f(\{X\}) = \sum_{i=1}^{nm} \rho_i A_i L_i \\ \text{subjected to :} & \begin{cases} \omega_j \le \omega_j^* \\ \omega_k \ge \omega_k^* \\ x_{i\min} \le x_i \le x_{i\max} \end{cases} \end{array} \tag{1}$$

where $\{X\}$ is the vector containing the design variables (including cross-sectional areas or/and nodal coordinates); ng is the number of design variables; $f(\{X\})$ is the objective function; nm is the number of elements of the structure; ρ_i, A_i and L_i denote the material density, cross-sectional area and the length of the ith member, respectively; ω_j is the jth natural frequency of the structure and ω_j^* is its upper bound; ω_k is the kth natural frequency of the structure and ω_k^* is its lower bound; $x_{i\min}$ and $x_{i\max}$ are the lower and upper bounds of the design variable x_i, respectively.

The most common constraint-handling approach is the penalty function method which is employed in this paper. When utilizing this technique, the objective function is redefined as follows:

$$f_{cost}(\{X\}) = (1 + \varepsilon_1.\upsilon)^{\varepsilon_2} \times f(\{X\}), \quad \upsilon = \sum_{j=1}^{n} \max\left[0, g_j(\{X\})\right] \tag{2}$$

where υ denotes the sum of the violations of the design constraints and the constants ε_1 and ε_2 are selected considering the exploration and the exploitation rate of the search space. Here, ε_1 is set to unity and ε_2 is selected in a way that it decreases the penalties and reduces the cross-sectional areas of elements. Thus, in the first steps of the search process, ε_2 is set to 1.5 and ultimately increased to 3 [17].

3. Optimization algorithms

3.1. Particle swarm optimization (PSO)

The particle swarm optimization (PSO) algorithm, introduced by Eberhart and Kennedy [14,15], is a meta-heuristic method based on the simulation of the social behavior of bird flocking and fish schooling. The PSO is a population based technique that involves a number of particles which represent the swarm being initialized randomly in an n-dimensional search space. Each particle represents a candidate solution of the optimum design problem and iteratively moves across the search space. Its movement is influenced by the best position achieved so far by the particle itself and the best location achieved so far across the whole population. Let $V_i(\upsilon_i^1, \upsilon_i^2, \ldots, \upsilon_i^n)$ and $X_i(x_i^1, x_i^2, \ldots, x_i^n)$ be the ith particle's velocity vector and position vector, respectively, and M be the number of particles in a population. The velocity and position update rules in this technique are given by:

$$\upsilon_i^j \leftarrow \upsilon_i^j + c_1 \cdot r_1^j \cdot (pBest_i^j - x_i^j) + c_2 \cdot r_2^j \cdot (gBest^j - x_i^j) \tag{3}$$

$$x_i^j \leftarrow x_i^j + \upsilon_i^j \tag{4}$$

where ***pBest***$_i(pBest_i^1, pBest_i^2, \ldots, pBest_i^n)$ is the historically best position of particle i ($i = 1, 2, \ldots, M$), ***gBest***$(gBest^1, gBest^2, \ldots, gBest^n)$ is the historically best position of the entire swarm, r_1^j and r_2^j are two random numbers uniformly distributed in the range of [0, 1], c_1 and c_2 are two parameters to weigh the relative importance of ***pBest***$_i$ and ***gBest***, respectively and j($j = 1, 2, \ldots, n$) represents the jth dimension of the search space. The following pseudo-code summarizes the PSO algorithm:

Step 1: Initialization.
Initialize PSO algorithm parameters. The positions of all particles are randomly set within predefined ranges and their associated velocities are set to 0. The objective function is evaluated for each particle and ***pBest***$_i$ and ***gBest*** are stored.

Step 2: Velocity and position updating.
Velocities are updated according to Eq. (3) and each particle moves to the new position as specified in Eq. (4).

Step 3: Updating ***pBest*** and ***gBest***.
The objective function is evaluated for each particle and ***pBest***$_i$ and ***gBest*** are updated.

Step 4: Terminating criterion controlling.
Repeat the optimization process until a fixed number of iterations is completed. Otherwise, go to Step 2 for a new round of iteration.

3.2. Particle Swarm Optimization with an Aging Leader and Challengers (ALC-PSO)

Almost every organism ages within a limited lifespan; furthermore, in a social animal colony, when the leader gets too old to lead, new individuals emerge to challenge and claim the leadership. In this way, the community is always led by a leader with adequate leading power. Inspired by this natural phenomenon, Chen et al. introduced a PSO variant with an aging leader and challengers (ALC-PSO) [16]. In this technique, the leader of the swarm ages and has a lifespan. The lifespan is adaptively adjusted according to the leader's leading power. If a leader shows strong leading power, it lives longer to attract the swarm toward better positions and once the leader reaches a local optimum, it fails to improve the quality of the swarm and gets aged quickly. In this case, new