Applied Soft Computing 28 (2015) 400–410

Contents lists available at ScienceDirect

Applied Soft Computing

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

An improved magnetic charged system search for optimization of truss structures with continuous and discrete variables

A. Kaveh[a,*], B. Mirzaei[b], A. Jafarvand[b]

[a] Centre of Excellence for Fundamental Studies in Structural Engineering, Iran University of Science and Technology, Narmak, Tehran 16, Iran
[b] Department of Civil Engineering, University of Zanjan, Zanjan, Iran

ARTICLE INFO

Article history:
Received 2 June 2013
Received in revised form 2 November 2014
Accepted 2 November 2014
Available online 9 December 2014

Keywords:
Magnetic charged system search
Harmony search
Truss structures
Size optimization
Discrete variables

ABSTRACT

In this study, an improved magnetic charged system search (IMCSS) is presented for optimization of truss structures. The algorithm is based on magnetic charged system search (MCSS) and improved scheme of harmony search algorithm (IHS). In IMCSS some of the most effective parameters in the convergence rate of the HS scheme have been improved to achieve a better convergence, especially in the final iterations and explore better results than previous studies. The IMCSS algorithm is applied for optimal design problem with both continuous and discrete variables. In comparison to the results of the previous studies, the efficiency and robustness of the proposed algorithm in fast convergence and achieving the optimal values for weight of structures, is demonstrated.

1. Introduction

In the last three decades, many meta-heuristic algorithms have been proposed and applied for optimization of structures. Every meta-heuristic method consists of a group of search agents that explore the feasible region based on both randomization and some specified rules. The rules are usually inspired by natural phenomena laws. Genetic algorithms (GA) proposed by Holland [1] and Goldberg [2] are inspired by Darwin's theory about biological evolutions. Niche Hybrid Parallel Genetic Algorithm (NHPGA) proposed by Wei et al. [3], Generative Algorithms (GA) by Allison et al. [4], Particle swarm optimization (PSO) proposed by Eberhart and Kennedy [5] simulates the social behaviour, and it is inspired by the movement of organisms in a bird flock or fish school. Ant colony optimization (ACO) formulated by Dorigo et al. [6] imitates foraging behaviour of ant colonies. Many other physical-inspired algorithms such as simulated annealing (SA) proposed by Kirkpatrick et al. [7], Harmony Search (HS) presented by Geem et al. [8], Gravitational Search Algorithm (GSA) proposed by Rashedi et al. [9], Big Bang–Big Crunch algorithm (BB–BC) proposed by Erol and Eksin [10] which improved by Kaveh and Talatahari [11], Bat-Inspired Algorithm proposed by Yang [12], Ray Optimization (RO) developed by Kaveh and Khayatazad [13], Krill Herd (KH) presented by Gandomi and Alavi [14], Dolphin Echolocation method by Kaveh and Farhoudi [15], Colliding Bodies Optimization (CBO) by Kaveh and Mahdavi [16], and Interior search algorithm (ISA) by Gandomi [17], in recent years.

A new meta-heuristic algorithm has been proposed recently, by Kaveh and Talatahari which is called Charged System Search (CSS) [18]. The CSS algorithm is based on the Coulomb and Gauss laws from physics and the governing laws of motion from the Newtonian mechanics. This algorithm can be considered as a multi-agent approach, where each agent is a Charged Particle (CP). Each CP is considered as a charged sphere with a specified radius, having a uniform volume charge density which can insert an electric force to the other CPs.

After a while the CSS algorithm was modified to Magnetic Charged System Search (MCSS) by Kaveh et al. [19]. This algorithm utilizes the governing laws for magnetic forces and includes magnetic forces in addition to electrical forces, so the movements of CPs due to the total force (Lorentz force) are determined using Newtonian mechanical laws.

In this paper, an improved magnetic charged system search (IMCSS) is proposed for optimization of some truss structures as the well-known benchmark problems, in order to comparison the efficiency of the IMCSS algorithm with recently presented meta-heuristic algorithms. In this algorithm, an improved harmony search scheme (HIS) is utilized and some of the most effective parameters in the convergence rate of the algorithm are improved.

* Corresponding author. Tel.: +98 21 44202710.
E-mail address: alikaveh@iust.ac.ir (A. Kaveh).

http://dx.doi.org/10.1016/j.asoc.2014.11.056
1568-4946/

In a recently presented research by the authors, optimal design of double layer barrel vaults has been proposed, in which a 384-bar barrel vault and a 693-bar braced barrel vault have been optimized via the IMCSS algorithm [20].

The authors have also introduced an optimization approach (IMCSS-OAPI) for the problem of simultaneous shape-size optimization of large-scale barrel vault frames, which deals with the interface between the IMCSS as the optimization algorithm and SAP2000 as the structural analysis software through the open application programming interface (OAPI) [21]. In this work a 173-bar and a 292-bar single-layer barrel vault frame have been optimized.

The present paper is organized as follows: in Section 2, the statement of the optimization problem is expressed and formulated. CSS and MCSS algorithm are reviewed in Section 3. In Section 4, the improved form of MCSS algorithm is introduced and also its discrete version is described. Section 5 contains several illustrative examples with continuous and discrete variables to determine whether the efficiency of the new algorithm could be enough, and finally in Section 6, some concluding remarks are derived.

2. Statement of the optimization problem

The principal objective of size optimization process is aimed at achieving the optimum values for member cross-sectional areas of structure A_i in order to minimize the structural weight W and simultaneously satisfying the constraints that the optimization problem imposes. Hence, the problem of size optimization of truss structures can be expressed as:

$$\begin{aligned}
&\text{Find} \quad X=[x_1,x_2,x_3,\ldots,x_n]\\
&\text{to minimize} \quad \mathrm{Mer}(X)=f_{\text{penalty}}(X)\times W(X)\\
&\text{subject to} \quad \sigma_{\min}<\sigma_i<\sigma_{\max} \quad i=1,2,\ldots,\mathrm{nm}\\
&\qquad \delta_{\min}<\delta_i<\delta_{\max} \quad i=1,2,\ldots,\mathrm{nn}
\end{aligned} \tag{1}$$

where X is the vector containing the design variables; for a discrete optimum design problem, the variables x_i are selected from an allowable set of discrete values; n is the number of member groups; Mer(X) is the merit function; $W(X)$ is the cost function, which is taken as the weight of the structure; $f_{\text{penalty}}(X)$ is the penalty function which results from the violations of the constraints corresponding to the response of the structure; nm is the number of members forming the structure; nn is the number of nodes; σ_i and δ_i are the stress and nodal displacements, respectively; min and max mean the lower and upper bounds of constraints, respectively. The cost function can be expressed as:

$$W(X)=\sum_{i=1}^{\mathrm{nm}}\rho_i\cdot A_i\cdot L_i \tag{2}$$

where ρ_i, L_i, and A_i are the material density, length and the cross-sectional area of member i, respectively.

The penalty function can be defined as:

$$f_{\text{penalty}}(X)=\left(1+\varepsilon_1\cdot\sum_{i=1}^{\mathrm{np}}(\phi_{\sigma(i)}^k+\phi_{\delta(i)}^k)\right)^{\varepsilon_2}, \tag{3}$$

where np is the number of multiple loadings. In this paper ε_1 is taken as unity and ε_2 is set to 1.5 in the first iterations of the search process, but gradually it is increased to 3 [22]. ϕ_σ^k is the summation of stress penalties and ϕ_δ^k is the summation of nodal displacement penalties for kth charged particle which mathematically expressed as:

$$\phi_\sigma=\sum_{i=1}^{\mathrm{nm}}\max\left(\left|\frac{\sigma_i}{\bar{\sigma}_i}\right|-1,0\right), \tag{4}$$

$$\phi_\delta=\sum_{i=1}^{\mathrm{nn}}\max\left(\left|\frac{\delta_i}{\bar{\delta}_i}\right|-1,0\right), \tag{5}$$

where σ_i, $\bar{\sigma}_i$ are the stress and allowable stress in member i, respectively, and δ_i, $\bar{\delta}_i$ are the displacement of the joints and the allowable displacement, respectively.

3. Introduction to CSS and MCSS

The CSS algorithm has been proposed by Kaveh and Talathari [18] for optimization of structures. This meta-heuristic optimization algorithm takes its inspiration from the physic laws governing a group of charge particles (CP). These CPs are sources of the electric fields, and each CP can exert electric force on other CPs. The movement of each CP due to the electric force can be determined using the Newtonian mechanic laws.

In physics, it has been shown that when a charged particle moves, produces a magnetic field. This magnetic field can exert a magnetic force on other CPs. Thus, for considering this force in addition to electric force, the CSS algorithm is modified to MCSS algorithm by Kaveh et al. The MCSS algorithm can be summarized as follows [19]:

Level 1. Initialization

Step 1: Initialization. Initialize CSS algorithm parameters; the initial positions of CPs are determined randomly in the search space

$$x_{i,j}^{(0)}=x_{i,\min}+\text{rand}\cdot(x_{i,\max}-x_{i,\min}),\quad i=1,2,\ldots,n. \tag{6}$$

where $x_{i,j}^{(0)}$ determines the initial value of the ith variable for the jth CP; $x_{i,\min}$ and $x_{i,\max}$ are the minimum and the maximum allowable values for the ith variable; rand is a random number in the interval [0,1]; and n is the number of variables. The initial velocities of charged particles are set to zero

$$v_{i,j}^{(0)}=0,\quad i=1,2,\ldots,n. \tag{7}$$

The magnitude of the charge is defined as follows:

$$q_i=\frac{\text{fit}(i)-\text{fitworst}}{\text{fitbest}-\text{fitworst}},\quad i=1,2,\ldots,N. \tag{8}$$

where fitbest and fitworst are the best and the worst fitness of all particles, respectively; fit(i) represents the fitness of the agent i; and N is the total number of CPs. The separation distance r_{ij} between two charged particles is calculated as:

$$r_{ij}=\frac{||X_i-X_j||}{||(X_i+X_j)/2-X_{\text{best}}||+\varepsilon}, \tag{9}$$

where X_i and X_j are the positions of the ith and jth CPs, X_{best} is the position of the best current CP, and ε is a small positive number to avoid singularities.

Step 2. CP ranking. Evaluate the values of the fitness function for the CPs, compare with each other and sort them in an increasing order.

Step 3. CM creation. Store CMS number of the first CPs and their related values of the objective function in the CM (based on CMS size).

Level 2: Search

Step 1: Force determination.

The probability of the attraction of the ith CP by the jth CP is expressed as:

$$p_{ij}=\begin{cases}1 & \dfrac{\text{fit}(i)-\text{fitbest}}{\text{fit}(j)-\text{fit}(i)}>\text{rand}\quad\text{or}\quad \text{fit}(j)>\text{fit}(i),\\ 0 & \text{else.}\end{cases} \tag{10}$$

where rand is a random number uniformly distributed in the range of (0,1). The resultant electrical force $F_{E,j}$ acting on the jth CP can be