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Water cycle, mine blast and improved mine blast algorithms for discrete sizing optimization of truss structures

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ABSTRACT

This paper presents the applications of the mine blast algorithm (MBA) and the water cycle algorithm (WCA), in addition to an improved version of MBA for weight minimization of truss structures including discrete sizing variables. The MBA mimics the explosion of landmines, while the WCA is inspired by the observation of water cycle process. An improved version of MBA (IMBA), is also presented. The efficiency of the three optimization algorithms is tested using classical benchmark discrete truss design problems. Optimization results show that MBA, IMBA, and WCA offer a good degree of competitiveness against other state-of-the-art metaheuristic techniques.

1. Introduction

Over the last decades, various algorithms have been used for truss optimization problems which are very popular in the field of structural optimization. Metaheuristic methods such as genetic algorithms (GAs), harmony search (HS), and particle swarm optimization (PSO) can efficiently be used in truss design optimization problems including discrete variables. GAs [1] mimic the processes of natural selection leading to the survival of the fittest.

For instance, Goldberg and Samtani [2] and Rajeev and Krishnamoorthy [3] performed sizing optimization of truss structures. Krishnamoorthy et al. [4] used GAs to optimize space truss structures in the context of an object-oriented framework. Sivakumar et al. [5] optimized steel lattice towers. Gero et al. [6] used GAs for design optimization of 3D steel structures.

Geem et al. [7] developed the HS that reproduces the musical process of searching for a perfect state of harmony. The harmony in music is analogous to the optimum design, and the musicians' improvisation is analogous to local/global search schemes [8]. The HS was successfully applied to truss optimization problems using discrete and continuous variables [9,10].

The PSO is a population-based algorithm developed by Kennedy and Eberhart [11]. Li et al. [12] developed an efficient heuristic PSO (HPSO) for truss structures which outperformed hybrid PSO with passive congregation (PSOPC) [13] and standard PSO.

The PSOPC was also combined with ant colony optimization (ACO) and HS by Kaveh and Talatahari [14] to form an efficient algorithm for truss optimization, called discrete heuristic particle swarm ant colony optimization (DHPSACO). Comprehensive reviews for applications of metaheuristic algorithms on skeletal structures have been presented in the literature [15,16].

Sadollah et al. [17] recently developed the mine blast algorithm (MBA) which mimics the explosion of landmines. The MBA was successfully applied to discrete sizing optimization of truss structures [17]. Furthermore, Eskandar et al. [18] proposed another metaheuristic algorithm, reproducing the water cycle process. The water cycle algorithm (WCA) was tested in mathematical and engineering problems [18]. The MBA and WCA algorithms were found to be superior over other optimization methods in terms of convergence rate and quality of optimized designs [17,18].

In this study, MBA is improved and its operators are enhanced in terms of efficiency so called improved MBA (IMBA). The relative performance of the MBA, IMBA and WCA algorithms in discrete optimization problems of truss structures are investigated in this research. Furthermore, the efficiency of three algorithms is compared with the results extracted in the literature.

The paper is organized as follows: the formulation of the discrete optimization problem is presented in Section 2. The IMBA and WCA algorithms and their constraint handling strategies are

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described in detail in Section 3. Section 4 discusses the optimization results comparing the developed algorithms with the literature. Section 5 presents a sensitivity analysis on the effect of algorithms internal parameters set by the user on the overall convergence behavior; the analysis is carried out for some of the test problems considered in this study. Finally, Section 6 summarizes the findings of this study.

2. Discrete structural optimization problems

In discrete sizing optimization problems of truss structures, the objective usually is to minimize the weight of the structure yet satisfying nonlinear constraints on element stresses, nodal displacements, critical loads, etc. The optimization problem can be formulated as follows:

$$\min \quad W(X), \quad X = [x_1, x_2, x_3, \ldots, x_N], \tag{1}$$

subject to:

$$g_j(x_1, x_2, \ldots, x_N) \leqslant 0 \quad j = 1, 2, \ldots, k, \tag{2}$$

$$x^d \in S_d = \{X_1, X_2, \ldots, X_p\}, \tag{3}$$

where $W(X)$ is the cost function corresponding to the structural weight; N and k are the number of design variables and inequality constraint functions, respectively. Each design variable can be chosen from a discrete set S_d $(X_1, X_2, \ldots, X_p)$ of P available cross-sections according to production standards.

3. Applied metaheuristic algorithms

3.1. Improved mine blast algorithm

MBA algorithm is inspired by the process of landmines explosion; shrapnel pieces are thrown away and collide with other mines in the vicinity of the explosion area causing further explosions. Consider a landmine field where the goal is to clear landmines. To clear all the mines, the position of the most explosive mine must be located. This position corresponds to the optimal design.

Landmines of different sizes and explosive power are planted under the ground. Landmine explosions cause many pieces of shrapnel to be propelled in the air. The casualties of each piece of shrapnel are evaluated using a cost function (fitness function) and, then, related to the presence of other landmines with different explosive power [17].

Often times, pieces of shrapnel collide with other mines and trigger more mine explosions. This behavior is helpful for finding the most explosive landmine. MBA algorithm was developed to find the most explosive landmine (i.e., the landmine with the most casualties). Table 1 lists nomenclature of MBA parameters.

The MBA algorithm requires an initial population of individuals, similar to several other metaheuristic methods. The population is generated from a first shot explosion that produces a number of individuals (shrapnel pieces). The size of initial population (N_{pop}) is taken as the number of shrapnel pieces (N_s). The MBA algorithm initially uses the lower and upper bounds of design variables and, then, randomly creates the first shot point as follows:

$$\vec{X}_0 = L\vec{B} + \{rand\} \otimes \{U\vec{B} - L\vec{B}\}. \tag{4}$$

Vector quantities are denoted by over sign. Assume X is the current location of a landmine; that is,

$$\vec{X} = [x_1, x_2, x_3, \ldots, x_m]. \tag{5}$$

Design variables (x_1, $x_2, \ldots, x_m$) can take real values in continuous optimization problems or they can be selected from a predefined set of discrete values. We assume that the first shot point (X_0) is the best solution ($X_{Best} = X_0$). For performing any optimization method, exploration and exploitation are considered as two critical steps.

The difference between the exploration and exploitation phases is how they influence the whole search process in finding the optimal solution. Similar to other metaheuristic algorithms, MBA algorithm starts with the exploration phase, which is responsible for comprehensively exploring the search space.

The exploration factor (μ) serves to explore different regions of design space. This parameter, used in the early iterations of MBA, is compared with an iteration number index (t): exploration takes place if μ is greater than t. The exploration phase of MBA is governed by the following equations [17]:

$$\vec{X}_e = \left\{\vec{d}_{t-1}\right\} \otimes \{randn^2\} \times \cos\theta \quad t = 1, 2, \ldots, \mu, \tag{6}$$

$$\vec{X}_e = \vec{X}_{Best} + \vec{X}_e \quad t \leqslant \mu, \tag{7}$$

where the d_{t-1} vector includes the shrapnel distance for exploded mines with respect to each coordinate direction. Fig. 1 demonstrates the concept and performance of Eq. (6) from a schematic point of view.

By taking the square of a normally distributed random number, better exploration is achieved at the beginning of the optimization process (see Eq. (6)). The value of μ determines the intensity of the exploration. For example, increasing μ makes it possible to explore more remote regions of design space. The shrapnel angle of incidence, denoted by θ in Eq. (6), is given by:

$$\theta = k \times \Delta \quad k = 0, 1, 2, \ldots, N_s - 1, \tag{8}$$

where $\Delta = 360/N_s$. The value of θ ranges from 0 to 360; the resulting value of $\cos(\theta)$ ranges between -1 and 1. The initial distance of each piece of shrapnel is $d_0 = (\text{UB–LB})$; thus, the best solution is in the range [LB, UB]. For example, the LB and UB of a four design variable problem are [−30–20−10–5] and [3020105], respectively. Then, the initial distance, d_0 (d_{t-1} when $t = 1$), is the vector of shrapnel distances [60402010].

Improved MBA (IMBA) modifies the exploitation phase in MBA and distance reduction of each shrapnel pieces. For the exploitation

Table 1
Nomenclature of MBA (IMBA) parameters.

Parameter	Definition	Parameter	Definition
Rand	Uniformly distributed random number between 0 and 1(vector)	X_{Best-1}	Previous best obtained solution (previous improved solution, vector)
Randn	Normally distributed random number (vector)	D	Euclidean distance between the current and previous best solutions (scalar)
X_0	Generated first shot point (initial solution, vector)	X_e	Location of exploded mine (vector)
d_0	Initial distance of shrapnel pieces (vector)	μ	Exploration factor (scalar)
LB	Lower bounds of design variables (vector)	t	Iteration index number (scalar)
UB	Upper bounds of design variables (vector)	θ	Shrapnel angle of incidence (scalar)
m	Number of design variables (scalar)	α	Reduction factor (scalar)
X_{Best}	Best obtained solution (current improved solution, vector)	N_s (N_{pop})	Number of shrapnel pieces (number of population, scalar)