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Performance evaluation of metaheuristic search techniques in the optimum design of real size pin jointed structures

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ABSTRACT

In recent years a number of metaheuristic search techniques have been widely used in developing structural optimization algorithms. Amongst these techniques are genetic algorithms, simulated annealing, evolution strategies, particle swarm optimizer, tabu search, ant colony optimization and harmony search. The primary goal of this paper is to objectively evaluate the performance of abovementioned seven techniques in optimum design of pin jointed structures. First, a verification of the algorithms used to implement the techniques is carried out using a benchmark problem from the literature. Next, the techniques compiled in an unbiased coding platform are evaluated and compared in terms of their solution accuracies as well as convergence rates and reliabilities using four real size design examples formulated according to the design limitations imposed by ASD-AISC (Allowable Stress Design Code of American Institute of Steel Institution). The results reveal that simulated annealing and evolution strategies are the most powerful techniques, and harmony search and simple genetic algorithm methods can be characterized by slow convergence rates and unreliable search performance in large-scale problems.

1. Introduction

Structural optimization provides tools for structural designers to determine the optimum topology or the optimum geometry and/or optimum cross-sectional dimensions for the members of a structure. This may be the prime reason why numerous research studies have been conducted in this topic in last three decades. Initially mathematical programming techniques are used in the development of optimum structural design algorithms [1]. One of the basic assumptions in mathematical programming techniques is that the design variables are assumed to have continuous values. With this assumption the early optimum structural design algorithms yielded values for the optimum cross-sectional areas of structural members that are neither available in the practice nor are economical to produce. The reality of the practice is that there are certain steel sections produced by steel mills that are available for a designer to choose from in the case of steel structures and there are practically accepted dimensions for the beams and columns among which the selection can be carried out in a reinforced concrete structure due to architectural reasons. Hence, the structural designer finds himself/herself in a restricted area where only discrete values are available when it comes to make a decision what sections he/she has to select for the members of a steel or reinforced concrete frame. Some mathematical programming techniques, such as branch and bound method and integer programming do allow design variables having discrete values. SODA [2] is one of the early commercial structural optimization software for practical building design. This software considered the design requirements from Canadian Code of Standard Practice for Structural Steel Design (CAN/CSA-S16-01 Limit States Design of Steel Structures) and obtained optimum steel sections for the members of a steel frame from available set of steel sections. Comprehensive review of the methods for discrete structural optimization problems is given in Arora [3]. The algorithms that are based on mathematical programming techniques are deterministic. They need an initial design point to initiate the search for the optimum solution and require gradient computations in the exploration process. In some cases, the objective function and constraints in the design problem may have irregular peaks for which the gradient search might become difficult [4,5]. However, these techniques are fairly rapid and well established, and there are a number of commercial structural optimization packages that make use of these algorithms.

Recently another group of optimization techniques have emerged that do not require gradient computations. These novel and innovative metaheuristic search algorithms make use of ideas inspired from the nature. The basic idea behind these techniques is to simulate natural phenomena, such as survival of the fittest, immune system, swarm intelligence and the cooling process of

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molten metals through annealing into a numerical algorithm [5–13]. These methods are non-traditional stochastic search and optimization methods, and they are very suitable and effective in finding the solution of combinatorial optimization problems. They do not require the gradient information of the objective function and constraints and they use probabilistic transition rules not deterministic ones. The optimum structural design algorithms that are based on these techniques are robust and quite effective in finding the solution of discrete programming problems. There are large numbers of such metaheuristic techniques available in the literature nowadays. A detailed review of these algorithms as well as their applications in the optimum structural design is carried out in Saka [14]. All of these algorithms employ random number call, and incorporate a set of parameters that require to be adjusted prior to their use. Their performance differs depending on the problem under consideration and also predefined values of these parameters.

There are a number of publications in the literature where comparison of metaheuristic techniques algorithms is carried out, such as Keane [15], Manoharana and Shanmuganathan [16], etc. However, only a selected few of these techniques have been included in each of these studies, and thus an overall comparison has not been pursued. The literature lacks more comprehensive studies where many metaheuristic techniques are assessed as a whole in a chosen problem area. This has led to the motivation of the current study.

In the paper, the performances of seven optimum structural design algorithms based on simulated annealing [17], evolution strategies [18], particle swarm optimizer [19], tabu search method [20], ant colony optimization [21], harmony search method [22] and simple genetic algorithm [23] are evaluated and compared in optimum design of pin jointed structures. The computational steps of these techniques are outlined in Section 3 in sufficient detail. It is important to highlight that there is no a unique formulation or a standardized algorithm used to implement any metaheuristic search technique; rather each technique has numerous different variants, extensions and modifications in the literature. It is well known that the performance of a technique may vary to a great extent depending on the algorithm used to formulate it. Here, both generality and performance criteria have been taken into account when selecting a particular algorithm for each technique. A standard test problem (25-member truss) chosen from the literature is studied to verify the effectiveness of the algorithms chosen. Although it is not the goal of the paper, improvements of some techniques are also achieved, which are clearly documented in their computational steps to give the complete details of the algorithms employed. Numerical performances of the techniques computerized in an unbiased coding platform are tested and identified using four real size design examples formulated according to the provisions of ASD-AISC (Allowable Stress Design Code of American Institute of Steel Institution) specification. These examples are as follows: a 113-member plane truss bridge with 43 design variables and 202 constraints, a 354-member braced truss dome with 22 design variables and 425 constraints, a 582-member space truss tower with 32 design variables and 523 constraints, and a 960-member double layer grid with 251 design variables and 751 constraints. All the structures are sized for minimum weight with each of the seven techniques, and a comparison is carried out in terms of accuracy of the optimum solutions attained by the techniques (i.e., solution accuracy) as well as their convergence rates and reliabilities observed in a number of runs. The results indicate that simulated annealing and evolution strategies show the best performance in terms of minimum weights located, and display a high convergence reliability producing near-optimum solutions in the majority of the runs. On the other hand, harmony search and simple genetic algorithm exhibit a substandard performance characterized by slow convergence rates and unreliable search efficiency in large-scale problems.

2. Discrete optimum design problem of steel trusses

For a pin jointed steel structure consisting of N_m members that are grouped into N_d design variables, formulation of the optimum design problem according to Allowable Stress Design Code (ASD-AISC) [24] yields the following discrete programming problem.

Find a vector of integer values **I** Eq. (1) corresponding to the sequence numbers of steel sections in a given profile list

$$\mathbf{I}^T = [I_1, I_2, \ldots, I_{N_d}] \tag{1}$$

to generate a vector of cross-sectional areas **A** for N_m members of the truss Eq. (2)

$$\mathbf{A}^T = [A_1, A_2, \ldots, A_{N_m}] \tag{2}$$

such that **A** minimizes the objective function

$$W = \sum_{m=1}^{N_m} \rho_m L_m A_m \tag{3}$$

and satisfies the following constraints:

$$g_m = \frac{\sigma_m}{(\sigma_m)_{all}} - 1 \leqslant 0, \quad m = 1, \ldots, N_m \tag{4}$$

$$s_m = \frac{\lambda_m}{(\lambda_m)_{all}} - 1 \leqslant 0, \quad m = 1, \ldots, N_m \tag{5}$$

$$\delta_{j,k} = \frac{d_{j,k}}{(d_{j,k})_{all}} - 1 \leqslant 0, \quad j = 1, \ldots, N_j \tag{6}$$

where W is the weight of the truss structure; L_m, ρ_m are the length and unit weight of member m, respectively; N_j is the total number of joints; the functions g_m, s_m and $\delta_{j,k}$ are referred to as constraints being bounds on stresses, slenderness ratios and displacements, respectively; σ_m and $(\sigma_m)_{all}$ are the computed and allowable axial stresses for the mth truss member, respectively; λ_m and $(\lambda_m)_{all}$ are the slenderness ratio and its upper limit for mth member, respectively; finally $d_{j,k}$ and $(d_{j,k})_{all}$ are the displacements computed in the kth direction of joint j and its permissible value, respectively.

In ASD-AISC [24] design code provisions, the maximum slenderness ratio is limited to 300 for tension members, and it is recommended to be 200 for compression members. Hence, the slenderness related design constraints can be formulated as follows:

$$\begin{aligned} \lambda_m &= \frac{K_m L_m}{r_m} \leqslant 300 \text{ (for tension members)} \\ \lambda_m &= \frac{K_m L_m}{r_m} \leqslant 200 \text{ (for compression members)} \end{aligned} \tag{7}$$

where K_m is the effective length factor of mth member (K_m = 1 for all truss members), and r_m is its minimum radii of gyration.

The allowable tensile stresses for tension members are calculated as in Eq. (8).

$$\begin{aligned} (\sigma_t)_{all} &= 0.60 F_y \\ (\sigma_t)_{all} &= 0.50 F_u \end{aligned} \tag{8}$$

where F_y and F_u stand for the yield and ultimate tensile strengths, and the smaller of the two formulas is considered to be the upper level of axial stress for a tension member.

The allowable stress limits for compression members are calculated depending on two possible failure modes of the members known as elastic and inelastic buckling, Eqs. (9)–(11).