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Adaptive dimensional search: A new metaheuristic algorithm for discrete truss sizing optimization

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ABSTRACT

In the present study a new metaheuristic algorithm called adaptive dimensional search (ADS) is proposed for discrete truss sizing optimization problems. The robustness of the ADS lies in the idea of updating search dimensionality ratio (SDR) parameter online during the search for a rapid and reliable convergence towards the optimum. In addition, several alternative stagnation-control strategies are integrated with the algorithm to escape from local optima, in which a limited uphill (non-improving) move is permitted when a stagnation state is detected in the course of optimization. Besides a remarkable computational efficiency, the ease of implementation and capability of locating promising solutions for challenging instances of practical design optimization are amongst the remarkable features of the proposed algorithm. The efficiency of the ADS is investigated and verified using two benchmark examples as well as three real-world problems of discrete sizing truss optimization. A comparison of the numerical results obtained using the ADS with those of other metaheuristic techniques indicates that the proposed algorithm is capable of locating improved solutions using much lesser computational effort.

1. Introduction

Today's literature of structural optimization is justifiably predominated by metaheuristic algorithms owing to their advantageous search features and wide range of applicability to diverse problem areas [1]. Almost all of these methods come up with an idea of employing a particular process or event in nature as a source of inspiration for the development of a search and optimization algorithm. Many robust metaheuristic techniques, such as simulated annealing, evolutionary algorithms, particle swarm optimization and ant colony optimization, have been introduced by the researchers in the last few decades by clearly identifying and formulating similarities between the algorithms and the processes they are modeled on. However, in time this trend of originating a new search method has turned into a way such that the researchers feel obligated to associate their innovative ideas with some natural events to provide a basis for justification of their thoughts and originality of their algorithms. As a result of this, the literature has abounded with metaheuristic algorithms that have weak or no similarities to the natural processes which they are purported to derive from.

Metaheuristic algorithms have also found plenty of applications in the field of structural optimization [2–8], including sizing optimization of truss structures. The rising popularity of these techniques arises from (i) the lack of dependency on gradient information; (ii) inherent capability to deal with both discrete and continuous design variables; and (iii) incorporating global search features to produce reasonable solutions for complicated problems. These advantageous features of metaheuristic techniques make it possible to avoid cumbersome formulations frequently encountered in the applications with conventional optimization techniques, such as mathematical programming [9] and optimality criteria approaches [10,11]. The state-of-the-art reviews of metaheuristic techniques in the context of structural design optimization are outlined in several comprehensive review articles, such as Refs. [12,13].

Generally speaking, efficiency of a design optimization algorithm is associated with two main factors: the accuracy of the final design obtained and the speed of the algorithm in reaching the optimum solution. The latter is usually measured with the number of iterations or structural analyses required in the overall optimization process to locate the optimum or at least a good near-optimum solution. Despite the sound reputation of metaheuristic techniques in locating promising solutions for challenging design optimization problems, the slow rate of convergence towards the optimum and the need for a high number of structural

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analyses are conceived as the downside of their search features in structural optimization [14]. Indeed, metaheuristic optimization techniques are still not in use much in practical design applications due to the fact that enormously time-consuming procedures of these techniques make practicing engineers reluctant to use them in real-world applications. In fact, the computational efficiency of metaheuristic techniques is somewhat far from satisfying today's need of real-world design applications since this requires optimization tools that are capable of handling such problems in a timely manner. Especially, it becomes almost impossible to use metaheuristic techniques for large-scale applications without utilizing expensive high-performance computing techniques. As a result, structural engineers have not yet benefited from metaheuristic techniques adequately in real-world applications where optimality of final designs has a significant economical importance. In order to facilitate a wider application of metaheuristic techniques to real-world design problems, we need enhanced discrete optimization techniques that are capable of locating promising solutions using fewer structural analyses, i.e. lesser computational effort.

In the present study an adaptive dimensional search (ADS) algorithm is developed for discrete truss sizing optimization problems. The algorithm developed differs from other metaheuristic techniques in the sense that it is neither based on nor associated with any natural or social phenomena. Rather, it employs a so-called search dimensional ratio (SDR) parameter, which is defined as the percentage of the design variables that are perturbed probabilistically while generating a candidate solution from the current (best) design. The rationale behind employing the SDR parameter is to follow a structural engineering design attitude. A structural designer tries to upgrade the previous design by changing few of the members' sections at a time to understand the effect of this change on the overall structural performance. The algorithm presented does the similar by updating the SDR parameter at each iteration to establish a satisfactory tradeoff between explorative and exploitative characteristics of the search process for a fast and reliable convergence towards the optimum. In addition, several alternative stagnation-control strategies are incorporated into the ADS algorithm, where a limited uphill (non-improving) move is permitted when the algorithm happens to get trapped in a local optimum during the search. Besides a remarkable convergence rate, the ease of implementation and capability of locating promising solutions for challenging instances of practical design optimization are amongst the advantageous features of the proposed algorithm. The efficiency of the ADS algorithm is investigated using two benchmark examples as well as three real-world problems of discrete sizing truss optimization. A comparison of the numerical results obtained using the ADS with those of other metaheuristic techniques reveals that the ADS is able to produce improved solutions using much lesser computational effort. The remaining sections of the paper are organized as follows. Section 2 provides a brief formulation of the considered design optimization problem. In Section 3 the concept of search dimensionality ratio (SDR) is described and the proposed ADS technique is outlined in details. Section 4 describes three alternative stagnation-control strategies integrated with the ADS for avoiding local optima. In Section 5, the efficiency of the ADS is investigated by solving discrete sizing optimization problems of steel trusses. A brief conclusion of the paper is provided in Section 6.

2. Statement of the sizing optimization problem

Typically in practical design optimization of truss structures the goal is to find a minimum cost or weight design by selecting the cross-sectional areas of structural members from a table of available sections such that the final design satisfies strength and serviceability requirements determined by standard design codes. For a given truss structure composed of N_m members grouped into N_d sizing design variables, the design optimization problem can be stated as follows.

2.1. Objective function

The objective is to find a vector of integer values **I** (Eq. (1)) representing the sequence numbers of standard sections in a given section table,

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

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

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

such that **A** minimizes the following weight objective function:

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

where W is the weight of the structure, ρ_m, L_m, A_m are unit weight, length, and cross-sectional area of the m-th member, respectively.

2.2. Design constraints

The design constraints consist of the following limitations imposed on overall structural response and behavior of individual members:

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

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

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

In Eqs. (4)-(6), the functions g_m, s_m and $\delta_{j,k}$ are the optimization constraints on stresses, slenderness ratios, and displacements, respectively; σ_m and $(\sigma_m)_{all}$ are the computed and allowable axial stresses for the m-th member, respectively; λ_m and $(\lambda_m)_{all}$ are the slenderness ratio and its upper limit for m-th member, respectively; N_j is the total number of joints; and finally $d_{j,k}$, and $(d_{j,k})_{all}$, are the displacements computed in the k-th direction of the *j-th* joint and its allowable value, respectively. In the present study, these constraints are implemented according to AISC-ASD [15] code specifications.

Accordingly, the maximum slenderness ratio is limited to 300 for tension members, and it is taken as 200 for compression members, Eq. (7).

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

where K_m is the effective length factor of m-th member (K_m = 1 for all members), and r_m is its minimum radius of gyration.

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

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

where F_y and F_u, respectively, 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.