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Comparison of robustness of metaheuristic algorithms for steel frame optimization

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ABSTRACT

In this study the robustness of six metaheuristic algorithms – ant colony optimization, genetic algorithm, harmony search, particle swarm optimization, simulated annealing and tabu search – and their three improved variants – design driven harmony search, adaptive harmony search and improved simulated annealing – are compared, and the characteristics that affect algorithmic robustness are investigated. *Algorithmic robustness* is defined as the ability of an algorithm to consistently converge to low cost designs regardless of the variable space and irrespective of the initial starting point. To this extent, the variable spaces present in steel frame design optimization problems are studied and two unique challenges of these spaces are identified and explained. Five benchmark steel frame designs, including moment and braced frames, are presented to serve as examples on which the algorithms can be tested, and the robustness of the algorithms is investigated using these representative designs. An in-depth discussion on the characteristics of metaheuristic algorithms that make them successful is presented. It is shown that the algorithms that exhibit *robustness* are those that incorporate intensification and diversification in ways that can effectively navigate the large variable spaces present in steel frame design optimization problems. The most robust algorithms are found to be design driven harmony search and tabu search.

1. Introduction

The optimization of steel frames is an important problem in engineering design that has been studied for the past few decades, with many different techniques and algorithms being adapted and used [1,2]. The goal of steel frame design optimization is to minimize the weight of a frame by choosing the lightest steel sections possible while still meeting building codes strength and drift constraints as well as practical constraints such as constructability. The complex and nonlinear design process causes the optimization problem to be highly nonlinear and thus difficult to solve. Furthermore, as the members used in a steel frame come from a finite number of standard cross-sections in the steel tables, the optimization problem is discrete in nature and requires metaheuristic (stochastic) algorithms that can operate on discrete variable spaces.

Metaheuristic or stochastic algorithms that are designed to operate on discrete variable spaces utilize randomness and memory to search large discrete variable spaces in order to find an optimal solution. Metaheuristic algorithms are typically based on phenomena that are observed in nature, and those used for steel frame design optimization are no exception. Simulated annealing, based on the behavior of cooling metals, was first used for steel frame design optimization by Balling [3]. Genetic algorithms attempt to emulate natural selection and were adapted for steel frame design optimization by Rajeev and Krishnamoorthy [4]. Harmony search is based on the ability of many musicians to contribute to one harmony and was first used for steel frame design optimization by Lee and Geem [5]. Camp et al. [6] adapted ant colony optimization, based on the observed ability of ant colonies to find the optimal path to a food source, for steel frame design optimization. Particle swarm optimization was originally used in steel frame design optimization by Perez and Behdinan [7] and mimics the ability of large swarms to travel together to a single point. Tabu search is a method that focuses on escaping local optima by avoiding areas that have previously been visited. It was adapted for steel frame design optimization by Bland [8]. The above six algorithms are the commonly used metaheuristic algorithms found in the literature for steel frame design optimization. As these algorithms are inspired from different processes, each metaheuristic algorithm attempts to navigate a discrete variable space in a unique manner in search of an optimum. However, the same

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overall characteristics of diversification and intensification are present in every metaheuristic algorithm. Diversification refers to the ability of an algorithm to search new regions of the variable space by incorporating randomness in the search. This helps to escape local optima by more thoroughly searching a variable space but will cause convergence issues as algorithms fail to converge to one solution. Intensification is the use of memory to seek out regions of the variable space that have been shown to produce good solutions. Intensification encourages convergence by continually drawing solutions from favorable regions of the variable space, but will increase the likelihood of converging to local optima. The performance of metaheuristic algorithms depends on a balance between the conflicting characteristics of diversification and intensification to search enough of the variable space while still converging to good solutions (see Yang [9]).

For the problem of steel frame design optimization, these metaheuristic algorithms work by searching the discrete variable space of steel sections while incorporating design code and other practical constraints through the use of penalty functions, ensuring that the optimal design achieved is within specifications. Steel frame design optimization problems have two unique properties that make them difficult to work with. First, the variable space for a realistically sized steel frame is exceedingly large, therefore search for global optimum is typically not possible. Instead the goal is to obtain good optimal solutions; however, this might also be difficult due to large variable spaces which can cause algorithms to prematurely converge to less optimal designs. Second, these problems are not guided by any one sense of metric due to the many properties inherent to a steel member cross section, meaning that different members in a frame may be governed by different properties. This causes the discrete variable space to be poorly organized and makes it difficult for algorithms to converge to good solutions if they incorporate intensification in a way that assumes a well-organized space as shown by Murren [10].

For steel frame design optimization to be useful in practice, the metaheuristic algorithms should be able to consistently converge to low cost designs. This is referred to as *algorithmic robustness*: the ability of an algorithm to consistently converge to low cost designs regardless of the variable space and irrespective of the initial starting point. Algorithmic robustness is an important property of a metaheuristic algorithm for successful application to steel frame design optimization problems. However, the aforementioned challenges inherent to these problems can severely hinder algorithmic robustness. The large variable spaces and lack of governing metric mean that a given metaheuristic algorithm can converge to two very different designs when run two separate times. In addition to this, algorithms that may appear robust when used on smaller variable spaces can quickly lose robustness as variable space is increased. Therefore, studying algorithms on small problems may not be sufficient to fully explore algorithmic performance, especially considering the large variable spaces present in realistically sized steel frames. Therefore in order to move steel frame design optimization in a direction that is more useful to practicing engineers, algorithmic robustness of metaheuristic algorithms must be investigated.

In this study the robustness of six metaheuristic algorithms is compared, and the characteristics that affect their robustness are carefully studied. Five benchmark steel frame designs are presented to serve as examples on which the algorithms can be tested. Planar and space moment and braced frames with varying design spaces are optimized. This is done in order to sufficiently test each algorithm on different types of steel frames. The six algorithms that are investigated include: simulated annealing, genetic algorithms, harmony search, tabu search, ant colony optimization and particle swarm optimization. To have an objective comparison, the best available version of each algorithm has been adopted and implemented within the authors' best judgment. Therefore, three additional variants of these algorithms found in the literature – improved simulated annealing, adaptive harmony search and design driven harmony search – are also investigated. To evaluate the algorithmic robustness, each algorithm is run 500 times on every planar frame and 200 times on every space frame, ensuring that the algorithms are adequately investigated. Thus, the objective of this study is to give an accurate representation of the robustness of these algorithms and the characteristics that affect their robustness, enabling researchers to understand how they compare in this aspect and improve upon existing algorithms or create new algorithms. The main contributions of this paper are as follows: (a) the robustness of these algorithms is investigated by performing a large number of optimizations on a variety of different variable spaces; (b) an objective comparison of all algorithms is given by using the same penalty factors and number of structural analyses for each algorithm; (c) the characteristics that control how each algorithm explores the variable space are discussed so as to be a reference on these algorithms for steel frame design optimization and for other engineering applications utilizing metaheuristic algorithms. The paper is organized as follows: Section 2 presents the formulation of the steel frame design optimization problem while Section 3 describes the metaheuristic algorithms. Section 4 details the five benchmark steel frames used for optimization and Section 5 discusses the optimization results. An in-depth discussion on the characteristics of metaheuristic algorithms that make them successful is presented in Section 6, and finally, Section 7 presents important conclusions.

2. Steel frame design optimization

2.1. Optimization problem

The discrete design optimization problem for steel frames can be expressed as follows:

$$\begin{aligned} &\min\ f(\boldsymbol{x}) \\ &\text{Subject to}: \\ &g_i(\boldsymbol{x}) \leqslant 0 \quad i = 1,\ldots,m \end{aligned} \tag{1}$$

where $f(\boldsymbol{x})$ is the objective function. The members in a steel frame are typically divided into groups with the same W-shape section assigned to all the members in a group. Therefore, the design vector $\boldsymbol{x}$ is of size n_g, where n_g is the total number of groups in a problem, and this vector represents a set of all values assigned, the values being the W-shape sections. If n_k $(k = 1, 2\ldots, n_g)$ are the possible choices of W-shapes for the member group k, then from a combinatorics standpoint there are $N_T = n_1 \times n_2 \ldots \times n_{n_g}$ distinct choices for the design variable $\boldsymbol{x}$. For practical problems N_T is prohibitively large and as a result an exhaustive search for the best solution is not possible. Metaheuristic algorithms that selectively and intelligently explore this large design space are the method of choice. The objective function is limited by the inequality constraints $g_i(\boldsymbol{x})$ which can be any combination of design strength, inter-story drift, top drift and constructability constraints. In Eq. (1) m is the total number of constraints considered.

The design strength constraint equations are taken from AISC–LRFD specifications [11] and are of the form:

$$g_r^s(\boldsymbol{x}) = \frac{P_{ur}}{\phi P_{nr}} + \frac{8}{9}\left(\frac{M_{uxr}}{\phi_b M_{nxr}} + \frac{M_{uyr}}{\phi_b M_{nyr}}\right) - 1.0 \leqslant 0 \quad \text{For } \frac{P_{ur}}{\phi P_{nr}} \geqslant 0.2 \tag{2}$$

$$g_r^s(\boldsymbol{x}) = \frac{P_{ur}}{2\phi P_{nr}} + \left(\frac{M_{uxr}}{\phi_b M_{nxr}} + \frac{M_{uyr}}{\phi_b M_{nyr}}\right) - 1.0 \leqslant 0 \quad \text{For } \frac{P_{ur}}{\phi P_{nr}} < 0.2 \tag{3}$$