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School based optimization algorithm for design of steel frames

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ABSTRACT

In this paper, a school-based optimization (SBO) algorithm is applied to the design of steel frames. The objective is to minimize total weight of steel frames subjected to both strength and displacement requirements specified by the American Institute of Steel Construction (AISC) Load Resistance Factor Design (LRFD). SBO is a metaheuristic optimization algorithm inspired by the traditional educational process that operates within a multi-classroom school. SBO is a collaborative optimization strategy, which allows for extensive exploration of the search space and results in high-quality solutions. To investigate the efficiency of SBO algorithm, several popular benchmark frame examples are optimized and the designs are compared to other optimization methods in the literature. Results indicate that SBO can develop superior low-weight frame designs when compared to other optimization methods and improves computational efficiency in solving discrete variable structural optimization problems.

1. Introduction

During the last decades, many optimization techniques have been developed for structural design problems. Among them, metaheuristic algorithms have been proven quite effective. Genetic algorithms (GA) [1–3], ant colony optimization (ACO) [4–8], particle swarm optimization (PSO) [9–12], harmony search (HS) [13,14], charged system search (CSS) [15–17], and colliding bodies optimization (CBO) [18–20] are some of the most popular techniques in structural optimization. Many optimization algorithms have been developed to solve steel frame optimization problems: Camp et al. used ACO [21]; Degertekin employed HS [22]; Kaveh and Talatahari employed imperialist competitive algorithm [23]; Hasancebi and Azad utilized Big Bang–Big Crunch [24]; Kaveh and Talatahari utilized CSS [25]; Togan used teaching-learning-based optimization (TLBO) [26]; Kaveh and Farhoudi proposed dolphin echolocation [27]; Maheri and Narimani used an enhanced HS [28]; Hasançebi and Carbas employed a bat-inspired algorithm [29]; Talatahari et al. utilized an eagle strategy [30]; Carraro et al. employed a search group algorithm [31]; Afzali et al. proposed modified honey bee mating optimization [32]; and Kaveh and Ilchi employed enhanced whale optimization [33].

A common approach in metaheuristic optimization is to randomly generate an initial population of potential solutions and gradually improve the overall fitness of the population in a systematic process. Standard metaheuristic optimization algorithms typically allow only intra-population collaboration; however, a more sophisticated approach is to utilize sets of independent parallel populations that collaborate – extending the explorative capabilities of the algorithm and improving the overall efficiency. An example of this approach is a two-stage optimization algorithm that employs a series of independent metaheuristics to explore different regions of the search space (first stage) and then focus the search on the sub-region with the most promising solutions (second stage) such as eagle strategy [34] and multi-class teaching-learning-based optimization (MC-TLBO) [35]. One of the challenges in the application of two-stage algorithms is the selection and implementation of the first stage termination criterion. The termination criterion introduces parameters that need to be tuned for a specific problem which, in result increases the complexity of the algorithm. To overcome this issue, Farshchin et al. [36] introduced a collaborative multi-population framework that utilized a TLBO algorithm and called it school-based optimization (SBO). SBO extends the simple model of teaching and learning within a classroom modeled by TLBO to a school of numerous collaborative classrooms where teachers can be reassigned to other classrooms and thus share knowledge across the school. Farshchin et al. [36] showed that SBO outperforms basic TLBO in finding low-weight designs of truss structures with frequency constraints in a continuous search space.

In this paper, the effectiveness of SBO in solving discrete optimization problems is investigated. The objective of these optimization problems is to minimize total weight of steel frames subjected to both strength and displacement requirements as specified by the American Institute of Steel Construction (AISC) Load Resistance Factor Design (LRFD) [37]. Three often cited benchmark frame structures are designed to provide a comparison between the performance of SBO and

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other algorithms in the literature. Due to the variety of structural modeling approaches and constraint implementations available in the literature, the analysis and design of these benchmark problems are explained in detail and SBO results are compared to relevant published designs.

2. Optimization algorithm

2.1. Teaching-learning-based optimization

TLBO is a metaheuristic algorithm inspired by the traditional educational process in a class of students [38]. Each student provides a solution for the optimization problem and a student with the best solution will be assigned as the teacher of the classroom. The algorithm considers two main mechanisms for exchanging information in a classroom: between a teacher and a student and inter-student collaboration. These mechanisms are implemented in two different consecutive processes: a Teacher Phase that simulates the influence of a teacher on students; and a Learner Phase that models the cooperative learning among students.

2.1.1. Teacher phase

To simulate this process in an optimization algorithm, the teacher mechanism should be applied across the entire range of the design variables. Each design variable is considered as different subjects in a course. During the Teacher Phase, students try to update their knowledge in each subject based on the information provided by the teacher. In mathematical terms, Teaching Phase is defined by:

$$X_{new}^{k}(j) = X_{old}^{k}(j) \pm \Delta(j) \tag{1}$$

$$\Delta(j) = T_F \times r|M(j) - T(j)| \tag{2}$$

where $X^k(j)$ denotes the jth design variable for the kth design vector, T_F is a teaching factor, r is a uniformly distributed random number within the range of [0,1], $M(j)$ is the mean of the class, and $T(j)$ is state of the teacher. In Eqs. (1) and (2), $\Delta(j)$ indicates the difference between the teacher and the class mean for each design variable (its sign should be selected in such a way that the student always moves toward the teacher). The teaching factor T_F in Eq. (2) is the only adjustable parameter in the TLBO algorithm and is used to specify the size of the local search space around the design. Rao et al. [38] presented data to indicate that a value of $T_F = 2$ is appropriate to balance both the exploration and exploitation aspects of the search in the Teacher Phase; this value is used in this study. At the end of each teaching cycle, the current best student will be used as the teacher of the class for the next iteration. In the original TLBO formulation presented by Rao et al. [38], the mean is given as

$$M(j) = \frac{1}{N}\sum_{k=1}^{N} X^k(j) \tag{3}$$

where N is the size of the population. However, a weighted mean based on the values of student performance provides better results [39]. The fitness-based mean is defined as

$$M(j) = \frac{\sum_{k=1}^{N} \frac{X^k(j)}{F^k}}{\sum_{k=1}^{N} \frac{1}{F^k}} \tag{4}$$

where F^k is the penalized fitness of kth student. The weighted mean puts more emphasis on qualified students and improves the overall performance of the TLBO algorithm.

2.1.2. Learner phase

Interactive learning among students within a classroom can improve individual performance and consequently the overall performance of the class. The procedure for the Learner Phase is given in the following steps:

(a) Randomly select a student, p
(b) Randomly select another student, q such that $p \neq q$
(c) Evaluate the fitness of both students
(d) If $F^p < F^q$ (student p is better than student q), then

$$X_{new}^{p}(j) = X_{old}^{p}(j) + r[X_{old}^{p}(j) - X^q(j)] \tag{5}$$

otherwise

$$X_{new}^{p}(j) = X_{old}^{p}(j) + r[X^q(j) - X_{old}^{p}(j)] \tag{6}$$

In Eqs. (5) and (6), r is a uniformly distributed random number within the range [0,1]. The student p moves towards student q if student q is better than student p ($F^p > F^q$) or away from student q otherwise. The direction and magnitude of the change depends on each student's current position in the search space and the difference in the solution of students' p and q. In either case, student p attempts to improve its state [39].

3. School based optimization (SBO)

SBO is a multi-population metaheuristic algorithm, which extends the single classroom teaching-learning environment with one teacher (TLBO) to a school with multiple classrooms and multiple teachers. In the SBO algorithm, independent classrooms explore the search space simultaneously, each using TLBO; then, at the end of each iteration, a pool of teachers (one teacher from each classroom) is assembled. Before the next iteration, each classroom is assigned a new teacher from the teacher pool allowing the transfer of knowledge between classrooms. Teachers are assigned to classrooms using a roulette wheel selection mechanism based on the teachers' fitness values. In addition, every newly assigned teacher for each classroom should have a better fitness than its current teacher.

Fig. 1 illustrates a flowchart of the SBO algorithm. During each iteration, all students in each classroom c are evaluated (there are a total of N_c classrooms) and the best student (measured by fitness) in each classroom is selected as the classroom's teacher T_c; all teachers are assembled into the teacher pool. Before each subsequent iteration, each classroom selects a new teacher NT_c from the teacher pool using a roulette wheel that is subdivided into segments based on the teachers' fitness values. The teacher assignment mechanism allows the SBO algorithm to use more than one teacher to guide the optimization. In result, this mechanism reduces the likelihood that the algorithm will converge to a local optimum. If for example, a classroom converges to a local optimum, that information will not necessarily be distributed to other classrooms since the performance of that classroom's teacher has a lower probability of being selected as a new teacher. Furthermore, the classroom that developed the local optimum has a chance to be improved from this state with the selection of a better teacher from one of the other classrooms. After each classroom receives a new teacher, TLBO teaching and learning mechanisms are applied to each classroom independently and another round of teacher identification and exchange is initiated. The collaborative interaction between parallel classrooms continues until a termination criterion is met, typically some number of analyses wherein the best solution remains unchanged [21,35,36].

4. Frame optimization

A general objective function for frame optimization problems that only accounts for a structure's weight W is

$$\text{minimize } W = \sum_{i=1}^{N_e} L_i w_n(\eta_i) \tag{7}$$