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Optimization of retaining wall design using recent swarm intelligence techniques

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ABSTRACT

In this paper, cantilever retaining wall design is studied as an important optimization task in civil engineering. The current study explores the efficiency of some recent swarm intelligence techniques: accelerated particle swarm optimization (APSO), firefly algorithm (FA), and cuckoo search (CS). These algorithms are verified using two benchmark case studies. In order to better determine the proficiency of the utilized algorithms, they are benchmarked with the particle swarm optimization (PSO) algorithm, a classical swarm intelligence algorithm. To that end, a code is developed to model retaining wall design based on the ACI 318-05 procedure. In this study, continuous variables are used for wall geometry and discrete variables are used for steel reinforcement to optimize the structural design. Moreover, the sensitivity of the proposed algorithms to surcharge load, base soil friction angle, and backfill slope are investigated with respect to the geometry and design parameters. Though CS and PSO reached nearly identical lowest cost and lowest weight designs of the wall under two case studies, CS has lower values for standard deviation, mean, and worst design, and therefore may be a better optimization algorithm for engineering design.

1. Introduction

A retaining wall is a structure used to enhance the stability of masses of earth that are unstable in their natural slopes. These soil slopes occur frequently in the construction of railways, highways, bridges, and other civil engineering projects; therefore, minimum cost design of reinforced concrete retaining walls is an important design optimization task because of its frequent application in civil engineering. Design of retaining walls must satisfy geotechnical, structural, and economic requirements. A trial and error approach is typically necessary to design retaining walls: designers must develop an initial trial design for the wall to reach a proper final design that satisfies all the requirements. However, there is no guarantee that the final design will be an economical design.

Optimal retaining wall design has been the subject of many studies in the past (e.g., [1–8]). Mathematical modeling of the wall design procedure as an objective function for optimization will be an efficient method to reach the optimal design. Recently, several researchers have attempted to utilize various metaheuristic optimization techniques for retaining wall design; for example, Ahmadi-Nedushan and Varaee [9] and Khajehzadeh et al. [10] used particle swarm optimization, Khajehzadeh et al. [11] used modified particle swarm optimization, Khajehzadeh and Eslami [12] used a gravitational search algorithm, Ceranic et al. [13] and Yepes et al. [14] utilized simulated annealing, Villalba et al. [15] applied CO_2 optimization, Ghazavi and Bonab [16] applied ant colony optimization, Kaveh and Abadi [17] adopted harmony search, Kaveh and Behnam [18] utilized the charged system search algorithm, Sheikholeslami et al. [19] used the hybrid firefly algorithm, and Camp and Akin [20] applied Big Bang Big Crunch. Furthermore, despite limited research on concrete retaining wall optimization, there are numerous studies on structural and geotechnical engineering optimization problems, including Sahab et al. [21], Pezeshk and Camp [22], Gholizadeh and Barati [23], Bekdas [24], Das [25], Das and Basudhar [26], Kashani et al. [27] and Khajehzadeh et al. [28,29].

Metaheuristic algorithms are techniques that can be used to solve complex problems like retaining wall design optimization. Metaheuristic algorithms are computational methods that use iterative improvement of a candidate solution by some predetermined rules to optimize a problem. These algorithms need no initial

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solution and are capable of searching a large possible solution space. Due to the stochastic performance of these algorithms, however, there is no guarantee that the final solution is the global optimum solution. Therefore, it is necessary to adopt a wide range of metaheuristic algorithms to a specific problem to find a robust algorithm that outperforms the other techniques. Metaheuristics are generally inspired by nature (e.g., bio-inspired [30] techniques) or by art (e.g., [31]). Metaheuristic optimization algorithms can be broadly classified into two categories: evolutionary algorithms and swarm intelligence algorithms [32]. This paper focuses on applications of swarm intelligence algorithms.

The particle swarm optimization (PSO) algorithm is the classical swarm intelligence algorithm and has been used in many structural optimization problems (e.g., [33]). Accelerated PSO (APSO) is a recent variant of PSO that has been successfully applied to structural engineering problems (e.g., [34]). Among other new proposed swarm intelligence techniques, the firefly algorithm (FA) and cuckoo search (CS) were the subject of structural optimization studies by Yang and Deb [35,36], Gandomi et al. [37–40], Talatahari et al. [41], and Kaveh and Bakhshpoori [42]. These algorithms have also been applied to slope stability analysis by Gandomi et al. [43]. Therefore, in this study, four swarm intelligence optimization algorithms (classical PSO, APSO, FA, and CS) are applied to retaining wall design optimization. Designs will be conducted using a program developed in MATLAB software based on ACI 318-05 [44] to minimize the weight and cost of the retaining wall. To explore the efficiency of the utilized algorithms, two numerical examples are considered from Saribaş and Erbatur [4]. Moreover, sensitivity of the proposed algorithms to surcharge load, base soil friction angle, and backfill slope are investigated through a parametric study.

2. Designing of retaining wall

Fig. 1 shows a retaining wall modeled by 12 design variables: width of the base ($X1$), toe width ($X2$), footing thickness ($X3$), thickness at the top of the stem ($X4$), base thickness ($X5$), the distance from the toe to the front of shear key ($X6$), shear key width ($X7$), shear key depth ($X8$), the vertical steel reinforcement in the stem ($R1$), the horizontal steel reinforcement of the toe and heel ($R2$ and $R3$, respectively), and the vertical reinforcement of the shear key ($R4$).

Variables $X1$ to $X8$ determine the wall geometry, and variables $R1$ to $R4$ represent the steel reinforcement. For $X1$ to $X8$, continuous variables are used, whereas for $R1$ to $R4$, a set of discrete values are considered, as shown in Table 1. A total of 223 reinforcement combinations were used to represent between 3 and 28 evenly spaced 10–30 mm diameter bars.

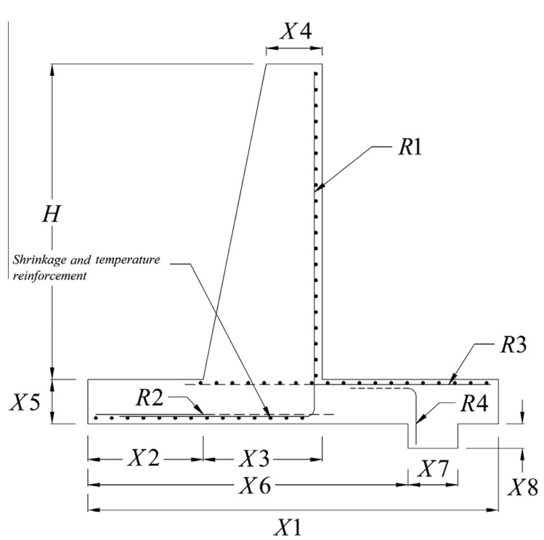

Fig. 1. Design variables for general retaining wall.

Retaining wall design is divided into two phases: geotechnical design and structural design. In the geotechnical design phase, the wall must be checked for the overturning, sliding, and bearing capacity failure modes. In the structural design phase, the wall must be checked for shear and moment failure at the stem, heel, toe, and shear key. A brief review of the geotechnical and structural design procedure is presented in this section.

All the effective forces on the wall are shown in Fig. 2, where W_C is the combined weight of all the sections of the reinforced concrete wall; W_S is the weight of backfill acting on the heel of the wall; W_T is the weight of soil on the toe of the wall; q is the distributed surcharge load (Q is the resultant surcharge load); P_A is the force resulting from the active earth pressure; P_k and P_T are the forces resulting from passive earth pressure on the base shear key and front part of the toe section, respectively; and P_B is the force resulting from the bearing stress of the base soil. The active and passive earth pressure coefficients are evaluated using Rankine theory [45] using Eqs. (1) and (2), respectively:

$$k_a = \cos\beta \frac{\cos\beta - \sqrt{\cos^2\beta - \cos^2\theta}}{\cos\beta + \sqrt{\cos^2\beta - \cos^2\theta}} \tag{1}$$

$$k_p = \tan^2\left(45 + \frac{\theta}{2}\right) \tag{2}$$

where β is the backfill slope and θ is the friction angle of the backfill slope.

Three geotechnical and six structural failure modes are considered to design a retaining wall based on Das [45] and Camp and Akin [20] as follows:

I. Geotechnical stability requirements:

The over turning factor of safety of the wall computed using Eq. (3):

$$FS_O = \frac{\sum M_R}{\sum M_O} \tag{3}$$

where $\sum M_R$ is the sum of resisting moments against overturning and $\sum M_O$ is sum of applied overturning moments.

The sliding factor of safety is defined by Eq. (4):

$$FS_S = \frac{\sum F_R}{\sum F_D} \tag{4}$$

where $\sum F_R$ is the sum of horizontal resisting forces against sliding and $\sum F_D$ is the sum of the horizontal sliding forces, defined by Eqs. (5) and (6), respectively.

Table 1
Steel reinforcement properties for design variables $R1$ to $R4$.

Index number (η)	Reinforcement		Total A_s (cm^2)
	Quantity	Bar size (mm)	
1	3	10	2.356
2	4	10	3.141
3	3	12	3.392
4	5	10	3.926
5	4	12	4.523
.	.	.	.
.	.	.	.
.	.	.	.
221	16	30	113.097
222	17	30	120.165
223	18	30	127.234