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OPTIMUM DESIGN OF REINFORCED CONCRETE RETAINING WALLS BY USING SPECIFIC PARAMETER-FREE METAHEURISTIC ALGORITHMS

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Abstract

In the optimum design of structural systems, the robustness and the performance are related to the best tuning of the parameters of the method. For metaheuristic algorithms inspired by phenomena in life, algorithm-specific parameters exist in addition to general parameters that are the population of the generated candidate solution and the number of iterations that are needed to find the final optimum solution. In the optimum design of reinforced concrete (RC) structures, the dimensions are optimized by considering the minimization of the total cost. These problems are highly constrained by the design requirements presented in design codes. Especially, RC retaining walls involve the check of stability conditions as geotechnical state limits in addition to structural state limits. This situation makes the optimization problem challenging. A better and robust algorithm is always in search. In the present study, two specific parameter-free metaheuristic algorithms are employed. These algorithms are teaching-learning-based optimization (TLBO) and Jaya algorithm (JA). Since JA is a single-phase algorithm and both phases of TLBO defined as teacher and learner phases are consequently applied, a switch probability is not needed. Also, the existing factor is defined randomly. These two algorithms were tested on three cases and the results were compared with three classical algorithms such as Genetic Algorithm (GA), Differential Evaluation (DE), and Particle Swarm Optimization (PSO). In this verification, JA needs less function evaluation to reach the optimum results. As conclusions, both TLBO and JA are robust methods for the optimization problem.

Keywords: Reinforced Concrete, Retaining Walls, Optimization, Metaheuristic Algorithms

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1 INTRODUCTION

Generally, engineering designs are carried out by taking two main objectives into consideration. The first of these is structural security, the other is cost. Good engineering design can be defined as the best combination or balance of these two objectives. The process in which this balance is investigated is called optimization and the obtained result is called optimum design.

Different methods have been developed and used from past to present in order to find the optimum design in engineering designs. Especially in recent years, metaheuristic algorithms are one of the methods used frequently for this purpose. Metaheuristic algorithms are methods developed by taking inspiration from nature. Examples of these are genetic (GA) [1,2] and differential evolution (DE) [3] algorithms from the evolutionary process, flower pollination (FPA) [4] from the pollination process of flowers, the bat algorithm (BA) [5] from the echolocation characteristics of bats, the gray wolf optimization (GWO) [6] from the herd hierarchy and hunting processes of the gray wolves, the particle swarm optimization (PSO) [7] from the herd movement of living things, ant colony optimization (ACO) [8] from the foraging process of ants, teaching-learning-based optimization (TLBO) [9] from the student-teacher relationship and learning in a classroom.

An optimization process is carried out using metaheuristic algorithms in many areas of structural engineering. One of these areas is the optimum design of reinforced concrete structures. Since reinforced concrete structures consist of two different mechanical and cost-effective materials, it is necessary to find a combination that will provide the lowest cost (optimum design) of concrete and steel. The optimum design of RC retaining walls is one of the areas that have been researched extensively. Various metaheuristic methods such as Simulated Annealing (SA) [10,11], PSO [12], Harmony search (HS) [13] Big Bang Big Crunch (BB-BC) [14], Firefly Algorithm (FA) [15], FPA [16] have been used in the design of RC retaining walls. In addition to these studies, there are also studies where performance evaluation of algorithms [17] is performed and modified or hybrid algorithms [18] are used.

In this study, the effect of different parameters on optimum RC retaining wall design was investigated. For this purpose, five different metaheuristic algorithm-based methods have been developed. In this way, as a result of the study, the researchers were informed about the effects of parameters as well as the most effective metaheuristic method for optimum design.

2 OPTIMUM DESIGN VIA METAHEURISTIC ALGORITHMS

Metaheuristic methods can generally be summarized with 3 stages as given in Fig.1.

In the first stage (pre-optimization), the design constants of the problem, the lower and upper limits of the design variables, the population number (pn), the algorithm-specific parameters and the stopping criteria of the optimization are defined. Then, candidate solutions (totally pn) are generated according to Eq. (1) and stored in initial solution matrix.

$$X_i = X_{i,min} + rand(X_{i,max} - X_{i,min}) \tag{1}$$

In Eq. (1), X_i, $X_{i,min}$ and $X_{i,max}$ represent i^{th} candidate solution, minimum and maximum limits of i^{th} solution respectively. rand is a function that is generated by random values between 0 and 1.

The second stage is the analysis stage. In this stage, the objective function of each solution is calculated, and the design constraints of the problem are checked. Objective functions of solutions that violate the design constraint are penalized using a penalization value. Within the scope of this study, the objective function is determined as the minimum material cost given as Eq.(2), and for the penalization, a high value is defined.

$$\min\big(f(x)\big) = C_c V_c + C_s W_s \tag{2}$$

In Eq. (2), C_c and C_s are unit concrete and unit reinforcing steel costs respectively. V_c and W_s represent the volume of the concrete and unit volume weight of the steel, respectively.

At the last stage (optimization stage), an iterative process is started. In this process, first of all new solution matrix is generated according to algorithm equations. In this study, 5 different algorithms, GA, DE, PSO, TLBO and JA were employed and algorithm-specific equations are given below.

Equation of genetic algorithm (GA):

$$X_{q,new} = \{\, mr > rand, \quad X_{q,min} + rand\,\left(X_{q,max} - X_{q,min}\right) \tag{3}$$

In Eq. (3), mr is mutation rate, q is a gene (design parameter) randomly-selected from the total design parameter. $X_{q,new}$, $X_{q,min}$ and $X_{q,max}$ are new design variable, lower and upper limit values of q^{th} design variable, respectively. Unlike GA, DE uses two equations (Eq. 4 and 5). New design variables are derived by selecting one of these two equations according to DE rules.

$$X_{i,new} = X_{i,p} + F\,\left(X_{i,q} - X_{i,r}\right) \tag{4}$$

$$\mathrm{X_{i,j}} = \mathrm{X_{i,new}} \quad \{\text{if rand} \le \mathrm{CR} \quad \text{or} \quad \mathrm{cs} = \mathrm{rand_{cs}} \tag{5}$$

In Eq. (4 and 5), $\mathrm{X_{i,p}}$, $\mathrm{X_{i,q}}$, $\mathrm{X_{i,r}}$ represent randomly selected different solutions and F is the weighting factor. *CR*, *cs,* and $rand_{cs}$ are crossover possibilities, current candidate solution, and randomly selected solution.

In PSO, new values are found by using a single equation as in GA. This equation as follows

$$X_{i,new} = X_{i,j} + V_{i,new} \tag{6}$$

where $X_{i,j}$ is the current position of j^{th} particle and $V_{i,new}$ can be calculated with Eq. (7).

$$V_{i,new} = w\,V_{i,j} + c_1 rand\big(X_{i,y_{best}} - X_{i,j}\big) + c_2 rand\,\left(X_{i,g_{best}} - X_{i,j}\right) \tag{7}$$

In Eq. (7), $V_{i,j}$ is current velocity j^{th} particle. $X_{i,y_{best}}$ and $X_{i,g_{best}}$ represent values of the best global and local positions respectively. c_1 and c_2 are positive constant parameters used to control velocity.

In the TLBO algorithm, two different equations are used in generating new solutions. However, unlike other two-equation algorithms, it uses both of the equations one after the other instead of choosing one of the equations. These equations are as follows

$$\mathrm{X_{i,new}} = \mathrm{X_{i,j}} + \mathrm{rand}\big(\mathrm{X_{i,best}} - (\mathrm{TF})\,\mathrm{X_{i,mean}}\big) \tag{8}$$

$$X_{i,new} = \begin{cases} OF_a < OF_b, & X_{i,j} + rand\,\left(X_{i,a} - X_{i,b}\right) \\ OF_a > OF_b, & X_{i,j} + rand\,\left(X_{i,b} - X_{i,a}\right) \end{cases} \tag{9}$$

where $\mathrm{X_{i,j}}$, $\mathrm{X}_{i,best}$, $\mathrm{X_{i,mean}}$ represent values of existing solution, best solution and mean values of existing solutions respectively, and TF shows teaching factor. $\mathrm{X_{i,a}}$ and $\mathrm{X_{i,b}}$ are randomly selected candidate solutions. Objective functions corresponding to these solutions ($\mathrm{X_{i,a}}$ and $\mathrm{X_{i,b}}$) are expressed with $\mathrm{OF_a}$ and $\mathrm{OF_b}$, respectively.

The other algorithm used in the study, JA uses a single equation given in Eq.(10).

$$X_{i,new} = X_{i,j} + rand\,\left(X_{i,best} - |X_{i,j}|\right) - rand\,\left(X_{i,worst} - |X_{i,j}|\right) \tag{10}$$

In Eq.(10), $X_{i,worst}$ is worst solution in terms of the objective function.

After the generation of new solution matrix, it is done comparation between solution matrix and existing one. In case of new solutions have better objective function value, new solutions replace existing solutions. In case new solutions have better objective function value, the existing solution matrix is updated with new solutions. This process is continued until satisfying stopping criteria of the problem. In this study maximum iteration number is determined as stopping criteria.

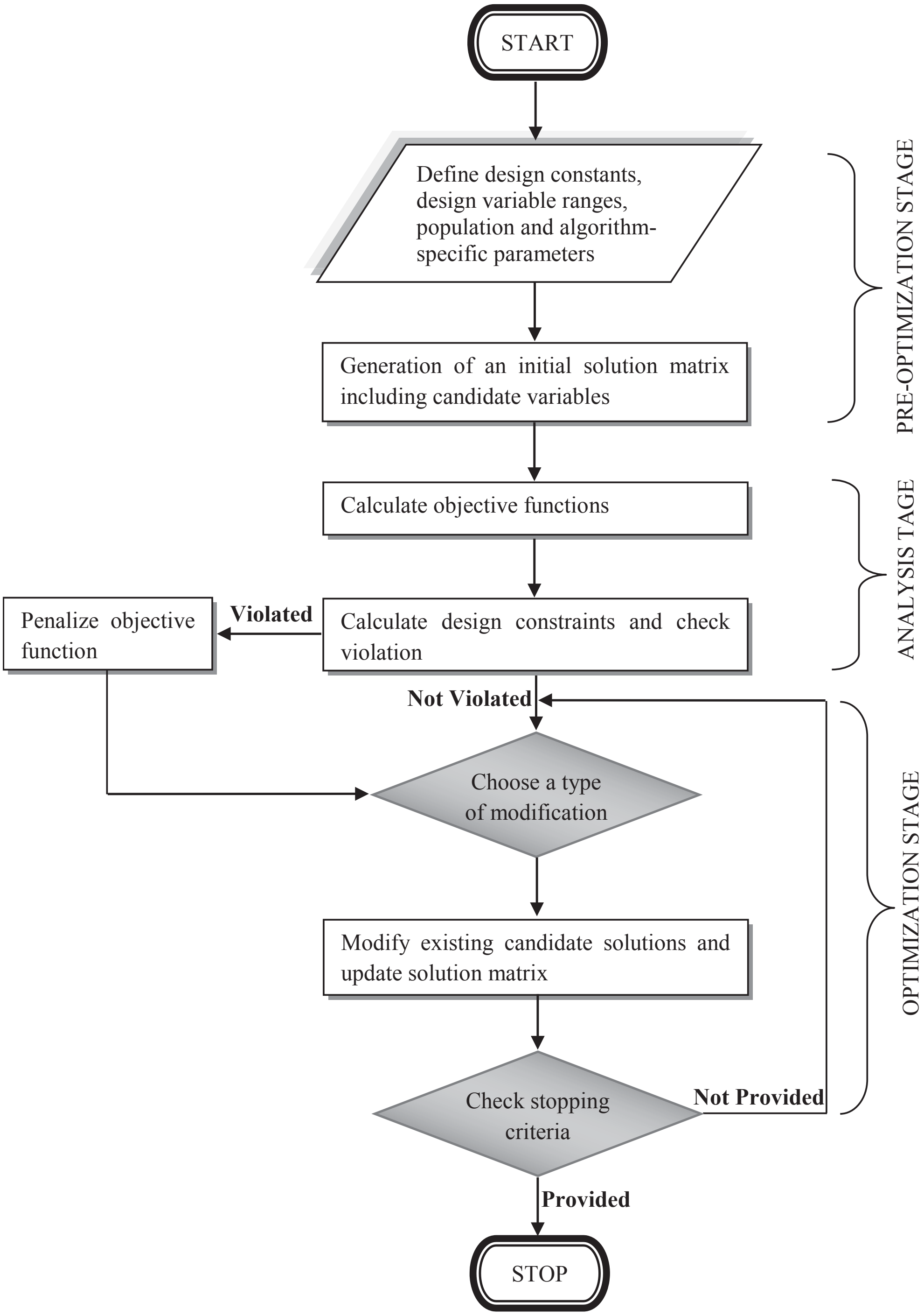

Figure 1: The optimization flowchart

3 NUMERICAL EXAMPLE

RC retaining wall that is investigated for the optimum design can be seen in Fig.2. As shown in the figure, there are 5 design variables. The limits of these design variables and the design constants are presented in Table 1. In reinforced concrete design, the constraints of ACI 318 [19] regulation were applied. Information on the constraints applied in the optimization process is given in Table 2. In addition to these, various load and safety factors are summarized in Table 3.

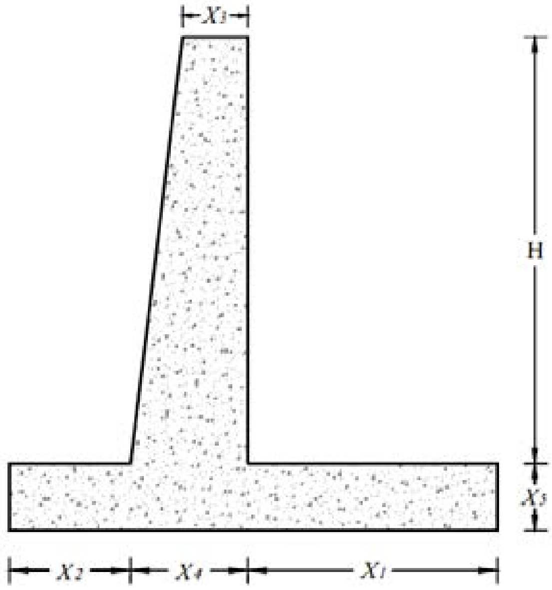

Figure 2: Design variables Cantilever retaining wall

Table 1. Optimization data for T shape walls respect to a specific design

	Definition	Symbol	Limit/Value	Unit
Design Variables	Heel slab/back encasement width of retaining wall	X_1	0-10	m
	Toe slab/front encasement width of retaining wall	X_2	0-3	m
	Upper part width of cantilever/stem of wall	X_3	0.2-3	m
	Bottom part width of cantilever/stem of wall	X_4	0.3-3	m
	Thickness of bottom slab of retaining wall	X_5	0.3-3	m
Design Constants	Difference between top elevation of bottom-slab with soil in behind of wall (active zone)/stem height	H	6	m
	Weight per unit of volume of back soil of wall (active zone)	γ_z	18	kN/m^3
	Surcharge load in active zone (on top elevation of soil)	q_a	10	kN/m^2
	Angle of internal friction of back soil of wall	Φ	30°	
	Allowable bearing value of soil	q_{safety}	300	kN/m^2
	Thickness of granular backfill	t_b	0.5	m
	Coefficient of soil reaction	K_{soil}	200	MN
	Compressive strength of concrete	f_c	25	MPa
	Tensile strength of steel reinforcement	f_y	420	MPa
	Elasticity modulus of concrete	E_s	200000	MPa
	Weight per unit of volume for concrete	γ_c	25	kN/m^3
	Weight per unit of volume for steel	γ_s	7.85	t/m^3
	Width of wall bottom slab	b	1000	mm
	Concrete unit cost	C_c	50	$\$/m^3$
	Steel unit cost	C_s	700	\$/ton

Table 2. The design constraints

Description	Constraints
Safety for overturning stability	$g_1(X)$: $FoS_{ot,design} \geq FoS_{ot}$
Safety for sliding	$g_2(X)$: $FoS_{s,design} \geq FoS_s$
Safety for bearing capacity	$g_3(X)$: $FoS_{bc,design} \geq FoS_{bc}$
Minimum bearing stress (q_{min})	$g_4(X)$: $q_{min} \geq 0$
Flexural strength capacities of critical sections (M_d)	$g_{5\text{-}7}(X)$: $M_d \geq M_u$
Shear strength capacities of critical sections (V_d)	$g_{8\text{-}10}(X)$: $V_d \geq V_u$
Minimum reinforcement areas of critical sections (A_{smin})	$g_{11\text{-}13}(X)$: $A_s \geq A_{smin}$
Maximum reinforcement areas of critical sections (A_{smax})	$g_{14\text{-}16}(X)$: $A_s \leq A_{smax}$

Table 3. ACI 318 Regulation values utilized in optimization process

Load Coefficients in ACI Regulation	Symbol	Value
Coefficient for load increment	C_l	1.7
Reduction coefficient for section bending moment capacity	FiM	0.9
Reduction coefficient for section axial load capacity	FiN	0.9
Reduction coefficient for section shear load capacity	FiV	0.75
Constant load coefficient	G_K	0.9
Live load coefficient	Q_K	1.6
Horizontal load coefficient	H_K	1.6
Safety coefficient respect to overturning	Os_{safety}	1.5
Safety coefficient respect to slipping	Ss_{safety}	1.5

Three different case analyses were performed using GA, DE, PSO, TLBO and JA. These cases are as follows:

Case 1: Optimum design variables are investigated using thirty multiple cycles of optimization. In the optimization process, twenty populations and five thousand iteration numbers are used.

Case 2: Effect of wall height on the optimum design as well as algorithm performances are investigated. As different from Case 1, H is defined as 10m.

Case 3: Best population and iteration number combination are investigated. For this investigation, optimization operations are carried out for different maximum iteration numbers from 1 to 5000 by increasing 499 in each step and for different population numbers such as 3, 5, 10, 15, 20, 25, 30.

The optimum results for these cases are shown in Table 4-6, respectively.

Table 4. Optimum design results for Case 1.

Algorithm	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**	**Min. Cost**	**Ave. Cost**	**Standard Dev.**
GA	4.1257	0.0003	0.2003	0.6212	0.4274	428.2421	449.3181	36.9566092
DE	4.1323	0.0000	0.2000	0.6098	0.4267	428.1139	433.3653	11.4300331
PSO	4.1322	0.0000	0.2000	0.6099	0.4267	428.1139	449.2315	40.6569904
TLBO	4.1323	0.0000	0.2000	0.6099	0.4267	428.1139	428.1139	0.0000005
JA	4.1323	0.0000	0.2000	0.6099	0.4267	428.1139	428.1139	0.0000012

Table 5. Optimum design results for Case 2.

Algorithm	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**	**Min. Cost**	**Ave. Cost**	**Standard Dev.**
GA	6.3735	1.5040	0.2010	1.3299	0.7140	1365.7614	1370.8030	5.8839356
DE	6.3480	1.4917	0.2000	1.3656	0.7086	1365.2365	1442.5197	146.3331618
PSO	6.3482	1.4879	0.2000	1.3655	0.7074	1365.2432	1473.0711	137.6288067
TLBO	6.3479	1.4920	0.2000	1.3658	0.7087	1365.2365	1365.2368	0.0001623
JA	6.3478	1.4919	0.2000	1.3660	0.7087	1365.2367	1371.6683	34.6327849

Table 6. Optimum design values of wall with the best population-iteration combinations

Algorithm	X_1	X_2	X_3	X_4	X_5	Min. Cost	Ave. Cost	Standard Dev.	Iter. Num.	Pop. Num.
GA	4.1304	0.0046	0.2001	0.6106	0.4240	428.2186	428.6384	0.34408003	2995	15
DE	4.1323	0.0000	0.2000	0.6098	0.4267	428.1139	428.1139	0.0000000	1997	30
PSO	4.1324	0.0000	0.2000	0.6096	0.4267	428.1140	699.2741	732.5740371	3993	30
TLBO	4.1323	0.0000	0.2000	0.6098	0.4267	428.1139	428.1139	0.0000126	4991	25
JA	4.1323	0.0000	0.2000	0.6099	0.4267	428.1139	428.1139	0.0000057	4492	25

4 CONCLUSION

4.1 Case 1

DE, PSO, TLBO and JA find close values in terms of objective functions (minimum cost), whereas GA could not reach the minimum value. Therefore, it can be said that all algorithms except GA are effective in finding the minimum result. However, as seen in Table 4, the standard deviation and average cost values of the DE and PSO algorithms are higher than other ones. Therefore, it can be concluded that TLBO and JA algorithms are more effective and stable for this structural model.

4.2 Case 2

Increasing the wall height from 6m to 10m caused the optimum X_2 value, that is found zero in Case 1. The minimum cost design has been obtained with DE and TLBO algorithms. Besides, it is seen that JA and PSO obtained results very close to these results. Considering all the parameters obtained from the analysis results of the algorithms, it can be said that TLBO is better than the others.

4.3 Case 3

It is seen that all algorithms except GA have reached the optimum value. When all the statistical values are evaluated together, it is understood that the DE algorithm seems better, but there is no significant difference between the TLBO and JA algorithms. In terms of the number of iterations, the DE algorithm again reaches a slightly faster result. In terms of population numbers, it can be said that 15 to 30 population numbers are the most suitable range for optimum analysis.

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