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Geliştirilmiş Öğretme-Öğrenme Tabanlı Optimizasyon Algoritmaları Kullanılarak Konsol İstinat Duvarı Tasarımının Optimizasyonu

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Öz

Dayanma yapıları, geoteknik mühendisliğinde zemin seviyelerini desteklenmesi, şev göçmelerinin önlenmesi ve tesfiye yüzeylerinin oluşturulması açısından önem arz etmektedirler. Bu yapıların tasarımı, malzeme kullanımını ve maliyeti en aza indirirken iç ve dış stabilite için optimizasyonu içerir. Bu çalışma, betonarme konsol istinat duvarlarının Öğretme-Öğrenme Tabanlı Optimizasyon (TLBO) algoritması ve aracılarla geliştirilmiş bir versiyonu (I-TLBO) kullanılarak optimize edilmesine odaklanmaktadır. Konsol istinat duvarı tasarım süreci iki amaç fonksiyonunu dikkate almaktadır: ağırlığı ve maliyeti en aza indirme. Çalışma, geometrik ve yapısal tasarım değişkenlerini, geoteknik ve yapısal kısıtları ve optimizasyon süreçlerini incelemektedir. Optimizasyon sonuçları, genetik algoritmalar, evrimsel stratejiler ve parçacık sürüsü optimizasyonu gibi literatürdeki diğer algoritmalarla karşılaştırılmıştır. Geliştirilmiş TLBO algoritması, daha düşük tasarım boyutları ve daha düşük maliyetler elde ederek görece daha başarılı sonuçlar vermiştir. Geliştirilmiş TLBO algoritması tasarım kısıtlamalarını sınırlarına yaklaştıran daha verimli çözümler sunmuş, daha uygun maliyetli ve yapısal olarak daha stabil konsol istinat duvarı tasarımları elde edilmesini olanak tanımıştır. Çalışma sonucunda, I-TLBO algoritmasının konsol istinat duvarı tasarımının optimizasyonunda diğer yöntemlere göre daha düşük maliyet ve daha düşük ağırlıkların ede edilmesi bakımından etkin sonuçlar sunduğu görülmüştür.

Anahtar kelimeler: İstinat duvarı tasarımı, Konsol istinat duvarı, Stabilite analizleri, Optimizasyon, Öğretme-öğrenme tabanlı optimizasyon (TLBO)

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Optimization Of Cantilever Retaining Wall Design Using Improved Teaching-Learning-Based Optimization Algorithms

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Abstract

Retaining structures play a crucial role in geotechnical engineering to support soil levels, prevent slope failure, and create flat surfaces for construction. Designing these structures involves optimizing internal and external stability while minimizing material usage and cost. This study focused on optimizing reinforced concrete cantilever retaining walls using the Teaching-Learning Based Optimization (TLBO) algorithm and an improved version (I-TLBO) with agents. In the context of the study, geometric-structural design variables, geotechnical -structural constraints, and optimization processes were examined. Minimizing weight and minimizing cost of the wall were the objectives considered in the cantilever retaining wall design process. The optimization results were compared with other algorithms in the literature, such as genetic algorithms, evolutionary strategies, and particle swarm optimization. The improved TLBO algorithm demonstrated superior performance, achieved lower design dimensions, and reduced costs. It provided more efficient solutions that pushed design constraints closer to their limits, resulting in a cost-effective and structurally sound cantilever retaining wall design. As a result of the study, the I-TLBO algorithm was found to be more cost and weight-effective than other methods in the optimization of cantilever retaining wall design.

Keywords: Retaining wall design, Cantilever retaining wall, Stability analyses, Optimization; teaching-learning-based optimization (TLBO)

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1. Introduction

Retaining structures used to support different soil levels, prevent slope failure, or create flat surfaces for construction projects have vital importance in geotechnical engineering. Various forms of the retaining structure, such as gravity walls, cantilever walls, sheet pile walls, gabion walls, or reinforced soil, can be used to support the forces exerted by the retained soil, water pressure, seismic load, or surcharge loads. The major matter in the design of retaining structures is to provide internal stability and external stability requirements cost-effectively. Determination of optimal balance between structural integrity and the use of the material has great significance in the engineering aspects. The essence of optimization applications for this purpose is to find cost-effective solutions, reduce material usage and at the same time provide structural efficiency.

Cantilever retaining walls are a widely used structure type to sustain lateral earth stability and the use of this type of walls has been gradually increased since World War II [1]. Unlike other retaining wall designs, which rely on additional support from braces or tiebacks, a cantilever wall derives its strength from a rigid, vertical stem that extends into the ground. The stem is typically thicker at the base and tapers towards the top, creating a triangular cross-section. The key feature of a cantilever wall is the presence of a horizontal arm or "heel" at its base, which provides a counterbalance against the lateral pressure exerted by the retained material. This arm allows the wall to resist the forces acting on it and maintain stability. Additionally, a shear key subjected to passive earth pressure can be used to increase the stability of the wall.

There are many studies in the literature about the investigation of optimization methods that can be used to design reinforced cantilever retaining walls. Genetic algorithms [2], teaching learning-based algorithm [3], charged system search (CSS) and improved harmony search [4], fuzzy adaptive metaheuristic algorithm [5], big bang–big crunch [6], particle swarm optimization [7], ant colony optimization [8], grey wolf optimization [9], simulated annealing [10], evolutionary algorithms [11,12], multi-objective optimization, firefly algorithm (FA), harmony search algorithm (HS) and improved firefly algorithm-harmony search (IFA-HS) [13] are major methods used in the studies. These optimization methods can be used individually or in combination with each other to solve optimization problems. Although the optimization of retaining walls in terms of weight and cost has been investigated using different algorithms in the literature, there are very few studies investigating the optimization performances of these walls with TLBO and I-TLBO algorithms.

The Teaching-Learning-Based Optimization (TLBO) algorithm is an optimization method that takes its cues from how students collaborate to grow as individuals [14]. TLBO offers advantages such as simplicity in implementation, fewer parameters to tune, population-based exploration, analogy to teacher-student dynamics for better exploration, adaptability to various problems, global exploration, balanced exploration-exploitation, and no need for gradient information [14–16]. In many studies, the TLBO mechanisms have demonstrated excellent results, particularly in terms of convergence. However, it has been observed and seen in studies that the algorithm tends to get stuck in local optima in some problems [17]. To overcome this disadvantage, this study aims to enhance the TLBO algorithm. If the algorithm does not show improvement over a certain number of iterations, except for the best individual, individuals in the population are replaced with randomly generated agents. The studies on optimum design of cantilever retaining walls several soil properties such as different soil characteristics [18], soil heterogeneity [8], permeability [19], particle size [20] were considered using above-mentioned optimization algorithms.

This study intended to examine the performance of TLBO and I-TLBO algorithms for the optimal design of reinforced concrete cantilever retaining walls. The algorithms were coded in C# software considering the weight and cost of the structure was the object function. In this context, a widely used cantilever retaining wall example was used in the optimization process to compare the performance of the TLBO and I-TLBO approaches with other algorithms in the literature.

2. Optimization Process

General outlines of the study were prepared considering [9]. For the optimal design of a reinforced concrete retaining wall, two different objective functions were used in the context of variables and constraints. The first objective function used aims to design the retaining wall in the lightest possible form, independent of cost. The first objective function can be expressed as follows:

$$f_{weight} = W_{st} + W_c \tag{1}$$

W_{st} and W_c represent the total weight of reinforcement and concrete used in the retaining wall, respectively. The second objective function used aims to minimize the total cost based on material weights and can be expressed as follows:

$$f_{\cos t} = W_{st} C_s + W_c C_C \tag{2}$$

C_S and C_C represent the unit cost of reinforcement and concrete, respectively. The design variables given in Fig.1 were considered for calculating the weight and cost of the wall. Weights of concrete and reinforcement were taken into account in the determination of the cost of the wall. During the optimization phase, constraints were established based on safety factors against sliding, overturning, and bearing capacity parameters.

2.1. Design variables

Seven geometric and three structural design variables seen in Fig.1 were considered in the optimization process of the cantilever retaining wall. In accordance with the geometry of the wall, geometric design factors were selected, and structural design variables were modeled in relation to the critical sections of the wall. The variables X_1, X_2, X_3, X_4, and X_5 represent the width of the foundation, width of the toe, stem thickness at the bottom, stem thickness at the top, and foundation thickness respectively. Additionally, expressions of the reinforcements of the wall are R_1: vertical reinforcement area, R_2: the horizontal reinforcement area of the foundation, and R_3: the horizontal reinforcement area of the heel per unit length of the wall.

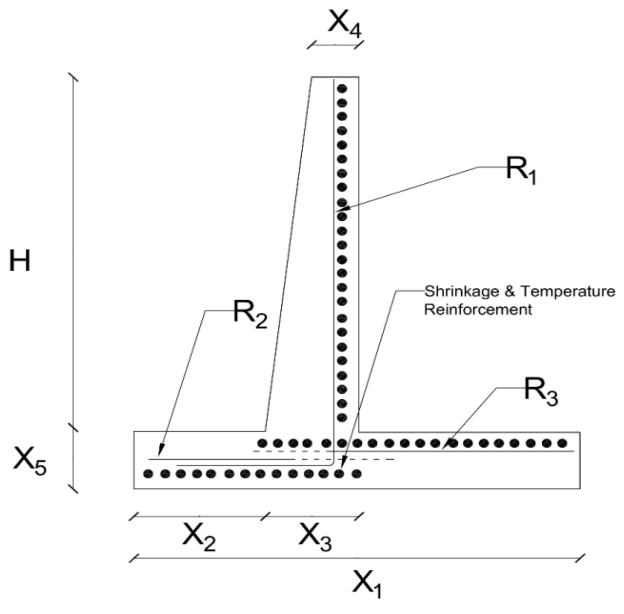


Figure 1. Design variables of the wall considered for the optimization process

The rebar used in the reinforcement design was limited to a range of 3 to 28 units in each direction, with diameters between 10 and 30. All possible cross-sections in this range that exceeded a total cross-sectional area of 127.42 cm^2 were excluded. In this context, a total of 264 cross-sections were used within the scope of optimization. The reinforcement pool prepared considering the abovementioned method is presented in Table 1.

Table 1. Reinforcement variable pool

Reinforcement index	Number of rebar	Bar size (mm)	Total steel area (cm^2)
1	3	10	2.356
2	4	10	3.141
3	3	12	3.393
4	5	10	3.927
.	.	.	.
.	.	.	.
.	.	.	.
131	14	18	35.626
132	18	16	36.191
133	8	24	36.191
134	24	14	36.945
.	.	.	.
.	.	.	.
.	.	.	.
261	20	28	123.150
262	28	24	126.669
263	18	30	127.234
264	24	26	127.423

2.1.1. Geotechnical modeling

Loads considered in the checks were presented in Fig. 2. In the context of the study following notation was assumed. W_S: weight of the wall, W_B: Weight of the soil block above the heel, Q_{SU}: Surcharge load, P_A: Active earth thrust actin on the soil block above the heel, P_B: Resultant of the base pressure, Pp_1: Passive earth thrust actin on the foundation, and Pp_2: Passive earth thrust acting on the stem of the wall. The plain-strain condition was supposed to simplify the problem. Therefore, loads per unit length of the wall were taken into account in the analyses.

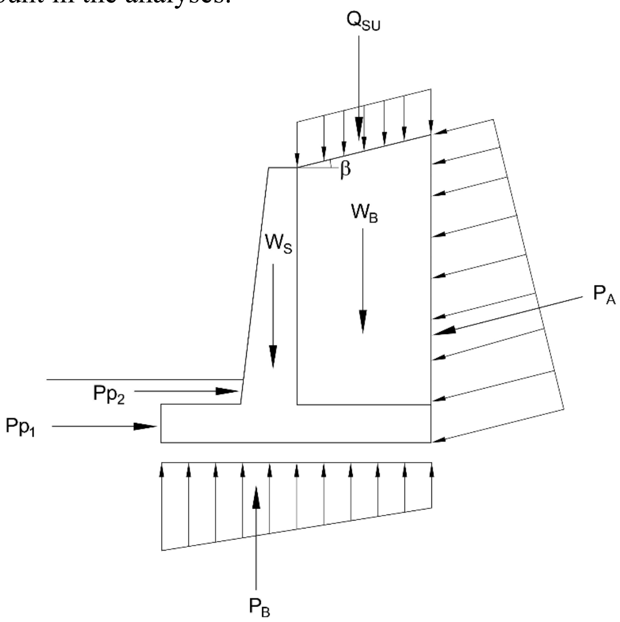


Figure 2. The thrusts considered in the optimization process

Active and passive lateral earth thrusts acting on the wall were calculated with Rankine Theory [21]. Active and passive earth pressure coefficients used for earth thrust calculations were obtained with Eq.(3) and Eq.(4) respectively. In the equations, the backfill inclination angle was represented with β and the internal friction angle of the backfill was represented with ϕ.

$$K_a = \frac{\cos\beta\left(\cos\beta - \sqrt{(\cos\beta)^2 - (\cos\phi)^2}\right)}{\cos\beta + \sqrt{(\cos\beta)^2 - (\cos\phi)^2}} \tag{3}$$

$$K_p = \left[\tan\left(45 + \phi/2\right)\right]^2 \tag{4}$$

Overturning, sliding, and bearing capacity checks are the major components required to control the external stability of the wall. Safety factors were taken into account in the checks. The safety factor for overturning was determined by dividing the sum of the moments of driving force (ΣMD) by the sum of the moments of resisting force (ΣMR) (Eq.5). The moments about the front face of the toe were considered in the analyses.

$$F_{so} = \frac{\Sigma M_R}{\Sigma M_D} \tag{5}$$

Eq.(6) was used in the sliding checks. F_{SS} representing the safety factor for sliding was determined by dividing the resisting forces (ΣF_R) into driving forces (ΣF_D). Resisting forces and driving forces were determined with Eq.(7), Eq.(8), and Eq.(9). In calculation of the resisting force (Eq.(7)), strength parameters of the base soil (ϕ_{base}, c_{base}) were taken into account. On the other hand, the strength parameters of the backfill soil were considered in the determination of the driving force (Eq.(8)). Passive earth thrusts acting on the foundation and the stem were determined using Eq.(10). The term D_1 is the depth between foundation base and the soil surface that leads to passive earth pressure.

$$F_{ss} = \frac{\Sigma F_R}{\Sigma F_D} \tag{6}$$

$$\Sigma F_R = (\Sigma N)\tan\left(2/3\,\phi_{base}\right) + \frac{2}{3}Bc_{base} + P_p \tag{7}$$

$$\Sigma F_D = P_A \cos\beta \tag{8}$$

$$\sum N = W_S + W_B + Q_{SU} + P_{a1y} + P_{a2y} \tag{9}$$

$$Pp = P_{p1} + P_{p2} = \frac{1}{2}\gamma_{fill} D_1^2 K_P + 2cD_1^2\sqrt{K_P} \tag{10}$$

The ultimate bearing capacity of the base soil and maximum pressure applied from the foundation was calculated as follows for the bearing capacity check.

$$F_{SB} = \frac{q_u}{q_{\max}} \tag{11}$$

Eq.(12) was used to determine the ultimate bearing capacity of the base soil. The Terzaghi ultimate bearing capacity theory [22] suggested for strip foundations was used to determine the qu value. Due to the backfill, the foundation of the wall is subjected to eccentric load. This leads to a decrease in the ultimate bearing capacity of the base soil and therefore it is required to revise Eq.(12). For that purpose, Meyerhof's Effective Area Method [23] was applied by reducing foundation width by twice the eccentricity (B-2e).

$$q_u = c_{base} N_c + \gamma_{fill} D_1 N_q + \frac{1}{2}\gamma_{base} N_\gamma \left(B - 2e\right) \tag{12}$$

Maximum and minimum pressure exerted from the foundation was calculated with Eq.(13). Eccentricity was calculated with Eq.(14). In the equation overturning moment was represented with M_O, the resisting moment was represented with M_R, and the total axial load was represented with ΣV.

$$q_{\min,\max} = \frac{\Sigma V}{B}\left(1 \pm \frac{6e}{B}\right) \tag{13}$$

$$e = \frac{\Sigma M_R - \Sigma M_O}{\Sigma V} \tag{14}$$

2.1.2. Structural modeling

Shear and moment capacity checks were performed for internal stability. Critical sections of the wall such as the heel, toe, and stem were taken into account in the checks. The study considered the parameters specified in Equation (15), where M_n represents the nominal flexural strength, E_s denotes the reduction factor, and M_d represents the design moment for the critical section, which is determined through the application of factored loads and forces.

$$E_s M_n \geq M_d \tag{15}$$

The strength reduction factor was assumed to be 0.9 considering the ACI 318-05 for tension controlled sections. Equations (16), (17), and (18), where T is the tension force acting on the nodal zone and C is the compression force acting on the nodal zone, were included in the calculation of M_n. Where f_y is the reinforcement's yield strength and is area, f_c is the compression strength of the concrete The stress block's width is denoted by b, its effective depth by d, and its equivalent rectangular stress block's depth by a.

$$M_n = T\left(d - \frac{a}{2}\right) \tag{16}$$

$$T = A_s f_y \tag{17}$$

$$C = 0.85 f_c b a \tag{18}$$

Eq.(21) was derived from Eq.(19) and (20). The equation was used to calculate the depth of the equivalent rectangular stress block (a) where c is the distance from the extreme compression bar to the neutral axis and β_1, is a factor based on f_c.

$$a = \beta_1 c \tag{19}$$

$$A_s f_y = 0.85 f_c b a \tag{20}$$

$$a = \frac{A_s f_y}{0.85 f_c b} \tag{21}$$

The creteria given in Eqs. (22), and (23) were considered in shear capacity design based on ACI 318-05 code.

$$E_s V_n \geq V_d \tag{22}$$

$$V_n = E_s 0.17\sqrt{f_c}bd \tag{23}$$

Shear and moment strengths of the structure of the stem, toe, and heel were determined separately by taking into account the load factors given in Eqs. (24) and (25) where D, L, and H represent dead load, live load, and earth thrust exerted by earth pressure and groundwater pressure respectively.

$$U = 1.4D + 1.7L + 1.7H \tag{24}$$

$$U = 0.9D + 1.7H \tag{25}$$

The stem's shear and moment strengths were calculated using Equations (26-29). L_h is the foundation slab's heel portion, and cc is the depth of the concrete cover in Equations (28 and 29). The critical section of the toe, d_s, is given in Eq. (29) and is situated at dt(X_5-cc) distant from the wall.

$$Md_{stem} = 1.7\left[qK_a\cos\beta\frac{\left(H_s+H\right)^2}{2} + K_a\gamma_{fill}\cos\beta\frac{\left(H_s+H\right)^3}{6}\right] \tag{26}$$

$$Vd_{stem} = 1.7\left[qK_a\cos\beta\left(H_s+H-ds\right) + K_a\gamma_{fill}\cos\beta\frac{\left(Hs+H-ds\right)^2}{2}\right] \tag{27}$$

$$H_s = \left(L_h\right)\tan\beta \tag{28}$$

$$ds = X_5 - cc \tag{29}$$

The shear and moment strength calculations for the toe were performed with Eqs. (30) and (31). In the equations D is the depth of soil above the toe. l_{toe} is the length of the toe q_2, q_{dt}, q_{max} and q_{min} were determined from the pressure distribution emanating from the foundation base. q_2 is the pressure acting on the intersection of stem and toe, and q_{dt} is the soil pressure at the critical section of the toe.

$$Md_{toe} = \left[1.7\left(\frac{q_2}{6}+\frac{q_{\max}}{3}\right) - 0.9\left(\gamma_c X_5 + \gamma_{fill}D\right)\right]t_{toe}^2 \tag{30}$$

$$Vd_{toe} = \left[1.7\left(\frac{q_{dt}+q_{\max}}{2}\right) - 0.9\left(\gamma_c X_5 + \gamma_{fill}D\right)\right]\left(l_{toe}-dt\right) \tag{31}$$

The shear and moment strength calculations for the heel were performed with Eqs. (32) and (33). In the equations q_1 was determined from the pressure distribution of the foundation. The pressure on the intersection of the heel and stem was considered as q_1. Wbs is triangular backfill mass above the stem. W_{bsdh} is the backfill mass of the critical section

$$Md_{heel} = \left[\left(\frac{1.7q+1.4\gamma_c X_5+1.4\gamma_{fill}H}{2}\right) + \left(\frac{1.4W_{bs}}{3}\right) + \left(\frac{q_1+2q_{\min}}{6}\right)\right]L_H^2 \tag{32}$$

$$Vd_{heel} = \left[\left(1.7q+1.4\gamma_c X_5+1.4\gamma_{fill}H\right) + 1.4\left(\frac{W_{bs}+W_{bsdh}}{2}\right) - 0.9\left(\frac{q_{dh}+q_{\min}}{2}\right)\right]\left(L_h-dh\right) \tag{33}$$

The minimum area of flexural reinforcement and minimum steel reinforcement ratio were determined with Eqs. (34) and (35) considering the ACI 318–05.

$$As_{\min} = 0.25\frac{\sqrt{f_c}}{f_y}bd \tag{34}$$

$$\rho = \frac{As}{bd} \tag{35}$$

The following formulations were used to determine the reinforcement ratio (ρ_b), development length (l_d), and development length of a standard hook (l_{dh}).

$$\rho_b = \left[\frac{0.85\beta_1 f_c}{f_y}\right]\left[\frac{600}{600+f_y}\right] \tag{36}$$

$$l_d = \left(\frac{12 f_y \psi_t \psi_e \lambda}{25\sqrt{f_c}}\right)d_b \rightarrow d_b \leq 19mm \tag{37}$$

$$l_d = \left(\frac{12 f_y \psi_t \psi_e \lambda}{20\sqrt{f_c}}\right)d_b \rightarrow d_b > 19mm \tag{38}$$

$$l_{dh} = \left(\frac{0.24 f_y}{\sqrt{f_c}}\right)d_b \tag{39}$$

3. Constraints

It is necessary to search a limited area for potential optimization problem solutions. The structural and geotechnical design constraints were established, and together these make up the search spaces[9]**.** In the context of the study, a total of 25 constraints were used in the optimization process**.** The constraints of the study can be classified into two subcategories: geotechnical constraints and structural constraints.

3.1. Geotechnical constraints

In the geotechnical constraints, factors of safety against slippage, overturning, and bearing capacity were considered. In this section, the constraints are expressed as follows in comparison with the design factors to avoid any collapse in the foundation soil.

$$g(1) = \frac{F_{SO_{design}}}{F_{S_O}} - 1 \leq 0 \tag{40}$$

$$g(2) = \frac{F_{SS_{design}}}{F_{S_S}} - 1 \leq 0 \tag{41}$$

$$g(3) = \frac{F_{SB_{design}}}{F_{S_B}} - 1 \leq 0 \tag{42}$$

3.2. Structural constraints

Components of a retaining wall have to fulfill the necessary requirements for reinforcing, moment, and shear capability. The following constraints were used to sustain internal integrity.

$$g(4) = q_{\min} - 1 \leq 0 \tag{43}$$

$$g(5-8) = \frac{M_d}{M_n} - 1 \leq 0 \tag{44}$$

$$g(9-12) = \frac{V_d}{V_n} - 1 \leq 0 \tag{45}$$

$$g(13-16) = \frac{A_{S_{\min}}}{A_S} - 1 \leq 0 \tag{46}$$

$$g(17-20) = \frac{A_S}{A_{S_{\max}}} - 1 \leq 0 \tag{47}$$

$$g(21) = \frac{X_2 + X_3}{X_1} - 1 \leq 0 \tag{48}$$

$$g(22) = \frac{X_6 + X_7}{X_1} - 1 \leq 0 \tag{49}$$

$$g(23) = \frac{l_{db_{stem}}}{X5 - cc} - 1 \leq 0 \text{ or } g(23) = \frac{l_{dh_{stem}}}{X5 - cc} - 1 \leq 0 \tag{50}$$

$$g(24) = \frac{l_{db_{toe}}}{X_1 - X_2 - cc} - 1 \leq 0 \text{ or } g(24) = \frac{12 l_{dh_{toe}}}{X_5 - cc} - 1 \leq 0 \tag{51}$$

$$g(25) = \frac{l_{db_{heel}}}{X_2 + X_3 - cc} - 1 \leq 0 \text{ or } g(25) = \frac{l_{dh_{heel}}}{X_5 - cc} - 1 \leq 0 \tag{52}$$

4. Improved Teaching-Learning Based Optimization Algorithm with Agents

The Teaching-Learning-Based Optimization (TLBO) algorithm is an optimization algorithm based on the process of students in a classroom interacting with each other to improve themselves [1, 24]. The algorithm consists of two main phases. In the first phase, the individual with the best objective function value in the population tries to improve other individuals. Individuals that show improvement in terms of the objective function are updated. In the second phase, individuals in the population engage in one-to-one interactions, striving for improvement. At this point, the individuals that show progress are updated to enhance the population. This algorithm has been tested in various optimization problems and has shown highly effective results in the context of structural optimization [2-5]. In many studies, the TLBO mechanisms have demonstrated excellent results, particularly in terms of convergence. The local optimum avoidance mechanisms of population-based algorithms are important for the results obtained. This study aims to enhance the TLBO algorithm, in this respect. When the algorithm gets stuck at the local optimum, it is usually due to the population clustering around a particular solution. Therefore, it is useful to have a mechanism for the algorithm to move out of this clustering area. There are numerous studies developed in this regard [3, 6]. In this study, a local optimum avoidance approach suitable for the problem is developed. Before activating the developed mechanism, the algorithm tries to find out whether it is stuck at the local optimum. This decision is determined as no improvement of the best solution over a predetermined number of generations. For this problem, this number was set to 10 generations. Then the mechanism switches on and replaces all individuals in the population with new individuals whose parameters are randomly determined, except for the best solution. These new individuals injected into the algorithm are identified as agents and the activation of the mechanism is tracked by the variable "agentcounter". Once the agents have been activated, the variable is reset to zero and the algorithm starts following the course of the algorithm again. The flowchart of this improved version of the TLBO algorithm is shown in Figure 3. The boundary values of the parameters for the optimization process are presented in table x.

Table 2. Boundries of the parameters [7]

Design variable	Lower Bound	Upper Bound
X1	1.3090 m	2.3333 m
X2	0.4363 m	0.7777 m
X3	0.2000 m	0.3333 m
X4	0.2000 m	0.3333 m
X5	0.2722 m	0.3333 m
R1	Index: 1 | 2.356 cm^2	Index: 264 | 127.423 cm^2
R2	Index: 1 | 2.356 cm^2	Index: 264 | 127.423 cm^2
R3	Index: 1 | 2.356 cm^2	Index: 264 | 127.423 cm^2

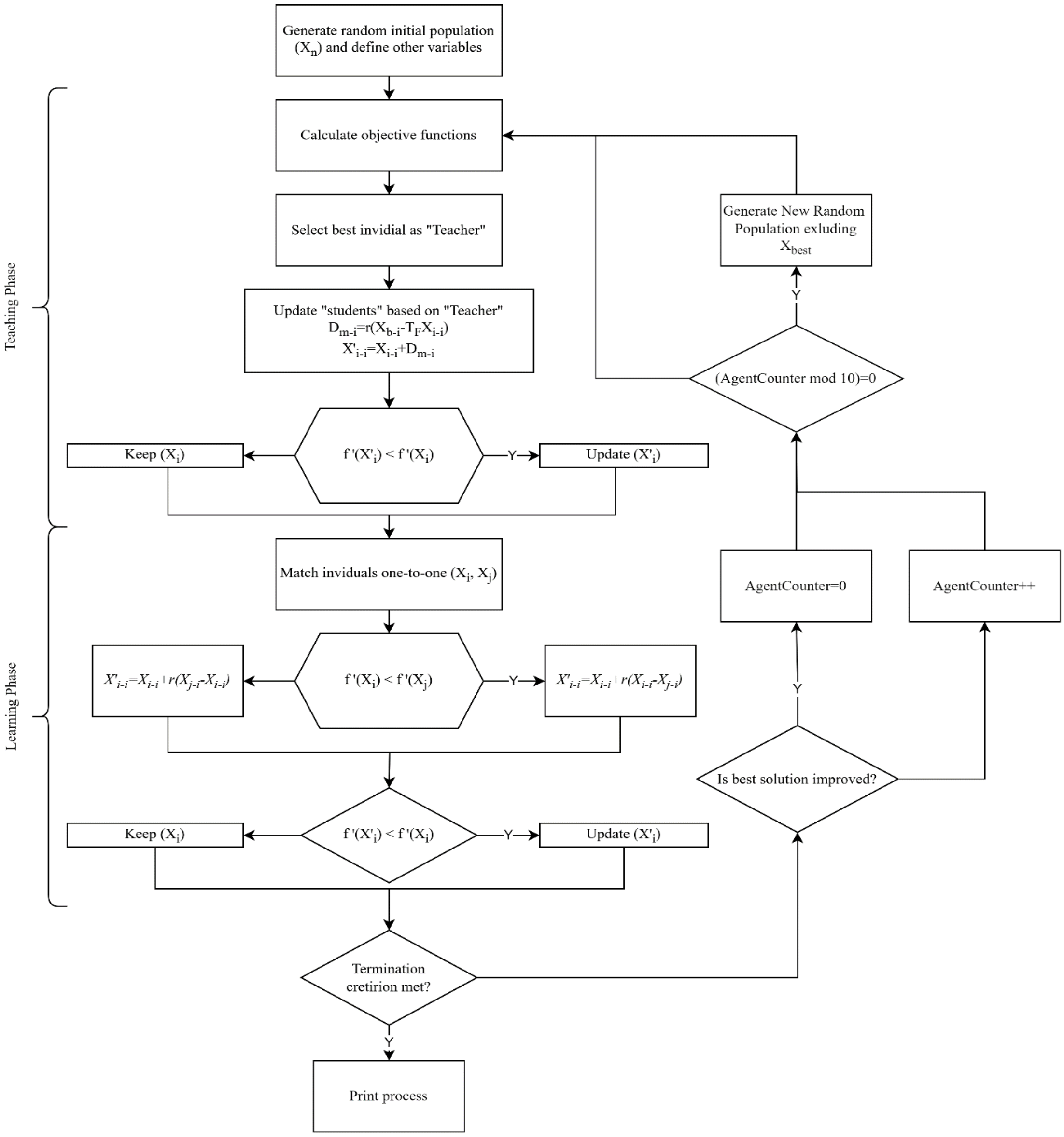


Figure 3. Flowchart of the I-TLBO with agents

A numerical example used by several studies [6, 9, 11, 25] was taken into account to evaluate the efficiency of the suggested algorithms. Table 3 displays the design parameters and wall measurements taken into account in the numerical example. The parameters in the Table 3 represents a case used in the optimizing the cantilever retaining wall. Field or laboratory tests were not performed to obtain the parameters.

Table 3. Parameters considered for the example [9]

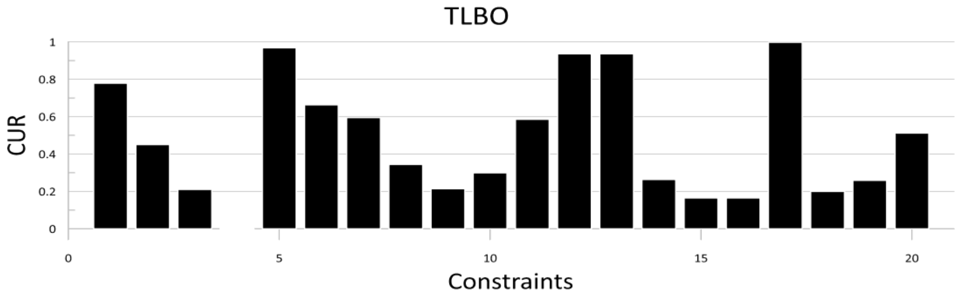
Input parameters	Symbol	Value	Unit
Height of stem	H	3	m
Steel reinforcement yield strength	f_y	400	MPa
Compressive strength of concrete	F_c	21	MPa
Concrete cover	cc	7	cm
Shrinkage and temperature reinforcement percentage	ρ_{st}	0.002	-
Surcharge load	Q	20	kPa
Backfill slope	B	10	°
Internal friction angle of base soil	ϕ_{base}	0	°
Internal friction angle of retained soil	ϕ	36	°
Unit weight of retained soil	γ_{fill}	17.5	kN/m^3
Unit weight of base soil	γ_{base}	18.5	kN/m^3
Unit weight of steel	Gs	78.5	kN/m^3
Unit weight of concrete	γ_c	23.5	kN/m^3
Depth of soil in front of the wall	D	0.5	m
Cost of steel	Cs	0.4	$/kg
Cost of the concrete	Cc	40	$/kg
The factor of safety for overturning stability	FSO_{design}	1.5	-
The factor of safety for sliding	FSS_{design}	1.5	-
The factor of safety for bearing capacity	FSB_{design}	1.5	-
The base soil's cohesiveness	c_{base}	125	kPa

The performance of TLBO was evaluated by several studies in the literature [26, 27]. In the study, TLBO was separately applied with both the traditional version and the version developed in this study for the two objective functions mentioned. As a result, four different optimization processes were planned. For each process, the stopping criterion of the algorithm was set as not improving the current best solution for 50 iterations. Each process was run five times, and the variable values and outcomes of the best solutions obtained were presented in Table 4.

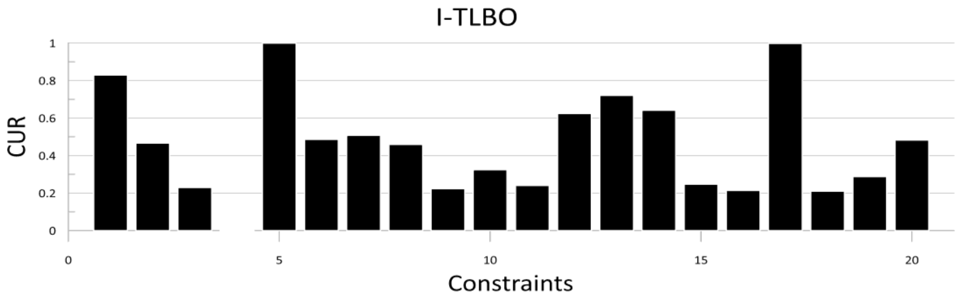
Table 4. Results of optimization processes.

	Best-Weight		Best-Cost	
	TLBO	I-TLBO	TLBO	I-TLBO
X_1	1.67	1.60	1.72	1.66
X_2	0.57	0.59	0.60	0.53
X_3	0.21	0.21	0.28	0.30
X_4	0.20	0.20	0.23	0.20
X_5	0.28	0.28	0.28	0.28
R_1	78	76	38	76
R_2	120	33	17	33
R_3	76	28	17	28
Best	2659.714 (kg)	2627.293 (kg)	74.8866 ($)	72.0398 ($)
Mean ± Std.D.	2779.05 ± 53.60	2694.69 ± 24.97	81.35 ± 2.62	75.36 ± 1.11

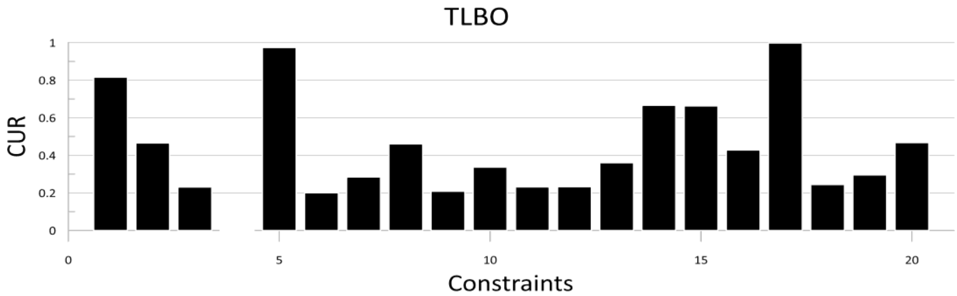
As can be seen, the improved version of the algorithm has produced better results in terms of both average and best values for both objective functions. The capacity utilization ratios (CUR) values were used to show the extent to which the algorithm is proportionally challenging the constraints to which it is subjected. In this way, it is tried to show how effective the optimization algorithm produces effective results from a different perspective in terms of the problem. The capacity utilization ratios of the obtained optimal designs in terms of constraints for each combination are presented in Figure 4. As can be seen in Figures 4a and 4b, where the CUR values for the weight-optimized designs are presented, the improved version of TLBO uses limiters with a higher capacity. The corresponding utilization ratios are on average 0.427 for TLBO and 0.459 for I-TLBO. It can be seen from Figs. 4c and 4d, the same is true for the optimization process for the best cost. In this context, the average CUR values are 0.476 for TLBO and 0.484 for I-TLBO. Therefore, it can be argued that for both optimization processes, the improved version of the TLBO algorithm pushes the bounding capacities to a higher extent than the original version.



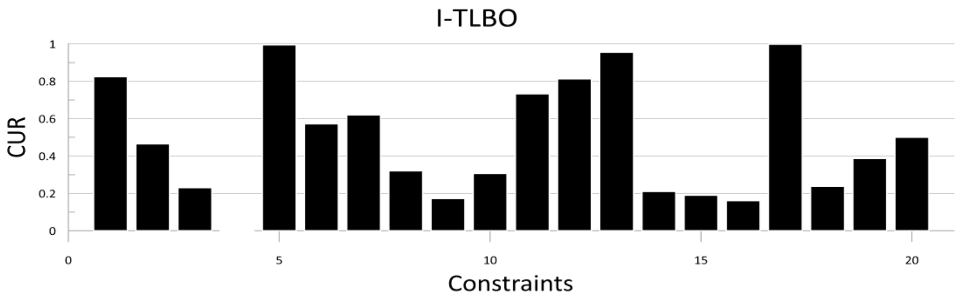
(a)



(b)



(c)



(d)

Figure 4. Capacity utilization ratios (CUR) of best solutions (a) TLBO-Best weight, (b) I-TLBO-best weight (c) TLBO-Best cost, (d) I-TLBO-Best cost

It can be observed that the improved TLBO approach brings the constraint capacities closer to their limits compared to the traditional version. Additionally, the convergence curves of the two algorithms used separately for each objective function are provided in Figs. 5 and 6 throughout the process.

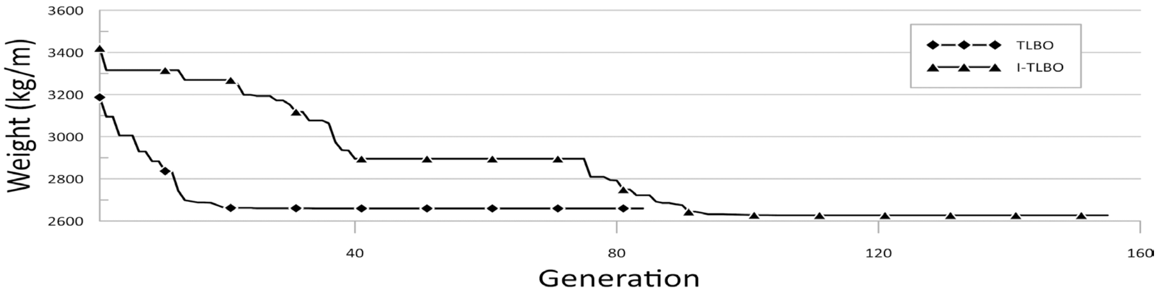


Figure 5. Convergence history for weight optimization

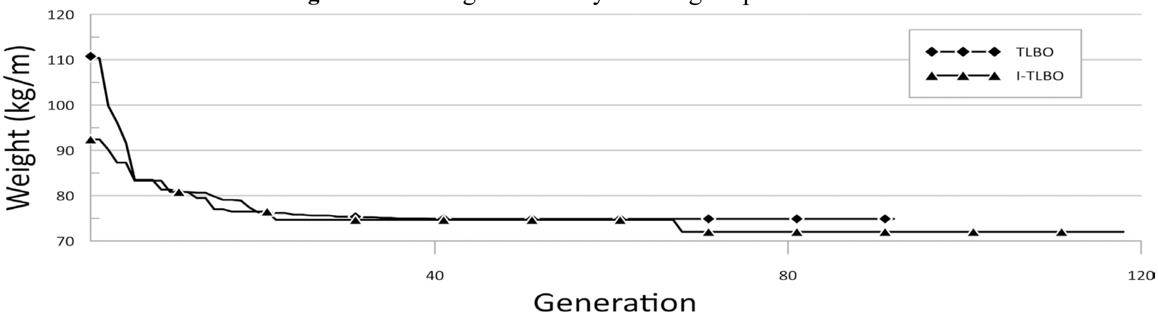


Figure 6. Convergence history for cot optimization

The wall's dimension (X_1-X_5) and the sections of reinforcements (R_1-R_3) of the reinforcements used in the wall were considered design variables. The optimum values of the X and the R variables were determined with TLB and I-TLBO algorithms based on minimum weight and minimum cost. In Table 5 and Table 6, the optimum values determined by TLBO and I-TLBO algorithms are compared with other algorithms in the literature. Grey Wolf Optimization (GWO) [9], Search Group Algorithm (SGA) and Backtracking Search Algorithm (BSA) [29], Big Bang–Big Crunch Algorithm (BB-BC) [6], Genetic Algorithm (GA) [11], Differential Evolution (DE), Evolutionary Strategy (ES), Biogeography Based Optimization Algorithm (BBO), Differential Evolution (DE), Evolutionary Strategy (ES), Biogeography Based Optimization Algorithm (BBO), Interior Search Algorithm (ISA) [30], Particle Swarm Optimization (PSO), Accelerated Particle Swarm Optimization (APSO) [28] were evaluated in the comparison. As can be seen from Table 5, TLBO algorithms yielded significantly lower dimensions than the other approaches, especially in X_1, X_2, and X_3 dimensions. As a result of the evaluation between TLBO and I-TLBO algorithms, it is seen that the I-TLBO algorithm gives a lower dimension for the X_1 dimension, and the TLBO algorithm gives a lower dimension for the X_2 dimension.

Table 5. Low-weight design variables determined with various optimization approaches

	X_1	X_2	X_3	X_4	X_5	R_1	R_2	R_3
TLBO (This study)	1.67	0.57	0.21	0.20	0.28	78	120	76
I-TLBO (This study)	1.60	0.59	0.21	0.20	0.28	76	33	28
GWO	1.80	0.67	0.21	0.20	0.28	82	15	15
SGA	1.71	0.65	0.20	0.20	0.27	77	23	17
BSA	1.71	0.64	0.20	0.20	0.27	77	14	14
BB-BC	1.74	0.65	0.20	0.20	0.27	77	17	17
ISA	1.84	0.75	0.39	0.20	0.27	34	15	15
DE	1.87	0.62	0.29	0.20	0.27	34	19	16
GA	1.91	0.58	0.27	0.20	0.28	50	21	15
BBO	1.84	0.74	0.27	0.20	0.27	37	14	14
ES	1.84	0.69	0.32	0.22	0.28	26	22	29
APSO	1.84	0.57	0.27	0.20	0.27	40	28	17
PSO	1.84	0.74	0.29	0.20	0.27	33	14	14

The mean and best objective function values for the algorithms are displayed in Table 6. It is seen from the table that TLBO algorithms are among the algorithms that give the lowest weight value. As a result of the comparison between TLBO and I-TLBO algorithms, it is seen that the I-TLBO algorithm provides a lower-weight design.

Table 6. Comparison of low-weight design results (kg/m)

	Best	Mean
TLBO (This study)	2659.714	2779.05 ± 53.60
I-TLBO (This study)	2627.293	2694.69 ± 24.97
GWO	2721.7915	2748.7809
SGA	2584.46	2589.00
BB-BC	2608.38	-
ISA	2665.8027	2677.5681
GA	2744.80	2850.90
DE	2726.50	2851.00
ES	2762.40	2845.00
BBO	2665.80	2677.70
PSO	2665.80	2687.60
APSO	2668.00	2687.60
FA	2666.50	2673.40
CS	2665.80	2665.80

The optimum values of the X and the R variables determined with low-cost design objective function were presented in Table 7. In this section, the cost-based performances of TLBO algorithms were compared with algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), Evolutionary Strategy (ES), and Biogeography Based Optimization (BBO) [28]. From Table 7, it is seen that TLBO algorithms offer lower cross-sections than the other algorithms especially for X_1 and X_2. As a result of the comparison between I-TLBO and TLBO algorithms, it is seen that lower values are obtained with the I-TLBO algorithm.

Table 7. Low-cost design variables determined with various optimization approaches ($/m)

	X_1	X_2	X_3	X_4	X_5	R_1	R_2	R_3
TLBO (This study)	1.720	0.600	0.280	0.230	0.280	38	17	17
I-TLBO (This study)	1.660	0.530	0.300	0.200	0.280	76	33	28
GA	1.91	0.586	0.272	0.201	0.280	40	21	15
DE	1.872	0.616	0.290	0.206	0.271	34	19	16
ES	1.845	0.691	0.320	0.221	0.280	26	22	29
BBO	1.842	0.737	0.277	0.200	0.270	91	36	44

Table 8 presents the final low-cost design objective function values, including the best, mean, and SD values. As shown in the table, the best low-cost design was achieved by the I-TLBO algorithm with the best of $72.0398/m. When the mean values are considered, it is seen that the I-TLBO algorithm offers the lowest cost design after the BBO algorithm. On a cost basis, the I-TLBO algorithm suggests a significantly lower cost design compared to the TLBO algorithm.

Table 8. Comparison of design cost for the example ($/m)

	Best	**Mean**
TLBO (This study)	74.8866	81.35 ± 2.620
I-TLBO (This study)	72.0398	75.36 ± 1.110
GA	77.6300	82.16 ± 1.600
DE	75.4900	82.23 ± 1.673
ES	78.0700	81.71 ± 1.308
BBO	73.0800	73.91 ± 0.827

5. Conclusions

This study intended to optimize the design of reinforced concrete cantilever retaining walls using the Teaching-Learning-Based Optimization (TLBO) algorithm and an improved version of TLBO called I-TLBO. The design objectives were to minimize the weight and the cost of the retaining wall while satisfying various geotechnical and structural constraints. The optimization process involved determining optimal values for design variables related to wall dimensions and reinforcement areas. Key conclusions drawn from the study are as follows:

- The TLBO algorithms, both the traditional version and I-TLBO, outperformed other optimization algorithms in terms of achieving lower weights and costs for the retaining wall design.
- The I-TLBO algorithm provided better results in terms of both mean and best values for both the weight and cost optimization objectives.
- Both TLBO algorithms, especially I-TLBO, brought the constraint capacities closer to their limits compared to the traditional version, indicating improved constraint satisfaction.
- The convergence history of the algorithms showed that I-TLBO converged faster and achieved better solutions compared to the traditional TLBO, highlighting the effectiveness of the introduced improvements.

In summary, the study demonstrated that the I-TLBO algorithm, an improved version of the TLBO algorithm, is highly effective for optimizing the design of reinforced concrete cantilever retaining walls. It consistently provided better results in terms of both weight and cost optimization compared to other algorithms considered in the study. While the study shows promise for I-TLBO, it would be beneficial to compare its performance with other well-established optimization algorithms for retaining wall design problems. This would provide a broader perspective on its effectiveness.

6. Credit Authorship Contribution Statement

Bilal Tayfur: Investigation, Conceptualization, Data analysis, Validation; Hakan Alper Kamiloğlu: Methodology, Investigation, Writing, Review and editing.

7. Ethics Committee Approval and Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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