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Teaching learning-based optimization for design of cantilever retaining walls

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Abstract. A methodology based on Teaching Learning-Based Optimization (TLBO) algorithm is proposed for optimum design of reinforced concrete retaining walls. The objective function is to minimize total material cost including concrete and steel per unit length of the retaining walls. The requirements of the American Concrete Institute (ACI 318-05-Building code requirements for structural concrete) are considered for reinforced concrete (RC) design. During the optimization process, totally twenty-nine design constraints composed from stability, flexural moment capacity, shear strength capacity and RC design requirements such as minimum and maximum reinforcement ratio, development length of reinforcement are checked. Comparing to other nature-inspired algorithm, TLBO is a simple algorithm without parameters entered by users and self-adjusting ranges without intervention of users. In numerical examples, a retaining wall taken from the documented researches is optimized and the several effects (backfill slope angle, internal friction angle of retaining soil and surcharge load) on the optimum results are also investigated in the study. As a conclusion, TLBO based methods are feasible.

Keywords: cantilever retaining wall; reinforced concrete structures; Teaching-Learning Based Optimization (TLBO); optimum design

1. Introduction

Engineering design can be defined as an optimization process considering certain objectives such as stability, strength capacities, displacements, weight, etc., by designer. Additionally, designers also try to find design with minimum cost. In engineering computations, numerical and analytical methods have been used for finding the extreme value. Although being suitable in many cases, these methods can be inadequate for complex or nonlinear problems. For example, reinforced concrete design contains the mechanical behavior of two different materials. The concrete section dimensions and the amount of steel reinforcements are both optimized. For that reason, the design of RC members is a nonlinear problem and existing of design constraints leads us to use iterative methods like metaheuristics.

Metaheuristic algorithms, such as Genetic algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Big Bang-Big Crunch (BBBC), Harmony Search (HS), Firefly Algorithm (FA), Bat Algorithm (BA), etc., are developed from the inspiration of natural

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phenomena. GA inspired from evolutionary concepts of natural selection of Darwin's theory (Holland 1975, Goldberg 1989), PSO imitates the social behavior of animals, i.e. flocking of birds, schooling of fish *inter alia* (Kennedy and Eberhart 1995), ACO uses the behavior of ants in seeking the most suitable route between their nest and food source (Dorigo *et al.* 1996), BBBC relies on the well-known theory of evolution of the universe (Erol and Eksin 2006), HS implements the musical process searching a perfect state of harmony that admire the audience (Geem *et al.* 2001), FA conceptualizes the flashing characteristic of fireflies during the search of prey and mates (Yang 2009), BA mimics the impressive echolocation characteristic of micro bats used for hunting and distinguishing types of insect (Yang 2010).

Recently, Rao *et al.* (2011) has been proposed an innovative metaheuristic algorithm conceptualized teaching-learning process in a classroom and considering the inspiration, called Teaching Learning-Based Optimization (TLBO) algorithm. TLBO algorithm considers both teacher's influences on learners and interaction between learners by employing an iterative process to improve the knowledge of the learners as well as the whole class. Thus, TLBO can be divided into two main components; teacher and learner phase. The knowledge and teaching ability of a teacher is consisted the "teacher phase" and sharing information, cooperation and interaction each other is consisted the "learner phase".

Although being relatively new, TLBO algorithm has been successfully applied to many engineering optimization problems. TLBO algorithm is firstly performed on some mechanical design optimization problems by Rao *et al.* (2013). Then, TLBO is employed for optimization of planar steel frames and in order to prove the effectiveness of algorithm, the result are also compared with GA, ACO, HS and improved ACO (Toğan 2012). TLBO algorithm has been employed in electric power generators under different objectives such as energy cost, emission, electrical energy losses, voltage deviations, etc. (Azizipanah-Abarghooee *et al.* 2012, Niknam *et al.* 2012a, 2012b, 2012c). Cooling capacity and coefficient of performance cooler is taken as objectives to optimize thermo-electric cooler by Rao and Patel (2013). Optimum design of some structural engineering problems, i.e., truss systems, I-beams, grillage structures are done under weight, stress and deflection objectives (Toğan 2013, Dede and Ayaz 2013, Degertekin and Hayalioglu 2013, Zou *et al.* 2013, Yildiz 2013, Dede 2013, Camp and Farshchin 2014). Some other applications of TLBO are the optimal setting of power flow (Ghasemi *et al.* 2014, Bouchekara *et al.* 2014), design of X-bar control chart (Ganguly and Patel 2014), flow shop rescheduling problem (Li *et al.* 2015), optimal design of heat pipe (Rao and More 2015), optimum design of robot gripper (Rao and Waghmare 2015), minimizing carbon emission of machining systems (Lin *et al.* 2015), etc.

Reinforced concrete retaining walls are structures constructed for resisting soils between two different elevations. In the analyses and design of RC retaining walls, due to soil-structure interaction, the designer gets into many difficulties such as stability of overturning and sliding, stress limitation for soil to provide settlement of the foundation and also in design flexural moment capacity, shear capacity, minimum and maximum reinforcement area, steel bar spacing, development length for reinforcement *inter alia*.

In the structural design process, cost minimization and safety are two main goals that must be satisfied simultaneously. Although researches has conducted researches on the subject for many decades, because of consisting from two materials with very different mechanical properties and costs in global markets, the cost minimization of RC structures is still an active area. The optimization of the RC retaining wall, one of the major application areas, dates back to 1980s. In these studies, cost optimization has been done for investigation of optimal shape, structural

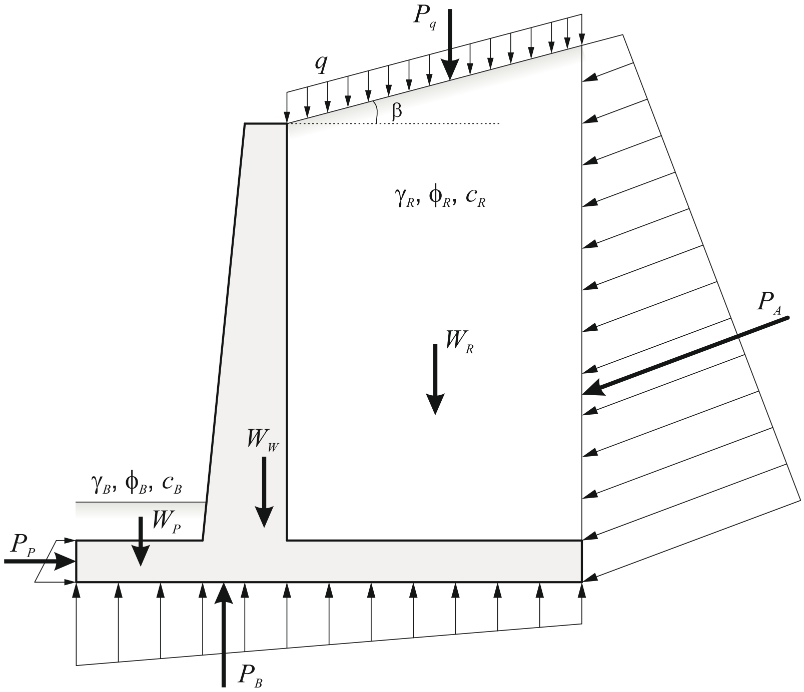

Fig. 1 Loads acting on a cantilever retaining wall

stability, bending moment minimization, optimum location (Rhomberg and Street 1981, Alshawi *et al.* 1988 Keskar and Adidam 1989, Dembicki and Chi 1989, Pochtman *et al.* 1988, Saribaş and Erbatur 1996, Chau and Albermani 2003, Sivakumar and Basha 2008). In addition to these studies, metaheuristic algorithms, including simulated annealing (Ceranic *et al.* 2001, Yepes *et al.* 2008), PSO (Ahmadi-Nedushan and Varaee 2009), HS (Kaveh and Abadi 2010), BBBC (Camp and Akin 2011), GA (Kaveh *et al.* 2013), FA (Sheikholeslami *et al.* 2014), charged system search (Talatahari and Sheikholeslami 2014) are also applied for optimum design of RC retaining walls. Being a challenging area due to various constraints involves from soil-structure interaction and RC design, in recent years, researches on retaining wall optimization using evolutionary algorithm are increasingly continues.

2. Design of retaining walls

A typical geometry and external loads used in the design of cantilever retaining walls can be seen in Fig. 1, where W_w, W_R and W_P respectively represent the weight of retaining wall, backfill on the heel and soil on toe; q is surcharge loads; P_A, P_P and P_B represent active earth pressure, passive earth pressure and bearing stress forces, respectively.

Common failure modes of retaining walls are overturning, sliding and bearing capacity. The safety factor for overturning SF_O can be defined as

$$SF_O = \frac{\sum M_R}{\sum M_O} \tag{1}$$

In Eq. (1), $\sum M_R$ is the sum of the moments that resist for overturning: moments resulting from surcharge loads, self-weight of the wall and the weight of backfill soil; $\sum M_O$ is the sum of the moments that overturn the system: moments resulting from active earth pressure. Generally, the effects of passive forces are not taken into consideration due to the possibility of removing of the soil. The active and passive loads are calculated by using active

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

and passive coefficient

$$k_p = \tan^2\left(45 + \frac{\theta}{2}\right) \tag{3}$$

given in Rankine theory. In Eqs. (2) and (3), β and θ are slope and internal friction angle of backfill. The safety factor of a failure mode for sliding is the ratio between the sum of resisting ($\sum F_R$) and sliding ($\sum F_D$) forces (Eq. (4)).

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

Resisting forces consist of the total weight of the wall, friction of the base soil and passive loads can be formulated as

$$\sum F_R = W_W \cdot \tan\left(\frac{2\cdot\phi_B}{3}\right) + \frac{2\cdot B\cdot c_B}{3} + P_P \tag{5}$$

and sliding forces which are the component of active forces can be written as

$$\sum F_D = P_A \cdot \cos\beta \tag{6}$$

In Eq. (5) and (6), $\sum W_w$ is total weight of the wall, ϕ_B is internal friction of the base soil, B is length of the base slab; c_{base} is adhesion of the soil below the base slab, P_a is active loads and

$$P_P = \frac{1}{2}\cdot\gamma_B\cdot D_1^2\cdot k_p + 2\cdot c_B\cdot D_1\cdot\sqrt{k_p} \tag{7}$$

where γ_B and D_1 are unit weight and depth of the soil, respectively. The ratio between ultimate bearing capacity (q_u) and maximum intensity of soil pressure (q_{max}) under the toe determines the safety factor of retaining wall for bearing failure (Eq. (8)).

$$SF_B = \frac{q_u}{q_{\max}} \tag{8}$$

By considering shallow foundation, the maximum ($q_{\max}$) and minimum ($q_{\min}$) intensity of soil stresses can be expressed as

$$q_{\substack{min\\max}} = \frac{\sum V}{B}\cdot\left(1 \pm \frac{6\cdot e}{B}\right) \tag{9}$$

where e is the eccentricity between moment (difference between the sum of resisting and overturning moments) and sum of vertical loads ($\sum V$) written as

$$e = \frac{B}{2} \cdot \frac{\sum M_R - \sum M_O}{\sum V} \tag{10}$$

2.1 Design variables

In the optimization problem, total eleven design variables were considered. These variables are related to cross-sectional dimension (X_1-X_5) (Fig. 2) and reinforcement design (X_6-X_{11}) of the retaining wall. In Table 1, description of variables can be seen.

2.2 Design constraints

Design process of retaining walls can be divided into two main stages; analysis and design. First, safety factors against failure modes are determined in the analysis and then, the reinforcement concrete requirements given in ACI 318-05 regulation are checked in design. The requirements of both stages can be expressed with

$$g_j(X) \le 0 \qquad j = 1, m \tag{11}$$

inequalities function that are directly or indirectly related to the design variable (Table 1) vector

$$X^T = \{X_1, X_2, ..., X_{11}\} \tag{12}$$

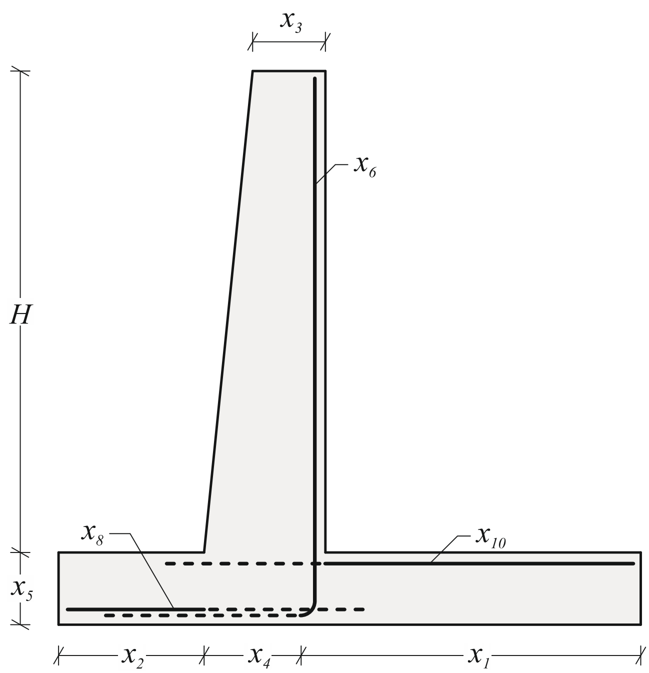

Fig. 2 Design variables for cantilever retaining wall

Table 1 Design variables

	Description	Design variable
Variables related to Cross-section dimension	Heel projection	X_1
	Toe projection	X_2
	Stem thickness at the top of the wall	X_3
	Stem thickness at the bottom of the wall	X_4
	Base slab thickness	X_5
Variables related to RC design	Diameter of reinforcing bars of stem, ϕ_s	X_6
	Distance between reinforcing bars of stem, S_s	X_7
	Diameter of reinforcing bars of the toe, ϕ_t	X_8
	Distance between reinforcing bars of the toe, S_t	X_9
	Diameter of reinforcing bars of the heel, ϕ_h	X_{10}
	Distance between reinforcing bars of the heel, S_h	X_{11}

In Eq. (11), m represents the number of design constraints given in Table 2. Reinforcement design is done only for critical sections (maximum internal forces) of stem, toe, and heel. In Table 2, the flexural moment, the shear force, the area of reinforcing bars, spacing between two bars, diameter of the bars are M_u, V_u, A_s and S and d_b, respectively.

The ACI 318 code allows using equivalent rectangular compressive stress distribution instead of parabolic or other stress distributions. By using this stress distribution, moment capacity of the cross-sections can be defined as

$$M_n = \phi \cdot A_s \cdot f_y \cdot \left(d - \frac{a}{2} \right) \tag{13}$$

where ϕ, is a strength reduction factor (ϕ=0.9). f_y is the yield strength of reinforcement. A_s is the area of longitudinal tension reinforcements and the ratio of that reinforcements must be less than that given by

$$\rho_{min} = 0.25 \cdot \frac{\sqrt{f_c}}{f_y} \geq \frac{1.4}{f_y} \tag{14}$$

and not less than

$$\rho_{min} = \frac{1.4}{f_y} \tag{15}$$

and must not be greater than $0.75\rho_b$ that written as

$$\rho_b = 0.85 \cdot \beta_1 \cdot \frac{f_c}{f_y} \cdot \left(\frac{600}{600 + f_y} \right) \tag{16}$$

These required reinforcements in sections must also satisfy the rules of minimum development length in order to provide the serviceability of RC member design. According to ACI-05 regulation, for deformed bars, development length (l_d) is defined as follows

Table 2 Constraints on strength and dimensions of wall

Description	Constraints
Safety for overturning stability	$g_1(X)$: $SF_{O,design} \geq SF_O$
Safety for sliding stability	$g_2(X)$: $SF_{S,design} \geq SF_S$
Safety for bearing capacity	$g_3(X)$: $SF_{B,design} \geq SF_B$
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, $A_{s\min}$	$g_{11\text{-}13}(X)$: $A_s \geq A_{s\min}$
Maximum reinforcement areas of critical sections, $A_{s\max}$	$g_{14\text{-}16}(X)$: $A_s \leq A_{s\max}$
Maximum steel bars spacing of critical sections, $S_{\max}$	$g_{17\text{-}19}(X)$: $S \leq S_{\max}$
Minimum steel bars spacing of critical sections, $S_{\min}$	$g_{20\text{-}22}(X)$: $S \geq S_{\min}$
Minimum concrete cover, c_c	$g_{23}(X)$: $c_c \geq 70$ mm
Sectional limits	$g_{24}(X)$: $(X_2 + X_3) \geq X_1$
	$g_{25}(X)$: $(X_6 + X_7) \geq X_1$
Reinforcement development lengths, l_{db} and hook lengths, l_{dh}	$g_{26}(X)$: $l_{db,stem} \geq (X_5\text{-}c_c)$ or $l_{dh,stem} \geq (X_5\text{-}c_c)$
	$g_{27}(X)$: $l_{db,toe} \geq (X_1\text{-}X_2\text{-}c_c)$ or $12d_{b,toe} \geq (X_5\text{-}c_c)$
	$g_{28}(X)$: $l_{db,heel} \geq (X_2+X_3\text{-}c_c)$ or $12d_{b,heel} \geq (X_5\text{-}c_c)$
	$g_{29}(X)$: $l_{db,key} \geq (X_5\text{-}c_c)$ or $l_{dh,key} \geq (X_5\text{-}c_c)$

$$l_d = \begin{cases} \left(\dfrac{f_y \cdot \psi_t \cdot \psi_e \cdot \lambda}{2.1 \cdot \sqrt{f_c}}\right) \cdot d_b \geq 300\,mm \quad for \;\; d_b < 19\,mm \\ \left(\dfrac{f_y \cdot \psi_t \cdot \psi_e \cdot \lambda}{1.7 \cdot \sqrt{f_c}}\right) \cdot d_b \geq 300\,mm \quad for \;\; d_b > 19\,mm \end{cases} \tag{17}$$

in which d_b represents the diameter of the bars. ψ_t, ψ_e and λ are the coefficients reflect the placement of reinforcements, the epoxy-coated or uncoated of reinforcements and lightweight or normal weight concrete (in this study, these coefficients is taken 1.0). If hooked reinforcement is used, the minimum hook length ($12d_b$) must be also provided.

In the Eq. (13), a is the depth of equivalent rectangular stress block that defined as β_1 times of the c; the depth of the neutral axis in compression section. The β_1 value, which is deepened on compressive strength of concrete (f'_c), can be written as

$$\begin{aligned} &\beta_1 = 0.85 \quad for \;\; 17\,MPa < f_c^{'} \leq 28MPa \\ &\beta_1 = max\left[0.85 - 0.0071428 \cdot \left(f_c^{'} - 28\right) \; and \;\; 0.65\right] \quad for \;\; f_c^{'} > 28\,MPa \end{aligned} \tag{18}$$

The shear strength of a reinforced section can be written as

$$V_n = \phi \cdot 0.17 \cdot \sqrt{f_c} \cdot b \cdot d \tag{19}$$

in which ϕ is a strength reduction factor (ϕ=0.75) and b is breadth of the section.

2.3 Objective function

The total material costs of concrete and reinforcing steel bars including costs of per unit volume/weight, transportation, workmanship installation, etc., are defined as objective function. Mathematically, this function can be written as

$$min\ f\left(X\right)=C_c\cdot V_c+C_s\cdot W_s \tag{20}$$

In Eq. (20), C_c, C_s, V_c, W_s are unit cost of concrete and steel, volume of concrete and weight of steel per unit length, respectively.

3. Teaching-Learning-Based optimization

Teachers are generally considered as persons who have a high level knowledge about a specific subject. The main task of the teachers is to carry the knowledge of the learners at a higher level. This is the outcome of learners and it can be evaluated with their grades. Certainly, the qualifications of the teacher affect the outcome of the learners and it would not be wrong to think that there is a correct proportion between qualification of teacher and grades of learners. Consequently, it can be said that teachers with good features provides better mean for learner grades.

In addition to teacher affect, student can also improve their knowledge as well as grades with different ways, such as interaction, sharing information, investigation, communication and cooperation etc. Rao *et al.* (2011) is conceptualized from this analogy of the teaching - learning process of teacher and learners in a classroom the Teaching Learning-Based Optimization (TLBO) algorithm. The TLBO process can be divided in two parts called “teacher phase: simulate the effect of teacher on grades of learners” and “learner phase: simulate personal efforts of learners on their grades”.

3.1 Optimum design of retaining walls via TLBO

The optimum design of retaining walls can be summarized in five steps:

Step I: There are only two parameters: the number of learners (population size) in the class and the maximum number of iterations (stopping criteria) must be defined, in the TLBO algorithm. In that way, the TLBO is the most simply algorithm in usage.

Step II: In this stage, initial matrix (class; CL) is filled with pn (student or population size) number of solution vectors that contains *vn* number of randomly generated design variables (X_i) between the upper ($X_i^{\max}$) and lower ($X_i^{\min}$) limit of the solution range (Eq. (21)).

$$X_i^{min}\le X_i\le X_i^{max}\quad i=1,vn \tag{21}$$

Thus, initial matrix (CL) can be written as

$$CL=\begin{bmatrix} X_{1,1} & X_{1,2} & \cdot & \cdot & \cdot & X_{1,vn} \\ X_{2,1} & X_{2,2} & \cdot & \cdot & \cdot & X_{2,vn} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ X_{pn-1,1} & X_{pn-1,2} & \cdot & \cdot & \cdot & X_{pn-1,vn} \\ X_{pn,1} & X_{pn,2} & \cdot & \cdot & \cdot & X_{pn,vn} \end{bmatrix} \tag{22}$$

in which each row of the matrix is a candidate retaining wall design that is correspond an objective function value.

$$f(X)=\begin{bmatrix} f(X_1) \\ f(X_2) \\ . \\ . \\ f(X_{pn-1}) \\ f(X_{pn}) \end{bmatrix} \tag{23}$$

Step III: This step is "teacher phase (tp)" of the TLBO algorithm. Due to teacher has the best knowledge, the variables with minimum objective function is assigned as a teacher ($X_{teacher}$) of the class. In the other word, the best learner in the class is determined as the teacher.

$$X_{teacher} = X_{min\, f(X)} \tag{24}$$

Then, knowledge of the teacher is used to increase the capacity of the whole class. The main aim is to increase of the mean (X_{mean}) of the class. For that reason the equation of new students is found, according to teacher and mean of the class as seen in Eq. (25).

$$X_{new,i}^{tp} = X_{old,i} + rnd(0,1)\cdot\left(X_{teacher} - T_F \cdot X_{mean}\right) \tag{25}$$

where T_F represents teaching factor defined as

$$T_F = round\left[1 + rnd(0.1)\right] \rightarrow \{1-2\} \tag{26}$$

and it takes a value 1 or 2 depending on the *rnd;* uniformly distributed random numbers that are within the range [0,1]. If the new solution ($X_{new,i}^{tp}$) is better than the old one in point of the objective function, the new solution is accepted.

Step IV: In the TLBO algorithm, after the teacher phase, the "learner phase (lp)" is proceed. As it stated above, students also have an important role in the learning process by communication, interaction, investigation, etc. This interaction can be expressed as follows

$$X_{new,i}^{lp} = \begin{cases} X_{old,i} + r_i \cdot \left(X_i - X_j\right); & f(X_i) > f\left(X_j\right) \\ X_{old,i} + r_i \cdot \left(X_j - X_i\right); & f(X_i) < f\left(X_j\right) \end{cases} \tag{27}$$

where X_i and X_j are randomly selected learners that are different each other. If the new solution ($X_{new,i}^{lp}$) is better, it is replaced with old one.

Step V: In this step, the stopping criteria usually is defined as the maximum iteration number is checked. If the stopping is satisfied, the optimization process is terminated, otherwise the iteration process continues from the step III. The flowchart of the process can be seen in Fig. 3.

In order to improve the performance of the algorithm, it is needed to do some modifications. Several modifications have been proposed. Rao and Patel (2013) suggest a modification in calculation of teaching factor as

$$T_F = \begin{cases} \dfrac{X_{total} - X}{X_{total} - X_{best}} & if \quad X_{total} - X_{best} \neq 0 \\ 1 & if \; X_{total} - X_{best} = 0 \end{cases} \tag{28}$$

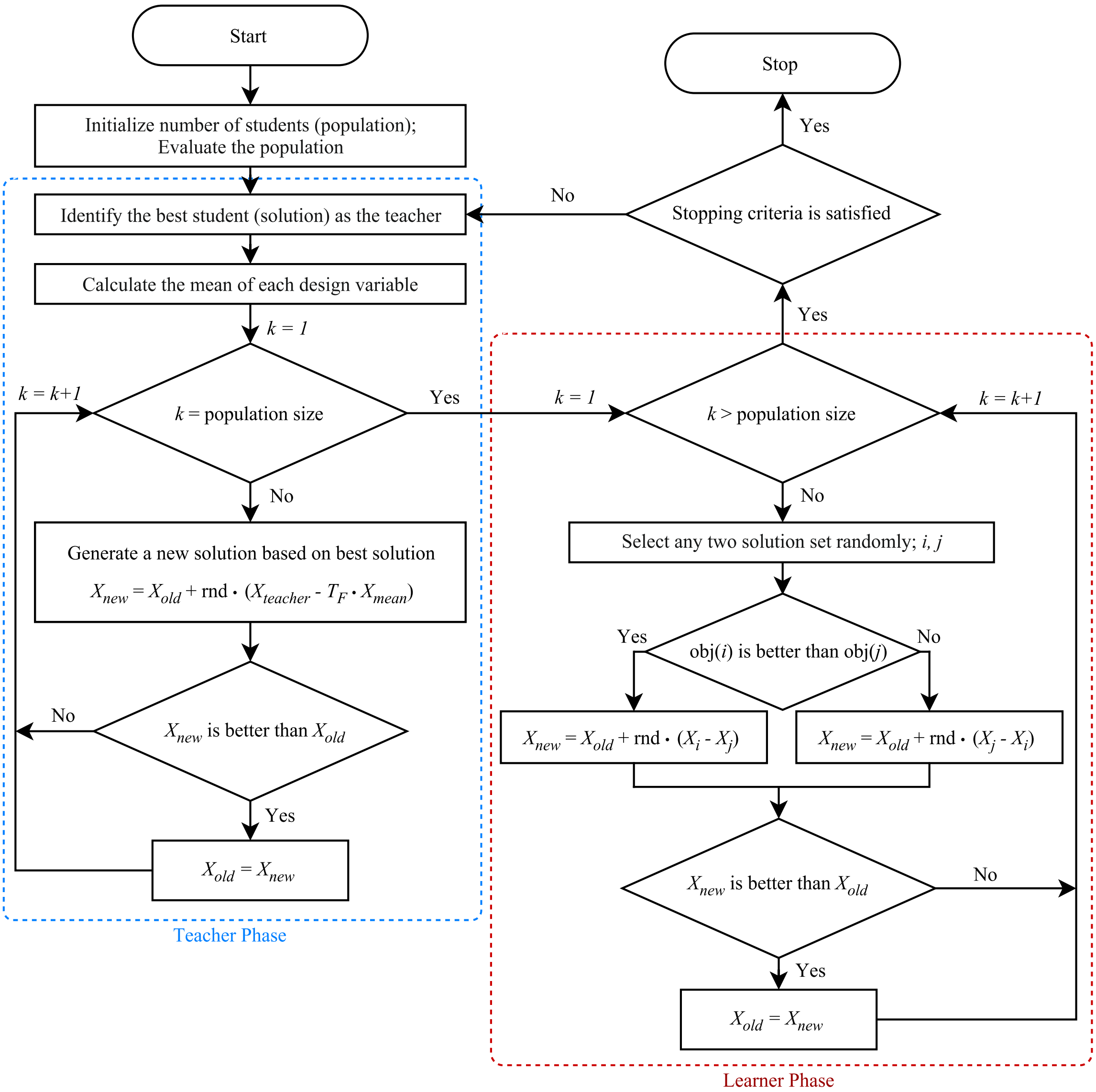

Fig. 3 Flowchart of the TLBO algorithm

and they called it improved TLBO (ITLBO) algorithm. Camp and Farshchin (2014) proposed a change in calculation of X_{mean}.

$$X_{mean} = \frac{\sum_{k=1}^{vn} \frac{X}{F_k}}{\sum_{k=1}^{vn} \frac{1}{F_k}} \tag{29}$$

where F_k is the fitness function of kth learner. They called the new approach modified TLBO (MTLBO).

Table 3 Design constants and ranges of design variables

Definition	Symbol	Unit	Value
Height of stem	H	m	3.0
Yield strength of steel	f_y	MPa	400
Compressive strength of concrete	f'_c	MPa	25
Concrete cover	c_c	mm	70
Max. aggregate diameter	D_{max}	mm	16
Elasticity modulus of steel	E_s	GPa	200
Specific gravity of steel	γ_s	t/m^3	7.85
Specific gravity of concrete	γ_c	kN/m^3	23.5
Cost of concrete per m^3	C_c	\$	40
Cost of steel per ton	C_s	\$	400
Design load factor		LF	1.7
Surcharge load	q	kPa	20
Backfill slope angle	β	°	10
Internal friction angle of retained soil	ϕ_R	°	30
Internal friction angle of base soil	ϕ_B	°	0
Unit weight of retained soil	γ_R	kN/m^3	17.5
Unit weight of base soil	γ_B	kN/m^3	18.5
Cohesion of retained soil	c_R	kPa	0
Cohesion of base soil	c_B	kPa	125
Depth of the soil in front of wall	D	m	0.5
Safety for overturning stability	$SF_{O,design}$	-	1.5
Safety for sliding stability	$SF_{S,design}$	-	1.5
Safety for bearing capacity	$SF_{B,design}$	-	3.0
Range of stem thickness at top	h_{stemt}	m	0.2-3
Range of heel projection	h_{basew}	m	0.2-10
Range of toe projection	h_{toepro}	m	0.2-10
Range of stem thickness at the bottom of wall	h_{stemb}	m	0.2-3
Range of base slab thickness	$h_{baseslab}$	m	0.2-3
Range of diameter of reinforcing bars of stem	ϕ_s	mm	16-50
Range of diameter of reinforcing bars of toe,	ϕ_t	mm	16-50
Range of diameter of reinforcing bars of heel	ϕ_h	mm	16-50

4. Numerical examples

The methodology is examined for different examples. In the first example, a cantilever retaining wall model which was investigated by Saribaş and Erbatur (1996) is used. For the other examples, the optimum design is investigated for different conditions, including backfill slope angle, internal friction angle of retaining soil and surcharge load. In these examples, other design constant is taken as the same as the first example. Three types of TLBO were investigated in this study. The results of these methods were compared with the other coded methods such as PSO (Ahmadi-Nedushan and Varaee 2009), BBBC (Camp and Akin 2011) and IHS (Kaveh and Abadi 2011).

4.1 Example 1

Design constants and ranges of design variables taken from Saribaş and Erbatur (1996) are given in Table 3. But, stem thickness at the top of the wall is also taken as design variables.

The optimum results of different metaheuristic methods are shown in Table 4. According to the results, all algorithm are effective on finding minimum cost value. However, effectiveness of TLBO based methods is seen for standard derivative values. In Fig. 4, convergence to optimum result can be seen for the different methods. As seen from the plot, the best convergence is shown for PSO and MTLBO methods.

In order to measure sensitivity of the methods, 100 independent designs were generated. The optimum cost results for each run can be seen in Fig. 5. As seen from the figures, in some of the analyses, cost of the wall is obtained 2.5 times (approximately 130 \$/m) bigger than the minimum optimum cost, for PSO and BBBC methods. Maximum difference is about 10% more than the minimum cost (approximately 58 \$/m) of IHS method. However, the same optimum result for all analyses were approximately found by using TLBO based approaches.

Table 4 Optimization results and comparison for the Example 1

	PSO	BBBC	IHS	TLBO	ITLBO	MTLBO
X_1	0.997394	0.997879	0.990126	0.997396	0.997388	0.997394
X_2	0.2	0.2	0.207743	0.2	0.200007	0.2
X_3	0.264208	0.264229	0.264239	0.264208	0.264208	0.264208
X_4	0.2	0.2	0.2	0.2	0.2	0.2
X_5	0.2	0.2	0.2	0.2	0.2	0.2
Minimum Cost (\$/m)	52.68932	52.69523	52.70028	52.68935	52.68935	52.68934
Standard Deviation	8.483914	14.00662	1.128207	0.002237	0.001376	0.001329

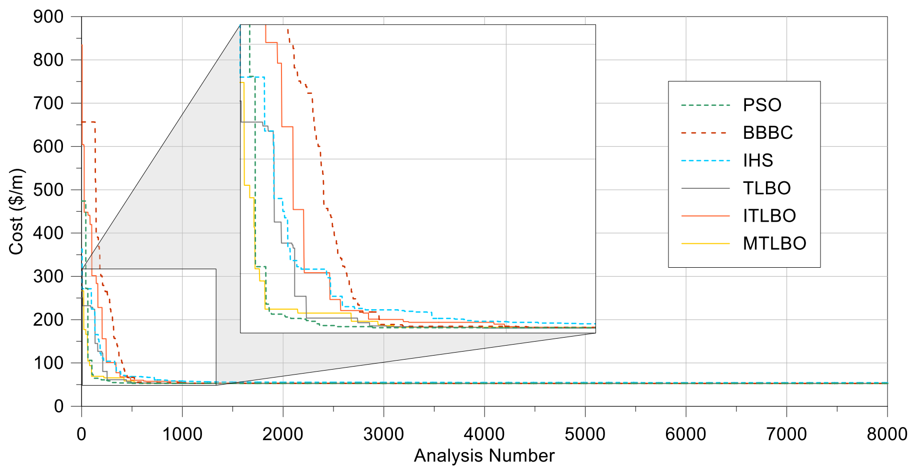

Fig. 4 Plot for convergence to optimum results (Example 1)

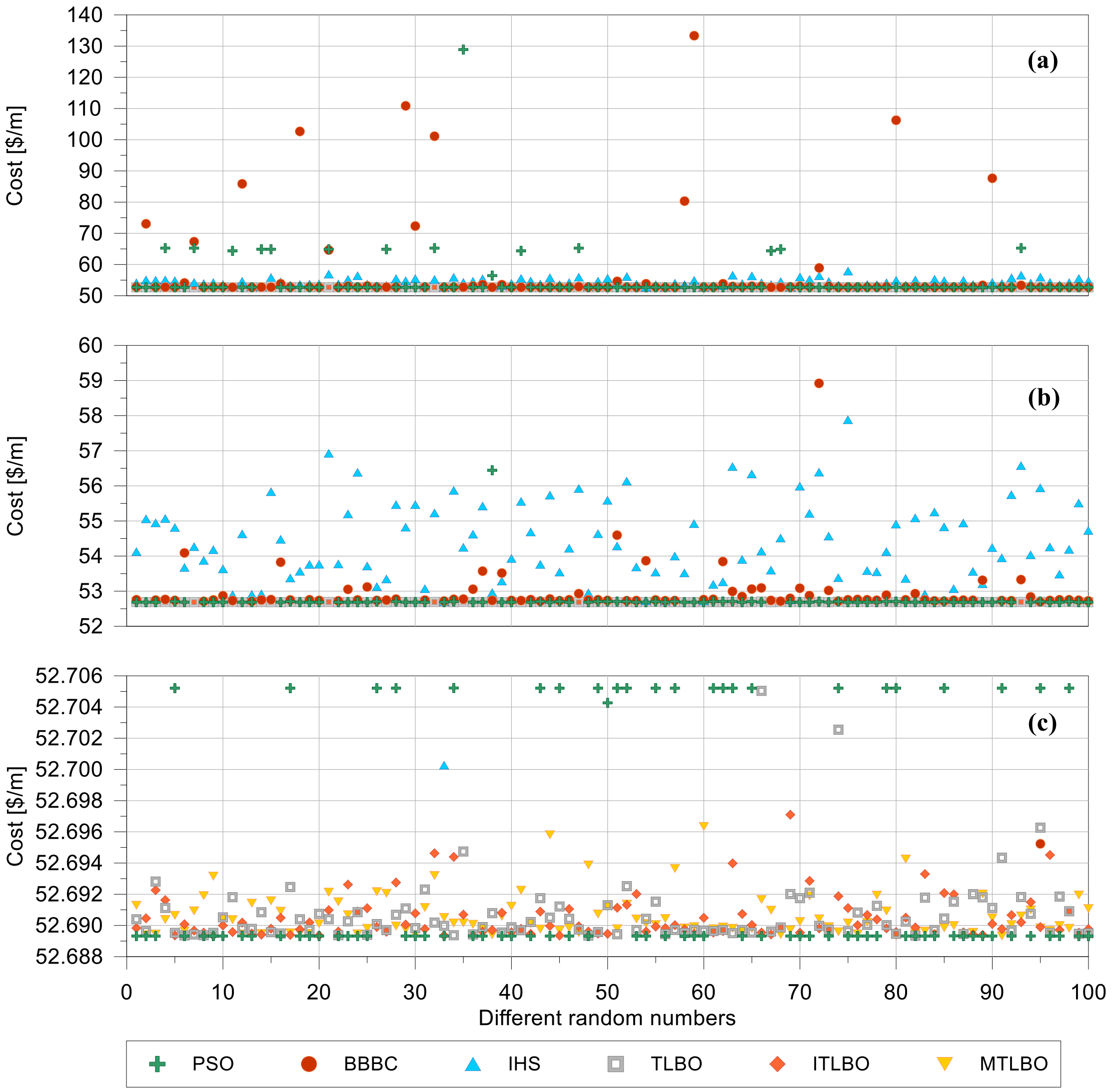

Fig. 5 Optimum cost distribution plot for 100 independent designs (Example 1); (a) All solutions (b) A more detailed graph of the 52-60 cost range (c) A more detailed graph of the 52.706-52.688 cost range

4.2 Example 2

For the example 2, the effect of backfill slope angle on the optimum design is investigated. The backfill slope angle is changed between 0° and 30° and the other design constraints are taken as the same with example 1. Optimum results of different backfill slope angles can be seen in Fig. 6. Comparing to example 1, the backfill slope angle has limited impact on the optimum result up to 20°, but for bigger degrees, it becomes an important parameter because of dramatic increase optimum cost value. According to the result of the example 1, the optimum results are approximately changed with -1%, 4%, 8% and 37% for angles 0°, 20°, 25°, and 30°, respectively.

For all methods, the convergence speed to optimum result is given in the Fig. 7. As seen from

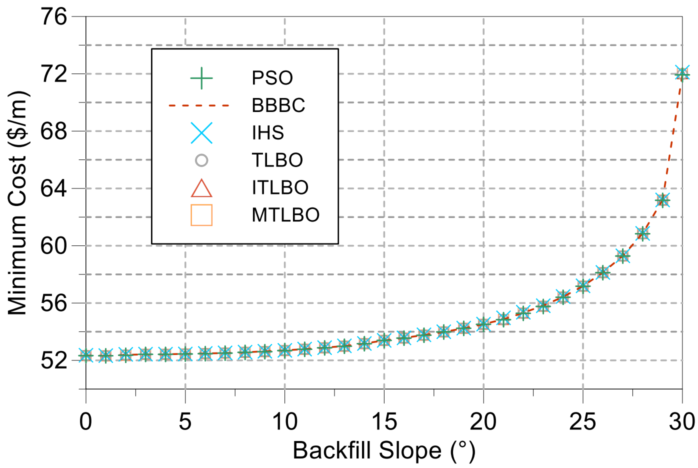

Fig. 6 Minimum cost values vs. backfill slope angles plot (Example 2)

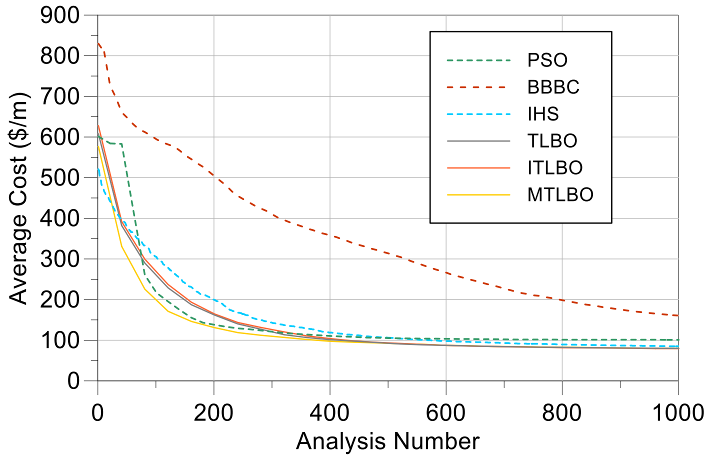

Fig. 7 History of average cost values (Example 2)

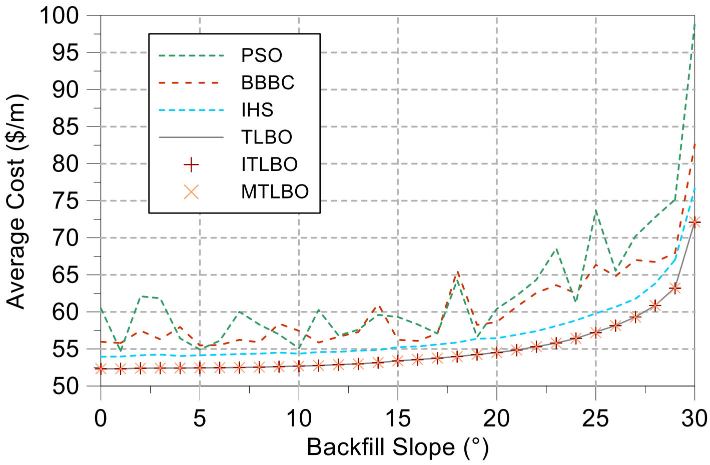

Fig. 8 Average cost values vs. backfill slope angles plot (Example 2)

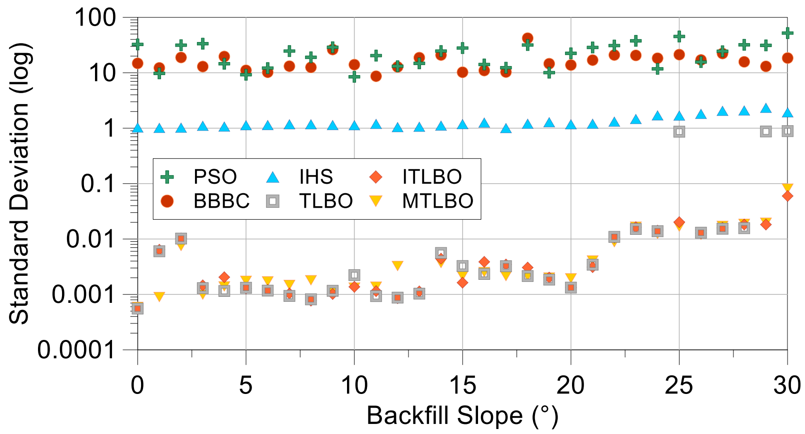

Fig. 9 Standard deviation vs. backfill slope angle plot (Example 2)

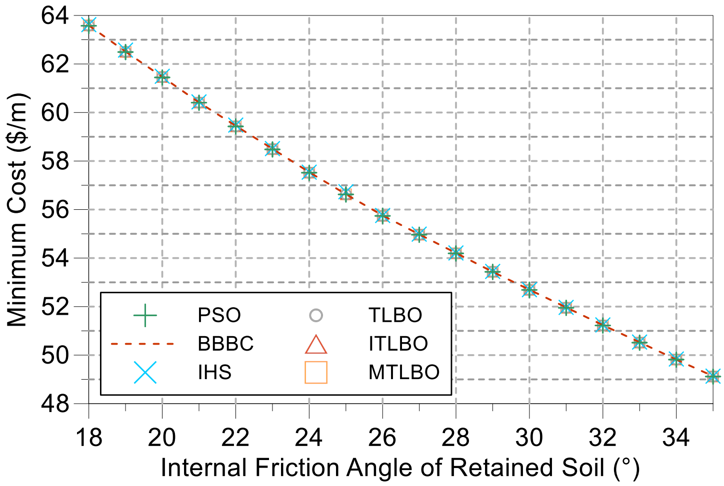

Fig. 10 Minimum cost values vs. internal friction angle of retained soil plot (Example 3)

the results, all methods seem good (except the BBBC) in point of convergence speed. However, TLBO methods are more effective than PSO and IHS methods, considering the standard deviation (Fig. 8) and the average cost (Fig. 9) values. The conclusion is obtained from the results are confirmed the determination about the effectiveness of the algorithm that is done in example 1.

4.3 Example 3

In this example, the relationship between the internal friction angle of retained soil and the optimum cost is investigated. By taking other design constant as same as example 1, the internal friction angle of retained soil is changed from 18° to 35°. This friction angle band covers most commonly used retained soil in designs. In the Fig. 10, the optimum cost values depending on the internal friction angle is given. According to the results, the optimum cost is varying between 64 $/m to 49 $/m for 18° and 35°, respectively. Also, a nearly linear relationship between internal friction angle and optimum cost is observed.

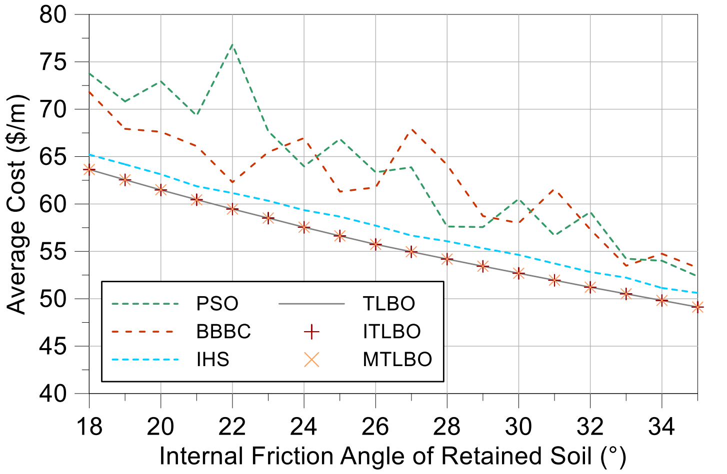

Fig. 11 Average cost value vs. internal friction angle plot (Example 3)

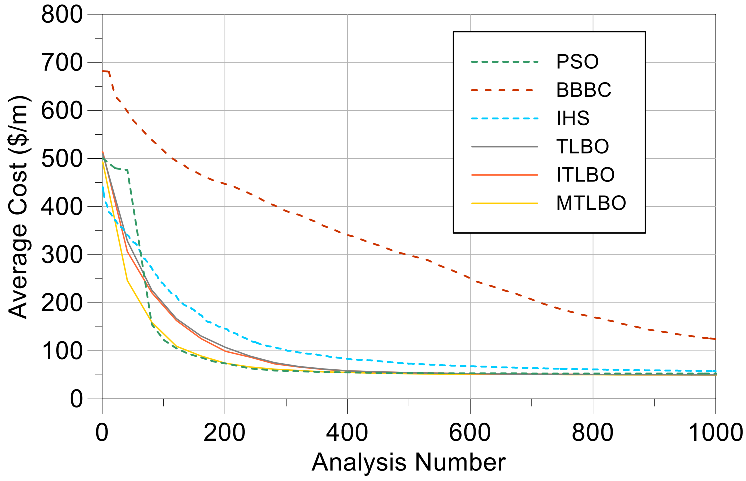

Fig. 12 History of average cost values (Example 3)

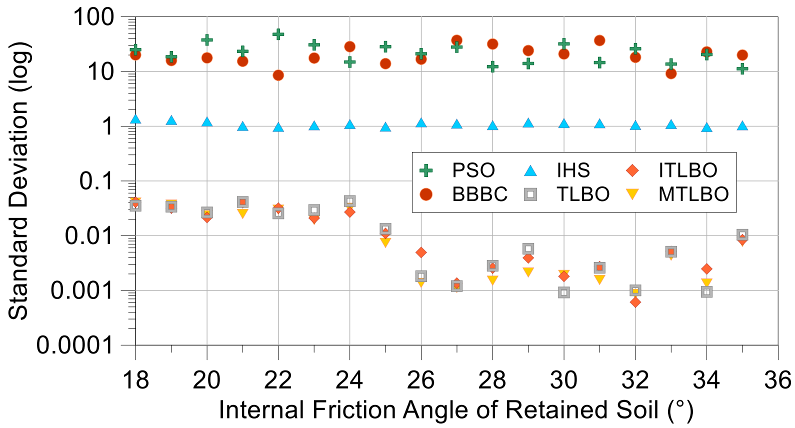

Fig. 13 Standard deviation vs. internal friction angle plot (Example 3)

Although being effective on finding optimum cost, there are important differences in convergence speed to average cost (Fig. 11), average costs (Fig. 12) and standard deviation (Fig. 13) values between the methods. As it is obtained from previous results, TLBO methods seem the most suitable ones in feasibility.

4.4 Example 4

In the last example, the role of surcharge load on optimum cost is investigated. The varying surcharge load is taken from the 0 kN/m^2 to 50 kN/m^2, the other design constraints are taken the same as the first example. As it is expected, by increasing surcharge loads on the wall, optimum cost value is also increased (Fig. 14). Similarly with the example 3 including cases of internal friction angle, the relationship between surcharge load and optimum cost seems proportional. The

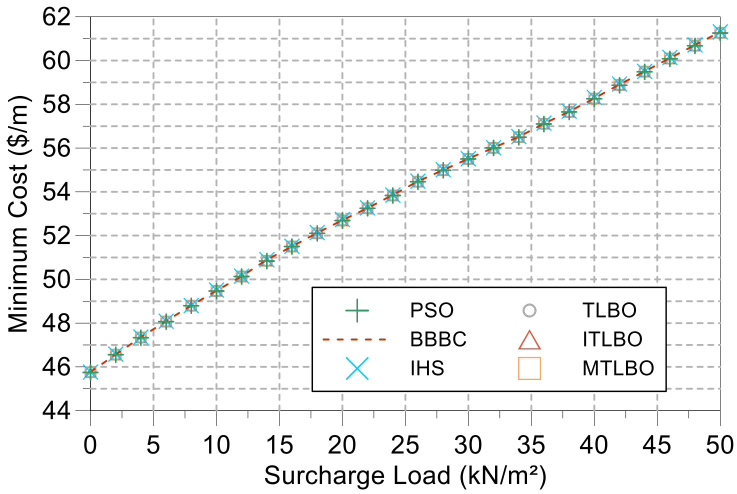

Fig. 14 Minimum cost values vs. surcharge load plot (Example 4)

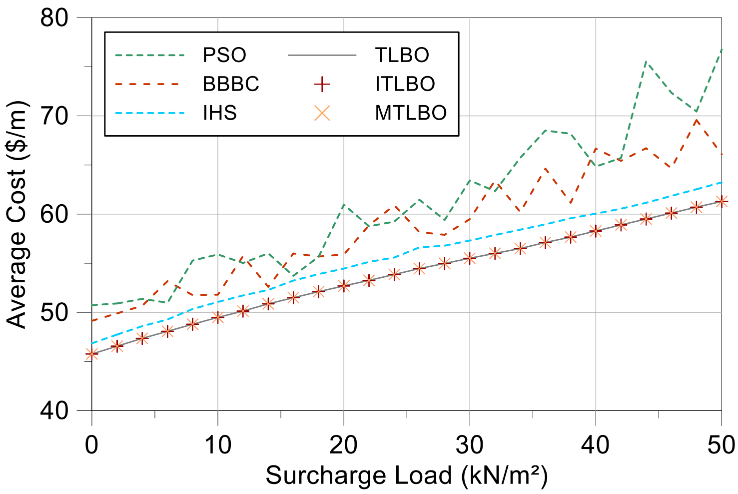

Fig. 15 Plot for convergence to average cost value (Example 4)

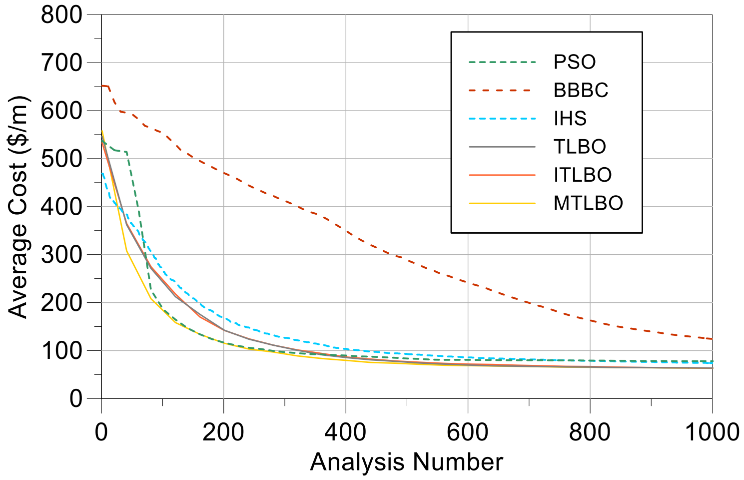

Fig. 16 History of average cost values (Example 4)

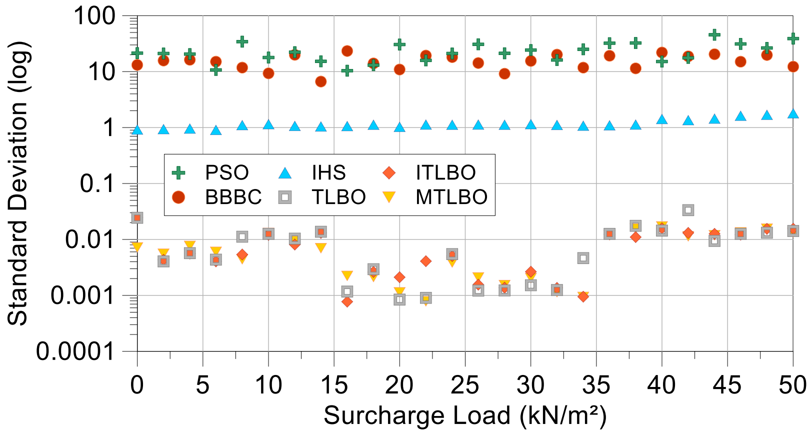

Fig. 17 Standard deviation vs. surcharge load plot (Example 4)

gradient of the line is approximately 0.31 which means optimum wall cost for a specific surcharge load is equal to sum of the cost of the wall without surcharge loading and 0.31 times of surcharge load intensity.

In the analyses, the same behavior of the optimization methods is also observed in the convergence of optimum values, average costs and standard deviation values (Figs. 15-17). Thus, TLBO based methods are also seems effective in these analyses.

5. Conclusions

In this paper, the optimum design of RC cantilever retaining walls is investigated. The problem is suitable for metaheuristic methods. Thus, a newly developed algorithm called TLBO is employed by including the future improvements of the (ITLBO and MTLBO). The proposed methodology is compared with the documented methods. The algorithms used in the documented methods are also coded for employed problem with 11 design variables and 29 design constraints.

According to the results of the first example, all algorithms are effective on finding the minimum optimum value. The essential difference can be seen in the robustness of the algorithms. The final results of the sets of design variables are nearly the same in the TLBO based methods and this situation can be clearly seen in the values of standard derivative. In the examples investigating the change of design constraints, the other algorithms (especially BBBC and PSO) express great differences on the optimum results for 100 independent runs.

Also, backfill slope angle is not effective on the optimum cost for a specific range (0°-20°) while it essentially effects on the optimum cost for the values bigger than 20°. The internal friction angle of retained soil and surcharge load has a linear effect on the optimum cost.

As a conclusion, TLBO based method is effective on finding optimum values for independent runs. Since the convergence and robustness performance of TLBO, it is a feasible method with effective improvements such as ITLBO and MTLBO.

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