



Challenge Journal of STRUCTURAL MECHANICS

Research Article

Optimal design of reinforced concrete cantilever retaining walls via simulated annealing

Yesim Tuskan ^{a,*}

^a Department of Civil Engineering, Manisa Celal Bayar University, 45140 Manisa, Türkiye

ABSTRACT

This study investigates the optimal design of reinforced concrete cantilever (RCC) retaining walls considering both environmental and economic objectives under three concrete alternatives: green, sustainable, and traditional concrete. The design problem is formulated as two independent single-objective optimization models aimed at minimizing CO₂ emissions and material cost while satisfying geotechnical, structural, and material constraints. A simulated annealing-based approach is employed to efficiently explore and obtain the optimal design. The results demonstrate a strong interdependence between cost and emissions for all material types. Green concrete consistently provides the lowest CO₂ emissions and cost values, followed by sustainable concrete, while traditional concrete yields the highest values for both objectives. Furthermore, the traditional concrete configurations require greater material consumption compared to green and sustainable alternatives, whereas green concrete consistently achieves the most efficient overall performance. Green concrete consistently achieved the best performance, reducing the material cost by up to 16.9% and carbon emissions by up to 20.3% compared with traditional concrete while satisfying all structural and geotechnical design requirements. Overall, the findings confirm that the proposed simulated annealing approach is a robust and effective tool for the two independent single-objective optimization of RCC retaining walls, enabling efficient decision-making between environmental and economic criteria.

ARTICLE INFO

Article history:

Received – April 27, 2026
Revision requested – June 8, 2026
Revision received – August 22, 2026
Accepted – September 27, 2026

Keywords:

Cantilever retaining wall
Simulated annealing
Structural optimization
Sustainable concrete
Green concrete
Cost optimization



This is an open access article distributed under the CC BY licence.
© 2026 by the Author.

Citation: Tuskan Y (2026). Optimal design of reinforced concrete cantilever retaining walls via simulated annealing. *Challenge Journal of Structural Mechanics*, 12(3), 296–311.

1. Introduction

Geotechnical retaining structures are crucial in civil engineering for ensuring slope stability and safeguarding nearby infrastructure as well as natural ecosystems. Furthermore, these structures are essential for preventing soil erosion, managing water runoff, and mitigating the risk of landslides and flooding. Among the various types of retaining walls, Reinforced Concrete Cantilever (RCC) retaining walls have long been a cornerstone of modern engineering, offering strength, durability, and versatility. However, the growing demand for environmentally responsible construction practices has prompted the need for more sustainable

design approaches in the construction of RCC retaining walls.

In recent decades, the importance of sustainability in civil engineering has grown significantly, with an increasing emphasis on designing structures that minimize emissions while maintaining functional integrity. Reinforced Concrete Cantilever (RCC) retaining walls are widely preferred in numerous engineering projects due to their ability to withstand complex loads, high soil pressures, and seismic forces (Kaveh et al. 2013). Their structural superiority lies in the synergy of concrete's compressive strength and steel's tensile capacity, allowing for versatile geometric configurations such as cantilever, counterfort, and anchored designs. This adaptabil-

* Corresponding author. E-mail address: yesim.tuskan@cbu.edu.tr (Y. Tuskan)
ISSN: 2149-8024 / DOI: <https://doi.org/10.20528/cjsmec.2026.1177>

ity ensures efficient integration into diverse urban and natural environments (Shakeel et al. 2022). However, as the construction industry seeks to reduce its massive carbon footprint, the challenge has shifted from purely functional design to achieving a balance between safety, cost-efficiency, and environmental preservation. The evolution of optimization research for RCC retaining walls can be categorized into three primary frameworks. The first category focuses on Geometric and Cost-Centric Optimization, where metaheuristic algorithms are used to minimize material weight or construction costs. Studies by Kashani et al. (2022) utilized genetic algorithms (GA), while Gandomi et al. (2017a) and Tayfur and Kamiloğlu (2024) employed evolutionary and improved optimization methods to achieve significant savings. Similarly, Kumar and Suribabu (2017) demonstrated that differential evolution could reduce wall weight by 15% compared to manual designs. While these studies, including the works of Kaveh et al. (2013, 2020a) and Kayabekir et al. (2021) using Teaching-Learning-Based Optimization (TLBO) and Collision Bodies Optimization (CBO), established the efficiency of metaheuristics, they primarily treated concrete as a conventional material with fixed environmental properties. The second category involves the Integration of Environmental Criteria, where CO₂ emissions are introduced as a secondary objective. Khajehzadeh et al. (2014) applied a hybrid gravitational search algorithm to minimize both cost and emissions, while Aydoğdu (2017) highlighted the benefits of lower-grade concrete in reducing the carbon footprint through Social Spider and Biogeography-Based Optimization. Despite these advancements, most existing literature (Akin et al. 2016; Das et al. 2016; Sheikholeslami et al. 2016; Ukritchon et al. 2017; Kaveh et al. 2022) relies on generic emission factors and a limited range of standard concrete mixes, often overlooking the complex performance characteristics of modern sustainable alternatives. The third and most recent framework, which defines the present study, addresses the gap between material science and structural optimization.

This research distinguishes itself by integrating a comprehensive mixture database (Naseri et al. 2022)—comprising green, sustainable, and traditional concrete types—directly into the optimization loop. Unlike traditional models that use simplified material inputs, our approach evaluates the specific binder intensities and cost-performance ratios of eco-friendly mixtures incorporating recycled aggregates and low-carbon additives. By utilizing a specifically tailored Simulated Annealing (SA) algorithm to navigate the non-linear constraints, this study provides a more nuanced understanding of how advanced material selection dictates the optimal geometry of low-carbon infrastructure. Accordingly, a significant gap exists between the use of theoretical concrete grades in optimization models and the practical application of real-world sustainable mixtures. Moreover, the present study fundamentally diverges from existing literature utilizing SA, Jaya, GA, TLBO, BBO, CBO, and other metaheuristic applications for RCC retaining walls in its systemic integration of material-stiffness-emission variables. While previous research has primarily focused on the mathematical convergence and computational speed of these algorithms (e.g., Kaveh et al. 2020b; Gandomi et

al. 2017b; Temur and Bekdaş 2016), they often treat the material input as a secondary, static constant. In contrast, our approach reconfigures the Simulated Annealing (SA) framework to act as a bridge between structural geometry and a mixture database. The distinctive contribution of this study is rooted in several key methodological advancements that separate it from traditional metaheuristic applications. Firstly, through algorithmic coupling, our modified Simulated Annealing (SA) framework simultaneously navigates a discrete set of green and sustainable concrete mixtures—each characterized by unique binder intensities and cost-performance ratios—rather than optimizing for a single, static concrete grade as seen in standard TLBO or Jaya implementations. Secondly, the study emphasizes constraint rigidity by maintaining high-fidelity compliance with rigorous safety factors. This ensures that the resulting optimal designs are technically reproducible in real-world engineering contexts, unlike many GA and BBO studies that simplify geotechnical and structural constraints to achieve faster convergence. Finally, by addressing the sensitivity to material volatility, this research explores the non-linear relationship between waste-based cementitious materials and structural volume. This critical analysis demonstrates that the efficacy of an optimization algorithm is fundamentally tied to the quality of the material database it operates upon, effectively shifting the research focus from purely numerical performance toward material-aware structural optimization. Unlike previous studies (Table 1), which generally focused on a single concrete type or solely on geometric optimization, this study investigates the optimal design of RCC retaining walls by simultaneously considering environmental and economic objectives for three different concrete alternatives. This unified framework enables a systematic comparison of the influence of different concrete materials on the optimal design, material cost, and environmental performance of RCC retaining walls.

Consequently, sustainable design in retaining walls involves not only considering geotechnical evaluation, structural stability, energy efficiency, and resource conservation. This includes optimizing material usage, reducing carbon footprints, and ensuring that materials and construction processes are in harmony with the surrounding ecosystem. Thus, incorporating sustainable design principles into RCC retaining walls requires a careful balance between geotechnical design, structural integrity, environmental responsibility, and cost-effectiveness. This study highlights the significance of sustainable RCC retaining wall designs in promoting infrastructure safety and longevity through the optimization of cost and CO₂ emissions by utilizing green and sustainable concrete compared to traditional mixtures. This paper is organized as follows. Section 2 describes the methodology, including the RCC retaining wall design variables, material properties, design constraints, objective functions, and the implementation of the Simulated Annealing (SA) algorithm. Section 3 presents and discusses the optimization results for the cost and CO₂ emission objectives, together with the sensitivity analysis, regression analysis, and comparison of the optimized designs. Finally, Section 4 summarizes the main findings, contributions, and limitations of the study.

Table 1. Summary of recent studies on RCC retaining wall optimization problem.

Study	Objective function(s)	Design variables	Constraints	Optimization technique
Shakeel et al. (2022)	Review of cost, weight, CO ₂ emission, and reliability-based optimization approaches	Various wall geometry, reinforcement, backfill, and foundation	Geotechnical stability, structural strength, and serviceability requirements	Complex method (CM); GA; PSO; SA
Villalba et al. (2010)	Minimize CO ₂ emissions	Wall dimensions, footing geometry, reinforcement quantities	Sliding, overturning, bearing capacity, and structural design requirements	Mathematical/parametric optimization GA; PSO; SA
Öztürk and Türkel (2019)	Minimize construction cost	Stem, toe, heel, base, key dimensions, and reinforcement details	Sliding, overturning, bearing capacity, flexural, and shear design constraints	Jaya Algorithm
Schmied and Karlsson (2021)	Simultaneous minimization of environmental impact and investment cost	Wall geometry, reinforcement ratios, and material selection	Eurocode structural design requirements and geotechnical stability constraints	Multi-objective optimization framework; PSO
Khajehzadeh et al. (2014)	Minimize construction cost and maximize stability	Geometric dimensions of retaining wall	Sliding, overturning, bearing capacity, and structural safety constraints	Hybrid Adaptive Gravitational Search Algorithm (HAGSA)
Kayabekir et al. (2020)	Simultaneous minimization of construction cost and CO ₂ emissions	Wall dimensions and reinforcement quantities	Sliding, overturning, bearing capacity, flexural, and shear design constraints	Multi-objective Harmony Search Algorithm
Khajehzadeh et al. (2013)	Minimize construction cost and environmental impact	Retaining wall geometry and reinforcement variables	Sliding, overturning, bearing capacity, and structural design constraints	Opposition-Based Gravitational Search Algorithm (OBGSA)
Kaveh and Behnam (2013)	Minimize construction cost	Wall geometry and reinforcement details	Geotechnical stability and reinforced concrete design constraints	Charged System Search (CSS)
Kaveh and Khayatizad (2014)	Minimize construction cost	Geometric dimensions and reinforcement variables	Sliding, overturning, bearing capacity, and structural requirements	Ray Optimization (RO)
Kaveh and Soilemani (2015)	Minimize construction cost	Wall geometry and reinforcement parameters	Geotechnical and structural design constraints	Colliding Bodies Optimization (CBO) and Democratic Particle Swarm Optimization (DPSO)
Kalemci et al. (2020)	Minimize construction cost	Wall dimensions and reinforcement variables	Sliding, overturning, bearing capacity, flexural, and shear constraints	Grey Wolf Optimizer (GWO)
Yücel et al. (2021)	Minimize construction cost with improved convergence performance	Wall geometry and reinforcement parameters	Strict geotechnical and structural design constraints	Adaptive hybrid optimization algorithm
Kaveh et al. (2022)	Minimize construction cost	Geometric dimensions and reinforcement variables	Geotechnical stability and reinforced concrete design constraints	Plasma Generation Optimization (PGO)
Keivanian et al. (2023)	Multi-objective optimization considering sustainability and cost	Wall geometry, reinforcement, and material parameters	Geotechnical stability, structural safety, and sustainability constraints	Hybrid metaheuristic optimization approach
Gandomi et al. (2017a)	Minimize construction cost	Wall geometry and reinforcement variables	Sliding, overturning, bearing capacity, and reinforced concrete design constraints	Evolutionary Algorithms
Gandomi et al. (2017b)	Minimize construction cost	Geometric dimensions and reinforcement details	Sliding, overturning, bearing capacity, and structural design constraints	Interior Search Algorithm (ISA) with different bound constraint handling strategies
Sheikholeslami et al. (2016)	Minimize construction cost	Wall dimensions and reinforcement quantities	Sliding, overturning, bearing capacity, flexural, and shear design constraints	Hybrid Firefly Algorithm with Upper Bound Strategy
Kashani et al. (2022)	Simultaneous minimization of construction cost and CO ₂ emissions (multi-objective)	Wall geometry, reinforcement quantities, and material parameters	Geotechnical stability and reinforced concrete design requirements	Comparative multi-objective metaheuristic optimization algorithms
Tayfur and Kamiloğlu (2024)	Minimize construction cost	Geometric dimensions and reinforcement variables	Sliding, overturning, bearing capacity, and structural safety constraints	Improved Teaching–Learning–Based Optimization (ITLBO) Algorithms

2. Methodology

The design process involves two groups of design parameters. The first group consists of the geometric dimensions of the RCC retaining wall, represented by variables X_1 to X_5 and illustrated in Fig. 1, which include the width of the toe slab (X_1), the width of the base slab (X_2),

the thickness of the stem at the top (X_3), the thickness of the base slab (X_4), and the thickness of the stem at the bottom (X_5). The second group involves the required steel reinforcement quantities, denoted as R_1 to R_3 , comprising the area of vertical reinforcement in the stem (R_1), the area of horizontal reinforcement in the toe (R_2), and the area of horizontal reinforcement in the heel (R_3).

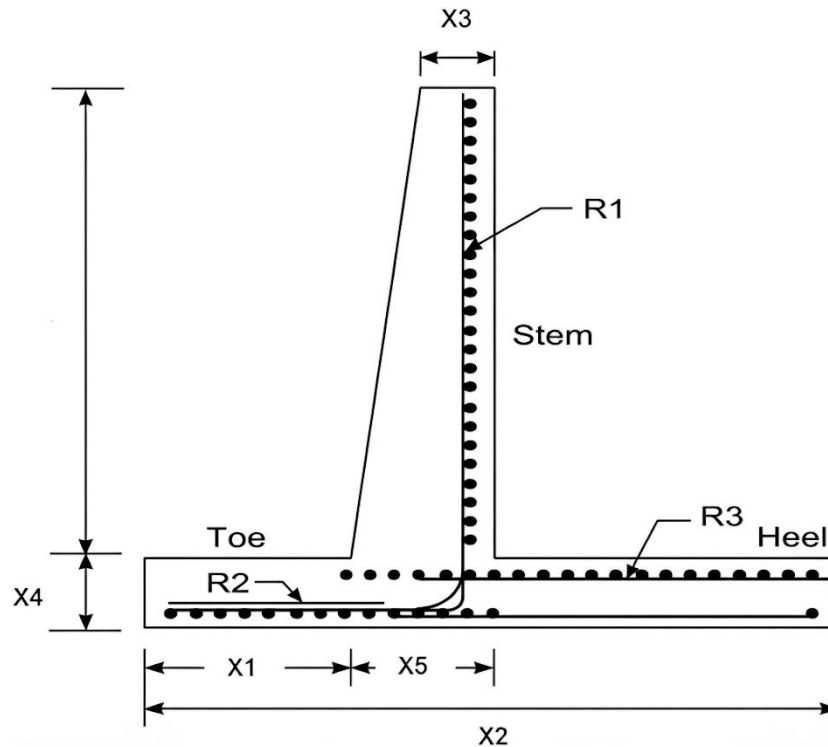


Fig. 1. Design variables of the RCC retaining wall.

The areas of steel reinforcement are represented by a combination of bar diameters and their spacings. Various reinforcement configurations were used, combining 3–30 evenly spaced bars with diameters ranging from 10 to 30 mm. These configurations were chosen to ensure that the reinforcement area per meter of wall length met the allowable minimum and maximum limits (ACI 318-14 2014) for the spacing between longitudinal bars, which is defined by the diameter of the maximum diameter of aggregate in the concrete and the diameter of the longitudinal reinforcements. For a given bar count (Bars #) and bar diameter (bar size), the corresponding total reinforcement area (A_s in cm^2) is calculated directly; for example, 3 bars of size 10 yield an A_s of 2.356 cm^2 ($\eta = 1$), 4 bars of size 10 yield 3.141 cm^2 ($\eta = 2$), and higher index combinations scale accordingly up to larger configurations such as 18 bars of size 30 yielding 127.234 cm^2 . To ensure practical constructability, lower and upper bounds for the geometric design variables were established based on commonly accepted reinforced concrete retaining wall design recommendations (ACI 318-05 2005). Specifically, the minimum stem top thickness was limited to 0.25 m, the minimum base slab thickness to 0.30 m, the toe projection was constrained within 0.10–0.15H, the base width was maintained 0.40–0.7H, and the stem bottom thickness was constrained to at least 0.08–0.10H. Simulated annealing was implemented to obtain optimum retaining wall designs with

respect to cost and CO_2 emissions over wall heights (H) of 4–10 m under constant soil conditions. The design variables considered in the optimization process and their corresponding lower and upper bounds are presented in Table 2.

The input parameters are defined with a reinforcing steel yield strength (f_y) of 400 MPa, and a concrete compressive strength (f'_c) of 21 MPa. The concrete cover (C_c) is 7 cm, and the shrinkage and temperature reinforcement percentage (ρ_{st}) is 0.002. The surcharge load (q) is set to 0 with a backfill slope (β) of 0° . For the soil properties, the internal friction angle of the retained soil (ϕ) is 36° , the internal friction angle of the base soil (ϕ') is 34° , the unit weight of the retained soil (γ_s) is 17.5 kN/m^3 , the unit weight of the base soil (γ'_s) is 18.5 kN/m^3 , the unit weight of concrete (γ_c) is 23.5 kN/m^3 , and the cohesion of the base soil (c) is 0 kPa.

2.1. Design of retaining wall

The Mononobe-Okabe (M-O) method, a commonly used pseudo-static approach developed by Mononobe and Okabe in the 1920s, was employed to determine the passive and active forces acting on a unit length of the retaining wall (Okabe 1924; Mononobe and Matsuo 1929). As an essential tool in modern geotechnical engineering, the Mononobe-Okabe (M-O) method offers a

more accurate representation of seismic effects on retaining walls than static methods, enabling the design of structures that maintain stability during seismic events. It is especially useful in seismic regions, where it is com-

monly applied to design earthquake-resistant structures such as highways, dams, and retaining walls. Fig. 2 illustrates the key forces involved in the Mononobe-Okabe (M-O) method.

Table 2. Boundary constraints of the design variables.

Design variable	Unit	Lower bound	Upper bound
X_1 (toe slab width)	m	0.480	1.300
X_2 (base slab width)	m	1.600	4.700
X_3 (stem top thickness)	m	0.270	1.350
X_4 (base slab thickness)	m	0.310	1.330
X_5 (stem bottom thickness)	m	0.550	2.400
R_1 (vertical reinforcement in stem)	(cm ²)	45.000	565.000
R_2 (horizontal reinforcement in toe)	(cm ²)	40.000	480.000
R_3 (horizontal reinforcement in heel)	(cm ²)	38.000	445.000

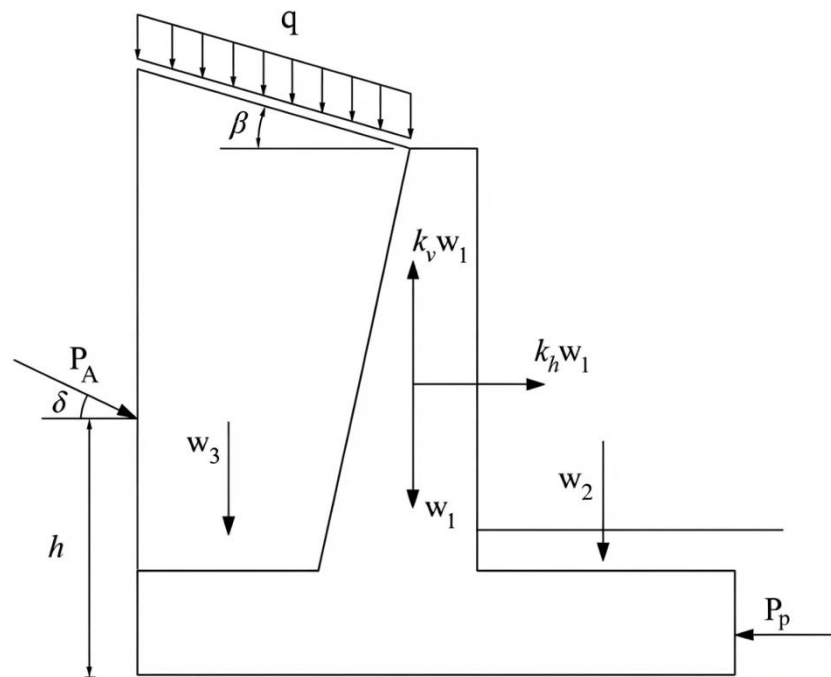


Fig. 2. Forces acting on an RCC retaining wall based on the M–O method.

These forces include: the weight of the concrete wall (W_1), the weight of the soil on the toe (W_2), the weight of the backfill material (W_3), the surcharge load (q), the inertial forces in both the horizontal ($k_h W_1$) and vertical ($k_v W_1$) directions, and the seismic passive and active earth pressures (P_p and P_a). The movement results in two forces ($k_v W_1$ and $k_h W_1$) that act in the vertical and horizontal directions, respectively. Here, k_v and k_h represent the vertical and horizontal coefficients that are specific to the local geographic conditions. In this study, the horizontal seismic coefficient was set at $k_h = 0.30$, while the vertical seismic coefficient was taken as $k_v = 0.15$. The total maximum active earth pressure acting on the wall (P_a) is given by the M-O theory as:

$$P_a = \frac{1}{2} k_a \gamma_{\text{soil}} H^2 (1 - k_v) \quad (1)$$

Here, H indicates the height of the wall, γ_{soil} stands for the unit weight of the soil, k_v is the coefficient of vertical acceleration, and k_a represents the dynamic active earth pressure coefficient, which is determined as:

$$k_a = \frac{\cos^2(\phi - \theta - \beta)}{\cos \theta \cos^2 \beta \cos(\delta + \theta + \beta)} \left[1 + \sqrt{\frac{\sin(\delta + \phi) \sin(\phi - \theta - i)}{\cos(\delta + \beta + \theta) \cos(i - \beta)}} \right]^2 \quad (2)$$

where, i represents the inclination of the backfill, θ defines the seismic inertia angle, ϕ is the soil's internal friction angle, β indicates the vertical inclination of the back wall, and δ denotes the angle of wall friction between the soil and the rear face of the stem. The passive earth pressure (P_p) is calculated similarly to the active earth pressure, as follows:

$$P_p = \frac{1}{2} k_{pe} \gamma_{\text{soil}} h^2 (1 - k_v) \quad (3)$$

where, the dynamic passive earth pressure coefficient (k_p), given by:

$$k_p = \frac{\cos^2(\phi + \theta - \beta)}{\cos^2 \theta \cos(\delta - \theta + \beta)} \left[1 + \sqrt{\frac{\sin(\phi - \delta) \sin(\phi + i - \theta)}{\cos(\delta - \beta + \theta) \cos(i - \beta)}} \right]^2 \quad (4)$$

where, the inclination of the backfill is represented by i , while β denotes the back wall angle. The internal friction angle of the soil is referred to as ϕ , and δ represents the friction angle between the stem and the soil. The seismic inertia angle θ is defined by the following equation:

$$\theta = \tan^{-1} \left(\frac{k_h}{1 - k_v} \right) \quad (5)$$

In this study, k_h represents the horizontal seismic acceleration coefficient, and combinations of horizontal and vertical (k_v) coefficients are applied, ranging from 0 to 0.3, with a step size of 0.15. The constraints for the optimization of RCC walls are analyzed using three core evaluation methods: (1) geotechnical requirement, (2) structural requirement, and (3) geometrical analysis.

2.1.1. Geotechnical requirements

Geotechnical stability checks include overturning, sliding, and bearing capacity analyses. Overturning stability is checked by calculating the factor of safety for overturning (FSO):

$$FSO = \frac{\sum MR}{\sum MO} \quad (6)$$

To ensure safety, the factor of safety must be at least 1.5 ($FSO \geq 1.5$), where $\sum MO$ denotes the sum of overturning moments and $\sum MR$ represents the sum of resisting moments. To check the sliding stability, the factor of safety for sliding (FSS) is evaluated as follows:

$$FSS = \frac{\sum FR}{\sum FD} = \frac{(\sum W_{wall} \cdot \tan(\frac{2\phi_{base}}{3})) + 2Bc_{base} + P_p + P_k}{P_a \cdot \cos \beta} \quad (7)$$

The sliding factor of safety must satisfy the condition $FSS \geq 1.5$, where, the base soil's internal friction angle is denoted by ϕ_{base} , while the adhesion between the base slab and soil is represented by c_{base} . P_a represents the active force, and P_p is the passive force located in front of the base. The sum of the horizontal driving forces is given by $\sum FD$, and $\sum FR$ denotes the sum of the horizontal resisting forces. The total weight of the wall is represented by $\sum W_{wall}$, and B indicates the width of the base slab.

The bearing capacity of the soil is assessed by the bearing factor of safety (FSB):

$$FSB = \frac{q_{ult}}{q_{max}} \quad (8)$$

where q_{ult} is the ultimate bearing capacity of the soil, and q_{max} is the maximum stress at the base slab. The ultimate bearing capacity is calculated using the following general expression:

$$q_{ult} = cN_c s_c + qN_q s_q + 0.5\gamma B' N_\gamma s_\gamma \quad (9)$$

where; c is Cohesion of the soil, q is Overburden pressure at the footing base level, B' is Effective footing width (B-2e) to account for eccentricity. N_c , N_q , N_γ are dimensionless bearing capacity factors based on the friction angle (ϕ). s_c , s_q and s_γ are the shape factors (Fredlund and Rahardjo 1993).

The limit stresses along the base slab are calculated using the equations below:

$$q_{max/min} = \frac{\sum V}{B} \left(1 \mp \frac{6e}{B} \right) \quad \text{and} \quad e = \frac{B}{2} - \frac{\sum M_R - \sum M_O}{\sum V} \quad (10)$$

where $\sum V$ is the sum of all of the vertical forces, and e represents the eccentricity of the corresponding distribution. The bearing strength criterion requires $FSB \geq 3$ (Gandomi et al. 2017a).

2.1.2. Structural requirements

The structural analysis includes verifying that the shear and moment capacities of all sections of the wall, such as the stem, heel, and toe meet the following conditions (ACI 318-05 2005):

$$\frac{M_n}{M_u} \geq 1 \quad \text{and} \quad \frac{V_n}{V_u} \geq 1 \quad (11)$$

The moment and shear capacities, M_n and V_n , were calculated for the toe, stem, and heel using following equations.

$$V_n = \phi_n 0.17 \sqrt{f_c} b d \quad \text{and} \quad M_n = \phi_m A_s f_y \left(d - \frac{a}{2} \right) \quad (12)$$

The shear strength is determined by ACI 318-05 (2005), where b is the width of the cross-section; f_c is the specified compressive strength of concrete; and ϕ_n is the nominal strength coefficient (equal to 0.75). In this context, a is the depth of the compressive stress block; d is the effective depth of the cross-section; f_y is the yield strength of steel; A_s is the cross-sectional area of the steel reinforcement; and ϕ_m is the nominal strength coefficient (equal to 0.9). As illustrated in Fig. 3, the pressure distribution from the base onto the foundation soil is non-uniform and is calculated using the following formulas for heel and toe. The ultimate shear and moment forces V_u and M_u are then used to compute the shear forces and design moment for the heel and toe slabs. The effective design forces acting on toe, heel, and stem are depicted in Fig. 3.

At the heel section of the base slab, the shear force and bending moment act on the critical section located a distance dh from the back face of the stem's base, defined as $dh = X4 - CC$. Similarly, the toe slab experiences its critical flexural moment at a section positioned dt away from the front face of the stem, where $dt = X4 - CC$. The shear force and bending moment requirement at the critical section of the toe slab are then determined using the following equations:

$$V_h = \left[1.6q + 1.2\gamma_c X_4 + 1.2\gamma_{rs} H + 1.2 \frac{W_{bs} + W_{bsdh}}{2} - 0.9 \frac{q_{dh} + q_{min}}{2} \right] (l_{heel} - d_h) \quad (13)$$

$$M_h = \left[\left(\frac{1.6q + 1.2\gamma_c X_4 + 1.2\gamma_{rs} H}{2} \right) + \frac{1.2W_{bs}}{3} - \left(\frac{q_1 + 2q_{min}}{6} \right) \right] l_{heel}^2 \quad (14)$$

$$V_t = \left[1.6 \left(\frac{q_{dt} + q_{\max}}{2} \right) - 0.9 (\gamma_c X_4 + \gamma_{bs} (D - X_4)) \right] (l_{\text{toe}} - dt) \quad (15)$$

$$M_t = \left[1.6 \left(\frac{q_2}{6} + \frac{q_{\max}}{3} \right) - 0.9 (\gamma_c X_4 + \gamma_{bs} (D - X_4)) \right] l_{\text{toe}}^2 \quad (16)$$

where, CC represents the concrete cover, while γ_c denotes the concrete's unit weight. The load resulting from the triangular distribution of the backfill soil at a height

dh behind the wall is represented as W_{bsdh} , with the corresponding soil pressure expressed as q_{dh} . The symbol W_{bs} identifies the peak load due to backfill acting at the heel section. At the bottom of the stem on the rear side, the soil pressure is denoted by q_1 , whereas q_2 corresponds to the pressure applied at the toe. The terms l_{heel} and l_{toe} describe the lengths of the heel and toe slabs, respectively.

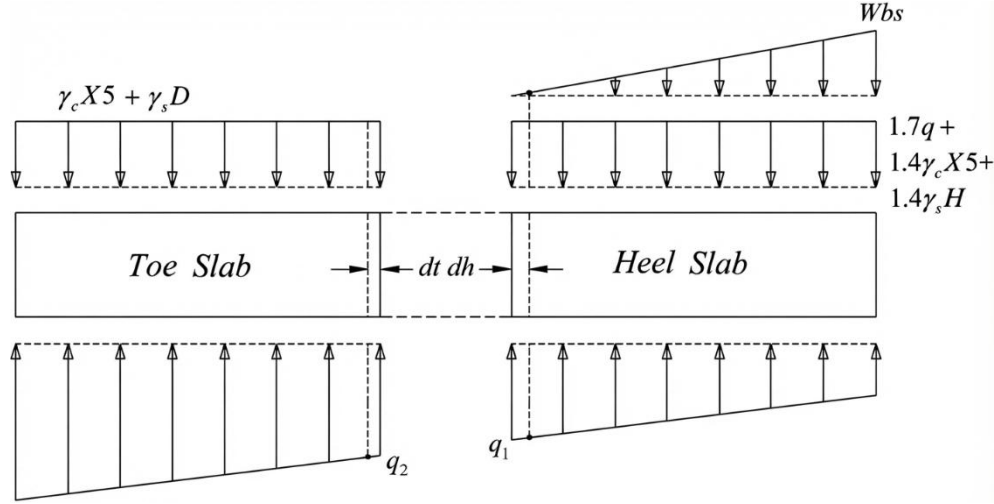


Fig. 3. The effective design forces on toe slab and heel slab.

Furthermore, the shear force and bending moment along the height of the stem, with the critical section for shear force located at a distance ds from the point where the stem intersects with the base slab ($ds = X_5 - CC$), can be represented as follows:

$$V_s = 1.6 \left(k_a q (H - ds) + \frac{1}{2} k_a \gamma_{rs} (H - ds)^2 \right) \cos \beta \quad (17)$$

$$M_s = 1.6 \left[\frac{1}{2} (k_a q H^2) + \left(\frac{1}{3} k_a \gamma_{rs} H^3 \right) \right] \cos \beta \quad (18)$$

In the final retaining wall design, all structural strength and geotechnical stability requirements must be satisfied. The optimization algorithm enforces the design constraints through a penalty-based approach. Designs satisfying all constraint conditions remain unpenalized, while infeasible solutions are assigned penalty values proportional to the extent of their constraint violations.

2.1.3. Geotechnical constraints

The design optimization of the retaining wall is governed by a set of inequality constraints that ensure structural integrity and geotechnical stability. The first constraint, $g_1(x) = (FS_{O\text{design}}/FS_O) - 1 \leq 0$ is defined to maintain overturning stability by ensuring the calculated factor of safety does not fall below the required design limit. Similarly, the sliding resistance is controlled by $g_2(x) = (FS_{S\text{design}}/FS_S) - 1 \leq 0$ which guarantees that the resisting forces are sufficient against lateral earth pressures. To prevent bearing capacity failure of the foundation soil, the constraint $g_3(x) = (FS_{B\text{design}}/FS_B) - 1 \leq 0$ is employed to keep the applied pressure within safe limits. Finally, to ensure the entire base of the wall remains in compression and

maintains full contact with the soil, the condition $g_4(x) = q_{\min} \geq 0$ is imposed, effectively preventing any tensile stress at the heel or toe.

2.1.4. Structural constraints

In addition to geotechnical stability, the structural integrity of the retaining wall components (stem, toe, and heel slabs) is maintained through a set of reinforcement-related inequality constraints. The primary structural safety is governed by the moment and shear capacity ratios; specifically, the constraints $g_{[5-7]}(x) = (M_u/M_n) - 1 \leq 0$ and $g_{[8-10]}(x) = (V_u/V_n) - 1 \leq 0$ ensure that the factored design moment and shear force do not exceed the nominal resistance capacities of the sections. Furthermore, to ensure ductile behavior and prevent sudden failure, the amount of reinforcement steel must stay within standardized limits. This is controlled by the minimum reinforcement constraint, $g_{[11-13]}(x) = (A_{s\min}/A_s) - 1 \leq 0$ which ensures sufficient steel area is provided, and the maximum reinforcement constraint, $g_{[14-16]}(x) = (A_s/A_{s\max}) - 1 \leq 0$ which prevents over-reinforcement and ensures the concrete reaches its crushing strain only after the steel yields. $g_{[5-7]}(x)$ are the moment capacity constraints for each section (stem, toe slab, and heel slab), $g_{[8-10]}(x)$ are the shear capacity constraints for each section, $g_{[11-13]}(x)$ are the minimum reinforcement area constraints, $g_{[14-16]}(x)$ are the maximum reinforcement area constraints

2.1.5. Geometric constraints

To ensure the constructability and structural stability of the retaining wall, several geometric and reinforcement development length constraints are implemented. The geometric constraint, $g_{17}(x) = (X_1 + X_3)/(X_2) -$

$1 \leq 0$ is used to maintain proportional dimensions between different parts of the wall structure. Furthermore, to ensure that the reinforcement bars can fully develop their design strength without slipping, the development length must be sufficiently accommodated within the concrete sections. These requirements are controlled by the following constraints: The stem reinforcement development within the footing is governed by $g_{18}(x) = (l_{db \text{ stem}})/(X_5 - \text{cover}) - 1 \leq 0$. The toe slab reinforcement development is ensured by $g_{19}(x) = (l_{db \text{ toe}})/(X_2 - X_1 - \text{cover}) - 1 \leq 0$. The heel slab reinforcement anchorage is checked using $g_{20}(x) = (l_{db \text{ heel}})/(X_2 + X_3 - \text{cover}) - 1 \leq 0$.

2.1.6. Objective functions

This study introduces an innovative automated optimization technique designed to improve geotechnical design and structural efficiency, applying a metaheuristic method for the first time to automate the dynamic analysis of sustainable and material cost-effective RCC walls. By optimizing 8 design variables, including 5 geometric and 3 steel reinforcement factors, the method aims to minimize material cost and CO₂ emissions using the simulated annealing technique:

$$\text{Cost} = C_s W_s + C_c V_c \quad (19)$$

$$\text{CO}_2 = e_s W_s + e_c V_c \quad (20)$$

The unit costs of steel and concrete are denoted by C_s and C_c , respectively, while W_s represents the weight of the reinforcing steel and V_c is the volume of concrete. The unit weight of concrete, scaled by a factor of 100, is represented by γ_c . The CO₂ emissions resulting from the RCC wall materials are calculated as shown in Eq. (20). The unit CO₂ emissions of reinforcement and concrete are referred to CO_{2s} and CO_{2c}, respectively, and are taken from Naseri et al. (2022). CO₂ emission for steel reinforcement is 2.82 kg/kg for traditional concrete (ITeC 2009). Concrete, the most widely used man-made material in construction, faces a growing demand worldwide. As a result, the use of eco-friendly concrete has become increasingly

important on geotechnical infrastructures. In this study, the environmental objective function accounts exclusively for the emissions associated with concrete and reinforcing steel. Accordingly, the system boundary and functional unit are clearly defined to reflect only the material-related embodied CO₂ emissions within the adopted database and system boundary.

The mixture proportions of eco-friendly concrete (green mixture and sustainable mixture) were evaluated in RCC retaining walls as a key environmental design element. Green concrete is defined as concrete with an optimal balance of cost-effectiveness, environmental footprint, workability, and strength. Sustainable concrete, considered a durable form of green concrete, provides the best balance in terms of these factors (Naseri et al. 2022). The methodology simultaneously considers various critical environmental factors in concrete mixture proportioning, including hazardous waste disposal (HWD), non-hazardous waste disposed (NHWD), and global warming potential (GWP) is considered in this study. The HWD represents the amount of hazardous waste generated throughout a material's life cycle and is expressed in kilograms (kg). Lower HWD values associated with hazardous waste management. The GWP quantifies the contribution of greenhouse gas emissions to climate change and is expressed as kilograms of carbon dioxide equivalent (kg CO₂-eq). Lower GWP values indicate lower greenhouse gas emissions and better environmental performance. The use of fly ash (FA) in mixture design helps mitigate the environmental impact of cement and improve concrete properties. Subsequently, the optimal mixture proportions for sustainable and green concrete are introduced in Table 3. Green concrete is designed to minimize environmental impacts while maintaining adequate strength, workability, and cost. Sustainable concrete further incorporates durability as an additional performance criterion. Tables 3 and 4 present the source material data adopted directly from Naseri et al. (2022). No recalculation or modification was performed, and the reported material properties were used without alteration. These literature-derived data were incorporated into the optimization model as the material properties of the reinforced concrete cantilever (RCC) retaining wall.

Table 3. Optimal mixture proportion of green and sustainable concrete with different strengths (Naseri et al. 2022).

Compressive strength (MPa)	Concrete type	Mixture ID	Cement (kg/m ³)	Water (kg/m ³)	Fine aggregate (kg/m ³)	Coarse aggregate (kg/m ³)	Fly ash (kg/m ³)
30	Green	G30	145	177.40	812.62	1020.40	174.13
40	Green	G40	145.02	173.25	892	939	183.17
50	Green	G50	177.59	170.80	804.74	982.21	205.24
60	Green	G60	209.09	165.08	709.08	1049	223.07
30	Sustainable	S30	158.39	179.79	892	942.28	154.23
40	Sustainable	S40	173.89	169.98	830.78	996.07	174.23
50	Sustainable	S50	207.81	160	785.30	1045.60	169.85
60	Sustainable	S60	239.31	160	737.95	1049	185.61
30	Traditional	T30	176.92	188.60	954.45	1015.86	171.18
40	Traditional	T40	194.45	178.48	889.94	1074.31	193.40
50	Traditional	T50	232.75	168.10	840.27	1129.25	188.80
60	Traditional	T60	269.10	176	789.61	1132.92	206.52

Furthermore, the costs of green (G), traditional (T) and sustainable (S) concrete with a mixture ID of G30, G40, G50, T30, T40, T50, S30, S40, and S50 are detailed in Table 4, with GWP (kg CO₂-eq), NHWD (kg), Carbona-

tion (mm), and HWD (kg) including material cost (Euros/m³). Table 4 summarizes the environmental impact indicators and unit material costs for the concrete types used in this study.

Table 4. The environmental impact indicators and unit material costs for green, sustainable, and traditional concrete (Naseri et al. 2022).

Mixture ID	GWP (kg CO ₂ -eq)	HWD (kg)	Cost (Euros/m ³)	NHWD (kg)	Carbonation (mm)
G30	139.13	0.021	59.66	0.335	26.77
S30	151.09	0.023	61.18	0.347	26.77
T30	265.99	0.057	91.36	0.572	26.51
G40	139.28	0.022	61.14	0.329	26.62
S40	165.36	0.025	62.91	0.378	19
T40	300.46	0.099	93.87	0.625	21.65
G50	169	0.026	64.86	0.386	26.53
S50	196.06	0.030	66.63	0.484	6.23
T50	392.41	0.067	98.77	0.777	10.36

2.1.7. Simulated annealing algorithm

The heuristic optimization approach adopted in this study is Simulated Annealing (SA), first introduced by Kirkpatrick et al. (1983). The method is inspired by the annealing process, where a material is heated and then gradually cooled to achieve a stable structure. At high temperatures, the algorithm may accept worse solutions, but this probability decreases as the temperature is lowered. In SA, a new solution is accepted based on the probability $\exp(-\Delta E/T)$, where ΔE is the change in the objective function and T is the current temperature. The temperature is reduced geometrically using a cooling coefficient, and a fixed number of iterations (Markov chain) is performed at each temperature level. This enables the algorithm to escape local optima at early stages and gradually converge as the temperature approaches zero. The performance of SA depends on parameters such as the initial temperature, cooling rate, and Markov chain length. In this study, the initial solution is generated randomly within the variable bounds and repeated until a feasible solution is obtained.

To ensure the rigorous technical reproducibility of the optimization procedure, the Simulated Annealing (SA) algorithm is implemented with precise control mechanisms and a robust thermal schedule. The optimization process initiates with the definition of an eight-dimensional design vector, $Y = \{Y_1, Y_2, \dots, Y_8\}$, representing the geometric dimensions ($X_1, \dots, X_5$) and reinforcement areas ($R_1, \dots, R_3$). The search space is bounded by practical engineering limits, and an initial feasible solution is generated through a stochastic sampling process. To maintain structural and geotechnical validity from the onset, the algorithm utilizes a rejection sampling technique, repeatedly generating initial candidate vectors until all inequality constraints—governing overturning, sliding, bearing capacity, and structural requirements—are strictly satisfied. The thermal schedule, which governs the exploration-exploitation balance, is

calibrated based on the initial sensitivity of the objective functions (Cost and CO₂).

The initial temperature, T_0 , is established at 100. This specific value is selected through pre-computational trials to ensure an initial acceptance probability, P , of approximately 0.8 for worsening moves, as defined by the Metropolis criterion: $P = \exp(-\Delta E/T)$. This high initial energy state allows the algorithm to perform extensive global exploration, effectively bypassing local minimum that frequently occurs in non-convex structural landscapes. The transition from exploration to fine-tuning (exploitation) is controlled by a geometric cooling law, $T_{k+1} = \alpha \cdot T_k$, where the cooling rate, α , is set to 0.95. This relatively slow cooling rate ensures a thorough search of the design space. At each discrete temperature level, a Markov chain length, L , of 100 iterations is maintained. This ensures that the system reaches a state of quasi-equilibrium, allowing the design variables to stabilize before the next temperature reduction. During each iteration, a neighborhood move is generated by applying a random perturbation to the current design vector, scaled by the variable's permissible range.

Constraint handling is managed through a sophisticated static penalty function approach. Given the highly constrained nature of RCC retaining wall design, a penalized objective function, $f_{\text{aug}}(x)$, is formulated to guide the search toward the feasible region:

$$f_{\text{aug}}(x) = f(x) + R \sum_{i=1}^{20} \max(0, g_i(x))^2 \quad (21)$$

where $f(x)$ is the raw cost or CO₂ emission, $g_i(x)$ represents the i -th inequality constraint, and R is a robust penalty multiplier set to 10^6 . This high penalty coefficient ensures that any violation of safety factors results in a significant increase in the energy state, making such solutions highly unlikely to be accepted in the later stages of annealing. The optimization procedure concludes based on dual-termination criterion. The algorithm stops when either the system temperature reaches

a final threshold of $T_{\text{final}} = 0.001$ (thermal convergence) or the best-found solution remains unchanged for 50 consecutive temperature steps (stagnation convergence). By integrating these specific parameters and penalty mechanisms, the optimization framework provides a reproducible and technically sound method for the design of sustainable geotechnical structures.

3. Results and Discussion

Table 5 summarizes the CO₂ emission results and computational times obtained from nine independent runs for wall heights ranging from 4 m to 10 m, considering green, sustainable, and traditional concrete alter-

natives. Across all wall heights, CO₂ emissions increase as expected with structural size. In terms of material performance, green concrete consistently provides the lowest emissions, followed by sustainable concrete, while traditional concrete yields the highest emission. The gap between minimum and average emission values remains small at lower heights but becomes more pronounced as the wall height increases, indicating higher variability for larger design cases. The standard deviation also tends to grow with height, particularly for traditional concrete, reflecting greater dispersion in solutions. CPU times show a slight increasing trend with wall height, while remaining largely similar across all three concrete types, suggesting that environmental performance differences do not significantly affect computational effort.

Table 5. Comparative CO₂ emissions of retaining walls for different wall heights and material alternatives.

<i>H</i> (m)	Concrete type	Min. emissions (kg CO ₂ -eq)	Avg. emissions (kg CO ₂ -eq)	Std. deviation	Avg. CPU time (s)
4	Traditional	1285.420	1290.115	1.250	92.450
4	Sustainable	1156.880	1158.310	0.840	95.120
4	Green	1024.350	1025.040	0.520	98.610
6	Traditional	2715.300	2724.850	6.420	96.180
6	Sustainable	2443.770	2448.320	4.150	98.340
6	Green	2165.210	2166.590	2.880	102.150
8	Traditional	4982.150	5012.440	84.120	100.240
8	Sustainable	4483.930	4505.210	52.340	103.550
8	Green	3968.450	3975.120	35.180	108.420
10	Traditional	8125.680	8182.350	105.400	105.820
10	Sustainable	7313.110	7345.920	92.150	109.140
10	Green	6475.240	6488.770	68.220	114.350

Table 6 presents the cost optimization results and corresponding CPU times for nine runs over wall heights from 4 m to 10 m, evaluated for green, sustainable, and traditional concrete alternatives. In all cases, costs increase progressively with wall height due to higher material and structural demands. Green concrete consistently achieves the lowest cost values, followed by sustainable concrete, whereas traditional concrete results in the high-

est costs among the three options. The differences between minimum and average costs remain relatively limited, indicating stable optimization performance across all scenarios. Although standard deviation increases slightly at higher wall heights, the overall variability remains moderate. CPU time exhibits a gradual increase with wall height, and similar to the emissions case, it is not significantly influenced by the type of concrete used.

Table 6. Comparative cost analysis of retaining walls for different wall heights and material alternatives.

<i>H</i> (m)	Concrete type	Minimum cost (euros)	Average cost (euros)	Standard deviation	Average CPU time (s)
4	Traditional	815.420	816.050	0.450	92.450
4	Sustainable	742.180	742.850	0.380	95.120
4	Green	676.806	677.187	0.344	96.734
6	Traditional	1618.300	1620.450	2.850	96.180
6	Sustainable	1475.250	1476.900	2.420	98.340
6	Green	1343.588	1344.762	2.166	100.619
8	Traditional	2758.120	2768.440	19.450	100.240
8	Sustainable	2515.650	2524.320	17.800	103.550
8	Green	2290.699	2298.642	16.300	103.894
10	Traditional	4228.950	4235.120	9.500	105.820
10	Sustainable	3852.400	3858.750	8.450	109.140
10	Green	3513.353	3518.385	7.724	107.788

A sensitivity analysis was conducted to evaluate the influence of the Simulated Annealing cooling rate on the optimization performance. Five cooling rate values ranging from 0.90 to 0.99 were examined while keeping all other algorithmic parameters constant. The cooling rate has a noticeable influence on both the solution quality and the computational performance of the Simulated Annealing algorithm. When the cooling rate is set to 0.90, the algorithm converges rapidly, resulting in the shortest CPU time (71.4 s); however, it produces the highest best and mean cost values (€681.52 and €683.41, respectively) together with the largest standard deviation (€1.74), indicating reduced solution quality and stability with 12,500 iterations. As the cooling rate increases, the performance gradually deteriorates: at 0.92, the metrics shift to a best result of €688.20, mean of €685.10, standard deviation of 1.05, 112.0 s CPU time, and 17,000 iter-

ations; at 0.95, the best, mean, and worst costs rise to €698.80, €690.50 with a standard deviation of 1.25, taking 155.0 s and 25,400 iterations; at 0.97, the values further increase to €705.30 (best), €702.15 (mean) with a standard deviation of 1.52, 195.4 s CPU time, and 36,100 iterations; and finally, at 0.99, the algorithm yields its highest costs with a best result of €707.52, mean of €704.41, standard deviation of 1.74, requiring the maximum computational effort of 245.6 s CPU time and 48,200 iterations. All tests were executed in Python 3.10 using an Intel Core i7 processor and 16 GB of RAM.

Fig. 4 illustrates the relationship between the minimum values of CO₂ emissions and costs (Cost) with respect to the total wall height. The results indicate that both responses follow a clear quadratic trend. The average CO₂ emissions can be approximated by a second-order polynomial of the form:

- $CO_{2(\text{traditional})}(\text{kg}) = 108.4484H^2 - 370.0634H + 1036.6668$, with a coefficient of determination $R^2 = 0.9998$ for traditional concrete.
- $CO_{2(\text{sustainable})}(\text{kg}) = 96.9188H^2 - 325.8765H + 911.9630$, with a coefficient of determination $R^2 = 0.9999$ for sustainable concrete.
- $CO_{2(\text{green})}(\text{kg}) = 85.7563H^2 - 290.6015H + 817.2530$, with a coefficient of determination $R^2 = 0.9996$ for green concrete.
- Similarly, the average cost (Cost) variation is well represented by a function given as:
- $\text{Cost}_{(\text{traditional})}(\text{euros}) = 41.3925H^2 - 9.2350H + 189.4650$, with $R^2 = 0.9995$ for traditional concrete.
- $\text{Cost}_{(\text{sustainable})}(\text{euros}) = 37.52375H^2 - 5.5765H + 163.4580$, with $R^2 = 0.9994$ for sustainable concrete.
- $\text{Cost}_{(\text{green})}(\text{euros}) = 34.5105H^2 - 9.2733H + 161.0901$, with $R^2 = 0.9995$ for green concrete.

These regression models confirm a strong nonlinear dependency between wall height and both objective functions, with excellent agreement between the fitted curves and the observed data. The results are evaluated independently for each objective. The comparative assessment of the traditional, sustainable, and green concrete alternatives is therefore based on their individual performances with respect to each optimization objective. Moreover, it should be noted that the proposed regression equations are empirical relationships derived from the optimization results obtained for the investigated retaining wall heights (4–10 m). Therefore, extrapolation beyond the investigated wall height interval requires additional optimization analyses and further validation.

The results indicate that both the minimum cost and minimum carbon emissions increase with retaining wall height due to the higher material demand. For all investigated wall heights, green concrete consistently achieved the lowest cost and carbon emission values, followed by sustainable concrete, whereas traditional concrete resulted in the highest values. Compared with traditional concrete, the use of green concrete reduced the minimum cost by approximately 17% and the minimum carbon emissions by approximately 20%, while maintaining the required structural and geotechnical performance. These findings demonstrate the economic and environmental advantages of adopting green concrete in optimized retaining wall design (Fig. 4).

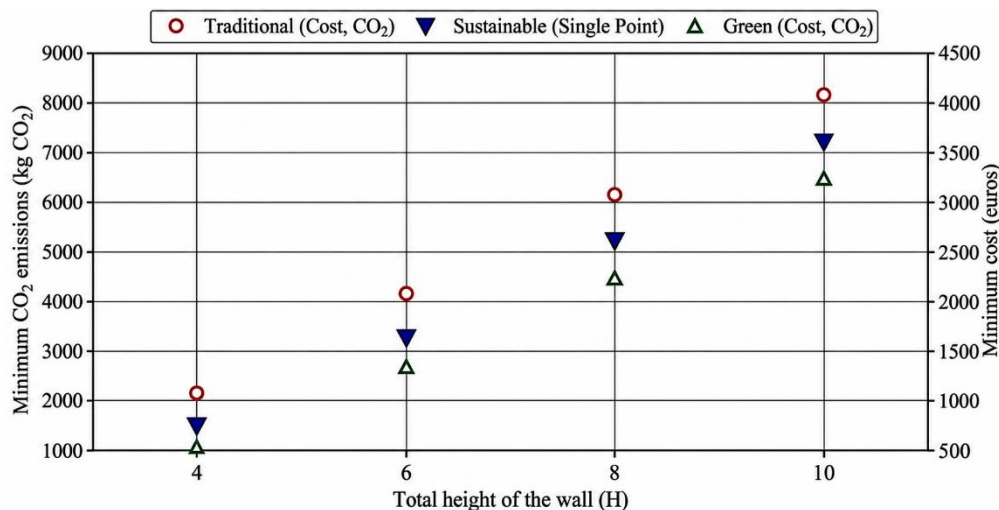


Fig. 4. Comparative variation of minimum cost and minimum emissions for traditional, sustainable, and green concrete types across the wall height.

Fig 5. illustrates the cost-versus-emission objective space for traditional, sustainable, and green concrete. As shown, green concrete consistently occupies the lower emission region, providing a clear visual representation of how variations in concrete type affect the balance between sustainability goals and budgetary

requirements.

Finally, it is necessary to analyze if the economic optimized walls and the emissions optimized walls present similar characteristics. The characteristics for these walls are compiled in Tables 7 and Table 8 for optimized emission and cost, respectively.

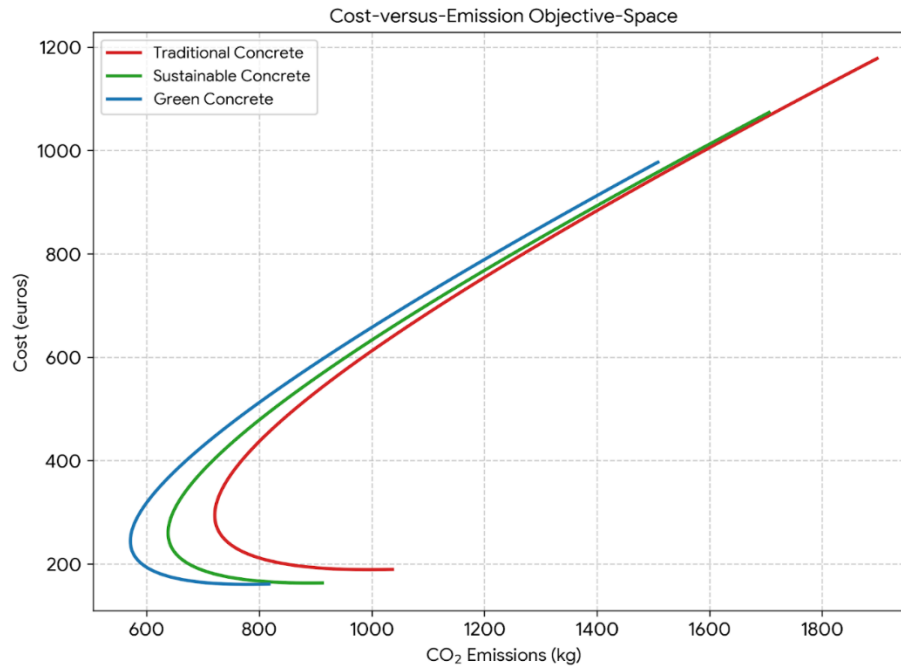


Fig. 5. The cost-versus-emission objective space for traditional, sustainable, and green concrete.

Table 7. Characteristics of RCC retaining walls with traditional, sustainable, and green concrete for emission optimization.

Design variables	H (m)	4	6	8	10
X1 (toe slab width) (m)	Traditional	0.640	0.960	1.150	1.260
	Sustainable	0.612	0.905	1.062	1.092
	Green	0.485	0.725	0.820	0.950
X2 (base slab width) (m)	Traditional	1.780	2.960	3.950	4.600
	Sustainable	1.685	2.748	3.781	4.286
	Green	1.650	2.460	3.280	4.040
X3 (stem top thickness) (m)	Traditional	0.360	0.600	0.900	1.220
	Sustainable	0.318	0.548	0.823	1.118
	Green	0.270	0.470	0.720	1.000
X4 (base slab thickness) (m)	Traditional	0.410	0.650	0.820	0.990
	Sustainable	0.362	0.588	0.742	0.903
	Green	0.310	0.500	0.650	0.800
X5 (stem bottom thickness) (m)	Traditional	0.700	1.150	1.650	2.200
	Sustainable	0.620	1.050	1.500	2.050
	Green	0.550	0.900	1.300	1.800
R1 (vertical reinforcement in stem) (cm ²)	Traditional	65.200	165.000	330.000	565.000
	Sustainable	56.870	142.880	287.940	492.330
	Green	45.000	115.000	230.000	390.000
R2 (horizontal reinforcement in toe) (cm ²)	Traditional	58.000	140.000	285.000	480.000
	Sustainable	50.120	121.760	252.880	420.780
	Green	40.000	100.000	200.000	330.000
R3 (horizontal reinforcement in heel) (cm ²)	Traditional	52.000	128.000	265.000	445.000
	Sustainable	45.500	112.000	235.000	395.000
	Green	38.000	92.000	190.000	320.000

The optimization results demonstrate a profound shift in the structural and environmental performance of RCC retaining walls when traditional design paradigms are replaced with metaheuristic-driven approaches. The primary finding of this study is the consistent superiority

of green concrete across all height parameters. At a structural height of 10 m, green concrete achieved a minimum CO₂ emission of 6475.24 kg, representing a substantial reduction of approximately 20% compared to the 8125.68 kg generated by traditional mixtures (Fig. 6).

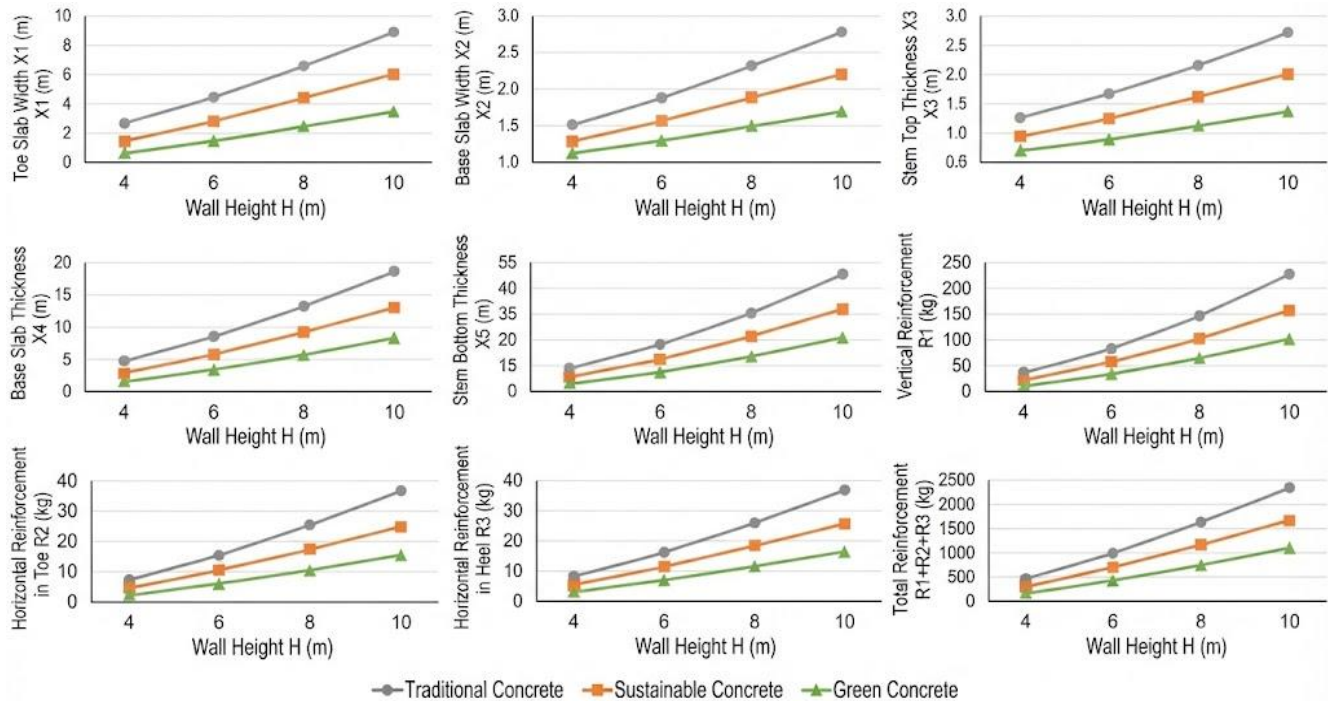


Fig. 6. Variation of design variables with wall height for optimized emissions.

This environmental efficiency is largely attributed to the optimized replacement of cement with fly ash, which significantly lowers the Global Warming Potential (GWP), where G30 concrete exhibits a GWP of only 139.13 kg-CO₂-eq compared to 265.99 kg-CO₂-eq for T30. These results suggest that the integration of fly ash does not merely serve as a waste-disposal solution in geotechnical infrastructure without sacrificing compressive strength.

The economic analysis further challenges the conventional assumption that sustainable construction materials necessarily incur a financial premium. The optimization results presented in Table 7 and 8 demonstrate that the selection of concrete type has a substantial influence on both the environmental and economic performance of the retaining wall while satisfying identical structural and geotechnical design requirements. Among the three alternatives, green concrete consistently produced the lowest cost and carbon emission values for all wall heights, followed by sustainable concrete, whereas traditional concrete resulted in the highest values. In addition to its superior environmental and economic performance, driven by the predefined material cost and emission factors, the use of green concrete achieved the optimum emission and cost values for the same wall height. Consequently, the optimized green concrete designs required the lowest quantities of both concrete and reinforcing steel. Sustainable concrete exhibited intermediate performance, providing noticeable reductions in material consumption, cost, and carbon emissions relative to traditional concrete, although its optimized dimen-

sions and reinforcement requirements remained higher than those of green concrete. These findings indicate that adopting green concrete enables more material-efficient retaining wall designs without compromising the required structural safety or geotechnical stability, thereby offering significant advantages in terms of both sustainability and economic efficiency. The data from Table 8 reveals that green concrete is consistently the most cost-effective option, with the 10 m wall configuration costing 3513.35 Euros—roughly 17% less than the 4228.95 Euros required for traditional concrete.

This cost-effectiveness is driven by the reduction in both material unit costs and Hazardous Waste Disposal (HWD) metrics. From a structural standpoint, the Simulated Annealing (SA) algorithm facilitated this by optimizing geometric variables to favor more efficient sections; for instance, the stem bottom thickness (X5) for a 10 m wall was reduced from 2.40 m in traditional designs to 1.85 m in green concrete configurations. This indicates that the optimization technique effectively exploits the material properties of eco-friendly mixtures to produce leaner, more efficient structural geometries that simultaneously minimize volume and cost.

Furthermore, the high predictive accuracy of the derived quadratic regression models ($R^2 > 0.998$) underscores a stable and predictable relationship between wall height and design objectives. The divergence between traditional and green concrete performance becomes more pronounced as wall height increases, as shown in the standard deviation trends in Table 9. While traditional concrete exhibited higher variability at 10 m

heights ($SD = 105.40$), green concrete remained more stable ($SD = 68.22$), suggesting that the SA algorithm finds more robust optima when working with sustainable mixture parameters. This stability, coupled with the negligible differences in CPU times across material types, confirms that the proposed automated optimization framework is computationally efficient. Ultimately, these results provide a scalable roadmap for geotechnical engineers to reconcile the often-conflicting goals of structural safety,

economic constraint, and environmental stewardship. To further validate the proposed optimization framework, the optimized retaining wall designs obtained using the Simulated Annealing (SA) algorithm were compared with the qualitative comparison with selected literature results reported by Gandomi et al. (2017a), in which Genetic Algorithm (GA), Differential Evolution (DE), Evolution Strategy (ES), and Biogeography-Based Optimization (BBO) were employed for cost optimization (Table 9).

Table 8. Characteristics of RCC retaining walls with traditional, sustainable, and green concrete for cost optimization.

Design variables	H (m)	4	6	8	10
X1 (toe slab width) (m)	Traditional	0.625	0.730	0.950	1.300
	Sustainable	0.510	0.692	0.875	1.150
	Green	0.480	0.630	0.760	0.900
X2 (base slab width) (m)	Traditional	1.850	2.520	3.850	4.700
	Sustainable	1.720	2.450	3.630	4.420
	Green	1.600	2.410	3.200	4.000
X3 (stem top thickness) (m)	Traditional	0.390	0.670	0.990	1.350
	Sustainable	0.345	0.590	0.885	1.200
	Green	0.300	0.500	0.750	1.050
X4 (base slab thickness) (m)	Traditional	0.420	0.760	0.980	1.330
	Sustainable	0.375	0.675	0.885	1.220
	Green	0.330	0.580	0.760	1.050
X5 (stem bottom thickness) (m)	Traditional	0.750	1.250	1.800	2.400
	Sustainable	0.660	1.100	1.600	2.150
	Green	0.580	0.950	1.350	1.850
R1 (vertical reinforcement in stem) (cm^2)	Traditional	68.000	165.000	330.000	540.000
	Sustainable	60.000	148.000	295.000	490.000
	Green	50.000	125.000	250.000	410.000
R2 (horizontal reinforcement in toe) (cm^2)	Traditional	60.000	145.000	300.000	480.000
	Sustainable	53.000	130.000	270.000	450.000
	Green	45.000	110.000	230.000	380.000
R3 (horizontal reinforcement in heel) (cm^2)	Traditional	55.000	135.000	280.000	440.000
	Sustainable	48.000	120.000	250.000	420.000
	Green	40.000	100.000	210.000	350.000

Table 9. Comparison of cost optimized designs for traditional, sustainable, and green concrete retaining walls with the qualitative comparison with selected literature results reported by Gandomi et al. (2017a).

Design variables	GA	DE	ES	BBO	SA (Traditional)	SA (Sustainable)	SA (Green)
X1 (toe slab width) (m)	0.586	0.616	0.691	0.737	0.625	0.510	0.480
X2 (base slab width) (m)	1.916	1.872	1.845	1.842	1.850	1.720	1.500
X3 (stem top thickness) (m)	0.272	0.290	0.320	0.277	0.390	0.345	0.300
X4 (base slab thickness) (m)	0.201	0.206	0.221	0.200	0.420	0.375	0.330
X5 (stem bottom thickness) (m)	0.280	0.271	0.280	0.270	0.750	0.660	0.580

The optimization results demonstrate that the superior performance of green concrete is a direct consequence of the algorithm's ability to adjust structural configurations to satisfy all geotechnical, structural, and geometric requirements. Rather than a simple material substitution, the optimization algorithm computes dis-

tinct wall dimensions for each material alternative to ensure compliance with critical safety standards. Green concrete designs often utilize more optimized geometric proportions—such as reduced base slab widths and reinforcement quantities—compared to traditional and sustainable alternatives. For instance, at a wall height of

10 m, the algorithm identifies a structural configuration for green concrete that achieves a 20% reduction in CO₂ emissions while maintaining full structural integrity. This confirms that the environmental and economic advantages are not merely a result of the input material database, but stem from the algorithm's effectiveness in identifying the most efficient structural geometry for each specific concrete type. The sustainability findings presented in this study are limited to the investigated retaining wall heights (4–10 m) and the material datasets considered in the optimization framework. Therefore, the observed improvements in cost and carbon emissions should be interpreted within the analyzed design conditions rather than as applicable conclusions. Further studies involving a wider range of wall geometries, loading conditions, and material datasets are recommended to extend the generality of these findings.

4. Conclusions

This study presented an optimization framework for reinforced concrete cantilever (RCC) retaining walls using the Simulated Annealing (SA) algorithm. The optimization was formulated as two independent single-objective problems, in which material cost and embodied CO₂ emissions were minimized separately while satisfying the specified geotechnical, structural, and geometric design constraints. Eight design variables, including five geometric dimensions and three reinforcement quantities, were considered, and infeasible solutions were handled using a penalty-based constraint approach.

The optimization results for wall heights between 4 m and 10 m showed consistent differences among the investigated concrete alternatives. Green concrete produced the lowest material cost and embodied CO₂ emissions across all wall heights, followed by sustainable concrete, while traditional concrete resulted in the highest values. For a 10 m retaining wall, the minimum embodied CO₂ emission obtained with green concrete was 6475.24 kg CO₂-eq, compared with 8125.68 kg CO₂-eq for traditional concrete. The corresponding minimum material costs were €3513.35 and €4228.95, respectively. Within the investigated material database and design assumptions, these results indicate that green and sustainable concrete alternatives can reduce both material cost and embodied CO₂ emissions relative to traditional concrete. The optimized wall configurations also varied according to the selected concrete type. In general, the green concrete solutions required smaller wall dimensions and lower total concrete and reinforcement quantities than the corresponding traditional concrete solutions while satisfying the prescribed design constraints. This indicates that the optimization procedure identified different feasible structural configurations depending on the material properties and the selected objective function.

The SA algorithm produced consistent optimization results over repeated runs, with relatively small differences between the minimum and average objective-function values for most cases. The sensitivity analysis showed that the cooling rate influences both solution quality and computational time, highlighting the im-

portance of parameter selection for this optimization problem. The quadratic regression equations obtained from the optimization results exhibited high coefficients of determination ($R^2 > 0.998$); however, these equations represent empirical relationships within the investigated wall-height range (4–10 m) and should not be extrapolated beyond this range without additional validation. Overall, the proposed optimization framework demonstrates the applicability of combining material-specific environmental and cost data with structural and geotechnical optimization for RCC retaining walls under the investigated design conditions. The conclusions of this study are limited to the considered wall heights, loading conditions, material database, and design assumptions, and further studies are required to evaluate the framework under different design scenarios and material datasets.

Acknowledgements

None declared.

Funding

The author received no financial support for the research, authorship, and/or publication of this manuscript.

Conflict of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available but are available from the corresponding author upon reasonable request.

AI Assistance

No AI-based tools were used in the preparation of this manuscript.

Author Contributions

The author declares sole responsibility for all aspects of the study, including conceptualization, methodology, formal analysis, investigation, data curation, visualization, writing of the original draft, and writing, review, and editing of the manuscript.

REFERENCES

- ACI 318-05 (2005). *Building Code Requirements for Structural Concrete (ACI 318-05) and Commentary (ACI 318R-05)*. American Concrete Institute, Farmington Hills, MI, USA.
- ACI 318-14 (2014). *Building Code Requirements for Structural Concrete (ACI 318-14) and Commentary (ACI 318R-14)*. American Concrete Institute, Farmington Hills, MI, USA.
- Akın A, Aydoğdu İ, Bilir T (2016). Cost and CO₂ optimization for RC short column sections subjected to axial load and uniaxial/biaxial bending using the social spider optimization algorithm. *Sustainable Construction Materials and Technologies*, 4, 293-303.
- Aydoğdu İ (2017). Betonarme konsol istinat duvarların çok amaçlı (maliyet ve karbondioksit) optimizasyonunda meta-sezgisel yöntemlerin karşılaştırılması. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 23(3), 221-231.
- Das MR, Purohit S, Das SK (2016). Multi-objective optimization of reinforced cement concrete retaining wall. *Indian Geotechnical Journal*, 46(4), 354-368.
- Fredlund DG, Rahardjo H (1993). *Soil Mechanics for Unsaturated Soils*. John Wiley & Sons, New York, NY, USA.

- Gandomi AH, Kashani AR, Roke DA, Mousavi M (2017a). Optimization of retaining wall design using evolutionary algorithms. *Structural and Multidisciplinary Optimization*, 55, 809-825.
- Gandomi AH, Kashani AR, Zeighami F (2017b). Retaining wall optimization using interior search algorithm with different bound constraint handling. *International Journal for Numerical and Analytical Methods in Geomechanics*, 41(11), 1304-1331.
- Hammond GP, Jones CI (2008). Embodied energy and carbon in construction materials. *Proceedings of the Institution of Civil Engineers - Energy*, 161(2), 87-98.
- ITeC (2009). *BEDEC PR/PCT ITeC Materials Database*. Catalonia Institute of Construction Technology, Barcelona, Spain. <https://itec.es/soporte/soporte-bedec/documentacion-bedec/> [accessed 01-04-2026].
- Kalemcı EN, İkizler SB, Dede T, Angın Z (2020). Design of reinforced concrete cantilever retaining wall using grey wolf optimization algorithm. *Structures*, 23, 245-253.
- Kashani AR, Gandomi AH, Azizi K, Camp CV (2022). Multi-objective optimization of reinforced concrete cantilever retaining wall: a comparative study. *Structural and Multidisciplinary Optimization*, 65(9), 262.
- Kaveh A, Behnam AF (2013a). Charged system search algorithm for the optimum cost design of reinforced concrete cantilever retaining walls. *Arabian Journal for Science and Engineering*, 38(3), 563-570.
- Kaveh A, Kalateh-Ahani M, Fahimi-Farzam M (2013b). Constructability optimal design of reinforced concrete retaining walls using a multi-objective genetic algorithm. *Structural Engineering and Mechanics*, 47(2), 227-245.
- Kaveh A, Khayatizad M (2014). Optimal design of cantilever retaining walls using ray optimization method. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 38(C1), 261-274.
- Kaveh A, Soleimani N (2015). CBO and DPSO for optimum design of reinforced concrete cantilever retaining walls. *Asian Journal of Civil Engineering*, 16(6), 751-774.
- Kaveh A, Izadifard RA, Mottaghi L (2020a). Optimal design of planar RC frames considering CO₂ emissions using ECBO, EVPS and PSO metaheuristic algorithms. *Journal of Building Engineering*, 28, 101014.
- Kaveh A, Hamedani KB, Bakhshpoori T (2020b). Optimal design of reinforced concrete cantilever retaining walls utilizing eleven metaheuristic algorithms: a comparative study. *Periodica Polytechnica Civil Engineering*, 64(1), 156-168.
- Kaveh A, Akbari H, Hosseini SM (2022). Plasma generation optimization for optimal design of reinforced concrete cantilever retaining wall structures. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 46(2), 1177-1200.
- Kayabekir AE, Arama ZA, Bekdaş G, Nigdeli SM, Geem ZW (2020). Eco-friendly design of reinforced concrete retaining walls: multi-objective optimization with harmony search applications. *Sustainability*, 12(15), 6087.
- Kayabekir AE, Bekdaş G, Nigdeli SM (2021). Optimum design of reinforced concrete T-beam considering environmental factors via flower pollination algorithm. *International Journal of Engineering and Applied Sciences*, 13(4), 166-178.
- Keivanian F, Chiong R, Kashani AR, Gandomi AH (2023). A fuzzy adaptive metaheuristic algorithm for identifying sustainable, economical, and earthquake-resistant reinforced concrete cantilever retaining walls. *Journal of Computational Science*, 70, 101978.
- Khajehzadeh M, Taha MR, Eslami M (2013). Efficient gravitational search algorithm for optimum design of retaining walls. *Structural Engineering and Mechanics*, 45(1), 111-127.
- Khajehzadeh M, Taha MR, Eslami M (2014). Multi-objective optimisation of retaining walls using hybrid adaptive gravitational search algorithm. *Civil Engineering and Environmental Systems*, 31(3), 229-242.
- Kirkpatrick S, Gelatt CD, Vecchi MP (1983). Optimization by simulated annealing. *Science*, 220(4598), 671-680.
- Kumar VN, Suribabu CR (2017). Optimal design of cantilever retaining wall using differential evolution algorithm. *International Journal of Optimization in Civil Engineering*, 7(3), 433-449.
- Mononobe N, Matsuo H (1929). On the determination of earth pressure during earthquake. In: *Proceedings of the World Engineering Congress*, Tokyo, Japan, Vol. 9, pp. 177-185.
- Naseri H, Jahanbakhsh H, Khezri K, Shirzadi Javid AA (2022). Toward sustainability in optimizing the fly ash concrete mixture ingredients by introducing a new prediction algorithm. *Environment, Development and Sustainability*, 24(2), 2767-2803.
- Okabe S (1924). General theory on earth pressure and seismic stability of retaining wall and dam. *Journal of the Japan Society of Civil Engineers*, 10(6), 1277-1323.
- Öztürk HT, Türkeli E (2019). Optimum design of reinforced concrete retaining walls with key section using Jaya algorithm. *Journal of Polytchnic*, 22(2), 283-291.
- Pei X, Xia Y (2012). Optimum design of retaining walls using different heuristic optimization algorithms. *Journal of Structural Engineering*, 138(10), 1231-1240.
- Schmied C, Karlsson V (2021). *Optimization of Reinforced Concrete Cantilever Retaining Walls Considering Environmental Impact and Investment Cost*. M.Sc. thesis, KTH Royal Institute of Technology, Stockholm, Sweden.
- Shakeel M, Azam R, Riaz MR, Shihata A (2022). Design optimization of reinforced concrete cantilever retaining walls: a state-of-the-art review. *Advances in Civil Engineering*, 2022, 4760175.
- Sheikholeslami R, Khalili BG, Sadollah A, Kim J (2016). Optimization of reinforced concrete retaining walls via hybrid firefly algorithm with upper bound strategy. *KSCE Journal of Civil Engineering*, 20(6), 2428-2438.
- Tayfur B, Kamiloglu HA (2024). Optimization of cantilever retaining wall design using improved teaching-learning-based optimization algorithms. *Firat University Journal of Experimental and Computational Engineering*, 3(2), 134-150.
- Temur R, Bekdaş G (2016). Teaching learning-based optimization for design of cantilever retaining walls. *Structural Engineering and Mechanics*, 57(4), 763-783.
- Ukritchon B, Chea S, Keawsawasvong S (2017). Optimal design of reinforced concrete cantilever retaining walls considering the requirement of slope stability. *KSCE Journal of Civil Engineering*, 21(7), 2673-2682.
- Villalba P, Alcalá J, Yepes V, González-Vidosa F (2010). CO₂ optimization of reinforced concrete cantilever retaining walls. In: *2nd International Conference on Engineering Optimization*, Lisbon, Portugal, pp. 1-10.
- Yeo D, Gabbai RD (2011). Sustainable design of reinforced concrete structures through embodied energy optimization. *Energy and Buildings*, 43(8), 2028-2033.
- Yücel M, Kayabekir AE, Bekdaş G, Nigdeli SM, Kim S, Geem ZW (2021). Adaptive-hybrid harmony search algorithm for multi-constrained optimum eco-design of reinforced concrete retaining walls. *Sustainability*, 13(4), 1639.