Journal of Engineering Science and Technology
Vol. 21, No. 4 (2026) 1036 - 1057

CONSTRAINED MULTI-OBJECTIVE COST AND CO_2 EMISSION DESIGN OF SUSTAINABLE DOUBLY REINFORCED CONCRETE BEAMS

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Abstract

Due to the increasing global demand for environmental protection, disposal of concrete waste and its use as recycled aggregates, a multi objective particle swarm optimization algorithm is developed, coded via MATLAB, verified, and applied to design doubly reinforced Recycled Aggregate Concrete (RCA) beams to minimize cost and carbon emission per unit flexural strength (CO_2/Mn) objective functions, with adhering to ACI 318-19 code constraints for flexural and shear capacities in addition to reinforcement amounts. The algorithm incorporated four design variables which are: tensile and compression steel areas (*As, A's*), beam depth (*h*), and stirrup spacing (*s*), and evaluated the impact of 0%, 30%, 50%, and 100% RCA replacement via four numerical case study beams corresponding to different RCA replacement ratios. The generated Pareto fronts revealed the fundamental trade-offs between the conflicting objectives. For all the beams, the minimum cost design is achieved by minimizing reinforcement area and compensating with increased beam depth. The 30% RCA replacement reduced the CO_2/Mn by approximately 15% at the knee point compared to the virgin concrete beam, with a negligible cost increase. This study demonstrates that the use of 100% RCA replacement is a premium strategy for maximizing sustainability, accepting its inherent penalties in cost and structural efficiency.

Keywords: Multi-objective, PSO, Pareto front, RCA, Sustainable design.

1. Introduction

The world is increasingly turning to sustainable energy to preserve natural resources, reduce gas emissions, and limit waste, which pose a real threat to the environment and humanity. One of the most important challenges facing civil engineers is trying to replace conventional concrete with concrete containing recycled content [1], as buildings contribute about 40% of carbon dioxide CO_2 emissions and energy consumption, which have a negative impact on the environment, accordingly, one of the primary causes of CO_2 emissions worldwide is concrete [2]. About 70% of the volume of a typical concrete mix used for structural purposes is composed of aggregates, both fine and coarse [3].

The majority of these are unprocessed aggregates that were taken from the banks and riverbeds. Therefore, using recycled concrete aggregate (RCA) is one method to reduce reliance on natural aggregate in relation to environmental issues to move towards green construction, hence, the goal is to lessen the waste that results from demolition and building.

As a result, the global trend towards environmental requirements requires the use of concrete waste as an alternative to aggregate, especially in light of the significant increase in this waste and the ongoing search to reduce the cost of concrete structures. In terms of material properties, using RCA instead of normal aggregate in concrete reduces compressive strength while maintaining a similar splitting tensile strength; the modulus of rupture for RCA concrete was marginally lower than that of conventional concrete; and the more ductile aggregate causes the modulus of elasticity to be lower than anticipated [4].

In addition, RCA also exhibits higher water absorption due to attached old mortar, which affects durability, bond behaviour, and long-term serviceability including crack width development. This RCA replacement ranges from 0%-100% with respect to the normal aggregate [5, 6]. The use of RCA replacement in concrete by 30%-100% produces 5%-15% cost increase, in addition to 20%-30% CO_2 emission reduction [7]. This cost increase is due to several factors: additional processing (crushing, sieving, and washing), increased quality control requirements, and cement modifications to counteract strength loss.

Transportation distance from demolition sites to concrete plants also influences overall costs [8]. These factors collectively contribute to the cost premium associated with RCA concrete. In addition to taking into account more environmentally friendly materials, optimizing structural material use could also help reduce CO_2 emissions in building structures.

Using optimization techniques can result in a more effective design that best satisfies a number of requirements. According to a certain objective that is in charge of evaluating the quality of the solution, optimization is defined as finding the optimum solution to a given problem while taking into account the limiting restrictions in the space of feasible options [9]. Considering several goals at once, particularly if they contradict, is an effective strategy. Both single-objective and multi-objective optimization techniques have been efficiently used more in reinforced concrete structure optimization [10-12], furthermore, optimization approaches have also been used in more recent times to address the issue of minimizing environmental impact [13-18].

Techniques for multi-objective optimizations might offer valuable perspectives on possible compromises between opposing objectives. They are supported by heuristic and metaheuristic algorithms like Genetic Algorithms, Simulated Annealing, Ant Colonies, Particle Swarm, Big Bang-Big Crunch, Artificial Neural Network, etc. [19]. The heuristic global neural network optimization technique known as Particle Swarm Optimization (PSO) was first proposed in 1995 by Kennedy and Eberhart [20].

Complex design issues involving a variety of goal functions can be solved quickly and effectively with PSO [21, 22]. This stochastic process is working with a set of possible solutions and fitness functions. Using the PSO's multi-objective strategy (MOPSO), each particle follows only one leader from a group of various leaders to update its position. The non-dominated solutions discovered thus far are kept in a repository, which is often kept in a separate place (referred to as an external archive). When the particle positions are updated, the solutions in the external archive are used as the set of leaders, and the external archive's content is often presented as the algorithm's final output.

In order to determine the Pareto front in the polar coordinate system for two objective function problems using MOPSO, the minimum angular distance information (MADI) technique was developed and verified via thirteen well-known test problems, which assigns the optimal local guide for every particle in the swarm. At the conclusion of each iteration, the nondominated particles were stored in an external repository (archive), and the front diversity and archive size were maintained for every test problem using a crowding distance technique. The constraint functions are handled using a self-adaptive penalty function technique, which converts the original objective functions into new penalized functions according to the degree of constraint violation at each iteration [23].

A constraint single objective PSO algorithm was developed for the optimum cost design of reinforced concrete deep beams via ACI 318-14 code method for four decision variables (beam height, vertical shear reinforcement, horizontal shear reinforcement, and main longitudinal reinforcement) [9]. Self-adaptive penalty function was used for strength and serviceability constraint handling. Furthermore, numerous strength and serviceability restrictions are addressed by design guidelines and algorithms for various concrete structures, such as doubly reinforced RCA concrete beams, which are found in all codes and the majority of literature recommendations. It is worthwhile to look for designs that result in the structure's minimal cost and minimal CO_2 emissions per unit strength among the numerous design scenarios that could satisfy those objectives.

Despite the scarcity of studies available in literature concerned the multi-objective optimization of reinforced concrete beams, whether using PSO or any other neural network technique, rare studies were found on the MOPSO for RCA concrete beams considering the minimization of cost and CO_2 emission. Moreover, although earlier research (e.g., Ozbakkaloglu et al. [4] and Marinković et al. [7]) optimized RC beams for overall CO_2 reduction, structural performance variations were not taken into consideration. This may result in less-than-ideal designs where reduced CO_2 is accompanied by either insufficient strength (requiring expensive retrofits) or excessive strength (wasting materials).

By directly measuring carbon efficiency per unit flexural strength Mn, the current CO_2/Mn metric fills this gap. Moreover, while recent studies have explored multi-objective optimization for cost and carbon emissions, a critical gap remains in translating these optimized solutions into practical design decisions. Designers face the challenge of selecting from a range of non-dominated solutions without clear guidance on which design best aligns with project-specific priorities such as budget constraints, sustainability targets, or material availability.

In addition, existing studies focus on: (1) minimizing total CO_2 emissions without normalizing to structural performance [24]; (2) optimizing material combinations at the frame level rather than beam-level serviceability [25]; or (3) employing complex machine learning frameworks that may not provide transparent design guidance [26]. The present study advances knowledge beyond these works by: (i) introducing CO_2 per unit flexural strength (CO_2/Mn) as a functional unit metric that links environmental impact directly to structural performance, aligning with life cycle assessment principles; (ii) systematically evaluating RCA replacement ratios (0%-100%) to quantify trade-offs between cost, carbon efficiency, and serviceability (crack width and deflection); and (iii) providing explicit design guidance through Pareto front analysis that enables practitioners to select optimal solutions based on project-specific priorities.

Therefore, the aim of the current study is to collect two objective functions (cost and CO_2 /Mn) in a new developed constraint MOPSO algorithm to examine the design Pareto fronts for sustainable RCA doubly reinforced concrete beams, via four design variables, with the benefit of self-adaptive penalty function to penalize the violated particles and MADI technique to assign the local guides. This study introduces CO_2 per unit flexural strength (CO_2/Mn) as a novel metric that relates environmental impact to structural performance, providing a more meaningful basis for comparing sustainable designs. By incorporating RCA with recorded 25%-30% carbon savings and 5%-15% cost premiums [7], the framework enables designers to quantify trade-offs and select optimal solutions according to project priorities.

2. Design of Reinforced Concrete Beam Sections

This study aims to optimize sustainable RCA doubly reinforced concrete rectangular beams to minimize cost and CO_2 emission per unit strength. To achieve these two conflicting objective functions, four design variables are considered, which are: main tension steel reinforcement area As, compression steel reinforcement area $A's$, total depth h, and stirrups spacing s. Based on ACI 318- 19 [27] provisions, a design procedure is followed for the doubly reinforced RCA concrete beam section for flexural strength, shear strength, and serviceability requirements. The beams are considered as simply supported with uniformly distributed factored dead and live loads. This study assumes simply supported beams with uniform loads, uses regional average cost and emission data, applies ACI 318 code equations, and omits building and demolition stages from the CO_2 evaluation.

2.1. Objective functions

Two conflicting objective functions are considered via several trials once the algorithm is achieved and verified. The first objective function F_C is to minimize the overall cost of the RCA doubly reinforced concrete beams, which are based on three factors. These factors are C_c (cost of RCA concrete), C_s (cost of steel), and C_f (cost of formwork), which refers to the cost of temporary moulds used to shape and support fresh concrete until it hardens, which is calculated based on the surface area of the beam in contact with the forms and is influenced by labour, material, and installation complexity. The materials cost is considered according to the local market in Iraq. Therefore, the cost objective function is formulated as:

$$F_c = C_c + C_s + C_f \tag{1}$$

where

$$C_c = L * b * h * C_c' \tag{2}$$

$$C_s = W_s * L * A_{sT} * C_s^1 + W_v * A_v * L_v * C_s^2 \tag{3}$$

$$C_f = L * (b + 2h) * C_f' \tag{4}$$

Here,

L, b, h: length, width, and height of beam, respectively,

C_c': cost of plain concrete per unit volume (RCA),

W_s, W_v : specific mass density of longitudinal and stirrup reinforcements, respectively,

A_{sT}: total tension and compression longitudinal steel area: $A_s + A_s'$

A_v, L_v: area and according to dimensions length of stirrups, respectively,

C_s^1, C_s^2: cost per unit mass for longitudinal and stirrup reinforcement, respectively,

C_f': cost of framework per unit area.

The second objective function F_E is to minimize the overall emission per unit flexural strength, which based on RCA concrete emission EM_c, steel emission EM_s, and beam nominal flexural capacity M_n. This objective function is formulated as:

$$F_E = (EM_c + EM_s)/M_n \tag{5}$$

where;

$$EM_c = CEm * (L * b * h) * W_c \tag{6}$$

$$EM_s = SEm * W_s * L * (A_{sT} + (A_v * 1000/s)) \tag{7}$$

$$M_n = A_s * f_y * \left(d - {}^{a}/_{2}\right) + A_s' * f_s' * (d - d') \tag{8}$$

here;

CE_m, SE_m: RCA concrete and steel emissions (kg CO_2/kg), respectively,

W_c: specific mass density for plain concrete,

s, d, d' : stirrups spacing, depth to bottom reinforcement, and depth to top reinforcement, respectively,

f_y, f_s' : yield stress for bottom reinforcement, and calculated stress for top reinforcement, respectively,

a: depth of the equivalent rectangular Whitney stress block, which is calculated according to ACI code equilibrium equations for doubly reinforced beam sections, which is calculated as follows:

$$a = \frac{A_s * f_y - A_s' * f_s'}{0.85 * f_{c,RCA}' * b * \beta_1} \tag{9}$$

$$f'_s = \begin{cases} f_y & if \epsilon'_s \geq \epsilon_y \\ E_s - 0.003 * \left(\frac{c-d'}{c}\right) & otherise \end{cases} \quad (10)$$

$$\epsilon'_s = 0.003 * \frac{c-d'}{c} \quad (11)$$

$$c = \frac{a}{\beta_1} \quad (12)$$

where;

$f'_{c,RCA}$: compressive strength of RCA concrete, taken as $\eta f'_c$, where η represents a reduction factor in the range of 0.8-0.95 depending on RCA replacement percentage [28],

β_1: flexural strength reduction factor, taken as 0.85 for $f'_c \leq 28$ MPa and reduces by 0.05 for each 7 MPa above 28 MPa but $\beta_1 \geq 0.65$,

E_s: steel elastic modulus,

c: neutral axis depth.

The emission value of normal concrete made of ordinary Portland cement is about 0.12 kg CO_2/kg for $f'_c \leq 30$ MPa and reaches 0.15 kg CO_2/kg for high strength concrete [29]. For the RCA concrete these values are significantly lower, and it can be as low as 84% of the conventional concrete emission. Furthermore, a value of 0.09 kg CO_2/kg for $f'_c \leq 30$ MPa is recommended [30]. Moreover, the recommended emission value of steel reinforcement is about 1.85 kg CO_2/kg. In order to achieve the optimization of these objective functions, many trials are to be run beginning with random poor values of the four mentioned design (decision) variables, which kept within permissible limiting upper and lower values. These variables are updated at each trial. All the other parameters are kept constant for each design case.

2.2. Constraints functions

The term “Constraint Optimization Problem” refers to the kind of realistic optimization problems where the decision variables are subject to specific constraints [9]. In reinforced concrete design, the parameters constraints are the limitations and conditions defined by ACI 318-19 [27] that must be followed in order to ensure the structural strength and serviceability limit states [31]. For the design to be optimized, the following three main constraints are considered:

2.2.1. Flexural capacity constraint

After trying initial values for the four design variables (A_s , A'_s, *h,* and *s*), *d* and *d’* can be approximately calculated. Hence, with the benefit of ACI 318-19 [27], the nominal flexural capacity can be calculated according to Eqs. (8)-(12). Therefore, the flexural capacity constraint can be denoted as:

$$\emptyset_1 * M_n \geq M_u \quad (13)$$

$$M_u = \frac{W_u * L^2}{8} \quad (14)$$

where;

M_u, W_u: ultimate nominal moment and ultimate dead W_D and live W_L combined load moment applied to the simply supported beam, respectively, where W_D represents the superimposed dead load W_{DL} and beam's self-wight W_B,

$\emptyset_1$: flexural strength reduction factor, taken typically as 0.9.

2.2.2. Reinforcement amount constraint

The amount of longitudinal reinforcement percentage $\rho = \frac{A_s}{b*d}$ provided for the doubly reinforced concrete beam should be within a minimum and maximum limit as;

$$\rho_{min} = \begin{cases} \frac{3*\sqrt{f'_{c,RCA}}}{f_y} \\ \frac{200}{f_y} \end{cases} \tag{15}$$

$$\rho'_{min} = 0.005 \tag{16}$$

$$\rho_{max} = 0.85 * \beta_1 * \frac{f'_{c,RCA}}{f_y} * \left(\frac{\epsilon_u}{\epsilon_u + \epsilon_t}\right) + \frac{A'_s}{b*d} \tag{17}$$

$$\epsilon_t = 0.003 * (\frac{d-c}{c}) \geq 0.004 \tag{18}$$

So, the constraints for the bottom and top reinforcements, respectively, are:

$$\rho_{min} \leq \rho \leq \rho_{max} \tag{19}$$

$$\rho' \geq \rho'_{min} \tag{20}$$

2.2.3. Shear capacity constraint

Since the spacing between stirrups *s* is taken into consideration as a design variable, therefore, shear capacity constraint is mandatory to be considered. This constraint is a function of beam nominal shear strength V_n, which represents the concrete and stirrup contributions, and ultimate applied shear stress V_u, which represents the shear stress applied by the factored applied dead and live loads at distance of half of beam total depth from the support. The equations related to this constraint are defined as follows:

$$V_n = 0.17 * \lambda * \sqrt{f'_{c,RCA}} * b * d + \frac{A_v * f_{yv} * b}{s} \tag{21}$$

$$V_u = \frac{W_u * L}{2} - W_u * (0.5 * h) \tag{22}$$

So, the constraint for the shear capacity is:

$$\emptyset_2 * V_n \geq V_u \tag{23}$$

where;

λ: a reduction factor for RCA replacement, taken as 0.75 for 100% RCA replacement and 0.85 for ≤ 30% RCA replacement, while it is taken as 1.0 for normal concrete [32],

A_v: two-legs cross-sectional area of stirrup reinforcement,

$\emptyset_2$: shear nominal strength reduction factor, taken typically s 0.75.

3. Particle Swarm Multi Objective Optimization Algorithm

PSO is an iterative technique in which the current optimums are followed by the possible solution, known as particles, as they fly through the problem space. Every particle records the coordinates in the problem space that correspond to the best solution achieved so far. This technique was developed originally by Kennedy and Eberhart [20]. Each particle has a distinct memory space to store the best position it has visited in the search space in order to recall prior experiences. We refer to this value as *pbest*. The best value so far attained by any of the particle's neighbours is another best value that the particle swarm optimizer tracks. This is referred to be the *best*. The best value, known as the global best or *gbest*, is obtained when a particle considers every member of the population to be its topological neighbours. The idea behind particle swarm optimization is to adjust each particle's velocity toward its *pbest* and *gbest* at each time step. Each particle updates its position and velocity based on the following equations once the optimal values have been determined:

$$V_{ij}^{(t)} = w^{(t)} * V_{ij}^{(t-1)} + iw^{(t)} * U_{(0,1)} * (pbest_{ij}^{(t-1)} - X_{ij}^{(t-1)}) + sw^{(t)} * U_{(0,1)} * (gbest_j^{(t-1)} - X_{ij}^{(t-1)}) \tag{24}$$

$$X_{ij}^{(t)} = X_{ij}^{(t-1)} + V_{ij}^{(t)} \tag{25}$$

where;

$X_{ij}^{(t)}$: component *j* of the position of particle *i* at iteration or time step *t*,

$V_{ij}^{(t)}$: component *j* of the velocity of particle *i* at time step *t*,

$w^{(t)}, iw^{(t)}, sw^{(t)}$: inertia, individuality, and sociality weights, respectively, at time *t*,

$U_{(0,1)}$: random number generated from a uniform distribution in the range [0,1],

$pbest_{ij}^{(t-1)}, gbest_j^{(t-1)}$: coordinate *j* of the best position found by particle *i* and by the whole swarm, respectively, up to time step *t-1*.

The value of *w(t)* is found using an annealing algorithm [33], and the maximum number of iterations serves as a stopping criterion for when the search process should end.

Main tension steel reinforcement amount A_s , compression steel reinforcement amount A'_s, beam height *h*, and stirrups spacing *s*, are considered as the four design (decision) variables for the doubly reinforced RCA concrete beams, with the rest of the specifications and parameters remaining constant. The optimized multi objective (fitness) functions encompass minimizing the construction cost and CO_2/Mn which are mentioned in Eqs. (1) and (5) with the three constraints mentioned through Eqs. (13)-(23). An improved constraint MOPSO algorithm is followed to get the Pareto optimal front for these two conflicting objectives using a number of particles and iterations [23].

In order to determine the optimal local guide for every particle in the swarm and obtain the Pareto front in the polar coordinate system, the minimum angular distance information (MADI) approach is used and validated. Furthermore, at the end of each iteration, the nondominated particles are stored in an external repository (archive), and the front diversity and archive size are maintained for every design problem using the crowding distance technique. Moreover, the constraint functions are handled using the self-adaptive penalty function technique, which converts the initial objective functions into new penalized functions according to the degree of constraint violation for each particle at each iteration, as shown in Fig. 1.

PSO is known to have a very high convergence speed. However, such convergence speed may be harmful in the context of multi objective optimization, because a PSO-based algorithm may converge to a false Pareto front (i.e., the equivalent of a local optimum in global optimization). This drawback of PSO is evident in some problems in which the original approach did not perform very well [34]. This motivated the development of a mutation operator that tries to explore with all the particles at the beginning of the search. Then, the number of particles that are affected by the mutation operator are to be decreased rapidly with respect to the number of iterations. The algorithm is developed via a MATLAB code, which verified using a common test function and then revised to solve constraint design problems of doubly reinforced RCA concrete beams.

```
START
  Initialize some parameters (total particles, total iterations,…, etc.)
  Initialize particles' position and velocity randomly
 for each iteration
    Set mutation operator value
   for each particle in the swarm
    Evaluate original objective functions and constraint functions
    Evaluate normalized objective function
     if any constraint is violated
      Use "Self-Adaptive Penalty Function" to evaluate the penalized objective functions
    end if
     Develop a global matrix with number of rows represents the number of particles in the swarm
and number of columns represents the set of parameters for each particle.
   end for
   for each particle in the swarm
    Evaluate best position ever found "pbest"
    Determine the case of current particle (dominated by other particles or nondominated)
    Store it either in dominated repository or in nondominated repository
   end for
   for each particle in the dominated repository
    Use "Minimum Angular Distance Information" technique to evaluate its "lbest" values
   end for
  Add the nondominated particles to a main external repository "Archive"
   for each particle in the archive
    Evaluate new penalty functions to get new objective functions
    Exclude particles dominated by other particles and add them to the dominated repository
   end for
   if size of archive is exceeded
    for iterations equal to the number of extra particles
     Apply "Crowding Distance" algorithm to exclude that particle with minimum value and add it
        to the dominated repository
    end for
   end if
   for each dominated particle
     Update particle velocity, according to Eq. (24)
     Update particle position, according to Eq. (25)
      if the updated velocity or the updated position exceeds the limits
       Assume new random position or velocity values within the range
      end if
   end for
   Set the total swarm particles to be total dominated particles, for the next iteration
   Plot Pareto front
  until stopping criteria is not satisfied
 end for (iterations)
END START
```

Fig. 1. The overall procedure for the developed constraint MOPSO algorithm.

4. Results and Discussion

4.1. MOPSO algorithm verification

To verify the developed MATLAB code, a constraint common multi objective optimization test problem is used, which is proposed by Chankong and Haimes [35]. It consists of minimizing two objective functions with two constraint functions subjected to two decision variables, as follows;

$$Min. \begin{cases} f_1(x_1, x_2) = 2 + (x_1 - 2)^2 + (x_2 - 1)^2 \\ f_2(x_1, x_2) = 9x_1 - (x_2 - 1)^2 \end{cases} \tag{26}$$

$$\text{subjected to: } \begin{cases} g_1(x_1, x_2) = x_1^2 + x_2^2 \leq 225 \\ g_2(x_1, x_2) = x_1 - 3x_2 + 10 \leq 0 \end{cases} \tag{27}$$

The range of the two decision variables x_1 and x_2 is, $-20 \leq x_i \leq 20$.

The suggested MOPSO algorithm uses a total of 200 fitness particles to draw the computed Pareto front in this scenario, convergent from 300 particles used as the entire swarm with 100 iterations. The computed Pareto front curve's graphic outputs demonstrate good agreement with the actual true Pareto front curve, as shown in Fig. 2.

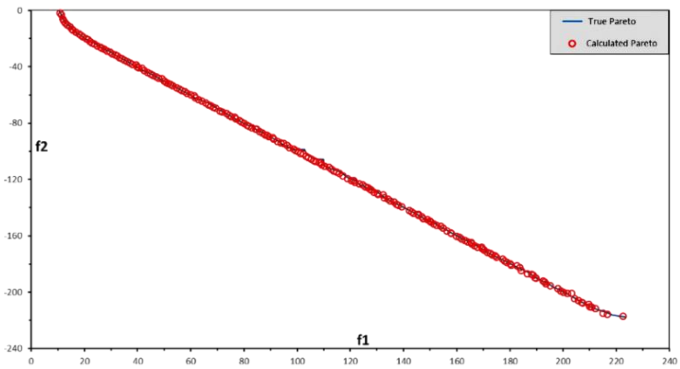


Fig. 2. True and calculated Pareto fronts for Chackong and Haimes test problem.

4.2. Reinforced beam case studies

After checking the efficiency and adequacy of the current algorithm, four RCA doubly reinforced concrete beams are optimized, and their Pareto fronts are determined for the two conflicting objective functions (total cost and CO_2/Mn) with three design constraints. The response of the four design variables (*As, A's, h*, and *s*) with the cost increase are, also, examined.

Table 1. represents the input design parameters which are assumed to be constant for all the four beam case studies, while Table 2. sets the variable parameters related to each RCA replacement ratio, which is assumed to be variable for each case study and ranging between 0% for beam B1 (control beam) to 100% for beam B4. Knowing that the dead and live loads mentioned are the unfactored service loads, selected to represent typical floor beam conditions in residential and office buildings based on standard load assumptions from ASCE 7-22 [36] for occupancy loads and self-weight calculations for reinforced concrete members.

These service loads are then factored to apply for ultimate strength design per ACI 318-19 [27].

Material costs were based on regional market in Iraq averages: concrete (C'_c) at 80 US$/m³, main reinforcing steel (C^1_s) at 1.2 US$/kg, shear reinforcing steel (C^2_s) at 2 US$/kg, and formwork at 30 US$/m² of beam surface area. Labour, transportation, and equipment costs are implicitly included in these unit rates. Embodied carbon values were sourced from the Inventory of Carbon and Energy (ICE) database [29]. Conventional concrete (≤30 MPa) was assigned 0.12 kg CO_2/kg, while RCA concrete used 0.09 kg CO_2/kg for 30% replacement, 0.08 kg CO_2/kg for 50% replacement, and 0.07 kg CO_2/kg for 100% replacement. Reinforcing steel was assigned 1.85 kg CO_2/kg for virgin steel and 1.60 kg CO_2/kg for recycled steel [29].

All these parameters are applied to design four numerical case study simply supported beams with uniformly distributed loads subjected to four RCA percentage replacements, as shown in Table 2. A parameter sensitivity analysis validated that a swarm size of 300 particles, total iterations of 500, with an inertia weight decreasing from 0.9 to 0.4 and cognitive/social coefficients of 1.5, produced consistent and reproducible result, thus confirming the robustness of the optimization.

Table 1. Constant input parameters for the four beam case studies.

Parameter	Unit	Value	Parameter	Unit	Value
f_y	MPa	400	C^1_s	US$/kg	1.2
f_{yv}	MPa	350	C^2_s	US$/kg	2
E_s	GPa	200	C'_f	US$/m^2	30
W_c	kg/m^3	2400	CEm	kg CO_2/kg	0.09
W_s	kg/m^3	7850	SEm	kg CO_2/kg	1.85
W_v	kg/m^3	7850	W_{DL}	kN/m	10
f'_c	MPa	28	W_{LL}	kN/m	8
b	m	0.4	A_v	m^2	0.0001571
L	m	6	d'	m	0.04
C'_c	US$/m^3	80	Total iterations	-	500
β_1	-	0.85	Total particles	-	300

Table 2. Variable input parameters for the four beam case studies.

Beam	RCA replacement (%)	η*	λ**	Concrete cost increase (%)	CO_2 emission reduction for concrete (%)
B1	0	1	1	0	0
B2	30	0.95	0.85	5	20
B3	50	0.88	0.80	10	25
B4	100	0.80	0.75	15	30

* RCA concrete compressive strength reduction factor
** RCA concrete shear strength reduction factor

4.2.1. Pareto front for the conflicting objectives

As a validation for the current proposed optimization algorithm, CO_2/Mn values obtained for all the designed beams align with the typical ranges for conventional beams designed by Paya-Zaforteza et al. [37], which reported CO_2/Mn intensities of 1.5 kg/kN.m to 2.5 kg/kN.m. Applying the current developed constraint MOPSO algorithm on the four RCA beam case studies yielded a well-defined the Pareto front, as shown in Fig. 3. Examining the overall behaviour of the Pareto fronts indicates that the lower cost designs are associated with high CO_2/Mn ratios, which demonstrates that the expensive designs tend to have greater environmental efficiency per structural performance unit.

The Pareto front for beam B1 with 0% RCA (i.e., made of conventional aggregate) reveals that as the cost increases, CO_2/Mn decreases, showing that spending more money produces a more environmentally efficient design strategies, and this applies to all the other beams B2, B3, and B4, which have 30%, 50%, and 100% RCA replacement, respectively. The Pareto fronts for all the designed beams have nonlinear response with diminishing returns noticed after specific cost levels. The Pareto front for beam B1 has a significant increase in slope between 370 US$ and 500 US$, followed by a gradual CO_2/Mn reduction as the cost increases. This implies that since increasing the initial cost produces a significant increase in carbon efficiency, additional enhancements require considerable spending for limited environmental benefits.

A noticeable knee point (steep slope change) is observed in the cost range of 484 US$ to 520 US$, where the CO_2/Mn decreases rapidly from 3.2 kg/kN.m to 1.7 kg/kN.m. This zone represents the most balanced objective trade-off (about 50% reduction in CO_2/Mn), where a significant gain in carbon efficiency occurs at a relatively small cost increase (about 30% from the minimal cost design). For instance, at 484 US$, CO_2/Mn is 1.79 kg/kN.m, compared to 3.2 kg/kN.m at 370 US$. This knee point is useful while it offers the designers to accomplish environmental sustainability without causing excessive cost increase. After this point, increasing the cost from 500 US$ to 1000 US$ only reduces the carbon emission by about 1.0 kg/kN.m, reflecting a decreased investment in efficiency.

The Pareto front for beam B2, with 30% RCA replacement, has the same behaviour but with slight difference while it has a steeper slope compared to that of beam B1, and at significantly higher cost range of 433 US$-514 US$ with CO_2/Mn range of 2.72 kg/kN.m-1.53 kg/kN.m. The knee point occurs at a similar cost value compared to beam B1; however, it achieves a significantly lower CO_2/Mn value of1.53 kg/kN.m, representing a 15% improvement in carbon efficiency compared to that gained from virgin concrete beam B1 of 1.79 kg/kN.m. This reveals the environmental benefit gained while using 30% RCA replacement at the same investment level.

The Pareto front for beam B3, with 50% RCA replacement and 373 US$ minimum cost-design accompanied with 2.74 kg/kN.m CO_2/Mn value, demonstrates a better improvement of 12% in environmental efficiency, but with a slight increased initial cost by 2% when compared with beam B1. In spite of that the knee point for beam B3 occurs at nearly the same cost of beam B1 but achieves a superior CO_2/Mn value of 1.48 kg/kN.m, which represents a 17% improvement in environmental efficiency compared to that of beam B1 knee point, making it more efficient than the two previous beams B1 and B2. The knee point for beam B4, with 100% RCA replacement, is nearly identical to that of beam B1, but delivers a superior environmental gain of 1.47 kg/kN.m, which represents 17% improvement in carbon efficiency, matching the performance of beam B3 at this point.

The minimum cost solutions for all the four designed beams are shown in Table 3. These solutions represent the most cost-effective solutions for each beam, which are accompanied by a high value of CO_2/Mn, but not the highest. Projects with limited budgets but low sustainability standards might benefit from such a design. This table also shows the minimum environmental impact, which is represented by minimum CO_2/Mn solutions, for all the four designed beams. These optimal solutions are also accompanied by the maximum cost, for instance, beam B1 has a minimum CO_2/Mn value of 0.7 kg/kN.m at a cost of 1004 US$, which is nearly three times of the minimum cost solution of 365 US$.

The highly increased cost is due to increase in reinforcement area and section dimensions to enhance the beam flexural capacity. Projects having high green building requirements or priority of carbon reduction life-cycle might benefit from such designs. When comparing these results with the minimum cost solutions of 370 US$ at 2.77 kg/kN.m for beam B2, it is clear that the RCA small amount usage in beam B2 provides 11% improvement in carbon efficiency for a negligible cost increase represented by 1.4%, compared to beam B1. This makes using 30% RCA is more efficient for budget-conscious projects, offering better sustainability against a small extra cost.

Beam B3, with 50% RCA replacement, reaches a new improvement in sustainability through a new low CO_2/Mn value of 0.41 kg/kN.m, which represents a 43% improvement over the virgin concrete in beam B1, but with 1391 US$ final cost or 39% excessive cost. The most environmental advantage is shown by beam B4, with 100% RCA replacement, which highlights its role as the best sustainable choice through the minimum CO_2/Mn value of 0.39 kg/kN.m, but with excessive cost increase of 1421 US$ to reach its lowest carbon emission. The reduction in CO_2/Mn value is by 46%, while the cost is increased by 42%, compared to beam B1. This property makes the 100% RCA replacement is the ideal choice for design structures with high sustainability and lowest environmental impact, regardless of cost.

Table 3. Optimal solutions for the four designed beams.

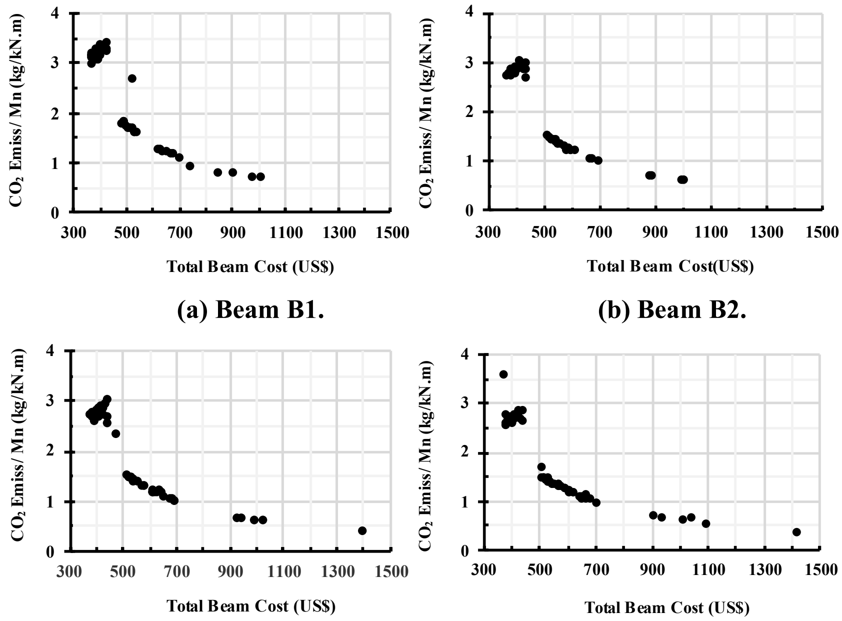
Beam	Optimum result	Cost (US$)	CO_2/M_n (kg/kN.m)	As (mm^2)	A's (mm^2)	h (mm)	s (mm)
B1	Min. Cost	365.32	3.200	604	604	403	159
	Min. CO_2/M_n	1003.67	0.718	3900	2263	1172	155
B2	Min. Cost	370.07	2.765	598	598	403	174
	Min. CO_2/M_n	1006.85	0.634	4140	2187	1133	156
B3	Min. Cost	372.92	2.736	600	600	401	164
	Min. CO_2/M_n	1390.99	0.412	4143	4140	1473	153
B4	Min. Cost	375.91	3.597	611	611	400	106
	Min. CO_2/M_n	1421.06	0.387	5470	3516	1432	127

Examining the Paetro front for the designed beams suggests three different design strategies according to different cost-carbon efficiency requirements. The first strategy is the low-cost region, which uses lower reinforcement ratios but with high CO_2/Mn values. For instance, beam B1 has low-carbon region at the cost range of 360 US$ - 400 US$. The second strategy is the knee region, where a cute enhancement in CO_2/Mn values is happening due to the shift towards improved reinforcement use and section dimensions to improve structural capacity. This zone for beam B1 appears at cost range of 484 US$ - 520 US$.

The third strategy is the high-cost region, where expensive materials, more efficient section geometry, and complex designs are required to gain more environmental efficiency. For beam B1, this strategy appears at cost range of 600 US$ - 1000 US$. The lower bound, for instance, of beam B1 Pareto front of 0.72

kg/kN.m is particularly aggressive, which reveals that the current algorithm can push the boundaries of the conventional concrete design.

In addition, examining the Pareto front for beam B2, with 30% RCA replacement, shows that it is shifted downward left, revealing the better carbon efficiency along the cost. Furthermore, it means that using RCA is structurally and economically efficient, not just an environmental need, hence, gives the designer the choice to achieve sustainability without excessive additional cost. The Pareto front for beam B3, with 50% RCA replacement, appears to be shifted downward, meaning lower carbon emission for the same cost, and slightly right, indicating regular efficiency gains.



(a) Beam B1. **(b) Beam B2.**

(c) Beam B3. **(d) Beam B4.**

Fig. 3. Pareto front for the optimized beams.

The Pareto front for beam B4 is shifted to the downward and right, particularly at the low-emission extreme to achieve the very lowest levels of CO_2/Mn with a higher cost compared to beam B1, while at low costs it is shifted to the downward offering nearly free carbon savings. This shift demonstrates that the 100% RCA replacement is not just a material substitution, but it is a fundamental change in design paradigm, enabling superior environmental performance that was unattainable with virgin materials.

Finally, as a result for the Pareto front analysis for the four numerically tested beams, three distinct design categories can be noticed. The first is the minimum-cost solutions (365 US$ - 400 US$), where designs have the highest CO_2/Mn (3.1 kg/kN·m - 2.4 kg/kN·m) but the lowest cost since they employ virgin or low RCA content. This is ideal for projects with low sustainability standards and a tight budget. The second is the knee-point solutions (400 US$ - 520 US$), where designs with 30%-50% RCA provide the best balance, lowering CO_2/Mn by 15% - 25% while only increasing costs by 5%-10%. This is the suggested compromise for the majority of real-world uses. The third is the extreme sustainability solutions (>520 US$), where 100% RCA designs demand a 20% - 30% cost premium and much deeper sections, but they obtain the lowest CO_2/Mn (0.6 kg/kN·m - 1.0 kg/kN·m). Appropriate for projects that put recycled content ahead of economy.

4.2.2. Design variables versus cost for the designed beams

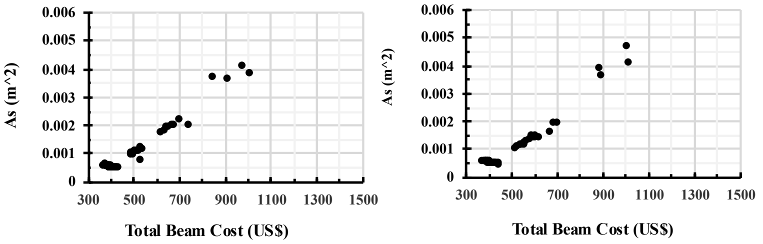
The cost versus the four design variables (*As*, *A's*, *h*, and *s*) relations for the four designed beams shown in Figs. 4-7 reveals the strategy that the developed constraint MOPSO algorithm used to find the cheapest design cases satisfying all the structural constraints. The algorithm successfully found the clear trade-off between the cost and the steel area (*As* and *A's*) for all the beams, furthermore, minimizing the steel area is the direct way to reduce the beam cost. The curves for beam B1 of virgin concrete shown in Figs. 4(a) and 5(a) show that the cheapest design (365 US$) consistently use the least amount of *As* and *A's* of 604 mm^2. Replacing the aggregate with 30% RCA in beam B2 gives a slight increase in cheapest design value (370 US$) and a slight decrease in *As* and *A's* (598 mm^2) compared to that of beam B1, which means that incorporating 30% RCA replacement does not impose a significant cost penalty, as shown in Figs. 4(b) and 5(b).

This confirms that moderate RCA replacement is a viable and economically sustainable choice. Furthermore, a knee occurs around 514 US$ cost where *As* jumps significantly to 1018 mm^2 and *A's* jumps to 1060 mm^2 and *h* increases to 0.57 m to harness strength of that additional steel efficiently. When using 50% RCA replacement in beam B3, the algorithm's strategy remains the same, as shown in Figs. 4(c) and 5(c).

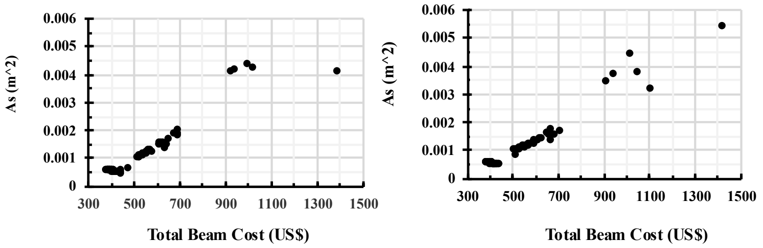
The cheapest design (373 US$) uses the least amount of *As* and *A's* (597 mm^2). A knee occurs around 510 US$-517 US$, marked by a jump in *As* to be 1050 mm^2 and *h* of 0.56 m. For the most extremely sustainable material choice represented by beam B4 with 100% RCA replacement, the cheapest design strategy remains the same. Its minimum cost (376 US$) represents the highest value compared to the three other designed beams. *As* is increased to be 611 mm^2, which is the higher value for all the designed beams, as shown in Figs. 4(d) and 5(d). A knee occurs around 505 US$, where *As* increases to 1040 mm^2 and *h* jumps to 0.54 m.

The cost versus beam depth *h*, as shown in Fig. 6, for all the beams reveals that the investment in reducing steel area is accompanied by significantly increasing the beam's depth. For beam B1, as shown in Fig. 6(a), the low-cost design (365 US$) is achieved by *h* of 0.4 m, while the high-cost design (1004 US$) is achieved by increasing *h* to 1.17 m. This is a classic trade-off in concrete design, which depends on the philosophy of using more concrete to save on more expensive steel. The low-cost design for beam B2 (370 US$) is achieved by a less increase of *h* to 1.13 m, showing the same response as that of beam B1.

For beam B3, while the starting depth accompanied with the low-cost remains nearly the same, the progression shows a more aggressive increase in depth to same low-steel area and low-cost strategy. The minimum cost increases to 373 US$, which indicates a small but real cost penalty for using more RCA replacement compared with that of virgin concrete, and this is due to the need for more material volume to achieve the same strength. For high-cost design, *h* is increased to 1.47 m, which reveals that to achieve the strongest design, 50% RCA replacement require larger and more massive beam section compared to 30% RCA replacement, which is 1.13 m. When using 100% RCA replacement in beam B4, deeper beams are reached in the algorithm results in order to compensate for the severely reduced strength and stiffness, especially for high-strength designs.



(a) Beam B1. **(b) Beam B2.**



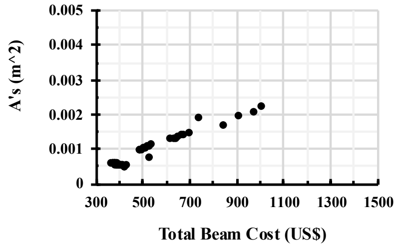
(c) Beam B3. **(d) Beam B4.**

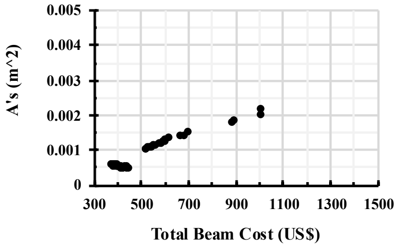
Fig. 4. Cost versus main steel area for the optimized beams.

The extreme high-cost designs show a massive investment in both steel and concrete to achieve strength, resulting in a very deep beam (1.43 m). This shows that to achieve the strongest designs; 100% RCA requires a beam that is over 20% deeper than one made with virgin concrete. This increased depth requirement stems from the inherent characteristics of RCA, particularly the porous residual mortar attached to the aggregate particles, which creates a weaker Interfacial Transition Zone (ITZ) and reduces the aggregate's intrinsic strength compared to natural aggregates [38]. The higher porosity and water absorption of RCA (typically 4% - 5% versus 0.5% - 1% for natural aggregates [39]) result in a less stiff composite material with reduced compressive strength and modulus of elasticity, necessitating larger cross-sections to meet serviceability requirements. This significantly increases the volume of material required.

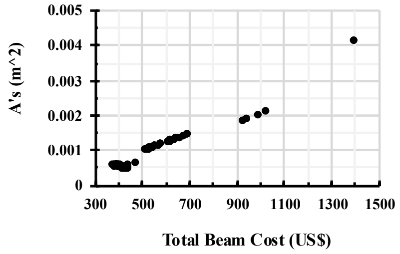
The cost versus stirrup spacing s for all the designed beams is shown in Fig. 7, which reveals that s remains relatively constant across most designs, suggesting that the shear requirements likely governed this variable and it was not the major lever for cost reduction in this constraint MOPSO strategy. For beam B1, the stirrups spacing is around 0.16 m - 0.18 m. From a practical point of view, although the optimization technique finds theoretically ideal designs, constructability constraints must be considered for practical viability.

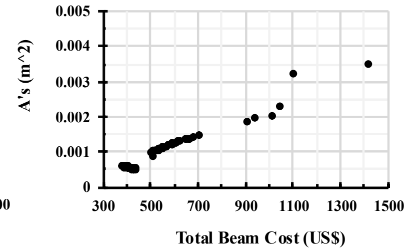
According to ACI 318-19 [27], additional side reinforcement may be necessary for fracture control in deep beams (>1 m). Congestion problems brought on by high reinforcing levels (>2%) can make placing concrete more difficult and lower the quality of the bond. It is advised that beam widths be at least 0.25 m in order to meet cover and standard bar spacing standards. Especially with RCA concrete, long-term creep may control deflection under service loads for deep sections. Therefore, before being implemented, designs that go beyond these realistic bounds should be assessed for constructability.





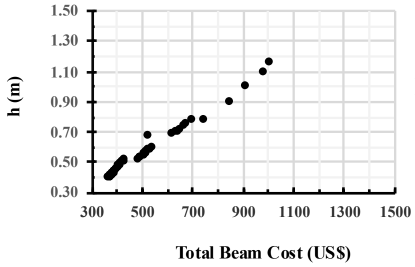
(a) Beam B1. **(b) Beam B2.**

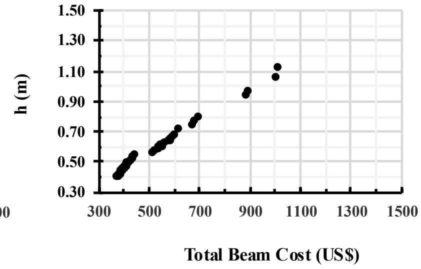




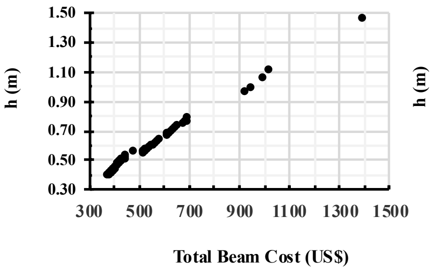
(c) Beam B3. **(d) Beam B4.**

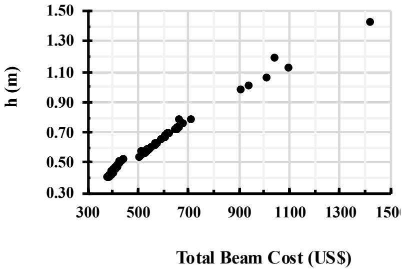
Fig. 5. Cost versus compression steel area for the optimized beams.





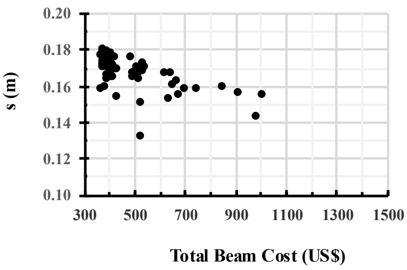
(a) Beam B1. **(b) Beam B2.**



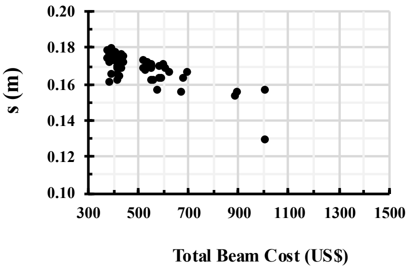


(c) Beam B3. **(d) Beam B4.**

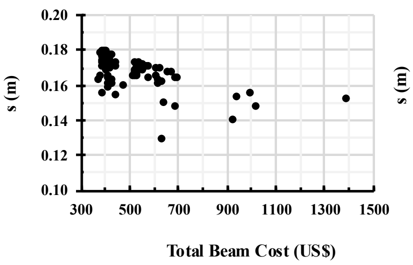
Fig. 6. Cost versus beam depth for the optimized beams.



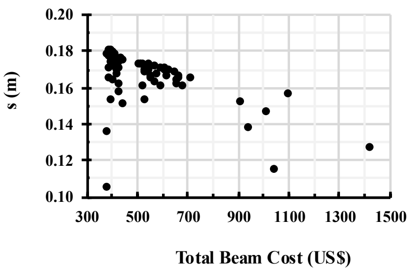
(a) Beam B1.



(b) Beam B2.



(c) Beam B3.



(d) Beam B4.

Fig. 7. Cost versus stirrup spacing for the optimized beams.

The above discussion means that the most expensive designs are not expensive because they are stronger, but because they are highly inefficient while they use large amount of steel area and a relatively deep beam. These are the designs that the algorithm panelised for being over-designed and were pushed to the high cost and high materials end of the Pareto front.

Furthermore, the cheapest design is not the smallest or most material-efficient in terms of concrete, but it is the most economically efficient, prioritizing cheaper concrete over more expensive steel. This strategy effectively shows the penalty of moving away from this optimal steel-concrete balance. As a result, obviously, the 100% RCA replacement represents the most expensive and least structurally efficient design option, but it is a strategic choice for designs where maximizing recycled aggregate is the absolute priority, outweighing concerns about cost and structural efficiency.

For balanced designs, 30% - 50% RCA replacement offers a much more efficient compromise. In brief, three different design strategies are identified by the analysis: (i) minimum-cost designs with virgin or low RCA content for projects with limited funds; (ii) knee-point designs with 30% RCA offering optimal balance achieving approximately 15% carbon savings with only a 2% - 5% cost increase; and (iii) extreme sustainability designs with 100% RCA delivering maximum carbon reduction (30% - 40%) but requiring 10% - 20% higher cost and deeper sections, making them appropriate only for projects that prioritize recycled content over economy.

Moreover, fundamental material behaviour is the basis for the patterns in RCA performance that have been observed. By eliminating emissions from the extraction of virgin aggregate and using waste materials with lower embodied carbon, a higher RCA content lowers CO_2/Mn. However, compared to virgin concrete, RCA's increased porosity and weaker interfacial transition zone result in a 15% - 30% reduction in compressive strength and modulus of elasticity.

5. Conclusions

The result of analysis led to the following main conclusions:

- By moving beyond traditional single-objective design, this research demonstrates that using PSO technique with its developments into multi objective designs is a powerful tool for reconciling the conflicting economic and sustainability objectives in structural engineering, in another words, it reveals a fundamental trade-off between the conflicting cost and CO_2/Mn objective functions. Therefore, the algorithm demonstrates the possibility to identify creative solutions to reduce the environmental impact without violating structural constraints or economic feasibility.
- The results identified that the most cost-effective design strategy across all the designed beams is to minimize the total reinforcement area (*As* and *A's*) and compensate for the resulting reduction in moment capacity by increasing the beam depth *h*. Hence, this strategy prioritizes the use of cheaper concrete over the expensive steel.
- The RCA replacement shows a viable way toward sustainable construction, especially when using 30% RCA replacement, which offers 15% improvement in carbon efficiency over the virgin concrete, with a negligible cost increase (only 2%).
- Although increasing RCA replacement ratios to 50% and 100% reduces the CO_2/Mn ratio, they introduce diminishing returns in their Pareto fronts. The increments increase the minimum cost and necessitate increasing the beam depth *h* to achieve high structural performance, and hence, reducing material efficiency. Therefore, the choice to use 50% - 100% RCA replacement is a perfect decision to prioritize the use of high replacement ratios over economic and structural efficiency.
- The Pareto fronts for all the RCA beams likely shift downward compared to that of virgin concrete, which means increasing carbon efficiency at any cost level, hence, confirms the RCA role in getting sustainable designs.
- The Pareto front for the peak usage of RCA replacement (100%) shows a rightward shift at the lowest emission levels, which confirms the excellent investment required to achieve the lowest levels of carbon emissions.
- While RCA offers significant environmental benefits, its implementation involves practical trade-offs. While higher replacement levels (50% - 100%) require deeper sections and greater investment, their viability is limited to projects where maximizing recycled content is the primary goal. In contrast, the 30% RCA replacement offers an ideal balance achieving significant carbon savings with minimal cost impact.

There are a number of limitations to this study that indicate areas for additional investigation. Future research might look at continuous beams, various support conditions, and shifting load patterns. First, only simply supported beams under uniform loading were taken into consideration. Second, further performance standards like fatigue, fire resistance, and ductility could be included. Third, more research should be done on practical implementation considerations, such as regional material availability, bar spacing restrictions, and building tolerances. Lastly, confidence in the suggested framework would be increased by experimental validation of optimized designs.

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