







Challenge Journal of STRUCTURAL MECHANICS

Research Article

Optimal metaheuristic design of CFRP wrapping for enhancing the shear capacity of reinforced concrete columns

Ammar Khalbous^a , Gebraül Bekdaş^a , Sinan Melih Nigdeli^{a,*} , Aylin Ece Kayabekir^b 

^a Department of Civil Engineering, İstanbul University-Cerrahpaşa, 34320 İstanbul, Türkiye

^b Department of Civil Engineering, İstanbul Gelişim University, 34310 İstanbul, Türkiye

ABSTRACT

Reinforced concrete (RC) columns are prone to brittle shear failure under lateral loads like earthquakes, especially in older structures. Carbon fiber reinforced polymer (CFRP) wrapping effectively enhances shear capacity, ductility, and energy dissipation. This study optimizes CFRP jacket design to increase shear strength while minimizing material volume per meter of column. The objective function includes the number of layers (n), strip width (W_f), spacing (S_f), and thickness (t_f), following ACI 440.2R-2017 and ACI 318-05 constraints on strain, shear contribution, and capacity. Three metaheuristic algorithms—JAYA, Teaching-Learning-Based Optimization (TLBO), and Flower Pollination Algorithm (FPA)—were used to solve the nonlinear problem in MATLAB with randomized populations, 100–500 iterations, and 30 independent runs. Analyses for 100–500 kN shear demands (20%–100% increases) yield valid designs. Low shear demands typically require minimal CFRP, often a single layer with moderate strip width and large spacing. Higher demands required more intensive reinforcement through increased layer count and reduced spacing, with width adjustments as needed to satisfy code constraints. FPA achieved the lowest CFRP volumes due to its Lévy-flight global search, TLBO produced the most stable results with low variability, and JAYA offered the fastest computation. Increasing iteration count and population size improved convergence in all algorithms, yielding solutions closer to the optimum. Results confirm that metaheuristics enable economical, reliable CFRP retrofitting, promoting sustainability. Future work could include multi-objective optimization for cost and constructability.

Citation: Khalbous A, Bekdaş G, Nigdeli SM, Kayabekir AE (2026). Optimal metaheuristic design of CFRP wrapping for enhancing the shear capacity of reinforced concrete columns. *Challenge Journal of Structural Mechanics*, 12(1), 55–64.

ARTICLE INFO

Article history:

Received – November 17, 2025
Revision requested – January 22, 2026
Revision received – January 29, 2026
Accepted – February 9, 2026

Keywords:

CFRP strengthening
Shear capacity
Metaheuristic optimization
JAYA algorithm
Teaching-learning-based optimization
Flower pollination algorithm



This is an open access article distributed under the CC BY licence.

© 2026 by the Authors.

1. Introduction

Shear reinforcement, typically in the form of stirrups, plays a critical role in reinforced concrete (RC) structures. It resists shear forces to ensure structural safety and durability. However, in cases involving increased seismic demands, retrofitting requirements, changes in building function, or structural extensions, an enhancement of the shear capacity beyond the original design may become necessary (Xie et al. 2005). Traditionally, this improvement has been achieved through sheathing,

where the structural member is encased to increase its load-bearing capacity. Although effective, this technique adds significant weight and stiffness, often requiring a comprehensive redesign to accommodate the redistribution of internal forces. To overcome these drawbacks, modern strengthening methods employ carbon fiber reinforced polymer (CFRP) strips, offering a lightweight and flexible alternative that enhances shear strength without altering the section's mass or stiffness, thereby maintaining the original structural performance while simplifying application (Gkournelos et al. 2021).

* Corresponding author. E-mail address: melihnig@iuc.edu.tr (S. M. Nigdeli)

Despite the proven structural efficiency of CFRP, the high material cost remains a primary constraint for its widespread application, particularly in large-scale retrofitting projects. Traditional manual design methods often lead to conservative, 'over-designed' solutions that utilize excessive amounts of expensive composite material. Consequently, determining the precise minimum volume of CFRP required to meet safety standards is not merely a technical challenge but an economic necessity. This creates a critical need for automated approaches that can rigorously minimize material usage while strictly adhering to design codes.

Optimization is the systematic process of determining design variables that achieve the best possible outcome under defined constraints. In structural engineering, it is widely applied to obtain cost-effective and high-performance designs. While conventional mathematical methods, such as linear or nonlinear programming, are efficient for simple problems, they often fail to converge for the nonlinear, discontinuous, or multi-modal objective functions typically encountered in RC design. To overcome these challenges, metaheuristic algorithms have emerged as robust tools capable of exploring large and complex search spaces without requiring gradient information (Ulusoy et al. 2020; Tomar et al. 2023). Beyond single objective cost minimization, recent structural design studies increasingly adopt multi objective or multi criteria frameworks that simultaneously enforce code based strength and serviceability requirements while minimizing direct material usage and project cost. Within these formulations, weighting coefficients or penalty terms are commonly used to balance competing design targets (e.g., minimum CFRP quantity versus safety margins) and to prioritize constructible solutions through discrete design choices. Accordingly, the metaheuristic search and data driven surrogate modelling logic used to reduce repetitive search runs in cost driven optimization can be extended to CFRP shear strengthening by learning the mapping between discrete design variables and key performance indices including code compliance, cost, and constructability (Çoşut et al. 2023).

Consistent with this direction, hybrid workflows that first generate optimization datasets via metaheuristic search and then train machine learning surrogate models have gained attention, because they enable rapid estimation of near optimal design variables and objective values under combined constraints, thereby reducing the need to re run computationally expensive search procedures (Aydın et al. 2024). Accordingly, in the present study, design alternatives generated by JAYA, TLBO, and FPA are used to train surrogate models that map discrete CFRP strengthening variables (e.g., strip width, spacing, and number of layers) to code compliant shear capacity and cost metrics, enabling fast screening of constructible and economically efficient retrofitting solutions without repeated full optimization runs.

In recent years, the application of metaheuristic optimization in the design of CFRP-strengthened RC members has gained significant traction. The primary objective of these studies is to determine the optimal configuration of parameters—such as FRP area, strip width, spacing, and number of layers—to maximize structural performance while minimizing material costs. Early con-

tributions focused heavily on traditional algorithms. For instance, Dugguh (2015) utilized Genetic Algorithms (GA) to perform multi-objective optimization of circular hollow sections strengthened with CFRP. Similarly, Rahman et al. (2012) employed GA to minimize the cost of both CFRP plates and epoxy adhesives for externally strengthened beams, ensuring compliance with serviceability limits. More recently, research has shifted towards modern algorithms. Kayabekir et al. (2018) applied the Jaya algorithm to optimize the strip width and spacing of CFRP for the shear strengthening of RC beams, highlighting the algorithm's implementation simplicity. In another study, Kayabekir (2018) investigated the use of Teaching-Learning-Based Optimization (TLBO) and Flower Pollination Algorithm (FPA) to enhance the shear capacity of T-beams, proposing optimal wrapping thicknesses and layouts. Comparative studies have also been conducted; for example, Yücel (2025) compared FPA and Particle Swarm Optimization (PSO) for CFRP plate placement on RC beams, demonstrating that FPA outperformed PSO in terms of objective function accuracy and structural weight minimization. Furthermore, hybrid approaches such as the GA-PSO-TLBO method proposed by Yun et al. (2023) have shown that combining algorithms can offer robust strategies for complex engineering problems.

However, a critical review of the literature reveals specific gaps. While previous studies have successfully applied algorithms like GA and PSO, these methods often require the tuning of complex control parameters (e.g., mutation rates, inertia weights), which can be a barrier for practical engineering applications. Moreover, the majority of existing optimization works treat design variables (e.g., strip spacing) as continuous values, yielding theoretical solutions that are difficult to implement on-site (e.g., a spacing of 137.5 mm). The present research addresses these limitations by specifically introducing parameter-free and parameter-light metaheuristics—JAYA (Rao 2016), Teaching-Learning-Based Optimization (TLBO) (Rao et al. 2011), and Flower Pollination Algorithm (FPA) (Yang 2012)—to the domain of CFRP shear strengthening.

Unlike previous works that focused on beam flexure or utilized complex algorithms requiring extensive parameter tuning, this study targets RC columns and strictly enforces discrete design variables (rounded to 10 mm increments) to ensure constructability. By comparing these modern algorithms against strict ACI 440.2R-17 safety constraints, this paper aims to provide a robust, engineer-friendly framework that balances mathematical optimality with practical execution. The central hypothesis is that these parameter-light metaheuristic algorithms can converge to globally optimal solutions more efficiently than traditional methods, effectively establishing a streamlined, automated framework for sustainable and economical CFRP retrofitting.

2. Methodology

The algorithms used in this research to optimize the design of CFRP in columns against shear forces are Jaya, TLBO and FPA.

2.1. Jaya Algorithm

The Jaya algorithm is a population-based metaheuristic optimization method proposed by Rao. The word "Jaya" means "victory" in Sanskrit, and the algorithm's goal is to move away from the worst solution while approaching the best solution. In this respect, the Jaya algorithm combines the "survival of the fittest" principle of evolutionary algorithms with the global optimality search of swarm intelligence. The Jaya algorithm is single-phase and has no algorithm-specific control parameters. The user only specifies the population size and stopping criteria, making its implementation simple and user-friendly (Rao 2016).

Metaheuristic algorithms focus on optimizing the objective functions of engineering problems by modeling processes and behaviors in nature. Jaya also adopts the concept of victory and defeat in nature: in each iteration, existing solutions are labeled as best (optimal) and worst (pessimum) solutions; then, all candidate solutions are randomly adjusted by two coefficients to get closer to the best solution and further away from the worst solution. Thus, Jaya attempts to achieve a balance between exploration and exploitation in a parameter-free manner (Niğdeli et al. 2023).

In each iteration, all design variables of each individual (candidate solution) are calculated as shown in Eq. (1):

$$X_{i,j}^{t+1} = X_{i,j}^t + r1(X_i^* - |X_{i,j}^t|) - r2(X_i^w - |X_{i,j}^t|) \\ i = 1, 2, \dots, n; j = 1, 2, \dots, p; t = 1, 2, \dots, t_{\max} \quad (1)$$

Here, $X_{i,j}^t$ represents the value of the i -th design variable of the j -th solution at the t -th iteration. X_i^* and X_i^w are the i -th variable values of the current best and worst individual, respectively. $r1$ and $r2$ are two randomly chosen numbers in the range $[0,1]$, providing the stochastic property of the algorithm.

The main steps of the algorithm can be summarized as follows:

1. Initial Population: P random candidate solutions (individuals) are generated within the design range. Each individual is a vector of n design variables. Initial solutions are typically selected as shown in Eq. (2).

$$X_i^j = X_{\min} + \text{rand}(1)(X_{\max} - X_{\min}) \\ i = 1, 2, \dots, n; j = 1, 2, \dots, p \quad (2)$$

2. Objective Function Calculation: The objective function value for each individual is calculated. Any restrictions are disciplined using a penalty method. The smallest (cost-minimizing) or largest (performance-optimizing) individuals are identified.

3. Best and Worst Solutions: The best (closest to the global optimum) and worst (worst performing) solutions among all individuals in the population are determined.

4. Individual Updating: Each individual's design variable is updated using the equation above. This way, individuals are drawn toward the best solution and away from the worst. If variables in the updated solution fall outside the bounds, they are included in the range by horizontalization or boundary correction.

5. Creating a New Population: A new population is created with updated solutions. If necessary, the costs of new and old individuals are compared, and better solutions are carried over to the next iteration.

6. Stopping Criterion: Steps 2-5 are repeated until the desired number of iterations or the convergence criterion is reached. The best solution is then recorded.

These steps constitute the core of the Jaya algorithm. In each iteration, only the current best and worst solutions are considered; since there are no additional control parameters, the algorithm is structurally simple and parameter-free (da Silva et al. 2022; Duysak et al., 2024; Niğdeli et al., 2023).

2.2. Teaching-Learning Based Optimization Algorithm (TLBO)

Teaching-Learning-Based Optimization (TLBO) is a metaheuristic optimization algorithm proposed by Rao et al. (2011). Similar to other algorithms inspired by natural processes (such as GA, PSO, and FPA), TLBO performs the search by simulating the teaching-learning process within a classroom. The knowledge of students (solutions) is enhanced by the teacher (the best solution) and further updated through interactions (knowledge sharing) among students. The algorithm employs a classroom population, where each individual represents a student, and the total performance obtained from the student's "subjects" (design variables) is associated with that student's grade (fitness, cost, etc.).

Solution generation occurs in two consecutive stages: In the Teacher Stage, the "teacher" (the best solution in the population) improves the population mean towards the optimum; in the Student Stage, the "students" (the solution vectors) improve their performance through pairwise interactions. Both stages iteratively improve the population until the stopping criterion is met. In the Teacher Stage of the TLBO algorithm, new solution vectors are generated by the following equation (see Eq. (3)):

$$X_{\text{new}} = X_{\text{old}} + \text{rand}(1) \times (X_{\text{teacher}} - TF \times X_{\text{mean}}) \quad (3)$$

Here:

X_{new} : Newly generated solution vector,

X_{old} : Current solution vector,

$\text{rand}(1)$: Uniform random number in the range $[0,1]$,

X_{teacher} : Best solution vector in the population,

X_{mean} : Arithmetic mean of all current solution vectors,

TF : Teaching Factor determines the teacher's influence on the classroom.

The teaching factor TF can take a randomly chosen value of 1 or 2 using the following relationship (see Eq. (4)):

$$TF = \text{round}(1 + \text{rand}) \rightarrow \{1, 2\} \quad (4)$$

This mechanism allows the teacher to try to raise the average knowledge level of the class relative to his or her own performance, thereby guiding the population towards better solutions.

In the Student Phase, new vectors are created based on two different solutions, X_i and X_j , randomly selected from the population. In this phase, new solution vectors

are generated using Eq. (5) by examining the objective functions ($f(X_i)$ and $f(X_j)$) of the existing solutions.

$$X_{\text{new}} = \begin{cases} X_{\text{current}} + \text{rand}(0,1) \times (X_i - X_j) & \text{if } f(X_i) > f(X_j) \\ X_{\text{current}} + \text{rand}(0,1) \times (X_j - X_i) & \text{if } f(X_i) < f(X_j) \end{cases} \quad (5)$$

A number of new solution vectors (pn) reflecting the initial population size are generated. Each candidate vector is recorded in the new solution matrix, and its objective function value is calculated. Each vector in this matrix is then compared with its counterpart in the existing solution matrix; if the new vector provides a superior objective function value, it replaces the existing vector. This generate–evaluate–replace cycle is repeated until a pre-defined stopping criterion is met (Dede and Ayvaz 2013; Camp and Farshchin 2014).

2.3. Flower Pollination Algorithm (FPA)

The Flower Pollination Algorithm (FPA), developed by Yang (2012), is a powerful optimization method inspired by the pollination processes that occur in plants. The algorithm mathematically models biotic (by living organisms) and abiotic (by environmental factors such as wind and water) pollination mechanisms and adapts these biological processes to optimize problem solving.

The algorithm's search mechanism is based on two main components: global pollination and local pollination. At each iteration, candidate solutions in the population are updated according to these two pollination strategies. Global pollination represents long-distance, random search capacity, while local pollination simulates the search for detailed solutions in a narrower search space. Thanks to this hybrid structure based on biological principles, FPA demonstrates balanced performance in both rapid convergence and preserving solution diversity.

FPA models the flower pollination process based on four fundamental rules (Abdel-Basset and Shawky 2019; Saber and Elhenawy 2021; Yang 2012):

1. Biotic and cross-pollination represent global pollination, and pollen is transported by Lévy flights.
2. Abiotic and self-pollination represent local pollination.
3. Floral constancy simulates the affinity of pollinators for specific flower types.
4. Global and local pollination are controlled by a crossover probability $p \in [0,1]$.

Based on these rules, global pollination is mathematically formulated as shown in Eq. (6):

$$X_{i,\text{new}} = X_{i,j} + L \times (X_{i,g \text{ best}} - X_{i,j}) \quad (6)$$

Here:

$X_{i,\text{new}}$: The new value of the design variable (solution vector).

$X_{i,j}$: The initial matrix value of the j -th flower of the i -th design variable.

$X_{i,g \text{ best}}$: The best solution in the population.

L : Represents the random step size generated from the Lévy distribution and is calculated as shown in Eq. (7):

$$L = \left(\frac{1}{2\pi}\right) \times (\text{rand}())^{-1.5} \times e^{\left(\frac{1}{2 \times \text{rand}}\right)} \quad (7)$$

Lévy flight allows the search space to be scanned in large steps, thus preventing the algorithm from getting stuck in local optima.

Subsequently, local pollination is expressed in Eq. (8) as:

$$X_{i,\text{new}} = X_{i,j} + \text{rand}() \times (X_{i,m} - X_{i,k}) \quad (8)$$

Here:

$X_{i,m}, X_{i,k}$: Different solutions from the same population.

rand: A random number between [0,1].

This mechanism allows exploring the local search space and improving existing solutions (Pavlyukevich 2007).

The choice between global and local pollination is controlled by the transition probability sp . This transition probability, defined in Rule 4, ensures a dynamic transition between the two stages.

3. Numerical Example

In this study, the optimal design of CFRP wrapping was carried out to enhance the shear capacity of reinforced concrete (RC) columns. The optimization procedure was conducted in compliance with ACI 440.2R-2017 and ACI 318-05 provisions. The objective function was defined as the minimization of CFRP volume required for a 1 m-long column segment.

The configuration of the CFRP system—characterized by the strip width W_f (mm), strip spacing S_f (mm), and total wrap thickness ($t_f \times n$) (mm)—is illustrated schematically in Fig. 1. These parameters constitute the principal design variables in the optimization process.

The optimization was performed using three metaheuristic algorithms: JAYA, Teaching–Learning–Based Optimization (TLBO), and Flower Pollination Algorithm (FPA). The analysis was repeated for various additional shear demand levels of 100 kN, 200 kN, 300 kN, 400 kN, and 500 kN, representing 20%, 40%, 60%, 80%, and 100% increases in the column's shear capacity, respectively.

The optimization problem targets the minimization of material consumption, quantified as the total volume of CFRP applied over a unit length ($L = 1000$ mm) of the column. The objective function, $F(X)$, is strictly defined by the column's geometric perimeter and the four optimization variables contained in the design vector $X = \{n, W_f, S_f, t_f\}$. These variables correspond to the number of layers, strip width, center-to-center spacing, and ply thickness, respectively. Accordingly, the objective function is explicitly formulated in Eq. (9):

$$F(X) = V_{\text{CFRP}} = \frac{n \times W_f \times t_f \times 2000 \times (b+h)}{S_f} \quad (9)$$

where b and h denote the cross-sectional dimensions of the RC column in mm. This formulation calculates the total volume of the transverse CFRP strips wrapping around the column perimeter within a one-meter height. By minimizing V_{CFRP} , the algorithm identifies the most cost-effective geometric configuration that strictly satisfies all strength and strain requirements specified in ACI 440.2R-17.

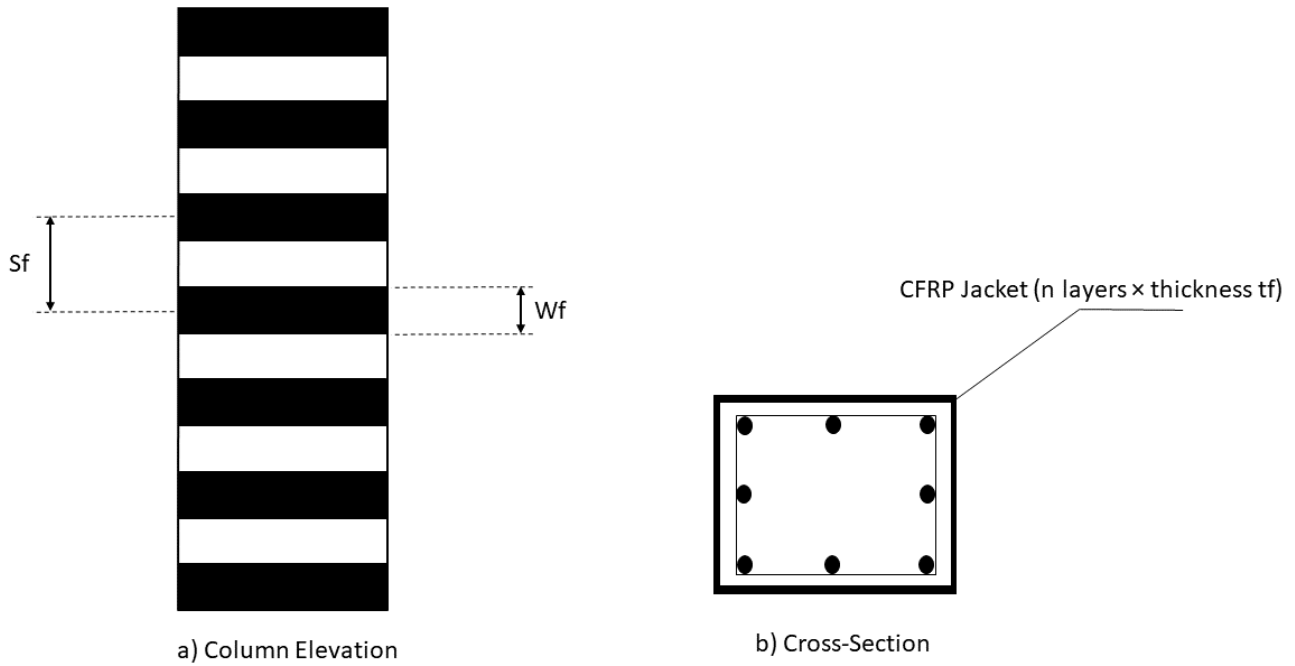


Fig. 1. Schematic definition of the optimization design variables.

All design variables are constrained within practical limits to ensure feasible CFRP configurations, as defined by Eqs. (10–13).

$$1 \leq n \leq 3 \tag{10}$$

$$0.2 \leq t_f \leq 2 \tag{11}$$

$$50 \leq W_f \leq 150 \tag{12}$$

$$10 \leq S_f \leq fix \left(\frac{d_f}{4/10} \right) \times 10 = 130 \tag{13}$$

To ensure practical constructability and address the discrete nature of the design parameters, specific handling mechanisms were implemented in the algorithms. The number of layers (n) is treated strictly as an integer; thus, continuous values generated during optimization are rounded to the nearest integer within the range [1,3]. Similarly, the strip width (W_f) and spacing (S_f) are constrained to be multiples of 10 mm to facilitate on-site application. Consequently, the algorithm rounds these variables to the nearest multiple of 10 within their respective bounds before evaluating the objective function.

The constraints of the optimization problem are as follows: Eqs. (14–16):

$$g_1: 0.75 \times \varepsilon_{fu} - 0.004 \geq 0 \tag{14}$$

$$g_2 = \frac{2 \times t_f \times n \times W_f \times E_f \times \varepsilon_{fe} \times d_f}{S_f} - V_{freq} > 0 \tag{15}$$

$$g_3 = \frac{2 \times t_f \times n \times W_f \times F_{fe} \times d_f}{S_f} + V_s - (2 \times (1 + 72.5 \times \frac{N_u}{A_g}) \times \sqrt{F_c} \times b \times d_f) < 0 \tag{16}$$

These constraints strictly enforce the safety provisions of ACI 440.2R-17:

- Strain Limitation (g_1): Eq. (14) ensures that the effective strain in the CFRP laminate does not exceed the maximum allowable limit of 0.004 (or $0.75 \times \varepsilon_{fu}$), preventing premature debonding failure before the concrete reaches its useful compressive strain.
- Shear Capacity Requirement (g_2): Eq. (15) guarantees that the shear contribution provided by the optimized CFRP configuration (V_f), when added to the existing steel and concrete resistance, is sufficient to meet the target shear demand (V_{freq}).
- Maximum Strengthening Limit (g_3): Eq. (16) serves as a brittle failure prevention check. It limits the total shear reinforcement ($V_s + V_f$) to prevent the concrete struts from crushing before the reinforcement yields, ensuring a ductile failure mode.

The key design parameters and their numerical values used in the optimization are listed in Table 1.

The overall flow of the optimization process, illustrating the sequence of algorithmic steps from initialization to final design selection, is presented in Fig. 2.

4. Results and Discussion

The optimization algorithms were implemented in MATLAB to evaluate their performance in determining the most efficient CFRP strengthening configurations. For each algorithm, a randomly initialized population was generated, followed by an iterative optimization process. To strictly enforce the safety limits defined in ACI 440.2R-17 (Eqs. 14–16), a static penalty method was employed to handle constraints. Unlike methods that add a soft penalty term, this approach assigns a prohibitively high constant value to any infeasible solution. The penalized objective function $F(X)$ is defined by Eq. (17):

$$F(X) = \begin{cases} V_{CFRP}(X) & \text{if } g_i(X) \text{ is satisfied; } i = 1, 2, 3 \\ 10^6 & \text{otherwise} \end{cases} \quad (17)$$

where $V_{CFRP}(X)$ is the calculated volume. By assigning a high value (10^6) to designs violating constraints, the algorithms are forced to discard non-compliant solutions and converge effectively toward the feasible region.

Table 1. Design constants.

Parameters	Description	Values
$b \times h$	Column dimensions (mm)	600×600
F_c	Concrete compressive strength (MPa)	20
d_f	Effective depth (mm)	540
E_f	CFRP modulus of elasticity (MPa)	170000
φ	Strength reduction factor (ACI 318-05)	0.85
C_E	Environmental reduction factor (indoor)	0.95
Ψ_f	Full confinement reduction factor	0.95
ϵ_{fu}'	CFRP rupture strain (mm/mm)	0.018
ϵ_{fu}	CFRP design strain (mm/mm)	$C_E \times \epsilon_{fu}' = 0.0171$
ϵ_{fe}	Effective CFRP strain (mm/mm)	$\min(0.004; 0.75 \times \epsilon_{fu}) \approx 0.004$
F_{fe}	Effective CFRP tensile strength (MPa)	$\epsilon_{fe} \times E_f = 680$
V_s	Stirrup shear capacity (kN)	500
V_{ek}	Additional shear demand (kN)	100, 200, 300, 400, 500
V_{freq}	Required CFRP shear contribution (kN)	$V_{ek} / (\varphi \times \Psi_f)$
N_u	Normal force (kN)	200
A_g	Gross concrete cross-sectional area (mm ²)	2920

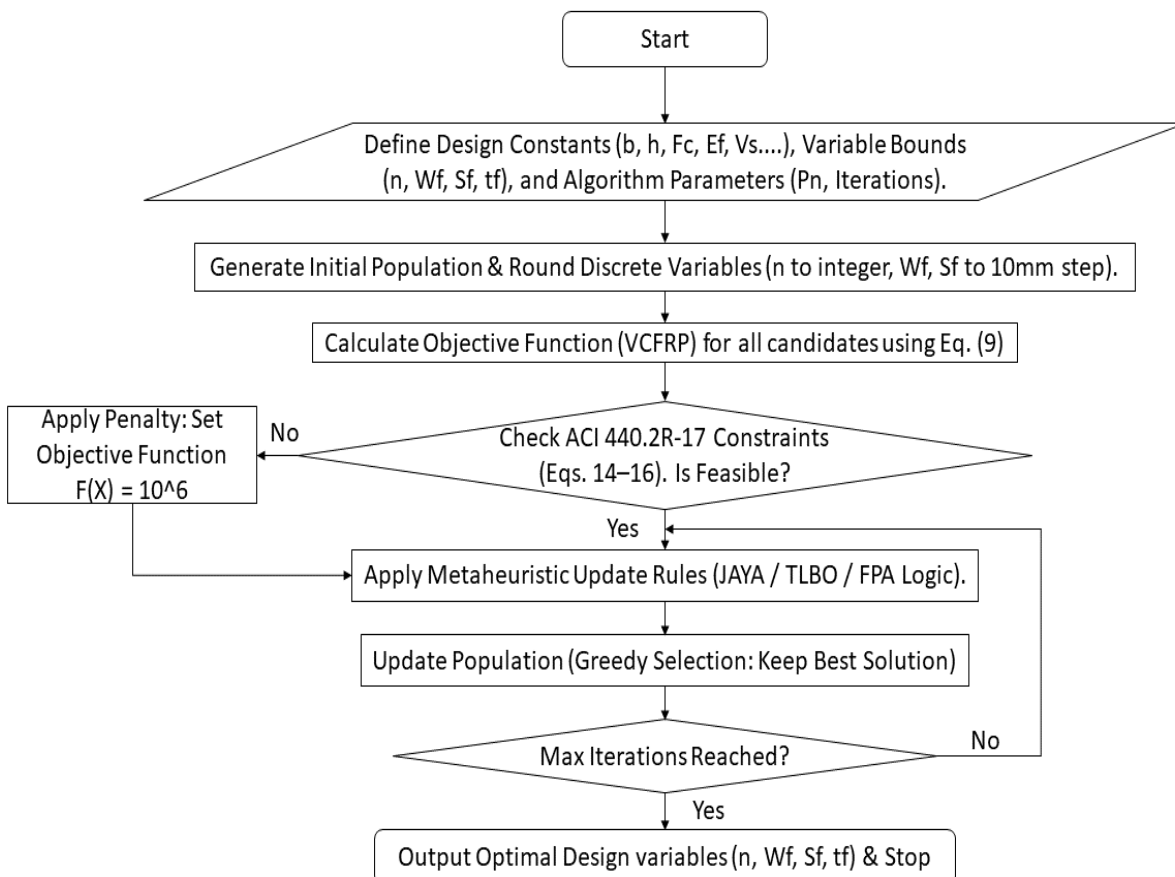


Fig. 2. Flowchart of the optimization framework and constraint handling.

To ensure statistical consistency, each algorithm was executed independently 30 times. The computational parameters were defined as follows: the population size varied between 20 and 25, and the number of iterations ranged from 100 to 500. These values were determined through a preliminary sensitivity analysis, which indicated that they provide an optimal balance between solution stability (minimizing standard deviation) and computational efficiency. For the FPA algorithm, the switching probability was set to $sp=0.5$.

In each scenario, the best CFRP volume (V_{best}), mean volume (V_{mean}), standard deviation, population size, number of iterations, and average iteration time were recorded to enable a comparative assessment of algorithmic performance. The top three distinct optimal configurations (yielding the lowest CFRP volumes) were extracted for each algorithm and shear demand level from the 30 independent runs to demonstrate design flexibility. The results are presented in Tables 2–6.

Table 2. CFRP strengthening optimization under 100 kN additional shear force (20% increase): Comparison of JAYA–TLBO–FPA.

Algorithm	Solutions (n, W_f, S_f, t_f)	V_{best} (mm ³ /m)	V_{mean} (mm ³ /m)	Standard deviation	Number of iterations	Population size	Iteration time (second)
JAYA	(1; 110; 130; 0.20) (1; 50; 120; 0.41) (1; 60; 130; 0.37)	404,729.64	405,685.62	1,239.07	100	20	0.014
TLBO	(2; 50; 120; 0.20) (1; 100; 120; 0.20) (1; 50; 60; 0.20)	404,705.20	404,835.98	298.08	100	20	0.109
FPA	(1; 60; 70; 0.20) (1; 100; 130; 0.22) (1; 110; 130; 0.20)	404,702.65	405,231.45	1,283.05	100	20	0.065

Table 3. CFRP strengthening optimization under 200 kN additional shear force (40% increase): Comparison of JAYA–TLBO–FPA.

Algorithm	Solutions (n, W_f, S_f, t_f)	V_{best} (mm ³ /m)	V_{mean} (mm ³ /m)	Standard deviation	Number of iterations	Population size	Iteration time (second)
JAYA	(2, 80, 100, 0.21) (2, 110, 130, 0.20) (1, 70, 70, 0.34)	809,408.38	810,061.75	952.92	100	25	0.014
TLBO	(1, 50, 110, 0.74) (1, 60, 70, 0.39) (1, 50, 120, 0.81)	809,412.23	809,515.50	130.41	100	25	0.127
FPA	(1, 80, 130, 0.55) (1, 50, 50, 0.34) (3, 50, 130, 0.29)	809,405.29	809,510.37	529.61	100	25	0.066

Table 4. CFRP strengthening optimization under 300 kN additional shear force (60% increase): Comparison of JAYA–TLBO–FPA.

Algorithm	Solutions (n, W_f, S_f, t_f)	V_{best} (mm ³ /m)	V_{mean} (mm ³ /m)	Standard deviation	Number of iterations	Population size	Iteration time (second)
JAYA	(1, 140, 100, 0.36) (2, 50, 80, 0.40) (1, 100, 40, 0.20)	1,214,120.70	1,214,881.24	1156.67	150	20	0.016
TLBO	(1, 50, 30, 0.30) (1, 60, 100, 0.84) (2, 50, 110, 0.56)	1,214,110.46	1,214,214.94	162.72	150	20	0.311
FPA	(3, 70, 110, 0.26) (2, 60, 100, 0.42) (3, 50, 130, 0.44)	1,214,107.93	1,214,108.91	2.92	150	20	0.068

Table 5. CFRP strengthening optimization under 400 kN additional shear force (80% increase): Comparison of JAYA–TLBO–FPA.

Algorithm	Solutions (n, W_f, S_f, t_f)	V_{best} (mm ³ /m)	V_{mean} (mm ³ /m)	Standard deviation	Number of iterations	Population size	Iteration time (second)
JAYA	(3, 90, 80, 0.20) (1, 50, 90, 1.21) (1, 130, 130, 0.67)	1,618,814.38	1,619,075.19	390.05	250	20	0.020
TLBO	(1, 50, 110, 1.48) (3, 50, 130, 0.58) (1, 130, 70, 0.36)	1,618,810.62	1,618,906.45	122.31	250	20	0.158
FPA	(3, 60, 130, 0.49) (2, 140, 120, 0.29) (1, 50, 130, 1.75)	1,618,810.58	1,618,875.45	251.55	250	20	0.079

Table 6. CFRP strengthening optimization under 500 kN additional shear force (100% increase): Comparison of JAYA–TLBO–FPA.

Algorithm	Solutions (n, W_f, S_f, t_f)	V_{best} (mm ³ /m)	V_{mean} (mm ³ /m)	Standard deviation	Number of iterations	Population size	Iteration time (second)
JAYA	(1, 60, 120, 1.69) (1, 120, 50, 0.35) (1, 90, 110, 1.03)	2,023,513.26	2,023,697.19	223.61	500	25	0.029
TLBO	(1, 60, 60, 0.84) (1, 50, 80, 1.35) (2, 90, 120, 0.56)	2,023,513.29	2,023,545.47	46.63	500	25	0.301
FPA	(1, 50, 110, 1.85) (1, 90, 90, 0.84) (2, 70, 80, 0.48)	2,023,513.22	2,023,513.24	0.08	500	25	0.102

The reliability of the optimization results was verified by performing a check on the optimal solution obtained for the first load case (100 kN additional shear). The configuration yielded by the FPA algorithm was subjected to rigorous manual verification, strictly adhering to the design procedures and illustrative examples provided in ACI 440.2R-17. This manual check confirmed that the calculated shear contribution (V_f) is identical to the algorithm's output. Furthermore, it verified that the proposed configuration fully satisfies all relevant code constraints, including strain limits, CFRP shear contribution restrictions, and total shear capacity limits. This validation confirms the accuracy of the implemented computational framework.

The results presented in Tables 2–6 reveal distinct behavioral characteristics of the applied metaheuristics. Although all three algorithms successfully satisfied the ACI 440.2R-17 constraints, FPA consistently achieved the marginally lowest CFRP volumes. This superior convergence capability can be attributed to its Lévy flight mechanism, which allows the algorithm to perform long-distance jumps across the search space. This feature is particularly effective in avoiding local minima in the non-linear landscape of shear design, enabling FPA to locate the global optimum more frequently than JAYA or TLBO.

On the other hand, TLBO demonstrated the highest stability, evidenced by the lowest standard deviation

across the 30 independent runs. This robustness is likely due to its 'Teacher Phase,' which consistently pulls the population mean towards the best solution, reducing the variance of the final outputs. Conversely, JAYA proved to be the most computationally efficient algorithm, achieving the shortest average iteration time. This speed advantage stems from its algorithmic simplicity; unlike TLBO, which requires two phases per iteration, JAYA utilizes a straightforward single-phase update mechanism without complex specific control parameters, making it highly suitable for rapid design iterations.

Regarding the magnitude of savings, while the numerical differences in CFRP volume between the algorithms may appear negligible for a single meter of column, their practical significance scales substantially. In large-scale retrofitting projects involving hundreds of structural members, these cumulative material savings translate into meaningful cost reductions and lower environmental impact, justifying the computational effort to find the absolute global minimum.

Beyond the numerical efficiency, these results carry significant practical engineering implications. First, the minimization of CFRP volume directly translates to cost reduction, making the strengthening projects more economically viable. Second, by constraining the design variables (strip width and spacing) to discrete 10 mm increments, the proposed solutions are standardized and 'site-ready,' reducing the risk of labor errors during in-

stallation. Ultimately, the presentation of multiple distinct solution sets for each load case provides engineers with crucial construction flexibility, allowing them to adapt to material inventory shortages without delaying the construction schedule.

5. Conclusions

This study presented a robust computational framework for the optimal design of Carbon Fiber Reinforced Polymer (CFRP) wrapping to enhance the shear capacity of RC columns. By employing three distinct metaheuristic algorithms—Jaya, Teaching–Learning–Based Optimization (TLBO), and Flower Pollination Algorithm (FPA)—the research successfully minimized material consumption while strictly adhering to the safety provisions of ACI 440.2R-17 and ACI 318-05. The investigation covered a wide range of shear demands (100–500 kN), demonstrating that automated optimization can yield feasible, code-compliant solutions that are significantly more economical than traditional manual designs.

A comparative performance analysis revealed distinct advantages for each algorithm. The FPA consistently achieved the absolute minimum CFRP volumes, at-

tributed to its Lévy-flight mechanism, which effectively avoids local minima. Meanwhile, TLBO demonstrated superior stability with the lowest standard deviation across independent runs, and JAYA proved to be the most computationally efficient, offering the fastest convergence speeds due to its parameter-free structure. Crucially, the reliability of these computational results was validated through a rigorous manual verification of the optimal solution for the initial load case, confirming exact alignment with standard code procedures.

Beyond numerical efficiency, this study bridges the gap between theoretical optimization and on-site application. Unlike previous works that relied on continuous variables, this research enforced discrete design variables (e.g., rounding strip widths and spacing to 10 mm increments). This approach ensures that the proposed configurations are "site-ready," reducing the likelihood of installation errors and enhancing constructability. Consequently, the proposed framework offers engineers a practical tool to reduce material costs and environmental impact in large-scale retrofitting projects. Future research should expand this methodology to include multi-objective optimization, considering factors such as total application time and labor costs, as well as applying these algorithms to other structural elements like T-beams or circular columns.

Acknowledgements

None declared.

Funding

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

Conflict of Interest

The authors declare 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

All authors made substantial contributions to the conception and design of the study, acquisition of data, analysis and interpretation of data; drafted or critically revised the manuscript for important intellectual content; and approved the final version to be published.

REFERENCES

- Abdel-Basset M, Shawky LA (2019). Flower pollination algorithm: a comprehensive review. *Artificial Intelligence Review*, 52(4), 2533-2557.
- 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 440.2R-17 (2017). Guide for the Design and Construction of Externally Bonded FRP Systems for Strengthening Concrete Structures. American Concrete Institute, Farmington Hills, MI, USA.
- Aydın Y, Ahadian F, Bekdaş G, Nigdeli S (2024). Prediction of optimum design of welded beam design via machine learning. *Challenge Journal of Structural Mechanics*, 10(3), 86-94.
- Camp CV, Farshchin M (2014). Design of space trusses using modified teaching-learning based optimization. *Engineering Structures*, 62-63, 87-97.
- Çoşut M, Bekdaş G, Nigdeli S (2023). Optimization of reinforced concrete frame structures and matrix displacement method. *Challenge Journal of Concrete Research Letters*, 14(1), 10-17.
- da Silva LS, Lúcio YL, Coelho LD, Mariani VC, Rao RV (2022). A comprehensive review on Jaya optimization algorithm. *Artificial Intelligence Review*, 56, 4329-4361.
- Dede T, Ayvaz Y (2013). Structural optimization with teaching-learning-based optimization algorithm. *Structural Engineering and Mechanics*, 47(4), 495-511.
- Dugguh LN (2015). Multi-objective optimization of carbon fibre reinforced plastic (CFRP) circular hollow section using genetic algorithm for engineering structures. *International Refereed Journal of Engineering and Science*, 4(12), 24-28.
- Duysak Y, Nigdeli SM, Bekdaş G (2024). Optimum design of reinforced concrete beam sections with JAYA algorithm. *Challenge Journal of Concrete Research Letters*, 15(4), 134-141.
- Gkournelos PD, Triantafyllou TC, Bournas DA (2021). Seismic upgrading of existing reinforced concrete buildings: A state-of-the-art review. *Engineering Structures*, 240, 112273.
- Kayabekir AE, Sayın B, Nigdeli SM, Bekdaş G (2018). Jaya algorithm based optimum carbon fiber reinforced polymer design for reinforced concrete beams. *AIP Conference Proceedings*, 1978(1), 260006.
- Kayabekir AE (2018). Yapı Mühendisliğinde Metasezgisel Algoritmalar ile Optimizasyon Uygulamaları [Optimization Applications with Metaheuristic Algorithms in Structural Engineering]. *M.Sc. thesis*, İstanbul University-Cerrahpaşa, İstanbul, Türkiye. (in Turkish)
- Nigdeli SM, Bekdaş G, Kayabekir AE (2023). Metasezgisel yöntemlerle betonarme yapı elemanlarının optimizasyonu [Optimization of reinforced concrete structural elements with metaheuristic methods]. *İstanbul University-Cerrahpaşa Yayınları*, İstanbul, Türkiye. (in Turkish)
- Pavlyukevich I (2007). Lévy flights, non-local search and simulated annealing. *Journal of Computational Physics*, 227(1), 183-190.
- Rahman MM, Jumaat MZ, Hosen MA (2012). Genetic algorithm for material cost minimization of external strengthening system with fiber

- reinforced polymer. *Advanced Materials Research*, 468–471, 1817–1822.
- Rao RV, Savsani VJ, Vakharia DP (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, 43(3), 303–315.
- Rao RV (2016). Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *International Journal of Industrial Engineering: Theory, Applications and Practice*, 7, 19–34.
- Saber S, Elhenawy I (2021). A survey on flower pollination algorithm. *Journal of Intelligent Systems and Internet of Things*, 2(1), 5–11.
- Tomar V, Bansal M, Singh P (2023). Metaheuristic algorithms for optimization: A brief review. *Engineering Proceedings*, 59(1), 238.
- Ulusoy S, Kayabekir AE, Bekdaş G, Nigdeli SM (2020). Metaheuristic algorithms in optimum design of reinforced concrete beam by investigating strength of concrete. *Challenge Journal of Concrete Research Letters*, 11(2), 26–30.
- Xie J, Liu XM, Zhao T (2005). Shear capacity of reinforced concrete columns strengthened with CFRP sheet. *Journal of Zhejiang University - Science A: Applied Physics & Engineering*, 6(8), 853–858.
- Yang XS (2012). Flower pollination algorithm for global optimization. In: Durand-Lose J, Jonoska N, editors. Unconventional computation and natural computation. *Lecture Notes in Computer Science*, 7445. Springer, London, UK, 240–249.
- Yun Y, Gen M, Erdene TN (2023). Applying GA-PSO-TLBO approach to engineering optimization problems. *Mathematical Biosciences and Engineering*, 20(1), 552–571.
- Yücel M (2025). Comparison of flower pollination algorithm and particle swarm optimization for structural weight minimization of RC beams with carbon fiber reinforced polymer (CFRP). *Afyon Kocatepe University Journal of Sciences and Engineering*, 25(2), 381–387.