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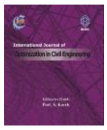

MATERIAL COST OPTIMIZATION OF ONE-WAY REINFORCED CONCRETE SLABS USING AN ELITIST GENETIC ALGORITHM: A SENSITIVITY ANALYSIS BASED ON ACI 318-19

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ABSTRACT

This study uses an elitist Genetic Algorithm (GA) to optimize material costs in one-way reinforced concrete slabs, adhering to ACI 318-19. A sensitivity analysis demonstrated the critical role of elitism in GA performance. Without elitism, the GA consistently failed to reach the target objective, with success rates often nearing zero across various crossover fractions. Incorporating elitism dramatically increased success rates, highlighting the importance of preserving high-performing individuals. With an optimal configuration of 0.3 crossover fraction and 0.45 elite percentage, a 92% success rate was achieved, finding a cost of 24.91 in 46 of 50 runs for a simply supported slab. This optimized design, compared to designs based on ACI 318-99 and ACI 318-08, yielded material cost savings of between 5.8% to 8.6% for simply supported, one-end continuous, both-ends continuous, and cantilevered slabs. The influence of slab dimensions on cost was evaluated across 64 scenarios, varying slab lengths from 5 to 20 feet for each support condition. Resulting cost versus slab length diagrams illustrate the economic benefits of GA optimization.

Keywords: Optimal design, Structural optimization, Reinforced Concrete Slabs, Genetic Algorithm, ACI 318-19, Elite Percentage, Sensitivity Analysis.

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1. INTRODUCTION

In an era marked by rapid urbanization and escalating demands on infrastructure, the construction industry confronts a pivotal challenge: the need to deliver structures that are not only safe and sustainable but also cost-effective. Reinforced concrete, a cornerstone material

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in modern construction, is celebrated for its durability and versatility. Nevertheless, its utilization is often accompanied by significant material and labour costs. Consequently, optimizing the design of reinforced concrete structures and elements, such as one-way slabs, becomes essential for minimizing material waste and maximizing resource efficiency without compromising the structural integrity. This optimization is critical to ensure that infrastructure development keeps pace with urban growth while adhering to economic and environmental sustainability goals.

The primary objective of an optimization algorithm is to either minimize the utilization of resources or to maximize the benefits obtained [1]. Optimization is defined as the process of identifying the most efficient solution within established constraints [2]. It involves determining the most advantageous outcome while adhering to a specific set of limitations.

Reinforced concrete is a predominant material in the construction industry, esteemed for its extensive applicability and reliability. A paramount objective within this domain is to reduce the costs associated with reinforced concrete structures. Over recent decades, significant emphasis has been placed on optimizing the design of these structures to enhance cost-effectiveness. The pursuit of more economically viable and resource-efficient reinforced concrete constructions has spurred extensive research into various facets of design optimization. A critical focus area involves augmenting the efficiency of traditional design methodologies by integrating advanced optimization algorithms to identify the most optimal configurations for structural elements such as frames [3, 4], beams [5, 6], columns [7, 8], slabs [9, 10], retaining walls [11], and other structural elements.

To demonstrate advancements in this area, various studies have employed a range of optimization techniques for cost-effective designs. For example, Kaveh and Shakouri Mahmud Abadi (2011) utilized the Harmony Search Algorithm to optimize slab formwork design. Inspired by musical harmony, this method aims to minimize costs while meeting constraints such as bending moments, shear forces, deflection limits, and compliance with code provisions. The study successfully identified optimal cross-sections and spacing for formwork elements like joists and stringers, resulting in significant cost reductions [12].

Kaveh and Behnam (2012) employed innovative physics-based algorithms, namely the Charged System Search (CSS) and the Enhanced Charged System Search (E-CSS), to optimize various floor systems, including composite slabs, waffle slabs, and concrete formwork, with an emphasis on minimizing costs. Their study compared the performance of CSS and E-CSS against the Improved Harmony Search algorithm, underscoring the potential advantages of CSS in achieving cost-effective solutions [9]. In another study, Kayabekir et al. applied multiple metaheuristic algorithms such as Harmony Search, Teaching-Learning-Based Optimization (TLBO), Flower Pollination, and Jaya to optimize the dimensions of T-beams in accordance with Eurocode regulations governing concrete design. Notably, the TLBO algorithm consistently yielded the most optimal T-beam dimensions among the evaluated methods, demonstrating its superior effectiveness for this specific optimization task [6]. Bekdas et al. (2022) used the Harmony Search algorithm to optimize reinforced concrete circular column dimensions, minimizing steel and concrete costs. Focusing on column diameter and steel area, they generated 3125 optimal designs. Using SHAP and ensemble learning, they analyzed variable impact and objective function relationships to develop high-performance machine learning models for structural design [13].

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Kaveh and Bijari (2014) utilized various metaheuristic algorithms, including Colliding Bodies Optimization (CBO) and Democratic Particle Swarm Optimization (DPSO), to minimize the construction costs of one-way reinforced concrete ribbed slabs. These algorithms were developed to address the premature convergence issues commonly associated with standard Particle Swarm Optimization (PSO). When compared to the Harmony Search algorithm, both CBO and DPSO demonstrated enhanced performance and faster convergence rates in the optimization process [10]. Ahmadi-Nedushan and Varaee (2009) applied a modified version of PSO algorithm to the optimal design of reinforced concrete earth-retaining walls, addressing dual objectives of minimizing both weight and cost [14].

Habibi et al. (2016) applied the Lagrange Multiplier Method (LMM) to design cost-effective singly and doubly reinforced rectangular concrete beams. Their objective function focused on minimizing the costs of concrete and steel materials while ensuring the beams met the ultimate flexural strength requirements as per the Iranian National Building Regulations (INBR9). The LMM enabled the derivation of closed-form solutions for optimal designs, which were graphically presented in the study. This approach effectively identified minimum cost designs without the need for iterative experimentation [15]. Shobeiri and Ahmadi-Nedushan (2019) used Bi-Directional Evolutionary Structural Optimization (BESO) to optimize 3D prestressed concrete beam layouts. Their study demonstrated BESO's effectiveness in finding optimal topologies while considering prestressing stress, geometric discontinuities, height limits, and strut-and-tie models. BESO improved both design efficiency and material use. [16].

Olawale et al. (2020) used a genetic algorithm (GA) to optimize reinforced concrete waffle slab design for cost-effectiveness by minimizing material and formwork costs. Their optimized designs achieved a low steel ratio of 2.2% [17]. Afsal et al. (2020) conducted a critical review of reinforced concrete (RC) structural design optimization, addressing a gap in the literature by providing a comprehensive overview of computational design optimization research for RC structures. The review examines various objectives, components, strategies, and computational tools, offering detailed insights into integrating optimization strategies with computational tools for RC structural design. Interested readers can refer to this article to explore further applications of optimization in concrete structures [18].

To narrow the scope from general studies to more relevant research, the ensuing section investigates developments in the optimization of reinforced concrete one-way solid slabs. Designed to bear all applied loads through bending in a single direction, one-way slabs typically have a width-to-length ratio of two or more. Early studies by Brown (1975) and Brøndum-Nielsen (1987) utilized simplifying assumptions in their optimization approaches. Brown (1975) addressed the optimal cost design of one-way concrete slabs by formulating it as a single-variable optimization problem aimed at determining the optimal thickness for uniformly loaded, simply supported slabs. This study considered only flexural deformations, relying on other simplifying assumptions to streamline the analysis [19]. Brøndum-Nielsen (1987) proposed a method to minimize reinforcement costs across various RC structures, including shells, folded plates, walls, and slabs. The approach involved minimizing the sum of forces within the steel reinforcement in two perpendicular directions. While the study

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provided an academic example, it did not incorporate code provisions into the optimization process [20].

While the methodologies developed by Traum and Brøndum-Nielsen were groundbreaking for their time, they inherently possess limitations due to their simplified frameworks. In 2005, Ahmadkhanlou and Adeli introduced a neural dynamics model aligned with the American Concrete Institute (ACI) code, marking a significant advancement toward practical design optimization [21]. Their research focused on the optimal cost design of reinforced concrete (RC) slabs in accordance with ACI 1999 code provisions. They formulated the optimization problem as a mixed integer-discrete variable model, incorporating three primary design variables: slab thickness, steel bar diameter, and bar spacing.

Building upon this foundation, Ahmadi-Nedushan and Varaee (2011) investigated the cost optimization of one-way concrete slabs using PSO, adhering to ACI 318-M08 code requirements. Recognizing that PSO is typically suited for unconstrained problems, they adapted the algorithm with a multi-stage dynamic penalty function to effectively manage constraints. Their study presented cost optimization results for four slabs under varying support conditions, comparing these outcomes to existing methods. The authors concluded that PSO demonstrates significant promise as a method for optimizing structural elements [14]. In 2017, Ghandi et al. employed the cuckoo optimization algorithm for the cost optimization of both one-way and two-way RC slabs, in compliance with ACI 318-99 standards [22]. The objective function aimed to minimize the total cost of the slabs, encompassing both concrete and reinforcing steel expenses. This study contributed to the existing literature by evaluating the cuckoo optimization algorithm within the context of structural optimization, seeking to enhance cost efficiency in concrete slab design. The discussion included comparisons with previous optimization algorithms, such as PSO, highlighting the relative strengths and potential applications of the cuckoo method.

Sedaghat Shayegan (2022) introduced a cost-minimization approach for designing reinforced concrete (RC) slabs by leveraging a hybrid metaheuristic algorithm [23]. This methodology employs the Mouthbrooding Fish Algorithm (MFA) as the primary optimization engine, capitalizing on its proficiency in efficiently exploring the design space. To further enhance performance and mitigate the risk of converging to local optima, the algorithm integrates the advantageous properties of the Colliding Bodies Optimization (CBO) method. In this study, continuous variables were utilized to represent the area of reinforcement bars (rebars). However, this approach overlooks a critical practical aspect of construction engineering: rebars are available only in discrete, standardized sizes. As a result, the model’s outputs may not translate effectively to real-world applications, limiting its utility in practical construction projects where material availability and standardized dimensions dictate design and execution.

Although previous studies have advanced the field of structural optimization, they have predominantly relied on outdated building code provisions. The latest edition of the American Concrete Institute’s building code (ACI 318-19) introduces updated design requirements for reinforced concrete structures, directly influencing cost-optimization strategies. To date, no research has investigated the optimization of one-way slabs using the provisions of ACI 318-19. This study addresses this gap by employing a GA to develop cost-effective designs that comply with the latest code requirements.

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Building upon earlier research, this article explores how a Eliticist GA-based optimization, aligned with ACI 318-19, can achieve cost-optimized designs for one-way slabs under varying support conditions. The optimization process considers key design variables, including slab thickness, rebar diameter, and spacing, with the objective of minimizing total material costs while adhering to the code's specifications. Additionally, this work examines the impact of the updated constraints in ACI 318-19 on cost-effectiveness by comparing them to earlier versions (ACI 318-99 & 08), thereby highlighting how the latest code revisions influence optimal design costs.

The article is structured as follows: Section 2 provides a comprehensive analysis of the optimization problems, detailing the design variables, objective function, and constraints imposed by ACI 318-19. Section 3 describes the Genetic Algorithm (GA) approach used for optimization. It explains the core GA principles of selection, crossover, and mutation, and how these operators guide the search for optimal solutions. The section also details the implementation in Matlab, emphasizing the handling of discrete variables and constraints using the Augmented Lagrangian Barrier Algorithm. Section 4 presents the optimization problems, focusing on minimizing material costs for four types of one-way reinforced concrete slabs with varying support conditions, subject to ACI 318-19 code constraints. It details the optimization process, including a sensitivity analysis of the genetic algorithm (GA) parameters, compares the GA results with existing literature, analyzes constraint values at optimal design points, and investigates the influence of span length on material costs. Finally, Section 5 concludes the article by summarizing the key findings and their implications.

2. THE DEFINITION OF OPTIMIZATION PROBLEM

An optimization problem is defined by several critical components: design variables, the objective function and constraints. Design variables are the parameters that can be adjusted or controlled within the optimization process. In the context of optimizing one-way slabs, these variables may include slab thickness, steel bar spacing, bar diameter, concrete compressive strength, and steel reinforcement yield strength. Each design variable corresponds to a specific aspect of the slab's geometry or material properties, which can be manipulated to achieve an optimal design. The objective function often referred to as the cost function in minimization problems, is a mathematical expression that quantifies the cost or performance of various design configurations.

In this study, the objective function primarily aims to minimize the total material cost, encompassing expenses related to concrete and steel reinforcement. The objective is to identify the combination of design variables that results in the lowest possible cost while satisfying all necessary requirements. Constraints are the mandatory conditions that a design must satisfy to be deemed feasible. For the optimization of one-way slabs, these constraints are derived from the ACI 318-19 provisions [24]. They encompass requirements for reinforcement placement, applied loads, strength reduction factors, and other structural specifications. Constraints ensure that the optimized design not only achieves cost minimization but also adheres to the safety and performance standards established by engineering codes.

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2.1 Design Variables

The optimization process is centered around three primary design variables: slab thickness (h), reinforcement bar spacing (s), and the diameter of reinforcing steel bars (d). The GA is employed to identify cost-effective design configurations under four distinct slab support conditions: simply supported, one end continuous, both ends continuous, and cantilevered. These varying support conditions introduce different structural behaviors and constraints, necessitating tailored optimization strategies to achieve the most efficient designs.

Fig. 1 illustrates the standard cross-sectional geometry of a one-way slab, highlighting the key design variables involved in this optimization study—slab thickness (h) and reinforcement bar spacing (s). Both slab thickness (h) and reinforcement bar spacing (s) are treated as discrete variables within the optimization framework, meaning they are adjusted in fixed increments that reflect standard construction practices and material availability. Specifically, slab thickness may vary within a predefined range to accommodate different load and span requirements, while bar spacing is selected from standardized intervals to ensure uniform distribution of reinforcement and adherence to structural standards.

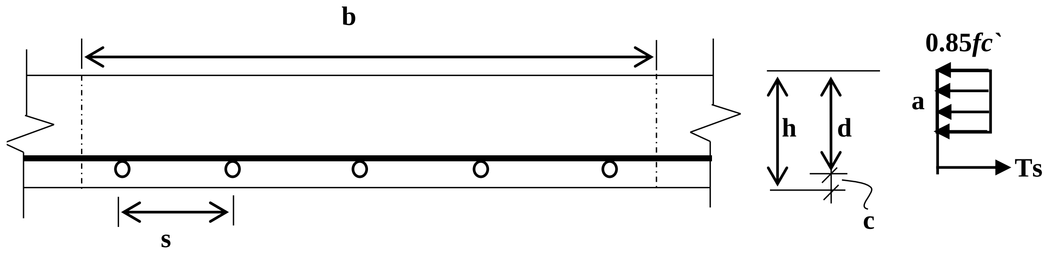

Figure 1: Typical geometry of one-way solid slab cross section

Similarly, the diameter of reinforcing steel bars (d) is considered a discrete variable, with eleven standardized options corresponding to bar sizes ranging from #3 to #18. These diameters span from 0.375 inches to 2.257 inches, providing a range of reinforcement options that balance structural strength with material cost. By constraining these variables to standardized values, the optimization process remains practical and aligned with real-world construction constraints.

2.2 Objective Function

The optimal design of a concrete slab is achieved by minimizing the total costs of materials, summing the expenses related to concrete and steel reinforcements. The objective function is structured to consider both the volume of concrete and the weight of steel reinforcement, with the goal to determine optimal values for the slab thickness (h), the steel bar diameter (db), and the bar spacing (s) that lead to cost minimization.This cost function can be expressed as:

$$\text{Minimize } f(h, d_b, s) = Pc + Ps = VcCc + WsCr \quad (1)$$

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Subject to

$$g_i(h, d_b, s) \leq 0, i = 1, \dots, m \tag{2}$$

where f denotes the cost function in monetary units (e.g., USD), Vc (measured in in³) represents the volume of concrete used, Pc is the cost associated with concrete (in USD), Ps is the cost associated with steel reinforcement (in USD), Cc (measured in USD/in³) is the cost per unit volume of concrete, Ws (measured in pound, lb) is the weight of steel reinforcement, and Cs (measured in USD/lb) represents the cost per unit weight of steel reinforcement. As per previous studies, the cost of formwork and labor are not included [21, 22].

The inequality constraints (gih,b,s≤0,,i=1,…,m) represent various design constraints that must be satisfied to ensure the structural integrity and compliance with design codes. The concrete cost is given by:

$$P_c = L \quad b \quad h \;\; C_c \tag{3}$$

where L, b, and h are the length, width, and thickness of the slab (all in inches), and P_c is the cost associated with concrete (in USD).

The steel cost is determined by:

$$Ps = \gamma s \;\; L \;\; As \;\; Cs \tag{4}$$

Here, γ_s is the unit weight of steel (kg/m³), A_s is the cross-sectional area of the steel bars (in²), and L is the span length (in). The cross-sectional area of the steel reinforcement A_s is computed as:

$$A_s = \frac{\pi {d_b}^2}{4} \frac{b}{s} \tag{5}$$

with d_b is the diameter of the steel bars (in) and s is the spacing between the bars (in).

2.3 Design Constraints

The design constraints $(g_i(h, d_b, s) \leq 0, , i = 1, \dots, m)$ are crucial in optimization problems as they establish the limits that any solution must satisfy to be viable. These constraints define the feasible search space and are categorized into two primary aspects of design evaluation: strength (focusing on flexural and shear capacities) and serviceability (emphasizing reinforcement limitations and deflection norms) in accordance with ACI 318-19 guidelines [24].

2.3.1 Flexural strength constraint

A fundamental constraint is ensuring adequate flexural strength, which is the slab's ability to resist bending moments. The nominal flexural strength, denoted as $\emptyset M_n$, must exceed the ultimate design moment M_u. This requirement can be expressed as the following constraint

$$g_1(x) = \frac{M_u}{\emptyset M_n} - 1 \leq 0 \quad \emptyset = 0.9 \tag{6}$$

The ultimate design moment M_u is determined using:

$$M_u = k.w.L_n^2 \tag{7}$$

where L_n represents the clear span length, k is the bending moment coefficient, and w denotes the factored distributed load. The bending moment coefficient is determined based on the type of slab support conditions. Bending moment coefficients, dependent on the type of slab support conditions, are enumerated in Table 1.

Table 1: Bending moment coefficients for different one-way slabs

Simply Supported	One end continuous	Both ends continuous	Cantilever
1/8	1/10	1/11	1/2

The factored uniform distributed load w is calculated as:

$$w = 1.2\ (DL\ \ b + DL_s) + 1.6\ \ LL\ \ b \tag{8}$$

Here, DL signifies the dead load excluding the self-weight of the slab, LL is the live load. DLs the slab's self-weight, calculated by:

$$DL_s = (h\ \ b - A_s)\ \ w_c + A_s\ \ w_s \tag{9}$$

In this equation, w_c is the weight of concrete per unit volume. The nominal flexural moment, $\emptyset M_n$ is described as follows:

$$M_n = A_s f_y \left(d - \frac{a}{2}\right) \tag{10}$$

The yield strength of the reinforcing steel bars is symbolized by f_y , and a, is depth of equivalent rectangular stress block, can be determined using as:

$$a = \frac{A_s f_y}{0.85 f_c'.b} \tag{11}$$

where f_c' defines the specified compressive strength of concrete.

2.3.2 Shear constraint

As detailed in Eq. 12, the constraint for shear strength requires that the ultimate factored shear force, V_u, should not exceed the nominal one-way shear strength, $\emptyset V_n$:

$$g_2(x) = \frac{V_u}{\emptyset V_n} - 1 \leq 0 \qquad \emptyset = 0.75 \tag{12}$$

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V_u , the ultimate factored shear force is calculated as:

$$V_u = k_v \frac{wL_n}{2} \tag{13}$$

where k_v is the shear force coefficient, which is determined based on slab support. The nominal one-way shear strength V_c is outlined as:

$$V_c = 2\lambda\sqrt{f_c'}bd \tag{14}$$

where λ is a modification factor reflecting the mechanical properties of lightweight concrete relative to normal-weight concrete of the same compressive strength, which is set to 1.0 for this scenario. The shear coefficients for different one-way slabs (Table 2) reveal the variations in shear resistance due to different slab support conditions.

Table 2: Shear coefficient for different one-way slabs

Simply Supported	One end continuous	Both ends continuous	Cantilever
1	1.15	1	2

2.3.3 Serviceability constraints

Serviceability constraints ensure that concrete structures perform their intended function over time while maintaining durability and appearance. A critical aspect of serviceability is controlling cracking and ensuring sufficient ductility, which are directly related to the strain compatibility between the concrete and the reinforcing steel. This relationship, depicted in Fig. 2, illustrates the tensile strain behavior of both materials under load. Understanding and managing this strain compatibility is essential for the long-term durability of the structure. To ensure this, design requirements include limitations on reinforcement tensile strain (ε_t), reinforcement area, and bar spacing. The tension-controlled criterion for the tensile strain of reinforcing bars (Eq. 15) ensures sufficient ductility:

$$\varepsilon_t \geq \varepsilon_{ty} + 0.003 \tag{15}$$

where

$$\varepsilon_{ty} = \frac{f_y}{E} \tag{16}$$

The ACI code provides a framework to calculate serviceability requirements. Equations 17 through 20 (g_3 to g_6) define the serviceability constraints, such as the strain compatibility condition (Eq. 17, g_3), which ensures that the actual strain in the tension steel (ε_t) surpasses the yield strain plus an additional strain component. The minimum area of reinforcement (Eq. 18, g_4), as well as the minimum (Eq. 19, g_5) and maximum (Eq. 20, g_6) spacing of the bars, are specified to control cracking and and maintain the structural integrity of the one-way slab.

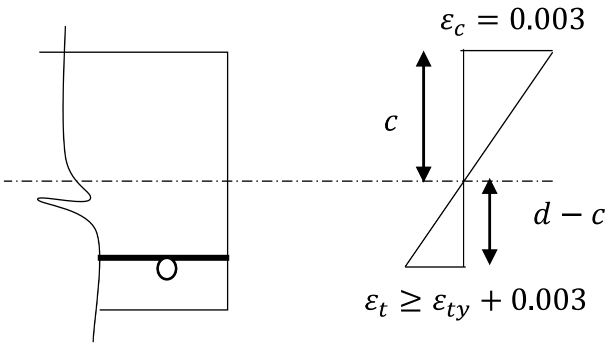

Figure 2: Tensile strain of concrete and reinforcing steel bars

$$g_3(x) = \frac{\varepsilon_{ty} + 0.003}{\varepsilon_t} - 1 \leq 0 \tag{17}$$

$$g_4(x) = 1 - \frac{A_s}{A_{smin}} \leq 0 \tag{18}$$

$$g_5(x) = \frac{s_{min}}{s} - 1 \leq 0 \tag{19}$$

$$g_6(x) = \frac{s}{s_{max}} - 1 \leq 0 \tag{20}$$

β_1 can be calculated as:

$$\beta_1 = \begin{cases} 0.85 & for\ f_c' \leq 4000\, psi \\ 0.85 - 0.05\left(\dfrac{f_c' - 4000}{1000}\right) \geq 0.65 & for\ f_c' > 4000\, psi \end{cases} \tag{21}$$

The minimum quantity of flexural reinforcement required for a safe, and serviceable design is specified through:

$$A_{s\,min} = 0.0018\, bh \tag{22}$$

The minimum and maximum values of bar spacing are defined as follows:

$$s_{min} = \max\left(1'', d_b, \frac{4}{3} d_{agg}\right) \tag{23}$$

$$s_{max} = \min(18'', 3h) \tag{24}$$

2.3.4 Deflection constraints

Deflection constraints ensure that slabs maintain structural integrity by controlling immediate and long-term deformations under service loads. The relationship between slab thickness and deflection control is emphasized by minimum thickness requirements in Table

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3, adjusted by support conditions and concrete type as per Equation (25). For one-way slab designs, deflection criteria require that slab thickness h meets or exceeds the minimum thickness $h_{\min}$:

$$g_7(x) = \frac{h_{min}}{h} - 1 \leq 0 \tag{25}$$

Here, $h_{\min}$ values correlate with the support conditions of the one-way slabs as specified in Table 3. Adjustment factors for slab thickness in Eq. 25 are defined as follows:

$$\left.\begin{aligned} \alpha_1 &= 0.4 + \frac{f_y}{100{,}000}\ .\ \text{for normal weight concrete} \\ \alpha_2 &= \max(1.65 - 0.005\, w_c.\, 1.09)\ ,\ \text{for lightweight concrete} \end{aligned}\right\} \tag{26}$$

Table 3: Minimum Thickness Values for One-Way Solid Slabs

Simply Supported	One end continuous	Both ends continuous	Cantilever
L/20	L/24	L/28	L/10

For normal weight concrete, α_1 adjusts the minimum thickness based on the yield strength (f_y) of the reinforcing steel. The α_2 factor for lightweight concrete accounts for the unit weight (w_c), of concrete, addressing variations in stiffness and mass inherent to different concrete materials. This adjustment is critical for deflection control, ensuring that lightweight concrete slabs meet serviceability requirements while maintaining safety and functionality.

The ACI 318-19 code introduced several key changes compared to previous editions, particularly ACI 318-99, impacting how reinforced concrete structures are designed. These modifications reflect advancements in understanding concrete behavior and aim to improve structural performance. The constraints specified by ACI 318-19 differ from those in ACI 318-99 in several key aspects:

1. Shear Strength Reduction Factor (φ): Reduced from 0.85 to 0.75.
2. Maximum Reinforcement: Now determined by the maximum strain in the tension reinforcement instead of the reinforcement ratio.
3. Minimum Area of Reinforcement: Unified for all concrete classes, regardless of compressive strength.
4. Ultimate Strain Limit: Changed from a fixed value of 0.004 to a function of yield strength and modulus of elasticity of steel.
5. Shear Strength Reduction Factor (λ): The reduction factor for shear strength (λ) has also been updated in the ACI 318-19 code.

These updates enhance the safety, durability, and serviceability of concrete structures, ensuring that design criteria align with modern construction practices and materials.

3. GENETIC ALGORITHM APPROACH FOR OPTIMIZATION

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GA is a population-based stochastic optimization method inspired by Darwinian evolutionary principles. It utilizes operators such as selection, crossover, and mutation to emulate natural selection and maintain genetic diversity within the population [25].

The GA process begins with an initial population of potential solutions, which evolves over successive generations. During each generation, the natural selection operator selects parent solutions based on their fitness, ensuring that higher-quality individuals have a greater probability of passing their genes to the next generation. The crossover operator then combines pairs of parents to produce offspring, promoting the exploration of new regions in the solution space by mixing genetic information. To preserve genetic diversity and prevent premature convergence, the mutation operator introduces random alterations to the offspring's genes.

After these genetic operations, the new population is evaluated against a predefined stopping criterion, such as reaching a maximum number of generations or achieving a satisfactory fitness level. This iterative process continues until an optimal or near-optimal solution is identified. As one of the pioneering population-based stochastic algorithms, GA effectively navigates complex discrete optimization problems by balancing exploration and exploitation within the search space [26]. Despite being a traditional algorithm, GAs remain effectively utilized in numerous structural engineering applications, as evidenced by recent research [27-32].

In this study, the implementation of the GA was conducted using Matlab's Global Optimization Toolbox [33]. To accurately represent the optimization problem, GA treats the discrete variables as integer variables. A mapping function then associates these integer representations with the actual discrete variables. Constraint handling is facilitated via the Augmented Lagrangian Barrier Algorithm, which incorporates both augmented terms and barrier functions into the objective function, penalizing constraint violations and integrating the constraints into GA's evolutionary process. Solutions that fail to meet constraints are penalized, lowering their fitness scores and reducing their likelihood of selection for subsequent generations [34].

The unique characteristic of the GA for integer programming lies in its adaptation of the standard evolutionary operators, which include creation, crossover (recombination), and mutation, to preserve the integer nature of variables. This adoptation ensures that the generated solutions remain feasible in the context of discrete optimization problems. During the creation phase, the algorithm is specifically designed to produce integer values rather than random real numbers. In the crossover process, offspring derived from parent solutions are constrained to maintain integer values. Similarly, mutation involves altering a variable by a discrete amount instead of a continuous shift. These modifications uphold the integrity of integer variables across generations, allowing the GA to effectively explore the discrete solution space. The integer-specific evolutionary functions are intentionally crafted to respect the discrete characteristics of the problem, thereby facilitating the discovery of solutions that are pertinent to real-world discrete optimization challenges [34].

4. OPTIMIZATION PROBLEMS

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In this study, we focus on minimizing the overall material costs for four distinct types of one-way reinforced concrete slabs, each exhibiting different support conditions. The optimization process adheres to specific constraints as mandated by the ACI 318-19 provisions. The variables under consideration include slab thickness (h), steel bar spacing (s), and bar diameter (d_b). Specifically, slab thickness ranges from 5 to 20 inches in 0.25-inch increments, steel bar spacing varies from 1 to 20 inches in 0.25-inch increments, and bar diameter is selected from a predefined set of values measured in square inches.

Common parameters for four optimization problems are listed below:

- Slab length (L): 156 inches
- Column width: 12 inches
- Dead load: 0.0694 lb/in^2
- Live load: 0.278 lb/in^2
- Concrete unit weight: 0.283 lb/in^3
- Steel unit weight: 0.0868 lb/in^3
- Modulus of elasticity: 29,000,000 psi
- The cost per unit volume of concrete (C_c): 0.0016 \$/in^3
- The cost per unit weight of steel reinforcement (C_s): 0.6486 \$/lb

The primary objective of this study is to assess the efficiency and robustness of the genetic algorithm (GA) when applied to one-way solid slabs under varying support conditions. The GA is employed to identify the most cost-effective design that complies with the ACI 318-19 code, taking into account the different support conditions across the cases. The optimization outcomes are subsequently compared to findings in existing literature [14, 21, 22], which underscores the GA’s efficacy in designing reinforced concrete structures. This is particularly relevant given that the optimal designs referenced in the literature were derived using previous editions of ACI provisions, highlighting the impact of evolving code provisions on optimal cost solutions.

4.1 Configuration and Sensitivity Analysis of GA Parameters

The optimization problems were addressed using the GA, with parameters meticulously determined through a sensitivity analysis performed on case 1 (a simply supported solid slab). This analysis aimed to pinpoint the most effective GA settings for achieving optimal performance. The maximum number of function evaluations (NFEs) was capped at 4000 for all optimization problems to limit computational expense. The algorithm terminates upon reaching this limit.A population size of 60 individuals was maintained to promote a diverse pool of potential solutions. MATLAB scripts were developed to systematically explore and identify the optimal crossover fraction and elite percentage. The crossover fraction was varied from 0.05 to 0.95 in increments of 0.1, and the elite percentage from 0 to 0.6 in increments of 0.05, resulting in a total of 117 distinct optimization runs.

Each parameter combination was rigorously tested over 50 independent runs. The success rate for each configuration, defined as the percentage of runs achieving a target value of 24.91, is visualized in both a surface plot (Fig. 3) and a heatmap (Fig. 4). The analysis clearly shows that including elitism in the genetic algorithm is essential. Without elitism (an elite percentage of 0), success rates drop sharply, often close to zero, regardless of the crossover fraction used.

This underscores the essential role of preserving top-performing individuals from each generation to guide the search process effectively. Conversely, increasing the elite percentage demonstrably improves the success rate, highlighting the benefit of leveraging the genetic information contained within these high-performing individuals. For instance, at a crossover fraction of 0.2, increasing the elite percentage from 0 to just 0.05 boosts the success rate from a meager 10% to a substantial 84% (See Fig. 4).

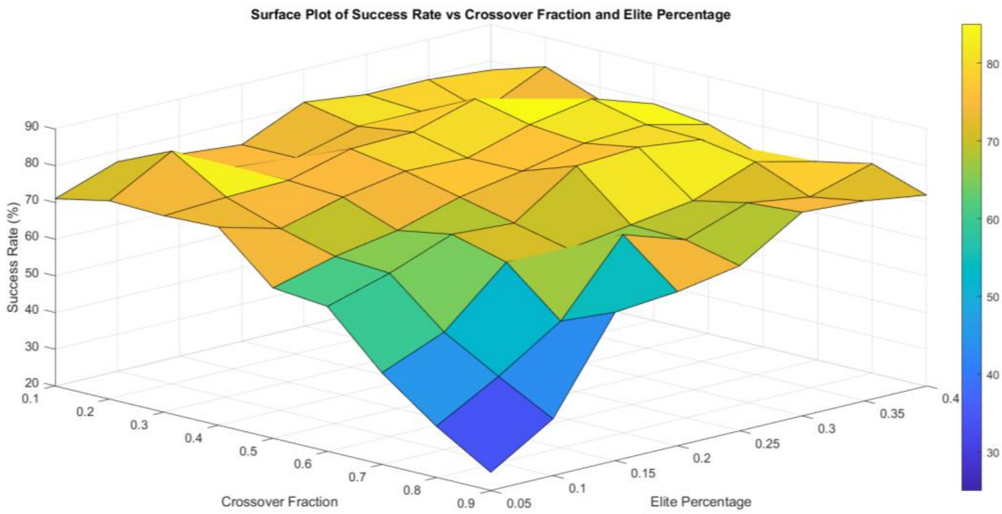

Figure 3: Surface plot of success rate versus Cross over fraction and Elite percentages

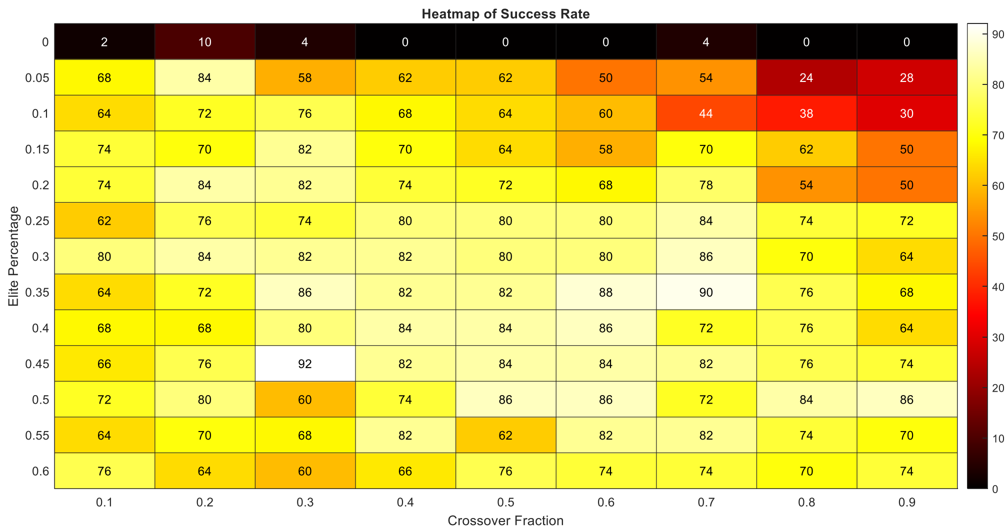

Figure 4: Heatmap of success rate versus Cross over fraction and Elite percentages

Analysis identified an optimal configuration (crossover fraction: 0.3, elite percentage: 0.45) achieving a 92% success rate (Fig. 4). For the simply supported one-way slab (Case 1), 46 of 50 runs reached the optimal cost function (24.91), representing a 92% success rate (Fig. 5). With a population size of 60, this configuration retains 27 elite individuals. The maximum iteration count was set to 120 to ensure that the primary termination criterion was the NFE limit rather than a premature iteration cutoff. This approach provides ample opportunity for convergence while mitigating excessive runtimes. The convergence histories of all 50 runs for Case 1, corresponding to a simply supported one-way slab, are depicted in Fig. 6.

For optimization of all problems in this article, a constraint tolerance of 1e-05 was implemented to ensure that the solutions strictly adhere to the defined constraints. The crossover fraction is set at 0.3, meaning that 30% of the population undergoes crossover operations, thereby promoting genetic diversity and enhancing the exploration of the solution space. Additionally, to ensure the reliability of the results, the GA was independently executed 50 times for each optimization problem, with the best outcomes from these runs being reported.

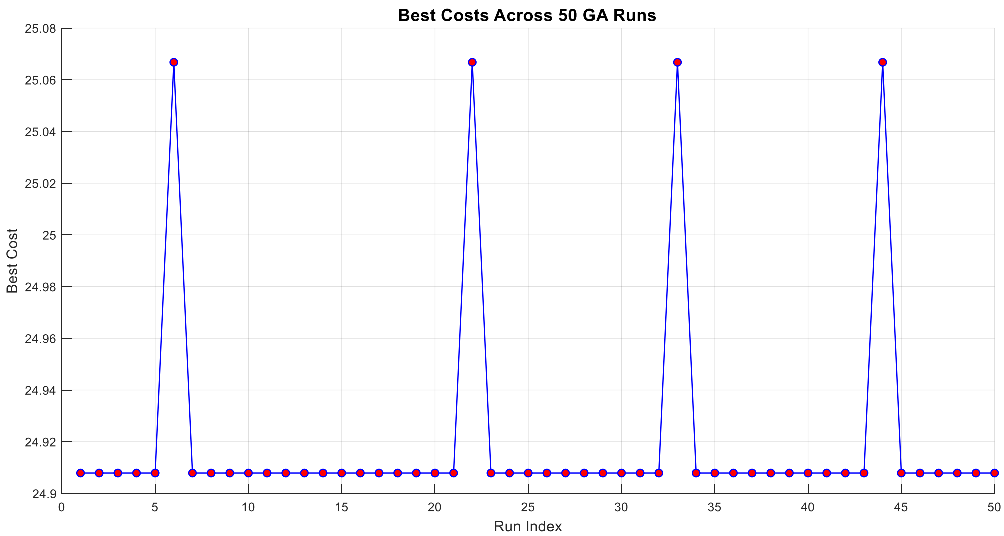

Figure 5: Best costs across 50 runs for case 1 (simply supported one-way slab)

4.2 Comparative Analysis of GA-Optimized Slab Designs Under Various Support Conditions

Table 5 presents a comparative analysis of optimal designs generated by the GA and those documented in existing literature using previous editions of ACI provisions. The selected design problems have been previously explored by several researchers. Ahmadkhanlou and Adeli employed a neural dynamics model [21], while Ahmadi-Nedushan and Varaee utilized Particle Swarm Optimization (PSO) [14] . Ghandi et al. implemented a Cuckoo Search algorithm [22]. Although Sedghadat Shyegan [23] also investigated the optimization of reinforced concrete slabs, their methodology employed a hybrid mouthbrooding fish algorithm with continuous variables representing rebar areas.

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This approach deviates from practical construction engineering constraints, where rebar sizes are inherently discrete and standardized. Consequently, incorporating their results into the comparative analysis would introduce inconsistencies and reduce the relevance of the comparison. Therefore, their findings are excluded to maintain the integrity and applicability of the comparative evaluation

The results presented in Table 4 demonstrate a clear trend of cost reduction in reinforced concrete slab design when using a Genetic Algorithm (GA) optimization approach, particularly when combined with the latest ACI 318-19 code provisions. Comparing the costs across the different ACI code years and the GA-optimized results reveals the magnitude of this improvement.

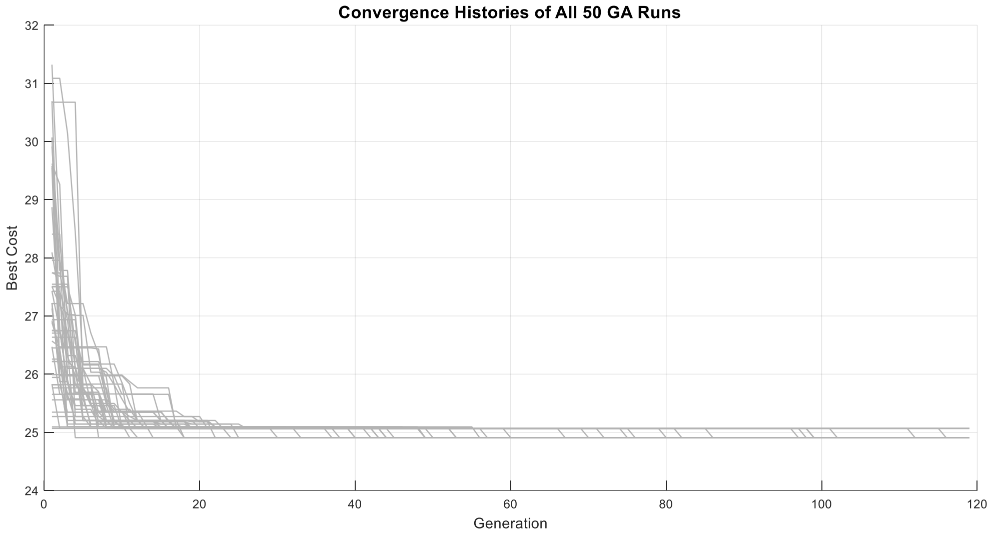

Figure 6: Convergence histories of all 50 runs for case 1 (simply supported one-way slab)

In Case 1, while previous studies using older ACI codes yielded costs clustered around 26.45, the GA-driven design using ACI 318-19 achieved a cost of \$24.908, a reduction of approximately 6-7%. In Case 2, while previous studies using older ACI codes yielded costs of 22.76, 22.78 and 22.98, the GA-driven design using ACI 318-19 achieved a cost of \$24.908, a reduction of approximately 8-9%. In Case 3 the GA-driven design results in a cost of \$20.316, which is marginally lower than the costs associated with ACI-2008 provisions (\$20.64).

The most notable difference is observed in Case 4. Previous studies utilizing older ACI codes reported costs between 59.31and 60.22. The GA approach with ACI 318-19 achieves a significantly lower cost of \$55.015, representing a reduction of roughly 7-9%. This noteworthy cost saving demonstrates the power of the GA to exploit the updated code provisions and identify a significantly more efficient design. Specifically, while the slab thickness (h) and bar diameter (d_b) are similar across the studies, the GA identified a markedly different reinforcing bar spacing (s = 12.0 in) compared to previous studies (s = 2 in, 9.5 in, and 12.5 in.

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These findings collectively emphasize the synergistic benefits of using GAs in conjunction with updated building codes. The GA's ability to explore a wider design space and exploit the nuances of the latest code provisions leads to significant cost savings and more efficient structural designs.

4.3 Analysis of Constraint Values at Optimum Design Points

Table 5 presents the values of various constraints at the optimum design points for each case. The value of constraint g_1, representing flexural strength, consistently approaches zero across all cases. This indicates that g_1 is an active constraint for all designs, signifying that the bending moment capacity is the primary governing factor. Specifically, in cases 1, 2, and 4, exhibits values of -0.006, -0.001, and -0.006, respectively.

Table 4: Results of GA for Slabs with different support conditions

Design Case	Design variables	ACI 318 – 99 [21]	ACI 318 – 08 [14]	ACI 318 - 99 [22]	ACI 318 – 19 This article
(1)	h (in)	6.75	6.25	6.25	6.25
	s (in)	6.5	9	14.5	6.5
	d_b (in)	0.375	0.5	0.625	0.375
	Cost ($)	26.45	26.57	26.36	24.908
(2)	h (in)	5.57	5.25	5.25	5.25
	s (in)	7	5.5	10	7.25
	d_b (in)	0.375	0.375	0.5	0.375
	Cost ($)	22.98	22.76	22.78	21.253
(3)	h (in)	4.75	4.5	4.5	5.0
	s (in)	7	5.5	10	7.5
	d_b (in)	0.375	0.375	0.5	0.375
	Cost ($)	19.93	20.64	20.5	20.316
(4)	h (in)	13.5	12.5	12.5	12.5
	s (in)	2	12.5	9.5	12.0
	d_b (in)	0.375	0.625	0.875	0.875
	Cost ($)	60.22	59.31	59.96	55.015

Table 5: The values of the constraints at optimum points for slabs with different support conditions

Design case	The values of the constraints						
	g_1	g_2	g_3	g_4	g_5	g_6	g_7
1	-0.006	-0.664	-0.908	-0.510	-0.846	-0.639	-0.002
2	-0.001	-0.581	-0.898	-0.612	-0.862	-0.540	-0.010
3	-0.026	-0.626	-0.895	-0.636	-0.867	-0.500	-0.109
4	-0.006	-0.563	-0.876	-1.182	-0.556	-0.875	-0.002

In contrast, case 3 records a g_1 value of -0.026, which, while still indicating compliance, is less proximate to zero compared to the other cases. This deviation arises from the

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utilization of discrete design variables, which restricts the optimization process to predefined values, thereby limiting the ability to achieve a g_1 value closer to zero without compromising structural integrity. The constraint g_7 ,pertaining to deflection, is marginally close to zero in cases 1, 2, and 4, with values of -0.002, -0.010, and -0.002, respectively. This proximity indicates that g_7 is also an active constraint in these cases, suggesting that deflection limitations play a significant role alongside flexural strength in influencing the design. However, in case 3, g_7 is considerably further from zero (-0.109), implying that deflection constraints are less restrictive in this scenario compared to the others. This discrepancy can be attributed to the discrete nature of the design variables employed, which constrains the optimization process and affects the interplay between various structural constraints. The remaining constraints (g_2 to g_6) consistently exhibit negative values across all cases, indicating compliance with the respective limitations. These constraints encompass various aspects of structural performance, such as shear strength, serviceability. The uniform compliance across these constraints underscores the robustness of the optimization approach in adhering to multifaceted structural requirements

4.4 Sensitivity Analysis: Influence of Span Length on Optimal Material Costs

To understand the impact of span length and support conditions on the optimal material costs of reinforced concrete slabs, a sensitivity analysis was performed. Sixteen span lengths ranging from 5 to 20 feet in one-foot increments were analyzed, along with four support conditions: Case 1: Simply Supported; Case 2: One End Fixed, One End Simply Supported; Case 3: Both Ends Fixed; and Case 4: Cantilever. This resulted in 64 optimization problems being solved using GA.

Fig. 7 illustrates the relationship between span length and optimal total material cost for each support condition. For shorter spans (less than 10 feet), optimal costs remain relatively stable. As span length increases beyond 10 feet, costs rise significantly, with the rate of increase varying depending on the support condition. Slabs with both ends fixed (Case 3) consistently demonstrated the lowest optimal material costs, approximately 92% lower than the cantilever case (Case 4) for a 15-foot span. Conversely, cantilever slabs exhibited the highest costs due to the increased bending moments they must resist. These results underscore the importance of optimizing support conditions early in the design phase, particularly for longer spans, to achieve cost-effective reinforced concrete slab designs

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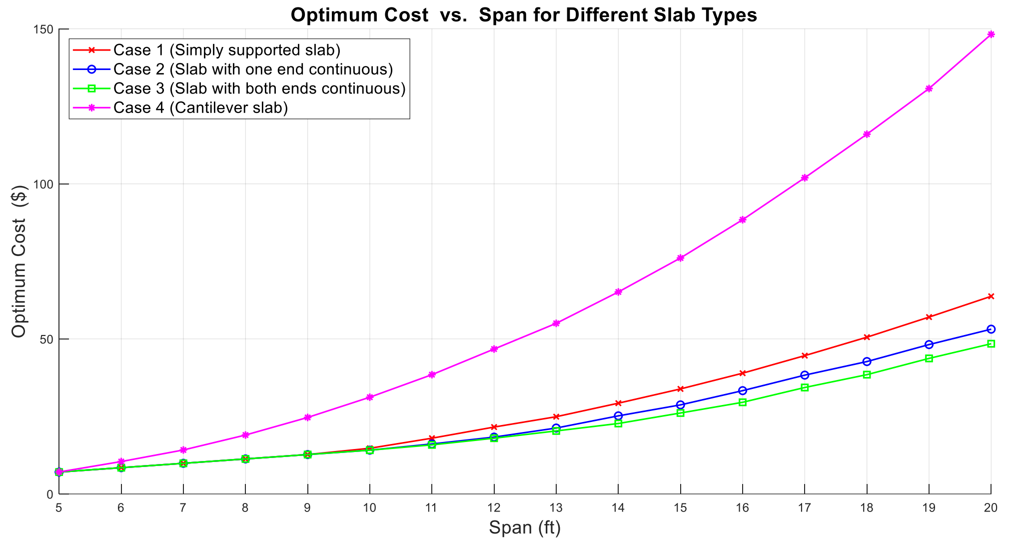

Figure 7: Influence of Span Length and Support Conditions on Optimal Material Costs for One-Way Reinforced Concrete Slabs

5. CONCLUSIONS

This study demonstrates the effectiveness of an elitist GA for optimizing the material cost of one-way reinforced concrete slabs. By adjusting key design variables: slab thickness, rebar diameter, and rebar spacing, the GA minimized costs for four support conditions: simply supported, one-end continuous, both-ends continuous, and cantilevered. Compared to designs based on ACI 318-99 and ACI 318-08, the GA achieved material cost reductions of between 5.8% to 8.6% for the different types of supports, all while adhering to the latest ACI 318-19 code requirements.

The GA's robustness is highlighted by its consistent compliance with flexural strength and deflection limits across all slab types. The optimized designs maintained structural integrity while achieving superior cost-effectiveness compared to previous standards. This integration of GA with ACI 318-19 ensures both material savings and adherence to stringent safety and performance criteria.

Careful tuning of the GA parameters, specifically the crossover fraction and elite percentage, was crucial for optimization success. An analysis of 117 experimental runs demonstrated the significant influence of these parameters on algorithm performance. Without elitism (elite percentage = 0), increasing the crossover fraction worsened performance, indicating difficulty in retaining good solutions, with success rates often dropping to 0%. Introducing elitism dramatically improved optimization by preserving top-performing individuals from each generation, stabilizing the search and increasing the likelihood of finding optimal or near-optimal solutions. A crossover fraction of 0.3 combined with an elite percentage of 0.45 yielded the highest observed success rate of 92%.

A comprehensive sensitivity analysis investigated the impact of slab length (from 5 to 20 feet in one-foot increments) across all support conditions, resulting in 64 unique

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optimization scenarios. The resulting cost versus slab length diagrams reveal a clear trend of increasing material cost with increasing slab length. Continuously supported slabs benefited from improved load distribution, leading to lower material costs as slab length increased. Conversely, cantilevered slabs exhibited higher material costs due to the increased reinforcement needed to manage larger bending moments over longer spans.

Material costs stay relatively constant for slabs shorter than about 10 feet. Beyond this length, costs increase significantly, with the rate of increase depending on support conditions. Continuously supported slabs are consistently the most economical due to efficient load distribution and reduced bending moments, requiring less reinforcement. For instance, a 15-foot continuously supported slab is about 92% cheaper than a cantilever slab of the same length. Cantilever slabs, experiencing the highest bending moments, are the most expensive option across all span lengths.

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