Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

ENHANCING STRUCTURAL EFFICIENCY: A COMPARATIVE STUDY OF EVOLUTIONARY OPTIMIZATION IN SHALLOW FOUNDATION DESIGN

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ABSTRACT: The optimization of foundation design represents a pivotal domain within structural engineering, addressing the dual imperatives of cost efficiency and structural performance. The focus of this study is on the optimization of shallow foundations, which are tasked with transferring complex loads while adhering to material and design constraints outlined by building codes. Traditional foundation design methods often depend on iterative manual calculations or initial assumptions, resulting in suboptimal solutions and increased design time. This research introduces a robust computational framework to optimize the design of combined footings by leveraging state-of-the-art optimization algorithms. Four algorithms—Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and the Nelder Mead method—are employed to explore the non-linear and multi-dimensional design space. The design variables considered include column loads, geometric parameters, material properties, and spatial constraints, while the optimization objectives aim to minimize the overall construction cost and ensure compliance with code requirements. The developed framework demonstrates substantial improvements in design efficiency and accuracy, offering a scalable solution adaptable to varying project complexities. Computational experiments reveal that, with the exception of the Nelder Mead algorithm—which tends to stagnate in local optima—all methods converged to a consistent optimal solution, with the GA exhibiting the fastest convergence speed.

1. INTRODUCTION

Optimal design in structural engineering is critical not only for ensuring safety and cost efficiency but also for minimizing the environmental impact of construction. With concrete and steel being major contributors to carbon emissions, designing foundations that use materials more efficiently is essential (Chamasemani et al., 2024). By reducing material usage and enhancing performance, optimal designs support sustainable development goals and help mitigate the environmental footprint of construction practices (Afshari et al., 2019). The design and optimization of shallow foundations constitute a cornerstone of modern structural engineering, where the dual imperatives of safety and cost efficiency drive continuous innovation (Pucker & Grabe, 2011). Traditionally, the design process for foundations has relied on iterative manual calculations, empirical correlations, and heuristic rules. Such conventional methods, while effective for simpler scenarios, often fall short when confronted with the inherent non-linearities and multi-dimensional complexities of contemporary engineering challenges. The diverse range of loading conditions, variable soil properties, and evolving building codes necessitates a more rigorous approach to ensure optimal performance while mitigating risks associated with overdesign or structural inadequacy. In this context, computational optimization emerges as a powerful tool, enabling a systematic exploration of the design space and facilitating the discovery of solutions that balance performance, safety, and economy (Afzal et al., 2020).

Recent advancements in computational intelligence have significantly expanded the toolkit available for tackling complex optimization problems in engineering. Evolutionary algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), have gained prominence due to their robust search capabilities in high-dimensional, non-linear spaces (Kayabekir et al., 2021). These algorithms employ mechanisms inspired by natural processes, selection, mutation, and social behavior, to navigate vast solution landscapes efficiently (Kashani et al., 2022). In contrast, traditional methods like the Nelder Mead technique, although useful for problems with fewer dimensions or smooth objective functions, often struggle with convergence in multi-modal settings, leading to entrapment in local optima. This divergence in performance underscores the necessity for a comparative evaluation that considers both convergence speed and solution quality, especially when applied to the problem of foundation design.

The literature on the structural optimization of reinforced concrete reveals a progressive shift from conventional gradient-based mathematical optimization methods towards advanced metaheuristic techniques (Mei & Wang, 2021). With the advent of computational intelligence, researchers have increasingly employed methods such as Genetic Algorithms, Particle Swarm Optimization, and Differential Evolution to navigate the complex design space of reinforced concrete structures (Lagaros et al., 2022). Tunca et al. (2024) used the Coati Optimization Algorithm, Fox Optimizer, and Pelican Optimization Algorithm (POA) for optimizing the design cost of reinforced concrete columns under Turkish Building Earthquake Code 2018 constraints, finding that the POA delivered the best performance. Chutani et al. (2017) used Particle Swarm Optimization (PSO) for the optimal design of reinforced concrete beams, minimizing the combined cost of concrete and rebars while satisfying Indian code requirements, and demonstrated its effectiveness through multiple examples. Izhar et al. (2024) used self-stopping Pareto domination-based multi-objective simulated annealing (PDMOSA) for optimizing reinforced concrete beams, minimizing weight, cost, and environmental impact by incorporating realistic loading, constructability parameters, and Indian code constraints, demonstrating that although market-based constraints resulted in increases of 1.33%, 13.33%, and 17.67% in weight, cost, and embodied carbon relative to global minima, they still achieved average savings of 23.67%, 15%, and 19% compared to traditional designs. Abdel Nour et al. (2021) used a Genetic Algorithm-based procedure for optimizing the total cost of a T-shaped prestressed concrete section, by simultaneously adjusting cross-sectional dimensions, steel reinforcement, and prestressing tendon configuration under Eurocode 2 geometrical and limit state constraints, demonstrating the effectiveness of integrating service and ultimate limit state verifications in a coherent design framework. These studies have demonstrated that metaheuristic algorithms can effectively minimize material usage and construction costs while satisfying strict safety and serviceability requirements.

Recent studies in foundation design optimization have employed advanced computational techniques to effectively manage the complexities of soil-structure interactions, material variability, and geometric constraints, thereby yielding cost-effective, sustainable, and resilient design solutions. Khajehzadeh et al. (2014) used a modified global-local gravitational search algorithm (GLGSA) with chaotic dynamics to optimize spread foundations, minimizing cost and CO_2 emissions under geotechnical and structural constraints, and demonstrated improvements in accuracy and efficiency over the original method. Nigdeli et al. (2018) used Harmony Search, Teaching-Learning Based Optimization, and Flower Pollination Algorithm for the cost optimization of RC footings, optimizing dimensions, column orientation, and reinforcement design under both structural and geotechnical constraints, and found these metaheuristic approaches to be highly competitive for optimal design. Arabali et al. (2022) used an adaptive tunicate swarm optimization (ATSA) algorithm, integrating a dual-phase search strategy, to optimize shallow spread foundations by minimizing both cost and CO_2 emissions under geotechnical and structural constraints, and demonstrated that ATSA outperforms conventional TSA and other algorithms based on benchmark tests and sensitivity analyses. Solorzano et al. (2020) used a genetic algorithm with dominance-based tournament selection to optimize ACI 318-19 compliant reinforced concrete isolated footings by encoding decision variables to minimize total cost and enforce demand–capacity constraints, achieving significant reductions in material cost and design time compared to traditional trial-and-error methods. Overall, these studies underscore the transformative potential of optimization algorithms in foundation design by enhancing cost-effectiveness, reducing environmental impact, and ensuring compliance with complex structural and geotechnical constraints.

In this study, we propose a comprehensive computational framework for the design of reinforced concrete combined footings based on ultimate limit state design principles and in accordance with the Egyptian Code of Practice for Concrete Design (ECP). The framework employs state-of-the-art optimization algorithms to systematically explore a design space defined primarily by two decision variables, the length and depth of the footing, with the objective of minimizing the total cost of concrete and reinforcement steel. A key feature of our approach is the calculation of stresses, including shear forces and bending moments, from first principles, which eliminates the need for computationally expensive finite element analyses and enhances the overall accuracy and efficiency of the design process. To ensure structural safety, depth constraints are imposed to prevent beam shear and punching shear failures, while ultimate limit state design requirements are used to determine the required steel area, rather than being directly incorporated as constraints, thereby reducing the complexity of the optimization problem and promoting faster convergence. A comparative study of various evolutionary algorithms reveals that, although all tested methods converge towards a similar optimal solution, the Genetic Algorithm exhibits the fastest convergence speed, while the Nelder Mead method is more prone to local optima. Overall, the proposed framework demonstrates significant promise for achieving cost-effective and efficient designs of combined footings in reinforced concrete structures.

The remainder of this paper is organized as follows: Section 2 details the design methodology and the optimization algorithms employed in this study, Section 3 presents the optimization results and performance analysis, Section 4 provides a discussion of the findings and their implications, and Section 5 concludes the paper with final remarks and suggestions for future research.

2. METHODOLOGY

2.1 Problem Definition

The design of combined footings is a crucial structural engineering challenge that arises when individual footings either overlap or when columns are placed too close to each other. Traditional design methods, such as those implemented in Excel Solver, have limitations in handling complex design scenarios, making it necessary to develop a more flexible and scalable optimization approach.

The primary goal of this methodology is to optimize the design of combined footings while minimizing costs. The optimization model considers both concrete and reinforcement costs, ensuring that the footing design meets structural constraints while remaining cost-effective.

2.2 Optimization Framework

To address these challenges, a Python-based optimization framework was developed. This model integrates advanced numerical methods to determine the most efficient footing dimensions and reinforcement details. The framework is designed to handle varying load conditions, soil characteristics, and material costs, ensuring adaptability to different engineering projects.

Objective Function

The optimization seeks to minimize the total cost of the combined footing, defined as:

[1] $\mathcal{F}cost$ = C_c V_c + C_r W_r

where:

- C_c – Concrete Cost/ton
- V_c – Volume of concrete
- C_r – Reinforcement Cost/ton
- W_r – Weight of reinforcement

This objective function ensures that both material costs are considered holistically, allowing engineers to find a balance between concrete volume and reinforcement weight to achieve an optimal design.

2.3 Decision Variables and Model Parameters

Figure 1 illustrates the decision variables employed in the optimization model. The primary decision variables include the footing length and the footing thickness. The footing length is determined based on the spacing between columns and the required bearing area, with a minimum value computed as the sum of the column spacing plus half of the widths of the two columns. The maximum footing length is dictated by a minimum footing width of 1.5 meters and the soil bearing capacity. The footing thickness plays a crucial role in structural integrity, with an allowable range between 300 mm and 1500 mm to ensure sufficient strength while optimizing material usage. The model utilizes these parameters as central inputs for calculating other key parameters, such as the required area of steel, effectively reducing the search space and enhancing model efficiency. By narrowing the scope to these foundational parameters, the model can efficiently explore the design space while maintaining robustness and accuracy in its outcomes. User input includes loads on both columns, column dimensions and locations, and material properties such as q_{net}, F_y, and F_{cu}, along with concrete unit cost and reinforcement unit cost. Additional parameters include the spacing between columns (S), the distances between the footing edge and the centers of columns 1 and 2 (X1 and X2), and the distance between column 1 and the footing center of gravity (Xcg). These variables collectively influence both the cost and structural performance of the footing, guiding the optimization process toward an efficient and cost-effective design.

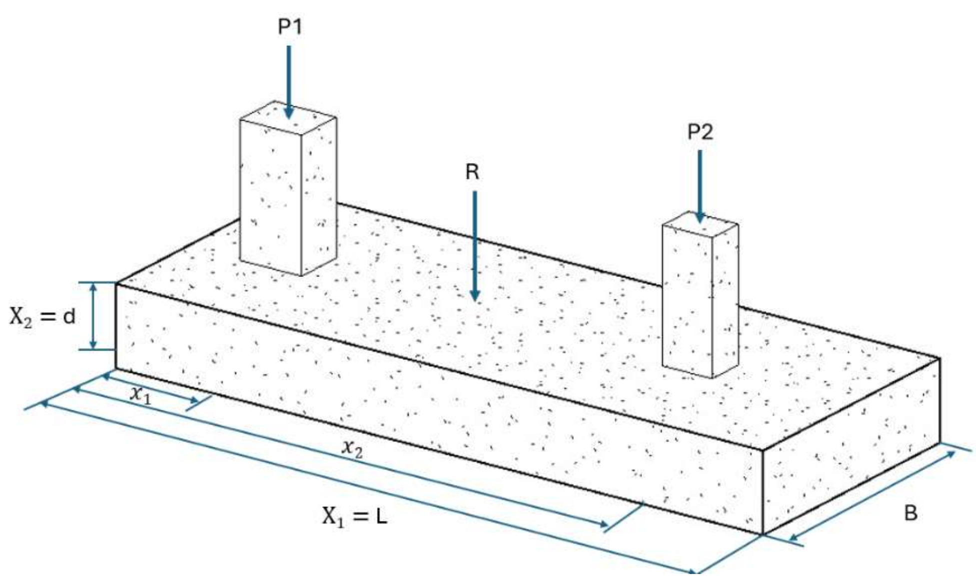

Figure 1- Python Model Decision Variables

2.4 Model Description

The model follows a structured optimization process, as illustrated in Figure 2. It begins by randomly assigning values to the design parameters (L and d). The center of gravity and the resultant force are then computed to ensure their alignment at a single point, establishing a foundation for further calculations. Next, the model determines the shear and moment at critical sections, which are essential for assessing structural integrity. The critical section shear force is used to evaluate the wide beam shear in the longitudinal direction, while the short direction shear is calculated similarly to isolated footing models but considers only the smaller column, as it is always the more critical one.

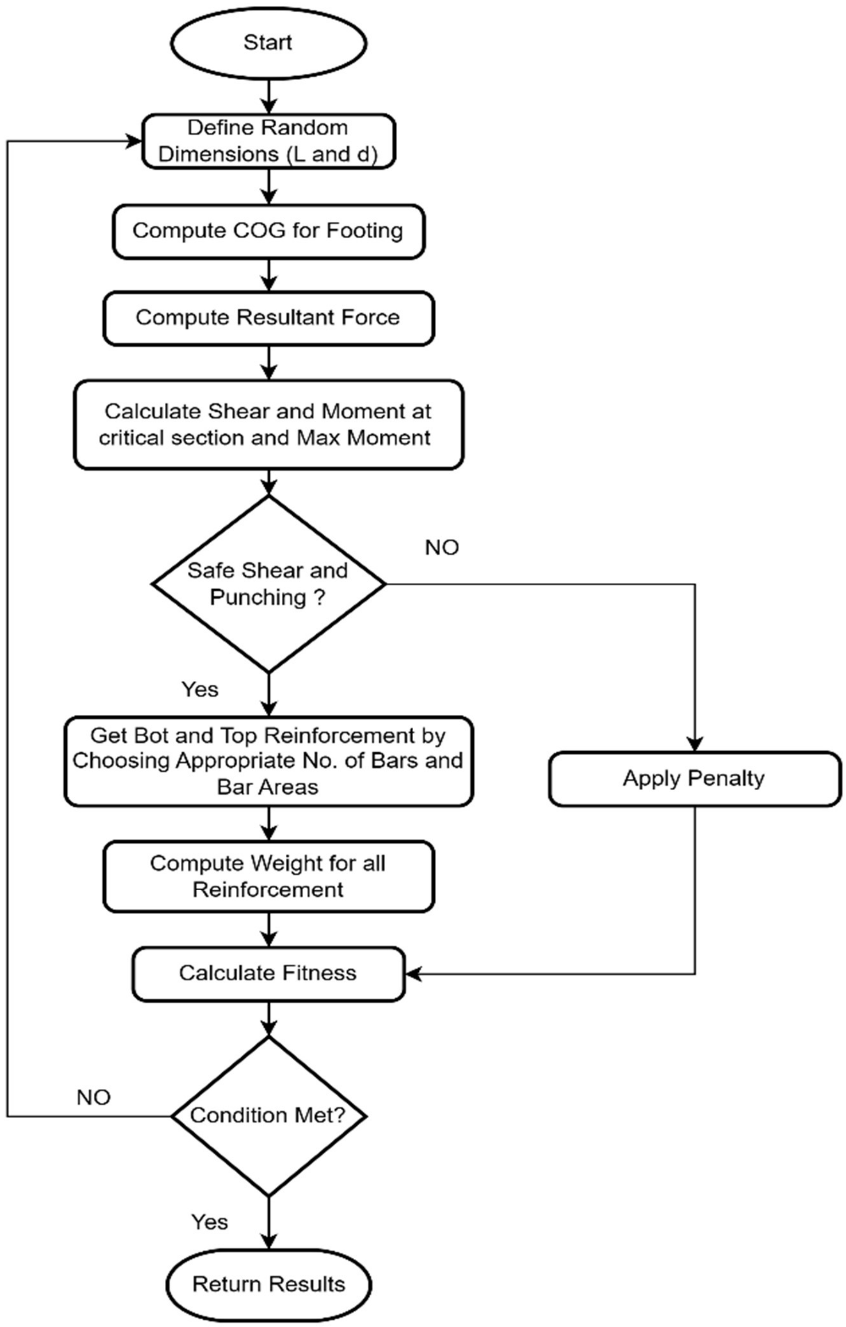

Figure 2- Combined Footing Optimization Chart

Punching shear is calculated for both columns with an additional consideration: an extra allowable shear value, q_{cup2}, which depends on the punching area and the column's location relative to the footing, as shown in Figure 3. This distinction accounts for cases where a column is positioned near the edge of the combined footing, impacting its resistance to punching shear. The punching shear strength is given by:

[2] $q_{cup2} = 0.8 * (\frac{\alpha \cdot d}{b_o} + 0.2) \cdot \sqrt{\frac{f_{cu}}{\gamma_c}}$

where b_o is the punching perimeter, and α is a factor that depends on the column's position relative to the footing.

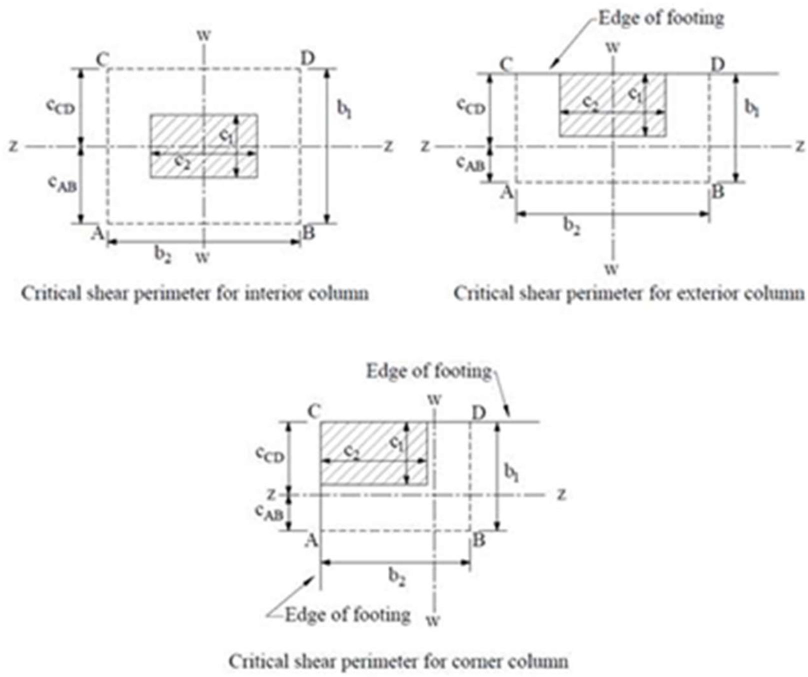

Figure 3- Critical Section for Punching

Once the structural checks are completed, the required reinforcement area is determined using R and μ design aid charts. The equation derived from these charts is applied to compute the required μ, which is then translated into an actual number of reinforcement bars with specified diameters. The total weight of the reinforcement is then calculated using:

[3] $W_r = A_{s\,actual} * L * 7.85\ t/m^3$

where A is the actual area of steel reinforcement (in m²) and L is the bar length.

The fitness of each design iteration is assessed based on its total cost, which includes reinforcement and concrete expenses. Additionally, any design that fails to meet the wide beam shear or punching shear constraints is penalized with a significantly high fitness value to ensure its exclusion from the final selection. The optimization algorithm iterates through multiple generations, refining the design variables to converge toward an optimal solution.

Figure 4 presents the key design values calculated by the model, as well as the shear force and bending moment diagrams, which provide insights into the structural performance of the optimized footing design.

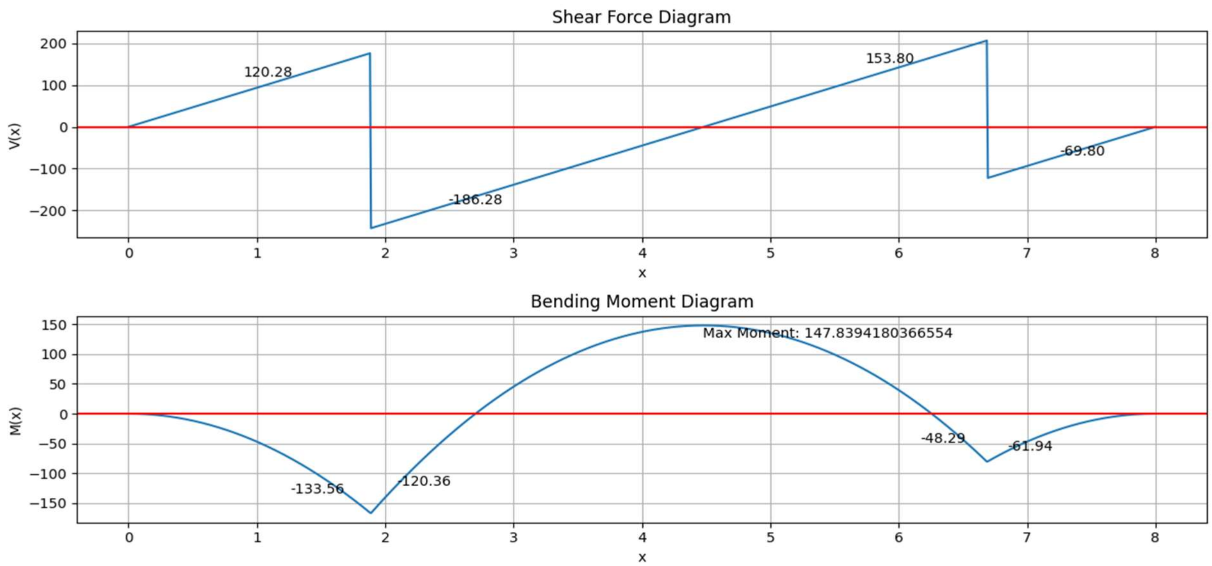

Figure 4- Critical Sections for Shear and Moment

3. RESULTS

To construct this optimization model, we utilized the Pymoo library in Python, renowned for its efficacy in both single and multi-objective optimization tasks. Pymoo provides a robust framework for research and development in optimization, offering a diverse array of algorithms such as genetic algorithms, particle swarm optimization, and differential evolution.

3.1 Algorithm Parameters

Five evolutionary algorithms were tested and compared, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Evolutionary Strategy (ES), and Nelder-Mead. Figure 5 elucidates the parameters utilized in these algorithms, such as population size and the number of generations.

```
problem = CombinedFootingDesign(xlow, xup,P1,P2,S,a1,b1,a2,b2,fcu,fy,qnet,ConcCost,RebarCost)

ga = GA(pop_size=50 ,eliminate_duplicates=True, crossover= 1, mutation= 0.01, elitism=True)
pso = PSO(pop_size=50)
de = DE(pop_size= 50,variant="DE/rand/1/bin",CR=0.3)
es = ES(n_offsprings=50, mu=5, sigma=0.5)
nd = NelderMead()

termination = get_termination("n_gen", 50) #max number of generations
```

Figure 5- Optimization Algorithms Parameters

3.2 Computational Experiments and Results

A computational experiment was conducted to evaluate and compare the performance of the five optimization algorithms and the efficiency of the developed model. Figure 6 illustrates the progression of the objective function (cost) across iterations for all models except Evolutionary Strategy (ES). Due to initially high predictions by the ES algorithm, which would have disrupted the graph's readability, its data points are not included. However, it is noteworthy that the ES model converged to the optimum solution by the 11th iteration.

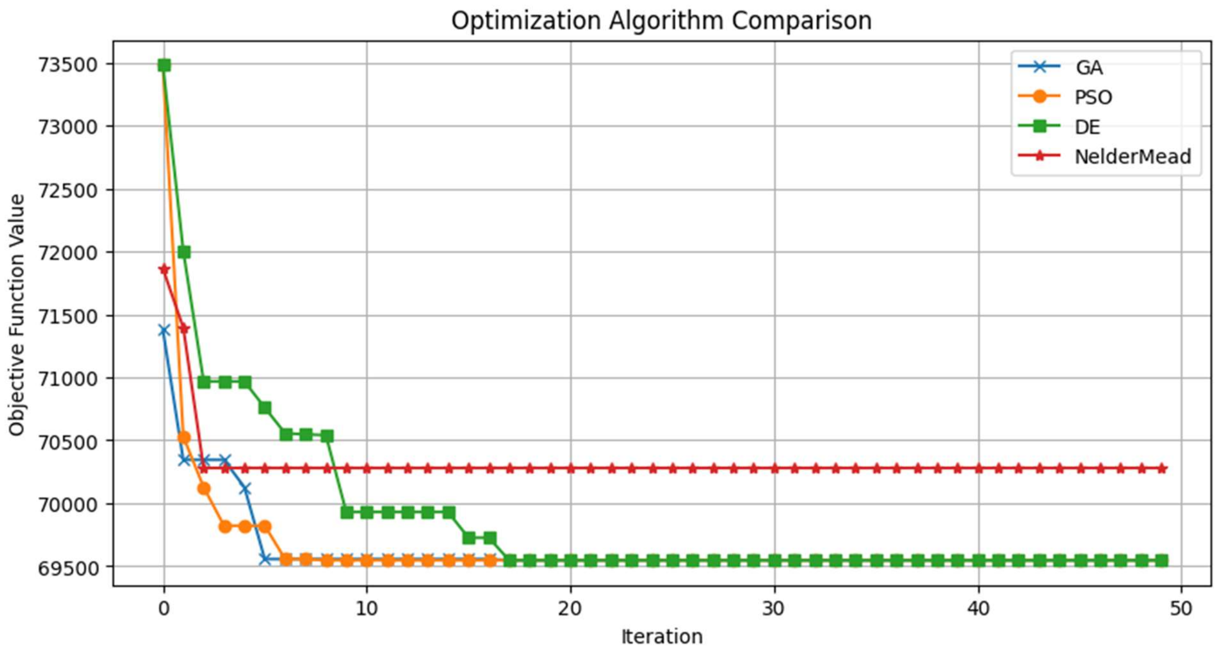

Figure 6- Algorithms' Results

Of the models depicted, the Genetic Algorithm showcased the most efficient performance, achieving the optimal cost by the 5th iteration. Following closely, Particle Swarm Optimization (PSO) attained convergence by the 6th iteration, showcasing superior performance in earlier iterations. Meanwhile, Differential Evolution required additional iterations, reaching the optimal solution by the 17th iteration. Conversely, Nelder-Mead did not reach the optimum solution within the analyzed iterations.

4. DISCUSSION

The optimization framework developed in Python significantly enhances the efficiency and accuracy of combined footing design. By incorporating advanced optimization algorithms, the model effectively reduces material costs while ensuring compliance with structural constraints. Among the five algorithms tested, Genetic Algorithm (GA) demonstrated the most efficient performance, converging to the optimal solution in the fewest iterations. Particle Swarm Optimization (PSO) also performed well, achieving convergence shortly after GA. Differential Evolution (DE) required more iterations but ultimately reached the optimal solution, while Evolutionary Strategy (ES) converged rapidly despite initial high-cost predictions. Conversely, Nelder-Mead failed to reach the optimal solution within the analyzed iterations.

These results highlight the advantages of evolutionary algorithms in structural optimization. The ability to automate and refine the design process using computational methods significantly reduces manual effort and enhances accuracy. Furthermore, the integration of the optimization model into a Revit plugin streamlines the design workflow by directly incorporating real-world project parameters.

5. CONCLUSION

This study presents a Python-based optimization framework for combined footing design, offering a more adaptable and computationally efficient solution compared to traditional methods. The integration of advanced optimization algorithms ensures that cost-effective and structurally sound designs are achieved. By automating the optimization process and incorporating real-time project data, the framework enhances efficiency and reduces human intervention.

Despite its advantages, certain limitations remain. The current model does not account for spatial constraints such as adjacent footings and property lines, nor does it consider alternative foundation systems like strap beams or raft foundations. Additionally, excavation and formwork costs are not included in the cost function, and environmental impact factors such as CO2 emissions are not considered. Addressing these limitations in future research could further enhance the applicability and effectiveness of the optimization framework, making it a more comprehensive tool for foundation design in structural engineering.

Future research can address these limitations by extending the framework to handle spatial constraints and more complex site geometries. Incorporating comparative evaluation of multiple foundation systems could improve design adaptability across diverse project contexts. Additionally, integrating construction-related cost components and sustainability metrics into the optimization criteria would result in a more comprehensive and practical decision-making tool for real-world foundation design scenarios.

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