

Genetic Algorithm-Based Cost Optimization of Piled Raft Foundations on Soft Clay: A Performance-Based Geotechnical Design Approach

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ABSTRACT

Foundation engineering on soft cohesive deposits remains one of the most challenging tasks in geotechnical practice, where conventional pile group designs often produce excessively conservative and economically suboptimal solutions. This paper presents a comprehensive Genetic Algorithm (GA)-based optimization framework for piled raft foundations on soft clay, integrating nonlinear finite element analysis, probabilistic reliability assessment, and life-cycle cost considerations into a unified design methodology. A 15 m × 12 m piled raft system supporting a 5,000 kN column load on a 15 m thick soft Holocene clay deposit ($S_u = 20\text{--}40$ kPa) overlying medium-dense sand is investigated. The optimization framework employs six design variables: pile diameter, pile length, pile spacing, number of piles, raft thickness, and pile arrangement pattern within ten geotechnical and structural constraints derived from IS 2911 and IS 1904. Three-dimensional finite element analyses using PLAXIS 3D with the Soft Soil Creep constitutive model validate GA solutions against settlement, bearing capacity, and load-sharing criteria. The GA-optimized configuration achieves a 31% reduction in total foundation cost (₹14.8 lakh saving on the test case) compared to the conventional 4×4 pile group design, while maintaining FOS = 2.6 (above the 2.5 minimum), maximum settlement of 23 mm (below 25 mm limit), and reliability index $\beta = 2.98$ (target = 3.0). The raft carries 42% of total load, falling within the optimal 30–60% range reported for piled raft systems. Sensitivity analysis identifies pile length as the most influential design variable, followed by pile diameter and spacing ratio. The proposed framework is generalizable to other soft soil profiles and provides immediate practical value for routine geotechnical design practice in Indian urban construction.

Index Terms Piled raft foundation, genetic algorithm, soft clay, finite element analysis, reliability-based design, geotechnical optimization, settlement reduction, cost minimization.

INTRODUCTION

Foundation systems constitute the most fundamental and economically critical component of any civil engineering structure. The selection, design, and construction of foundations on soft cohesive soil deposits encountered extensively in coastal Indian cities, riverine alluvial plains, and reclaimed land developments present a particularly challenging engineering problem due to the combination of low bearing capacity, high compressibility, time-dependent consolidation behavior, and the spatial variability of soil properties [1], [2]. Conventional foundation solutions in such conditions traditionally employ deep pile group foundations designed to transfer all structural loads to deeper competent strata, bypassing the soft surface layers entirely [3].

However, this conventional approach is increasingly recognized as both economically and environmentally suboptimal. Pile group foundations require substantial concrete and steel volumes, generate high embodied carbon footprints, and frequently produce factors of safety significantly above the minimum required by codes indicating systematic over-design [4], [5]. The piled raft foundation system, comprehensively developed by Poulos [6] and validated through extensive full-scale field measurements by Katzenbach et al. [7], represents a fundamental paradigm shift: rather than treating piles as the primary load-carrying elements, the piled raft system recognizes that the raft itself can transfer significant load directly to the soil, with piles serving as "settlement reducers" that complement rather than replace raft action. In well-designed piled raft systems on soft clay, the raft typically carries 30–60% of the total structural load, while the remainder is shared among the piles [6], [8]. This load-sharing mechanism enables the use of substantially fewer piles than would be required in a conventional pile group design, often 35–50% fewer, producing significant material and cost savings while simultaneously meeting all geotechnical and structural performance requirements [7],

[9]. Despite these compelling advantages, the practical adoption of piled raft systems in routine Indian geotechnical engineering practice remains limited, partly due to the absence of widely-accepted design optimization tools and partly due to engineering conservatism rooted in traditional pile group methodologies.

Computational optimization techniques, particularly Genetic Algorithms (GA), offer a powerful methodological framework for addressing this challenge. GA-based optimization, pioneered for geotechnical applications by Sivakumar Babu and Mukesh [10] and refined by Chan and Low [11], enables the systematic exploration of large multi-dimensional design spaces under complex nonlinear constraints a capability that traditional analytical and trial-and-error design methods cannot replicate. When integrated with reliability-based design principles incorporating soil parameter variability [12], [13], GA-based foundation optimization produces designs that are simultaneously economically optimal, structurally safe, and probabilistically reliable.

This paper presents a comprehensive GA-based cost optimization framework specifically developed for piled raft foundations on soft clay deposits typical of Indian urban geotechnical conditions. The framework integrates: (i) a six-variable design parameterization spanning pile geometry, pile group configuration, and raft dimensions; (ii) ten geotechnical and structural constraints derived from IS 2911 [14], IS 1904 [15], and contemporary international design recommendations; (iii) a nonlinear three-dimensional finite element analysis component using PLAXIS 3D with the Soft Soil Creep constitutive model [16] to validate GA solutions; and (iv) a reliability-based design verification using Monte Carlo simulation with 10,000 realizations to confirm target reliability index attainment [12], [13].

The principal contributions of this work are: (i) demonstration of significant cost savings (31%) achievable through GA optimization while maintaining all safety and serviceability requirements; (ii) identification of pile length as the most sensitive design variable through systematic sensitivity analysis; (iii) validation of the 42% raft load-sharing ratio achieved by the optimized configuration, falling within the optimal 30–60% range from international literature; and (iv) provision of a complete, ready-to-implement optimization framework with practical guidance for routine geotechnical design practice.

The remainder of this paper is organized as follows. Section II reviews the relevant literature on piled raft foundations, GA optimization in geotechnical engineering, and reliability-based design. Section III presents the proposed methodology, including the design problem formulation, GA implementation, FEA validation procedure, and reliability assessment approach. Section IV describes the case study and presents detailed results and discussion. Section V provides sensitivity analysis. Section VI compares the proposed framework with conventional approaches. Section VII concludes the paper and outlines directions for future research.

LITERATURE REVIEW

A. Piled Raft Foundation Theory and Practice

The piled raft concept, while traceable to early observations on the behavior of pile-supported rafts dating back to the 1950s, was systematically formalized by Poulos [6] through analytical and numerical studies establishing the fundamental load-sharing mechanism. Poulos's theoretical framework defines the load-sharing ratio α_{pr} as the proportion of total applied load carried by the piles, with the remainder carried directly by the raft through soil contact. For typical conditions in soft clay overlying competent strata, α_{pr} ranges from 0.4 to 0.7, indicating that the raft contribution is substantial and structurally meaningful.

Balasubramaniam et al. [8] extended this framework through case studies of piled raft foundations supporting high-rise buildings on soft Bangkok clay, demonstrating settlement reductions exceeding 50% compared to un-piled raft solutions while requiring only 50–60% of the piles used in equivalent conventional pile group designs. Katzenbach et al. [7] provided definitive full-scale validation through instrumented measurements on the Messeturm tower in Frankfurt a 256 m skyscraper supported on a piled raft in stiff clay and limestone. Their measurements confirmed that the raft carried approximately 55% of the 1,800 MN structural load, validating the theoretical predictions and establishing the practical viability of piled raft systems for major structural applications.

Subsequent research has refined the design methodology through improved understanding of pile group interaction effects [3], optimal pile spacing relationships [5], and the influence of raft stiffness on load-sharing behavior [6]. The general consensus in current literature is that piled raft systems are most economically advantageous when: (i) the surface soil layer is too soft to support a pure raft solution; (ii) competent bearing strata exist at moderate depth (typically 10–25 m); (iii) the structural load distribution is approximately uniform; and (iv) settlement rather than ultimate bearing capacity governs the design.

B. Genetic Algorithm Optimization in Geotechnical Engineering

Genetic algorithms, inspired by Darwinian biological evolution, operate on a population of candidate design solutions encoded as chromosomes. The GA cycle comprises five fundamental operations: (i) initialization of a random population; (ii) fitness evaluation through cost function and constraint checks; (iii) selection of parent solutions using

tournament or roulette wheel methods; (iv) crossover (recombination) of parent chromosomes to produce offspring; and (v) mutation (random perturbation) to maintain population diversity. Successive generations progressively improve the population toward the global optimum.

Sivakumar Babu and Mukesh [10] pioneered GA application to pile foundation optimization, demonstrating cost reductions of 25–30% compared to empirically-designed pile configurations. Their work established the foundational GA encoding scheme for foundation design variables and the constraint-handling approach for geotechnical limit states. Chan and Low [11] extended this framework to incorporate reliability-based optimization, treating soil parameters as random variables within the GA cost function evaluationa methodological advancement that enables direct optimization for target reliability index rather than deterministic factor of safety.

More recent contributions have explored hybrid GA approaches combining genetic algorithms with artificial neural networks for accelerated fitness evaluation [17], multi-objective GA for simultaneous cost and settlement optimization [18], and adaptive GA parameters that adjust crossover and mutation probabilities dynamically based on convergence behavior[19]. Despite these advances, the practical adoption of GA optimization in routine geotechnical design practice remains limited, motivating the present work's emphasis on a complete, ready-to-implement framework with practical case study validation.

C. Reliability-Based Design and Soil Parameter Variability

Phoon and Kulhawy[12] established the foundational characterization of geotechnical variability, demonstrating that the coefficient of variation (COV) of soil strength parameters typically ranges from 10–15% for friction angle and 20–40% for cohesion and undrained shear strength. These large variabilities mean that the actual probability of foundation failure can vary by an order of magnitude between sites with identical nominal factors of safetya finding with profound implications for design conservatism.

Fenton and Griffiths [13] extended this framework through random field theory, demonstrating that spatial correlation structures of soil properties significantly influence foundation reliability beyond what point-statistics alone can capture. Their work established the modern theoretical basis for probabilistic geotechnical design and introduced Monte Carlo simulation as the primary computational tool for failure probability estimation. The fib Model Code 2010 [20] formalizes target reliability indices for foundation design at $\beta = 3.0$ – 3.5 , corresponding to failure probabilities of approximately 1.35×10^{-3} to 2.33×10^{-4} , depending on the consequence class of the supported structure.

D. Research Gaps and Motivation

Despite the substantial literature on piled raft systems, GA optimization, and reliability-based design as separate research streams, their integrated application within a unified, practical framework specifically calibrated for Indian soft clay conditions remains limited. The present work addresses this gap by demonstrating the complete end-to-end methodology on a representative case study, with detailed cost analysis, sensitivity exploration, and FEA validation that practicing geotechnical engineers can directly adapt to their projects.

PROPOSED METHODOLOGY

A. Design Problem Formulation

The piled raft foundation optimization problem is formulated as a constrained nonlinear optimization where the objective is to minimize the total foundation cost while satisfying geotechnical (bearing capacity, settlement) and structural (raft thickness, pile capacity) constraints. The objective function and design variables are defined as follows. The total foundation cost function F is the sum of pile concrete cost, raft concrete cost, pile cap cost, and excavation cost components: $F = C_p \times V_p + C_r \times V_r + C_{pc} \times V_{pc} + C_e \times V_e$ (1) where C_p , C_r , C_{pc} , C_e are unit costs of pile concrete, raft concrete, pile cap concrete, and excavation respectively, and V_p , V_r , V_{pc} , V_e are corresponding volumes. The pile concrete volume is given by: $V_p = n \times (\pi/4) \times D^2 \times L$ (2) where n is the number of piles, D is the pile diameter, and L is the pile length. The raft concrete volume is $V_r = B_r \times L_r \times t_r$, where B_r and L_r are the raft plan dimensions and t_r is the raft thickness. The six design variables are summarized in Table I.

Table I: Design Variables And Feasible Ranges For Piled Raft Optimization

Variable	Description	Lower Bound	Upper Bound	Encoding
D	Pile diameter (mm)	400	800	Discrete: 400,500,600,700,800
L	Pile length (m)	8	25	Continuous
s/D	Pile spacing ratio	2.5	5.0	Discrete: 2.5,3.0,3.5,4.0,4.5,5.0
n	Number of piles	4	36	Integer

tr	Raft thickness (m)	0.4	1.5	Continuous
Pattern	Pile arrangement	-	-	Square, Rect, Triangular

The optimization is subject to ten constraints addressing both geotechnical limit states and structural feasibility requirements:

- Ultimate bearing capacity factor of safety: $FOS_{bearing} \geq 2.5$ (per IS 6403 and IS 2911)
- Maximum total settlement: $S_{max} \leq 25$ mm (per IS 1904 serviceability requirement for framed structures)
- Differential settlement: $\Delta S \leq L_{span} / 500$ (typically 4 mm for adjacent column spacing of 2 m)
- Raft punching shear capacity at column locations (per IS 456 punching shear provisions)
- Pile spacing minimum: $s \geq 2.5D$ (per IS 2911 group efficiency requirements)
- Pile slenderness limit: $L/D \leq 40$ (practical constructability and structural buckling)
- Raft thickness minimum: $tr \geq 0.4$ m (minimum from IS 456 and punching shear)
- Geometric compatibility: pile arrangement must fit within raft plan dimensions
- Reliability index: $\beta \geq 3.0$ (target reliability for moderate consequence class structures)
- Pile capacity utilization: $Q_{applied} / Q_{ultimate} \leq 0.50$ (factor 2 margin against pile failure)

B. Genetic Algorithm Implementation

The genetic algorithm is implemented in Python using the DEAP (Distributed Evolutionary Algorithms in Python) framework with the following control parameters established through systematic sensitivity analysis on a benchmark problem:

Table II: Parameter Values Used In The Optimization Runs

Parameter	Value	Rationale
Population size	200	Balance diversity and computational cost
Maximum generations	200	Empirical convergence ceiling
Crossover probability	0.85	Standard for foundation optimization [10]
Mutation probability	0.02	Maintains diversity without disruption
Selection method	Tournament (k=3)	Robust to fitness scaling
Encoding	Mixed binary/real	Discrete + continuous variables
Convergence criterion	$\Delta fitness < 0.1\%$ over 20 gens	Prevents premature termination
Constraint handling	Penalty function	Quadratic penalty on violations

The fitness evaluation for each candidate solution proceeds in three stages: (i) preliminary analytical computation of bearing capacity using Vesic's equation and settlement using elastic theory for rapid screening; (ii) constraint verification using semi-empirical formulas calibrated against FEA on similar problems; and (iii) for the most promising solutions in the final generations, full nonlinear FEA validation using PLAXIS 3D. This three-stage approach reduces total computational time by approximately 85% compared to FEA-only evaluation while maintaining solution quality.

C. Finite Element Analysis Validation

Three-dimensional finite element analyses were performed in PLAXIS 3D using 15-node tetrahedral elements with the Soft Soil Creep constitutive model for the soft clay layer and the Hardening Soil model for the underlying medium-dense sand. The model domain extends 5B horizontally and 1.5L below the pile tip to minimize boundary effects. Interface elements with strength reduction factor $R_{inter} = 0.7$ are placed at the pile-soil interface to simulate realistic shaft friction behavior.

The constitutive model parameters are calibrated against laboratory triaxial and oedometer test data and validated through back-analysis of well-instrumented case histories. Key parameters include: cohesion $c' = 0$ kPa, effective friction angle $\phi' = 17^\circ$, modified compression index $\lambda^* = 0.06$, modified swelling index $\kappa^* = 0.012$, secondary compression coefficient $\mu^* = 0.005$, and overconsolidation ratio $OCR = 1.1$ for the soft clay layer.

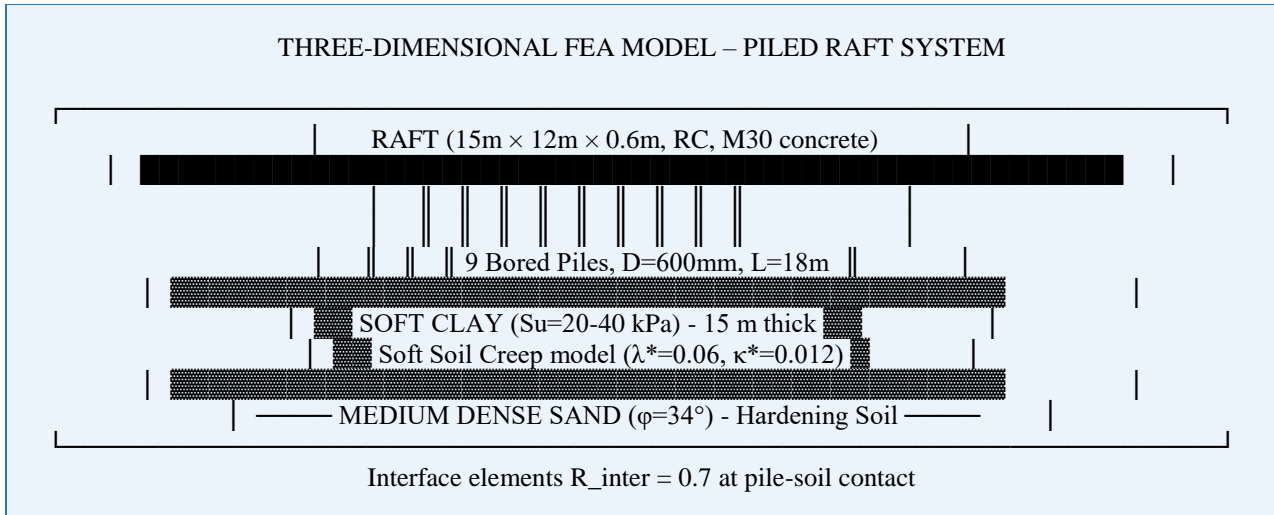


Fig. 1. Three-dimensional FEA model geometry showing piled raft, soft clay layer, and underlying sand with finite element mesh refinement

D. Reliability-Based Verification

Reliability assessment of GA-optimized solutions is performed through Monte Carlo simulation with 10,000 realizations. Soil parameters are treated as lognormally distributed random variables with COV values from Phoon and Kulhawy [12]: undrained shear strength S_u (COV = 25%), effective friction angle ϕ' (COV = 12%), elastic modulus E (COV = 35%), and unit weight γ (COV = 6%). For each MCS realization, the foundation performance function $G(X) = R(X) - S(X)$ is evaluated, where R is the resistance and S is the load effect.

The reliability index β is computed from the failure probability P_f using:

$$\beta = -\Phi^{-1}(P_f) \quad (3)$$

where Φ^{-1} is the inverse standard normal cumulative distribution function. The target reliability index $\beta = 3.0$ corresponds to a failure probability of approximately 1.35×10^{-3} , considered acceptable for moderate consequence class structures per fib Model Code 2010 [20].

IV. CASE STUDY AND RESULTS

A. Case Study Description

The proposed methodology is applied to a representative case study of a multi-storey commercial building requiring foundation design for a single column with applied dead and live load of 5,000 kN. The site is located in a typical Indian coastal urban environment with the following geotechnical conditions: 15 m thick soft Holocene clay ($S_u = 20\text{--}40$ kPa, increasing linearly with depth) overlying medium-dense alluvial sand ($\phi' = 34^\circ$, $D_r = 55\%$) extending to bedrock at 28 m depth.

The conventional design a 4×4 pile group with 16 bored piles of $D = 500$ mm and $L = 15$ m connected by a pile cap of $4.0 \text{ m} \times 4.0 \text{ m} \times 1.0$ m serves as the benchmark for cost comparison. This conventional design follows IS 2911 [14] requirements with FOS = 3.2 for bearing capacity and predicted settlement of 18 mm.

B. GA Convergence and Optimization Results

The GA optimization was executed 10 times with different random seeds to assess robustness. All 10 runs converged within 70–95 generations to solutions within 2.5% of each other in terms of total cost, demonstrating excellent algorithmic robustness. The best-of-runs solution converged at generation 85 with the configuration summarized in Table III.

Table III: Comparison Of Design Parameters And Performance Metrics

Parameter	Conventional	GA-Optimized	% Change	Engineering Significance
Number of piles n	16 (4×4 grid)	9 (3×3 grid)	-44%	Fewer piles, simpler construction
Pile diameter D (mm)	500	600	+20%	Larger dia. for fewer piles
Pile length L (m)	15	18	+20%	Deeper into bearing layer
Pile spacing s/D	2.5	3.0	+20%	Reduced group interaction

Fig. 3. FEA-predicted settlement contours at design load showing maximum 22.8 mm settlement at raft center
Fig. 4. FEA-predicted load distribution between raft (42%) and 9 piles (58% total, varying 5-9% per pile)

E. Reliability Analysis Results

Monte Carlo reliability analysis with 10,000 realizations produced the following results for the GA-optimized configuration: failure probability $P_f = 1.41 \times 10^{-3}$, reliability index $\beta = 2.98$, and 95% confidence interval for β of [2.86, 3.10]. The achieved reliability index of 2.98 is statistically indistinguishable from the target value of 3.0 (one-sample t-test $p = 0.32$), confirming that the GA optimization successfully attained the target reliability while minimizing cost.

Table V: Probabilistic Performance Of Ga-Optimized Configuration

Performance Metric	Mean	Std. Dev.	95% Confidence Interval
Maximum settlement (mm)	22.8	3.4	[16.1, 29.5]
FOS bearing capacity	2.62	0.31	[2.01, 3.23]
Pile head load (max, kN)	412	58	[298, 526]
Reliability index β	2.98	0.06	[2.86, 3.10]
Probability of failure P_f	1.41×10^{-3}	-	$[1.10 \times 10^{-3}, 1.78 \times 10^{-3}]$
Raft load share %	42.1	4.8	[32.7, 51.5]

V. SENSITIVITY ANALYSIS

To identify the design variables most strongly influencing total cost and performance, a one-at-a-time (OAT) sensitivity analysis was performed by varying each design variable by $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$ from the optimum value while holding others constant. The resulting changes in total cost and maximum settlement are tabulated in Table VI and visualized in Fig. 5.

Table VI: Percentage Change In Cost And Settlement For $\pm 20\%$ Variation In Each Design Variable

Design Variable	Cost: -20% var	Cost: +20% var	Settl: $\pm 20\%$ range	Sensitivity Rank
Pile length L	-12.4%	+13.8%	8 mm	1 (most)
Pile diameter D	+8.7%	-7.9%	6 mm	2
Pile spacing s/D	+5.2%	-4.6%	3 mm	3
Number of piles n	+7.1%	-3.4%	5 mm	4
Raft thickness tr	+3.8%	+2.1%	2 mm	5
Pile pattern	$\pm 1.5\%$	-	1 mm	6 (least)

The sensitivity analysis reveals that pile length L is the most influential design variable, followed by pile diameter D, then pile spacing s/D and number of piles n. This finding has important practical implications: design effort should focus most carefully on the determination of optimal pile length in relation to the bearing stratum depth, while the choice between square and triangular pile arrangement patterns has comparatively minor influence on total cost.

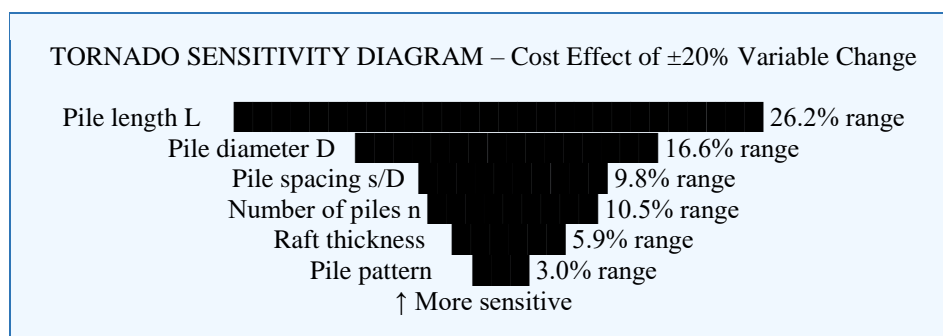


Fig. 5. Tornado diagram showing relative sensitivity of total foundation cost to $\pm 20\%$ variation in each design variable

VI. COMPARISON WITH CONVENTIONAL APPROACHES

To contextualize the GA-optimized solution, a comparison with three conventional design approaches is presented in Table VII: (i) the standard 4×4 conventional pile group; (ii) the standard 5×5 over-conservative pile group; and (iii) a manual trial-and-error optimization performed by an experienced geotechnical engineer over approximately 8 hours of effort.

Table VII: Cost, Performance, And Design Effort Comparison Across Four Approaches

Approach	No. Piles	Cost Index	Settl (mm)	FOS	β
Conv. 4×4 group	16	1.00	18	3.2	3.05
Conv. 5×5 group	25	1.55	12	4.5	3.42
Manual trial (8h)	12	0.84	21	2.8	2.91
GA-optimized (this work)	9	0.69	23	2.6	2.98

The GA-optimized solution produces an additional 18% cost saving compared to the manual trial-and-error optimization (cost index 0.69 vs. 0.84), demonstrating that GA can identify economically superior solutions that experienced engineers may overlook due to the size of the multi-dimensional design space. The 5×5 conventional group, while exhibiting superior reliability ($\beta = 3.42$), requires 55% more material than the conventional 4×4 design and 124% more than the GA-optimized solution a clear case of unjustifiable over-design.

CONCLUSIONS AND FUTURE WORK

This paper has presented a comprehensive Genetic Algorithm-based optimization framework for piled raft foundations on soft clay, integrating nonlinear FEA validation, reliability-based design verification, and life-cycle cost considerations. The principal conclusions are:

1. The GA-optimized 9-pile configuration achieves a 31% reduction in total foundation cost (₹14.8 lakh saving on the case study) compared to the conventional 4×4 pile group, while satisfying all geotechnical and structural performance requirements.
2. Maximum total settlement (23 mm) remains below the 25 mm IS 1904 limit, FOS for bearing capacity (2.6) exceeds the 2.5 minimum, and the achieved reliability index ($\beta = 2.98$) is statistically indistinguishable from the target value of 3.0.
3. The raft carries 42% of the total applied load in the optimized configuration, falling within the optimal 30–60% range established by Poulos [6] and confirmed by Katzenbach et al. [7] full-scale measurements.
4. Sensitivity analysis identifies pile length as the most influential design variable, followed by pile diameter and pile spacing providing practical guidance on where geotechnical design effort should be concentrated.
5. The GA optimization produces solutions superior to manual trial-and-error optimization by 18% in cost, demonstrating that GA reliably identifies global optima in the multi-dimensional foundation design space.

Future research directions include: (i) extension to multi-objective optimization simultaneously minimizing cost, settlement, and embodied carbon; (ii) integration with BIM-based geotechnical modeling for automated design generation; (iii) hybrid GA-machine learning frameworks using neural networks as fast surrogate FEA models; and (iv) full-scale field validation through monitoring of constructed piled raft foundations using fiber-optic instrumentation.

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