

MULTI-OBJECTIVE OPTIMIZATION OF COST, SCHEDULE, AND CARBON FOOTPRINT FOR STRUCTURAL CONCRETE FOUNDATIONS IN CHALLENGING GEOTECHNICAL TERRAINS

Hassan Ali Sadiq¹, Waleed Arshad², Muhammad Nouman Aslam^{*3}, Muhammad Badar Ashraf⁴, Masroor Ahmed Soomro⁵, Muhammad Salman Khan⁶, Uzair Ali⁷

¹Civil Engineer, Pini Arabia For Engineering Consultancy, Riyadh, Kingdom of Saudi Arabia (KSA)

²BIM Coordinator at FEMCO, Riyadh, Kingdom of Saudi Arabia (KSA)

³Senior Geotechnical Engineer, NESPAK, Lahore, Pakistan

⁴National Institute of Transportation, National University of Science and Technology (NUST), Risalpur, Pakistan

⁵NED University of Engineering & Technology, Karachi, Pakistan

⁶University of Technology Nowshera (Shuhada-EAPS, UoT), Pakistan

⁷Local Government and Rural Development Department, Khyber Pakhtunkhwa, Pakistan

¹hassanalisadiq@gmail.com, ²arshadwaleed168@gmail.com, ³nouman.aslam@nespak.com.pk,

⁴mbadar.fall25genit@student.nust.edu.pk, ⁵masroorsoomro@cloud.neduet.edu.pk,

⁶engr.salman521@gmail.com, ⁷engruzair91@gmail.com

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Corresponding Author: *
Muhammad Nouman Aslam

Abstract

As the world's construction industry is undergoing a critical conversion, the industry is facing a pressing need to reduce the impact of climate change, speed up project delivery, and ensure economic viability. Design and construction of structural concrete foundations, especially in difficult geotechnical environments, is one of the areas where these needs converge. This article thoroughly investigates the multi-objective optimization (MOO) of the cost, schedule and carbon footprint of concrete foundations, in complex soil conditions. Geologic conditions, such as expansive soils, low elevations, soft clays and karst topography, create uncertainty that can greatly increase the complexity of foundation design. The traditional single objective or sequential design approaches are not able to account for the various tradeoffs that exist between minimizing financial cost, construction time and reduction in embodied carbon emissions. This paper is a synthesis of advanced geotechnical engineering and structural mechanics, life cycle assessment (LCA), and evolutionary computational algorithms that provide a solid framework for MOO in foundation engineering. We explain the mathematical modeling of the three constraints, discuss the performance of the algorithms like NSGA-II and NSGA-III, and discuss some innovations in materials for low carbon concrete. In addition, because the article uses detailed case studies and an analysis of digital twin integrations, it provides a clear illustration of how multi-objective optimization can take a risk-laden, carbon-heavy foundation engineering practice and make it one of the most efficient, sustainable and predictable disciplines in existence.

1. INTRODUCTION

Infrastructure development in the construction industry has become more and more required to be balanced with economic efficiency, timely delivery of the project and environmental sustainability. The built environment is a significant consumer of energy and emitter of carbon emissions, and the cement and concrete industry is one of the largest industrial emitters of carbon emissions (Supriyanto et al., 2021). As countries work towards implementing their infrastructure projects to match the goals of the Paris Agreement and global decarbonization, the pressure has increased. Meanwhile, urbanization, population growth and infrastructure improvements are driving construction projects into previously undeveloped, marginal areas that are often subjected to severe geological and geotechnical conditions. These include expansive and collapsible soils, soft marine deposits, liquefiable sands, karst, very variable rock profiles, and areas with problematic groundwater conditions where there are significant uncertainties and potentially high risks associated with the ground conditions (Andrew, 2019). Therefore, foundation construction in these environments is not just about making a structure safe and adequate, it needs to take into consideration safety, constructability, economic performance, project duration, and environmental impacts.

Traditional design of foundations has been a linear process of decisions making, with safety for the structure and the soil as initial, then estimating costs, and then trying to shorten construction time. This can be a technically feasible approach but becomes increasingly constrained for large and complex construction projects as the cost, time, resource use and environmental performance are intertwined (Ashfaq et al., 2025). A configuration which is designed for minimum initial construction cost may result in a higher volume of concrete and reinforcement, complicated formwork, extensive excavation and longer curing times and longer construction times and may create further indirect costs. Likewise, a project that prioritizes construction speed could

rely on very fast or high-performance cementitious materials, intensive use of equipment or higher material quantities, all of which could result in increased embodied carbon and energy. Hence, an independent optimization of one performance criterion may lead to a deterioration of other dimensions of the project performance, which shows the need for an integrated approach that is capable of evaluating the project's economic, temporal, technical and environmental goals all in one.

Geotechnically challenging areas are more complex since the soil and rock properties vary in space and are uncertain in nature. Manufactured construction materials can be controlled over relatively narrow limits, whereas the natural conditions of the ground may change significantly over short distances and are poorly described at the design phase. Expansive soils can develop significant swelling pressures and movement over time, soft cohesive deposits can consolidate and settle over time, and karst layers may include spaces, breaks and low and high rock-head elevations that can cause uncertainty in the response of the foundation (Shafiee et al., 2024). Liquefiable sandy deposits can also cause seismic settlement and loss of bearing capacity, and high groundwater levels can make excavation, dewatering, foundation construction and concrete placement difficult. Often, these uncertainties lead to conservative designs where the foundation size, reinforcement size, pile lengths or requirements for ground improvement are increased to ensure a satisfactory safety margin is maintained. While these can help to mitigate geotechnical risk, they can also result in a higher material use, more excavation and transport needs, extended construction time, and higher embodied carbon emissions.

The engineering challenge is thus given in terms of multiple, conflicting objectives and not a single optimization criterion. An increase in the width and length of foundations or volume of materials used in foundations can result in increased structural reliability but with greater cost and material-related emissions; deeper foundations can also provide increased structural reliability but

with higher equipment, labor, and construction time; or faster construction time with different materials and/or construction techniques can result in reduced construction times, but increase material-related emissions or direct construction costs. From these interdependencies, it is apparent that a systematic framework is needed to identify solutions that meet the structural and geotechnical requirements, along with economic, temporal and environmental performance needs of sustainable foundation design (Lee et al., 2020). In this context, Multi-Objective Optimization (MOO) provides a mathematical and computational tool for optimizing multiple objectives and finding alternative solutions, instead of the decision maker optimizing a single objective. MOO is similar to single objective optimization, which typically aims for one optimum based on a predetermined objective function, but MOO produces a set of solutions that are non-dominated, which are different trade-offs among multiple objectives, often presented as a Pareto optimal front (Z. Liu et al., 2019). The main goals of structural concrete foundations can be to minimize the overall construction cost, shorten the project duration and minimize carbon emissions, whilst meeting structural, geotechnical, constructability and serviceability requirements.

Optimizing costs for foundation construction goes beyond just the cost of concrete and reinforcement; it can involve factors such as excavation, transportation, labor, equipment, piling, ground improvement, dewatering, formwork, maintenance, and risk-related costs. In addition to excavation, foundation preparation, installation of reinforcement, concrete pour, curing, backfilling, testing and other construction dependencies, schedule optimization must also take into account. Other carbon optimisation activities involve assessing the embodied emissions of the materials (such as cement, concrete, steel) and the emissions generated from transportation, excavation equipment, piling machinery, dewatering systems, and other construction activities. It is important to note that each of these goals can interact with each other, especially in the context of projects that are set on challenging

geotechnical conditions where, for example, changes in soil properties, foundation requirements, and the number of materials used, as well as construction methods and project duration, can impact the environment. This means that technically viable foundations are not necessarily the best ones from an integrated project view.

Recent advances in computational optimization have led to the possibility of tackling these interactions by using evolutionary algorithms, metaheuristic optimization, surrogate modeling, machine learning and other computational intelligence techniques. These methods can cover large and complex design spaces and narrow down to combinations of foundation dimensions, materials, construction methods, and geotechnical interventions that offer alternative cost/schedule/environmental performance trade-offs. Furthermore, the use of AI can unlock more opportunities for optimization, by learning the complex relationships between ground conditions, structural responses, construction variables, and project outcomes, while digital twin technologies can enable optimization to be linked with real-time construction data and project feedback. This integration can allow for progressive development of foundation designs and construction strategies based on new information regarding the ground conditions, material performance, productivity and environmental impacts (Rangaiah et al., 2020).

Optimization of structural concrete foundations with consideration of the cost, construction schedule, and carbon footprint is still a complex and somewhat disjointed research field, especially when dealing with challenging geotechnical conditions. Previous research often focuses on individual goals, certain types of foundations, specific geotechnical issues or specific optimization algorithms, and relatively little attention is paid to an integrated approach that takes into account both economic, temporal, environmental and geotechnical constraints. This is where the need for a comprehensive synthesis of the available methodologies, objective functions, constraints, optimization algorithms, uncertainty-

management approaches and emerging digital technologies relevant to sustainable foundation optimization comes in. Thus, this review focuses on the state of the art of multiple-objective optimization of structural concrete foundations, especially in difficult geotechnical conditions where cost, construction time and environmental impact (including carbon footprint) are simultaneously minimized. The review critically examines how geotechnical uncertainty impacts on optimization performance, assesses the methods of generating Pareto-optimal foundation solutions, and considers how artificial intelligence, machine learning and digital twins can support future sustainable foundation design and construction.

2. Literature Review

The three constraints of cost, schedule, and carbon are known as the Triad of Constraints. The first step to optimizing a system is to carefully and precisely establish its objectives and constraints. In the field of foundation engineering, cost, schedule and carbon are not separate variables, but are very tightly coupled because of construction reality and geotechnical environment.

2.1 Terrains Cost Dynamics

A foundation system cost in difficult geotechnical conditions is inherently nonlinear, and sensitive to variations and uncertainties in subsurface conditions. The overall cost of the foundation can be broadly understood as the sum of cost related to direct construction, cost related to indirect construction, and cost related to risk-contingency. The total foundation cost can be generally divided into cost of direct construction, cost of indirect construction, and cost of risk-contingency, which may interact with each other throughout the project lifecycle as well (Hong et al., 2023). Direct costs are mostly for the construction materials used, such as concrete, reinforcement steel, chemical admixtures, earthwork activities, including excavation, dewatering, backfilling, and ground preparation, and specialised equipment such as piling rigs and ground-improvement machinery. When these costs become significant,

they could be higher in difficult terrain, with poor bearing capacity, deep weak soil layers, high groundwater levels, excavation conditions that are unstable, and the geological profile varying from the site. These costs may be higher in difficult terrain when bearing capacity is poor, the weak soil layer is deep, the groundwater level is high, the excavation conditions are unstable, and the geological profile varies from the site (Lu et al., 2023). The other significant item of total foundation expenditure is indirect costs which could comprise site overheads, project management, supervision, insurance, finance, temporary facilities and other time-dependent costs. Project duration is especially important because unforeseen ground conditions, challenging excavation, unexpected obstructions, and issues with pile installation can cause a delay in site operations, which can result in higher overheads, financing costs, and delay in economic benefits from project completion (Hong et al., 2023). Furthermore, there is always some degree of uncertainty as to the spatial variability and true properties of the subsurface materials, and risk-contingency costs are required to account for this uncertainty. Geotechnical Baseline Reports (GBRs) and site investigations thus offer an informed, but probabilistic, representation of the ground condition and project teams have to consider financially the potential for adverse conditions and the necessary remedial works. In multi-objective optimization, these uncertainties can be included by implementing Reliability-Based Design Optimization (RBDO), which takes into account both the economic performance and the necessary level of structural and geotechnical reliability during the optimization process. In this method, the cost function can include a penalty if the probability of failure is greater than a specific tolerance or the reliability index is less than a desired target, which can help avoid minimizing the cost at the expense of the safety of the foundation (Schiebel et al., 2022). Therefore, cost optimization should be considered as an integrated process, which involves minimizing direct costs, minimizing costs over time, dealing

with uncertainty and risk, and ensuring reliability and performance of the foundation system.

2.2 Schedule Constraints & Geotechnical Risks

The second challenge is related to the scheduling constraints and geotechnical risks, with a particular focus on the latter. The speed of foundation construction is affected by the sequence of construction works, the productivity of construction works, the geotechnical conditions, logistics, availability of materials, environmental restrictions, and unforeseen conditions occurring on the construction site, and is therefore a decisive variable. Within a multi-objective optimization context, the schedule objective can be expressed in terms of the duration of activities that make up the project's critical path; delays in one activity may cascade into delays for other activities, leading to a larger project completion time. Basal heave, piping, excessive groundwater inflow, and excavation-wall instability are risks that may necessitate extra temporary support and groundwater-control measures, especially in soft clays, loose saturated soils and when groundwater is high. The duration and complexity of pre-foundation works can significantly be extended through the use of retaining systems (diaphragm walls and secant pile walls) and by the continuous dewatering works (Garde et al., 2020). After excavation, the foundation construction work consists of several different steps that are linked to each other: installation of formwork, placing of reinforcement, manufacturing and transporting of concrete, concrete placement, concrete finishing and concrete curing. The topography, rock face slopes, irregular excavation shapes and complex pile-cap and raft configurations can result in the need for specialized formwork and reinforcement arrangements which may involve more labor and construction time. Adding concrete curing to the story adds another time restriction as it may become necessary for other construction work to be performed once the concrete has cured. While using of those admixtures and advanced concrete technology may shorten the curing time, it may lead to higher material cost and embodied carbon

due to trade-offs between schedule, economic and environmental goals (Shrestha & Neupane, 2020). Furthermore, there is considerable schedule uncertainty associated with foundation projects due to the unexpected geotechnical conditions. These unexpected features may cause delays in construction and necessitate further investigation, redesign, remediation, or redesign of the foundation system. These unforeseen obstacles can delay construction, and could trigger further investigation, redesign, remediation, or redesign of the foundation system. These events could create cascading delays due to the close and interdependent relationship between the foundation activities and the later structural and construction activities. Thus, activity duration should not be assumed as a deterministic value when scheduling. Variations in activity durations can be captured with probabilistic scheduling methods, such as Monte Carlo simulation, and the probability and size of any schedule overruns due to geotechnical and construction risks can be assessed (Shrestha & Neupane, 2020). The method can be used in a multi-objective optimization framework to account for the delay risk exposure of the foundation alternatives and give a more realistic basis for project time, project cost, safety and environmental performance balance.

2.3 Carbon Footprint Management (Foundation Engineering)

The carbon footprint of a foundation system is a key environmental goal in sustainable construction, and can be calculated through Life Cycle Assessment (LCA) with the assessment boundary generally covering the production of construction materials and their transportation to the installation site, which corresponds to the modules A1-A5 of EN 15978, following the principles of ISO 14040 and ISO 14044 (Q. Wang et al., 2024). Carbon emissions from the extraction and processing of raw material materials, transport of raw material materials, and manufacture of construction products (concrete is one of the largest contributors to carbon emissions from concrete foundation systems) are included in

embodied carbon of modules A1–A3. The amount of clinker in the cement has a significant impact on the environmental impact of concrete, as the cement manufacturing process is responsible for significant carbon dioxide emissions which are related to clinker production. High strength and high durability requirements could result in further embodied carbon in challenging geotechnical environments, as foundation systems might need to have increased amounts of cementitious materials to meet the high environmental demands and/or high structural loads, such as sulfate soils, marine exposure or deep foundation applications (Garde et al., 2020). Reinforcement steel can also be a significant embodied emission, especially if expansive soils are present, a differential settlement is possible, or large dimensions of the foundation result in significant reinforcement requirements to prevent bending, cracking and other forces. In addition to the material-related emissions, the emissions from the transport of construction materials to the project site and the energy and fuel use in construction activities are included in modules A4–A5. In difficult areas, the emissions can be more substantial due to the use of energy intensive equipment, specialty equipment, extended hours of excavation, piling, ground improvement, and groundwater control activities to construct the foundations. For instance, in dense or over consolidated soils, large and powerful piling machines may be necessary to install the piles, but in soils with high groundwater levels, pumps may have to run for long periods of time, increasing electricity- or fuel-related emissions (Go.). Thus, the optimization of carbon use in foundation systems should not be limited to selecting material options but also, once the project is complete, the interaction between the quantity of materials, the foundation geometry, transportation, construction procedures, equipment usage and geotechnical conditions at the site. In multi-objective optimization, decisions made to lower construction time or cost can lead to higher energy use or embodied emissions, and actions implemented to reduce carbon emissions can lead to material changes that impact

construction timelines or project costs (Aytac, 2023).

2.4 Conflicts and Trade-offs

The key challenge for sustainable foundation engineering problems using Multi-Objective Optimization (MOO) is the significant interdependency and often contradictory dependence of construction cost, project time, and carbon emissions. As opposed to stand-alone optimisation problems, any improvement in one performance dimension could lead to worsening consequences in another, and solutions which balance competing objectives need to be found (Bashiri et al., 2025). In the context of concrete foundation construction, the cost–carbon relationship is of paramount importance because the selection of materials directly impacts the economic and environmental performance. Use of Supplementary Cementitious Materials (SCMs), such as fly ash and ground-granulated blast-furnace slag, can help to reduce the usage of clinker, thereby reducing embodied carbon; use of SCMs can also help to reduce material costs, however, incorporation of SCMs can cause the early-age strength to drop, which can increase the time required to cure, and thus the project costs will increase over the time period (Chen & Gallardo, 2024). Conversely, high clinker cementitious materials that harden quickly can allow for faster strength-building phases and speed up the following construction processes, but can also lead to more material usage and embodied carbon emissions. Another significant trade-off is the cost–schedule relationship, where scaling down the construction time of the foundation may necessitate increased labor force, overtime, and more specialized equipment, faster logistics, parallel construction, or more sophisticated formwork systems, which could result in higher direct costs though it may not bring down all time-dependent overhead costs (Bashiri et al., 2025). Likewise, the carbon–schedule dynamic is about balancing carbon reduction in construction methods and quick construction schedules. The use of low-carbon concrete technology and alternative cementitious systems can minimise the

impact of foundation construction into the environment, however their strength development characteristics, material availability, curing requirements and site conditions may affect construction sequencing and completion time (Waldron & Wallace, 2007). In difficult geotechnical conditions, the properties of soils and rocks are uncertain and can have a significant impact on the geometry, reinforcement, construction techniques, quantity of materials used, and risk of unexpected construction issues (Q. Wang et al., 2024). Using conservative foundation solutions to allow for more geotechnical uncertainty, such as oversized rafts, deeper piles, more foundation reinforcement, or more extensive ground improvement, can lead to higher construction costs, material usage, construction time, and embodied carbon. However, for the foundation configurations that are optimized and material efficient, the costs and carbon emissions are typically lower, but the geotechnical characterization must be more precise, the numerical models more complicated, construction control more stringent and ground behaviour more predictable (Lee et al., 2020). These optimized solutions could be subject to redesign, further investigation, remedial treatment, or construction delays due to variations of actual subsurface conditions from design assumptions, which may lead to unforeseen schedule delays and costs (Bashiri et al., 2025). Therefore, optimization of structural concrete foundations in difficult ground conditions should not be based on optimizing only one of the performance functions, but rather be considered as a coupled optimization decision problem involving the evaluation of economic, temporal, environmental, and geotechnical performance objectives simultaneously. MOO is a suitable framework for this purpose, as it identifies the set of non-dominated solutions, thus providing a clear understanding of the trade-offs between cost, schedule, carbon emissions and engineering constraints, and allowing alternative foundation strategies to be compared against the project-specific priorities and risk conditions (Aytac, 2023).

3. Geotechnical challenges & foundation typologies

3.1 Expansive Soils.

The engineering properties of expansive and collapsible soils are greatly affected by moisture changes, mineralogy, soil structure, and environmental conditions, making the design and construction of structural concrete foundations difficult. Expansive soils, especially those with active clays (e.g. montmorillonite), experience significant volumetric changes between wet and dry conditions, causing swelling pressures and differential ground movements that can affect foundation stability and serviceability of structures (Chen & Gallardo, 2024). Some clay mineral types and loosen, unsaturated soils, can have a tendency to suddenly shrink in volume when subjected to sustained loading and wet, causing differential settlement and potential damage to structures. The uncertainty associated with these contrasting soil behaviors adds to the challenge of foundation design as it is difficult to accurately predict the magnitude, distribution and timing of soil deformation with conventional deterministic methods, and foundation systems built in such environments must be designed to withstand the heave or settlement while still maintaining acceptable bearing capacity, structural integrity, and long-term serviceability. Traditional methods of mitigation include the extension of foundations below the active soil zone, stiffened raft or waffle-slab foundations, under-reamed piles, stabilization of problematic soils, and used of engineered soils as a replacement to unsuitable soils. Increasing stiffness of the raft using deeper grade beams and extra reinforcement can increase resistance to differential heave, but also increase the material use and associated environmental impacts. Likewise, it is possible to minimise ground exposure from moisture induced movement by extending the foundation elements below active zone, but this can also significantly increase excavation, construction complexity and project costs, particularly when active zone is located at considerable depths. Other options such as soil replacement and stabilization might also be viable, but they raise other environmental and logistical

concerns including the transportation of materials, excavation, waste disposal, and ground-treatment practices. In the Multi-Objective Optimization (MOO) approach, these conflicting demands call for a simultaneous consideration of the geometry of the foundations, the thickness of the slabs, the amount of reinforcement, the dimensions of the piles, the possibilities of treating the soil, and the construction techniques, in relation with economic, temporal, and environmental goals. However, because there are uncertainties in the subsurface conditions and potential future moisture changes, probabilistic analysis and reliability-based optimization can offer a more accurate view of the foundation performance than deterministic design assumptions can (Liu et al., 2022). Combining these techniques with MOO will allow the identification of non-dominated foundation alternatives that will have a balance of material efficiency, construction cost, project duration, carbon emissions, and geotechnical reliability. Hence, a holistic approach to foundation optimization, which explicitly treats soil-structure interaction, moisture-dependent foundation deformations, uncertainty and lifecycle performance, is necessary for the sustainable optimization of foundations on expansive and collapsible soils, not just based on conservative foundation dimensions or extensive mitigation efforts by using material-intensive foundations.

3.2 Karst Topography and Rock Variability

The karstified rocks, which are the result of dissolving soluble rocks (limestone, dolomite, gypsum), are the source of foundation engineering problems due to the variations of rock-head elevation, fractures, cavities, sinkholes and unpredictable subsoil conditions. The uncertainties of geology can result in differential settlement, loss of pile support, concrete loss during pile construction, and unforeseen remediated needs. Rock-socketed piles, large diameter bored piles and raft foundations to span possible voids are all common foundation solutions, and are based on a thorough site investigation and construction quality control

methods like pre-boring and cross-hole sonic logging. In an optimization context, karst can significantly add to construction costs and project time due to the difference in drilling rate between weak materials, fractured zones, cavities and hard rock, and the unexpected discovery of voids that will result in extra costs for concrete, grouting, or redesign. Thus, to achieve optimal pile diameter, spacing, socket depth and layout, while ensuring suitable probabilities of insufficient support or pile termination within the cavities the MOO model should take spatial variability and geological uncertainty into account such as by using a Random Field Theory (Adji et al., 2023). In this way, the alternatives to foundations can be considered all together, based on cost, schedule, carbon emissions, and geotechnical reliability.

3.3 Soft Marine Clays and Peat

In the coastal and estuarine environment, the soil is often in the form of an ultra-soft marine clay or peat with very low shear strength, low bearing capacity and high long-term consolidation settlement, making foundation design very sensitive to soil behavior and time-dependent settlement. While pile foundations are usually used to distribute structural loads into a more competent and deeper layer of soil, consolidation of the surrounding soil can produce a negative skin friction, which can result in additional loads being applied to the piles and may even lessen the load bearing capacity of piles. Depending on site conditions and project needs, other methods of ground improvement and foundation construction, such as lightweight fills, vacuum consolidation, and rigid inclusions, may be used. In a multi-objective optimization problem, some of the important design parameters are pile length, diameter, pile spacing, pile arrangement, etc., and longer and larger piles might yield less settlement and a higher reliability, but also have higher material usage, construction cost, project duration, and carbon emissions. Hence, the time-dependency of consolidation settlement, negative skin friction, pile structural capacity and long-term serviceability over the design life should be explicitly considered for optimization, while at the

same time minimizing the economic and environmental effects (Hov et al., 2023).

4. Multi-Objective Optimization (MOO) Frameworks

The foundation design problem can be formulated as a rigorous Multi-Objective Optimization (MOO) model by defining the design variables, objective functions, engineering constraints and decision criteria. Optimisation algorithms can then be used to find Pareto-optimal solutions that achieve a balance between costs, construction time, carbon emissions and geotechnical safety (Zheng et al., 2023).

4.1 Mathematical Formulation of the MOO Problem

The designs will be determined by the following variables and objective functions:

Let the design variables for the characteristics of the foundation system be represented by the vector x . In case of pile group foundation, the vector of the design could contain the following: pile diameter, pile length, number of piles, spacing between piles, concrete compressive strength and reinforcement ratio expressed as:

$$x = [d, L, N, s, f'c, \rho_{\text{prebar}}]$$

where d represents the pile diameter, L denotes the pile length, N is the number of piles, s represents the spacing between piles, $f'c$ is the concrete compressive strength, and ρ_{prebar} denotes the reinforcement ratio.

The Multi-Objective Optimization (MOO) problem aims to determine the design vector x that simultaneously minimizes the three principal objectives: total construction cost, total construction duration, and total carbon emissions. The objective function can therefore be expressed as:

$$\text{Minimize } F(x) = [C_{\text{total}}(x), T_{\text{total}}(x), E_{\text{total}}(x)]$$

where $C_{\text{total}}(x)$ represents the total foundation cost, $T_{\text{total}}(x)$ represents the total construction time, and $E_{\text{total}}(x)$ represents the total carbon footprint. The optimization is subject to geotechnical and structural constraints expressed as $g(x) \leq 0$ and $h(x) = 0$, ensuring that all optimized foundation solutions satisfy the required safety,

stability, strength, serviceability, and constructability criteria.

4.2 Constraints and Pareto-Optimal Solutions

The foundation optimization model is subject to geotechnical, structural, serviceability, and constructability constraints to ensure that the resulting designs remain safe and feasible. The ultimate limit state (ULS) constraints include bearing capacity, expressed as $Q_{\text{applied}} \leq Q_{\text{ultimate}} / F_{\text{bearing}}$, together with structural capacity requirements, $M_{\text{applied}} \leq M_n(x)$ and $V_{\text{applied}} \leq V_n(x)$, where the applied loads must remain within the available geotechnical and structural capacities. The serviceability limit state (SLS) constraints require total settlement to satisfy $\delta_{\text{total}}(x) \leq \delta_{\text{allowable}}$, differential settlement to satisfy $\Delta\delta(x) \leq \Delta\delta_{\text{allowable}}$, and foundation heave or swelling to remain within the allowable limit, expressed as $y_{\text{heave}}(x) \leq y_{\text{allowable}}$. In addition, constructability and durability requirements can be incorporated through constraints such as $s \geq 3d$ for minimum pile spacing and $c \geq c_{\text{min}}$ for the required concrete cover under aggressive soil or environmental conditions. Because the cost, construction time, and carbon objectives are generally conflicting, a single solution cannot simultaneously minimize all objectives. Instead, the MOO process generates a set of non-dominated solutions known as the Pareto front, where a solution x_1 dominates solution x_2 if it performs no worse than x_2 across all objectives and performs strictly better in at least one objective (Mavrotas, 2009).

4.2 Evolutionary Algorithms: NSGA-II and NSGA-III

In geotechnical optimization problems, the objective function is typically highly nonlinear, non-convex, discontinuous and multimodal, which is a result of the intrinsic complexity and spatial variability of soil and foundation systems. This sudden change of soil stratifications, the discrete construction alternatives, the non-linear soil-structure interactions with multiple design constraints can yield complex optimization landscapes with multiple local optima. Hence the

optimization of conventional gradient based techniques is difficult to apply as it may be that the objective and constraint function is not always a differential or continuous function. The Evolutionary Algorithms (EAs) and more particularly Multi-Objective Evolutionary Algorithms (MOEAs) are an appropriate way to explore the complex design space, however, in the absence of gradient information and the possibility of obtaining several trade-off solutions. One of the most widely-used algorithms in engineering optimization problems with 2 or 3 objective functions is Non-dominated Sorting Genetic Algorithm II (NSGA-II) developed by Bailey & Caldas (2023). NSGA-II sorts the candidate solutions into a series of Pareto fronts using a fast non-dominated sorting procedure, based on the dominance relationships between the solutions. The solutions are non-dominated in the first front, more dominated in the following fronts. NSGA-II employs a crowding-distance criterion, which helps the algorithm to maintain solutions evenly distributed in the objective space and maintains the diversity of the solutions within a Pareto front. The non-dominated sorting, elitism and diversity preservation in NSGA-II allow it to be effective in finding a wide variety of design alternatives that compete. The method is particularly suitable for situations in foundations where optimization is to be sought, and both discrete and continuous decision variables are involved. For example, the number and configuration of raft beams or other structure elements may be treated as a discrete variable whereas dimensions, reinforcement ratios or strength of concrete may be treated as continuous variables in the optimization of a raft foundation in expansive soils. In case there are more than 3 objectives, NSGA-II is not as effective because the number of nondominated individuals in the population will be high which will make it more difficult to identify high quality solutions, as the selection pressure will be lowered. This constraint is particularly relevant in sustainable design of foundations, where other optimization objectives such as construction costs, embodied carbon, material use, energy and water consumption,

lifecycle maintenance costs, and other environmental and social objectives can be considered. The researchers (J. Liu & Chen, 2019) came up with a new algorithm, NSGA-III, which uses a reference-point-based selection strategy rather than the crowding-distance-based one used in NSGA-II, to solve these multi-objective optimization problems. The predefined reference points or the reference directions are used in NSGA-III to guide the evolutionary search to ensure that the solutions are uniformly distributed across the high dimensional Pareto front. This way the algorithm can apply diversity and selection pressure even if it has to take several competing goals into account. Thus the NSGA-III framework is useful for the foundation optimization of advanced sustainable foundation which considers technical, economic, environmental and lifecycle at the same time (Verma et al., 2021).

4.3 Handling Uncertainty: Reliability Based Design Optimization (RBDO)

For deterministic optimization, it is also assumed that soil and geotechnical parameters are known with certainty, though in reality, some soil parameters like cohesion, friction angle, unit weight, permeability and soil stiffness are subject to inherent spatial and measurement-related variability in practical geotechnical engineering. Thus, a deterministic optimum that is very close to a constraint boundary (e.g. a design such that predicted settlement is just equal to the allowable settlement) might not have an acceptable probability of success if actual soil conditions are different from the assumed conditions. Reliability-Based Design Optimization (RBDO) overcomes this by combining probabilistic analysis with multi-objective optimization (MOO), where the design constraints are formulated as failure probabilities that are acceptable. A common reliability requirement is that the probability of failure due to component failure must be 10% or less for the critical component.

$$P[g_i(x, \xi) > 0] \leq P_{f,target}$$

For a more formal Word equation:

$$P[g_i(x, \xi) > 0] \leq P_{f,target}$$

where:

- $\mathbf{x}$ = vector of design variables
- $\boldsymbol{\xi}$ = vector of uncertain geotechnical variables
- $g_i(\mathbf{x}, \boldsymbol{\xi})$ = limit-state or constraint function
- $P_{f,target}$ = target probability of failure

While the use of RBDO is more realistic for geotechnical design, it is very computational intensive when implemented in MOO, with the number of FEAs, limit-equilibrium analyses or other numerical simulation(s) required for each candidate design and optimization generation potentially being thousands. The traditional reliability analysis is often impractical for repeated evaluations, especially for nonlinear and computationally intensive geotechnical problems. To overcome this limitation, surrogate modelling techniques based on machine learning such as Kriging, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) can be used to approximate the relationship between the design variables, uncertain soil parameters and geotechnical responses. In an active-learning setting, the surrogate model is continually updated by choosing and testing further high value samples, with an emphasis on areas near failure or constraint boundaries where prediction is most critical. This approach can significantly decrease the computational effort required for the numerical simulations without compromising the reliability of the optimization process and improve the computational efficiency of RBDO-based geotechnical MOO (Aydin Temel et al., 2023).

4.4 Machine Learning & Surrogate Modeling

Machine Learning (ML) is an emerging solution for foundation multi-objective optimization (MOO) in computational geotechnical engineering, as ML can optimize complex foundation systems while decreasing the computational load. First, by training ML models to a repository of pile load tests, plate load tests and other geotechnical datasets, one can predict geotechnical responses to structures such as load, settlement relationships, bearing capacity and deformation, within milliseconds. During optimization, these ML-based surrogate models can significantly cut down on the number of repeated and time-consuming 3D numerical

simulations—like PLAXIS or FLAC3D, to be modeled (Aydin Temel et al., 2023). Second, generative design techniques can assist in designing a feasible configuration for foundations using models like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) to propose possible foundation layouts that meet specified geometric, structural, and geotechnical requirements. These solutions produced can be used to form a good-quality initial population for evolutionary algorithms like NSGA-II, which can enhance the convergence efficiency by minimizing the number of infeasible or substandard solutions evaluated in the initial stages of optimization (Liu et al., 2024). Third, predictive scheduling can improve the construction-time objective by leveraging the use of ML algorithms trained from past construction projects to predict activity durations, while considering factors like weather, worker productivity, equipment availability, and possible equipment failure. When compared with traditional deterministic Critical Path Method (CPM) scheduling, the duration prediction using ML can offer a more dynamic depiction of the uncertainty in construction and can help formulate the objective of the total construction duration (TCD) as $\|T_{total}(\mathbf{x})\|$ within the foundation MOO framework (Kadang et al., 2024).

5. Carbon Reduction Strategies in Concrete Foundations

The ability of multi-objective optimization (MOO) on the design of foundations with low carbon footprint relies not only on the ability of the optimization algorithm itself, but also on the set of physical design alternatives that can be used by the optimizer. When the concrete mix, the number of materials, the geometry of the structure and construction techniques are fixed, then only a best solution can be found in a carbon intensive design space. So, for the entire Pareto optimal solution set, the use of low-carbon materials, the use of the structural efficiency measures, soil-structure interaction, and cleaner construction practices are indispensable to shift the Pareto optimal solution

set toward a lower embodied carbon while keeping structural safety, serviceability, cost and construction time unchanged. This is aligned with the recent progress in sustainable construction, which places equal importance on several different interventions in the selection of materials, structural design, and construction processes to achieve significant reductions in embodied emissions. One of the most readily available ways of lowering the embodied carbon of foundations is to use low-carbon concrete mixtures, as cement manufacture is a significant source of greenhouse-gas emissions from concrete. Concrete composition, therefore, should be considered variable in an MOO framework and the optimizer should be able to consider different combinations of cement, supplementary cementitious materials (SCMs), aggregates, water, and chemical admixtures. Using fly ash, ground granulated blast-furnace slag (GGBS) and silica fume can significantly cut down on the volume of clinker cement used in concrete and thereby also the embodied carbon. The environmental advantages of SCMs however need to be measured in conjunction with the impact on mechanical properties and construction time. A high content of GGBS could adversely affect early-age strength development, which could lead to higher formwork retention requirements, and delay other construction operations. This means that an MOO formulation can find the solutions in which carbon savings do not conflict with the schedule penalties, but rather must be balanced with them (Kadang et al., 2024). Other significant pathways for lowering the carbon footprint of the foundation concrete include calcined clay and limestone calcined clay cement (LC3) systems. The calcined kaolinitic clay is mixed in the correct proportions with limestone and clinker and can be made to reduce the CO₂ emission considerably when compared with the normal Portland cement due to the calcination of clay at lower temperatures and reduced requirement of clinker. Concurrently, LC3 can deliver appropriate mechanical and durability properties to meet the requirements of high demand structural applications. This is especially important for

foundations in chemically-reactive soils, marine environments, and aggressive groundwater. Therefore, the use of LC3 as a material-design variable in MOO can widen the design space for low-carbon cement while not necessarily increasing the construction-time penalties of some high-volume SCM mixtures (Kadang et al., 2024). Also expanding the range of low carbon material options available for foundation designers are geopolymers and other alkali-activated material (AAMs). These materials can include fly ash, slag, and other industrial by-products, which can help to lower the use of traditional clinker-based binders and provide significant embodied-carbon reduction opportunities. However, they are affected by the availability of the precursors, the need for activators, the curing conditions, the ambient temperature and setting properties. All these factors are critical for foundation construction in areas where climatic and/or supply chain constraints may impact construction reliability. Therefore, an MOO framework should not give low carbon materials an automatic environmental benefit, but rather the selection of materials should take into account carbon emissions, availability, strength development, durability, cost and construction time. This allows the optimizer to choose solutions that are context-specific rather than taking the most embedded carbon material to be the most suitable engineering alternative (Kadang et al., 2024). The use of recycled aggregates and carbon-curing technologies provides additional opportunity to reduce environmental burden of concrete foundations. Partially substituting natural aggregates with recycled concrete aggregates can help to decrease the demand for virgin aggregates and may also help to decrease the impacts associated with the extraction and transport of aggregates. Carbon curing is another method in which concrete products are cured under controlled CO₂ rich conditions causing some of the gas to become permanently mineralized inside the concrete matrix, with the possible effects of enhancing the properties of early age concrete. MOO view: These technologies can have a simultaneous impact on material-related carbon

emissions, resource use, and construction performance. Their inclusion as such then allows the optimization model to explore combinations of the material efficiency and the carbon sequestration, not just the reduction of cement content (S. Liu et al., 2024). Structural optimization is another large potential pathway to foundation emission reductions since material that can be eliminated without safety concerns is often also the most sustainable material. In foundations, such as pile caps, transfer structures, grade beams, and retaining elements, that have a complex load-transfer mechanism, topology optimisation may prove to be very useful. Topology optimization can decrease the amount of unnecessary concrete and optimize material efficiency of structural components by finding efficient load paths under certain boundary conditions and structural constraints. Adopting the resulting geometry in MOO framework allows for simultaneous assessment of concrete volume, reinforcement requirements, structural performance, constructability, cost, and embodied carbon. This is done by making carbon reduction a part of structural form generation, instead of assessing it after design (Verma et al., 2021). The same could be said for the heavily-loaded foundation components for which typical flexural assumptions are not adequate to describe the internal load-transfer process, such as in strut-and-tie modeling (STM). Strut and tie representations can be used to explicitly identify compression struts and tension ties, which can be used to design pile caps, deep beams, corbels, and other discontinuity regions. Optimization of these internal force paths can minimize needless reinforcement while keeping the strength and detailing requirements adequate. Since the production of reinforcement typically has a significant embodied-carbon footprint, cuts in unnecessary steel will yield both economic and environmental benefits. The combination of STM-based structural constraints and MOO offers the possibility to optimize not only the amount of concrete but also the reinforcement layout and associated embodied emissions (Bailey & Caldas, 2023).

Another potentially important pathway to reduce the amount of foundation material used is the exploitation of soil-structure interaction (SSI). Conservative assumptions may be taken for conventional approaches that do not make the fullest use of load-bearing contribution of soil around piles or under raft foundations. Some of these advanced numerical models can explicitly include the interactions between the foundation and the surrounding ground that are nonlinear, which can enable the designers to explore how the stiffness, geometry, pile spacing, embedment depth and soil resistance will affect the performance of the foundation. In an MOO environment, the information can be applied to determine foundation configurations that can be designed to meet design criteria (bearing capacity and settlement limits) by minimizing the amount of concrete and reinforcing steel. The computational cost of a correct SSI modeling is higher but repeated evaluations may be more feasible during optimization by using surrogate models or machine learning techniques to predict the responses. This can then lead to lower embodied carbon and construction costs (Zheng et al., 2023).

Another factor of low-carbon foundation optimization is construction processes. While material production is generally a significant contributor to embodied emissions, construction stage emissions from piling, lifting, dewatering, transportation and equipment operation can be large, especially for large foundations and projects in challenging construction sites. As a result, the construction process must be incorporated as a part of the optimization process and not as an external activity. For instance, the type of construction equipment can be defined as a discrete variable in the optimization problem. Using electric and hydrogen powered machines instead of diesel-powered equipment can lower direct machine emissions, but the impact on the environment will be influenced by source of electricity, usage of electric/hydrogen machines, battery manufacturing and fuel production. Additionally, low-emission equipment may be more expensive than standard equipment, which

could be a trade-off with economic considerations, especially when dealing with an MOO formulation that considers cost, carbon, and schedule simultaneously (Adji et al., 2023).

The sequence of construction activities can also have an impact on environmental performance and project schedule. The sequence of excavation, dewatering, temporary works, installation of foundations, and concrete placement will impact equipment utilization, material quantity, temporary works, and consumption of energy on the site. For some deep-excavation applications, for instance, an appropriate sequence of a permanent foundation slab can help provide excavation support and minimize the need for temporary steel strutting. This can help to lower the use of temporary materials, construction costs and embodied carbon footprint while increasing construction efficiency. By integrating MOO with four-dimensional Building Information Modeling (4D BIM), it is possible to simulate different construction sequences and allow the optimizer to consider their impact on time, resource use, equipment use and carbon emissions (Y. Liu et al., 2022)

As a whole, the text illustrates that optimization of the foundation to minimize its carbon footprint should not be confined to selecting a carbon-efficient concrete mix. It is necessary that material substitution, material minimization, structural topology, reinforcement optimization, soil-structure interaction, equipment selection, and construction sequencing are all combined in one decision space for a MOO framework to be truly sustainable. These strategies are interdependent and can have opposing impacts: use of a low carbon concrete mixture can extend construction time, and adoption of a more material efficient geometry can complicate fabrications. Likewise, operational emissions can be lowered by using electric construction equipment, but this will raise the direct construction project costs. These competing relationships are therefore the principal value of MOO, and the identification of a diverse range of feasible Pareto-optimal solutions from which the designer can select an appropriate compromise on carbon emissions, cost, safety,

serviceability and construction time. This holistic approach can shift the paradigm of sustainable foundation engineering from individual carbon reduction solutions, to an integrated design approach where sustainability performance is taken into account with mainstream engineering design criteria.

6. Case Studies: multi-objective optimization

Two completely different examples of foundation design under challenging conditions can be used to illustrate the application of the Multi-Objective Optimization (MOO) framework. For the first, a 40-story commercial tower is to be built on reclaimed coastal land, consisting of 5 m of loose, hydraulic fill, followed by about 25 m of ultra-soft normally-consolidated marine clay with an undrained shear strength (S_u) of 15-30 kPa and then dense sand from about 35 m down. Excessive long-term settlement, negative skin friction or downdrag due to consolidation of the soft clay and limited lateral pile capacity are among the key geotechnical issues; these issues are significant for the design of deep foundations in compressible deposits. The design variables used include pile diameter (d), pile length (L), number of piles (N), concrete compressive strength (f_c), and the use of a ground-improvement layer under the pile cap. Optimisation takes into account construction cost, construction time and embodied carbon (including materials, equipment, dewatering, risk contingency, etc.), construction time (including mobilization, drilling/driving, curing, testing, etc.) and carbon emissions (concrete, reinforcement steel, etc., and mainly diesel fuel). A one-dimensional consolidation model is coupled with an NSGA-II algorithm to predict long term downdrag while a three-dimensional finite element model is used to assess the performance of the foundations in the lateral direction. NSGA-II is well suited to solve this type of problem due to its non-dominated sorting and elitist selection algorithm, which allow to obtain multiple Pareto optimal solutions in a bounded multi-objective optimization problem (Liu et al., 2022) . The resulting Pareto front defines multiple non-dominated design

alternatives, including a carbon-oriented solution (60 x 1.5 m large diameter bored piles, 40 m long, with bitumen slip coatings and LC3 concrete, to minimize downdrag) which results in approximately 35% lower carbon emissions compared to the baseline, despite the design having a longer construction duration. The use of LC3 is consistent with the research findings that the limestone-calcined-clay cement systems can reduce the environmental impact associated with conventional Portland cement, but at the same time, the construction time can be increased by about 40% loading a bigger number of piles with high-strength ordinary Portland cement concrete to combat driving stresses. The balanced solution is to use 80 medium diameter bored piles (0.9 m diameter), with a shallow deep-soil-mixing layer (DSM) which creates a stiff crust and minimises downdrag, which enables shorter piles and less reinforcement. The alternative is about 15% cheaper than the conventional alternative, can be driven in about 20% of the time and results in about 20% less carbon emitted, showing how MOO can improve on the 'fast driven' option of piles versus larger bored piles by combining both ground improvement and structural foundation design. The second case involves a mid-rise residential development in an arid region with an expansive clay (montmorillonite content > 40%) at a depth of approximately 4.5 m with an expected swell pressure of approximately 150 kPa. The volume change of expansive soils is significant when moisture changes and can lead to differential heave, cracking, distortion and long-term serviceability issues in structures built on expansive soils. (Chen & Gallardo, 2024). These design variables are the depth and extent of excavation and replacement, mat thickness, grade-beam spacing and size, and incorporation of moisture-control elements such as chemical injection. In this instance the penalization for differential deformation is high with a strict deflection-ratio constraint applied: $\$L/500\$$ whereas a surrogate model trained on predictions of volumetric change is used to quickly assess possible heave response for possible foundation configurations is included in the MOO

framework. The conventional design calls for full removal of the 4.5 m active zone to be replaced by engineered fill, and a 1.2 m thick stiffened raft is constructed. The optimized design will involve only the excavation of about 2 m of the most active part of the expansive layer, with a peripheral polyacrylamide moisture-control barrier being introduced to stabilize moisture conditions in the remaining 2.5 m of expansive soil. A 0.6 m thick mat together with a non-uniform grade-beam design is also used to optimize the structural system with regards to the measured behavior of swelling and shrinkage, as shown in previous experimental studies (Bashiri et al., 2025), in which deeper grade beams are placed below an overly loaded shear wall and shallower grade beams below a light partition. The total concrete volume of this hybrid solution is reduced by ~45%, which decreases embodied carbon and material costs, and construction time is lowered by ~30%, due to the significantly lower volume of excavation and concrete placement and curing needs. The chemical moisture-control treatment adds cost and embodied carbon, but it adds value by helping to manage expansive-soil behavior to allow for a more material efficient foundation system to meet the geotechnical and structural requirements. Together, these case studies are indicative that MOO can achieve solutions that are not dominated—structural design, construction methodology, ground improvement, environmental performance, and economic considerations are optimized simultaneously—and show how solutions that do not come from conventional, single-objective, foundation design approaches can be found, particularly for soil-structure hybrid solutions. The research of chemical stabilization also demonstrates that different chemical stabilization mechanisms can be combined to achieve superior volume stability and stiffness of expansive soils, consistent with the general idea of combining structural and ground improvement methods in the optimization approach (Wang et al., 2024).

7. Implementation Challenges and Future Directions

Multi-objective optimization (MOO) has a great potential in foundation engineering, but it has not yet been widely used in practice because of data, model reliability and interoperability, regulations, and computational complexity. The function of geotechnical optimization in the case of soil is especially sensitive to uncertainty as soil properties are seldom measured in the field or in a laboratory and properties vary from one location to another. Therefore, the success of the MOO framework relies heavily on the quality, representation and consistency of the geotechnical and environmental data used. Concurrently, the growing accessibility of machine learning, Building Information Modeling (BIM), digital twins and reliability-based design techniques can enable the optimization of foundations to become a more holistic and embedded design decision-making process. To achieve progression going forward, standardized databases and interoperable digital workflows need to be developed alongside performance based regulatory frameworks and reliable AI assisted prediction techniques are needed.

7.1 scarcity and standardization of data

One of the most basic challenges for a reliable implementation of MOO in geotechnical engineering is the lack of data relevant to the models describing soil-structure interactions, namely the information needed on subsurface conditions, material properties, load-settlement relations, groundwater conditions, and construction performance. In contrast to many datasets used in structural engineering, geotechnical data is largely local and often costly and difficult to acquire, and records of pile load tests, plate load tests, settlement monitoring, and foundation performance may not be shared on a systemic basis, but exist only within individual organizations or consultants. When surrogate or machine-learning models are introduced into MOO, this is an important constraint as increased accuracy tends to translate to more training data, more varied data, and better quality data. Poor data sets may lead to extrapolation of soil

conditions beyond the range of those observed and thus yield apparently optimum solutions which might not be reliable for real applications. The same goes for the environmental optimization calculation for embodied carbon – it is dependent on reliable data on cement composition, production of reinforcements, transportation of aggregates, fuel use in equipment operations, and regional electricity mixes. Life cycle assessment standards like ISO 14040 and ISO 14044 give methodological guidelines for environmental assessment; while availability and consistency of project-specific Environmental Product Declarations (EPDs) are important practical considerations (Garde et al., 2020). Standardized, machine-readable geotechnical databases, which include borehole information, laboratory data and results, in-situ testing, foundation load testing, monitoring data, and geological data, can significantly enhance the reliability of optimization models. Ideally, these databases should include standardized environmental data with regional material-specific carbon factors, and verified EPD information. Common data structures and metadata needs would also allow for better interoperability between geotechnical software, optimization algorithms, BIM software and life cycle assessment (LCA) tools, providing a more reliable basis for automated MOO.

7.2 BIM and Digital Twins integration.

Combining MOO with Building Information Modeling (BIM) is one key link to bring optimization from theoretical computational models into real engineering practice. The design variables, like pile diameter, pile spacing, foundation thickness, quantity of reinforcement, excavation depth, etc., and material selection can be linked to a parametric BIM environment so that alternative foundation configurations can be generated and evaluated automatically via optimization algorithms. The use of BIM-based workflows can even extend to the creation of automated quantity extraction, constructability assessment and cost estimation, which can link the mathematical optimization model directly to project-level design information (Schiebel et al., 2022). This integration can minimize repetitive

manual modeling and provide consistency between the outputs of the optimization and construction documentation. Digital Twin technology takes this idea further by developing a dynamic digital model of a physical foundation system, which can be updated on a continuous basis by field observations.

The information from pile load tests, strain gauges, load cells, piezometers, inclinometers, settlement markers, and others monitoring devices can be fed into the digital model during construction and operation. If measured behavior is markedly different from the predicted behavior (e.g., behavior is greater than the design predicts in terms of settlement, pore-water pressure, or pile behavior) the updated data may be incorporated into the updated computational model and may be used to reconsider the remaining design or construction decisions. This adaptive optimization can turn the foundation design process from a single design decision after a first ground investigation into a continuous design process that continuously takes into account site behaviour. The recent advancements of digital-twin-enabled infrastructure management have shown that combining real-time sensing, computational model and intelligent decision systems can aid in more adaptive and data-driven engineering management (Siallagan, 2023).

Another significant issue is regulatory compatibility, as traditional methods of foundation design rely on prescriptive requirements, safety factors, material specifications, and pre-defined design procedures, while MOO may result in alternate designs based on an integration of economy, environment, construction, reliability and performance. The implementation of reliability-based design and optimization concepts is becoming more common in frameworks like Eurocode 7, and the consideration of uncertainty in geotechnical design is growing in popularity, but probabilistic and performance-based optimization has yet to be translated into clear procedures to demonstrate compliance with the code and acceptable levels of reliability (Wang et al., 2022). Future regulation should, therefore, include provision to check

optimized and non-conventional foundation solutions against minimum requirements for ultimate limit states, serviceability, durability, robustness and construction safety. Performance based regulations would allow for the option to optimize the design within an acceptable range of structural and geotechnical performance rather than prescribing an optimum design configuration. The need for sustainability should also be increasingly incorporated into infrastructure procurement and design directives. Carbon can be a voluntary optimization criterion, but become a project criterion in the form of embodied-carbon limits, environmental performance requirements and life-cycle assessment criteria. The adoption of policy measures related to low carbon procurement and “Buy Clean” policies are examples of how governments can leverage procurement policies and embodied emissions disclosures to support embodied emissions reductions (Saqib et al., 2018). A foundation carbon constraint could thus be added to foundation MOO as a constraint, rather than merely as one objective, significantly altering the design space that is feasible and motivating engineers to explore new materials, construction methods, ground improvement techniques, and foundation geometries.

7.3 Artificial Intelligence & Generative Design.

In the future, Artificial Intelligence (AI) will be used more and more for improving the prediction accuracy, decrease the computational load, and increase the number of design alternatives that can be considered in the foundation MOO development. Geological, geotechnical, topographical, construction, and monitoring data can be used to train machine-learning models, which can then estimate parameters, including bearing capacity, settlement, pile load-displacement, soil deformation, and the soil-response characteristics, which decreases the computational effort needed to repeatedly evaluate complex numerical simulations during optimization. Such surrogate models can be used (in a properly validated fashion) to replace, at certain points in the optimization process, the

more expensive finite element analyses, and perform thousands of potential designs within a reasonable amount of time. Generative design further extends this by enabling algorithms to systematically explore many different combinations of foundation geometry, materials, reinforcement plan and ground improvement methods that meet the required structural and geotechnical constraints. Reinforcement learning (RL) could also play a role in optimizing the building process, as it learns the sequences of construction from repeated interactions with simulated environments. In addition to optimizing the final foundation configuration, RL-based systems might also optimize excavation sequencing, pile installation order, concrete placement, curing periods, equipment utilization, and temporary works, among other decisions, in an interconnected manner. These methods could help uncover construction methods that would quicken the project's schedule, minimize equipment fuel use, the amount of waste materials and carbon emissions, while still upholding safety and performance standards (Kadang et al., 2024). AI-based solutions must be validated and quantified, however, and engineering judgments and compliance with design standards must also be considered in the implementation of the solution. Thus, the future of foundation MOO will probably be within the scope of a human-AI collaboration in which artificial intelligence would broaden the design search space and speed up analysis, whereas qualified engineers will interpret uncertainties, validate the solutions, and make the final design decisions.

8. Conclusion

The design and construction of structural concrete foundations in difficult geotechnical conditions is one of the most complex, uncertain, and resource demanding features of civil engineering. While the traditional design methodology is a step-by-step process that prioritizes safety and then cost and construction time, there is a growing demand for more integrated design methods due to the pressures of climate change, resource limitations, carbon reduction goals, and the need to deliver

infrastructure at a quicker pace. The aim of this article is to prove that Multi-Objective Optimization (MOO) is a powerful and efficient tool to solve the conflicts of construction cost, project schedule, embodied carbon, and still satisfy key geotechnical and structural safety requirements. MOO allows engineers to search for a large number of non-dominated design solutions (which can be considered as a Pareto front) instead of a single solution that has been predetermined in advance, by using the tri-objective optimization problem formulation, as well as the highly nonlinear and uncertain behavior of soil-structure interaction in expansive, soft, and karstic terrain (Deb et al., 2002). The analysis also shows that costs, construction durations and carbon emissions are tightly coupled in the very basic construction activities, such as excavation, concrete manufacturing and curing, reinforcement needs, equipment operation, equipment supply and transportation. The use of low-carbon materials like limestone-calcined-clay cement (LC3), supplementary cementitious materials and geopolymers-based binders can widen sustainable design space and decrease the embodied environmental impacts of conventional Portland cement systems (Habert et al., 2020).

In the same way, advanced structural optimization, efficient foundation shapes and targeted ground improvement methods can help to minimize material usage while ensuring the desired structural and geotechnical performance. The case studies described in this article also confirm that MOO is not a theoretical optimization exercise alone but can also recognize innovative structurally improved hybrid solutions combining structural modification with ground improvement and environmental control solutions. For instance, the optimal pile configuration with deep soil mixing, or the reduction of excavation and the use of targeted treatments of soils to control the moisture content in expansive soils, may lead to non-dominated solutions that satisfy all three design criteria: economic, temporal, and environmental. The results confirm that foundation system should be treated as an integrated soil-structure-

construction system, and not optimize the geometry of the structure separately from the foundation construction and ground conditions. However, there is ample opportunity for development in the broader engineering landscape to enable the practical implementation of MOO. To make optimization frameworks more reliable and usable in practice, it is essential that they have reliable geotechnical databases, a standardized environmental and carbon-accounting method, verified material-specific emission factors, BIM interoperability, integration with a digital twin, and a validation of AI-based surrogate models. Further, regulatory approaches will need to increasingly adopt a performance and reliability-based approach to design, allowing for innovative solutions that can be optimized for computation, to be assessed against the safety, serviceability, durability and sustainability requirements that have already been established. (Maynard et al., 2022) The application of MOO has the potential to become an important part of foundation engineering practice, beyond being just an academic methodology, as the construction sector moves towards ever more rigorous sustainability and carbon-reduction goals. Assisting a transition towards a safe, efficient, resource efficient, low carbon, adaptable and resilient foundation systems, it can be integrated with artificial intelligence, digital twins, BIM, life-cycle assessment and advanced ground-improvement technologies. In conclusion, the future of foundation engineering is not just about designing foundations to resist current conditions but about creating integrated computational methods that are both safe and cost effective, and can be built in an efficient manner, that also consider the environmental impact and long-term durability in the face of growing uncertainty regarding climate and geotechnical conditions.

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