Applying Quality-Diversity Algorithms to Construction Site Layout Planning

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Abstract –

Construction Site Layout Planning (CSLP) involves the spatial arrangement of temporary facilities to optimize safety, operational efficiency, and adaptability under dynamic site conditions. Traditional optimization-based approaches, while effective at improving objective performance, often converge toward a narrow set of solutions and overlook diverse yet feasible alternatives that are critical for scenario analysis and informed decision-making. This paper introduces CSLP-Elites, a hybrid framework that integrates multi-objective optimization with quality-diversity principles to generate a structured repertoire of high-performing and safety-compliant construction site layouts. The framework employs Pareto-based selection within a behavioral archive, enabling the simultaneous optimization of performance objectives and systematic exploration of spatial-functional diversity. Comprehensive analyses of reproducibility, scalability, and sensitivity, together with comparative evaluations against baseline algorithms (MAP-Elites and NSGA-II), demonstrate that CSLP-Elites achieves a high feasibility rate (83.9%), generating 333 distinct layout solutions while covering 99.2% of the behavioral space. In contrast, MAP-Elites achieves lower coverage and produces infeasible layouts, while NSGA-II produces very few feasible solutions and offers no behavioral diversity. By maintaining Pareto-optimal solution sets within each behavioral niche, CSLP-Elites delivers a balanced trade-off between exploration breadth and constraint-aware optimization. To enhance practical applicability, the 2-Dimensional layout solutions generated further transformed into 3-Dimensional visualizations, supporting intuitive interpretation and scenario-based evaluation for construction planning.

Keywords –

CSLP, Quality-diversity, Multi-objective optimization, CSLP-Elites, MAP-Elites, NSGA-II.

1 Introduction

Construction Site Layout Planning (CSLP) is a critical decision-making task in the architectural, engineering, and construction (AEC) industry, involving the spatial arrangement of temporary facilities to support safety, operational efficiency, and resource coordination under dynamic site conditions. Poorly planned layouts can result in inefficient material handling, congestion, safety risks, and reduced worker productivity [1], whereas effective site layouts contribute to smoother workflows, improved safety performance, and cost optimization [2]. However, CSLP remains challenging due to multiple competing objectives, evolving constraints, and the discrete and project-specific nature of construction sites, making the identification of a single "best layout" highly context-dependent.

To address this complexity, CSLP has commonly been formulated as a multi-objective optimization problem, often modelled as a quadratic assignment problem to capture spatial interactions between facilities and locations [3]. Metaheuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) have been widely adopted to approximate Pareto-optimal solutions that balance transportation efficiency, equipment utilization, and safety considerations [4]. While these approaches have demonstrated effectiveness in improving objective performance, they primarily focus on convergence toward a limited set of optimal solutions [5] and are susceptible to premature convergence in complex or highly constrained problems [6]. In CSLP, this often results in layouts that produce similar spatial patterns, limiting the exploration of alternative site configurations [7]. Such low spatial variance restricts the range of distinct planning scenarios available for logistic analysis, safety assessment, and operational decision-making [8].

More recently, generative design and artificial intelligence-driven approaches have been explored to expand the range of layout alternatives. Procedural modelling and deep generative models offer the ability to produce diverse configurations by learning or encoding spatial patterns [9]. However, procedural approaches often struggle to incorporate quantitative performance requirements, while data-driven generative models depend heavily on large, high-quality datasets that are rarely available in construction contexts [10]. Moreover, generative methods can still suffer from limited diversity in practice, producing visually varied but operationally suboptimal or unsafe layouts when constraints are not explicitly enforced.

In this context, quality-diversity algorithms provide a promising alternative paradigm for CSLP. Rather than seeking a single optimal solution, quality-diversity methods aim to discover a repertoire of diverse yet high-performing solutions by explicitly balancing behavioral exploration and performance optimization [11]. This perspective aligns well with construction planning practice, where planners often evaluate multiple feasible site arrangements to account for uncertainty, changing conditions, and stakeholder preferences.

This paper proposes CSLP-Elites, a hybrid framework that integrates multi-objective optimization with quality-diversity principles for construction site layout generation. Rather than identifying a single optimal solution, the proposed approach systematically explores the solution space to produce a structured archive of diverse, high-quality, and feasible layouts using manually defined behavioral descriptors. The framework is evaluated against conventional optimization and diversity-driven baselines, including NSGA-II and MAP-Elites, to demonstrate its ability to balance optimization performance and behavioral coverage without reliance on training datasets. To enhance practical applicability, the generated 2-Dimensional (2D) layouts are further transformed into 3-Dimensional (3D) visualizations, supporting intuitive interpretations and scenario-based evaluation for construction planning and safety-related decision support.

The structure of the paper is as follows: Section 2 reviews related work on construction site layout planning, including optimization-based, generative, and quality-diversity approaches. Section 3 presents the proposed CSLP-Elites framework and its methodology. Section 4 reports the experimental setup and comparative results. Section 5 discusses the implications of the findings and outlines directions for future research. Finally, Section 6 concludes the overall paper.

2 Literature Review

Early approaches to CSLP relied on rule-based and knowledge-driven systems that encoded planner expertise into explicit heuristics, often implemented within computer-aided design environments or expert systems [12]. These methods positioned temporary facilities according to predefined adjacency rules, safety clearances, and workflow constraints, providing practical support for small or well-structured projects. However, as construction sites became more complex, such deterministic rules struggled to capture the interdependent interactions among facilities, logistics, and evolving site constraints, limiting their ability to explore the large combinatorial layout space.

To address these limitations, CSLP was progressively formulated as an optimization problem, commonly modelled as a quadratic assignment problem [3]. Metaheuristic algorithms such as GA, PSO, and ACO were widely adopted to balance objectives including material handling efficiency, crane utilization, and safety performance [13]. Subsequent studies introduced richer objective functions and hybrid metaheuristic models to improve realism and convergence robustness [14]. Despite these advances, optimization-based CSLP remains inherently focused on convergence toward a narrow set of optimal or near-optimal solutions, also known as local optima problem (Fig. 1). This approach is prone to premature convergence in discrete and highly constrained problems [15], limiting the availability of diverse yet feasible layout alternatives.

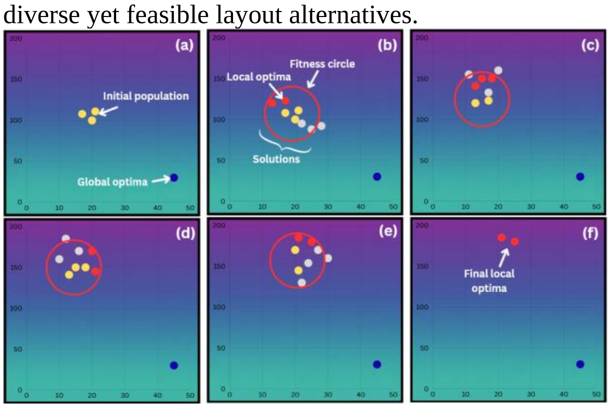

Figure 1. Visual representation of the local optima problem.

To expand design exploration beyond optimization, researchers investigated generative design and AI-driven approaches. Early procedural methods such as shape grammars and L-systems enabled the generation of diverse layout configurations through rule hierarchies [16], but often struggled to encode quantitative performance requirements [10]. More recently, data-driven generative models such as generative adversarial networks have been applied to CSLP, enabling automated layout generation from drawings or datasets [17]. While these approaches offer powerful generative capabilities, their effectiveness is constrained by limited availability of high-quality CSLP datasets [18] and susceptibility to mode collapse, where solution diversity is lost despite a large feasible design space [19].

Quality-diversity algorithms provide an alternative search paradigm that explicitly balances solution quality and behavioral descriptors. Unlike traditional optimization, which prioritizes convergence toward a Pareto front, quality-diversity methods aim to discover a repertoire of diverse yet high-performing solutions by illuminating the structure of the search space. Representative quality-diversity algorithms, such as MAP-Elites and novelty-based evolutionary methods, organize solutions within a behavioral space defined by user-selected behavioral descriptors and retain the best-performing solution in each behavioral niche [11]. Quality-diversity approaches have demonstrated strong potential in robotics, procedural content generation, and design exploration [20,21], and have recently begun to appear in AEC-related applications [5,22]. However, their application to CSLP remains limited [23]. Table 1 shows the CSLP approaches reviewed.

Table 1 Summary of CSLP approaches.

Category	Limitations
Rule-based	Struggle to capture complex spatial interactions
Optimization-driven	Converge optimal solutions narrowly
Generative design	Mode collapse, and low datasets availability

The limitations highlight the need for a quality-diversity-driven framework for CSLP to generate diverse, feasible, and interpretable layout alternatives without reliance on large training datasets.

3 Methodology

This study proposes CSLP-Elites, a hybrid optimization framework that integrates multi-objective optimization with quality-diversity search to generate construction site layouts that are both high-performing and behaviorally diverse. As illustrated in Figure 2, the framework formulates layout generation as an iterative evolutionary process in which candidate layouts are evaluated against multiple objectives, characterized by behavioral descriptors, and organized within a discretized behavioral archive. Global Pareto-based selection in objective space guides performance improvement, whereas archive-based diversity preservation across behavioral niches prevents premature convergence and encourages exploration across distinct behavioral niches. Rather than converging toward a single Pareto front, CSLP-Elites maintains a structured repertoire of elite solutions that jointly capture optimization quality and spatial–functional diversity.

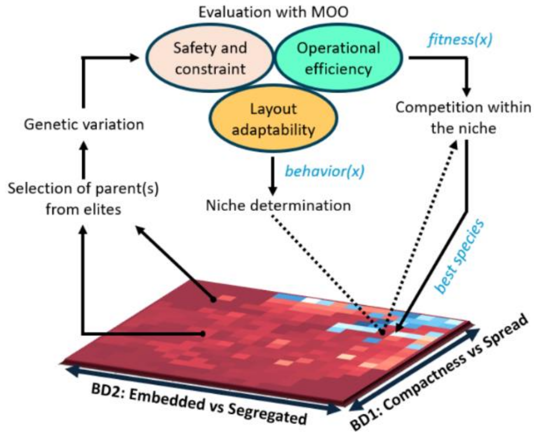

Figure 2. CSLP-Elites model.

3.1 Layout Representation and Constraints

Each construction site layout is represented in a normalized 2D workspace, where temporary facilities are modelled as rectangular entities defined by their center coordinates and dimensions. Facility types include operational elements (e.g. cranes, storage areas, core work zones) and worker-related facilities (e.g. site offices and welfare areas). All layouts are generated within a fixed site boundary and are subject to hard geometric constraints, including full containment within the site and non-overlap between facilities. Constraint handling is performed through an explicit deterministic feasibility-check procedure rather than a penalty-based method. After each candidate layout is generated, facility positions are checked against the site boundary and pairwise overlap conditions, and any layout that violates these constraints is discarded prior to objective evaluation. These constraints ensure that only geometrically feasible and safety-compliant layouts are admitted into the optimization process.

3.2 Multi-objective Optimization Formulation

The performance of each candidate layout is evaluated using three objectives that reflect key priorities in construction site planning: safety compliance, operational efficiency, and layout adaptability. These objectives are jointly maximized using a Pareto-based evolutionary strategy, allowing trade-offs between competing criteria to be explored without aggregating them into a single scalar measure. Equation (1) shows the multi-objective optimization problem:

$$\text{Maximise: } F(x) = \big(f_1(x), f_2(x), f_3(x)\big) \tag{1}$$

The safety objective quantifies the degree to which worker-related facilities avoid hazardous interactions with cranes, penalising layouts where facilities intrude into crane danger zones. Operational efficiency captures the effectiveness of material flow, equipment accessibility, and work-sequence support within the layout. Adaptability reflects the flexibility of the configuration under changing project conditions, favouring layouts that preserve usable space, alternative routes, and ease of reconfiguration. Together, these objectives guide the evolutionary search toward layouts that are both high-performing and practically viable.

3.3 Behavioral Descriptors

To promote diversity among feasible layouts, CSLP-Elites introduces behavioral descriptors that characterise qualitative spatial properties rather than objective performance. As illustrated in Figure 3, behavioral descriptors define a low-dimensional behavioral space in which solutions are organised into a structured grid, allowing the algorithm to preserve and refine diverse layout strategies rather than converging toward a single optimum.

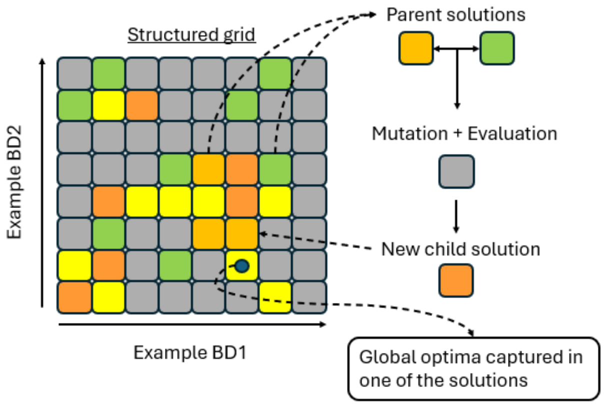

Figure 3. Role of behavioral descriptors in quality-diversity algorithm.

In this study, two manually defined descriptors are used: (i) compactness versus spread of facilities across the site, and (ii) spatial separation between worker-related and operational facilities. In Equation (2), each descriptor is normalised to the range [0,1], and together they define a two-dimensional behavioral space:

$$\mathrm{B}(x) = \big(b_1(x), b_2(x)\big) \in [0,1]^2 \qquad (2)$$

Compactness measures how tightly facilities are clustered around the layout centroid, distinguishing centralised from dispersed spatial arrangements. Worker-operational separation captures the average distance between worker facilities and nearby operational zones, distinguishing integrated from segregated layouts. These descriptors are discretised into a fixed grid that partitions the behavioral space into distinct niches, each representing a specific spatial strategy.

3.4 Site Layout Diversity Generation Process in CSLP-Elites

Following evaluation using the objective functions in Eq. (1) and behavioral characterisation in Eq. (2), CSLP-Elites generates layout diversity through an iterative hybrid evolutionary process (Fig. 4). Candidate layouts are evolved using selection, crossover, and mutation, with parent selection guided by Pareto dominance to favour strong trade-offs among safety, operational efficiency, and adaptability. Each offspring layout is first checked for geometric feasibility and then evaluated before being mapped into the behavioral space.

The behavioral archive discretises the descriptor space into a fixed grid, where each cell represents a distinct spatial-functional layout category. When a new layout is mapped into a cell, it competes only with layouts already stored in that niche. A layout is retained if it is non-dominated with respect to existing elites, ensuring that local solution quality improves over time while preserving behavioral diversity.

The final archive forms a structured catalogue of diverse and feasible site layyot strategies rather than a single optimal solution. To enhance practical interpretability, selected 2D layouts are automatically transformed into 3D representations, enabling clearer understanding of spatial relationships, circulation space, and overall site organisation for scenario-based evaluation and decision-making.

4 Experiments and Results

4.1 Experimental Setup

The CSLP-Elites framework was implemented in Python and evaluated on a synthetic construction site layout planning benchmark involving between 3 to 8 temporary facilities, including a core work zone, tower crane, material storage areas, site offices, and welfare facilities. The site was represented as a normalized 2D unit square [0,1]x[0.1], such that facility positions and dimensions were expressed as relative proportions of the site rather than real-world dimensions. All experiments were conducted under identical modelling assumptions across algorithms, including layout encoding, geometric constraints, objective functions, and safety thresholds, to ensure fair comparison (Table 2). CSLP-Elites was benchmarked against two baseline methods: MAP-Elites, which emphasizes behavioral descriptors, and NSGA-II, which focuses on Pareto-optimal performance. Each algorithm was executed using the same population size, number of generations, and final performance was

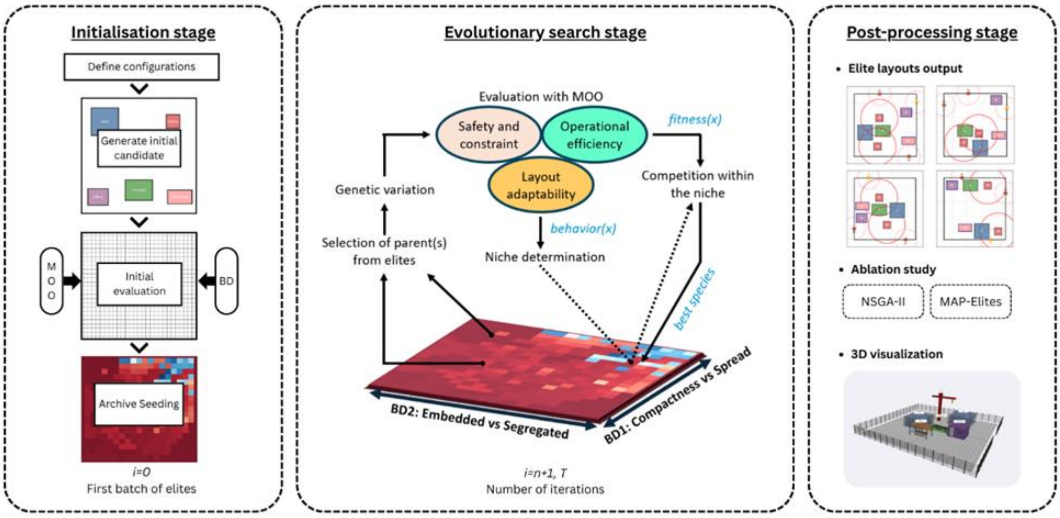

Figure 4. CSLP-Elites workflow summary.

analyzed based on the resulting layout sets, with feasible and safety-qualified subsets reported explicitly where relevant.

Table 2 Parameters used.

Parameter	Value
Population size	500
Generations	15000
Archive grid size	20x20 cells
Max elites per cell	12
Crossover rate	0.8
Mutation rate	0.1

4.2 Quantitative Performance Comparison

Table 3 summarizes the comparative performance of CSLP-Elites, MAP-Elites, and NSGA-II under identical configurations based on a single representative run. CSLP-Elites achieve high feasibility rate (83.9%), generating 333 valid layouts while covering 99.2% of the behavioral space. MAP-Elites achieves lower feasibility (31.7%) while covering 70.2% of the behavioral space, indicating that broader behavioral exploration can still admit infeasible layouts. In contrast, NSGA-II generates very few feasible solutions and does not maintain a behavioral archive. These results highlight a fundamental trade-off between exploration breadth and constraint-aware optimization. By maintaining Pareto-optimal solution sets within each behavioral niche, CSLP-Elites delivers the most balanced performance across feasibility, diversity, and objective quality.

Table 3 Algorithmic performance comparison under identical configuration.

Algorithm	Feasible solutions (%)	Occupied behavioral grid cells (%)
CSLP-Elites	83.9 (333/397)	99.2
MAP-Elites	31.7 (89/281)	70.2
NSGA-II	5 (5/100)	-

4.3 Qualitative Layout Diversity

Qualitative differences between the three algorithms are illustrated in Figure 5, which presents representative layouts generated under identical configurations. NSGA-II produces layouts that are visually consistent, differing mainly through minor positional variations, indicating strong convergence toward a narrow region of the solution space. MAP-Elites generates a wider range of spatial patterns but frequently violates boundary margins, clearance requirements, or crane safety zones, particularly as layout complexity increases. In contrast, CSLP-Elites generates layouts that remain fully safety-compliant while exhibiting clear variation in spatial organization, spanning compact and dispersed configurations and different degrees of functional separation. These visual results confirm that the hybrid quality-diversity and multi-objective optimization strategy effectively balances behavioral exploration with constraint-aware optimization.

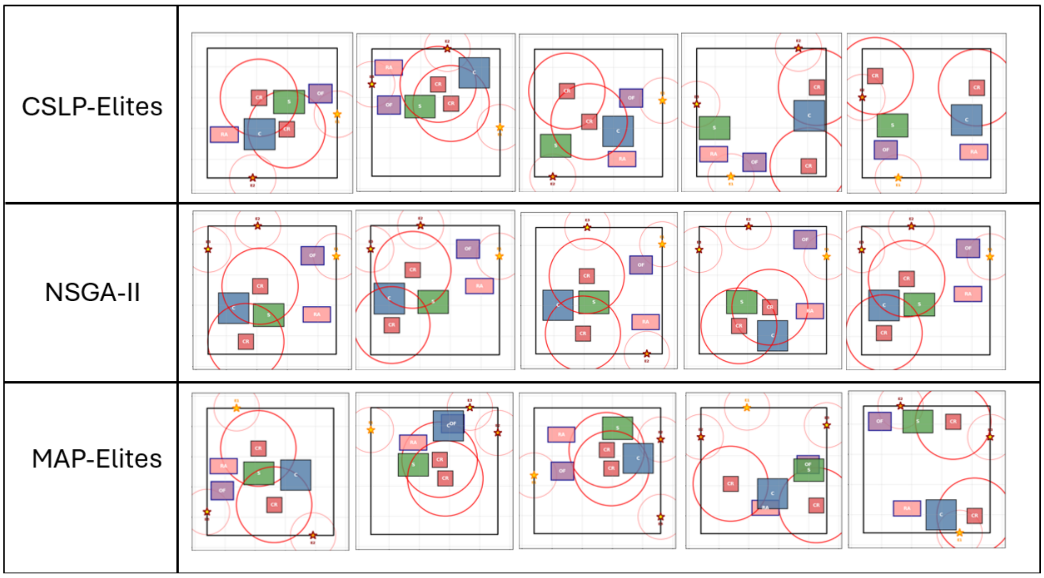

Figure 5. Comparison of example layouts generated by each algorithm.

4.4 2D-to-3D Visualization

To enhance practical interpretability, selected 2D layouts generated by CSLP-Elites are automatically transformed into 3D representations through a standardized JSON-based pipeline. After optimization, each layout is exported as a structured JSON file containing facility attributes such as type, center coordinates, dimensions, and associated safety zones, which is used to reconstruct the site in a 3D viewer through extrusion of the 2D facility footprints.

As shown in Figure 6, the resulting 3D scenes provide clearer insight into spatial relationships, circulation space, and overall site organization than 2D plans alone. This automated transformation supports rapid comparison of alternative layouts and demonstrates how CSLP-Elites can bridge algorithmic layout generation with downstream planning, visualization, and training workflows.

5 Discussion

5.1 Theoretical Implications

The comparative evaluation highlights fundamental differences in how CSLP-Elites, MAP-Elites, and NSGA-II navigate the construction site layout design space. MAP-Elites demonstrates strong exploration capability, rapidly populating a wide range of behavioral niches. However, its reliance on scalar fitness aggregation and limited constraint awareness allows unsafe or geometrically invalid layouts to enter the archive, reducing its practical applicability. NSGA-II, by contrast, provides robust objective optimization but consistently converges toward a narrow region of the solution space, producing layouts that differ mainly through small positional adjustments. These behaviors indicate that objective-space diversity alone is insufficient for CSLP problems that are strongly constrained by geometry, safety requirements, and

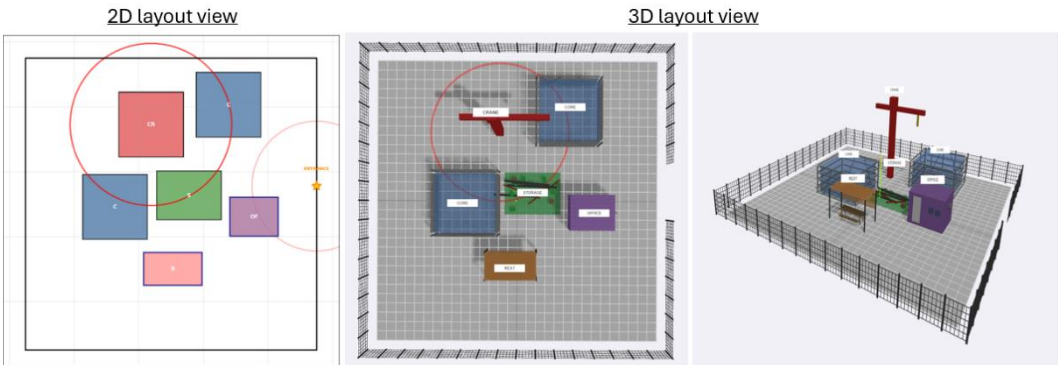

Figure 6. 2D-to-3D layout transformation.

operational feasibility.

CSLP-Elites advances the state of CSLP by tightly coupling Pareto-based multi-objective optimization with quality-diversity search. By embedding non-dominated sorting within behaviorally defined niches, the framework preserves diversity across meaningful spatial typologies while ensuring that all retained solutions satisfy strict geometric and safety constraints. This structure enables CSLP-Elites to explore the design space more effectively than either optimization-only or diverse-only approaches, revealing alternative layout strategies that would otherwise be suppressed by premature convergence or diluted by infeasible exploration.

However, the proposed archive structure has theoretical limitations worth noting. The effectiveness of CSLP-Elites depends critically on the quality of the behavioral descriptors. A poor selection of descriptors will yield niches that do not correspond to meaningful design strategies. Additionally, while Pareto front retention within niches improves solution quality relative to scalar aggregation, the archive is still a discretization of the continuous design space. Finally, as design problems become more complex, per-cell Pareto front management may become computationally expensive and the interpretability advantage may diminish.

5.2 Practical Implications and Future Work

From a practical perspective, CSLP-Elites generates a structured catalogue of buildable layout alternatives that can be directly inspected, compared, and adapted to project-specific requirements. Unlike NSGA-II, which yields limited spatial variation, and MAP-Elites, which may produce unsafe configurations, CSLP-Elites delivers diverse yet fully feasible layouts that support scenario analysis, risk assessment, and stakeholder communication.

The automated 2D-to-3D transformation further enhances the framework's applicability by enabling intuitive visual inspection of generated layouts. 3D representations make spatial relationships, circulation space, and safety zones easier to interpret than 2D plans alone, supporting faster and more informed decision-making. Future work will focus on integrating this pipeline into broader planning and simulation environments, including building information modelling platforms, digital twins, and immersive training systems. Further improvements in scalability, adaptive seardch strategies, and richer logistics modelling could strengthen its decision-support value for more complex construction sites.

6 Conclusion

This study introduced CSLP-Elites, a hybrid framework that integrates quality-diversity search with multi-objective optimization for CSLP. By combining behavioral exploration with Pareto-based optimization, the framework extends conventional optimization beyond singular or narrowly clustered optima to generate a diverse set of high-performing and spatially distinct layout configurations. Comparative results demonstrate that CSLP-Elites achieves a more balanced trade-off between feasibility, diversity, and objective performance than baseline optimization and diversity-driven approaches, providing planners with a structured archive of alternative layouts that jointly address safety, operational efficiency, and adaptability.

Despite these advantages, several limitations remain. The current implementation operates in a simplified two-dimensional environment and relies on manually defined behavioral descriptors, which may not capture all contextual, temporal, or operational factors present in real construction sites. In addition, computational cost increases with higher behavioral grid resolutions and larger per-cell Pareto archives, which may constrain scalability for large-scale or time-sensitive applications. The evaluation metrics are also based on abstracted representations of site performance rather than empirical project data, which may limit direct transferability to data-driven construction environments.

Future research will focus on addressing these limitations by incorporating more adaptive behavioral representations, surrogate modelling techniques, and calibration using real-world site information. Further integration of the automated 2D-to-3D transformation pipeline with building information modelling platforms, digital twin environments, and interactive simulation tools could enhance practical applicability for safety training, operational planning, and stakeholder decision-making. Overall, the findings suggest that quality-diversity principles can strengthen automated CSLP by producing diverse, feasible, and interpretable layout alternatives that better reflect the multi-scenario nature of construction planning.

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