AI-Based Early-Stage Planning Framework for Modular and Conventional Construction Projects

Aman Yadav
PG Student
Department of Civil Engineering
MITS DU Gwalior

Prof. Gautam Bhadoriya
Assistant Professor
Department of Civil Engineering
MITS DU Gwalior

Abstract

Early-stage planning decisions exert a decisive influence on the cost, duration, and overall performance of large construction projects. These decisions are typically made during the Front-End Loading (FEL) phases, when project definition remains limited and uncertainty is high. Although alternative construction methods such as modular and off-site construction have demonstrated significant benefits in terms of productivity, safety, quality control, and schedule reduction, their selection is still predominantly guided by organizational experience rather than systematic planning-based evaluation. Conventional early-stage schedules are often highly aggregated and do not explicitly reflect the structural and temporal differences between construction modes, thereby limiting informed decision-making. This paper proposes an artificial intelligence–based early-stage planning framework that explicitly integrates conventional and modular construction methods within the tactical planning context. The framework combines hierarchical construction planning principles with reinforcement learning and Monte Carlo Tree Search (MCTS) to generate, evaluate, and iteratively improve aggregated project schedules during the FEL2 and FEL3 phases. By modeling early-stage planning as a sequential decision-making problem, the proposed approach enables systematic exploration of alternative scheduling strategies without requiring exhaustive enumeration of all feasible plans.

Keywords

Early-stage construction planning; Modular construction; Construction technology and management; Reinforcement learning; Monte Carlo Tree Search; Tactical scheduling

1. Introduction

The construction industry plays a critical role in economic development, infrastructure provision, and urban expansion. Despite its significance, the sector continues to face persistent challenges, including labor shortages, stagnant productivity growth, safety risks, cost overruns, and schedule delays. These challenges are particularly pronounced in large construction projects, where complexity, uncertainty, and stakeholder interdependencies amplify the consequences of early planning decisions [1-6]. It is widely recognized that decisions taken during the initial phases of a project have a disproportionate impact on downstream performance, often determining achievable cost and schedule outcomes long before construction activities commence.

Among the most influential early-stage decisions is the selection of the construction method. Conventional on-

site construction remains the dominant approach due to its familiarity, established workflows, and widespread industry expertise [7]. However, alternative construction methods—particularly modular and off-site construction—have gained increasing attention in recent years as potential responses to industry inefficiencies. Modular construction involves the fabrication of building components or volumetric modules in controlled factory environments, followed by transportation and on-site assembly. This shift in production location fundamentally alters the structure of construction schedules, resource allocation patterns, and spatial constraints.

Numerous studies and industry reports have documented the advantages of modular construction, including reduced construction duration, improved quality consistency, enhanced worker safety, and reduced exposure to weather-related disruptions. These benefits are particularly attractive in the context of large and complex projects. However, the realization of these benefits is highly dependent on early-stage planning decisions [8]. Poor integration of modular activities into early schedules can negate potential advantages and introduce new coordination risks related to logistics, sequencing, and interface management between off-site and on-site operations.

Despite this dependence on early planning, the choice of construction method is often made based on organizational precedent, contractor expertise, or perceived cost considerations, rather than through systematic evaluation of planning alternatives. Early-stage schedules developed during the FEL phases are typically highly aggregated, focusing on major milestones rather than detailed work packages [9-15]. While such aggregation is necessary due to limited project definition, it also obscures the structural differences between construction methods. As a result,

planners lack tools capable of assessing how alternative construction modes influence early-stage schedules in terms of duration, sequencing flexibility, and overall feasibility.

Hierarchical planning frameworks, such as those formalized by the AACE schedule classification system, recognize the evolving nature of schedule detail as projects progress through definition phases. Class 4 and Class 3 schedules, commonly developed during FEL1 through FEL3, support feasibility assessment and budget authorization. However, existing hierarchical planning approaches implicitly assume a fixed construction method and do not provide mechanisms for generating or comparing schedules that incorporate different construction modes. This limitation becomes increasingly problematic as modular construction gains relevance and complexity.

From a computational perspective, integrating alternative construction methods into early planning significantly expands the number of feasible scheduling alternatives. Even at an aggregated level, the number of possible sequences grows rapidly as different construction modes are assigned to work packages. Traditional deterministic scheduling techniques, such as critical path analysis, are ill-suited to explore this combinatorial solution space, particularly under uncertainty and limited data availability [16]. Exhaustive enumeration of alternatives is computationally infeasible, while heuristic rules risk biasing decisions toward familiar construction practices.

Recent advances in artificial intelligence, particularly reinforcement learning and Monte Carlo Tree Search, offer promising opportunities to address these challenges. These techniques have demonstrated strong performance in complex decision-making environments characterized by large search spaces and delayed rewards. By framing planning problems as

Schedule Class	Project Definition Level (% of complete definition)	Final Use	Method Used
Class 5	0% to 2%	Concept selection	Top-down planning
Class 4	1% to 15%	Feasibility study	Top-down planning; Semi-detailed
Class 3	10% to 40%	Budget, authorization or control	Top-down planning; Semi-detailed
Class 2	30% to 70%	Control or tendering/bid submission	Bottom-up planning; Detailed
Class 1	50% to 100%	Control or tendering/bid submission	Bottom-up planning; Detailed

sequential decision processes, learning-based approaches can iteratively improve decision quality through experience, without requiring explicit enumeration of all possibilities. This paper builds on these advances by proposing an AI-based early-stage planning framework specifically tailored to construction projects involving alternative construction methods.

Table 1 Definition of schedule classes, adapted from (Aace International, 2010) [1]

The primary objective of this study is to demonstrate the feasibility and potential value of learning-based planning tools for early-stage construction scheduling. Rather than optimizing a specific project instance, the focus is on validating whether artificial intelligence can systematically support planning decisions during the FEL phases, when information is limited but strategic flexibility remains high. By doing so, the paper aims to contribute to the emerging body of research on AI-assisted construction planning and provide a foundation for future development of practical decision-support systems

Early-stage planning for large construction projects has been widely studied in the context of project management, operations research, and construction engineering.

1.1 Hierarchical Planning in Construction Projects

Table 1 summarizes this classification system and establishes the planning context relevant to this study. Class 5 schedules, developed during the conceptual phase, provide highly aggregated representations of project phases with minimal detail. As projects progress through the Front-End Loading (FEL) phases, schedules evolve toward Class 4 and Class 3, which support feasibility assessment, budget authorization, and strategic alignment. These schedules typically represent work at the level of work packages rather than individual activities, reflecting the limited availability of detailed engineering information.

Hierarchical planning frameworks are particularly important for large construction and engineering projects due to their scale, complexity, and stakeholder diversity. Aggregated schedules facilitate communication among decision-makers, support high-level trade-off analysis, and enable early validation of project objectives. However, most hierarchical planning models implicitly assume a fixed construction approach and focus on sequencing predefined work packages without considering alternative construction modes. As a result, early-stage schedules often fail to reflect the structural differences introduced by modular or off-site construction.

1.2 Planning Implications of Modular and Off-Site Construction

Modular construction represents a fundamental departure from traditional on-site construction by transferring substantial portions of production to factory environments. This shift alters not only where work is performed, but also how it is planned, sequenced, and coordinated. In modular construction, off-site fabrication and on-site assembly can occur in parallel, creating opportunities for schedule compression but also introducing new coordination challenges.

Numerous studies have highlighted the benefits of modular construction, including reduced construction duration, improved quality consistency, enhanced safety performance, and reduced exposure to adverse weather conditions. Industry reports from organizations such as the Modular Building Institute emphasize productivity gains and waste reduction associated with factory-based production. Academic studies further confirm that modular construction can deliver superior outcomes when integrated effectively into project planning.

Traditional early-stage planning methods are poorly equipped to capture these differences [23]. Aggregated schedules often represent modular and conventional construction activities in similar ways, obscuring the distinct temporal and spatial characteristics of each approach. As a result, planners lack tools to systematically evaluate how alternative construction modes influence early-stage schedules in terms of duration, flexibility, and risk exposure.

1.3 Decision-Support Approaches for Construction Method Selection

Several studies have attempted to support construction method selection through decision-support tools based on qualitative and quantitative criteria. These approaches typically identify factors influencing the suitability of modular construction, such as project size, site constraints, labor availability, transportation logistics, and organizational expertise. Questionnaire-based tools and multi-criteria decision-making frameworks have been proposed to assist managers in evaluating these factors.
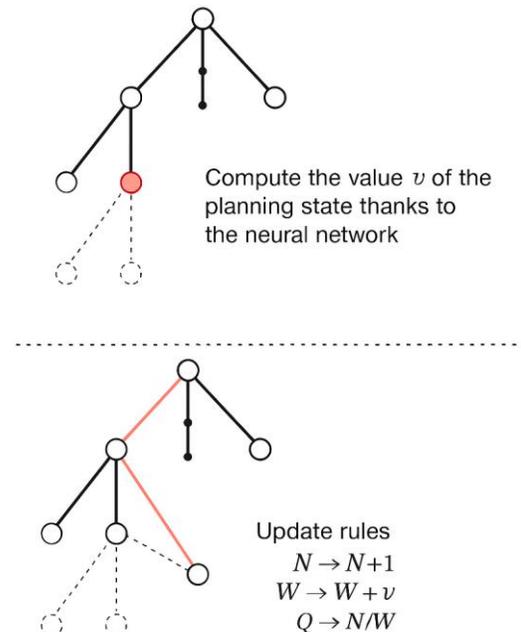

Fig 1. An iteration of the MCTS

1.4 Artificial Intelligence in Construction Planning

Recent advances in artificial intelligence have opened new possibilities for addressing complex planning problems in construction. Machine

learning techniques have been applied to predict project duration and cost based on historical data, with neural networks often outperforming traditional regression models. However, these approaches typically focus on outcome prediction rather than schedule generation and rely heavily on large datasets from completed projects [25].

Learning-based approaches to schedule generation are less common but particularly relevant to early-stage planning, where data scarcity and uncertainty limit the applicability of supervised learning. Reinforcement learning, which enables agents to learn optimal policies through interaction with an environment, offers a promising alternative. By framing planning as a sequential decision-making problem, reinforcement learning can iteratively improve scheduling strategies without requiring labeled datasets.

Monte Carlo Tree Search (MCTS) has emerged as a powerful method for navigating large decision spaces in sequential problems. The MCTS algorithm balances exploration of new alternatives with exploitation of known high-performing strategies through iterative tree traversal. Figure 1 illustrates the four phases of an MCTS iteration—selection, expansion, simulation, and backpropagation—which collectively enable efficient search in combinatorial spaces.

The integration of MCTS with neural networks, as demonstrated in game-playing systems such as AlphaGo, has shown remarkable success in complex domains. In construction planning, this integration enables the estimation of planning state values and action probabilities, guiding the search process toward promising scheduling alternatives while avoiding exhaustive enumeration. However, existing applications of these techniques in construction have primarily focused on operational-level sequencing or component installation, rather than early-stage aggregated planning.

2.1 Research Methodology

The objective of this research is to investigate whether artificial intelligence–based approaches can effectively support early-stage construction planning when alternative construction methods, such as modular and conventional construction, are considered simultaneously. Given the exploratory nature of this objective and the limited availability of real-world early-stage planning data, the study adopts a structured yet flexible research methodology focused on model development, controlled experimentation, and comparative evaluation rather than empirical validation on a single real project.

2.1.1 Research Design and Objectives

The research is designed as a methodological and computational study aimed at proposing and validating a novel planning framework rather than optimizing a specific construction project. The primary research objective is to develop a model capable of generating aggregated construction schedules during the Front-End Loading (FEL) phases while explicitly incorporating alternative construction modes. Secondary objectives include assessing the learning behavior of the model, identifying key parameters influencing performance, and comparing the proposed approach with baseline planning strategies.

This methodological orientation reflects the current state of practice in early-stage planning, where uncertainty, limited project definition, and lack of detailed data constrain the applicability of traditional empirical validation methods. Instead of relying on historical project schedules—which often reflect implicit biases toward conventional construction—the

study emphasizes controlled experimentation to isolate the effects of learning-based planning mechanisms.

The overall research workflow is illustrated in Figure 2 of the thesis, which presents the sequential and iterative structure of the methodology. The workflow consists of five
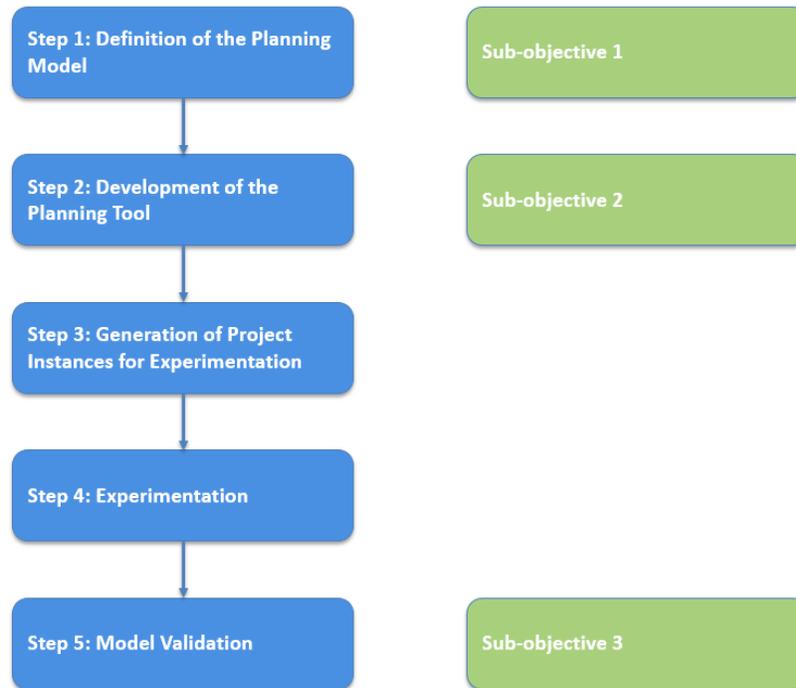

Figure 2. Steps in the research method

main stages: definition of the planning framework, development of the learning-based model, generation of project instances, experimental evaluation, and comparative validation.

The first stage involves defining a planning framework suitable for early-stage construction projects. This includes identifying the appropriate level of schedule aggregation, determining how construction modes are represented within work packages, and establishing performance indicators for schedule evaluation. Particular attention is given to ensuring compatibility

with Class 4 and Class 3 schedules as defined by the AACE schedule classification system.

The second stage focuses on the development of the learning-based planning model. This includes formalizing early-stage planning as a sequential decision-making problem, selecting

appropriate artificial intelligence techniques, and implementing the computational architecture that combines Monte Carlo Tree Search and a neural network trained through reinforcement learning.

2.1.2 Planning Context and Level of Detail

A critical methodological decision concerns the level of planning detail addressed by the model. The study focuses on early-stage tactical planning rather than detailed operational scheduling. Work is represented at the level of aggregated work packages, consistent with Class 4 and Class 3 schedules. This choice reflects the practical realities of early-stage planning, where detailed activity definitions and resource assignments are typically unavailable.

By operating at this level of aggregation, the model supports strategic decision-making related to construction method selection and high-level sequencing, rather than day-to-day execution control. This distinction is essential, as the primary goal is to evaluate the planning implications of alternative construction modes rather than optimize construction operations.

2.1.3 Formulation of the Planning Problem

Early-stage planning is formulated as a sequential decision-making problem in which planning decisions are made incrementally. At each decision step, the planner selects a work package and assigns a construction mode, such as conventional on-site construction or modular off-site construction. The cumulative effect of these decisions determines the structure and performance of the resulting aggregated schedule.

This formulation enables the use of reinforcement learning techniques, which are well suited to problems involving delayed rewards and large decision spaces. Rather than evaluating complete schedules exhaustively, the model learns to prioritize decisions that lead to higher overall planning performance, measured through composite indicators combining schedule duration and planning feasibility.

2.1.4 Use of Synthetic Project Instances

The use of synthetic project instances is a deliberate methodological choice driven by both practical and scientific considerations. Real-world early-stage schedules are often proprietary, incomplete, or biased toward conventional construction practices. Moreover, they rarely document alternative planning scenarios that were considered but not adopted.

Synthetic instances enable systematic control over key project characteristics, such as building size, number of work packages, construction modes, and cost–duration relationships. These instances are generated using parameter ranges informed by industry practices and literature, as summarized in Table 2. By maintaining consistency across experiments, synthetic instances support meaningful comparison of model performance under varying conditions.

3. Proposed AI-Based Planning Framework

This section presents the proposed artificial intelligence–based framework for early-stage construction planning that explicitly integrates alternative construction methods within aggregated schedules. The framework is designed to support decision-making during the Front-End Loading (FEL) phases, when project definition is limited but strategic flexibility remains high. The objective of the framework is not to produce a final execution schedule, but to generate and evaluate feasible early-stage planning alternatives that reflect different construction modes and sequencing strategies.

3.1 Conceptual Foundations and Planning Perspective

The proposed framework is grounded in the recognition that early-stage construction planning

differs fundamentally from detailed operational scheduling. At this stage, planners work with incomplete information, high uncertainty, and aggregated representations of work. Traditional optimization-based scheduling approaches, which rely on detailed activity networks and fixed resource constraints, are therefore poorly suited to early planning contexts.

To address this limitation, the framework conceptualizes early-stage planning as a sequential decision-making process, in which planning decisions are made incrementally as information becomes available. Each decision corresponds to the selection of a work package and an associated construction mode, such as conventional on-site construction or modular off-site construction. The cumulative sequence of decisions defines an aggregated project schedule. This perspective enables the use of learning-based methods that can improve decision quality over time through experience, rather than relying on exhaustive enumeration of all feasible planning alternatives. Importantly, it allows planners to explore how different construction methods influence early-stage schedule structure, overlap opportunities, and overall project duration.

3.1.1 Overall Architecture of the Framework

The overall architecture of the proposed framework is illustrated in Figure 3. The framework integrates three main components:

- a representation of the planning environment,

- a Monte Carlo Tree Search (MCTS) engine for exploring planning alternatives, and

- a neural network trained through reinforcement learning to guide the search process.
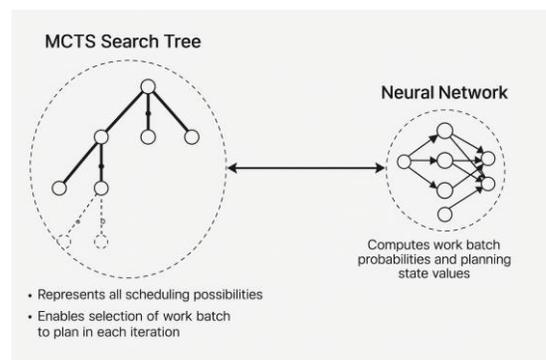

Figure 3. Overall Mode

3.1.2 Analogy with Game-Theoretic Decision Processes

A key conceptual contribution of the framework is the analogy between early-stage construction planning and single-player games with perfect information. In this analogy, the planner acts as a player making sequential moves in a deterministic environment,

where each move corresponds to a planning decision.

The objective of the game is to maximize a cumulative reward that reflects planning performance, such as minimizing overall project duration or improving schedule feasibility.

This analogy provides a theoretical foundation for applying MCTS and reinforcement learning techniques that have been successfully used in strategic games. Unlike competitive games, early-stage planning involves no adversary; instead, uncertainty arises from incomplete information and the combinatorial nature of planning alternatives. The game-theoretic framing allows the planning problem to be decomposed into manageable decision steps while retaining the ability to evaluate long-term consequences of early decisions. While MCTS provides a powerful mechanism for search, its effectiveness depends on the quality of state evaluation and action selection. To enhance these capabilities, the framework incorporates a neural network trained through reinforcement learning. The neural network serves two complementary functions: estimating the expected value of a planning state and predicting the probability distribution over feasible actions. The value estimate provides an approximation of how favorable a given partial schedule is in terms of expected final performance. This estimate enables the MCTS engine to prioritize branches of the search tree that are likely to lead to high-quality schedules.

The action probability estimate guides exploration by suggesting which work package and construction mode combinations are most promising at a given planning state. The integration of the neural network with MCTS significantly reduces the computational burden associated with search and accelerates learning. Rather than relying solely on random simulations, the framework leverages accumulated experience to inform future planning decisions. The learning process follows an iterative reinforcement learning paradigm. Initially, the neural network has limited knowledge of the planning environment and provides relatively uninformed guidance to the MCTS engine. As simulations are performed and planning outcomes are evaluated, data generated during search iterations are used to update the neural network parameters. This iterative process enables progressive improvement in planning performance. Over successive iterations, the framework learns to recognize patterns in planning decisions that lead to better schedules, such as effective sequencing of modular and on-site activities or favorable combinations of construction modes. The result is a planning tool that adapts to the characteristics of the problem rather than relying on fixed heuristics.

4. Results and Discussion

This section presents and interprets the experimental results obtained from applying the proposed AI-based

early-stage planning framework to the generated project instances. The discussion focuses on learning behavior, sensitivity to key parameters, comparative performance against baseline approaches, and the implications of the findings for early-stage construction planning involving alternative construction methods.

4.1 Validation of Learning Behavior

The first objective of the experimental analysis is to verify whether the proposed framework exhibits meaningful learning behavior over successive training iterations. Learning behavior is assessed by observing the evolution of the composite planning score as the model undergoes repeated cycles of Monte Carlo Tree Search exploration and neural network training.

Figure 4 illustrates the progression of the planning score as a function of training iterations. The results show a clear upward trend during the initial iterations, indicating that the model rapidly acquires useful information about effective planning decisions. This phase corresponds to the neural network learning basic relationships between planning states, construction modes, and schedule outcomes.
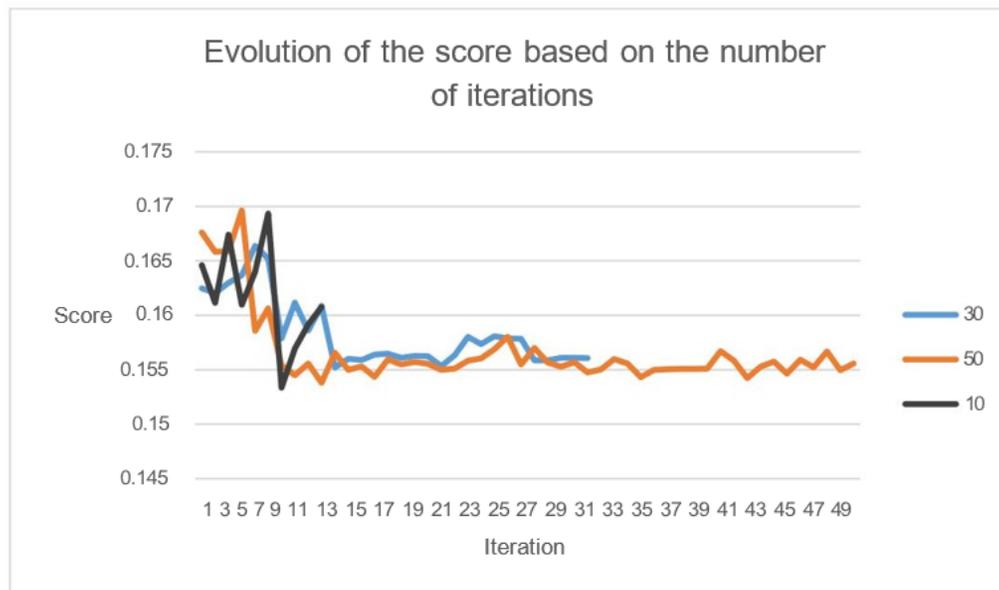

Figure 4 Evolution of the score as a function of the number of iterations

As training progresses, the rate of improvement gradually decreases, and the planning score stabilizes, suggesting convergence toward a locally optimal planning policy. This convergence behavior is consistent with reinforcement learning paradigms applied to large but finite decision spaces.

Importantly, the absence of oscillatory or erratic behavior in the score trajectory indicates that the learning process is stable and not dominated by stochastic noise.

From an early-stage planning perspective, this result is significant. It demonstrates that even at an aggregated level of detail, where information is limited and uncertainty is high, learning-based approaches can identify consistent planning strategies that outperform uninformed decision-making.

4.2 Influence of Monte Carlo Tree Search Parameters

The second set of experiments examines the sensitivity of the framework to key Monte Carlo Tree Search parameters, particularly the number of simulations performed at each decision step. These parameters directly affect the balance between solution quality and computational effort.

Figures 5 and 6 present the impact of varying the number of MCTS simulations on planning performance. As expected, increasing the number of simulations leads to improved planning scores, reflecting deeper exploration of the decision space and more accurate evaluation of planning alternatives. However, the marginal gains diminish beyond a certain threshold, indicating diminishing returns from additional simulations.
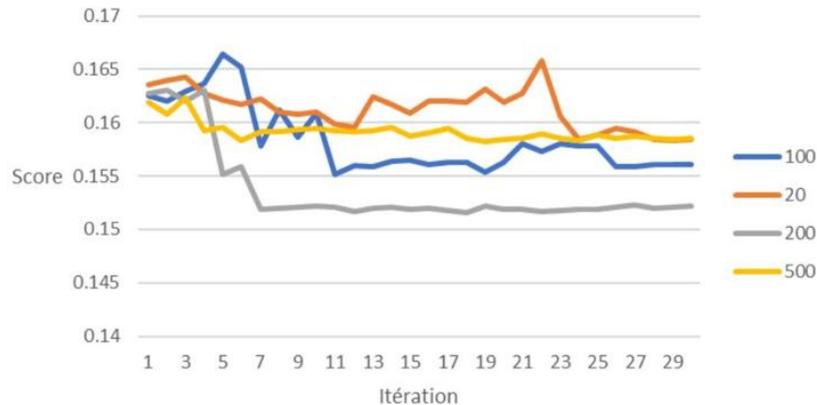
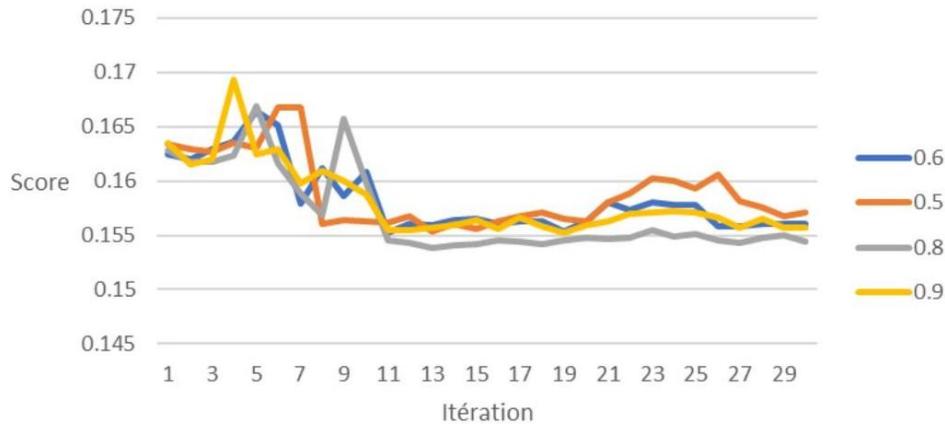Figure 5 Evolution of the score as a function of the variation in *numEps*

Figure 6 Evolution of the score according to the variation of the update threshold

This observation highlights a practical trade-off for early-stage planning applications. While deeper search improves decision quality, computational efficiency is a critical consideration during FEL phases, where planners may need to evaluate multiple scenarios rapidly. The results suggest that moderate simulation counts can deliver substantial performance improvements without incurring prohibitive computational costs

4.3 Sensitivity to Training Dataset Size

Another important factor influencing learning performance is the number of training examples generated during each iteration. Larger datasets provide richer information for neural network training but increase computation time.
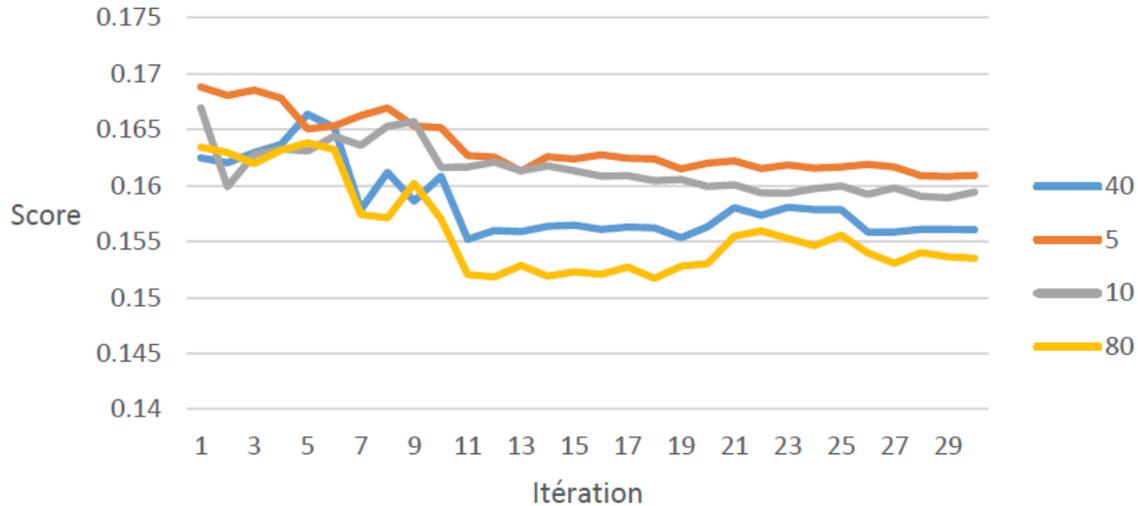
Figure 7 Evolution of the score as a function of the variation of *numMCTSSims*

Figure 7 illustrate the effect of training dataset size on convergence behavior. The results show that insufficient training data can lead to slow or unstable learning, as the neural network struggles to generalize from limited examples. Conversely, excessively large datasets provide diminishing performance improvements relative to their computational cost.

These findings underscore the importance of carefully selecting learning parameters to balance model accuracy and efficiency. For practical deployment in early-stage planning contexts, parameter tuning should consider both available computational resources and the desired level of planning accuracy.

However, the learning-based framework demonstrates superior performance in scenarios where modular construction introduces opportunities for parallelization and schedule overlap. In these cases, the framework identifies planning strategies that leverage off-site fabrication more effectively than fixed

heuristics. This capability is particularly valuable during early-stage planning, where the benefits of modular construction are not always intuitively apparent.

5. Conclusion

This paper presented an artificial intelligence–based framework for early-stage construction planning that explicitly incorporates alternative construction methods within aggregated project schedules. By combining hierarchical planning principles with reinforcement learning and Monte Carlo Tree Search, the proposed framework

addresses a critical gap in existing planning approaches, which typically assume a fixed construction method during the Front-End Loading phases. Through controlled experimentation using synthetic project instances, the study demonstrated that the framework exhibits stable learning behavior and consistently outperforms random planning strategies. The results further showed that learning-based planning can identify scheduling strategies that effectively leverage modular construction when planning conditions are favorable, while also highlighting scenarios in which conventional construction remains competitive. The primary contribution of this work lies in demonstrating the feasibility and potential value of AI-assisted planning tools for early-stage construction decision-making. Rather than prescribing a single optimal solution, the framework enables systematic exploration of planning alternatives and supports informed evaluation of construction methods under uncertainty.

As the construction industry continues to evolve toward greater technological integration and alternative production methods, decision-support tools capable of addressing early-stage planning complexity will become increasingly important. This study provides a foundation for future research and development in this area and contributes to the broader discourse on the role of artificial intelligence in construction technology and management.

REFRENCES

[1]   AACE International. (2010). ACE International recommended practice No. 27R-03 Schedule classification system. :

[2]   Alcaraz, J., Maroto, C., & Ruiz, R. (2003). Solving the multi-mode resource-constrained project scheduling problem with genetic algorithms. Journal of the Operational Research Society, 54(6), 614-626.

[3]   Alpaydin, E. (2020). Introduction to machine learning: MIT press.

[4]   Bertram, N., Fuchs, S., Mischke, J., Palter, R., Strube, G., & Woetzel, J. (2019). Modular construction: From projects to products. McKinsey & Company: Capital Projects & Infrastructure, 1-34.

[5]   Bikitsha, L., & Haupt, T. (2011). Impact of prefabrication on construction site health and safety: Perceptions of designers and contractors.

[6]   Bouleimen, K., & Lecocq, H. (2003). A new efficient simulated annealing algorithm for the resource-constrained project scheduling problem and its multiple mode version. European journal of operational research, 149(2), 268-281.

[7]   Burkov, A. (2019). The hundred-page machine learning book (vol. 1): Andriy Burkov Canada. CCQ. (2017). Annual Statistics.

[8]   CEFRIO. (2011). Improving the efficiency and productivity of the construction sector through information technologies.

[9]   Cherkaoui, K. (2017). Tactical planning of large engineering and construction projects. (École Polytechnique de Montréal).

[10]   Choi, JO, Chen, XB, & Kim, TW (2019). Opportunities and challenges of modular methods in dense urban environments.

[11] International Journal of Construction Management.
doi:10.1080/15623599.2017.1382093

[12] Cottrell, W.D. (1999). Simplified program evaluation and review technique (PERT). Journal of Construction Engineering and Management, 125(1), 16-22.

[13] Coulom, R. (2006). Efficient selectivity and backup operators in Monte-Carlo tree search.

[14] Paper presented at the International Conference on Computers and Games (pp. 72-83).

[15] De Boer, R. (1998). Resource-constrained multi-project management. (PhD thesis, University of Twente, The Netherlands).

[16] Elmaghraby, S.E. (1964). An algebra for the analysis of generalized activity networks.

[17] Management Science, 10(3), 494-514.

[18] Gans, D., Corbusier, L., & Plattus, A. (2006). The Le Corbusier Guide: Princeton Architectural Press.

[19] Gibb, A.G. (1999). Off-site manufacturing: prefabrication, pre-assembly and modularization: John Wiley & Sons.

[20] Gibson Jr, G., Kaczmarowski, J., & Lore Jr, H. (1995). Preproject-planning process for capital facilities. Journal of construction engineering and management, 121(3), 312-318.

[21] Guo, J.-X., Hu, C.-M., & Bao, R. (2019). Predicting the duration of a general contracting industrial project based on the residual modified model. KSCE Journal of Civil Engineering, 23(8), 3275-3284.

[22] Hammad, A.W.A., Akbarnezhad, A., Rey, D., & Grzybowska, H. (2017). Decision support system for modular construction scheduling. from Drawn

[23] Hwang, B.G., Shan, M., & Looi, K.Y. (2018). Key constraints and mitigation strategies for prefabricated prefinished volumetric construction. Journal of Cleaner Production. doi:10.1016/j.jclepro.2018.02.136

[24] Leon, GP d. (2011). Scheduling a Project at Different Levels.

[25] Lepelley, D., Paul, M., & Smaoui, H. (2013). Introduction to game theory (1): non-games cooperatives.

[26] Li, L., Li, Z., Wu, G., & Li, X. (2018). Critical success factors for project planning and control in prefabrication housing production: A China study. Sustainability (Switzerland). doi:10.3390/su10030836