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# A Simulation-based Genetic Algorithm Schedule Optimization Method for Bridge Construction

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**Abstract**

Off-site construction has become widely acknowledged for its advantages, such as saving time, enabling faster assembly, and being cost-efficient. The sector's rapid growth has driven the demand for more advanced and effective methods of construction scheduling. Construction scheduling is naturally complicated due to the numerous constraints it involves, including those connected to workforce and resource availability. Conventional approaches, like the Critical Path Method (CPM), fail to account for multiple constraints, which limits their effectiveness in practical project scenarios. This research presents a simulation-based Genetic Algorithm (S-GA) approach to develop optimal construction schedules while accounting for constraints in labour and resources. Reducing the total project duration is the objective of proposed method. The proposed S-GA framework enhances the ability to manage scheduling across all construction phases. A real-world case which contains a prefabricated bridge with 6 spans was conducted to assess the method. For comparison, traditional methods and the evolution algorithm (EA) were adopted, and the findings indicated that S-GA not only produced superior construction schedules but also operated with less computational time. Proposed S-GA generated the best construction schedule with shortest project duration within least computational time. As a result, the proposed approach offers an advanced scheduling method that is applicable to real-world construction projects. Project managers could use proposed method to make plans for their construction projects.

# 1 Introduction

Automated construction scheduling offers project managers support in effectively handling labor, equipment, timelines, costs, and other key project aspects. This approach serves as a decision-making tool, pinpointing necessary tasks and establishing both the timing and method for their execution. According to Ding et al. (2023), automated scheduling in construction aligns with the Resource Constrained Project Scheduling Problem (RCPSP) framework. Typically, a construction schedule divides the entire workload into a hierarchy of work breakdown structures and specific tasks, which are then assigned to corresponding subcontractors (Bai et al., 2009). Construction planning not only includes scheduling but also integrates various planning functions, such as material handling, site layout arrangement, equipment mobilization, and general site logistics. A skilled scheduler with substantial prior experience is required to carefully manage all on-site information to complete a construction schedule, although this task can demand considerable time and effort (Amer et al., 2021).

A range of methods and theories have been formulated to support construction scheduling. Construction project scheduling, as a decision-making process, seeks to determine the best sequence of activities and allocate diverse resources to tasks while navigating a range of constraints (Zhou et al., 2013). The Critical Path Method (CPM) is one of the most widely applied techniques (Koskela, 2000), breaking down projects into distinct work breakdown structures (WBS). It requires manual work to reorder WBS for better scheduling. Alamode and Plaza (1994) introduced case-based reasoning (CBR) techniques, where past cases are used as references to solve new scheduling challenges. Although these techniques rely heavily on prior experiences, they often lack the flexibility necessary for managing a range of construction projects. Heuristic methods and Genetic Algorithms (GA) offer a different approach to scheduling by framing it as an optimization problem, where specific conditions limit one or more objectives to be achieved (Ahmed et al., 2021; Bettemir & Sonmez, 2015; Erdal & Kanit, 2021; Lin et al., 2022; Yuan et al., 2021). Christodoulou (2010) introduced an agent-based ant colony optimization (ACO) approach to address resource limitations in construction projects. Cheng et al. (2016) applied a symbiotic organisms search (SOS) method for tackling multiple project scheduling challenges. El-Rayes and Jun (2009) used a genetic algorithm to minimize unwanted resource fluctuations and reduce idle time. Ma et al. (2021) examined the construction order for various PC and CiS components and introduced a multi-objective discrete symbiotic organisms search method aimed at reducing the project makespan. Liu et al. (2021) created a heuristic-driven GA designed to assist construction managers in reaching target profits and enhancing project oversight. Despite their strengths, these methods generally struggle with adaptability to various construction. Organizing tasks in real-world construction projects presents challenges, as multiple constraints—such as labor, resources, and construction techniques—determine the sequence in which activities can proceed.

Combining simulation methods with GA (S-GA) to solve schedule optimization problems offers several advantages. First, simulation provides a realistic model of the complex, dynamic interactions within scheduling systems, capturing variability in factors such as resource availability, processing times, and demand fluctuations. This realism enhances the quality of solutions, as they are tested in conditions that closely mimic actual operations. Meanwhile, GAs offer a robust search mechanism capable of exploring a wide solution space by using evolutionary principles of selection, crossover, and mutation. The combination allows for effective exploration and exploitation of scheduling options, as GAs can efficiently search through potential solutions while the simulation evaluates each solution's performance in a realistic environment. This hybrid approach is especially beneficial for complex scheduling problems, where traditional optimization methods may struggle due to non-linearity or high-dimensionality. In summary, integrating simulation with GA enhances solution robustness, adaptability, and practical applicability in real-world scheduling environments.

# 2 Method

## 2.1 Problem Definition

The construction process for a prefabricated bridge is organized into different structural categories, including the superstructure and the substructure. Figure 1presents a simplified WBS of a bridge, divided into two main sections: the superstructure and the substructure. The superstructure includes precast girders and joints, with 3 and 4 sub-activities, respectively. The substructure comprises precast pier caps, precast piers, pile caps, and piles, with each component involving 4, 4, 6, and 7 sub-activities, respectively. This hierarchical structure helps to organize and manage the construction tasks involved in building the bridge.

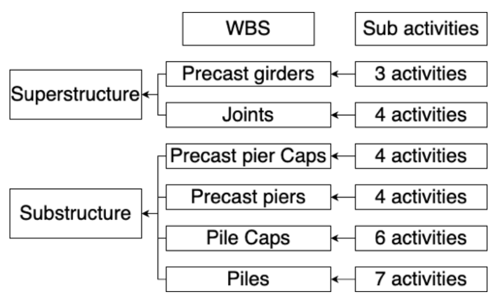


**Figure 1: Construction activities representation**

The proposed optimization focuses on minimizing the total duration of the construction project to achieve earlier completion than scheduled (Equation 1). This approach operates within the boundaries of resource limitations and task order dependencies (Equations 2 to 4).

Objective:

$$minimize\ D_{project} \tag{1}$$

Subject to:

$$\sum R_t(a_{i,j,k}) \leq R \tag{2}$$

$$t_{k+1} - t_k \geq d_k \tag{3}$$

$$N_c = 0 \tag{4}$$

Where $D_{project}$ denotes the total duration of the project; $R_t(a)$ denotes the resources required for activity $a$; $R$ represents the resources for each operation; $t_k$ denotes the starting time of the $k^{th}$ activity; $d_k$ represents the duration of $k^{th}$ activity; $N_c$ denotes the number of constraint violations.

## 2.2 Environment Development

This flowchart (Figure 2) represents a simulation process for generating and evaluating a genetic algorithm chromosome in a scheduling optimization context. The process begins with the initialization of a new chromosome, which represents a potential solution by encoding a sequence of activities to be executed. Structure groups within the chromosome are identified, and activities are selected and looped through, where each activity's crew and equipment requirements are allocated. Activities are then added to an activity buffer and executed, with their duration monitored and incremented. For each activity, the system checks if its duration has been completed; once an activity ends, the allocated resources (crew and equipment) are released. Completed activities are recorded along with essential information such as structure group ID and segment ID. After each activity completion, the simulation updates three main states: the resource usage state (Rt), which tracks resource availability and utilization; the structure state (Gt), which monitors the progress of each structure group; and the ongoing activity state (Pt), which reflects the progression of activities. This looping process continues until all activities within the chromosome have been executed. By simulating the execution and resource allocation for each chromosome, this process allows the GA to evaluate and optimize scheduling performance, promoting efficient resource usage and timely completion of tasks.

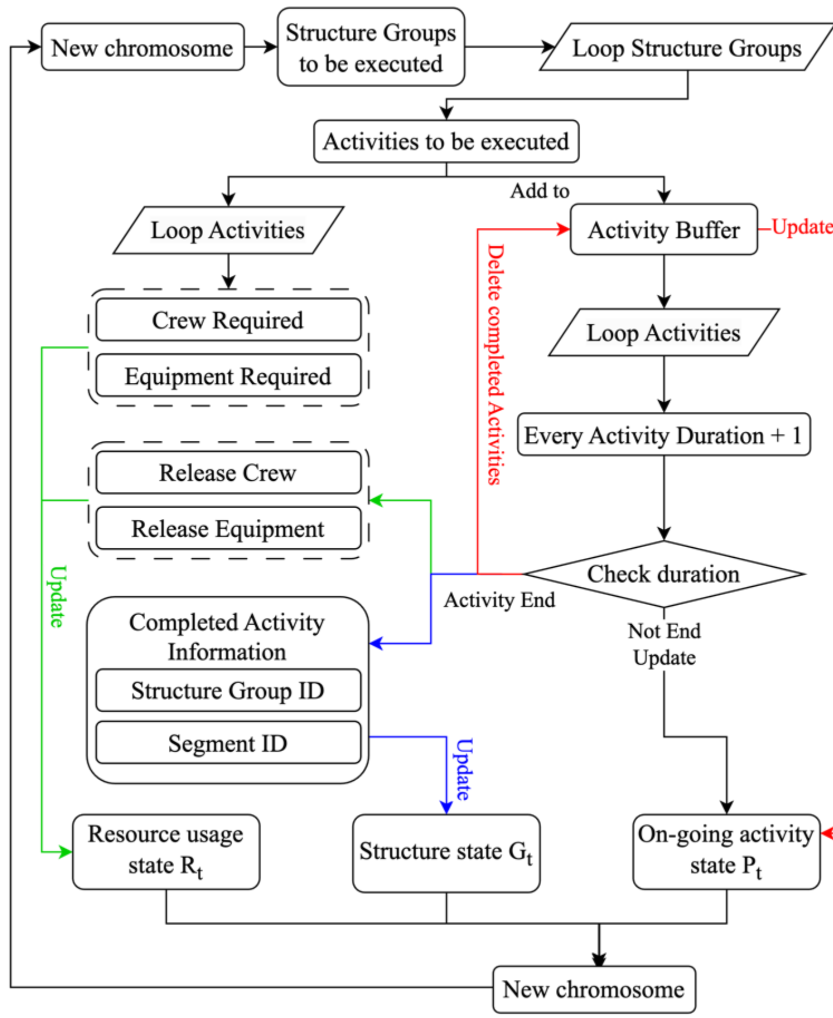


**Figure 2: Simulation environment**

## 2.3 GA Design

Due to the diverse cases and assumptions in existing studies, current scheduling algorithms are not directly applicable to this research. To address this, a new approach is developed that integrates a simulation-based GA. This approach merges a modified S-GA with a simulation model, where each gene represents a specific construction activities, and the gene sequence determines the order in which these activities are arranged. The model tackles construction scheduling challenges by using the simulation environment as a decoder for GA chromosomes, ensuring optimal utilization of resources and labours. For generating the initial population, the algorithm employs regret-based biased random sampling (RBRS) alongside a serial schedule generation scheme (SSGS). The evolutionary process involves selecting the best individuals, performing two-point crossover, swapping genes (swap mutation), and applying a mutation method with a probability that gradually changes over time (parameters detailed in Table 1). The study's results are compared with a conventional scheduling method, namely Critical Path Method (CPM) and an artificial intelligence method, namely Q-Learning. The GA configurations are displayed in Table 1.

**Table 1: S-GA parameters**

| | |
|---|---|
| Population Size | 200 |
| Crossover Rate | 0.8 |
| Mutation Rate | 0.2 |
| TOP | 0.15 |

## 2.4 Case Study

This study focuses on a prefabricated construction project located on Longdong Avenue in Shanghai, China. In prefabricated bridge construction, the majority of above-ground components are cast off-site. The on-site construction work breakdown structure (WBS) includes tasks such as pile construction and platform casting. Following these steps, precast structures—such as columns, cover beams, and girders—are assembled sequentially. Multiple crews will handle various tasks with different equipment types. For instance, a dedicated lifting crew, equipped with a walking crane, will manage activities like lifting piles, piers, pier caps, and girders. In this study, the construction process is broken down into 28 distinct activities, involving 12 crews and 4 types of equipment. Segment classifications are based on bridge structures and construction methods, including: 1) piles, 2) pile caps, 3) piers, 4) pier caps, 5) girders, and 6) seams. The 9-span bridge consists of 10 sets each of piles, pile caps, piers, and pier caps, along with 9 sets of girders and seams. Each segment encompasses various activities, totalling 273 sub-activities. There are 4 lifting and hammer & piling crews, while other crews number 2 each. The equipment includes 4 units of mobile cranes and hammers, with 2 units each of other equipment.

# 3 Results

The result of proposed method is compared with other algorisms and displayed in Table 2. The manual schedule is derived from the initial master plan, which sets a 45-day completion target for the project. With a standard workday of 8 hours, this timeframe equates to a total construction period of 360 hours. The manual outcome is then modified with CPM and the total duration is shortened to 336h. Q-learning performs better than traditional methods with better schedule duration. GA generates the best outcome with 310h. From the perspective of algorithm running time, Q-learning runs for over 500s and GA only costs 135.1s.

Table 2: Scheduling results

| Method | Manual | CPM + manual | Q-Learning | S-GA (150 iters) |
|---|---|---|---|---|
| Duration (h) | 360 | 336 | 321 | 310 |
| CPU times | / | / | 518.7s | 135.1s |

# 4 Discussion

The results summarized in Table 2 highlight the effectiveness of various scheduling methods, including a S-GA, Q-learning, and conventional manual and CPM-modified schedules. Each method's performance was assessed based on both the project completion time and the computational efficiency of the algorithm. The manual schedule, set against a 45-day completion target with an equivalent work period of 360 hours, serves as a baseline. When adjusted with CPM, the project duration is reduced to 336 hours. This improvement shows that the CPM method can enhance scheduling efficiency to some degree by identifying and optimizing the critical path, though its capability remains limited by the static nature of the initial master plan.

In comparison, Q-learning demonstrates a further improvement over CPM, achieving a project duration of 321 hours. As a reinforcement learning technique, Q-learning offers the advantage of learning optimal actions over time through interaction with the environment. However, its prolonged runtime of 518.7 seconds indicates a significant computational cost, which could hinder its applicability in scenarios requiring rapid scheduling adjustments or where computational resources are limited. The S-GA method outperforms all other approaches, reducing the project duration to 310 hours and achieving the best balance of efficiency and effectiveness among the tested methods. S-GA’s capacity to explore a wide range of possible solutions through iterative optimization allows it to find a near-optimal solution with only 150 iterations. Notably, S-GA achieves this result in a significantly shorter time (135.1 seconds) than Q-learning, suggesting that S-GA is more computationally efficient while also producing the most favorable project schedule.

This study exists some limitations. First, the proposed method only considers shortening the duration as the only objective. All the algorithm features are designed for single objective purpose. Secondly, proposed S-GA architecture is very simple, larger case studies is still required to test its effectiveness. Thirdly, the method considers the construction process as statistic process without unexpected disruptions.

# 5 Conclusion

The comparison of scheduling methods reveals that the proposed S-GA significantly outperforms traditional scheduling techniques and Q-learning in both project duration and computational efficiency. The manual schedule and CPM-modified plan provide a foundational timeline, but they lack the adaptability and optimization capacity necessary to achieve the best outcomes. Q-learning, while effective in reducing project time compared to traditional methods, comes with a high computational cost, making it less practical for environments requiring quick adjustments. In contrast, S-GA achieves the shortest project duration of 310 hours with a computation time of only 135.1 seconds, showcasing its ability to optimize effectively within a limited runtime. This combination of fast processing and superior schedule reduction underscores the suitability of S-GA for complex scheduling tasks where both time efficiency and resource allocation are crucial. Consequently, S-GA emerges as the preferred method, providing a balanced solution for scheduling in dynamic and time-sensitive project environments.

Building on the promising results of the S-GA in optimizing project scheduling, future research could explore hybrid approaches that combine S-GA with other machine learning techniques, such as Q-learning or neural networks, to enhance both scheduling accuracy and adaptability. Hybrid models may harness the exploration capacity of reinforcement learning to guide S-GA toward more diverse solutions, potentially improving performance in highly dynamic environments where project parameters frequently change. Additionally, future work could focus on optimizing the S-GA parameters and exploring real-time scheduling adjustments in response to project changes. Integrating real-time data inputs and developing adaptive scheduling mechanisms could enable a more responsive model that recalibrates the schedule in real-time as project conditions evolve. Lastly, the application of these methods to larger, multi-phase projects could test scalability and reveal insights into S-GA's efficiency across complex, resource-intensive scheduling scenarios.

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