Optimizing High-Mix Low-Volume Prefabrication Scheduling: A Hybrid Simulation-Based Optimization Framework for Dual-Resource Constrained Systems

Nima Moghimi[1*], Sahar H. Shamaee[2], Qipei Mei[3], Vicente A. Gonzalez[4], Farook Hamzeh[5]

[1*]Corresponding Author, Ph.D. Student, Department of Civil and Environmental Engineering, University of Alberta
[2]Graduate Research Assistant, Department of Civil and Environmental Engineering, University of Alberta, Canada
[3]Assistant Professor, Department of Civil and Environmental Engineering, University of Alberta, Canada
[4] Hal Kvisle Professor and Tier 1 Canada Research Chair in Digital Lean Construction, Infrastructure Human Tech (IHT) Lab, Strategic Projects Insight Centre in Engineering (SPICE), Department of Civil and Environmental Engineering, University of Alberta, Canada
[5]Professor, Department of Civil and Environmental Engineering, University of Alberta, Canada
nmoghimi@ualberta.ca, hamedsha@ualberta.ca, qipei@ualberta.ca, vagonzal@ualberta.ca, hamzeh@ualberta.ca

Abstract

The shift toward Off-Site Construction (OSC) is constrained by the complexity of High-Mix, Low-Volume (HMLV) production, where geometric variability and reliance on manual labour create highly stochastic processing times. In these Dual-Resource Constrained (DRC) systems, workers act as flexible assets who move across stations to relieve bottlenecks—behaviour that static scheduling methods cannot capture. To address this, this study presents a Hybrid Simulation-Based Optimization (HSBO) framework that combines a Genetic Algorithm (GA) with a Hybrid Discrete Event/Agent-Based Simulation (DES/ABS) model. The simulation captures workforce-driven production dynamics, including cross-station assistance and bottleneck relief, enabling schedule evaluation under stochastic operating conditions. The framework was applied to a stair prefabrication line in Edmonton, Canada, to optimize the balance between Just-In-Time (JIT) delivery and internal flow efficiency. Results show that the optimized schedule reduced the external finished-goods buffer by 66% (from 3 days to 1 day), while increasing average internal lead time by approximately 20% (from 17 to 20.5 hours). These findings highlight the trade-off between delivery precision and internal flow efficiency in storage-constrained prefabrication systems and demonstrate the value of HSBO as a decision-support approach for dynamic scheduling in DRC environments.

Keywords – Off-Site Construction (OSC); Simulation-Based Optimization; Dual-Resource Constrained Scheduling; Hybrid Agent-Based Simulation; Just-In-Time (JIT) Production

1 Introduction

The construction industry is increasingly shifting toward off-site construction (OSC) and prefabrication to mitigate traditional inefficiencies [1]. Yet, unlike the high-volume, low-mix environments of automotive manufacturing [2], construction prefabrication operates under High-Mix, Low-Volume (HMLV) conditions where customized components—such as precast stairs or wall panels—produce substantial variability in processing times and resource allocation [3]. This variability intensifies logistical challenges, particularly on urban sites with limited storage, making precise Just-In-Time (JIT) delivery essential to avoid disrupting the critical path or causing site congestion [4,5]. Compounding this complexity is the Dual-Resource Constrained (DRC) nature of prefabrication, where productivity depends not only on machinery but also on a flexible, multi-skilled workforce capable of moving between stations to relieve bottlenecks [6–8]. While this flexibility can enhance efficiency, it also renders static scheduling tools (e.g., CPM, Gantt charts) ineffective, as they assume fixed resource allocations and cannot capture stochastic human performance or dynamic behaviours such as multi-station collaboration [9]. Consequently, static schedules quickly diverge from real shop-floor conditions, leading to “shop floor nervousness,” widening plan–reality gaps, and reinforcing inefficiencies that deterministic models cannot resolve [6].

The optimization of production scheduling has been widely explored in manufacturing, with foundational work centered on the Job Shop Scheduling Problem (JSSP) and its Flexible variant (FJSP) [10]. Approaches in this domain range from exact methods such as Mixed-

Integer Linear Programming (MILP), which guarantee optimality but struggle to scale, to metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), which efficiently navigate the combinatorial complexity of large production systems [11]. Although these algorithms excel at improving machine uptime and minimizing makespan in standardized, deterministic environments [12], they typically assume resources—both machines and workers—have fixed availability and constant performance [13,14]. Such static assumptions are incompatible with Dual-Resource Constrained (DRC) settings like construction prefabrication, where output depends equally on equipment and a flexible, multi-skilled workforce capable of shifting stations, assisting bottlenecks, and experiencing fatigue [15]. These dynamic behaviours—central in High-Mix, Low-Volume (HMLV) production—are largely absent from traditional JSSP/FJSP models [11,13], leaving a notable research gap in methods that merge the prescriptive strength of metaheuristic optimization with the behavioural realism needed to capture human-driven crew interactions in complex OSC environments.

To address this gap, following a Design-Science Research approach, this study introduces a Hybrid Simulation-Based Optimization (HSBO) scheduling artifact that couples an evolutionary search algorithm with a simulation-based behavioural model of workforce-driven production dynamics. At its core is a Hybrid Discrete Event/Agent-Based Simulation (DES/ABS), in which workers are represented as autonomous agents capable of collaboration and fatigue-driven performance changes [16,17]. This hybrid simulation serves as the fitness evaluator for a Genetic Algorithm (GA), enabling candidate schedules to be assessed based on emergent crew behaviours rather than nominal processing times. By iteratively exploring how alternative timetables influence system performance, the framework leverages worker flexibility to identify lookahead schedules that improve JIT adherence while controlling internal lead-time growth. The approach is validated using a stair prefabrication line at a modular construction facility in Edmonton, Canada, where a labour-intensive, HMLV process highlights the operational value of flexible crew coordination under real-world variability. Finally, the paper outlines a path toward integrating Reinforcement Learning to learn adaptive, policy-based scheduling—effectively a “digital scheduler” capable of generating plans across varying lookahead scenarios [18,19].

2 Methodology

This study adopts a Design-Science Research (DSR) methodology [20], which focuses on designing and rigorously evaluating prescriptive artifacts that address real operational problems. In this paper, the artifact is the proposed Hybrid Simulation-Based Optimization (HSBO) scheduling framework for Dual-Resource Constrained (DRC) prefabrication. This simulation-based optimization paradigm—where candidate decisions are iteratively evaluated through stochastic simulation and refined toward improved performance—has also been adopted in other uncertainty-driven engineering decision contexts [21,22]. Following the DSR cycle, the study proceeds through: (i) problem identification, formalizing the planning–execution gap in HMLV DRC environments; (ii) artifact design and development, coupling a Genetic Algorithm with a hybrid DES/ABS simulation evaluator to test candidate schedules under stochastic operating conditions; and (iii) demonstration and evaluation, assessing the artifact through the industrial case study and performance results reported in the subsequent section(s).

2.1 Artifact Design: HSBO Framework Overview

This research proposes an HSBO framework (Figure 1) designed to solve the dynamic scheduling problem in Dual-Resource Constrained (DRC) prefabrication. The framework utilizes a nested optimization architecture, where a Genetic Algorithm (GA) serves as the global optimizer for determining production timetables, and a Hybrid Discrete Event/Agent-Based Simulation (DES/ABS) serves as the fitness evaluation engine to test these timetables under stochastic operating conditions [23]. The simulation is implemented as a digital-twin-inspired virtual representation (digital shadow) of the physical production system that enables validation of schedules before execution, accounting for real-world variability and emergent workforce dynamics [24,25]. The artifact is demonstrated and evaluated in the subsequent case-study section by comparing its performance against baseline scheduling approaches under identical production scenarios. The artifact outputs a planned start-time timetable for projects in the lookahead window, which is then stress-tested in simulation before deployment.

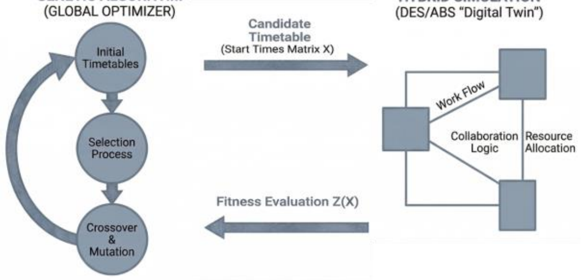

Figure 1: Schematic of the proposed HSBO framework, coupling a Genetic Algorithm with a

Hybrid DES/ABS model to generate and evaluate robust production timetables.

2.2 Problem Definition: Lookahead Scheduling

The scheduling problem is defined over a finite Lookahead Window—a bounded planning horizon representing the immediate, actionable production schedule for the factory. Specifically, let W denote the lookahead window duration (e.g., $W = 2$ weeks), and let P_{window} be the subset of projects (e.g., modular components, prefabricated stairs) released for production within this horizon. The production environment consists of a set of workstations K, where processing is constrained by both machinery availability and the flexible allocation of a multi-skilled workforce.

The objective is to assign a specific Planned Start Date ($ST_{p,k}$) for every project $p \in P_{window}$ at the initial workstation of its required assembly sequence. The scheduling problem is subject to three critical constraints. (1) Technological Precedence ensures that a downstream operation cannot commence until its upstream predecessor is complete, maintaining the assembly logic of complex prefabricated components. (2) Resource Availability dictates that a task cannot start if the required workstation or crew agents are occupied by other work. (3) Shift Constraints require that all processing must occur within valid factory shift hours and operational calendars.

Crucially, while the optimization algorithm generates Planned Start Times (ST_p), the Actual Start Times (S'_p) are stochastic, dependent on the emergent behavior and autonomous collaboration decisions of the workforce. The simulation bridges this planning-reality gap by predicting actual completion times under dynamic conditions.

2.3 Hybrid DES/ABS Simulation Model

To capture the gap between static planning and operational reality, the framework employs a Hybrid Discrete Event/Agent-Based Simulation approach. The simulation serves as a digital-twin-inspired virtual testbed, executing candidate schedules under realistic conditions to evaluate feasibility and performance.

2.3.1 Agent-Based Collaboration Logic

Unlike traditional scheduling models that assume fixed, immutable resource capacities, this framework models workers as autonomous agents capable of cross-training and dynamic collaboration [26]. Agents continuously monitor system state (e.g., queue lengths, throughput rates, bottleneck intensity) and autonomously traverse between compatible workstations to alleviate production constraints.

The simulation implements two primary behavioral rules governing crew agent decision-making:

Downstream Pull: An agent at a downstream station j may autonomously move upstream to station i to provide assistance if the feed rate drops below a critical threshold, preventing starvation (idle time) at downstream workstations.

$$\text{Count}_{\text{completed}}(j) > \text{Count}_{\text{completed}}(i) + \delta_{\text{pull}} \quad 1$$

Upstream Push: An agent at an upstream station i may autonomously move downstream to station j to provide assistance if the intermediate buffer exceeds capacity, preventing congestion and excessive Work-In-Process (WIP) accumulation.

$$\text{QueueLength}(j) > \delta_{\text{push}} \quad 2$$

These rules are continuously evaluated at each discrete event during simulation, enabling emergent, dynamic crew reallocation without explicit pre-planning.

2.3.2 Dynamic Processing Rates Under Collaboration

The simulation explicitly models the non-linear productivity impact of worker collaboration. When a workstation k operates with a primary crew and N_{helpers} assisting agents, the effective processing speed $v_{\text{eff}}(t)$ is formulated as:

$$v_{\text{eff}}(t) = v_{\text{base}} \times \left(1 + \eta \cdot N_{\text{helpers}}\right) \quad 3$$

where v_{base} is the baseline processing rate of the primary crew working alone, η represents the Collaboration Efficiency Factor (e.g., $\eta = 0.5$), accounting for coordination overhead and diminishing returns, N_{helpers} is the number of agents simultaneously assisting at the station.

The parameter $\eta < 1$ reflects realistic crew dynamics: adding additional workers accelerates processing but with sublinear productivity gains due to coordination constraints and task indivisibility [27].

2.4 Optimization Model Formulation

2.4.1 Decision Variables

The decision variable X is a continuous vector of time values representing the Planned Start Time for each project in the current lookahead window:

$$\mathrm{X} = \left\{ ST_p \mid p \in P_{window} \right\} \quad 4$$

It is to be noted that the simulation logic determines the Actual Start Time (S'_p) as:

$$S'_p = \max\left(ST_p, \text{ResourceAvailability}_p\right) \quad 5$$

The schedule is penalized if the planned time ST_p is infeasible (i.e., if $S'_p > ST_p$), reflecting poor schedule quality.

2.4.2 Objective Function: Multi-Criteria JIT-Aware Fitness

The fitness of a candidate schedule is evaluated by executing a complete simulation run, which returns the actual Completion Time and Start Time for each project under dynamic workforce conditions. The objective function minimizes a weighted sum of normalized Earliness, Lateness, and Maximum Lead Time, ensuring that objectives with different magnitudes do not dominate the optimization process:

$$MinimizeZ(X) = \frac{\alpha}{T_d}\sum_{i=1}^{n} E_i + \frac{\beta}{T_d}\sum_{i=1}^{n} L_i + \gamma\frac{C_{max}}{N_{max}} \quad 6$$

where Earliness (E_i) penalizes early completion of project i to minimize site storage costs and outdoor exposure risks. Lateness (L_i) penalizes delays beyond the target due date to protect the critical path and maintain schedule adherence. Maximum Lead Time (C_{max}) minimizes the longest project cycle time, preventing excessive Work-In-Process (WIP) accumulation within the factory.

Normalization Factors scale raw time values into dimensionless, comparable ranges: T_d represents the maximum allowable JIT deviation (e.g., the lookahead window duration), while N_{max} represents the maximum theoretical project cycle time. This ensures that JIT and flow efficiency terms are commensurable and neither dominates due to scale differences.

Weighting Coefficients (α, β, γ) are user-defined values representing managerial priority. Typical values may include equal weight to earliness and lateness, with adjustments based on whether WIP or JIT precision is prioritized.

This multi-criteria formulation enables the GA to discover schedules that are both temporally precise (meeting JIT targets) and operationally efficient (minimizing internal WIP). The objective structure is flexible: additional metrics such as makespan, resource utilization, or crew overtime can be incorporated or substituted based on facility-specific constraints and priorities.

3 Framework Evaluation: A Case Study

3.1 Case Study Overview

This section demonstrates the framework's implementation in a prefabricated timber factory in Edmonton, Alberta. The Stair Assembly Station is used as the testbed, representing a High-Mix, Low-Volume (HMLV) system with high customization, variable processing times, and labor-intensive work Figure 2. The station operates as a Dual-Resource Constrained (DRC) flexible flow shop with four sequential phases: Stringer Construction (S), Landing Fabrication (L), Frame Building (F), and Final Cage Assembly (C). The workforce is organized into two semi-coupled teams—Upstream (S–L) and Downstream (F–C)—with the upstream team typically working one day ahead to sustain flow. When one team becomes ahead or idle, crews may move to assist the other ("partitioned flexibility"), requiring agent-based modeling to capture feasibility and throughput beyond rigid flow-shop assumptions.

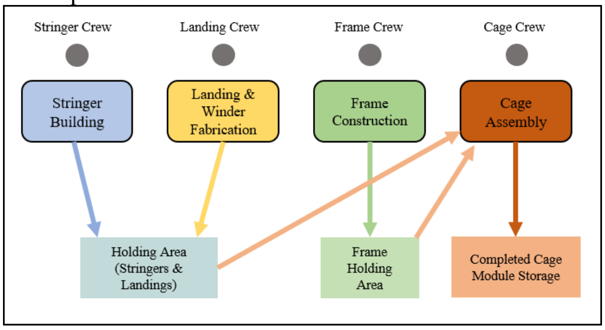

Figure 2: Schematic layout of the stair station.

3.2 Simulation Model Development

To capture the stochastic dynamics of the stair line, a Hybrid Discrete Event/Agent-Based Simulation (DES/ABS) model was developed in Python using the SimPy library. This hybrid approach enables the coupling of material flow logic (DES) with autonomous crew decision-making (ABS).

3.2.1 Data Collection and Parameterization

Historical production data were collected to characterize the variability of manual execution times. Probability distributions were fitted to the duration data for all four tasks (S, L, F, C). To ensure modeling accuracy and avoid double-counting of collaboration effects, only tasks completed independently by single crews were used for fitting; collaboration effects (which reduce duration) were excluded from the baseline distributions and instead generated dynamically by the simulation's agent logic.

3.2.2 System Constraints and Operational Logic

The simulation enforces system constraints observed during field studies. First, Resource Exclusivity ensures that each crew can process only one project at any given time. Second, Technological Precedence and Partial Dependencies are modeled to capture critical operational nuances where downstream phases may overlap with upstream work based on specific progress thresholds. Specifically, the Cage Assembly phase is permitted to commence once the upstream Framing phase reaches approximately 50% completion, and the installation of stringers and landings typically begins once the Cage assembly reaches approximately 70% completion. This partial overlap mechanism reflects the flexibility and adaptive nature of the modular construction workflow, where work does not strictly follow finish-to-start dependencies but rather progresses dynamically based on material readiness and crew availability.

These partial-dependency rules were explicitly incorporated into the model to capture the realistic overlap between production phases. By allowing downstream tasks to begin before upstream completion, the model prevents the introduction of artificial blocking effects that would otherwise skew the simulation results and underestimate true system capacity.

3.2.3 Agent-Based Behavioural Logic

The simulation implements autonomous "collaboration" rules governing crew decisions. When the Downstream Team is idle or ahead of schedule, agents move upstream to assist the Upstream Team, and vice-versa. The model logic was validated through walkthroughs with production crews to ensure face validity, particularly regarding the fidelity of these autonomous collaboration behaviors.

3.3 Optimization Specification

The optimization problem focuses on generating an optimal production timetable for a representative Lookahead Window of two weeks. A dataset of 25 unique stair projects, sourced from the plant's operational backlog, served as the experimental sample.

3.3.1 Problem Formulation

The objective is to determine the optimal Planned Start Times (X) for both teams. The multi-objective function balances three conflicting goals:

- Lateness ($\alpha = 2$): Minimizing delays beyond target due dates to protect the critical path and maintain synchronization with site schedules.
- Earliness ($\beta = 1$): Minimizing early completions to prevent outdoor storage and weather-induced quality degradation.
- Maximum Lead Time ($\gamma = 0.5$): Minimizing internal production cycle time to enhance factory throughput efficiency.

The prioritization of JIT adherence (α, β) over lead time (γ) reflects the specific constraints of the Edmonton facility, as detailed below.

3.3.2 Managerial Rationale for Weight Assignment

This prioritization reflects specific facility constraints that distinguish this operation from standard manufacturing. The plant lacks indoor storage for finished goods; projects completed early must be stored outdoors, exposed to harsh Western Canadian weather conditions (snow, freeze-thaw cycles, temperature extremes, moisture). Such exposure poses significant quality risks to high-value prefabricated stairs, including material degradation, warping, and corrosion.

Conversely, Internal WIP (partially finished stairs in progress) remains sheltered indoors between workstations, where environmental conditions are controlled. Therefore, prioritizing a schedule that minimizes external exposure (balancing Earliness and Lateness) even at the cost of slightly longer internal lead times is logical. This reflects a realistic operational trade-off: in constrained facilities with outdoor storage vulnerabilities, *delivery precision* often outweighs *internal throughput* as the primary scheduling objective.

3.3.3 Algorithm Configuration and Search Enhancements

The Genetic Algorithm (GA) was configured with a population size of 50 individuals, an evolution horizon of 25 generations, and tournament selection with a tournament size of 3. To navigate the partitioned solution space effectively and accelerate convergence toward high-quality schedules, three domain-specific search enhancements were implemented.

Smart Initialization (Heuristic Seeding) seeded the initial population with heuristic schedules constructed using domain knowledge, where Buffer represents a conservative estimate of required lead time based on historical data. This approach accelerates convergence by providing high-quality starting points rather than relying on random initialization, allowing the optimizer to begin from a region of promising solutions.

Coupled Mutation (Topology-Aware Move) was implemented as a mutation operator that shifts linked Team 1 and Team 2 task start times simultaneously. This topology-aware move allows the optimizer to "slide" entire projects along the timeline while preserving the internal synchronization between the Stringer/Landing phase and the Framing/Cage phase. Formally, if a project's Team 1 start time is adjusted by Δ, the Team 2 start time is automatically adjusted by the same amount, maintaining the phase coupling relationships.

Deadline Snapping (Goal-Oriented Refinement) implemented a local search operator to force project start times toward their zero-penalty Just-In-Time dates. This operator refines temporal precision in the latter stages of evolution by exploiting the known good region of the solution space, thereby improving final schedule quality without excessive computational cost.

4 Results and Discussion

To evaluate the efficacy of the proposed HSBO framework, a comparative analysis was conducted between the facility's baseline production schedule and the optimized timetable generated by the Genetic Algorithm. To ensure a rigorous comparison, the same set of stochastically sampled processing times across all four assembly stages was used for both the baseline simulation and the optimization routines. This ensures that any observed performance differences are attributable solely to scheduling decisions rather than random variation.

4.1 Baseline Schedule Performance

The baseline performance was established by simulating the 25-project sample schedule using the original planned start days and project sequence extracted from the factory's operational records. Figure 3 presents the resulting execution timeline for this baseline scenario, including the simulated project execution windows and their completion positions relative to the assigned crane dates.

Figure 3a illustrates the total project duration relative to the assigned "Crane Dates" (delivery deadlines). As shown, there is a consistent, significant buffer—averaging 2 to 3 days—between project completion and the deadline. While this buffer is strategically intended to absorb production variability, in the context of the Edmonton facility, it represents finished goods sitting outdoors in harsh weather for extended periods, incurring high quality risks.

Figure 3b provides a granular view of team-level execution. Visually, the gap between Team 1 (Stringer/Landing) and Team 2 (Framing/Cage) is minimal, indicating a tightly coupled flow with low Internal WIP. Quantitatively, the average project lead time in this baseline state is approximately 17 hours. However, comparing Figure 3a and 3b reveals a systemic imbalance: the facility maintains very low internal buffers (protected indoor WIP) but incurs massive external buffers (risky outdoor WIP).

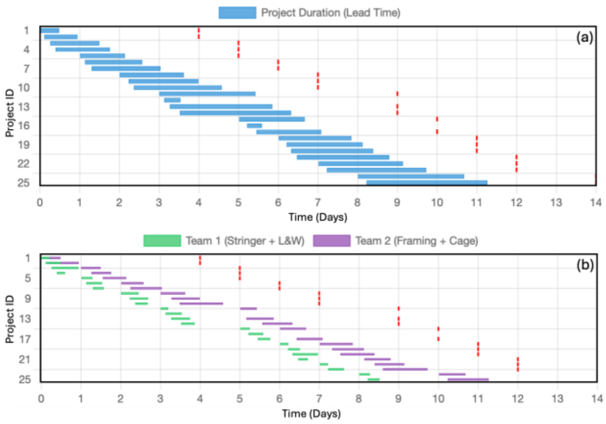

Figure 3: Baseline simulation results: (a) project execution windows relative to crane dates (red dashed lines); (b) Team 1 and Team 2 workload distribution.

4.2 Optimization Results

Following the baseline analysis, GA optimization was executed with objective weights prioritizing JIT adherence ($\alpha = 2, \beta = 1$) over internal lead-time minimization ($\gamma = 0.5$). The results are presented in Figure 4.

Compared with the baseline (Figure 3a), the optimized timetable (Figure 4a) shifts planned start times so completions align more closely with crane dates, reducing average outdoor finished-goods storage from 3 days to 1 day (66%). This does not eliminate the buffer entirely, but it substantially reduces exposure of finished stairs to harsh weather and related damage risk.

Figure 4b shows a clear structural change at the team level: increased spacing between Team 1 completion and Team 2 activity, indicating greater internal WIP (semi-finished components held indoors). Consistent with this, average project lead time increases by approximately 20% compared to the baseline (from ~17 hours to ~20.5 hours).

Overall, the optimizer trades a modest increase in safe indoor flow time for a large reduction in risky outdoor storage, with the Maximum Lead Time term ($\gamma = 0.5$) acting as a guardrail that penalizes excessive decoupling while still meeting delivery targets.

A side effect of JIT prioritization is schedule extension: the baseline executes from Day 0–11, whereas the optimized plan shifts to Day 1–13 and introduces a non-working gap at Day 12, increasing operational makespan. This occurs because delaying early projects reduces storage penalties, but the objective lacks an explicit makespan-compression term to discourage such gaps.

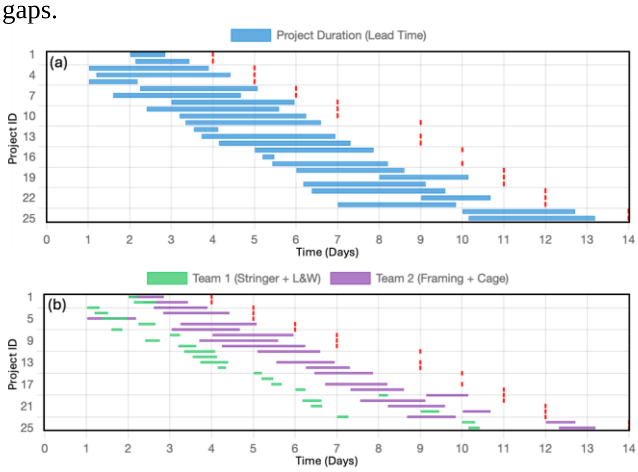

Figure 4: Optimized simulation results: (a) project execution windows relative to crane dates (red dashed lines); (b) Team 1 and Team 2 workload distribution.

From a managerial perspective, this trade-off should be interpreted as a deliberate buffer relocation rather than a simple loss in efficiency. In the case facility, reducing outdoor finished-goods storage from approximately 3 days to 1 day lowers the exposure of completed stairs to harsh weather, handling damage, and site coordination uncertainty, all of which carry quality, rework, and logistical risks. The corresponding increase in internal lead time indicates that more buffer is being held indoors as semi-finished Work-In-Process, where it is better protected and more controllable. For decision-makers, this means the proposed framework can support context-specific prioritization: in storage-constrained or weather-sensitive projects, accepting a moderate increase in internal lead time may be preferable if it substantially reduces external risk exposure. Conversely, in facilities where indoor space is more constrained or rapid flow is the dominant priority, the weighting structure of the objective function can be adjusted to place greater emphasis on lead-time compression or makespan reduction. Thus, the framework is not intended to prescribe a single best schedule universally, but to provide a decision-support tool that helps managers explicitly balance delivery precision, labor flow, and risk according to operational priorities.

4.3 Limitations and Future Directions

The results show the trade-off between delivery alignment and internal flow efficiency in HMLV systems. The 20% lead time increase indicates that reducing External WIP and improving Just-In-Time delivery required accepting some loss in factory flow performance. Two limitations remain. First, the objective function focuses on global maximum lead time, allowing local inefficiencies such as longer and more variable Team 2 flow times. Future models could include team-level penalties, though this would increase complexity. Second, the current Genetic Algorithm solves each schedule from scratch through repeated simulation, making it too slow for real-time use. Future work will explore DRL to learn reusable scheduling policies that can generate faster decisions while balancing delivery timing, lead time, and resource utilization.

5 Conclusion

This research addressed dynamic scheduling in High-Mix, Low-Volume (HMLV) off-site construction, where static planning tools struggle to represent the stochastic behavior of flexible, multi-skilled workforces. Following a Design-Science Research approach, the study developed and evaluated a prescriptive HSBO scheduling artifact that couples a Genetic Algorithm with a hybrid DES/ABS simulation model. The simulation served as a digital-twin-inspired evaluation testbed, enabling timetable optimization while capturing emergent collaboration behaviors in Dual-Resource Constrained (DRC) environments. Applied to a stair prefabrication line in Edmonton, Alberta, the optimized schedule reduced the average external finished-goods buffer from 3 days to 1 day (66%), lowering exposure risk, while increasing internal project lead times by about 20% (17 to 20.5 hours). The results also indicate that start-time decisions influence workforce dynamics by changing opportunities for upstream crews to assist downstream bottlenecks. Finally, the study highlights limitations of static evolutionary optimization: emphasizing JIT goals can increase schedule fragmentation and requires costly re-optimization as backlogs change. Future work will transition toward Deep Reinforcement Learning (DRL) to learn adaptive scheduling policies that provide real-time decision support under evolving system states.

6 Acknowledgement

This research is supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) Alliance grant ALLRP 581074–22, Discovery Grant RGPIN-2020-04420, and NSERC Alliance—Alberta Innovates Advance Program 232403286. All findings and conclusions expressed in this paper are those of the authors and do not reflect those of the contributors.

7 References

[1] Thibault D, Osman T, Brown A, Efficiency NE. Benefits and Opportunities of Off-Site Construction: Analysis of Indiana and Pennsylvania 2024.

[2] Barnes O. A Study of Lean Production Techniques in High-Volume Manufacturing Systems. American Journal Of Industrial And Production Engineering 2024;5:6–10.

[3] Amaresh A, Oooramvely K. Standardization in a High Mix Low Volume Company: A Case Study 2020.

[4] Hussein M, Zayed T. Critical factors for successful implementation of just-in-time concept in modular integrated construction: A systematic review and meta-analysis. J Clean Prod 2021;284:124716.

[5] Zhang C, Jiang J, Xia C, Fu Y, Liu J, Duan P. Dual-objective optimization of prefabricated component logistics based on JIT strategy. Sci Rep 2024;14:31267.

[6] Magalhães R, Santos F, Vieira S, Sousa JMC. Dual Resource Flexible Job Shop Scheduling Problems: The xBTF Algorithm. International Conference on Information Processing and

Management of Uncertainty in Knowledge-Based Systems, Springer; 2024, p. 115–25.
[7] Dhiflaoui M, Nouri HE, Driss OB. Dual-resource constraints in classical and flexible job shop problems: a state-of-the-art review. Procedia Comput Sci 2018;126:1507–15.
[8] Daniels RL, Mazzola JB, Shi D. Flow shop scheduling with partial resource flexibility. Manage Sci 2004;50:658–69.
[9] Krishnan M, Chinnusamy TR, Karthikeyan T. Performance study of flexible manufacturing system scheduling using dispatching rules in dynamic environment. Procedia Eng 2012;38:2793–8.
[10] Xiong H, Shi S, Ren D, Hu J. A survey of job shop scheduling problem: The types and models. Comput Oper Res 2022;142:105731.
[11] Zhang W, Bao X, Hao X, Gen M. Metaheuristics for multi-objective scheduling problems in industry 4.0 and 5.0: a state-of-the-arts survey. Frontiers in Industrial Engineering 2025;3:1540022.
[12] Shan D, Wang Y. A review of the application of genetic algorithms for solving flexible job shop scheduling problems. Proceedings of the 2nd International Conference on Information Technologies and Electrical Engineering, 2019, p. 1–5.
[13] Delgoshaei A, Ariffin MKAM, Maleki S, Leman Z. Review evolution of dual-resource-constrained scheduling problems in manufacturing systems: modeling and scheduling methods' trends. Soft Computing-A Fusion of Foundations, Methodologies & Applications 2023;27.
[14] Rahman M, Han SH. Performance Evaluation of Genetic Algorithm and Particle Swarm Optimization in Off-Site Construction Scheduling. ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, vol. 41, IAARC Publications; 2024, p. 275–82.
[15] Pourrahimian E, Salhab D, Fayek AR, Hamzeh F. Fuzzy-Chaos Framework for Analyzing and Quantifying Uncertainty in Labour Productivity in Complex Construction Environments. ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, vol. 42, IAARC Publications; 2025, p. 571–9.
[16] Sorbi T, Getuli V, Capone P, Rahimian FP. AGENT-BASED SIMULATION FRAMEWORK FOR ENHANCED CONSTRUCTION SITE RISK ESTIMATION AND SAFETY MANAGEMENT. Journal of Information Technology in Construction 2024;29.
[17] Eltahan A, Lee G, Hamzeh F. Exploring Cognitive Load and Task Complexity in Dynamic Tracking Tasks: Insights for Construction Workflows. ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, vol. 42, IAARC Publications; 2025, p. 532–9.
[18] ElMenshawy M, Wu L, Gue B, AbouRizk S. Exploring the potential of reinforcement learning in pipe spool scheduling in industrial projects. Proc., 41st Int. Symp. on Automation and Robotics in Construction, 2024, p. 965–71.
[19] Moghimi N, Arshang O, Hamzeh F. Digital twins in offsite construction: Current implementations, challenges, and future pathways. Autom Constr 2026;183:106820.
[20] Hevner AR, March ST, Park J, Ram S. Design science in information systems research. MIS Quarterly 2004:75–105.
[21] Moghimi N, Kashani H. A probabilistic framework to design the financing scheme for resilience enhancement of infrastructure systems. Reliab Eng Syst Saf 2025;262:111179. https://doi.org/10.1016/j.ress.2025.111179.
[22] Moghimi N, Kashani H. Probabilistic Modeling to Develop the Optimal Seismic Resilience Enhancement Strategy for Industrial Facilities. Journal of Infrastructure Systems 2026;32:04025041. https://doi.org/10.1061/JITSE4.ISENG-2754.
[23] Fu MC. Optimization for simulation: Theory vs. practice. INFORMS J Comput 2002;14:192–215.
[24] Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital Twin in manufacturing: A categorical literature review and classification. Ifac-PapersOnline 2018;51:1016–22.
[25] Alsakka F, Yu H, El-Chami I, Hamzeh F, Al-Hussein M. Digital twin for production estimation, scheduling and real-time monitoring in offsite construction. Comput Ind Eng 2024;191:110173. https://doi.org/10.1016/j.cie.2024.110173.
[26] Barkokebas B, Al-Hussein M, Hamzeh F. Assessment of digital twins to reassign multiskilled workers in offsite construction based on lean thinking. J Constr Eng Manag 2023;149:04022143.
[27] Bonabeau E. Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences 2002;99:7280–7.