Discrete-Event Simulation–Based Optimization of Time Buffers for Space-Constrained Modular Production Lines

Nima Moghimi[1*], Sahar H. Shamaee[2], Leonard Irerih[3], Qipei Mei[4], Vicente A. Gonzalez[5], Farook Hamzeh[6]

[1*]Corresponding Author, Ph.D. Student, Department of Civil and Environmental Engineering, University of Alberta, Canada
[2]Graduate Research Assistant, Department of Civil and Environmental Engineering, University of Alberta, Canada
[3]MSc Student, Department of Civil and Environmental Engineering, University of Alberta, Canada
[4]Assistant Professor, Department of Civil and Environmental Engineering, University of Alberta, Canada
[5]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
[6]Professor, Department of Civil and Environmental Engineering, University of Alberta, Canada
nmoghimi@ualberta.ca, hamedsha@ualberta.ca, irerih@ualberta.ca, qipei@ualberta.ca, vagonzal@ualberta.ca, hamzeh@ualberta.ca

Abstract

Modular construction offers significant efficiency benefits over traditional methods, yet its production systems remain vulnerable to workflow variability caused by product customization and manual operations. While buffering is a standard strategy to mitigate such variability, the unique constraints of modular factories (e.g., specifically the large physical footprint of modules and high labor costs) often render traditional inventory and capacity buffers impractical. This study proposes a novel time buffer allocation methodology to absorb process variability and protect throughput in space-constrained modular production lines. Adopting a simulation-optimization approach, the study integrates Discrete-Event Simulation (DES) with the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm to determine optimal project-specific time slacks. The framework is evaluated through a case study of a prefabricated timber wall assembly line in Edmonton, Canada. The results demonstrate that the optimized time buffer strategy reduces the workload at the bottleneck loading station by approximately 20% compared to a continuous flow scenario, effectively preventing starvation. Crucially, the optimized approach avoids the upstream blocking and excessive Work-in-Progress (WIP) accumulation observed under uniform buffering policies. The findings provide factory managers with a practical, data-driven method for scheduling releases that harmonizes upstream production efficiency with downstream logistics constraints.

Keywords –
Modular Construction; Simulation-Optimization; Buffer Allocation; Discrete-Event Simulation; Time Buffers

1 Introduction

Modular construction offers significant advantages over traditional methods, including reduced project schedules and improved quality control [1]. However, the operational reality of modular factories is characterized by substantial variability. The make-to-order nature of the industry necessitates extensive customization in component geometry, structural details, and finishing requirements, which introduces heterogeneous processing times at individual workstations [2,3]. This inherent variability, compounded by manufacturing tolerances and material handling uncertainties, frequently leads to production imbalances, bottleneck formation, and reduced overall efficiency [4,5].

To mitigate such variability, manufacturing systems typically employ inventory, capacity, or time buffers [6]. While effective in high-volume manufacturing, standard buffering strategies face unique hurdles in modular construction. Inventory buffers are often impractical because the large physical footprint of wall panels and volumetric modules severely restricts the available floor space between workstations [7–9]. Similarly, capacity buffering, maintaining excess labor or equipment, is constrained by the high costs of skilled labor, union restrictions, and crew specialization [10–12].

Given physical and economic constraints, time buffers emerge as the most operationally feasible mechanism for absorbing process variability, utilizing temporal slack to protect critical workstations without requiring the additional space or redundant resources associated with inventory or capacity buffers [13,14]. This approach is well supported by the literature. Building on the foundational concept of strategic temporal protection for release-based scheduling introduced by Gao [15], subsequent work has shown that time buffers can be used to approximate the Buffer Allocation Problem by reformulating traditional integer programming models into more tractable linear formulations [16]. Furthermore, this approach was validated in the construction domain through the development of a stochastic optimization model integrating Monte Carlo simulation with critical chain techniques, which achieved a 37% reduction in project delays and a substantial improvement in schedule reliability [17].

However, existing research on time buffering remains predominantly grounded in Critical Chain Project Management (CCPM), prioritizing project-level schedule protection over the station-to-station flow control required for manufacturing contexts [18,19]. While CCPM methodologies have introduced advanced sizing techniques, including network decomposition [14] and entropy-based methods [20], they do not adequately address the dynamics of flow lines, an area where buffer allocation research has traditionally focused on inventory rather than time [21,22]. Consequently, there is a distinct lack of methodologies tailored to the stochastic dynamics of modular production lines. The unique combination of high process variability, space constraints, and make-to-order production in modular construction creates specific buffering challenges that necessitate station-level stabilization—a gap currently unaddressed by existing optimization frameworks.

This study addresses this gap through a Design-Science approach by developing and evaluating a prescriptive simulation-optimization decision-support artifact for time-buffer allocation in modular prefabrication. By integrating discrete-event simulation [23] with evolutionary optimization techniques [24], the proposed framework identifies project-specific buffer times that mitigate downstream starvation while avoiding excessive upstream blocking, thereby improving overall production performance under space constraints. The artifact is demonstrated and evaluated through an industrial case study at a prefabricated timber construction factory in Edmonton, Canada, providing actionable, data-driven guidance for planners in space-constrained manufacturing environments [25].

2 Methodology

This study adopts a Design Science Research (DSR) methodology [26], which emphasizes the development and evaluation of prescriptive solutions to real-world operational problems. The DSR artifact developed in this paper is a simulation-optimization decision-support framework for project-specific time-buffer allocation in space-constrained modular construction factories. The framework is implemented through a simulation-based optimization engine that recommends release slacks for downstream loading activities. Consistent with DSR, the study is structured around three stages: (i) problem identification and motivation, where spatial limitations and stochastic variability restrict the use of conventional inventory and capacity buffers; (ii) framework design and implementation, where the discrete-event simulation model and the optimization mechanism are developed; and (iii) evaluation, where the proposed framework is assessed in an industrial case study and benchmarked against baseline buffering policies.

2.1 Framework Design: Simulation-Optimization Approach

The proposed framework is designed using a simulation-optimization approach in which the Discrete-Event Simulation (DES) model functions as a black-box objective function [27]. In this framework, the optimizer treats the simulation as an evaluative function f(x) that accepts candidate time buffer allocations as inputs and returns performance metrics as outputs, without requiring explicit mathematical formulation of system dynamics [28]. This black-box approach is particularly suitable for modular construction environments where stochastic variability, customization-induced heterogeneity, and spatial constraints create complexities that resist traditional mathematical optimization methods [6]. The optimizer iteratively explores the buffer allocation space, executing the simulation for each candidate configuration and refining the solution toward optimal configurations based on performance feedback [29].

2.1.1 Discrete-Event Simulation Model Development

The discrete-event simulation model captures the stochastic dynamics of modular construction production lines by representing the system as a sequence of discrete events, such as job arrivals, station completions, and transfers between workstations, each causing a change in system state [30]. Jobs are characterized by distinct types reflecting different product configurations and customization requirements. Processing times at each workstation are sampled from job-specific probability distributions to represent production variability [31]. Blocking and starving are explicitly modelled through limited intermediate buffers, such that a station may be starved by insufficient upstream supply or blocked by saturated downstream capacity. The primary performance metric is Workload Time, defined as the total active processing time required for a segment to complete its assigned jobs.

2.1.2 Optimization Framework

The optimization framework addresses a constrained single-objective minimization problem. The decision variables are the time-buffer parameters assigned to entities (jobs, tasks, or production batches) within a defined two-stage production line segment.

Let $\mathbf{s} = (s_1, s_2, \dots, s_n)$ denote the vector of time-buffer parameters, where each $s_i \in [s_{\min}, s_{\max}]$ represents the time slack assigned to entity i.

The optimizer treats the simulation as a black-box stochastic function [32]. For each stochastic simulation replication k with random inputs ω_k, the simulation returns:

$W_{\text{up}}(\mathbf{s}, \omega_k)$: The total active processing time accumulated by the upstream stage.

$W_{\text{down}}(\mathbf{s}, \omega_k)$: The total active processing time accumulated by the downstream stage.

The optimization objective is to minimize the expected total workload of the coupled two-stage segment:

$$\min_{\mathbf{s} \in [s_{\min}, s_{\max}]^n} \mathbb{E}_{\omega}\left[W_{\text{up}}(\mathbf{s}, \omega) + W_{\text{down}}(\mathbf{s}, \omega)\right] \quad (1)$$

Since the true expected value is intractable, a Monte Carlo approximation is employed over K simulation replications with independent random seeds $\{\omega_k\}_{k=1}^{K}$:

$$\hat{J}(\mathbf{s}) = \frac{1}{K} \sum_{k=1}^{K} \left[W_{\text{up}}(\mathbf{s}, \omega_k) + W_{\text{down}}(\mathbf{s}, \omega_k)\right] \quad (2)$$

The problem is subject to simple box constraints:

$$s_{\min} \le s_i \le s_{\max}, i = 1, \dots, n. \quad (3)$$

Operational constraints (resource limits, blocking/starving rules) are enforced internally within the simulation logic.

2.1.3 Optimization Algorithm

Because the objective is evaluated through a discrete-event simulation treated as a black-box stochastic function, and its expectation is approximated via Monte Carlo replications, analytic gradients are unavailable and finite-difference gradients are unreliable due to simulation noise and non-smooth event logic. Therefore, a derivative-free stochastic optimization algorithm is used to iteratively propose candidate buffer vectors S and refine the search. In this study, the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is employed due to its effectiveness in handling continuous bounded domains and stochastic objective functions [33].

CMA-ES adapts its search distribution based on the history of evaluated solutions, making it well-suited for expensive black-box optimization. Depending on problem dimensionality and computational budget, alternative metaheuristic approaches such as particle swarm optimization, simulated annealing, or surrogate-assisted methods may also be suitable [34].

2.2 Evaluation Design

The framework is evaluated using an industrial case study of a modular wall-panel production line under space-constrained conditions. Performance is assessed by comparing the optimized time-buffer policy against baseline buffering strategies (e.g., zero buffering and a uniform buffering rule) under identical production scenarios. All candidate policies are evaluated through multiple Monte Carlo replications to account for stochastic variability and to ensure fair comparison of expected workload outcomes for the coupled upstream–downstream segment. The case-study implementation and benchmarking results are presented in the section 3, which operationalizes the framework in an industrial setting and reports the comparative evaluation outcomes.

3 Framework Evaluation

3.1 Case Study Overview

This section presents the implementation of the proposed framework in the wall assembly line of a prefabricated timber factory in Edmonton, Alberta, producing components for residential modular buildings. The factory operates two adjacent plants manufacturing walls, roofs, floors, stairs, decks, and finishing elements. The wall line was selected because it reflects the main characteristics of the target production environment: hybrid automation-manual operations, severely constrained intermediate buffers, and high product variety driven by customization. Together, these features create heterogeneous workstations and specification-dependent processing-time variability. Figure 1 shows the wall assembly line and overall production flow.

The line consists of six interconnected sections: Framing, Sheeting, CNC Nailing, Packaging, Doors and Windows (DW) Installation, and Loading. Framing uses one CNC machine and one crew to assemble multiwall (MW) panel frames, which move through limited-capacity buffers to Sheeting, CNC Nailing, and Packaging. After Packaging, interior panels are routed to storage, while the remaining panels proceed to four parallel DW lanes for finishing before being transferred by cart to the Loading buffer. At Loading, two crews use a loading cart to place panels onto delivery trailers.

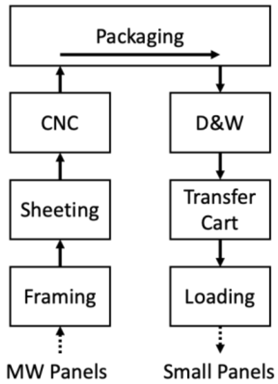

Figure 1: Schematic Layout of the Wall Assembly Line.

3.2 Simulation Model Development

Processing time data were collected through field observation and sampled production records, including panel durations and job specifications (e.g., interior/exterior classification and installation requirements). This provided a practical basis for model parameterization in a data-limited industrial setting, although the input assembly process remained partially manual. A sample of panel records per station was obtained, capturing both quantitative processing times and contextual factors influencing variability. Triangular distributions were selected for modeling processing times due to practical advantages in data-limited environments [35,36]. Parameters were derived from empirical data and validated with shopfloor experts.

The simulation model was developed in Python using SimPy to capture the stochastic dynamics of the wall assembly line. The model represents process flow, resource contention, and buffer limitations using capacity-limited SimPy Store objects enforcing first-in, first-out (FIFO) discipline. Single-capacity stores represent transfer elements; multi-capacity stores model buffers (e.g., DW: 4 lanes × 4 panels = 16 panels capacity; Loading: 6 lanes × 4 panels = 24 panels capacity). Blocking and starving arise naturally from resource constraints. Routing logic dynamically assigns panels at Packaging based on panel type and queue lengths, replicating observed load-balancing behavior.

Model validation against real production data (84 MW panels, 135 small panels) demonstrated acceptable accuracy: Framing ($R^2 = 0.95$), DW ($R^2 = 0.89$), Loading ($R^2 = 0.88$), with mean absolute percentage errors of 16–18% (acceptable for complex construction simulations) [36].

3.3 Optimization Specification

This study focuses on optimizing the time buffer between the upstream production segment (Framing through DW Installation) and the Loading station. Loading, constrained by external trailer logistics, can load a maximum of three projects per day, regardless of project size or upstream production rate. This external constraint positions Loading as a system bottleneck regarding project throughput. Furthermore, the transfer cart section, identified as the internal bottleneck based on panels' expected processing times, feeds directly into the constrained Loading buffer.

Currently, plant management decouples Loading from upstream stations using an average one-day time buffer. However, this uniform buffer policy does not account for project-specific variability or system dynamics. Given the severely limited inventory buffer capacity (24 panels total across six lanes), excessive time buffers cause WIP accumulation that blocks or slows upstream production, while insufficient buffers lead to Loading starving and underutilization [37]. This segment therefore represents an excellent case for testing the effectiveness of the proposed time buffer optimization technique, where the goal is to determine project-specific loading slacks that balance upstream production flow with downstream logistics constraints.

Projects flow through the upstream production segment (Framing through DW Installation), generating production workload W_{prod}. The time buffer s decouples this from the constrained Loading station (workload W_{load}), as illustrated in Figure 2. The optimization objective is to determine per-project buffer allocations that minimize the combined workload $W_{\text{prod}} + W_{\text{load}}$.

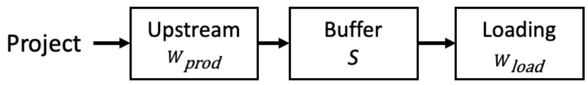

Figure 2: Schematic representation of the proposed time buffer allocation approach.

The selected test schedule comprises 14 projects of varying sizes, mimicking a one-week workload of the production line. For each project i, the decision variable s_i represents the time slack (loading buffer in hours) between when project i reaches the Loading buffer from upstream stations and when it is released to the Loading station. The bounds on s_i are determined by project-specific delivery deadlines: $s_i \in [0, d_i]$, where d_i is the maximum allowable slack for project i based on its deadline. For the plant's operations, typical deadlines following the loading date are within 2–3 days; thus, bounds reflect this practical constraint.

The production workload $W_{\text{prod}}(\mathbf{s}, \omega)$ represents the total active processing time required by the upstream (i.e., Framing, Sheeting, CNC Nailing, Packaging, DW Installation, and transfer cart stages) to complete all 14 projects, while the loading workload $W_{\text{load}}(\mathbf{s},\omega)$ measures the Loading station's active processing time for the same project set. The optimization objective is to minimize the expected total workload of the coupled production-Loading system:

$$\min_{\mathbf{s}\in[0,d_1]\times\cdots\times[0,d_{14}]} \mathbb{E}_{\omega}\left[W_{\text{prod}}(\mathbf{s},\omega)+W_{\text{load}}(\mathbf{s},\omega)\right] \quad (4)$$

With an effective buffering strategy, the total makespan for finishing the 14-project set is expected to remain relatively constant; however, strategic time buffer allocation changes the distribution of workload and utilization patterns between the production segment and Loading. By decoupling the upstream production from the constrained Loading station through optimized project-specific slacks, the buffer creates a more consistent arrival flow at Loading, smoothing demand variability and reducing starving events. This workload redistribution improves Loading station utilization while preventing upstream blocking, thereby enhancing overall system efficiency [37].

The CMA-ES algorithm was configured with population size proportional to the 14-dimensional decision space and standard initial step size. Monte Carlo estimation used $K = 50$ simulation replications during candidate evaluation and final validation of the best solution, ensuring reliable stochastic objective function approximation [38].

3.4 Results

Three scenarios were simulated to evaluate the proposed time-buffer optimization framework: (1) continuous production with no buffer slack, representing uninterrupted flow; (2) uniform buffering with an 8-hour slack for all projects, reflecting current plant practice; and (3) optimized buffering with project-specific slacks determined by the optimization model. The test schedule included 14 projects of varying sizes released over a four-day horizon. Figure 3 compares the execution timelines of the upstream production segment and the Loading station under the three scenarios.

In the continuous production scenario, the upstream segment completed its work in 31.77 hours, consistent with the four-day production window, but the Loading station required 21.92 hours and extended to a fifth day because of the three-project-per-day trailer logistics constraint. This indicates poor decoupling, with the Loading station frequently starved despite uninterrupted upstream flow.

Under the uniform 8-hour buffer policy, Loading workload decreased to 16.71 hours, indicating fewer starving events and more stable downstream operation. However, upstream workload increased to 37.12 hours, exceeding the four-day window and requiring substantial overtime. This occurred because the uniform slack caused excessive WIP accumulation in the space-constrained buffer, which increased upstream blocking and reduced throughput.

The optimized buffer scenario achieved a better balance between upstream and downstream performance. Loading workload was reduced to 17.11 hours, close to the uniform-buffer case, while upstream workload remained at 31.83 hours, comparable to the continuous-flow scenario and still within the four-day production window. This shows that project-specific slacks can effectively decouple Loading from upstream variability, improving downstream utilization without causing upstream blocking or significant overtime. Although Loading still required five days because of the external logistics constraint, its workload was about 20% lower than in the continuous scenario, creating opportunities to reassign the Loading crew to other value-adding tasks.

The results highlight the critical importance of strategic time buffer allocation in production systems with coupled internal and external bottlenecks. While a uniform buffer policy improves downstream efficiency, it negatively impacts upstream production due to physical space constraints. The proposed optimization framework effectively addresses this challenge by determining project-specific slacks that absorb variability without overwhelming buffer capacity. The optimized solution achieves the best of both scenarios: it maintains upstream production efficiency comparable to a continuous flow model while achieving downstream workload reductions similar to a large uniform buffer, thereby maximizing overall system efficiency and labor productivity. These findings provide a validated foundation for implementing dynamic, data-driven buffering strategies in modular construction factories.

Overall, the results demonstrate that strategic time-buffer allocation is critical in systems with coupled internal and external bottlenecks. A uniform buffer improves downstream stability but degrades upstream performance under space constraints. In contrast, the proposed framework identifies project-specific slacks that absorb variability without overwhelming buffer capacity. As a result, it preserves upstream efficiency while achieving downstream workload reductions similar to the uniform-buffer case. From an implementation perspective, the optimized slacks can be directly incorporated into production schedules as project-specific release delays from upstream production to the Loading buffer, providing managers with simple and actionable scheduling guidance.

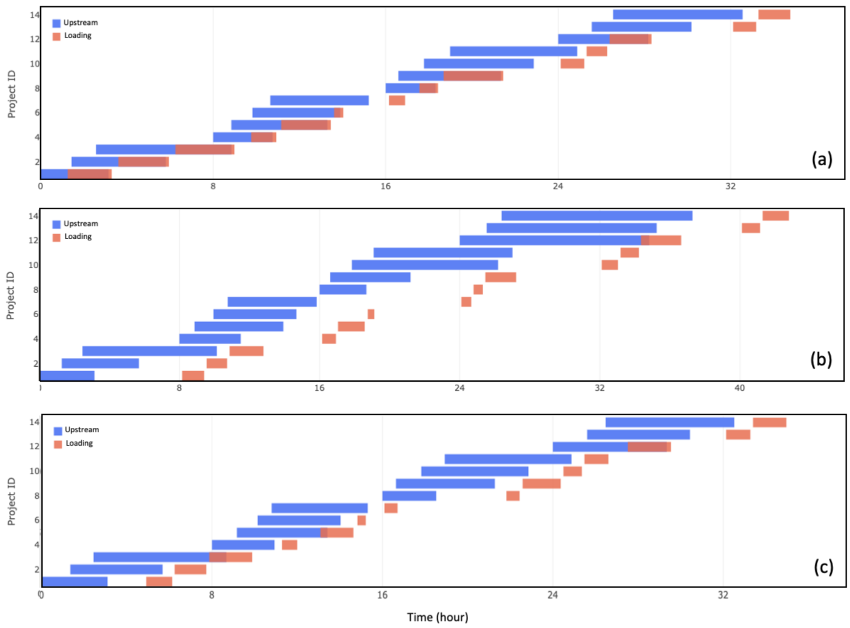

Figure 3: Project execution timelines for upstream segment and loading station under three buffering scenarios: (a) no buffer, (b) uniform 8-hour buffer, and (c) optimized project-specific buffers.

3.5 Practical Implementation

The proposed framework is intended to operate as a decision-support layer on top of the factory's existing planning process rather than as a stand-alone tool that production planners must model manually. In practice, the required inputs are already generated during routine weekly or monthly planning, including the project list, project sequence, target release dates, and station-level production assumptions. These data can be transferred from the plant's scheduling spreadsheets or production management system into the simulation-optimization engine with limited preprocessing.

From an implementation perspective, the main technical requirement is not that every planner or manager possess simulation expertise, but that the organization have access to an industrial engineer, analyst, or digital-production specialist capable of maintaining the simulation model and periodically updating its input parameters. Once this model is established, end users interact only with the results, which can be delivered as a lookup table or simple scheduling rule: for each project in the weekly schedule, apply the recommended loading slack before releasing it to the Loading buffer. In this way, the complex stochastic behavior captured by the DES-CMA-ES framework is translated into concrete release times that are directly usable in operational planning.

This implementation logic minimizes disruption to current manual or semi-automated scheduling practices while still enabling data-driven decision-making. The operational value of the approach lies in converting simulation outputs into actionable project-level dispatch adjustments that reduce Loading crew overtime, improve labor utilization, and maintain upstream production within the expected four-day window. Nevertheless, wider deployment at industrial scale would benefit from a user-friendly interface and automated data exchange between the scheduling platform and the optimization engine, which remains an important direction for future development.

4 Conclusion

This study addressed production variability in modular construction factories where space constraints limit the use of inventory buffers and labor costs restrict capacity buffering. Following a Design Science Research (DSR) methodology, it developed a simulation-optimization framework that combines discrete-event simulation with CMA-ES to allocate project-specific time buffers without requiring additional space or redundant resources. The framework was evaluated on a prefabricated timber wall production line in Edmonton, Canada, as a real-world demonstration case under space-constrained modular production conditions. The optimized time-buffer policy outperformed both zero-buffer (continuous) operation and the plant's uniform buffering practice, reducing bottleneck Loading workload by approximately 20% while preventing downstream starvation. Unlike uniform buffering—which stabilizes the downstream station by blocking upstream work and extending lead times—the optimized solution maintained upstream efficiency within the targeted four-day window. Overall, the results indicate that time buffers can provide a practical alternative to inventory buffers in space-constrained off-site construction. From a managerial perspective, the framework translates complex stochastic system behavior into simple project-specific scheduling rules that can improve labor utilization and throughput reliability.

While the findings are promising, the present study should be interpreted as a preliminary industrial evaluation with several limitations. First, the framework was assessed using a single demonstration case on one prefabricated timber wall production line, which limits immediate generalizability to other factory layouts, product mixes, and operating conditions. Second, as with any simulation-based study, the analysis depends on modelling assumptions regarding workflow logic, variability representation, and system constraints that may differ across industrial settings. Third, the DES input data in this study were assembled from field observations and sampled production records, which was practical for the case-study context but still required partial manual preprocessing.

Future research should therefore validate the framework across additional production lines, broader project portfolios, and alternative buffering scenarios. It should also extend the method to more complex factory environments, such as multi-line and multi-product systems with interacting bottlenecks. In addition, more systematic data acquisition should be explored through integration with digital production reporting systems, shop-floor sensing, and digital-twin-oriented data pipelines, enabling more automated model updating and more scalable industrial implementation.

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6 References

[1] Egege CO. Off-site modular construction as a method of improving construction quality and safety. International Journal of Structural and Civil Engineering Research 2018;7:259–68.

[2] 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.

[3] Bhatia A, Moselhi O, Han SH. Optimized production scheduling for modular construction manufacturing. ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, vol. 40, IAARC Publications; 2023, p. 270–7.

[4] Shahtaheri Y, Rausch C, West J, Haas C, Nahangi M. Managing risk in modular construction using dimensional and geometric tolerance strategies. Autom Constr 2017;83:303–15.

[5] Panahi R, Louis J, Podder A, Pless S, Swanson C, Jafari M. Automated progress monitoring in modular construction factories using computer vision and building information modeling. 40th International Symposium on Automation and Robotics in Construction. Retrieved from: the US Department of Energy Office of Scientific and Technical Information: https://www. osti. gov/biblio/2203915, 2023.

[6] Zhang M, Pastore E, Alfieri A, Matta A. Buffer allocation problem in production flow lines: A new Benders-decomposition-based exact solution approach. IISE Trans 2022;54:421–34.

[7] Sadeghi H, Cheung CM, Yunusa-Kaltungo A, Manu P. A systematic review of occupational safety and health in modular integrated construction. Saf Sci 2025;189:106897.

[8] Salhab D, Alsakka F, Hamzeh F. A narrative review of workspace planning in construction: Challenges and insights. Proc., 31st Annual Conf. Int. Group for Lean Construction (IGLC31), 2023, p. 1208–19.

[9] Moghimi N, Arshang O, Hamzeh F. Digital twins in offsite construction: Current implementations, challenges, and future pathways. Autom Constr 2026;183:106820.

[10] Salama T, Salah A, Moselhi O. Integration of linear scheduling method and the critical chain project management. Canadian Journal of Civil Engineering 2018;45:30–40.

[11] Srisuwanrat C, Ioannou PG. The investigation of lead-time buffering under uncertainty using simulation and cost optimization. Proceedings of the 15th Annual Conference of the International Group for Lean Construction, 2007, p. 580–9.

[12] 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.

[13] Nie X, Zheng Y, Gu X, Su B, Wang B. Calculation of buffer size on critical chain based on duration distribution, multiresource constraints, and relay potential. Sci Program 2022;2022:6591223.

[14] She B, Chen B, Hall NG. Buffer sizing in critical chain project management by network decomposition. Omega (Westport) 2021;102:102382.

[15] Gao H. Building robust schedules using temporal protection: An empirical study of constraint-based scheduling under machine failure uncertainty. 1997.

[16] Alfieri A, Matta A, Pastore E. The time buffer approximated Buffer Allocation Problem: A row–column generation approach. Comput Oper Res 2020;115:104835.

[17] Abuhussain M. Advanced Time Buffer Optimization Model for Construction Schedule Management Using Stochastic Analysis. vol. 2025. 2024.

[18] Zhang J, Song X, Díaz E. Buffer sizing of critical chain based on attribute optimization. Concurrent Engineering 2014;22:253–64.

[19] Zohrehvandia S, Soltanib R. Journal of Project Management. Journal of Project Management 2022;7:121–32.

[20] Sun W, Abdullah LN, Khalid FB, Suhaiza Binti Sulaiman P. EAR-CCPM-Net: A Cross-Modal Collaborative Perception Network for Early Accident Risk Prediction. Applied Sciences 2025;15:9299.

[21] Weiss S. Optimization of buffer allocations in stochastic flow lines 2016.

[22] Kassoul K, Cheikhrouhou N, Zufferey N. Simultaneous allocation of buffer capacities and service times in unreliable production lines. Int J Prod Res 2024;62:644–64.

[23] Afifi M, Al-Hussein M, Abourizk S, Fotouh A, Bouferguene A. Discrete and continuous simulation approach to optimize the productivity of modular construction element. ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, vol. 33, IAARC Publications; 2016, p. 1.

[24] 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.

[25] Barkokebas B, Martinez P, Bouferguene A, Hamzeh F, Al-Hussein M. Digitalization-based process improvement and decision-making in offsite construction. Autom Constr 2023;155:105052.

[26] Hevner AR, March ST, Park J, Ram S. Design science in information systems research. MIS Quarterly 2004:75–105.

[27] 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.

[28] Yeomans JS, Imanirad R, Yang X-S. A stochastic biologically-inspired metaheuristic for modelling-to-generate-alternatives. Lecture Notes in Management Science 2013;5:1–9.

[29] Juan ÁA, Keenan P, Martí R, McGarraghy S, Panadero J, Carroll P, et al. A review of the role of heuristics in stochastic optimisation 2023.

[30] Alsakka F, Darwish M, Yu H, Hamzeh F, Al-Hussein M. The impacts of lean implementation revealed in the course of building a digital twin of a construction manufacturing facility. Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC), Emonton, Canada, 2022, p. 890–901.

[31] Bhatia APS, Han S, Moselhi O. A simulation-based statistical method for planning modular construction manufacturing. Journal of Information Technology in Construction 2022;27.

[32] 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.

[33] Hansen N, Ostermeier A. Completely derandomized self-adaptation in evolution strategies. Evol Comput 2001;9:159–95.

[34] Bianchi L, Dorigo M, Gambardella LM, Gutjahr WJ. Metaheuristics in stochastic combinatorial optimization: a survey. TechReport: Dalle Molle Institute for Artificial Intelligence 2006.

[35] AbouRizk SM, Halpin DW, Sawhney A. Modelling Uncertainty in Construction Simulation. MACHINE INTELLIGENCE AND PATTERN RECOGNITION 1994;17:287.

[36] Law AM, Kelton WD, Kelton WD. Simulation modeling and analysis. vol. 3. Mcgraw-hill New York; 2007.

[37] Hopp WJ, Spearman ML. Factory physics. Waveland Press; 2011.

[38] Tekin E, Sabuncuoglu I. Simulation optimization: A comprehensive review on theory and applications. IIE Transactions 2004;36:1067–81.