Integrated Digital Twin Framework for Adaptive Production Planning and Control in Precast Construction

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September 30, 2024

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Abstract

Precast construction faces challenges that arise from differing priorities in terms of production optimization between the production and the erection functions. Factories prefer large production batches, which does not align with the needs of erection crews for sets of varied pieces at each step in erecting a building. We propose a Digital Twin Construction framework for closed-loop monitoring and control of precast concrete production and construction. A core module in the framework performs adaptive global optimization of the system. The optimization module compiles sets of production plan parameters using planning heuristics, evaluates the plans using agent-based simulations, and then optimizes for plan parameters using a genetic algorithm. A novel utility function works to minimize production waste throughout the system, rather than seeking shortest project duration. The result has minimum cost with greatest value. Once implemented, the framework as a whole may enable automated monitoring and control in a closed loop that optimizes production plans to enhance efficiency, reduce waste, and improve coordination, ultimately streamlining the entire precast construction process.

Keywords: Digital Twin Construction, Precast Construction, Lean, Optimization, Production Planning and Control

1 Introduction

Like all off-site production for construction, precast concrete leverages factory manufacture to streamline the production process, promising significant improvements in efficiency, time reduction, cost savings, and quality control compared to traditional cast-in-place methods. The primary goals of precast construction are to reduce onsite labor, shorten timelines, and improve quality control through standardized production in a controlled factory environment (Sacks et al., 2004).

However, offsite manufacturing introduces its own set of challenges. Factories aim to minimize setup costs by producing identical elements in large batches. However, they must also manage inventory overheads from elements produced in excess, which may not yet be required at the construction site. Critical issues that arise include production and erection plans that derive from local optimizations and are thus contradictory, and production controls that are exacerbated by a lack of coordination and communication between factories and construction sites. This leads to inefficiencies and increased costs (Anvari et al., 2016; Sacks et al., 2003).

Additionally, managers on-site frequently lack information regarding the operational status of offsite factories. This information gap prevents them from aligning their production schedules with onsite process requirements. From a game theory perspective, the fragmented communication and conflicting interests result in lose-lose scenarios (Korb and Sacks, 2021). General Contractors (GCs) demand that factories commit to punctual and defect-free delivery of precast elements according to the project schedule. To offset the cost of inventory, factories demand that GCs pay for elements produced, regardless of whether they are delivered to the site.

The disconnect between factory schedules and erection schedules means that the overall production system is inflexible and has difficulty coping with variances and disruptions. Decision-making is fragmented and open-looped, lacking feedback mechanisms to adapt to continuously changing conditions in the project. From a lean manufacturing perspective, this rigid, fragmented structure results in significant waste (Ballard et al., 2002).

Developments in Building Information Modeling (BIM), automated progress monitoring, and AI tools for data fusion and prediction bring us closer to realizing Digital Twin Construction (DTC) systems (Sacks et al., 2020). These systems are designed to capture Project Status Information (PSI) and Project Intent Information (PII) throughout the supply chain and construction site, making the information centrally accessible to all stakeholders with low latency and high accuracy, thus improving situational awareness and offering the opportunity for global optimization of production.

These challenges and opportunities raise numerous questions concerning the feasibility and the potential of closed-loop automated production control for precast construction. Although all the technologies required to achieve closed-loop production control already exist, integrating them into a cohesive system to support fully automated, holistic decision-making remains a challenge. How can computer algorithms make decisions in a fair way, finding globally optimal solutions that balance the conflicting interests between stakeholders? What is expected of the system's capabilities and trustworthiness to transition decision-making from human-driven to automated decision-support, and ultimately to fully autonomous control?

In this paper, we address these issues by discussing the process and decision-making cycles in precast construction holistically. We explore how closed-loop decision-making could function and propose a hybrid optimization framework to facilitate automated decision-making within these cycles. Our approach focuses on optimizing production plans based on the lean principle of waste reduction rather than merely reducing time and cost.

2 Background

In recent years, progress has been made in the technologies supporting precast construction. These include automated progress monitoring systems (Ergen et al., 2007; Golparvar-Fard et al., 2011), digital twin repositories for managing project data (Schlenger et al., 2022; Soman et al., 2020; Zheng et al., 2021), and optimization algorithms for offsite production (Wang et al., 2021) and site assembly (Huang et al., 2022). Additionally, project management systems facilitate communication and coordination between factories and construction sites.

Nevertheless, while these advances significantly improve local aspects of precast construction, they operate largely in isolation, leading to missed opportunities for optimization. Gaps remain in integrating these technologies into cohesive, closed-loop systems involving continuous feedback and dynamic adjustment. Effective integration would enable real-time data exchange and holistic decision-making, addressing inefficiencies arising from fragmented communication and coordination.

Jiang et al. (2022) made a significant contribution towards integration in proposing a digital twin-enabled real-time synchronization system (DT-SYNC) for planning, scheduling, and erection in precast on-site assembly. DT-SYNC uses high-fidelity digital twins to provide real-time resource status and construction progress information. This system enhances simplicity and resilience by ensuring appropriate resources are spatiotemporally allocated to activities. Their numerical experiment and robotic testbed demonstration validated the concept, showing improved coordination and efficiency in urban areas with limited buffers of pieces on site.

Similarly, Wang et al. (2021) introduce a hybrid rescheduling optimization model for precast production that addresses disruptions such as machine breakdowns. This model combines genetic algorithms with simulations to optimize rescheduling, minimize costs, and ensure on-time delivery. By simulating production uncertainties, the model achieves a trade-off between a high service level and maximizing profits. Case studies demonstrate the model's superiority over other methods, highlighting its practical applicability and cost-reduction benefits in precast construction.

Current research often treats factory production and site assembly as separate optimization problems, failing to consider their interdependencies. Anvari et al (2016) address these interactions with a multi-objective GA-based optimization model that integrates manufacturing, transportation, and assembly. This holistic approach evaluates the cost and time impacts of decisions from manufacturing to assembly, aiming to minimize time and cost while maximizing safety. Their work highlights that a unified approach, viewing these as interconnected sub-systems within a single production system, is essential for modeling the complexities and achieving globally optimal solutions. Such an approach would better address the dynamic interactions and conflicting interests between factory operations and on-site assembly.

Implementing closed-loop systems in precast construction introduces the potential for automated decision-making. With continuous feedback loops and the integration of digital twin systems, computers can process vast amounts of data to identify optimal solutions in real-time, surpassing human intuition-driven practices. However, the transition to automated decision-making necessitates further exploration of technological and organizational factors. While some studies hint at this potential (Agrawal et al., 2023; Sacks et al., 2020), comprehensive discussions on the requirements and implications of such systems remain sparse.

In summary, while existing technologies for precast construction are well-developed, there is a significant gap in their integration into a cohesive, closed-loop system. Additionally, the separate optimization of factory production and site assembly needs to be unified to address their interdependencies effectively. Lastly, the potential for automated decision-making in such systems requires more extensive discussion and exploration. This paper aims to address these gaps by proposing a hybrid optimization framework that leverages existing technologies to create an integrated, automated decision-making system for precast construction.

3 Proposed Framework

Effective decision-making is crucial for optimizing production, delivery, and assembly in precast construction. Our proposed framework integrates three critical decision cycles: 1) batching and scheduling off-site production, 2) coordinating delivery schedules, and 3) sequencing on-site assembly.

Batching and scheduling off-site production involve balancing factory capacity with setup times and aligning batches with fluctuating demand and project timelines. The main challenge is minimizing setup changes while adhering to project deadlines, necessitating a dynamic and complex decision-making process that balances operational efficiency with project requirements.

Coordinating deliveries ensures that necessary elements are on-site when required, without overwhelming on-site storage capacities. This involves managing transportation logistics, lead times, and the readiness of assembly tasks. Disruptions in this phase require adjustments to delivery and assembly schedules to maintain project flow.

The sequence of assembling elements on-site must comply with technical constraints and project specifications. Planners must account for structural dependencies, such as the order in which elements must be assembled to ensure stability, safety regulations, and potential site disruptions. Assembly decisions depend on the availability of delivered elements on-site. While adjustments in assembly sequencing are more flexible due to the absence of predefined lead times, they must align with changes in delivery schedules.

Balancing the conflicting interests between factory operations, logistics, and general contractors (GCs) on-site presents significant challenges. Factories aim to maximize efficiency by producing large batches of the same elements. Logistics require consistent delivery schedules to optimize transport, while GCs need elements delivered in a specific order to minimize site inventory and streamline assembly processes.

Figure 1 illustrates the production flow from the factory production to site assembly as a series of planned and coordinated steps. The process begins with production in batches in the factory, managed through distinct production cycles. Preparing the constituent components for the pieces – rebar fabrication, procurement of hardware and of finishing materials – requires lead time from the point of decision to commit to produce until the start of production, and this is indicated by a decision point and a red lead-time line in the figure. Once produced, the batches are then moved into factory inventory, where elements are organized and prepared for delivery. Delivery occurs in planned batches committed for transport at specific intervals. Elements are transported from the factory inventory to the site inventory, from which they are subsequently drawn for assembly.

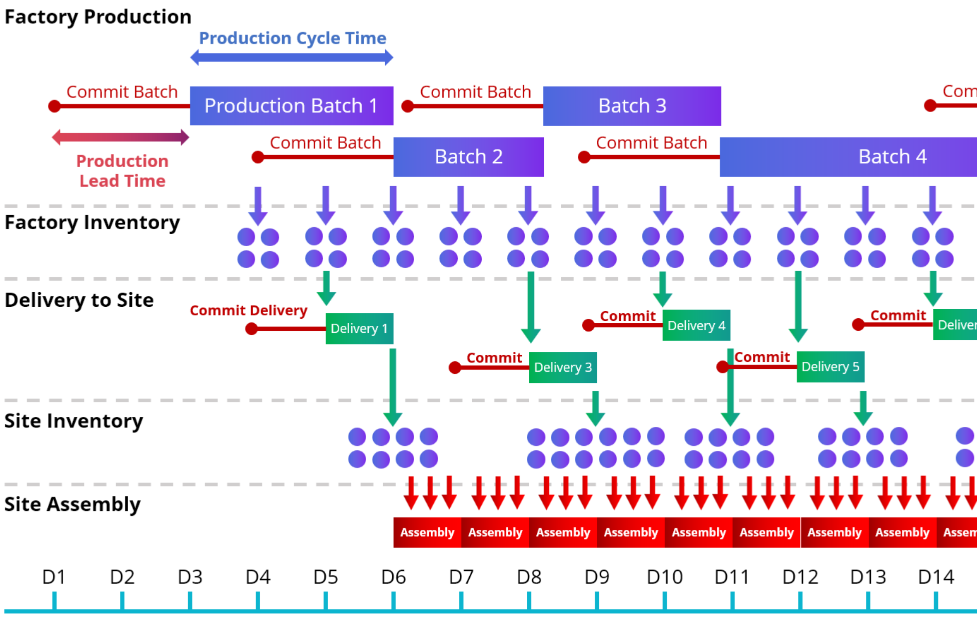

Figure 1. Process Flow and Decision-Making for Precast Frame Erection

Cycle time and lead time are crucial parameters in the production system. Lead time encompasses the period from committing to a production plan, acquiring materials from suppliers, and setting up production. For deliveries, it includes locating elements, organizing them, calling up trucks, and loading the elements. Figure 1 shows these commitment points explicitly, because it is at these points that planners can decide to follow or change the production plan. This flexibility enables real-time adjustments, but the longer the lead times, the less flexibility there is for adapting or optimizing production overall. Theoretically, one could re-plan before the assembly of each individual piece. However, daily cycles for commitment to assembly plans are more practical, and this is shown in Figure 1.

3.1 Closed-loop Decision-Making

Closed-loop decision-making cycles leverage continuous feedback and iterative adjustments to refine production plans based on real-time data and performance outcomes. This approach contrasts with open-loop systems, which lack feedback mechanisms and rely on static plans, making them less resilient to changes or disruptions.

The closed-loop cycle involves several key stages: planning, execution, monitoring, feedback, and adjustment. Initially, planners establish production plans and schedules based on forecasted demand, resource availability, and production capacity. During execution, these plans are implemented, and progress is monitored continuously. Data on various aspects of the production process, such as output quality, resource utilization, and process efficiency, is collected and analyzed. This feedback allows for necessary adjustments to the production plan and processes, ensuring they align with desired outcomes such as timely project completion and resource efficiency. The feedback loop in a closed-loop system is integral, enabling dynamic updates to the production plan to reflect real-time conditions and performance. This approach allows for adaptive responses to unforeseen disruptions, changing demand patterns, and variances in production rates.

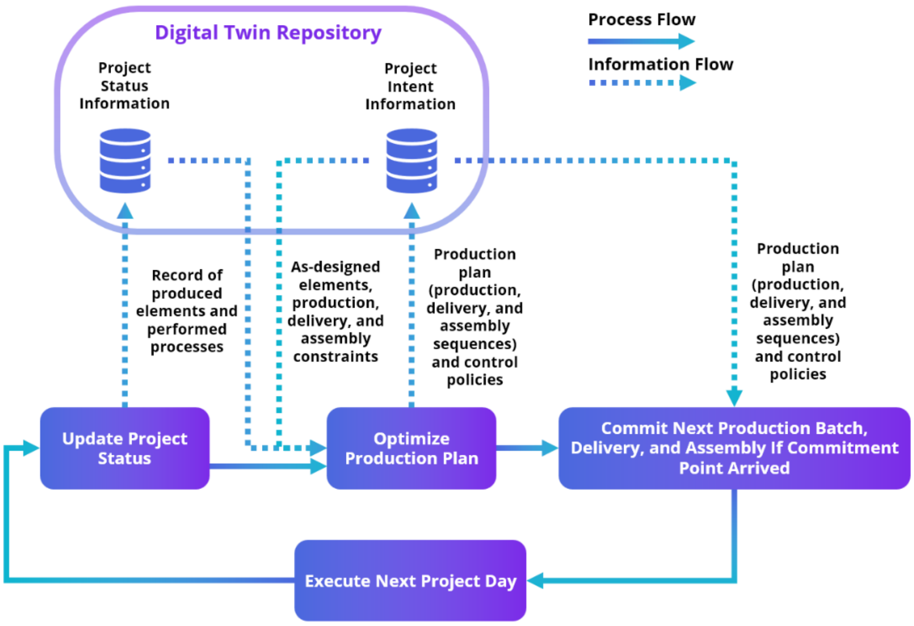

Figure 2. A digital twin-enabled closed-loop Plan-Do-Check-Act cycle for precast construction

The integration of automated progress monitoring technologies and digital twin information systems makes closed-loop systems possible. Various commercial solutions exist for recording as-performed processes and modeling as-built products. For example, RFID systems, which track logistics by scanning tagged elements, provide real-time updates on the location and status of materials (Ergen et al., 2007). Reality capture technologies, such as LiDAR and computer vision, construct as-built BIM models (Golparvar-Fard et al., 2011). Bluetooth beacons track onsite labor and equipment, and IoT sensors monitor site conditions. Each of these technologies provides a part of the overall information, with varying degrees of latency and accuracy (Hasan and Sacks, 2023).

Central to the effectiveness of closed-loop systems in precast construction is the digital twin repository, which integrates and interprets real-time data. The digital twin repository stores both project status (produced elements and performed processes) and project intent (planned products and processes) (Schlenger et al., 2022). By comparing these, the system can identify deviations and inform necessary adjustments.

As depicted in Figure 2, the closed-loop control cycle for precast construction involves several steps. Updating the project status requires recording of real-time data on production and site conditions into the digital twin repository. This updated status is then used to optimize the production plan, considering current conditions and performance metrics. At each commitment point, planners decide whether to adhere to the current plan or to initiate a new round of optimization before committing the next step to execution. Once the next production batch, delivery batch, or assembly schedule is committed, the execution step for the next project day begins.

The levels of automation in each step can vary significantly. Updating the project status can range from manual input by inspectors or workers to continuous scanning by autonomous robots and UAVs. Optimizing the production plan and committing the production schedule can range from human-driven decisions to automated decision-support systems and eventually to fully autonomous decision-making algorithms (Agrawal et al., 2023).

3.2 Hybrid Optimization Module

Our objective is to seek global optima—solutions balancing stakeholders' interests with minimum overall waste. Given that a 'brute force' approach in which every possible production plan is enumerated and evaluated is impossible due to the combinatorial scale of the problem, we frame the problem in a form that can be solved using heuristics and a genetic algorithm. The approach is two-tiered. It begins by applying planning heuristics to narrow down the set of possible production plan parameter values to those sets that define feasible plans. Next, a metaheuristic Genetic Algorithm (GA) guides the selection process within this set. Within the GA cycle, each selected plan is processed with a stochastic simulation where factory and site agents dynamically generate and execute production schedules based on defined control parameters (e.g., batch size and buffer size) and the current project status. Disruptions, such as quality defects and delivery delays, are stochastically introduced to assess the robustness of each plan.

The simulator performs multiple runs for each plan to capture the variability and potential risks. A multi-objective cost function processes the time-series data from these, yielding a composite production plan score that reflects the plan's overall performance. These scores are then fed back into the GA, informing the next round of guided search. The optimization cycle continues until a stopping condition is met (either based on a pre-defined number of cycles or convergence of scores). The best production plan is then integrated into the digital twin repository as the new baseline.

Figure 3 illustrates the hybrid optimization module, detailing the stages from heuristics-based plan generation to metaheuristic optimization with evaluation using simulation. A production plan is defined by three components: groupings of precast pieces into work packages, technical precedence constraints between work packages, and control parameters. Production plans are generated through a structured process that ensures feasibility.

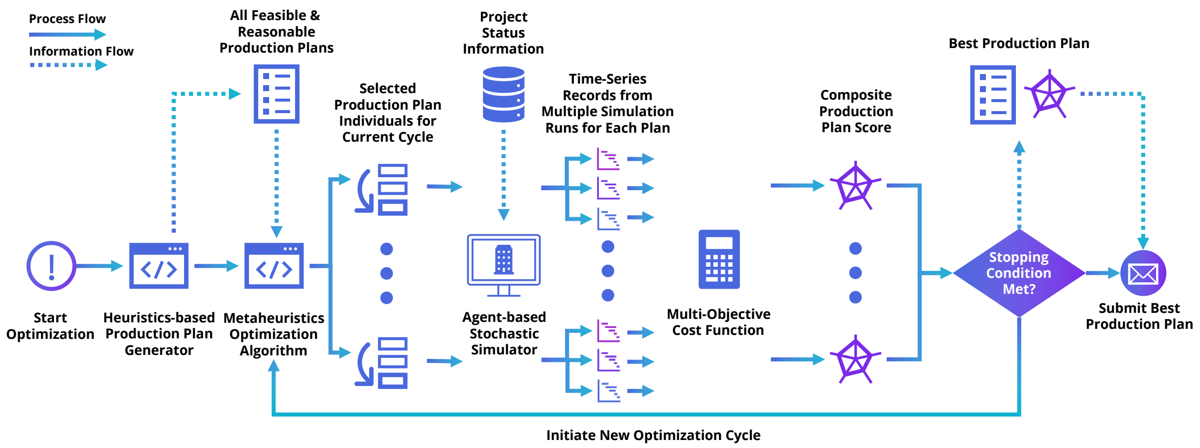

Figure 3. Hybrid optimization module for determining an optimal production plan using heuristics, meta-heuristics, and agent-based simulation for evaluating production plans.

Candidate production plans are compiled using production logic heuristics in three steps, as described in Figure 4 and outlined here:

1) First, as-designed building element information is extracted from the BIM model or retrieved from the project intent information in the digital twin repository. Elements are then grouped into assembly work packages based on criteria that include location, element type, and construction sequence constraints. This practice is common in precast construction: work packages are designed to facilitate the completion or closure of specific zones, enabling subsequent construction activities. For example, planners might group a set of vertical contiguous elements that enclose an apartment, enabling work on the slab above the apartment to commence in the next production cycle.
2) Next, possible sequences for the work packages are derived using rules similar to strategic moves in chess, where initial moves define a set of legal sequences. Rules might dictate that the starting work package must be from a corner or that sequences should prioritize the closure of locations. These sequencing rules help to generate feasible sequences that respect practical and efficient assembly processes.
3) Lastly, the feasible range of production control parameters—namely, production batch size and site inventory buffer—is applied. The production batch size influences the

production lead time and cycle time, while the site inventory buffer determines when deliveries are triggered from the site, aiming to maintain optimal site inventory levels. Constraints from the factory and onsite inventory restrict the feasible ranges of these parameters.

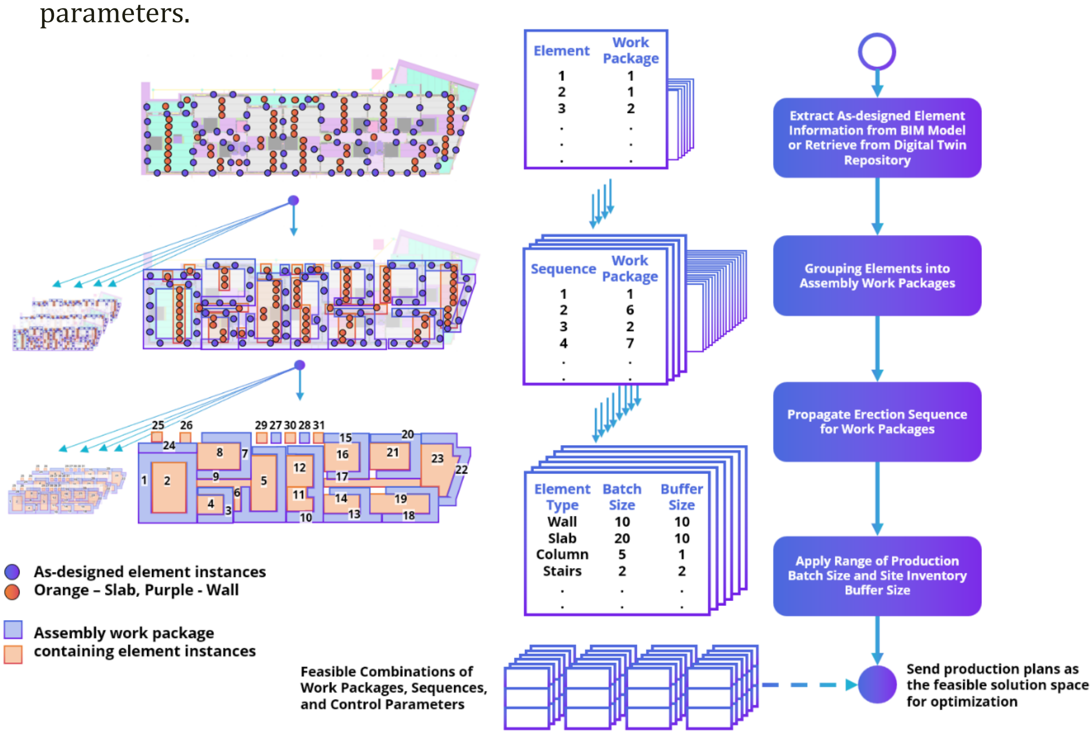

Figure 4. Application of heuristics to generate production plan candidates for optimization.

3.3 A Lean Multi-Objective Cost Function

Lean construction principles guide the optimization of production planning discussed in the previous section. Lean construction aims to maximize customer value while minimizing waste in production processes (Koskela et al., 2012). This approach emphasizes steps to reduce effort without compromising the value delivered to customers. In lean construction, some costs are essential and value-adding, while others, which do not contribute to customer value, are considered waste. Our framework seeks to minimize these types of waste.

To implement these principles effectively, one must identify and eliminate the following seven types of waste: overproduction, waiting, transportation, overprocessing, inventory, motion, and defects (Koskela et al., 2013). Overproduction refers to producing more than needed or producing it too early, leading to excess inventory and storage costs. Waiting is the idle time caused by delays, reducing productivity and extending project timelines. Transportation waste involves unnecessary movement of materials or equipment, which increases handling costs and risks. Overprocessing entails performing more work than necessary, including redundant inspections or overly complex processes. Inventory waste arises from excess materials that are not immediately needed, leading to increased storage costs and potential obsolescence. Motion waste is the unnecessary movement of workers, such as searching for tools or materials, leading to inefficiencies and increased labor costs. Defects involve work that is incorrect or incomplete, requiring rework or repair, resulting in additional costs and delays.

Our optimization framework focuses on minimizing waste throughout the production, delivery, and assembly processes. Rather than minimizing overall time and cost, the objective is to identify a production plan and control policy that results in the least waste. The multi-objective cost function (Equation 1) integrates various waste reduction goals into a single monetary value, making it easier to evaluate and compare different production plans. For instance, to measure the waste in labor productivity, we would calculate the cost of non-productive work hours onsite within the simulation run, which is the hourly rate multiplied by hours not working. The overall score of the function is the average of the sum of the costs for each objective from all simulation runs for a given production plan.

$$C = \frac{\sum_{run}\left[C_{crew} + C_{flow} + C_{WIP} + C_{batch} + C_{logistics} + C_{rework}\right]}{n_{runs}}, \qquad (1)$$

Table 1 outlines the components of the cost function and the types of waste each component addresses. Assembly Crew Productivity measures the cost of non-productive labor hours on site and is associated with the wastes of waiting and movement. Process Flow considers the cost of upstream trade waiting for work. This component also inversely measures the value delivered to the customer, the upstream trades. Inventory accounts for the cost of inventory overhead both onsite and offsite, addressing overproduction and inventory wastes. Offsite Batch Production includes the costs of production setup times, linked to motion waste. Logistics evaluates the cost of underutilized transportation capacity, relating to transportation waste. Rework measures the cost of production time and transport of defective elements, addressing defects.

Table 1. Description of components in the cost function and their associated waste categories

Waste component	Description	Waste Category
Assembly Crew Productivity	Cost of non-productive labor work hours on site	Waiting, Movement
Process Flow	Cost of upstream trade waiting for work	Waiting
Inventory	Cost of inventory overhead on site and off site	Overproduction, Inventory
Offsite Batch Production	Cost of production setup	Motion
Logistics	Cost of underutilized transportation capacity	Transportation
Rework	Cost of production and transport of defective elements	Defects

Formulae to compute the waste components' values are detailed in Table 2. Assembly Crew Productivity ($\boldsymbol{C_{crew}}$) is calculated as the sum of all nonworking hours per crew multiplied by the hourly rate for the crew. Process Flow ($\boldsymbol{C_{flow}}$) is the sum of the daily cost for nonworking upstream trade crews. Inventory ($\boldsymbol{C_{WIP}}$) involves summing the inventory cost per day within and beyond the designed storage capacity. Off-site Batch Production ($\boldsymbol{C_{batch}}$) is calculated as the sum of production cycles multiplied by the setup cost per cycle per element type. Logistics ($\boldsymbol{C_{logistics}}$) involves the sum of the cost multiplied by the percentage of unutilized capacity per delivery. Rework ($\boldsymbol{C_{rework}}$) is the production and transport cost of defective pieces.

Table 2. Formulae for computing the components of the utility function

Waste component	Equation	Explanation
Assembly Crew Productivity	$C_{crew} = \sum_{crew}\left[\sum_{onsite\ day} NWH \cdot C_{WH,crew}\right]$	Sum of all nonworking hours (NWH) per crew multiplied by the hourly rate for the crew ($C_{WH,crew}$)
Process Flow	$C_{flow} = \sum_{day}\left[\sum_{upstream\ trade} NWC \cdot C_{w,trade}\right]$	Sum of nonworking crew (NWC) per upstream trade multiplied by the daily cost of waiting for the trade crew ($C_{w,trade}$)
Inventory	$C_{WIP} = \sum_{day}\begin{cases} x \cdot C_{rs},\ if\ x \leq cap_s \\ cap_s \cdot C_{rs} + (x - cap) \cdot C_{es}, x > cap_s \end{cases}$	Sum of inventory cost per day within (C_{rc}) and beyond (C_{es}) designed storage capacity (cap_s)
Offsite Batch Production	$C_{batch} = \sum_{element\ type}\left[\sum_{cycle} C_{setup,type}\right]$	Sum of production cycles multiplied by the setup cost per cycle per element type
Logistics	$C_{logistics} = \sum_{delivery}\left[\left(C_{trip} + WT \cdot C_{w,t}\right) \cdot \left(1 - \frac{payload}{cap_t}\right)\right]$	Sum of the cost of transport (C_{trip}) and waiting on site (C_w) multiplied by the percentage of unutilized truck capacity (cap_t) per delivery
Rework	$C_{rework} = \sum_{defect\ piece}\left[C_{prod} + C_{trip}\right]$	Sum of the production cost (C_{prod}) and transport cost (C_{trip}) per defective piece

4 Discussion and Conclusion

Given the inherent inefficiencies that arise in precast construction due to conflicting objectives in production control and the separation of factory from site (Zhai et al., 2017), the relative simplicity of tracking large prefabricated pieces, and the growing maturity of automated progress monitoring technologies (Ergen et al., 2007), precast concrete construction may be a prime candidate for closed-loop Digital Twin Construction systems. For this to become practical, an overall information system framework is needed, and a robust global and adaptive optimization module is essential (Wang et al., 2019).

Our proposed holistic framework integrates factory production, logistics, and on-site assembly, with the goal of reducing waste and improving efficiency by treating the entire process as a unified system. Previous methods often isolated factory production or on-site assembly, leading to suboptimal outcomes (Anvari et al., 2016). The problem formulation depicted in Figures 1 and 2 defines the precast construction system as a single production system with interconnected sub-systems, expressing the needs, costs, and values of both the factory and construction site.

By focusing on a waste-centric objective function, our framework aligns with lean construction principles, ensuring that cost reductions do not compromise value. This avoids the pitfalls of the more common multi-criteria objective functions for optimization that incorporate parameters such as overall project duration and overall project cost, with different units of measure that require weighting systems that can obscure the purpose (Heon Jun and El-Rayes, 2011; Wang et al., 2021). This is the second key contribution of this paper.

A key simplification in our study is that factories produce precast pieces for a single project in isolation. However, factories commonly serve multiple projects simultaneously, necessitating sophisticated algorithms to manage increased complexity. When factories serve multiple sites from the same general contractor, portfolio-wide optimization can achieve a global optimum. Advanced scheduling algorithms and comprehensive data integration across multiple sites balance competing demands and optimize resource utilization, improving resource allocation and reducing costs despite increased complexity. Indeed, this overall optimization is one of the key value propositions of Digital Twin Construction.

Implementing closed-loop systems is a critical step toward fully autonomous decision-making by computer algorithms, processing vast amounts of data to identify optimal solutions within the decision commitment windows that the system imposes. However, this transition will require consideration of technological and organizational factors, including ethical considerations like job displacement and maintaining human oversight. Autonomous systems must collaborate with human operators, ensuring critical decision points remain under human control.

Future research should focus on implementing the proposed framework in both laboratory and real-world settings to evaluate robustness and effectiveness. Metrics for success include production efficiency, waste reduction, and adaptability to disruptions. Additionally, exploring the evolving role of human planners in closed-loop systems is essential, as automation increases, shifting planners' roles from decision-making to oversight and management, necessitating new skills and training.

Acknowledgments

This work is funded in part under grant No. 2033719 from the Israel Ministry of Science, Technology and Innovation.

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