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A LABORATORY SETUP FOR EXPLORING DIGITAL TWIN CONSTRUCTION PLANNING AND CONTROL

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Abstract

Digital Twin Construction (DTC) is a data-centric approach to construction management, enabling real-time "Plan-Do-Check-Act" (PDCA) cycles for production control. Despite its potential to streamline processes and reduce waste, DTC remains untested in full-scale projects due to technical and practical barriers. To explore the feasibility of DTC, we therefore developed a controlled lab setup using a 1:25 scale model and automated monitoring to simulate DTC-driven planning. The setup enables experimentation across different levels of automation with the goal of testing feasibility and viability for real-time planning and control. This research contributes to understanding DTC's potential to transform production control in construction.

Introduction

The scale and complexity of construction projects pose significant challenges for production managers when making planning decisions concerning resource allocations, construction methods, and activity sequences. Among the challenges are a lack of project situational awareness and reliable tools to predict the outcomes of decisions. Digital Twin Construction (DTC) aims to automate decision-making by incorporating information and monitoring technologies into a lean closed-loop planning and control system. However, a range of technological and commercial questions concerning DTC remain unanswered, and this prevents full-scale implementation. Therefore, we propose to design and implement a prototype DTC system in a controlled laboratory setting to test DTC-enabled automated 'Plan-Do-Check-Act' planning and control cycles in various configurations.

The scope of our experimental setup is the particular case of precast concrete construction, because modeling the construction process at small scale is straightforward. The experimental method includes:

a) Design and build a 1:25 scale model precast building that faithfully models the work packages and methods of the original building. The precast concrete pieces were fabricated using laser cutting and 3D-printing according to a structural BIM model.
b) Develop an automatic process of data acquisition to monitor the entire precast construction process in the lab, from the production of individual precast pieces to their delivery and construction. The system couples QR codes on the pieces and four video cameras for real-time onsite monitoring.
c) Develop and implement the software to interpret the monitoring data into actionable information and to compile a status model in a cloud repository.
d) Design and implement a production simulation and optimization system to support managers' decision-making.
e) Test and compare alternative decision-making scenarios at increasing levels of automation by repeatedly simulating construction of the precast building.

In this paper, we present the experimental setup, demonstrate its validation, and outline the research questions that it can be used to explore.

Background

Digital Twin Construction

Digital Twin Construction (DTC) is a paradigm for automated production system design, planning and control of production in construction projects using a twin system (Parn et al. 2024; Sacks et al. 2020). The digital twin part of the system comprises Project Intent Information, contained in BIM models, construction schedules and so on; Project Status Information, which captures the as-built state of a building and the as-performed record of the work done; and a set of software modules. The software modules serve to interpret the raw monitoring data to derive product and process status information; to simulate work going forward from any point in time to evaluate the efficacy of any proposed changes to the production system; to communicate the likely outcomes and recommend action to construction managers through the decision support interfaces.

Research to date has developed the concept and proved feasibility for different aspects of DTC. For example, Schlenger et al. (2022) developed a comprehensive data schema for DTC and demonstrated the efficacy of implementing it in a graph database in the cloud using Orange Inc.'s *Thing'In* platform. Teizer et al. (2022)

developed and demonstrated the use of the status information together with real-time tracking of workers and equipment to monitor safety conditions on site. The BIM2TWIN project and others funded by the EU Horizon program have contributed significantly to R&D of the key components of DTC systems (BIM2TWIN 2021). Nevertheless, to date there are no examples fully-fledged operational closed-loop DTC systems, neither in industry nor in academia.

Experimental Methods for Research of Construction Planning and Control

Planning and control in construction can be studied using empirical, simulation or experimental methods (Fellows and Liu 2015). Empirical methods are challenging because it is difficult to establish causation, or even correlation, between construction managers' decisions and the outcomes observed in project records. Even if reliable records are kept, the range and impact of potentially confounding parameters are large.

Simulation methods include discrete-event (DES) and agent-based simulations (ABS). DES is useful if the subjects behave in clearly predictable ways. For example, planning the operations of earthworking equipment (Martinez and Ioannou 1999; Szczesny et al. 2011). Where behaviours must be modelled explicitly, such as the decision-making of subcontractor trade crews in resource allocation, ABS is preferred (Ben-Alon and Sacks 2017).

Experiments to evaluate the impact of managers' decisions on the flow of work can be conducted in the field or in the laboratory. Field experiments to test the impacts of specific interventions in the ways projects are managed are very difficult a) because identifying control cases is extremely difficult and b) due to the very wide variation in project outcomes (Priven and Sacks 2016).

For these reasons, researchers often turn to lab experiments with human subjects. The major advantage of this approach is that the independent parameters can be closely controlled, leaving only the parameters of interest to vary within experimental scenarios crafted to clearly distinguish between the different controlling parameters. Simulation games such as LEAPCON and Villego use this method (Sacks et al. 2007) (Warcup and Reeve 2014). Simulations of this kind used for experimentation or education are often called 'serious games' (Martinez et al. 2023).

Experimental Setup

Overview

The experimental setup is a laboratory-scale simulation environment designed to replicate and analyse the frame erection process in precast construction. As illustrated in Figure 1, the setup consists of a 1:25 scale model of a precast concrete building, where workers interact with precast elements to simulate the assembly and concreting processes, and a software component which comprises a digital twin repository, which stores real-time monitoring data, project status updates, and decision-support information. The digital twin services utilize this data to provide situational awareness, recommendations, and operational support.

The setup incorporates four key roles: the construction manager, who plans and controls the project based on real-time data; the assembly and concreting workers, who physically build the model by placing and securing the precast elements; and the supplier, responsible for delivering precast elements from the off-site factory to the construction site. This controlled environment enables the study of decision-making processes under varying conditions, facilitating insights into adaptive project management strategies. The design principles of the platform emphasize the integration of a physical building and a digital twin.

The physical building is a 1:25 scale model of a residential precast concrete building project named Postiaukio in Helsinki, Finland. It captures the complexity of the assembly process, the spatial and technical constraints, and inherent variances in work quantities between work locations. The original building was 5,000 m^2, eight stories with two elevator and stairwell cores, 61 apartments, and a total of 1,300 precast pieces. The model enables workers to interact directly with precast elements, simulating assembly and concreting activities. The simulation includes the ability to model events that disrupt the workflow, such as quality defects on precast pieces and pieces not delivered on time.

The digital twin repository consists of an SQL database and a BIM model. The SQL database stores all data

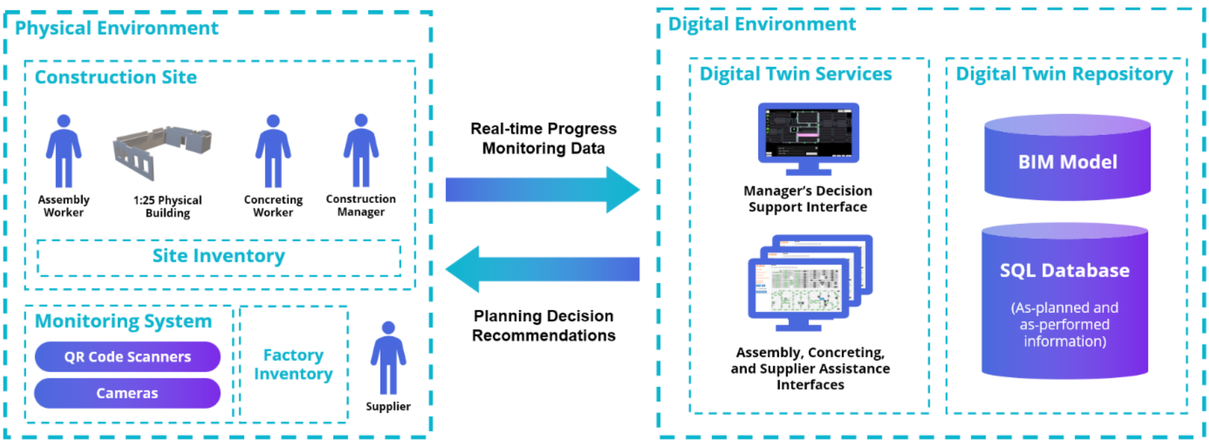


Figure 1: Experiment Setup Overview

streams from the monitoring system and aggregates project status information derived from data fusion. It also stores the assembly, delivery, and production schedules used in the experiment. The BIM model represents the digital counterpart of the physical building, providing a detailed virtual structure. By combining the BIM model with project status information, the digital twin repository serves as the central information storage, while digital twin services leverage this data to provide real-time insights and decision-support functionalities. Information exchange within the repository is managed by a Python-based server that facilitates communication via RESTful APIs.

The real-time progress monitoring system functions as the primary input mechanism to the digital twin repository, linking the physical and digital environments by capturing and processing real-time status updates from the construction site. Utilizing four cameras placed at each corner of the building, the system tracks placement of precast elements in real-time. QR codes on the pieces are read before element delivery and on assembly to associate pieces with the locations into which they are placed and to provide detailed status updates. The monitoring data is processed and stored into the digital twin repository, thus creating a continuously updated and accurate representation of the construction site.

The setup includes four digital twin services that operate on the digital twin repository and are designed to support the different roles in the construction process. The Manager's Decision Support Interface dashboard provides information, insights and recommendations, and it enables managers to adapt project plans based on real-time data and feedback. Additional interfaces are provided for the assembly work crew, concreting work crew, and the off-site factory, presenting relevant information and instructions required to perform their respective tasks in the experiment.

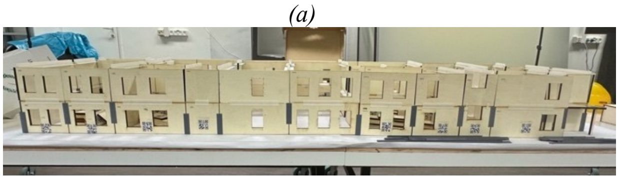
The following subsections describe the technical implementation of each component.

Experimental building

The experimental building is a 1:25 scale model of a residential building constructed in Helsinki, Finland, for which we have the full BIM model and the ground truth construction sequence in the form of time-lapse videos. The model building has two floors. Each comprises 11 spaces, two balconies, two elevator shafts, two stairwells and seven bathroom-pods. Figure 2 shows construction of the first floor of the experimental building and construction of the vertical pieces on the second floor.

Each floor has six main component types: walls, hollow-core slabs, concrete joints for walls, concrete joints for slabs, stair wells and bathroom-pods. The wall and slab elements were laser cut using 8mm wood sheets. The concrete joints were 3D printed in grey plastic. Additionally, red triangular temporary supports (Figure 3) were 3D printed. Each building component is labelled with a QR code, which is scanned twice during construction: first, when it is delivered to the site; and second, when it is placed in a specific location during erection. Note that pieces are not unique – some pieces can be placed in more than one possible location. The entire building has 308 precast pieces, 14 bathroom-pods and 298 cast-in-place concrete joints.

(a)



(b)

Figure 2: Experimental building (a) first floor, (b) two floors.

Monitoring system

The monitoring system records, interprets and reports the precast construction process, from the production of individual precast pieces to their delivery and construction. Figure 4 shows the main apparatus of the system. It includes four tripod-mounted Logitech BRIO webcams, positioned at optimal locations, heights, and angles to collaboratively monitor the construction area (3.6m × 0.8m), ensuring that the piece being erected remains visible in at least two camera views even when workers or other installed pieces obstruct any camera during construction. The cameras are connected to a high-performance computer via powered USB extension cables and hubs. The computer, equipped with an NVIDIA RTX 4090 GPU, supports deep learning-based object detection algorithms deployed in the system.

Figure 5 illustrates the software architecture of the monitoring system, which is designed in a modular fashion to ensure robustness and reliability. Specifically, the system consists of two pre-processing modules (Pre1 and Pre2) and five modules that run in real-time (RT1 to RT5), operating in parallel using multithreading techniques. The pre-processing modules must be executed in advance to prepare the necessary inputs required for real-time modules.

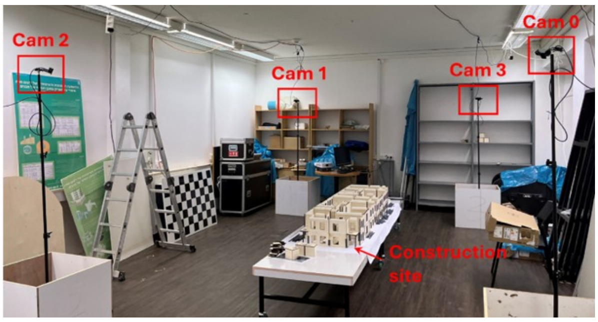


Figure 4: Apparatus of the camera network-based onsite monitoring system.

Pre1: Camera network calibration. This module calibrates all four cameras relative to the construction site, providing the interior and exterior parameters necessary for the RT4 module to track and localize pieces in 3D space and link them to BIM elements. Calibration follows the standard chessboard-based method (Zhang 2000). When determining exterior parameters, the chessboard is placed in a location on the construction site with a pose that enables assessment of the spatial relationship between the world coordinate system (WCS) and the BIM model's coordinate system (BCS).

Pre2: Object detection model preparation. This module develops fast and accurate object detection models for RT3. We selected YOLO11, the latest in the YOLO series, known for state-of-the-art real-time detection in both speed and accuracy Ultralytics 2024). Specifically, YOLO11-Pose is used directly for worker and pose detection, while a customized version of YOLO11 is fine-tuned for detecting pieces, temporary supports (TSs), and concrete joints. Fine-tuning was performed on a dataset of 3,355 images (90% for training, 10% for validation) captured from the four cameras during trial runs. To reduce annotation efforts and align with RT3 and RT4 requirements, only "active" pieces and joints—those held or touched by workers—were labeled. For TSs, both installed and active ones were annotated. This resulted in 3,500 labeled pieces, 1,500 joints, and 17,000 TSs.

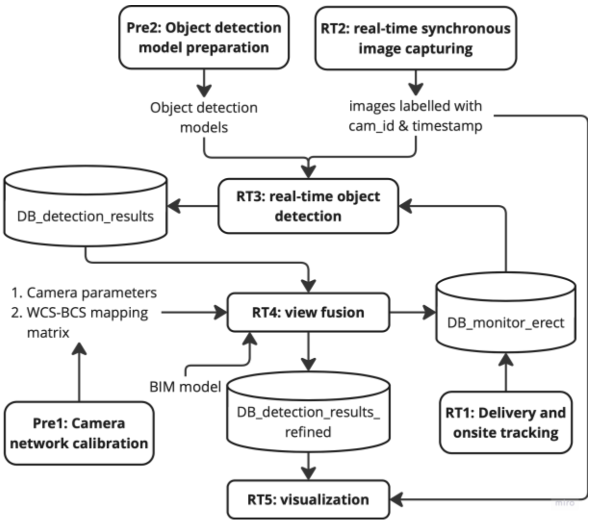


Figure 5: Software architecture of the monitoring system

RT1: This module implements a QR code scanning system to facilitate registration and tracking of precast pieces from offsite production and delivery to onsite erection with handheld code readers. It uses OpenCV library for QR code recognition and the NiceGUI library for handling the graphical user interface (GUI). The GUI of the desktop configuration displays the production request and a log of scanned pieces, allowing for continuous monitoring. As pieces are prepared at the offsite factory location, they are scanned and registered, recording each piece's ID, type and a timestamp marking its delivery time. When workers pick up a piece for installation, scanning its QR code registers the piece and records a new timestamp as the erection start time. Once the scan is successful, the system provides an audible confirmation. This allows workers to maintain their focus on the task at hand. All the scan data is automatically uploaded to the cloud-based database *DB_monitor_erect* (see Figure 5).

RT2: Real-time synchronous image capturing. This module controls all four cameras to continuously capture construction site images at a specified frame rate. FFmpeg is used for its robustness and reliability in capturing high-resolution images over extended periods at high frequencies. In our current implementation, images are recorded at 10 fps with a resolution of 3840×2160 to ensure precise piece localization in RT4. Each captured image is timestamped and labeled with the camera index, enabling RT3 to track pieces under erection. While the cameras are not perfectly synchronized, the time differences are acceptable (within 0.1s).

RT3: Real-time object detection. This module processes images from all four cameras in real time using a multi-threaded batch processing mechanism. Detection results are recorded and stored in the cloud database *DB_detection_results*. Each image undergoes three key tasks:

The first task is to detect the builder and concreter. In our context, the builder wears a yellow helmet and concreter a pink helmet. The human pose detection model was first used to detect all the people and their poses in the image. The builder and concreter are then identified by detecting their helmets through image analysis. The second task detects active pieces, joints, and both installed and active TSs using the trained object detection model. To reduce false positives, only pieces and joints held by the builder are retained, determined by the proximity between the object's bounding box (BB) center and the builder's wrist point. Lastly, the detected pieces need to be enriched with ID for tracking across frames and camera views. The enrichment step is achieved by first extracting the timestamp stored in the image and then checking with the *DB_monitor_erect* database, which logs every delivered piece's information including ID and erection start times.

RT4: View fusion. This module fuses time-series detection results from multiple camera views to identify installed pieces, determine their erection finish times, find corresponding BIM elements, and track concreting and TS status. First, current detection results from DB_detection_results are grouped and sorted into batches based on the timestamps, with each batch containing the detection results of four images taken simultaneously. False detections are filtered by checking whether detected pieces are already installed. The refined results are then fused through three consecutive branches.

The first branch deals with pieces. If a piece appears in fewer than two views, the batch is ignored. Otherwise, the two views with the largest BBs are selected for accuracy. Using their 2D BBs, the 3D center point in the BCS is computed via geometric triangulation. Installation

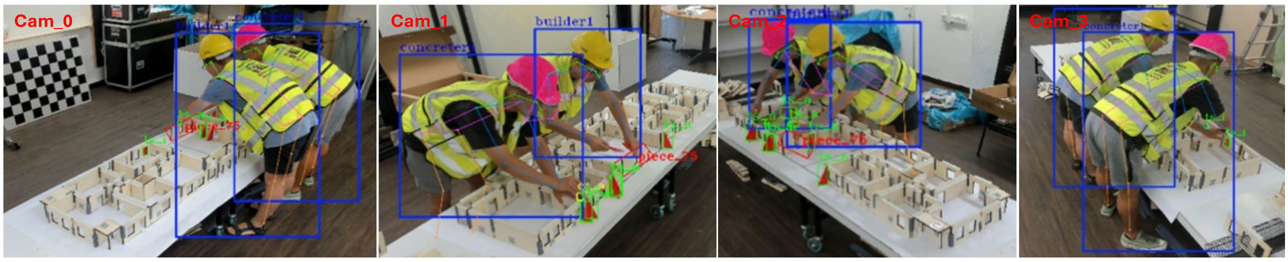


Figure 6: Visualization of detection results: (1) builder and concreter and their poses (blue boxes); (2) active piece (red boxes); (3) active joint (yellow box in cam_1); and (4) installed (ts_i) and active (ts_a) temporary supports (green boxes).

completion is determined when a piece disappears from detection for ten consecutive batches, indicating that the builder has released it for at least one second. The timestamp of the final occurrence is recorded as the finish time and the corresponding 3D position and BBs are used to identify the corresponding BIM element. The second branch monitors the installation process of each joint to determine its completion time and the pieces it concretes. This method resembles active piece tracking but differs in how it identifies the associated pieces. It achieves this by measuring the distance between the 3D center point of the installed joint and the side surfaces of all previously installed pieces. Unlike pieces and joints, TSs are reused. This branch thus tracks both installation and removal of TSs. The first part is similar to that of joints. To achieve the second part, the branch continuously checks the differences of installed TSs between two adjacent batches to find the disappeared installed TSs and their associated pieces.

RT5: Visualization. The module sequentially displays refined detection results in a time-series manner. Each image in a batch is overlaid with key detection data, including the builder and concreter's pose, the active piece's BB and ID, and the BBs of all TSs, as shown in Figure 6. This visualization effectively illustrates the construction process.

Decision support

A prototype Decision Support System application has been developed using Unity Engine, a real-time development platform widely used for interactive simulations in the Architecture Engineering and Construction (AEC) industry (Schaumann et al. 2019). This system provides an interactive interface (Figure 7 and Figure 8) to assist the Builder and Manager roles in the project. The application portrays a digital twin representation of the building model, displaying production-related data for each element in the building, as well as their dynamic states (delivered, erected, concreted or fully assembled). These states are continuously updated in real time as the application retrieves live data from the DTC database using Unity's web-request features.

Additionally, unpredictable disruptions, such as defective or missing pieces, can be communicated via the interface to the Manager as they are detected by the DTC system, prompting them to respond by adapting the work plan. The Manager's interface enables the manager to make informed decisions and adjust the construction plan by providing a comprehensive and up-to-date overview of the full erection process. Changes committed by the Manager are communicated back to the DTC database, which processes them to generate and distribute updated production requests, delivery plans, and erection sequences. These erection sequences are updated and displayed on the Builder's interface, which utilizes helpful UI features such as rotating views and isolating elements to ensure that erection-related data, such as correct piece orientation, is clearly represented, thus enhancing productivity and minimizing possible mistakes or assembly errors.

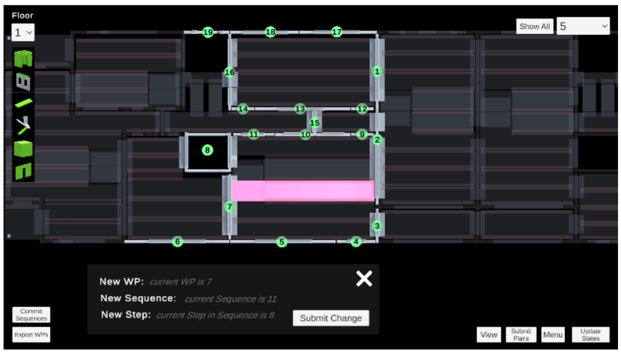


Figure 7: Manager interface showing assembly steps filtered by floor and WP selection, including a 'popup' panel allowing editing of an element's assembly step and WP association in a TOP view of the building model

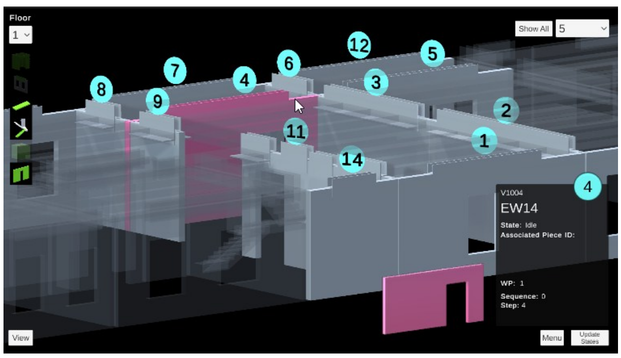


Figure 8: Builder interface showing a 'popup' 3D isolated representation of a hovered element, and a 'tooltip' display of its data, in a rotatable 3D view of the building model.

System Validation

A series of trial experiments were implemented to check to what extent our current experimental setup could meet the functional expectations. In these experiments, a manager, a supplier, a builder, and a concreter were required to erect the two-story building model. Each role was trained to behave according to the pre-defined protocols.

Real-time monitoring system validation

To evaluate the accuracy and reliability of the system in monitoring and interpreting the construction process, a 10-min recording of the construction process in an experiment was selected. The recording captures the erection of 14 pieces, as shown in Figure 9.

A ground truth table was prepared manually by reviewing around 24,000 images captured by the four cameras during this period. The table includes essential information regarding the erection process of each piece (except two that were incorrectly installed), including piece ID, erection start and finish times, corresponding BIM element ID, and the coordinates of the 3D centre of the BIM element.

(a) Start-time status (b) End-time status

Figure 9: Construction period selected for validation

To evaluate the performance of the monitoring system quantitatively, a set of metrics was established that includes accuracy of installed pieces detected (acc_piece), accuracy of associated BIM elements identified ($acc\_element$), position accuracy of installed pieces ($acc\_position$), deviation of erection start times (dev_st), and deviation of erection finish times (dev_ft).The calculation methods for these metrics are outlined below:

$$acc\_piece = num\_p\_detected / num\_p\_gt \quad (1)$$

where $num\_p\_detected$ and num_p_gt refer to the number of installed pieces correctly (correct piece ID) detected by the system and the relevant ground truth respectively.

$$acc\_element = num\_e\_detected / num\_e\_gt \quad (2)$$

where $num\_e\_detected$ and num_e_gt refer to the number of installed pieces whose associated BIM elements are correctly detected by the system and the relevant ground truth respectively.

$$acc\_position = \frac{\sum_i dist(p_i.center, e_i.center)}{num\_e\_gt} \quad (3)$$

where $p_i.center$ and $e_i.center$ refer to the 3D centre of detected installed piece i and the 3D centre of the associated BIM element respectively. The $dist$ function calculates the Euclidean distance of the two input 3D centre points.

$$dev\_st = \frac{\sum_i |p_i.e\_st\_detect - p_i.e\_st\_gt|}{num\_p\_gt} \quad (4)$$

Where $p_i.e\_st\_detect$ and $p_i.e\_st\_gt$ refer to the erection start time of the piece i recognized by the system and the relevant ground truth, respectively.

$$dev\_ft = \frac{\sum_i |p_i.e\_ft\_detect - p_i.e\_ft\_gt|}{num\_p\_gt} \quad (5)$$

Where $p_i.e\_ft\_detect$ and $p_i.e\_ft\_gt$ refer to the erection finish time of the piece i recognized by the system and the relevant ground truth, respectively.

Table 1 presents the evaluation results based on the defined metrics.

Table 1: Evaluation results

acc_piece	$acc\_element$	$acc\_position$	dev_st	dev_ft
100%	90.9%	54.2 mm	0.0 s	1.2s

As seen from Tab. 1, all the installed pieces in the selected construction period were successfully detected (acc_piece). Regarding the erection processes of these pieces, the starting times were also accurately detected by the system (dev_st). Although there are deviations regarding the finishing times, the average deviation is within 1.2 second (dev_ft), which is acceptable for DTC experiments. Regarding the identification of associated BIM elements, the system achieved an accuracy of approximately 91% ($acc\_element$). One of the 12 pieces was not matched with a corresponding BIM element due to the failure to meet algorithmic requirements. Further analysis of all images related to the erection of this piece revealed that the object detection module underperformed in both detection and BB prediction. This issue, though more pronounced for this specific case, was found to be common across all detected pieces, even those for which the correct BIM element was identified. To some extent, this could be reflected by a relatively large position error of 54.2 mm ($acc\_position$). These findings highlight the need to improve the object detection module, which is fundamental to the monitoring system's ability to accurately identify associated BIM elements.

In summary, the experiment results show that in the current laboratory environment, the monitoring system exhibits promising potential for tracking the construction process at a high resolution at the piece level to provide accurate and timely project status information in an automatic manner. This could lay the foundation for DTC-driven construction planning and control experiments within laboratory settings. However, the experiment results also reveal that the accuracy and robustness of the current object detection module on piece detection needs to be significantly improved. Considering the current object detection model was trained with a very small dataset (containing only 3,500 instances), as a next step, we will focus on expanding the dataset significantly, aiming at obtaining a robust and accurate object detection model.

Discussion

Research Opportunities

The experimental setup provides a fully controlled environment to investigate a range of decision-making scenarios and planning and control strategies. It is an open-ended experimental setup that can be used to test different things. The performance and the outcomes of candidate control strategies can be compared to a baseline ‘traditional’ workflow not only qualitatively, but also quantitatively, because the environment is controlled and isolated from the random events that confound such research in the field. The following text provides examples of questions that can be investigated.

Degree of Automation of Planning and Control

The following list details a set of scenarios that can be implemented to investigate the degree to which planning and control may be automated. These are but a few of the many scenarios that can be investigated.

1. **Conventional**: Managers rely on pen and paper to manually update project status.
2. **Best Current Practice**: Project status is tracked and updated using spreadsheets like Excel.
3. **Digital Shadow**: Real-time monitoring provides automatic updates on project status information.
4. **Digital Twin with Decision Support**: The system offers managers recommended plans, which they can use as a reference while designing their own.
5. **Digital Twin Autonomous Planning**: The system autonomously generates and executes optimized plans without the manager’s input or intervention.
6. **Human-in-the-Loop Planning**: Human managers actively contribute to the machine optimization process, tweaking parameters and heuristics in the planning loop.

For any scenario, the setup can provide continuous data to measure, amongst other things:

- Whether and to what extent increased access to situational awareness (SA) affects managers' ability and behaviour patterns in responding to disruptions.
- How managers’ perceptions and performances vary across the automation spectrum.
- The interaction between human customization and system contributions in Scenarios 4, 5, and 6, focusing on the ways in which managers’ decisions are influenced by the "optimal" solutions generated by the system, the extent to which managers accept the utility function provided by the system, and managers’ preferences and choices when tweaking parameters to align the optimization outcomes with their own decision-making priorities.

Global optimization vs. Local optimization

Another area of interest is the degree to which global optimization of prefabrication and erection, across factory and site together, can reduce waste in the system. While local optimization problems such as production scheduling within a factory or transportation planning have been widely studied in the field, global optimization remains a significant gap. Few researchers consider integrating multiple domains, such as factory production, transportation logistics, and on-site assembly, into a unified optimization framework. Extending the experimental setup to include a ‘virtual’ factory allows us to systematically compare the efficacy of local and global optimization approaches. By resetting the experiment to the same base point and running it multiple times, we can test how different strategies perform under identical conditions. This capability enables an in-depth analysis of the interactions and trade-offs between local and global optimization and highlights the potential benefits of adopting a holistic approach.

Impacts of Disruptions to Flow

Disruptions such as material defects, equipment delays, or delayed or inaccurate information interrupt construction workflows and generate variability. These challenges cause waste and complicate decision-making. A DTC system addresses this by detecting disruptions in real-time, informing managers, computing optimal responses and recommending a course of action. In our controlled experimental setup, we can purposefully introduce disruptions, such as material defects or equipment breakdowns, to simulate real-world scenarios. This allows us to evaluate how managers respond and to compare their decisions with optimized solutions generated by the DTC system. The findings may highlight the practical value of real-time data monitoring and of global optimization in managing unexpected disruptions.

Features and Limitations of the Setup

The experimental setup offers a controlled environment for comparing decision-making scenarios, and for evaluating planning and control strategies. Although the setup has been demonstrated through a particular use case, its flexibility allows for the exploration of alternative construction processes using customized configurations, including alternative real-time monitoring strategies, building components, and interface setup. Its major advantage is the ability to hold most factors constant so that the impacts of isolated factors of interest can be measured.

As the setup evolves to support new experimental designs, several key considerations must be addressed: (a) the scale and fabrication of the building components chosen for assembly, (b) accurate calibration of camera sensors to comprehensively capture the construction site and worker activities, (c) optimization of computational efficiency for tracking objects and people, (d) customization of interaction and data visualization tools to accommodate the diverse perspectives of construction stakeholders, and (e) rigorous testing of the setup to validate both the accuracy of the digital twin and the reliability of the decision-making process in replicating real-world scenarios.

The limitations of the current system are primarily technical:

- Simplified assembly methods: Wood pieces with plastic connectors are different to real-world precast concrete connections, undermining the validity of assembly time and effort metrics.
- Scalability: The scale model (308 pieces) and four workers are a microcosm that may not replicate the complexity of full-scale projects involving thousands of components, supply chain variability, and coordination of multiple crews.

- The dataset for object detection in the monitoring system was limited (3,500 piece instances). This reduces the monitoring system's accuracy and robustness in construction process monitoring.

There are also practical constraints that limit the confidence in validity of the results that can be achieved because the complexity of each run limits the number of replications that can be performed for each scenario. Each experimental run requires four people and some three hours for constructing two full floors. Also, multiple behavioural factors (of the manager and workers) influence the workflow and the outcomes, and thus a strict experimental protocol must be enforced to ensure comparability of the results from scenario to scenario.

Conclusions

This paper proposed a DTC setup using a 1:25 scale model and automated monitoring to simulate DTC-driven planning. First, the paper outlined the different components of the system, including an experimental building, a real-time monitoring system, and a decision-support interface. Next, the paper presented a validation study conducted to test the system's viability for real-time planning and control. The results indicate that the proposed monitoring and control system shows promise for high-resolution tracking of the construction process to provide accurate and timely project status information to project managers. This setup can be used to compare decision-making scenarios at increasing levels of automation. Next steps include improving the accuracy of the object detection process.

Future work involves exploring the implications of local versus global optimization methods, by extending optimization to include factory production and transpiration logistics. The impact of flow disruptions due to defective materials or delayed deliveries will also be considered.

References

Ben-Alon, L., and R. Sacks. 2017. "Simulating the behavior of trade crews in construction using agents and building information modeling." *Autom. Constr.*, 74: 12–27. https://doi.org/10.1016/j.autcon.2016.11.002.

BIM2TWIN. 2021. "BIM2TWIN: Optimal construction management & production control | BIM2TWIN project | fact sheet | H2020."

Fellows, R. F., and A. M. Liu. 2015. Research methods for construction. John Wiley & Sons.

Martinez, J. C., and P. G. Ioannou. 1999. "General Purpose Systems for Effective Construction Simulation." J. Constr. Eng. Manag. ASCE, 125: 265–276.

Martinez, J. G., T. Yeung, R. Sacks, Y. Shahaf, and L.-O. Sharoni. 2023. "Situational Awareness in Construction Using a Serious Game." J. Constr. Eng. Manag., 149 (3): 04022183. https://doi.org/10.1061/JCEMD4.COENG-12521.

"NiceGUI." 2025. Accessed January 27, 2025. https://nicegui.io/.

"OpenCV." 2025. Accessed January 27, 2025. https://pypi.org/project/opencv-python/#description.

Parn, E. A., R. Sacks, I. Brilakis, M. Enzer, and L. Soibelman. 2024. Twin Systems: Digital Twins of the Built Environment. Twin Systems in the Built Environment. Twin Systems.

Priven, V., and R. Sacks. 2016. "Impacts of the Social Subcontract and Last Planner System Interventions on the Trade-Crew Workflows of Multistory Residential Construction Projects." J. Constr. Eng. Manag., 142 (7): 04016013. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001102.

Sacks, R., I. Brilakis, E. Pikas, H. S. Xie, and M. Girolami. 2020. "Construction with digital twin information systems." Data-Centric Eng., 1: e14. https://doi.org/10.1017/dce.2020.16.

Sacks, R., A. Esquenazi, and M. Goldin. 2007. "LEAPCON: Simulation of Lean Construction of High-Rise Apartment Buildings." J. Constr. Eng. Manag., 133: 529–539.

Schaumann, D., N. Putievsky Pilosof, H. Sopher, J. Yahav, and Y. E. Kalay. 2019. "Simulating multi-agent narratives for pre-occupancy evaluation of architectural designs." Autom. Constr., 106: 102896. https://doi.org/10.1016/j.autcon.2019.102896.

Schlenger, J., T. Yeung, S. Vilgertshofer, J. Martinez, R. Sacks, and A. Borrmann. 2022. "A Comprehensive Data Schema for Digital Twin Construction." Proc. 29th EG-ICE Int. Workshop Intell. Comput. Eng., 34–44. EG-ICE.

Szczesny, K., M. König, M. Hamm, and V. V. Nguyen. 2011. "Optimization of Construction Schedules with Discrete-Event Simulation Using an Optimization Framework." Comput. Civ. Eng., 682–659.

Teizer, J., K. W. Johansen, and C. Schultz. 2022. "The Concept of Digital Twin for Construction Safety." Constr. Res. Congr. 2022, 1156–1165. Arlington, Virginia: American Society of Civil Engineers.

"Ultralytics." 2024. Accessed January 27, 2025. https://docs.ultralytics.com/models/yolo11/.

Warcup, R., and E. Reeve. 2014. "Using the Villego® Simulation to Teach the Last Planner® System." Lean Constr. J., 1–15.

Zhang, Z. 2000. "A flexible new technique for camera calibration." *IEEE Trans. Pattern Anal. Mach. Intell.*, 22 (11): 1330–1334. https://doi.org/10.1109/34.888718.