Yeung, T., Martinez, J. G., Sharoni, L., Sacks, R., Pitkäranta, T. (2023). Predictive simulation for automated decision-support in production planning and control. *Proceedings of the 31st Annual Conference of the International Group for Lean Construction (IGLC31),* 1279–1290. doi.org/10.24928/2023/0186

PREDICTIVE SIMULATION FOR AUTOMATED DECISION-SUPPORT IN PRODUCTION PLANNING AND CONTROL

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ABSTRACT

Production system design, planning and control are limited both by the incomplete situational awareness of planners and by their inability to predict the range of possible outcomes of their planning and control decisions. With the development of information technologies for monitoring products and processes on construction sites, it is increasingly possible to provide detailed status information describing the as-built products 'as-built' and processes 'as-performed'. This opens the door to applying predictive analytics to provide decision-makers with frequent predictions of the outcomes for a range of changes they might contemplate to the production system design, even during construction. Within the BIM2TWIN project, we are designing and implementing an agent-based simulation engine that is a core component of an Automated Decision Support System. Currently, the simulation can be calibrated to accurately predict the range of likely project durations for a residential construction project. However, certain aspects of the trade crews' performance, particularly with respect to the completion of tasks, appear to differ from the behaviours described by industry experts and encapsulated in the crew agent behaviour tree in the simulation.

KEYWORDS

Production system design, production planning and control, agent-based simulation, decision-support.

INTRODUCTION

The design of a production system plays a critical role in determining its overall performance. A well-designed system not only ensures efficient production processes but also provides the foundation for effective planning and control. However, if the system's configuration is not optimal from the outset, even the most sophisticated planning and control techniques may not achieve the desired outcomes (Schramm et al. 2006).

The status quo in production system design (PSD) is that it is primarily performed until construction begins, at which point the production system configuration becomes largely static, and actions are limited to the scope of production control. This often leads to suboptimal

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solutions as the planners struggle to find the optimal configuration among the exponentially increasing solution space due to the large number of interconnected and interdependent variables at play. Without automation, planners must rely on known best practices, trial-and-error and their intuition and experience. This results in static production systems that are suboptimal with respect to the dynamic circumstances of construction sites, as opposed to the relatively stable environment of manufacturing plants.

An alternative approach is to apply automation to explore continuous optimisation of the production system configurations and parameters within the degrees of freedom of the system. This implies a shift from PSD as a planning exercise performed exclusively before construction to being an integral layer of production planning and control during construction. In this scenario, an automated decision support system (ADSS) would search the solution space to optimise the process, enabling the identification of multiple feasible alternatives. Additionally, it would provide forward-looking situational awareness (Lappalainen et al. 2021; Martinez et al. 2023), allowing planners to understand how the current production system configuration, as well as any alternative configurations, are likely to perform in the near future. Thus, planners could make better-informed decisions about the production system.

ADSS systems leverage the power of modern machines and information technologies to process data, optimise solutions, and analyse results (Bucklin et al. 1998; Payne 2000; Power and Sharda 2007). The core function of an ADSS is to predict the future behaviour of the production system based on its configuration and current status using digital simulation or statistical methods such as machine learning. The goal of an ADSS is to perform objective, comprehensive analyses of current and alternative production system configurations in very short times by virtue of automation, thus making continuous PSD through construction possible.

We present a novel predictive agent-based simulation framework for use within an automated decision support system (ADSS) for production planning and control. The framework is driven by 15 production system design parameters and generates 17 types of output data for performance evaluation. The capabilities of the simulation are demonstrated through the use of a real-world construction project in Finland, highlighting its current prediction capabilities and limitations. Furthermore, the paper outlines areas for improvement to further enhance the simulation's prediction accuracy and usefulness in real-world scenarios.

BACKGROUND

Automated decision-support systems (ADSS) are computer-based systems that augment decision-making by leveraging computer power to process data, make calculations, and generate information and knowledge to enhance situational awareness (Feng et al. 2009). ADSS can explore larger and more precise solution spaces than traditional trial-and-error-based planning approaches. This is achieved using advanced algorithms, such as mathematical optimisation, machine learning, and simulation, that can generate multiple solutions in a short period of time. With access to a large solution space, planners can identify feasible options, including some that may not have been considered previously, and select the most optimal for the project (Beynon et al. 2002; Marakas 2003). Thanks to automation, this can be done in much shorter times and with minimum effort (Gonzalez 2005).

Additionally, the use of computer algorithms helps ensure that solutions are not only optimal but also consistent, thus reducing the impact of human error and bias, which is especially relevant in the context of rapidly changing and uncertain construction environments. Future ADSS for construction may leverage data collected onsite, such as through digital twin and automated progress monitoring technologies (Kunath and Winkler 2018), to make evidence-based, explainable decisions that can improve the transparency and accountability of the planning process, as well as enhance trust and collaboration among project stakeholders (Coelho et al. 2021; Yeung et al. 2022).

Researchers have developed decision-support tools and systems for PSD. Draper and Martinez (2002) evaluated alternative production system designs for selected building construction processes with discrete event simulation (DES) to expose waste and artificial constraints hidden in the production system. Schramm et al. (2008) applied DES models in the decision-making process for the design and operation of house-building projects. The simulation models identified configuration options that reduced the total construction time. This, in turn, provided construction company production managers the ability to evaluate different scenarios and develop more efficient construction sequences, which led to a reduction in non-value-adding activities. Jadid and Badrah (2012) implemented a decision-support system for material selection based on value engineering to enhance interdisciplinary knowledge-sharing. These solutions have shown that proper decision-support systems can facilitate continuous improvement in all projects to improve their performance (Dave and Koskela 2009) and enhance the competitiveness of organisations with high absorptive capacity (Cohen et al. 1990).

Many existing decision-support systems use computer simulation as the mechanism for optimisation (AbouRizk 2010). Production systems in construction involve many heterogenous and interdependent components with stochastic behaviours, making it difficult to describe them with mathematical models without oversimplification (Abdelmegid et al. 2020). Simulation modelling allows for the description of a production system's components and their interactions, leveraging computer processing power to project and analyse the performance of the system. Additionally, a simulation can be used to optimise different aspects of the production system, such as resource allocation, scheduling, and process design, by changing the input parameters and observing the resulting output (Martinez 2010).

Of the main modelling approaches, agent-based simulation (ABS) particularly excels in producing explainable results (Bonabeau 2002). ABS uses a bottom-up, actor-oriented approach to represent systems as collections of autonomous agents interacting with each other and the environment. The interactions between agents give rise to emergent phenomena that can be observed at system-wide levels. Faithful reproduction of the behaviours of the individual agents within the system supports a comprehensive understanding not only of the overall system performance but also of the contributions of individual components (Macal 2016).

In recent years, researchers have applied ABS to investigate various aspects of construction production systems. Ben-Alon and Sacks (2015) developed the EPIC simulation tool to assess the impact of production control methods and information flow on production. Shehab et al. (2020) simulated construction crew performance using a hybrid ABS-DES model to facilitate weekly work planning in the Last Planner System. Barazi et al. (2021) proposed using ABS to study how parameter changes in vertical logistics systems can impact production performance in high-rise building projects.

SYSTEM DESIGN AND IMPLEMENTATION

The proposed system aims to assist planners in promptly exploring and optimising PSD at multiple points in a project by using project status and intent information. Specifically, by using parametric agent-based simulation, the ADSS can explore and evaluate a set of decision parameters, including changes in labour and/or resource allocations and in production control policies.

To design the system architecture, define the PSD decision parameters and outline the parametric agent-based simulation, we conducted a four-step process that included a literature review, gathering information from an expert panel, interviewing production planners, and observing and mapping agents' behaviours on construction sites. An expert panel of eight construction professionals from Finland, Spain, and France were consulted to specify the system features and functionalities. To define typical decision parameters used to make changes in production plans, we conducted 18 semi-structured interviews with production planners

(Martinez et al. 2022). Through a behaviour mapping exercise on construction sites, we identified and mapped the behaviours of crews, supervisors, and site engineers in traditional building construction projects using decision trees. To design the overall system architecture, we applied a backward design approach and used a BPMN diagram to illustrate the system components and process flow, considering the functional requirements specified in the first step (Sacks et al. 2020).

The ADSS system comprises five main modules: 1) the User Input Module, 2) Simulation Module, 3) Alternative Plan Evaluation Module, 4) Alternative Plan Optimisation Module, and 5) Recommendation Dashboard Module. These modules work together to provide comprehensive decision support for construction production planning and control. The User Input Module receives the user's input information and selects the most suitable set of alternative production plans for simulation. The Simulation Module, designed according to agent behaviour specifications and implemented in AnyLogic® software, simulates the sets of alternative plans. The Alternative Plan Evaluation Module receives the raw outputs from the Simulation Module, evaluates alternative plan performance, and compiles decision aid elements and KPIs. The Alternative Plan Optimization Module enables users to generate additional alternative plans and simulation iterations based on optimisation algorithms. The Recommendation Dashboard Module presents the simulated production plans and their decision aids, allowing users to make informed decisions on the production plan to be applied in the next production cycle. The ADSS system includes two databases: 1) a Local Database that contains the baseline production plan, the constructed complete alternative production plans, their evaluation results and visualisation data, and 2) a Digital Twin Platform, which is a graph-based online repository for storing up-to-date project information.

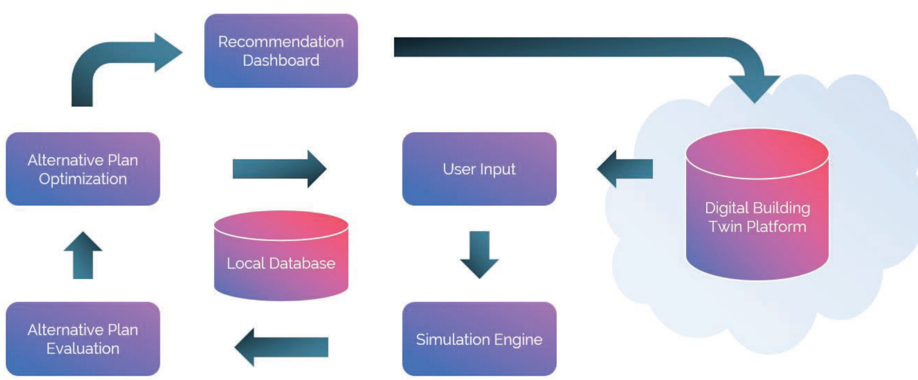

Figure 1: Overall System Architecture.

Table 1 details the 15 production system parameters that users can explore in the proposed ADSS. If a user decides to explore alternative production systems by modifying some of the parameters, such as adjusting crew sizes, the simulation engine can interpret the changes and apply them to the simulation before each run. In any given situation, there are multiple agents (managers, crews, equipment, materials, locations, suppliers, designers, etc.); each agent has multiple parameters, and each parameter can have some set of discrete values. For example, a 'drywall crew' agent may have a 'crew size' parameter, which may range from 4 to 6 workers. As such, the potential solution space is a complex product of the number of agents, parameters and possible parameter values. This yields combinatorially large numbers of production system configurations.

The predictive simulation engine in this ADSS uses the agent-based modelling approach. Agent-based modelling is a computational approach that simulates the behaviour of individual agents within a complex system. These agents have their own attributes, behaviours, and decision-making processes. They interact with one another in a decentralised fashion to create emergent system-level outcomes. In agent-based simulation models, agent classes are used to represent the general types of entities in a system, and specific instances of these agents are generated during a simulation run based on input data. This allows the model to represent the system at the individual level while also capturing the collective behaviour and interactions that arise between the agents.

Figure 2 gives an overview of the agent-based simulation engine's structure which includes the five classes of agents in the agent-based simulation model developed for this study: Work Crew, General Contractor Management (GC), Subcontractor Management (SC), Supplier, and Design Firm. The colour-coded rectangular boxes represent the different behaviours that each agent possesses, and the dotted lines show the interactions between these behaviours. This visual representation provides an overview of the behaviours and interactions of the different agents within the model and helps to understand how the system functions as a whole. For more details on the parametric generation framework, please refer to our recent paper (Yeung et al. 2022).

Table 2: Production system parameters.

Category	Parameter	Description
Labour	Production rate	The production rate for the specific crew (probabilistic-deterministic)
	Crew size	The crew size for each specific crew
	Number of crews	Add or remove a crew
	Crew calendar	Adjust the crews' calendars
Equipment	Maintenance rate	The equipment maintenance rate
	Number of equipment	Assign or remove equipment for a specific Work Package
	Equipment availability	Modify the availability time of equipment
Material	Material batch size	Change the material batch size for any material
	Material delivery frequency	Vary the material delivery frequency
	Material's buffer quantity	Vary materials' buffer quantities (percentage)
WBS	Task sequence	Change the task sequence
	Prerequisite tasks	Vary the prerequisite tasks
LBS	Construction site zones	Modify the construction site zones (Location-Based Schedule (LBS))
Production Control Policies	Material arrival strategy (pull or push)	Defines the material arrival strategy (push or pull)
	Work Package or location selection based on production planners' preference	The system gives priority to work packages where the largest quantity of productive work is available
		The system gives priority to spaces where work has already begun
		The crews assign the highest priority to spaces with the smallest amount of remaining work (Constant Work in Progress (CONWIP))
	Logistics Policy	The user changes the logistics supply chain type for a certain material

Each of the behaviours shown in Figure 2 was first defined in a behaviour map by construction experts and then coded as software routines in the simulation model. As an example, **Error! Reference source not found.** shows a behaviour map for the task assignment behaviour of the GC Management agent. A section of the corresponding logic tree in the AnyLogic software is shown in Figure 4.

Table 3 lists some of the result data that the simulation engine produces per simulation run. Each output is time series data, meaning that it is recorded at a specified frequency. This data is provided for each activity and resource, allowing diagnosis of the performance of the system at a fine-grained level. The abundance of high-resolution output data can be used to boost the ADSS's explainability to users, giving them confidence in the recommended solutions. It also enables calibration and validation of the simulation engine's prediction capability with high precision.

Table 3: Result data provided by the simulation engine.

Category	Output	Description
Trans-formation	Productivity	Work quantity completed per unit of resource input
	Resource Consumption	Quantities of material, equipment and labour effort consumed
	Earned Value	Accumulated value of work completed
	Project Progress	Percentage of work completed out of the whole project
Flow	Cycle Time	Amount of time it takes to complete a unit of product (e.g., apartment, floor)
	Throughput	Number of products completed within a given period
	Work In Progress	Amount of work in progress at a given time
	Non-Value Adding (Idle) Time	Amount of time a crew has been initiated but is not actively working on a task
	Space Conflicts	Number of times two or more crews require the same work location
	Material Buffer Size	Amount of material stored at a location at a given time
	Delivery Delays	Number of material deliveries delayed
	Equipment Capacity Utilisation	Percentage of total available time an equipment was utilised
Value	Material Delivery Date	Timestamp when a material order was fulfilled
	Resource Consumption	Quantities of material, equipment and labour effort consumed
	Rate of Rework	Percentage of tasks/products requiring rework
	Quality Control	Percentage of tasks/products containing defects
	Handover Date	Timestamp when a unit of product was handed over to the customer

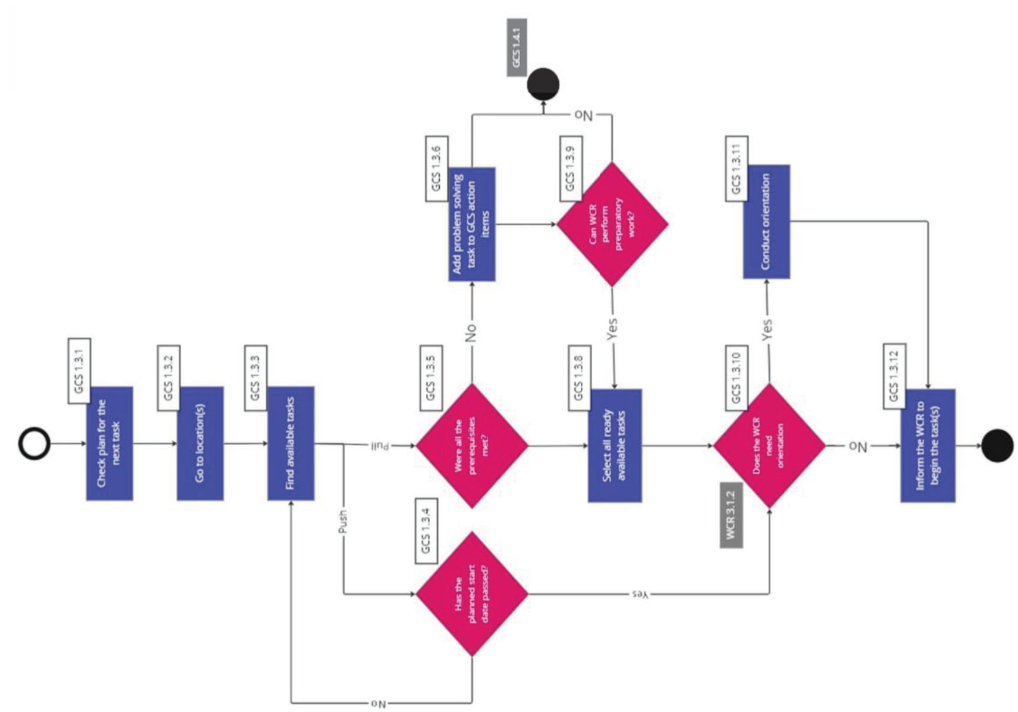

Figure 2: Behaviour map for GC Management task assignment behaviour as defined by experts.

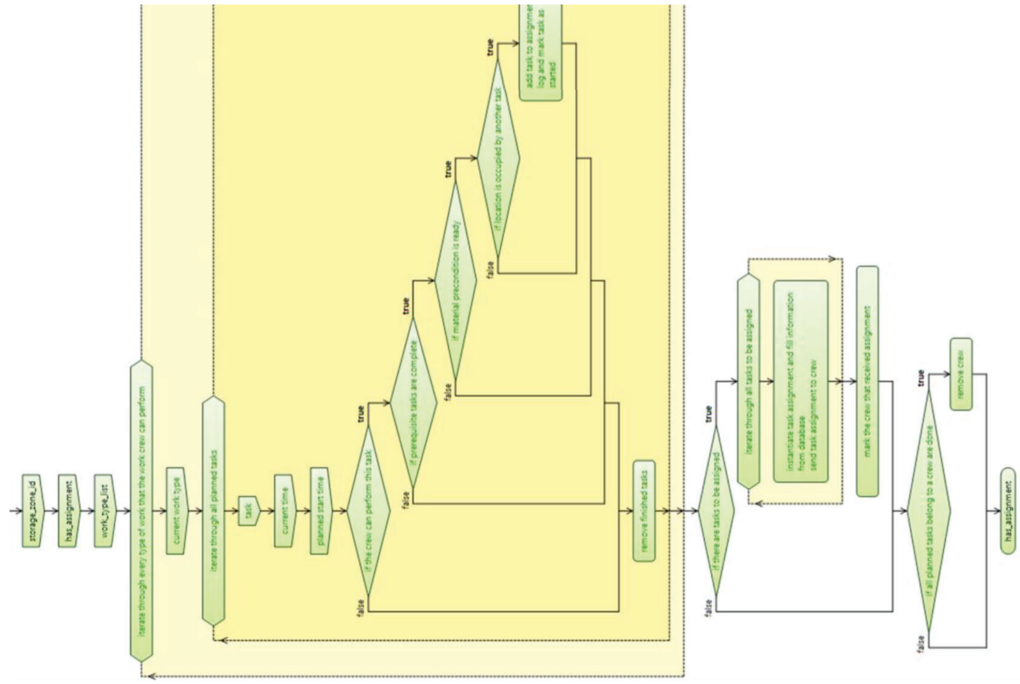

Figure 3: Behaviour map for GC Management task as programmed in the simulation.

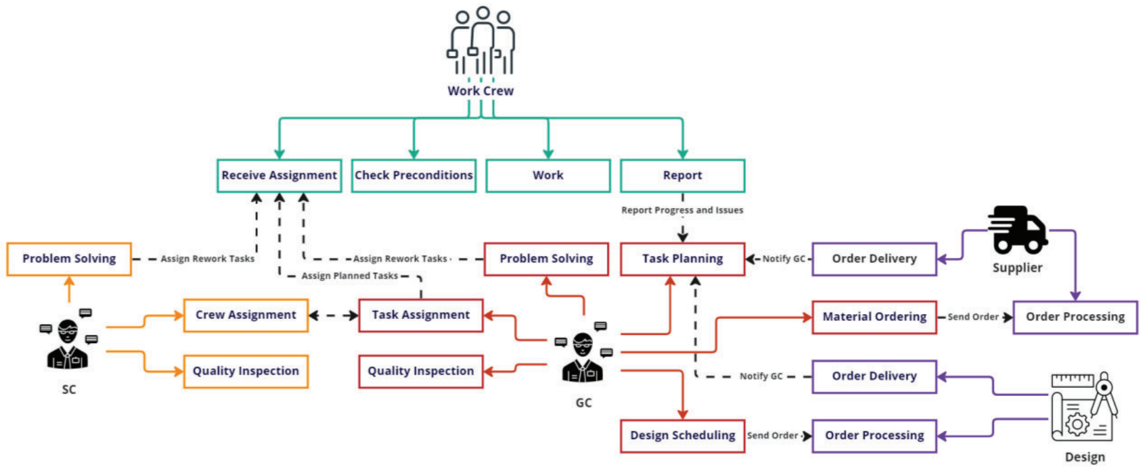

Figure 4: Agent classes and their behaviours in the ABS model.

CALIBRATION AND VALIDATION

To test and demonstrate the forecasting capabilities of the simulation engine, we apply it to an as-performed project dataset captured in a construction project of an eight-story prefabricated concrete residential building in Finland. The dataset covers the interior finishing phase of the project. It includes as-planned and as-performed progress, work quantities, planned production rates, a detailed work breakdown structure, and a location breakdown system. We used the progress data for validation and the rest of the data to set the initial production system parameters for the simulation. We ran 500 simulation runs using a Monte Carlo sampling method where the variance in supply chain reliability fluctuates randomly.

Figure 5 visualises the trajectory of project progress through time as a percentage of total tasks completed from the chosen start point (day 60 of the project). The as-planned progress curve is plotted in black, and the actual progress curve is plotted in red. The trajectory of each simulation run is plotted in a green spectrum, where lighter greens indicate earlier project end dates and darker greens indicate later dates. The figure shows a) that the actual progress deviated significantly from the planned schedule and b) that the actual trajectory falls within the range of the simulation's predictions.

Note that the planned trajectory lies at the left side of the distribution, suggesting that it was highly improbable, as would be expected in the case of a plan prepared using the Critical Path Method (CPM). This can be seen clearly in the histogram of project end dates presented in Figure 7. Here, we see that the actual end date and the planned end date are more than 30 working days apart, while the mean of the distribution of end dates is just ten working days earlier than the actual end date. The planned end date intersects the cumulative distribution curve at around 0.2 (i.e. a 20% probability of completing the project as planned).

Although the simulation results are promising in terms of projecting progress, a careful analysis of operational flow in these runs reveals that there is still much room for improvement in accurately simulating the actual flow patterns in real-world projects. Figure 8, a histogram of average cycle time per floor, shows that although the simulation results are closer to the actual results than are the actual outcomes for cycle times, they do not capture the actual patterns of flow. This discrepancy is also apparent in Figure 7, where the planned line of balance schedule is plotted against the actual status and against a representative simulation run. Towards the end of the project, there are multiple independent finishing activities scheduled in a tight time window. According to the actual record, these activities overlapped and intersected with one another in every location. In contrast, in the simulation run, the activities were performed in a relatively ordered way despite being scheduled tightly together.

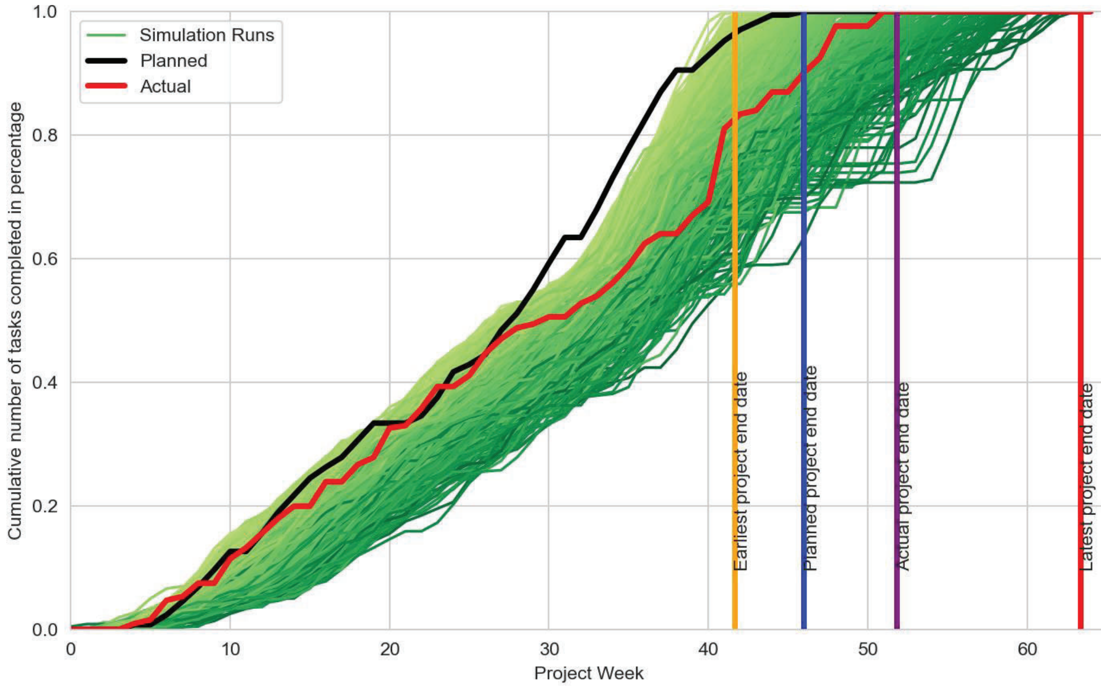

Figure 5: Progress trajectory of 500 simulation runs (green) plotted against the planned (black) and actual (red) progress.

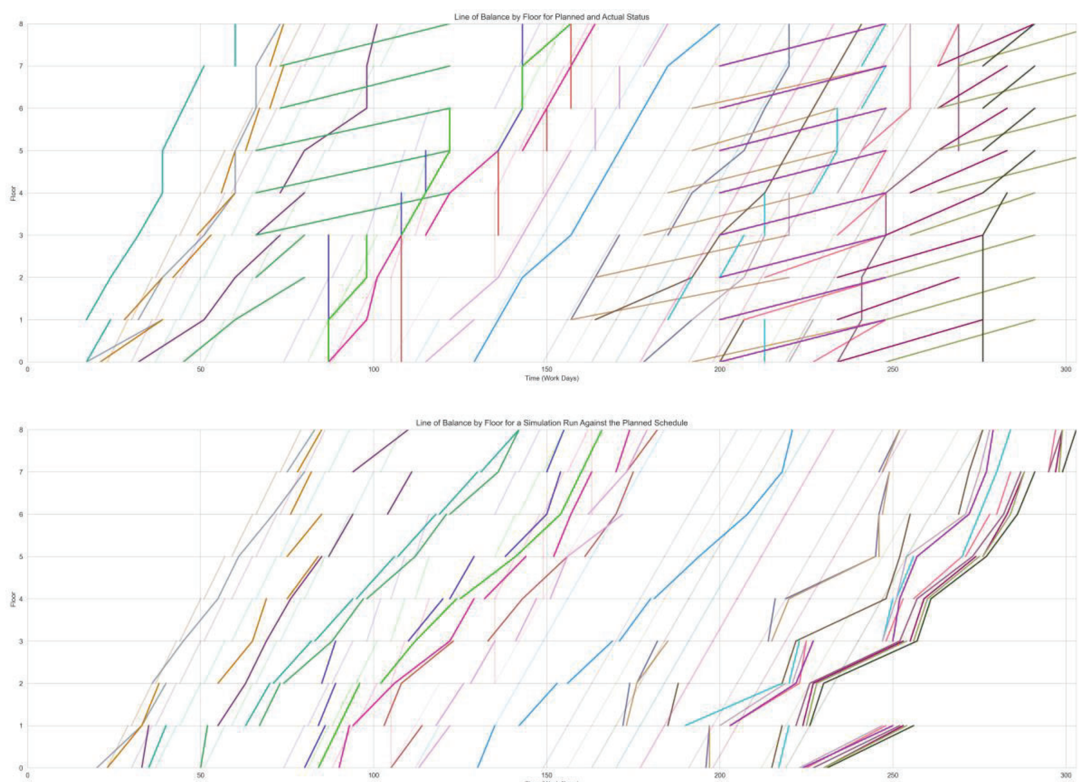

Figure 6: Line of Balance Charts. The top plot is the planned schedule versus the actual status. The bottom plot is the planned schedule versus a sample simulation run. In both plots, the as-planned schedule is plotted in semi-transparent colours.

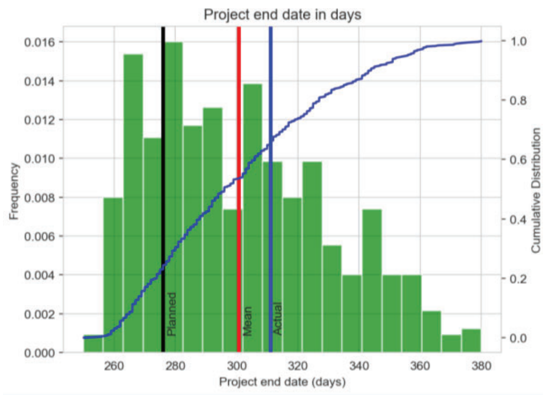

Figure 7: Histogram of project end date

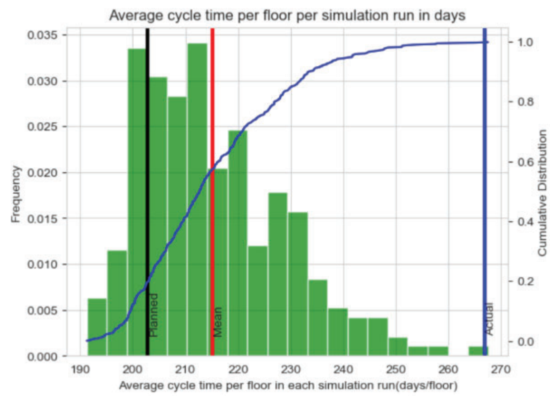

Figure 8: Histogram of average cycle time per floor

CONCLUSION AND FUTURE WORK

Automated Decision-Support Systems (ADSS) are essential components for adopting a broader view of production system design (PSD), extending PSD from a static, one-off design endeavour to a dynamic process of continuous improvement with optimisation. An automated ADSS can potentially help production planners explore the full feasible solution space to find optimal, evidence-based decisions in very short response times, making PSD a feasible exercise within the scope of lookahead production planning, and even weekly control, during the construction phase. The core function of such an ADSS is a predictive simulation engine that can project the probable future behaviour of a production system given its configuration, its current status, and the behaviours of its agents.

The paper detailed the input, output, and overall structure of a predictive simulation engine for an ADSS that is part of our ongoing effort to build such a system within the context of the BIM2TWIN project (BIM2TWIN 2021). Although the simulation can, at present, generate predictions of project duration that are a very good fit to the actual record of a validation project, a closer analysis of the results reveals that important discrepancies between the simulation results and the actual patterns of operation flow behaviours remain. This appears to be the result of discrepancies between the ways in which construction professionals at all levels understand and thus describe their behaviours and the ways in which they actually behave. This manifests in particular when crews complete the majority of the work in a given task or work package, but leave the final details unfinished, resulting in multiple instances of re-entrant flow in the actual record, and long cycle times for apartments, for example. Work remains to refine the behaviour of the agents to reflect this behaviour and to identify the production system parameters under which it occurs.

ACKNOWLEDGEMENT

This work was funded in part by the BIM2TWIN project of the European Union's Horizon 2020 research and innovation program under grant agreement no. 958398. The authors thank our BIM2TWIN colleagues from TUM, Orange, Fira Oy, SPADA, ACCIONA, and IDP for their support in the ongoing research on simulation and process prediction in the framework of DTC. Special thanks are due to Enni Laine, Kasperi Koivu, Oskari Kruth and Otto Alhava of Fira Oy for providing the project data and giving valuable feedback throughout the development process.

REFERENCES

Abdelmegid, M. A., V. A. González, M. Poshdar, M. O'Sullivan, C. G. Walker, and F. Ying. 2020. "Barriers to adopting simulation modelling in construction industry." *Automation in Construction*, 111: 103046. https://doi.org/10/gnhm8b.

AbouRizk, S. 2010. "Role of Simulation in Construction Engineering and Management." *J. Constr. Eng. Manage.*, 136 (10): 1140–1153. https://doi.org/10/dhbd32.

Barazi, A. A., O. Seppanen, E. Pikas, J. Lehtovaara, and A. Peltokorpi. 2021. "Enhancing Internal Vertical Logistics Flows in High-Rise Construction: An Exploratory Study." 717–726. Lima, Peru.

Ben-Alon, L., and R. Sacks. 2015. "Simulating and Vizualising Emergent Production in Construction (EPIC) Using Agents and BIM." *23rd Annual Conference of the International Group for Lean Construction*, O. Seppänen, V. A. González, and P. Arroyo, eds., 371–380. Perth, Australia.

Beynon, M., S. Rasmequan, and S. Russ. 2002. "A new paradigm for computer-based decision support." *Decision Support Systems*, 33 (2): 127–142. Elsevier. https://doi.org/10.1016/S0167-9236(01)00140-3.

BIM2TWIN. 2021. "BIM2TWIN: Optimal Construction Management & Production Control | BIM2TWIN Project | Fact Sheet | H2020." *CORDIS | European Commission*. Accessed October 11, 2021. https://cordis.europa.eu/project/id/958398.

Bonabeau, E. 2002. "Agent-based modeling: Methods and techniques for simulating human systems." *Proceedings of the National Academy of Sciences*, 99 (Supplement 3): 7280–7287. https://doi.org/10.1073/pnas.082080899.

Bucklin, R., D. Lehmann, and J. Little. 1998. "From Decision Support to Decision Automation: A 2020 Vision." *Marketing Letters*, 9 (3): 235–246. https://doi.org/10.1023/A:1008047504898.

Coelho, F., S. Relvas, and A. Barbosa-Póvoa. 2021. "Simulation-based decision support tool for in-house logistics: the basis for a digital twin." *Computers & Industrial Engineering*, 153: 107094. Elsevier. https://doi.org/10.1016/j.cie.2020.107094.

Cohen, W. M., D. A. Levinthal, and others. 1990. "Absorptive capacity: A new perspective on learning and innovation." *Administrative science quarterly*, 35 (1): 128–152. Thousand Oaks. https://doi.org/10.2307/2393553.

Dave, B., and L. Koskela. 2009. "Collaborative knowledge management—A construction case study." *Automation in construction*, 18 (7): 894–902. Elsevier. https://doi.org/10.1016/j.autcon.2009.03.015.

Draper, J. D., and J. Martinez. 2002. "The evaluation of alternative production system designs with discrete event simulation." *Annual Conference Of The International Group For Lean Construction*.

Feng, Y.-H., T.-H. Teng, and A.-H. Tan. 2009. "Modelling situation awareness for context-aware decision support." *Expert Systems with Applications*, 36 (1): 455–463. Elsevier. https://doi.org/10.1016/j.eswa.2007.09.061.

Gonzalez, C. 2005. "Decision support for real-time, dynamic decision-making tasks." *Organisational Behavior and Human Decision Processes*, 96 (2): 142–154. Elsevier. https://doi.org/10.1016/j.obhdp.2004.11.002.

Jadid, M. N., and M. K. Badrah. 2012. "Decision support system approach for construction materials selection." *Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design*, 1–7.

Kunath, M., and H. Winkler. 2018. "Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process." *Procedia Cirp*, 72: 225–231. Elsevier. https://doi.org/10.1016/j.procir.2018.03.192.

Lappalainen, E. M., O. Seppänen, A. Peltokorpi, and V. Singh. 2021. "Transformation of construction project management toward situational awareness." *Engineering, Construction and Architectural Management*, ahead-of-print (ahead-of-print). https://doi.org/10.1108/ECAM-12-2020-1053.

Macal, C. M. 2016. "Everything you need to know about agent-based modelling and simulation." *Journal of Simulation*, 10 (2): 144–156. https://doi.org/10.1057/jos.2016.7.

Marakas, G. M. 2003. *Decision support systems in the 21st century*. Prentice Hall Upper Saddle River.

Martinez, J. C. 2010. "Methodology for Conducting Discrete-Event Simulation Studies in Construction Engineering and Management." *J. Constr. Eng. Manage.*, 136 (1): 3–16. https://doi.org/10.1061/(asce)co.1943-7862.0000087.

Martinez, J. G., T. Yeung, R. Sacks, Y. Shahaf, and L.-O. Sharoni. 2023. "Situational Awareness in Construction Using a Serious Game." *Journal of Construction Engineering and Management*, 149 (3): 04022183. American Society of Civil Engineers. https://doi.org/10.1061/JCEMD4.COENG-12521.

Martinez, J. R., T. Yeung, and R. Sacks. 2022. "Scope of action of production planners in the context of Digital Twin Construction." 12 pps. Amman, Jordan: Al-Zaytoonah University.

Payne, T. H. 2000. "Computer Decision Support Systems." *Chest*, 118 (2, Supplement): 47S-52S. https://doi.org/10.1378/chest.118.2_suppl.47S.

Power, D. J., and R. Sharda. 2007. "Model-driven decision support systems: Concepts and research directions." *Decision Support Systems*, Integrated Decision Support, 43 (3): 1044–1061. https://doi.org/10.1016/j.dss.2005.05.030.

Sacks, R., T. Yeung, and J. Martinez. 2020. *System Design--Requirements and Specifications for Simulation and Prediction*. Public. BIM2TWIN.

Schramm, F. K., A. A. Rodrigues, and C. T. Formoso. 2006. "The role of production system design in the management of complex projects." *14th Annual Conference of the International Group for Lean Construction, Santiago, Chile, Pontificia Universidad Catolica de Chile*.

Schramm, F. K., G. L. Silveira, H. Paez, H. Mesa, C. T. Formoso, and D. Echeverry. 2008. "Using discrete-event simulation to support decision-makers in production system design and operations." *Proceedings of the 16th Annual Conference of the International Group for Lean Construction*, 131–142.

Shehab, L., A. Ezzeddine, F. Hamzeh, and W. Power. 2020. "Agent-Based Modelling and Simulation of Construction Crew Performance." 1021–1032. Berkeley, California, USA.

Yeung, T., J. R. Martinez, L. Sharoni, and R. Sacks. 2022. "The Role of Simulation in Digital Twin Construction." *Proceedings of the 29th EG-ICE International Workshop on Intelligent Computing in Engineering*. Aarhus, Denmark: Aarhus University.