Discrete Event Simulation Tool for Productive, Resource-Efficient, and Safe Construction Management

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Abstract. Construction planning and scheduling is complex due to frequent deviations from the initial schedule. Since the internal sequences are similar across projects and production activities are repetitive, ongoing projects offers valuable opportunities for continuous learning and improvement. This paper proposes an adaptable discrete event simulation tool for prefabricated column mounting work processes, based on a discrete event system specification formalism for modelling the system, to support decision-making during project management. By using data-based input parameters in the form of productivity density functions for activity durations, the tool facilitates ongoing construction management. The tool enables testing of different construction options and what-if scenarios by modifying resource allocations and delivery options. The tool simulates a multitude of construction possibilities stochastically and forecasts productivity, resource-efficiency, and safety-related key performance indicators. This provides project managers with a solid foundation for taking control actions and enables straightforward data-based construction management.

1. Introduction

Despite comprehensive planning and scheduling efforts before construction starts, the production process often deviates from the initial plans, entailing unproductive, resource-inefficient (Teicholz 2013; ECSO 2021), and hazardous working conditions (Eurostat 2022). These challenges arise due to unique products being built by varying teams under different site, regulatory, and external conditions. While internal procedures and logics are similar across construction projects, external circumstances, which are inevitable and uncontrollable, distinguish each project (Teicholz 2013; Behzadan et al. 2015). Therefore, the construction sector is increasingly using prefabricated components to standardise production processes, with a predicted 30% increase in prefabricated buildings in the European market from 2020 to 2026 (Research and Markets 2021). Prefabricated components are manufactured in factories and delivered to construction site for mounting, leading to benefits such as reduction of storage space on site, less waste, and safer working conditions (Lu et al. 2018). However, construction by prefabricated components requires increased planning efforts before and during construction to ensure a smooth operation. Delayed material deliveries entail idle time for the resources, while early deliveries can lead to congestion on site (Zhong et al. 2017). Ongoing projects present valuable opportunities for continuous learning and improvement due to the repetitive nature of production activities. Currently, weekly planning meetings are held to discuss completed works and intervene if necessary, but participants rely on subjective opinions and traditional problem-solving methods (Abdelmegid et al. 2020; Hartmann 2021). However, reliable and timely information is needed for successful construction management, especially when using prefabricated components (Zhong et al. 2017).

To overcome the lack of relevant, up-to-date information, the concept of digital twins has attracted attention in the construction sector. During the construction phase, the digital twin concept aims to collect real-time process data to derive meaningful project status information using artificial intelligence. This project status information can be used to continuously update a digital model, the digital twin. Before implementing digital twins, it is essential to determine the specific purpose for collecting data and using the gained information, e.g. to manage ongoing construction processes (Brilakis et al. 2019; Sacks et al. 2020; Jiang et al. 2021). Despite its potential benefits, the digital twin concept has been rarely applied during the construction phase so far (Sacks et al. 2020; Deng et al. 2021) due to the dynamic nature of production on large-scale sites, which poses significant implementation challenges. To enable data-driven decision-making during construction in a timely manner, the major challenge is to establish methods and systems that can integrate field data into project management (Behzadan et al. 2015). Modelling and simulation is an effective method to support construction management (Leite et al. 2016). Discrete event simulation (DES) is particularly suitable for handling the operational interactions of complex construction processes (Martinez 2010). Implementing DES in construction management faces two major challenges: the need for reliable input parameters and the laborious process of developing DES models (Behzadan et al. 2015; Abbasi et al. 2020; Abdelmegid et al. 2020; Rashid and Louis 2022). Thus far, rather static DES models have been created, which rely on generic assumptions from before the start and are incapable of being used during construction. In a previous paper (Jungmann et al. 2022), the authors presented a procedure to collect real-time data during crane operations and analyse them using machine learning classifiers to extract action durations. Next, suitable probability distribution functions (PDFs) were determined to consider construction dynamics and perform a data-based DES model calibration. As it is of utmost importance to use process information gained for construction management, adaptable DES models that can consume dynamic input parameters according to current site conditions are required. This will enable more reliable forecasts and data-based decision-making (Wu and AbouRizk 2021). The proactive management of construction processes by the digital twin concept in consideration of lean construction principles is called digital twin construction (Sacks et al. 2020).

This paper presents the development of an adaptable DES tool based on a created Discrete Event System Specification (DEVS) formalism for proactive and timely management of prefabricated columns mounting. The tool requires several inputs, including data-based PDFs for activity durations, and generates key performance indicators (KPIs) related to productivity, resource-efficiency, and safety as outputs. Thus, the stochastic simulations offer valuable forecasts to enable meaningful decision-making in a straightforward way. The tool's applicability was tested on a demonstration site to compare the impacts of different construction options by changing resource allocations and delivery scenarios. The paper is structured as follows: Chapter 2 provides an explanation of the topics DEVS and DES. Next, section 3 describes the developed DES tool, followed by the presentation of the real-world demonstration site in section 4. To provide evidence for the tool's value, it was applied to manage ongoing construction works in section 5. To conclude, section 6 outlines contributions, limitations, and future research fields.

2. Theoretical Background

At the beginning of each modelling and simulation application in construction, it is essential to acquire knowledge about the logic and sequences of the system's processes (AbouRizk et al. 2011). These findings have to be reported in a formalism that defines the system's semantics and supports a conceptual understanding of its complexities (Zeigler et al. 2018). In a formalism, the blocks of a system's model are described mathematically. For DES, the formalism aims to identify critical state variables that have to be adapted because of deviations from previous assumptions and, thus, facilitates decision-making (Behzhadan et al. 2015). DEVS is a widely used and powerful formalism invented and refined by Zeigler et al. (2018). In their review, Behzadan et al (2015) investigated underlying challenges associated with model development and data integration to lay the foundation for future research and implementation efforts in real-time construction simulation. They presented details about DEVS for construction operations and developed a DEVS formalism for earthmoving operations to facilitate decision-making. In general, DEVS can consist of atomic and coupled models. Coupled models explain the whole structure of a system, including the connection of different (atomic) submodels, and describe the input-output relations. Figure 1 displays an exemplary depiction of the semantics of coupled models (Zeigler et al. 2018). External input couplings (EIC) are the external inputs for the DES model, while external output couplings (EOC) are the outputs. Different basic models ($M_d = A1, A2, A3$), which can be atomic or coupled, are connected by internal couplings (IC), while the output of the previous model serves as the input for the succeeding model. Additionally, X is defined as the set of input events for the simulation, while Y is defined as the set of output events.

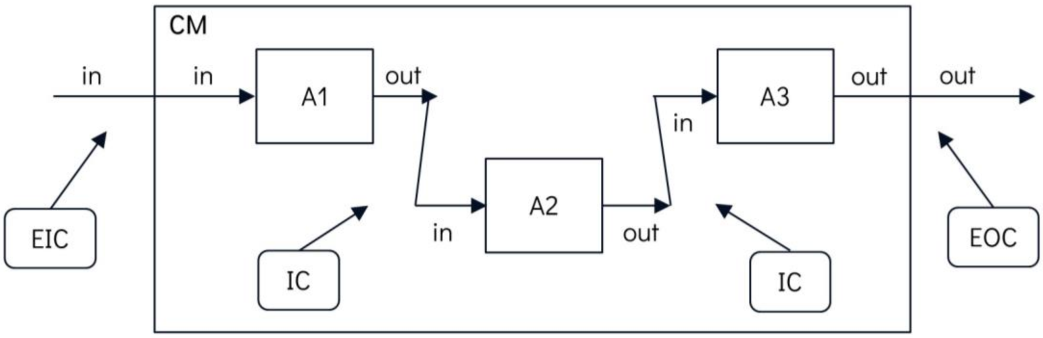

Figure 1: Coupled DEVS model

DES enables the mimicking of the processes of real-world systems in a virtual environment and offers a cost-effective and risk-free technique to test different management decisions regarding complex problems (Wainer 2009). A DES model consists of a list of interrelated events that consider the interaction of entities, the system's objects of interest. According to the occurrence of discrete events, the system's state variables change. DES is particularly suitable for managing construction works by dividing the schedule into discrete processes (AbouRizk 2010) and testing different options, such as changing the number of resources. Stochastic DES enables to simulate real-life construction works by considering dynamics and uncertainties (Liu et al. 2015a).

In recent years, research has tended to use building information modelling (BIM) as an information base for DES. König et al. (2012) developed a concept to store interdependencies between activities in the BIM model to enable DES. Lu and Olofsson (2014) created an integrated framework that allows the DES model to respond to product modifications by directly incorporating changes made to the BIM model. Liu et al. (2015b) presented a BIM-based integrated scheduling approach for panelled wall construction under resource constraints. Abbasi et al. (2020) utilised BIM-based information to estimate the cycle time of construction processes and used this information to optimise just-in-time delivery through DES. However, these approaches consider product-centric changes, but not process-centric. Simulations based on generic process-related assumptions made prior to construction are inadequate for consistently managing production effectively. Processes will unavoidably differ and, therefore, these approaches are only valid prior to the start of construction. Moreover, in the initial planning, an inadequate allocation of resources is stated regularly, which entails adverse impacts on the execution (Abbasi et al. 2020). Continuous updating of simulations is not yet done in the construction domain, which impedes successful management (Behzadan et al. 2015). Akhavian and Behzadan (2013) showed the importance of data-driven DES, which entails more accurate results. Rashid and Louis (2022) combined data-based process mining with DES to forecast performance during earthmoving operations.

Although data-based DES has been demonstrated to enhance forecasting accuracy, there is currently a shortage of comprehensive management tools that can effectively integrate up-to-date process data. Most of the existing DES research is static and it is impossible to modify the simulation. Given the significant effort of skilled experts, invested time, and associated costs required to create a DES model, current approaches are uneconomical, as these models can only be used during the early planning stages, but cannot be efficiently integrated with deviations during later stages (AbouRizk 2010). Dynamic DES models are required, which can be adapted according to current site conditions in a timely manner. Due to the possibility of collecting and analysing real-time data efficiently by artificial intelligence nowadays, reliable information can be provided in a timely manner to facilitate meaningful decision-making (Alvanchi et al. 2021; Rashid and Louis 2022). There is a lack of research in data-driven simulation for managing ongoing construction through the use of forecasted KPIs. Thereby, it is essential to compare the impacts of different options with different resource allocations and delivery options under uncertainties, such as weather forecasts, and to consider lean construction principles, such as just-in-time delivery, to support the decision-making process with data-based information.

3. DES Tool

The DES tool was developed using R to simulate the work process pattern of prefabricated columns mounting, as shown in Figure 2. The related DESV for the construction work process pattern is defined by equation 1:

$$MPC = < X, Y, D, M_{MPC} \mid d \in D, EIC, EOC, IC, select > \quad (1)$$

X = {Column ID};

Y = {Column ID};

D = {Truck drive, Mounting}

$M_{MPC} = \{M_{Truck\ drive}, M_{Mounting}\}$

EIC ⊆ { ((Truck start, out), (Truck drive, in)); ((Traffic, out), (Truck drive, in)); ((Weather, out), (Mounting, in))}

EOC ⊆ { ((Mounting, out), (Self, out))}

IC ⊆ { ((Truck drive, out), (Mounting, in))}

select = {Truck drive, Mounting}

At a certain interval, trucks start to deliver a stated number of columns, which may be delayed due to traffic conditions. For each column, a unique ID is created as an input event according to the DEVS formalism. When a truck arrives at the construction site, the availability of location, mobile crane, and workers is necessary for mounting the columns. If the required resources are already being seized for another activity, the truck has to wait in a queue. Once the resources come available, they are seized and the mounting process begins. Hence, the DES model involves two activities, the truck drive and the mounting, which are internally coupled. Adverse weather conditions can affect the mounting process, either leading to delays or increased risks during production. The three EICs are the truck start, the traffic, and the weather. When a column was mounted an output event is generated for its ID and the next column carried by the truck can be mounted. When the truck is empty, it leaves and the resources are released for handling the next delivery. Once all columns have been mounted, the simulation ends.

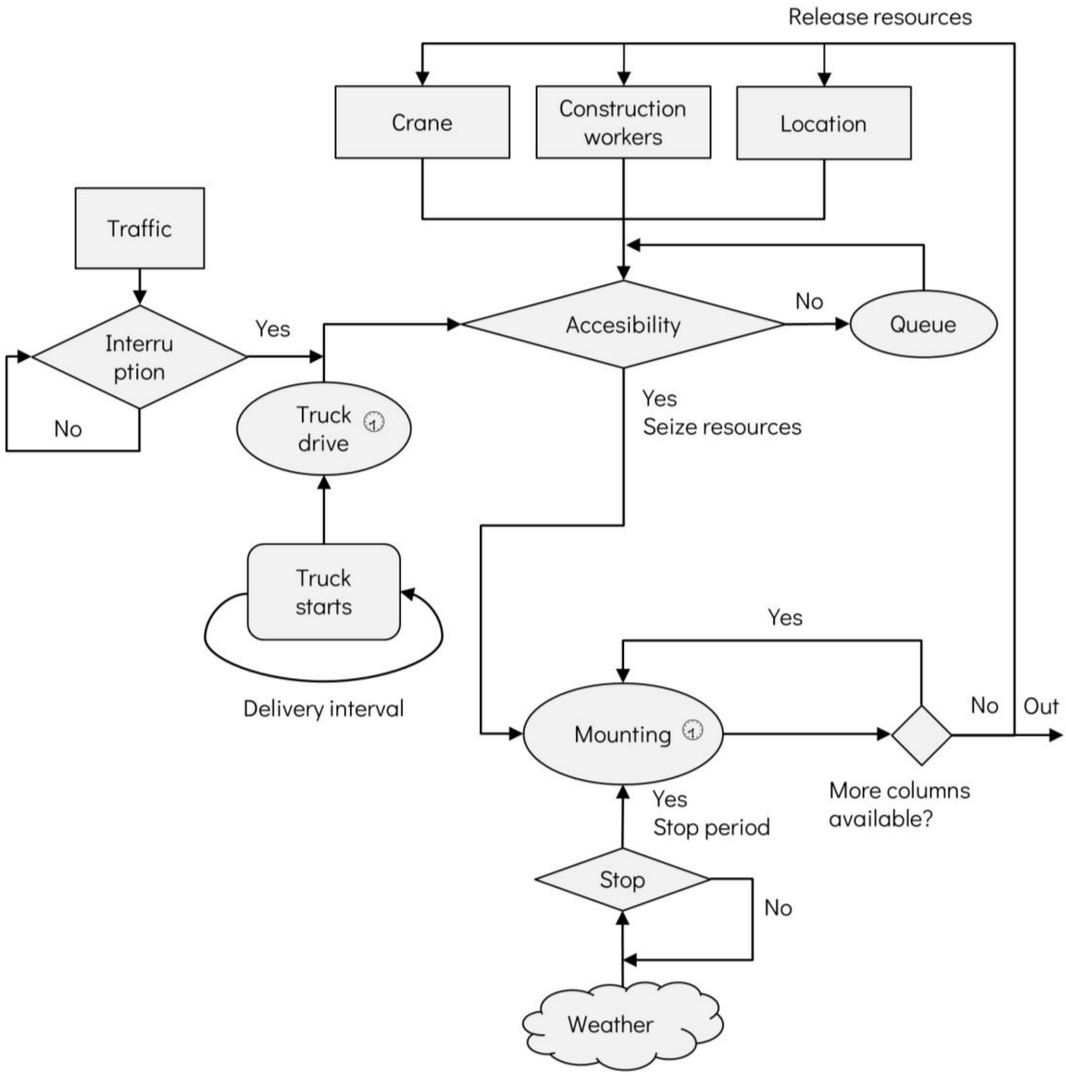

Figure 2: DES structures for mounting prefabricated columns

The tool enables modelling and simulation of a multitude of different construction options. Therefore, different inputs are required (Table 1). The simulation inputs comprise of general information such as the total number of columns, delivery-related factors including the number of columns per delivery and the delivery interval, and the activity durations specified as PDFs for the delivery and the mounting activities. Additionally, the number, maximum number because of constraints, and costs of resources have to be defined in the model. The number of mobile cranes and workers must be adjusted, as cranes require workers for operation. One mobile crane requires three workers for the mounting of a column. Hourly weather forecasts can be incorporated as a table. Moreover, risky and maximum admitted wind speed are further required settings to determine when the operation becomes risky and when it should be stopped according to the provided weather forecasts. Thus, using the tool makes it possible to efficiently test different construction options by changing resource allocations or delivery scenarios.

Table 1: DES tool inputs.

Input	Characteristic	Input	Characteristic	Input	Characteristic
Total columns	Number	Construction worker	Number	Weather forecast	Table
Columns per delivery	Number	Mobile crane	Number	Risky wind speed	Number
Delivery interval	PDF/Number	Maximum cranes	Number	Maximum wind speed	Number
Delivery	PDF	Costs per worker	Number		
Mounting	PDF	Costs per crane	Number		

The DES tool calculates various productivity, resource-efficiency, and safety-related KPIs based on the inputs. These KPIs form a basis for the pending decision-making process during ongoing production. Stochastic simulations are enabled through the use of the Monte-Carlo method and for each KPI, the resulting median value is selected. The construction duration is simulated by the DES. The productivity rate is a crucial factor in evaluating project performance, calculated by dividing the output by the input. In the tool, the productivity rate is calculated by dividing the number of mounted columns by the product of the resource number and the construction duration for the cranes and the workers, respectively. The usage of heavy equipment, such as cranes, is inefficient during construction (Slaton et al. 2020). Therefore, the utilisation rate of cranes is an important KPI and is calculated by dividing the sum of the active crane usage time by the total duration. As the construction industry is the sector with the highest number of fatal and non-fatal accidents (Eurostat 2022) and especially cranes entail high risk operations due to lifting activities, a safety factor is calculated. The safety factor indicates the time cranes are used during risky wind according to weather forecast. This is the range from a risky to a maximum allowed wind speed. As costs are a decisive factor in construction management, the personnel costs are calculated by multiplying the construction duration in hours by the number of resources and the respective costs for the resources.

4. Demonstration Site

The demonstration site is an industrial building, which consists of two halls with a total floor area of almost 30,000 m² and is constructed mainly by prefabricated components on an open field in the centre of Germany. The prefabricated components are delivered by trucks and set on its respective position by a mobile crane and construction workers. This study focuses on the mounting of the 166 prefabricated columns.

In the first two weeks, 96 columns were mounted to construct the first hall with a total duration of 1,440 minutes. During the production, a high-definition webcam gathered time-lapsed photos each ten minutes to derive the durations for each mounting process. The set of durations was used for stochastic productivity modelling as presented in Jungmann et al. (2022) to determine a suitable PDF for the mounting activity resulting in a Weibull distribution with the parameters (2.803, 16.904). As it was not possible to track the delivery trucks, the delivery durations were derived by checking google maps between 07:00 a.m. and 03:00 p.m. on weekdays. The distance from the warehouse to the construction site was around 70 kilometres and the analysis of the durations for the delivery activity resulted in a Logistic distribution containing the parameters (75.772, 1.230).

5. Application

The calibrated DES tool was used to plan the upcoming mounting of further 70 columns for the construction of the second hall by using the detected and validated data-based PDFs as input parameters. According to a discussion with the project manager, the number of cranes was limited to two because of logistic reasons. Costs of 36.60 €/h (Eurostat 2021) were provided for the workers and 100 €/h for a mobile crane according to the project manager. Weather forecasts were implemented and the risky wind speed was set to 10 m/s and the maximum to 20 m/s according to Jin et al. (2020). The further inputs distinguish between four different options as listed in Table 2. The first two options provide only one mobile crane and three workers, while Option 3 and 4 consider two mobile cranes and six workers. Within Option 1, an hourly delivery of two columns is intended. Option 2 and 3 schedule four columns per delivery, but Option 3 considers a 90 minutes' delivery interval. Within Option 4, eight columns are delivered every 60 minutes.

Table 2: Construction options.

	Option 1	**Option 2**	**Option 3**	**Option 4**
Columns per delivery	2	4	4	8
Delivery interval [min]	60	60	90	60
Number cranes	1	1	2	2
Number worker	3	3	6	6

Each option was modelled in the DES tool and the simulation was repeated 1,000 times, resulting in the listed KPIs in Table 3. Option 4 showed the lowest construction duration with 626 minutes, as two mobile cranes were provided and eight columns were delivered each time. This duration was almost the half of that of Option 2 (1,155 minutes) and less than a third of Option 1 (2,146 minutes). Option 4 achieved the second highest productivity for cranes and the workers. Option 2 outperformed with 1.17 columns/working hour (wh) for the workers and 3.50/wh for the crane, as only one mobile crane and the associated workers were used. This was an improvement of around 80% in comparison to Option 1.

Table 3: DES Results.

KPIs	**Option 1**	**Option 2**	**Option 3**	**Option 4**
Duration [min]	2,146	1,155	1,632	626
Productivity $_{\text{Worker}}$ [column/wh]	0.65	1.17	0.42	1.06
Productivity $_{\text{Crane}}$ [column/wh]	1.94	3.50	1.25	3.18
Utilisation rate $_{\text{Crane}}$ [%]	50.87	97.65	34.27	96.70
Safety [min]	180	120	180	0
Personnel costs [€]	7,553	4,196	11,749	4,616

Option 3 resulted in the worst productivity, utilisation rate, and cost values due to a longer delivery interval of 90 minutes, resulting in significant idle time, although 2 cranes were provided. Option 2 and Option 4 had similar utilisation rates, just below 100%. The personnel costs for both options were close, but Option 2 had the lowest expenses of 4,196€, which is around 10% less than Option 4 and around 65% less than Option 3. As Option 4 finished faster than the other options, no risk time due to high wind occurred. For Option 2, a risky period of

120 minutes was calculated and for the remaining two options, 180 minutes were forecasted according to the entered weather forecasts. If a fast execution is requested, Option 4 is the best choice due to the lowest duration, low costs, high productivity, and high utilisation rates. However, Option 2 is even cheaper, achieving more productive and resource-efficient construction, while taking slightly more time.

6. Conclusions

This paper presented an adaptable DES tool for efficient management of ongoing construction works. The sequences during construction processes resemble, but due to varying external circumstances, the durations differ and generic assumptions hinder successful construction management. This is especially applicable for construction by prefabricated components. Nowadays, process data are increasingly being collected during construction using sensors, videos and other technologies, in line with the digital twin concept. Research analyse these collected data using artificial intelligence to extract meaningful process information. However, it is not only important to gain data-based information, but also to use the gained information effectively to manage ongoing production. The tool's easy adaptability makes it a valuable method for optimising the production process in various construction projects.

The developed DESV and the visualised structure of the DES facilitate understanding and usage of the tool by describing input-output relations of the real system. This helps users to investigate data interfaces and handle production deviations. The created DES tool for managing mounting prefabricated columns offers the possibility to provide meaningful KPIs based on stochastic simulations and consider deviations during project management. By forecasting productivity, resource-efficiency, and safety-related KPIs, project managers receive a solid foundation for taking control actions. Thus, data-based management of construction is enabled in a timely manner.

Even though the real construction will differ from the data-driven forecasts made by the tool, the data-driven simulations provide more accurate forecasts compared to generic assumptions. In the application, different resource allocations and delivery scenarios were compared. The results show that significant different impacts are expected for each option. Option 4 requires less than one third of the duration of Option 1 and Option 2 entails almost one third of the costs of Option 3. The application on a demonstration site presents how the tool can offer valuable insights for facilitating the decision-making process and the potential of data-based management for improving production, but the final decision is up to skilled project managers.

While the focus of this study was on mounting columns, the tool's usage can be expanded in the future to include other types of prefabricated components for a more comprehensive approach. One limitation of this research is the usage of Google Maps information for the delivery durations since tracking the delivery trucks was impossible. In the future, the delivery times of trucks should be observed by a GPS tracker, as proposed by Vahdatikhaki and Hammad (2014). Additionally, continuous data collection would be expedient to investigate the gap between forecasted and real performance since productivity close to 100% is hypothetical. Moreover, the results' visualisations would be of great benefit. The development of a dashboard that provides an overview of executed works, possible construction processes, and resulting KPIs would improve communication and strengthen confidence among stakeholders.

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References

Abbasi, S., Taghizade, K., and Noorzai, E. (2020). BIM-based Combination of Takt Time and Discrete Event Simulation for Implementing Just in Time in Construction Scheduling under Constraints, Journal of Construction Engineering and Management 146 (12), 04020143.

Abdelmegid, M. A., Gonzàlez, V. A., Poshdar, M., O'Sullivan, M., Walker, C. G., and Ying, F. (2020). Barriers to adopting simulation modelling in construction industry, Automation in Construction 111, 103046.

AbouRizk, S. (2010). Role of Simulation in Construction Engineering and Management, Journal of Construction Engineering and Management 136 (10), pp. 1140–1153.

AbouRizk, S., Halpin, D., Mohamed, Y., and Hermann, U. (2011). Research in Modeling and Simulation for Improving Construction Engineering Operations. Journal of Construction Engineering and Management 137(10), pp. 843-852.

Akhavian, R. and Behzadan, A. H. (2013). Knowledge-Based Simulation Modeling of Construction Fleet Operations Using Multimodal-Process Data Mining, Journal of Construction Engineering and Management 139 (11), 04013021.

Alvanchi, A., Baniassadi, F., Shahsavari, M., and Kashani, H. (2021). Improving materials logistics plan in road construction projects using discrete event simulation, Engineering Construction & Architectural Management 28 (10), pp. 3144-3163.

Behzadan, A. H., Menassa, C. C., and Pradhan A. R. (2015). Enabling Real Time Simulation of Architecture, Engineering, Construction, and Facility Management (AEC/FM) Systems: A Review of Formalism, Model Architecture, and Data Representation, Journal of Information Technology in Construction 20, pp.1-23

Brilakis, I., Pan, Y., Borrmann, A., Mayer, H.-G., Vos, C., Pettinato, E., and Wagner, S. (2019). Built Environment Digital Twinning, Report for the International Workshop on Built Environment Digital Twinning.

Deng, M., Menassa, C.C., and Kamat, V. R. (2021). From BIM to digital twins: A Systematic review of the evolution of intelligent building representations in the AEC-FM industry, Journal of Information Technology in Construction 26, pp. 58-83.

Eurostat (2021). Labour cost levels by NACE Rev. 2 activity, https://ec.europa.eu/eurostat/databrowser/view/lc_lci_lev/default/table?lang=en.

Eurostat (2022). Accidents at work – statistics on causes and circumstances. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_-_statistics_on_causes_and_circumstances. Accessed: 03.01.2023.

European Construction Sector Observatory (ECSO) (2021). Digitalisation in the construction sector – Analytical Report.

Hartmann T. (2021). Virtual construction with digital twins – The key for leanly planned complex construction systems. Kongress Zukunft Bau Wien, Vienna, Austria.

Jin, L., Liu, H., Zheng, X, and Chen, S. (2020). Exploring the Impact of Wind Loads on Tower Crane Operation. Mathematical Problems in Engineering, 2807438.

Jiang F., Ma L., Broyd T., and Chen K. (2021). Digital twin and its implementation in the civil engineering sector, Automation in Construction 130, 103838.

Jungmann, M., Ungureanu, L., Hartmann, T., Posada, H., and Chacon, R. (2022). Real-Time Activity Duration Extraction of Crane Works for Data-Driven Discrete Event Simulation. Winter Simulation Conference 2022, pp. 2365-2376.

König, M., Koch, C., Habenicht, I., and Spieckermann, S. (2012). Inteligent BIM-Based Construction Scheduling Using Discrete Event Simulation, In: Proceedings of the Winter Simulation Conference 2012, pp. 662-673.

Leite, F., Cho, Y. K., and Behzadan, A. H. (2016). Visualization, Information Modeling and Simulation: Grand Challenges in the Construction Industry, Journal of Computing in Civil Engineering 30 (6), 04016035.

Liu, H., Altaf, M. S., Lei, Z., Lu, M., and Al-Hussein, M. (2015a). Automated production planning in pannelized construction enabled by integrating discrete-event simulation in BIM. Conference: The Canadian Society for Civil Engineering 5th International/11th Speciality Conference.

Liu, H., Al-Hussein, M., and Lu, M. (2015b). BIM-based integrated approach for detailed construction scheduling under resource constraints. Automation in Construction 53, pp. 29-43.

Lu, W. and Olofsson, T. (2014). Building information modeling and discrete event simulation: Towards an integrated framework, Automation in Construction 44, pp. 73-83.

Lu, W., Chen, K., Xue, F., and Pan, W. (2018). Searching for an optimal level of prefabrication in construction: An analytical framework, Journal of Cleaner Production 201, pp. 236-245.

Martinez, J. C. (2010). Methodology for Conducting Discrete-Event Simulation Studies in Construction Engineering and Management, Journal of Construction Engineering and Management 136 (1), pp. 3-16.

Teicholz, P. (2013). Labor-Productivity Declines in the Construction Industry: Causes and Remedies. https://www.aecbytes.com/viewpoint/2013/issue_67.html. Accessed: 03.01.2023.

Sacks, R., Brilakis, I., Pikas, E., Xie, H. S., and Girolami, M. (2020). Construction with digital twin information systems, Data-Centric Engineering 1, E14.

Slaton, T., Hernandez, C., and Akhavian, R. (2020). Construction activity recognition with convolutional recurrent networks. Automation in Construction, 113, 103138.

Rashid, K. M. and Louis, J. (2022). Integrating Process Mining with Discrete-Event Simulation for Dynamic Productivity Estimation in Heavy Civil Construction Operations, Algorithms 15, 173.

Research and Markets (2021). Report: Prefabricated Building Market in Europe – Industry Outlook and Forecast 2021-2026.

Vahdatikhaki, F. and Hammad, A. (2014). Framework for Near Real-Time Simulation of Earthmoving Projects Using Location Tracking Technologies, Automation in Construction 42, pp. 50-67.

Wainer, G. A. (2009). Discrete-Event Modeling and Simulation: A Practitioner's Approach, Boca Raton: CRC Press.

Wu, L. and AbouRizk, S. (2021). Numerical-Based Approach for Updating Simulation Input in Real-Time, Journal of Computing in Civil Engineering 35(2), 04020067.

Zeigler, B. P., Muzy, A., and Kofman, E. (2018). Theory of Modeling and Simulation, 3rd edition, Academic Press.

Zhong, R. Y, Peng, Y., Xue, F., Fang, J., Zou, W., Luo, H. et al. (2017). Prefabricated construction enabled by the Internet-of-Things, Automation in Construction 76, pp. 59-70.