Discrete Event Simulation (DES)-Based Abstraction of Construction State Machines and Robotic Simulations for Site-Wide Optimization Using BIM and Gazebo

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Abstract: The construction industry is one of the most labor-intensive and least digitized and automated industries worldwide, facing low productivity, worker shortages, and safety issues. Since the last decade, automation and robotics have witnessed great development in building their capacity to enhance productivity, sustainability, and adaptability on-site. To allocate a large number of human and robotic resources, a strategy needs to be designed for an entire construction site. Such planning activities require the development of a representation of elements at a granularity level that considers detailed geometrical data, the robotic equipment placement, and the safety of all the workers.

Therefore, the paper proposes an integrated collaborative approach of computational architecture in the form of a Building Information Model (BIM), a simulation interface of Gazebo for developing a robotic construction site, and real-time Discrete Event Simulation (DES) for optimization of resources and evaluation of safe construction spaces. As a part of the research, a case study is selected where the construction of prefabricated factory halls is planned, considering the resources like robots, delivery trucks, cranes, and the on-site human fleet. Thus, the paper will contribute to an elaborate integration of optimizing robotic construction processes and logistics supply chain planning.

Keywords: DES, Robotic simulation, BIM, Automation in Construction, Gazebo.

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1 Introduction

1.1 Problem Statement

The construction industry, which is vital to Europe's economy, has been much slower to apply advanced and scientific methods for analyzing complex construction processes, most likely due to the labor shortages, skills mismatches, low productivity growth, and slow technology uptake [1]. Automating processes in the construction sector requires the application of many different robots and equipment to work in close collaboration.

Construction sites with automated equipment, robots, and human workers face high uncertainty, affecting activity durations, material delivery, machine reliability, and labor productivity [2]. To manage this complexity, strategic resource planning is essential. One effective method is creating a virtual project model using simulation. This allows decision-makers to analyze workflows, allocate resources, and manage risks. Among simulation types: System Dynamics, Agent-Based Modeling, and Discrete Event Simulation (DES), DES is widely used for addressing such uncertainties.

DES, a computational method, models a system's changing behavior and performance as a sequence of discrete events over time, offering granular insight into equipment placement, material deliveries, or human–robot interactions. However, DES alone can be limited in resource allocation or design, requiring manual updates to the model, resulting in time-consuming revisions and limiting industry adoption. Research has shown that linking DES with a central BIM database allows real-time updates and automated model changes [3]. To address uncertainty and variability in such dynamic environments, stochastic models can be incorporated, such as Monte Carlo simulations, Weibull, and logistic distributions. Monte Carlo methods allow for probabilistic risk analysis through repeated sampling, while Weibull distributions help model equipment lifespans or failure probabilities, and Logistic distributions capture decision-making under uncertainty. Including these models enhances the robustness of DES by accounting for random events and probabilistic behavior. Moreover, for real-time updates to the simulation model, it is essential to establish a connection to a central database, achievable through the integration of BIM with the overall computational architecture.

BIM is a central digital tool for designing, planning, and managing construction projects, containing detailed geometry and data. When integrated with robotic simulation, it supports automated construction. However, while BIM has advanced, less focus has been placed on linking it with robot operations and semantics. Technologies like Robotic Operating System (ROS) are enabling greater robot adoption, but strategic planning methods for full-site robotic work are still lacking. Therefore, effective planning will require simulation models that can represent various robotic tasks and allow user-controlled actions across different levels.

1.2 Research Objective

The objective of this research was, therefore, to develop and validate an integrated simulation framework that combines BIM, robotic simulation using Gazebo, and DES to support the planning, coordination, and optimization of construction site operations. The framework aimed to abstract complex construction workflows into discrete state machines, enabling dynamic evaluation of resource allocation strategies, spatial safety constraints, and construction sequencing in real-time. By applying this framework to a real-world case study involving prefabricated factory hall construction, the study aimed to demonstrate its effectiveness in improving operational efficiency and site-wide automation.

2 State of the Art - Literature Review

2.1 BIM and Robotic Systems

Recent research has increasingly focused on the simulation of robotic construction tasks. To date, much of this work has emphasized the development of strategic simulation models for factory-based prefabrication. Notable examples include the frameworks proposed by [4] and [5], which integrate robotic production planning with established BIM standards to simulate the prefabrication of building components. Similarly, [6] developed a BIM-based simulation model for the prefabrication of wooden frames.

In contrast, relatively few studies have addressed the simulation of on-site robotic construction activities. Among those, a key area of interest lies in developing interfaces between BIM and ROS to enable task-level coordination. These studies typically address specific, narrowly scoped applications. For instance, [7] demonstrated BIM–ROS integration for simulating automated indoor painting. [8] investigated robotic masonry using a cable-driven system, while [9] proposed a simulation framework for robotic excavation.

2.2 Discrete Event Simulation in construction planning

DES models complex systems as chains of sequential states, each representing a process step. In construction, a crane lifting operation might follow: (a) fastening the load, (b) lifting it, and (c) installing it. State transitions occur after time delays or external events. The DES formalism extends this by including resource constraints, such as material availability or truck arrivals.

Applying DES in construction faces two key challenges: (a) accurately modeling construction sequences and (b) accounting for variable activity durations due to site dynamics. The first requires linking DES with BIM to reflect design-specific sequences and geometries [10]. The second involves integrating real-time data from sensors to model productivity variability [11].

Given these challenges, DES is best viewed as part of a hybrid modeling approach, effective for automated and robotic workflows, especially when integrated with BIM and simulation tools like Gazebo.

2.3 Gaps in Current Research

In summary, there is limited research exploring how robot-assisted construction work can be effectively represented and simulated. Existing studies largely focus either on modeling prefabrication processes in controlled factory settings or on highly specific robotic automation tasks. However, they rarely address how such tasks can be integrated and situated within the complex, dynamic environment of construction sites, an environment that requires stochastic modeling to capture its inherent variability. In the next section, a framework is proposed to integrate these tasks and apply the techniques to real-world situations.

3 Research Methodology

3.1 Conceptual Framework of the Study

The proposed framework integrated two main domains: data-driven BIM and cyber-physical robotic production resources, enabling realistic simulation of on-site robotic construction tasks. The integration process was organized into three key components: the BIM interface, the DES environment, and the simulation loop, as defined in Figure 1.

BIM data, exported in Industry Foundation Classes (IFC) format, served as the foundation for the simulation. The BIM Interface extracted essential parameters such as task identifiers, site coordinates, element types, and material quantities. This parsed data was processed by an IFC File Parser, which transformed it into construction-related inputs, including schedules and logistics data, that were then

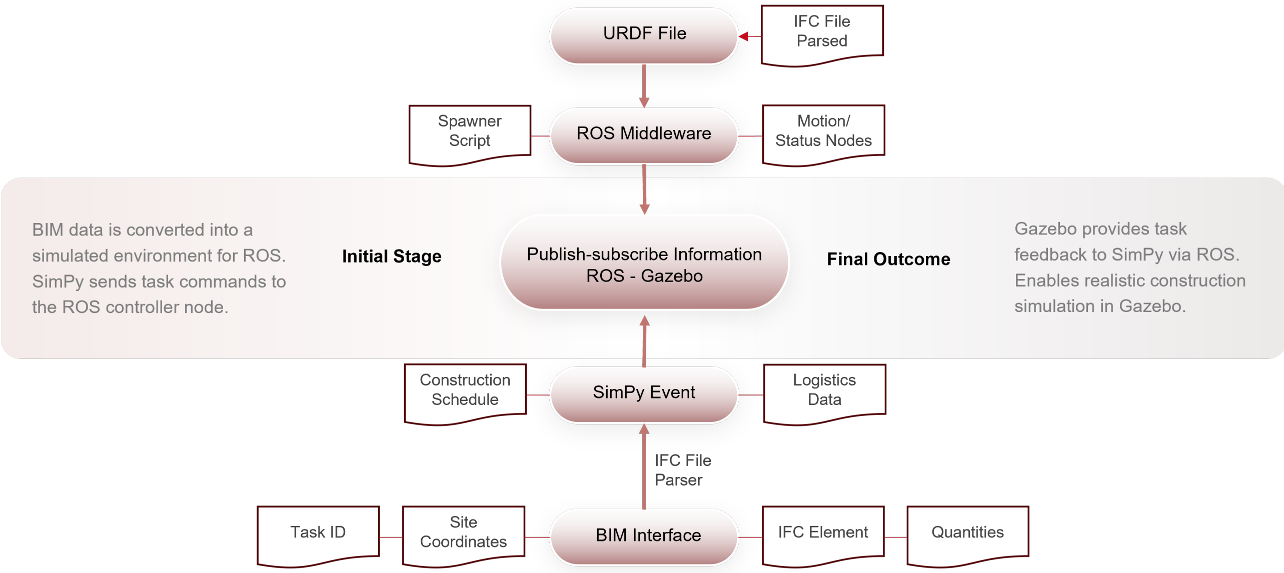

Figure 1: Data flow from BIM to DES to Gazebo

input into Python-based SimPy to generate discrete construction events. Additionally, the construction schedule was also added to the DES model, which was then implemented in the SimPy library. Within SimPy, stochastic processes and Monte Carlo sampling allow the system to estimate task durations, resource utilization, and performance variations under different site conditions.

The ROS-Gazebo middleware acts as the bridge between the DES and the simulated robotic resources. The models in the format of Unified Robot Description Format (URDF) were parsed from BIM-derived geometry and spawned into Gazebo via ROS spawner scripts. Motion and status nodes enabled continuous bidirectional communication: SimPy sends task execution commands to ROS controllers, while Gazebo provides real-time task feedback back to SimPy.

This publish–subscribe integration enabled dynamic simulation where task duration, logistics, and operational constraints are updated during runtime. The framework not only estimated productivity and efficiency for robotic operations but also allowed planners and designers to test alternative resource configurations, site layouts, and weather delay scenarios before physical placement.

3.2 Case Study Context and Data Modeling

To validate the framework, a case study from the Horizon 2020 ASHVIN project was used, which focused on the construction of a prefabricated factory hall spanning 30,000 square meters and 12 meters in height. The dataset included the two-week delivery and mounting schedule of prefabricated columns. A robotic agent was integrated into the SimPy-based DES model to perform mounting tasks alongside human workers, while a robotic tower crane was modeled for placing the columns into position.

Upon the truck's arrival at the construction site, the operational workflow followed the logic shown in Figure 2. First, parking availability was checked; if no space was available, the truck waited in a parking queue until one was freed. Once parked, the system verified the availability of critical resources—namely, the tower crane, robots, human operators, and the designated mounting location. If any of these were occupied, the truck remains in the parking queue until all were released.

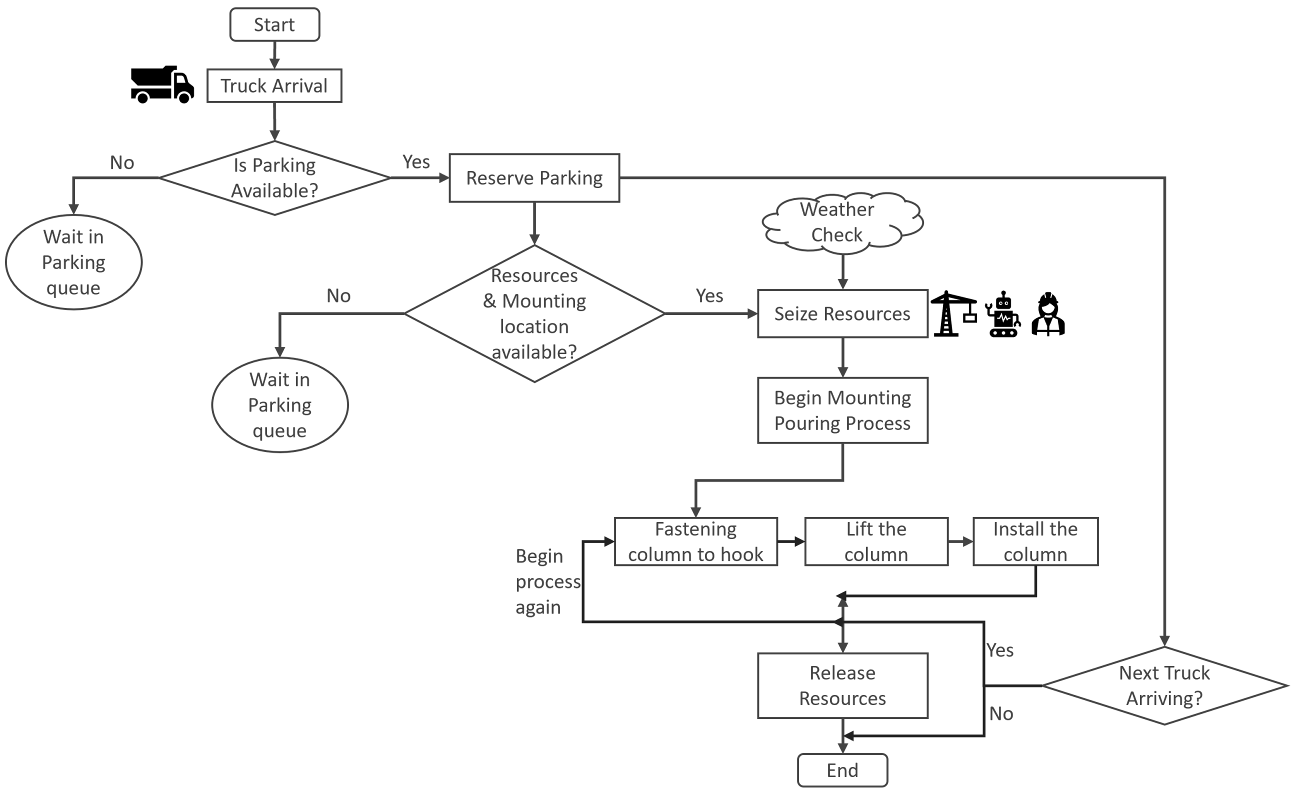

Figure 2: DES model for the crane

When parking and resources were available, a weather check was performed to ensure safe operating conditions. In the event of extreme weather, all activities were paused until conditions improved. If conditions were acceptable, the resources were seized and the mounting process began. The duration of each mounting cycle was determined using a probability distribution function (PDF), defined here as a statistical model representing the likelihood of different task durations based on historical records, sensor measurements, and stochastic analysis. Sampling from this PDF allows the simulation to capture real-world variability in operator speed, alignment precision, and minor delays, rather than assuming fixed times.

The mounting cycle consists of fastening the column to the crane hook, lifting the column, and installing it in position with the help of a robot and a human. This process repeats for each column transported by the truck. Once all columns were installed, the resources and parking slot were released, the truck departs, and the system transitioned to the next truck's arrival, repeating the sequence.

4 Implementation and Results

The framework was developed using Python 3.10 with the SimPy library for handling discrete-event scheduling, resource management, and queuing processes. Weather conditions were included as external factors influencing the simulation flow. In the model, key resources such as robots, human workers, cranes, trucks, and parking spaces were represented with capacities matching the case study setup. The workflow was divided into three main steps: a delivery truck arriving and parking, a crane lifting and positioning a column, and a worker–robot team mounting the column in place. Each step required the relevant resources to be available, and SimPy's request/wait mechanism ensured that tasks were queued when resources were busy. Task durations were based on realistic timing data and included variation to reflect real-world uncertainty.

To evaluate system performance under uncertainty, the model was tested using a Monte Carlo approach. For each experimental setup, the simulation environment was reset and run until all columns were assembled, with the total completion time recorded at the moment the final column was mounted. To assess how different resource allocations affect productivity, multiple scenarios were created by varying the numbers of robots, workers, cranes, and trucks. Each scenario was simulated repeatedly to capture the effects of randomness, and the results were averaged to provide reliable performance estimates.

4.1 Results

Three categories of resources: robots, cranes, and trucks, were evaluated for their impact on project completion time. The results were obtained from 100 Monte Carlo runs per configuration to account for stochastic variability in delivery and mounting durations. The simulations examined the effect of varying human and robotic resource allocations on project completion times, accounting for operational constraints such as traffic and weather delays.

Robots vs Workers Allocation: The heatmap in Figure 3 illustrates the average completion times for different combinations of robots (2 to 8 units) and human workers (4 to 10 units). Across all configurations tested, average completion times ranged narrowly between 3146 and 3153 minutes, indicating that the marginal gains from increasing either resource type alone were minimal under the tested operational model. Notably, certain configurations with moderate resource levels (e.g., 6 robots and 6 workers) yielded slightly longer completion times than others with lower or higher counts, suggesting nonlinear interactions between workforce composition and task sequencing efficiency.

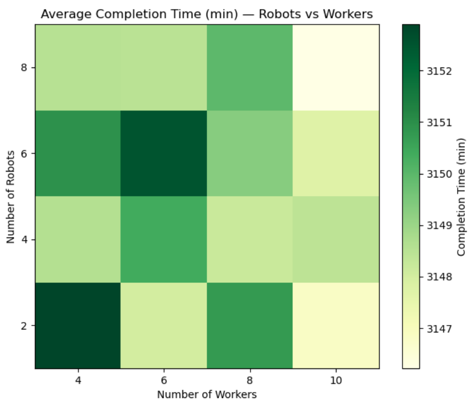

Figure 3: Average completion time

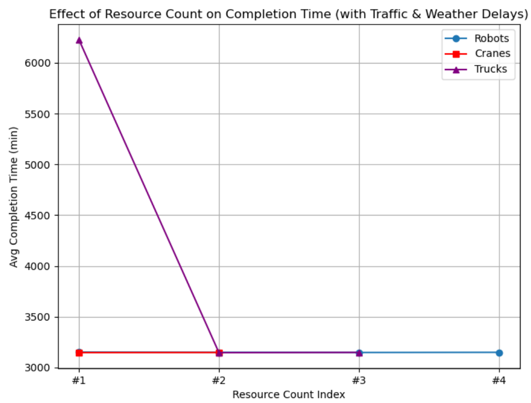

Figure 4: Effect of Resources on Completion Time

Effect of Resources on Completion Time: Figure 4 presents the influence of resource counts for robots, cranes, and trucks when traffic and weather delays were introduced. Here, the effect of truck availability was most pronounced: with a low truck count, completion times peaked at over 6200 minutes, more than doubling the baseline. Increasing truck count immediately reduced completion times to the same level as the best-performing crane and robot configurations (3110 minutes). This emphasizes that logistical constraints in material delivery can overshadow productivity gains from on-site automation alone. From a general safety perspective, the ability of the framework to simulate spatial constraints in real time allows informed placement of robots and human workers, maintaining operational safety margins even under high-density deployment.

5 Conclusion and Future Work

Although the framework included plans for integration with the Gazebo simulation platform, work is still in progress to support more realistic robotic kinematics, advanced environment sensing, and robust collision detection. While the results demonstrated clear potential for improving resource planning, several limitations remain. The current simulation environment assumed idealized equipment performance and operator reliability, which may not fully reflect the effects of mechanical failures, human error, or learning curves. Disturbance modeling was restricted to generic traffic and weather delays, whereas real-world scenarios often involved more complex factors such as variable delivery lead times, on-site congestion, and unexpected environmental hazards.

Future work will address these limitations by integrating probabilistic failure models, extending the model to capture complex logistical uncertainties, and coupling the spatial safety module with real-time perception and adaptive path-planning algorithms. Additionally, validating the framework against real-world project data will be critical to assessing its predictive accuracy and operational feasibility. These enhancements will strengthen the maturity of the framework and support its adoption as a decision-support tool for safe, efficient, and adaptive human–robot collaboration in construction.

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