Rethinking Infrastructure Deconstruction Through Reality Data Capture and Interactive Simulations

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Chapters 3, 4, and 5 are adapted from articles written in collaboration with Yinghui Zhao, Yun-Ha Jung, and Manolis Katsimpalis at University of Waterloo under the supervision of Dr. Carl Haas. In order to provide maximum transparency, an additional statement of contributions is provided at the start of each of these chapters regarding the division of labor.

Section 8.1 is adapted from articles written in collaboration with Alexander Thoms, Nicholas Charron, and other minor contributors as part of the former Sensing and Robotics for Infrastructure Lab at University of Waterloo under the supervision of Dr. Sriram Narasimhan.

Abstract

The demand for careful infrastructure deconstruction and disassembly increases every day, as the market for building material reuse grows, and the reality of construction landfill waste weighs on the environment. Mid-century nuclear power plants are one example of infrastructure that are reaching life expectancies and require massive deconstruction initiatives. These projects span multiple decades and bear massive costs, making effective planning a requirement. However, despite active research efforts in infrastructure lifecycle stages such as design, construction, inspection, and maintenance, deconstruction remains relatively unexplored. Meanwhile, applicable technologies like autonomous robotics, virtual reality headsets, and 3D simulation software are more capable and cost-effective than ever.

In this research, the use of reality data capture and virtual reality simulations as tools for planning deconstruction projects is studied. Novel planning workflows using these technologies are designed, implemented, and tested for validation. The completion of this research yields the contribution of three novel planning methodologies. They are 1) a methodology for cutting and packing planning, 2) a methodology for building material reuse planning, and 3) methodology for automated critical path schedule generation. Several scientific problems are addressed in support of developing and validating the proposed methodologies. While the methodologies each address a different workflow within deconstruction planning, they build upon each other in terms of the scientific problems that are addressed, with the final methodology bearing the most significant and novel contributions.

In the methodology for cutting and packing, the topics of creating immersive virtual reality simulations from reality data as well as conducting human-computer collaborative cutting and packing planning based on reality data are addressed. An optimal reality data processing approach for deconstruction planning simulations is detailed based on a quantitative comparison of reality data capture methods as well as qualitative observations. A simulation environment with rich feedback based on the processed reality data is designed to enable human-computer collaborative cutting and

packing planning. These developments build upon prior work with similar capabilities, but that do not incorporate reality data.

In the methodology for building material reuse planning, the problem of simultaneously optimizing deconstruction planning and reuse-based architectural design is studied. A gamified virtual reality simulation is developed and presented to address the underconstrained nature of this problem, which enables users to create a high level initial solution. A workshop with human participants is held and quantitative metrics from questionnaires as well as qualitative feedback on the simulation is collected. The feedback is analyzed in order to support future work in refining the methodology.

In the methodology for automated critical path schedule generation, the most significant contributions of the thesis are presented, where the problem of efficiently and automatically generating accurate critical path schedules based on a virtual reality simulation run is addressed. In the methodology presented, a series of novel algorithms are designed to deduce the requisite information to produce a critical path schedule that reflects a user's actions in a virtual reality environment. The algorithms support 1) detecting the occurrence of construction-centric actions within the virtual reality environment, 2) estimating the corresponding real-world durations of detected actions, and 3) deducing the precedence relationships of detection actions. Using this information, an automated approach for assembling a critical path schedule that is enhanced with rich metadata about the planning process and that is not resource constrained is presented.

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Dedication

This work is dedicated to the teachers that led me to graduate school. To my dad, thank you for teaching me how to succeed in the world with hard work and belief. To my mom, thank you for teaching me the joy of curiosity by answering my unending stream of questions about the world. To my grandpa, thank you for teaching me my passion for technology and engineering by inspiring me and passing on your wisdom.

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Chapter 1

Introduction

1.1. Research Hypothesis

This research serves to evaluate the following hypothesis:

Deconstruction planning can be reimagined to incorporate reality data capture and virtual reality (VR) technologies with the effect of enabling planners to engage with 3D reconstructions of deconstruction assets and leverage simulation environments to optimize and automate aspects of deconstruction planning such as schedule deliverable generation.

To evaluate this hypothesis, this research seeks to investigate the development of key required techniques and technology for the proposed planning paradigm. These contributions are presented and implemented in this thesis in order to validate the research hypothesis through demonstration. Chapter 5 represents the culmination of the study, where interactive VR planning is conducted in environments based on reality data, and a critical path schedule deliverable is automatically generated from the user's actions.

1.2. Research Motivation

The study of infrastructure lifecycle management technology has given civil engineers previously unthinkable capabilities. Researchers and asset owners now measure projects as-built with millimeter accuracy, automate defect detection, continuously optimize maintenance planning, and much more. Of the lifecycle management stages, operation and maintenance has seen perhaps the greatest research focus, as the prevention of catastrophic failure, optimization of infrastructure budgets, and repeatability of inspection results are important priorities. The construction and procurement stage has seen the next most focus, as researchers seek

to understand how contracts affect project outcomes and optimize worker safety and efficiency. Deconstruction is receiving attention as a critical activity for a circular economy in the built environment. It is an area lacking research, but ripe with opportunities to rethink current workflows with recent technologies to improve project outcomes.

Improvements to deconstruction workflows are key to the future needs of our built environment. As our cities age, infrastructure projects more and more seek to rebuild, renovate, and replace. Massive quantities of concrete structures developed in post-war urban booms are reaching their 50-to-100-year life expectancies, and efficient replacement and rehab is a key engineering challenge of the coming decades. In Ontario, Canada, multi-decade efforts to decommission 20th century nuclear power plants are challenging teams of engineers, researchers, vendors, and laborers. In these hazardous scenarios, classical heavy demolition approaches are not an option, and the asset owners find that the costly development of novel workflows and technologies to plan and execute these deconstruction operations is the only acceptable option to manage risk.

Construction annually consumes over 3 billion tons of raw materials, substantially contributing to waste; by 2025, the generated C&D waste is projected to reach 2.2 billion tons, with 60% ending up in landfills (Guerra et al., 2021; Ellen MacArthur Foundation, 2020; United States Environmental Protection Agency, 2018). Amidst global sustainability efforts, the construction industry is shifting towards a Circular Economy (CE) for building materials, focusing on their reuse rather than disposal due to inconveniences at a building's end-of-life. This shift necessitates motivated building owners, designers skilled in reused material integration, and reliable sourcing by construction firms (Mollaei et al., 2023).

As the circular economy of the built environment grows and evolves, the reuse of building materials is becoming more viable and economically motivating. Careful, methodical deconstruction offers much greater adaptive material reuse potential compared with conventional demolition. Adaptive reuse, a key waste-reduction strategy in the circular economy, presents a compelling business case and environmental

motivation for the adoption of smart deconstruction, adding to improvements in project time, risk, and certainty.

1.3. Research Objectives

This dissertation seeks to lay groundwork for new smart deconstruction workflows, motivated by expected improvements in deconstruction project goals such as cost and schedule performance, predictability, quality, safety, and participant satisfaction. To this end, a smart deconstruction pipeline where information flows from reality data capture to interactive VR simulation and project insight and deliverable generation is desired, as depicted in Figure 1.

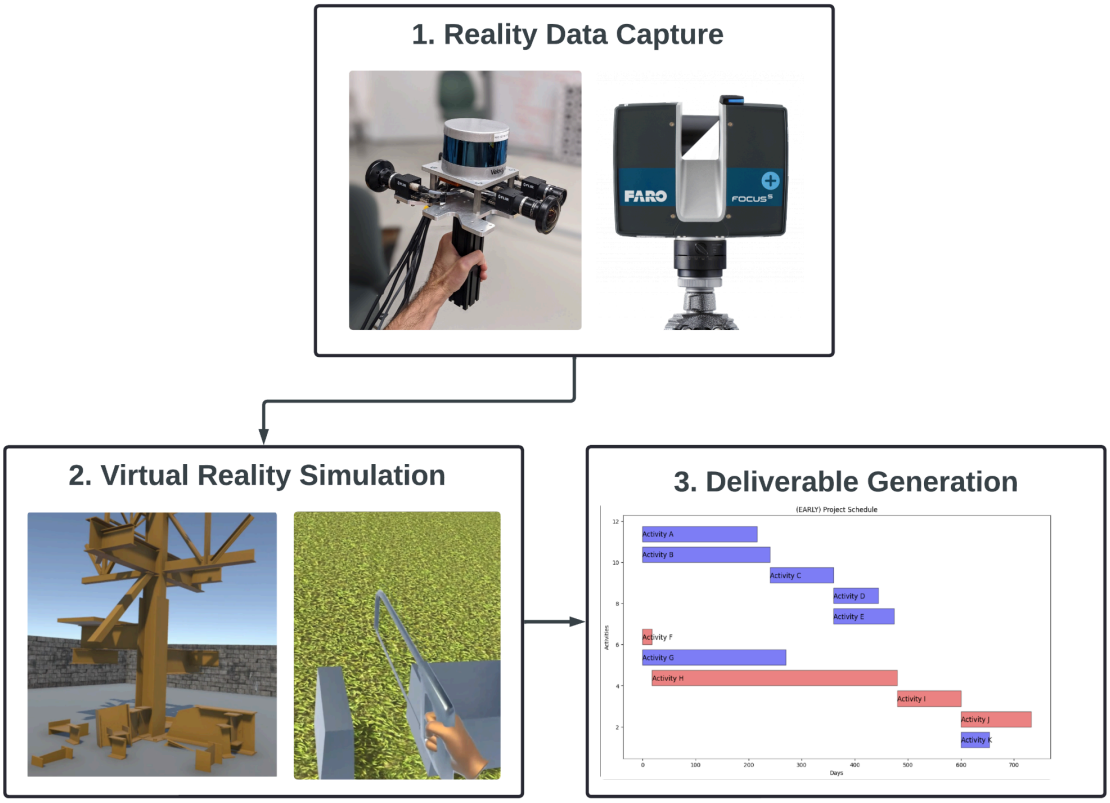


Figure 1: Smart deconstruction information pipeline

This research specifically addresses the following objectives:

- **Demonstrate the use of VR in deconstruction planning.** This research seeks to explore, develop, demonstrate, and test the use of VR-based solutions for key deconstruction planning tasks. Along the way, novel algorithms, techniques, and methodologies needed to support this exploratory research are developed, formalized, and contributed.

- **Demonstrate the use of 3D reconstructions in deconstruction planning.** This research seeks to develop techniques for deconstruction planning that tightly integrate 3D scan data into planning processes. This data portrays rich insights about the project area's nature, condition, and geometry. This research seeks to explore the opportunity to present planners with this information in the intuitive context of VR.

- **Enable human-computer collaborative deconstruction planning.** VR environments offer unique ways to communicate computed feedback and results with human operators as well as a rich 3D environment to garner computational inputs. This research seeks to investigate using interactive VR-based deconstruction planning to seamlessly integrate computational optimization and solving techniques into planning workflows.

- **Automate the drafting of deconstruction project deliverables.** Deliverables such as critical path schedules are the key to communication between planners and project teams. VR planning presents an opportunity to automate the transcription of recognizable project deliverables from the VR operator's actions. This research seeks to develop the techniques and algorithms required for such automation.

1.4. Research Methodology

This research aims to introduce and validate novel processes for planning deconstruction projects that are based on reality data capture and VR technology. To achieve this, a constructive research approach is adopted, which focuses on the

creation of innovative solutions to practical problems, thereby contributing to both the practical and theoretical understanding of deconstruction project planning.

Following the methodology framework suggested by Peffers et al (2007), the research commenced with the identification of specific research motivations and objectives derived from a comprehensive review of existing literature on deconstruction planning, as detailed in Section 2, Literature Review. Each aspect aims to explore the potential of reality data capture and VR technology in enhancing a specific activity related to deconstruction planning. Subsequently, each question is addressed by designing a VR-based planning process, which is then implemented to validate its efficacy and generalizability in real-world construction project planning. For each solution, the results are discussed on the basis of conclusions, implications, and impact.

The implementation phase involves an exploration of robotic reality data capture platforms and the development and testing of a series of VR simulation environments tailored for deconstruction planning. The simulations incorporate features like the capture and analysis of user interactions or automated generation of project deliverables, corresponding to solutions to the research motivations and gaps identified.

1.5. Contributions

The completion of this research yields three main contributions. Each contribution represents a methodology for executing one key aspect of deconstruction planning using VR that has been designed, implemented, demonstrated, and validated. Within each contribution, there is a greater methodology that is presented, as well as smaller pieces such as requisite techniques and algorithms. The three aspects of deconstruction planning which are studied are 1) cutting and packing planning, 2) building material reuse planning, and 3) derivation of critical path schedules from VR deconstruction trials.

1.5.1. Methodology for cutting and packing planning

First, this research contributes to an innovative methodology for synergistic cutting and packing planning using VR, addressing a critical aspect of deconstruction and material reuse. By integrating cutting and packing processes into a single VR simulation, this approach facilitates the co-optimization of both activities, ensuring that the planning of how materials are cut aligns closely with how they are subsequently packed and transported. This methodology not only enhances efficiency but also promotes sustainability by maximizing material reuse and minimizing waste.

Central to this contribution is the use of VR technology to create an interactive simulation environment that provides real-time feedback to users. This dynamic setting enables planners to immediately see the implications of their cutting and packing decisions, allowing for iterative adjustments and improvements. Importantly, the simulation environment is designed to augment human decision-making with computational optimization techniques, bridging the gap between intuitive planning and algorithmic precision. This blend of human insight and computational power exemplifies the potential of human-computer collaboration in complex planning tasks. This collaborative approach not only leverages the strengths of human intuition and experience but also harnesses the capabilities of computational algorithms to identify optimal solutions that might not be immediately apparent.

1.5.2. Methodology for building material reuse planning

Second, this research contributes a novel approach to building material reuse planning by implementing a VR simulation that enables planners to simultaneously visualize and experiment with deconstruction and reconstruction at the same time. The VR simulation, developed from detailed 3D models of assets, provides a dynamic platform for experimentation, offering users immediate feedback on the efficiency and feasibility of various strategies. This interactive environment supports iterative trials, allowing deconstruction planners to refine their approaches in a repeatable, low-cost, and risk-free setting. The emphasis on human-computer collaboration within this

simulation underscores its utility in enhancing decision-making processes for material reuse.

By developing a VR platform that allows for the simultaneous consideration of cutting plans and the potential structural integrity of reused materials, this methodology addresses a critical gap in achieving a successful circular economy for building materials. The distinctiveness of this contribution lies in its focus on bridging the planning of deconstruction activities with the design considerations for the reuse of salvaged materials, marking it as the first of its kind to tackle these challenges concurrently.

A key aspect of this contribution is the evaluation of the VR simulation's effectiveness through a workshop with multidisciplinary participants. This practical application demonstrated the simulation's ability to engage users in immersive planning tasks, facilitating a deeper understanding of the complexities involved in material reuse. Feedback from the workshop revealed the simulation's potential to empower planners with insights into the design's de-constructability and structural integrity, thereby advancing circular economy practices in construction. The qualitative evaluation provided by the workshop participants further validated the VR simulation as a powerful tool for improving planning outcomes in building material reuse, highlighting its significance as a contribution to the field of deconstruction planning.

1.5.3. Methodology for automated critical path schedule generation

Third, this research contributes an approach for automating critical path schedule generation for construction planning by harnessing the capabilities of VR. Addressing the challenge of translating the complex outcomes of construction planning simulations into actionable and coherent planning deliverables, the proposed methodology enables construction planners to interact with a VR environment, from which a comprehensive critical path schedule is automatically generated based on their actions. This innovative workflow facilitates repeated trials of tasks in a risk-free, cost-effective, and human-computer collaborative setting, culminating in the production of essential planning deliverables without necessitating additional effort from the planners.

Central to this contribution is the development of a schedule generation methodology that utilizes the advanced modular capabilities of modern VR engines. By compiling a detailed ledger of user interactions within the simulation, the system adeptly identifies construction-centric activities from a sequence of event logs. This process not only streamlines the identification of critical tasks but also lays the foundation for the subsequent generation of a critical path schedule. An algorithm is contributed to establish real-world precedence relationships derived from the virtual event logs. This algorithm employs pre-defined reasoning to analyze the sequence of events, enabling the identification of dependencies and informing a strategy for the parallelization of construction activities. Finally, a series of algorithms estimate activity durations directly from these logs, providing a detailed basis for the automated scheduling. This process allows for the efficient production of critical path schedules that are both recognizable and directly applicable to the construction industry.

1.6. Potential Research Impacts

Decrease Cost and Time: Research consistently shows that effective planning is crucial for improving project outcomes in construction. Studies have demonstrated a strong correlation between key performance indicators, such as fewer requests for information and supplemental instructions, and improved project profitability and timeliness (Cleary & Lamanna, 2022). Similarly, Shehu and Akintoye (2009) found that effective planning in construction projects had the highest criticality index among all critical success factors they studied. They concluded that thorough planning had the strongest influence on achieving cost and schedule objectives, further emphasizing the vital role of planning in construction project performance. The automation of critical path schedule generation could be particularly impactful, allowing for the rapid creation of optimized plans that would otherwise require significant manual effort and time. By leveraging automated scheduling, project teams can explore a wider array of scenarios, enabling them to identify the most efficient strategies without the extensive time investment typically associated with manual planning.

Risk Mitigation Through Enhanced Understanding of In-Situ Conditions: Accurate project planning in deconstruction critically depends on precise knowledge of the current state and dimensions of the asset. By utilizing a reality data-based approach, this research ensures that up-to-date scans of the deconstruction site are integrated into the planning process, replacing reliance on outdated construction as-built drawings. This real-time data integration is anticipated to enhance the accuracy of structural evaluations and packing optimizations and significantly reduces the risk of costly errors and unforeseen issues. Furthermore, the use of accurate in-situ Building Information Modeling (BIM) representations in automated schedule generation mitigates the uncertainties commonly encountered during the planning phases of deconstruction. The resulting schedules, grounded in current site conditions, provide action sequences that are anticipated to minimize the potential for delays and safety hazards, thereby improving both the reliability and safety of the deconstruction process.

Optimized Management of Hazardous Materials and Worker Exposure: Accurate, non-destructive measurements of hazardous materials, combined with automated schedule generation, provide a powerful toolset for managing and reducing worker exposure to dangers on-site. The simulation of tasks within a VR environment offers planners a calculated understanding of the expected exposure levels for various scenarios. This information is invaluable in developing strategies to protect workers, such as determining the safest order of operations or identifying tasks that can be automated or conducted by robotic workers. Additionally, the ability to simulate and optimize the storage and handling of hazardous materials through automated planning algorithms ensures that these operations are carried out with the utmost safety and efficiency.

Automated Deliverable Generation: The system's ability to deduce minimal precedence relationships and apply logical constraints enables the automatic generation of schedules reflecting the optimal early finish time, assuming unlimited resources. This offers the potential to improve project planning efficiency by allowing teams to explore a wider range of "what-if" scenarios that might not be feasible to test manually. Grounded in human-computer collaboration, the methodology integrates

expert knowledge and computational logic to propose optimized task sequences. While further empirical studies are required to substantiate the broader impacts on real-world project outcomes, this approach provides a promising framework for refining deconstruction workflows and facilitating quicker iterations during the planning phase.

Chapter 2

Literature Review

2.1. Reality data capture in infrastructure applications

Robotic platforms offer the opportunity to improve and automate many infrastructure management processes traditionally done by hand. In structural health monitoring (SHM) research, the use of robotic platforms carrying suites of sensors are paired with condition assessment approaches to perform inspections. For example, In Khaloo and Lattanzi (2018), an unmanned aerial vehicle (UAV) is used to produce a precise dense scan reconstruction of the Placer River Trail Bridge in Alaska using a modified structure from motion (SfM) approach described in Khaloo and Lattanzi (2017). The reconstruction can then be visually inspected to achieve condition assessment. Chen et al. (2019) follow a similar approach.

Other works opt for automated approaches to condition assessment. For example, in Ellenberg et al. (2016) the use of an UAV carrying RGB and thermal cameras is used to automate delamination identification on a bridge deck. In McLaughlin et al. (2020), a mobile ground robot is used, a 3D reconstruction step is included, and the delamination detection algorithm is replaced with a deep learning approach. LiDAR data, images, and inertial odometry measurements are fused using a simultaneous localization and mapping (SLAM) approach to develop a maximum a posteriori estimate of the trajectory of the robot and the colorized map of the bridge. Then, a convolutional neural network (CNN) is used to perform pixel-wise delamination predictions on the thermal images of the concrete surface. The detected damage locations are reprojected onto the 3D map using ray tracing, since the pose of the robot and the orientation of the thermal camera is known. Similar platforms and sensor suites have been implemented for concrete crack detection rather than delamination, leveraging the *wealth* of crack detection literature (Lee and Chung, 2000; Zou et al. 2012; Zhang et al. 2016; Mohan and Poobal 2018; Alipour et al. 2019; Fang et al. 2020).

Overall, robotic platforms with remote sensing capabilities applied to SHM activities have been found to reduce human subjectivity, decrease inspection time, and uninhibit usage of the infrastructure. Compared to non-robotic remote sensing approaches such as terrestrial laser scanning (TLS), robotic platforms can automate data collection and generate maps in real-time, reducing inspection time (Charron et al. 2019).

Robotic platforms have also been applied to construction research. UAVs are the main type of robotic platforms found on construction sites, given navigation challenges, but unmanned ground vehicles (UGV) and even aquatic unmanned surface vessels (USV) have seen usage (Izadi Moud et al. 2018). Construction site mapping is one common application of robotic platforms. Some works focus only on site mapping. These works routinely apply developments in general robotics and computer vision research to construction, and may include construction site specific augmentations. For example, Asadi et al. 2018 use deep learning to detect objects found in construction sites to add obstacle avoidance to the autonomous navigation of a data collection platform.

Other construction site mapping works go further, demonstrating project insight generation utilizing the generated models. Progress monitoring is one application, as autonomous robotics enable regular scans of the construction site (Lin and Golparvar-Fard, 2020). Ekanayake et al. 2021 and Prieto et al. 2020 provide studies on progress monitoring with techniques such as as-planned BIM and schedule comparison. Other applications include safety hazard identification, disaster recovery, and defect detection.

The use of robotic platforms that participate in construction activities is also studied. In Jud et al. 2021, an autonomous walking excavator named HEAP is developed. A detailed system description of its various systems is provided, including a state estimation approach that is robust to excavator wheels which slip often. HEAP demonstrates autonomous excavation of a free-form 3D landscape and placement of large rocks to build a wall. The authors found that the autonomous excavator delivers higher absolute accuracy than a human operator in many tasks, but falls short in

unpredictable tasks. Kim et al. 2020 address the use of a BIM model to aid task planning for a construction robot.

Additionally, the use of multi-robot systems to perform construction is studied. Petersen et al. 2019 present a review of collective robot construction (CRC) works. Han et al. 2021 present a review that adds human robot interaction to CRC for a discussion of collective human-robot construction. The authors argue that this is a more realistic application of multi-robot systems, as humans will likely be present on construction sites for a long time to come.

2.2. Mixed reality in infrastructure applications

In this review, mixed reality (MR) is defined as an umbrella term for any experience that incorporates either VR simulations, augmented reality (AR) technology, or both. The use of mixed reality (MR) in infrastructure applications is currently being explored from various angles. Training is a primary target of such efforts. One review discovers 66 papers applying MR in construction training published between 1996 and 2017 (Wang et al. 2018). Sacks et al. (2013) develop a virtual construction site to facilitate worker safety training. The VR safety training is compared to a traditional classroom training method and the MR approach was found to be more effective, especially for stone cladding work and cast-in-situ concrete work. The level of alertness and concentration in the MR approach lasted for the entire period of training, compared to only the first hour in the traditional approach.

Zhao and Lucas, 2015 study the development of VR training programs where a hazardous task can be rehearsed to prevent mistakes in the real-world. Hilfert et al. 2016 and Golovina et al. 2019 develop similar programs, with a focus on collecting data about the users' safety performance. Wolf et al. 2022 demonstrate a VR worker safety training environment that learns from user actions and provides personalized feedback. The study finds that many participants performed poorly in hazard recognition and overestimated their safety performance.

MR is also researched in construction progress tracking workflows. Ali et al. 2021 present a MR workflow that starts with standard job site 3D scanning and 3D model reconstruction. Then, a visual inspection of the 3D model is conducted in an immersive VR environment from the construction office. The inspection feedback can be viewed in real time on the job site using AR. Golparvar-Fard et al. 2009 present an automated approach for overlaying as-planned BIM progress models on construction site images to assist progress tracking.

Van Den Berg et al. 2017 explore the use of VR environments as visual aids for design review meetings with project stakeholders. The simulations were found to encourage user exploration, facilitate user participation in addressing design problems, and increase feedback.

Ghobadi and Sepasgozar, 2020 present an investigation on the adoption of MR workflows in the construction industry. Questionnaires were collected from 33 top UK construction firms, affirming that the use of MR is currently implemented or considered in many large construction firms in some capacity. MR system performance expectations, effort expectations, social factors, use-case conditions, and trust are identified as the main factors that affect VR technology adoption.

The intersection of VR and construction robotics is another usage of MR in an infrastructure application. One such topic is Imitation Learning (IL), which is the study of transferring construction skills from humans to robots. DelPreto et al, 2020 and Liang et al, 2020 are two examples of IL paradigms where a human expert demonstrates an action for a robotic system using VR to conduct the demonstration, and AI facilitates the transfer of skills to robotic programming. Yu et al, 2024 build upon the scalability of such a paradigm with a virtual demonstration framework that is capable of interpreting a virtual reality user's actions, storing them in a robot knowledge database, and decoding the actions into construction cloud robot programming.

2.3. Deconstruction

Deconstruction refers to the process of disassembling a building in a controlled fashion. The study of disassembly and deconstruction is a historically sparse research field showing signs of upcoming growth. Circular Economy (CE) is a term used in various industries to describe an economy where resources serve multiple roles throughout their life span, reducing consumption rates compared to a traditional take-make-dispose approach (Korhonen et al. 2017; Pomponi and Moncaster, 2017). In the construction industry, CE refers to finding alternatives to demolishing construction projects, which destroys the remaining value of materials and generates massive landfill waste. This movement is motivated by environmental impacts and the financial prospect of reuse. However, CE practices require deconstruction rather than heavy demolition at a building's end of life (EoL). Selective disassembly refers to a hybrid approach where highly reusable components are disassembled, and the rest are demolished. Adaptive reuse refers to the refurbishment of an entire building for a new use case, and may include selective disassembly for parts of the building that are to be replaced.

Design for disassembly (DfD) is one strategy for enabling material reuse and reducing construction waste landfilling. DfD is the practice of designing easily-deconstructable infrastructure to keep the building materials from being wasted at the project EoL. Rios et al. 2015 conclude that widespread adoption of DfD principles is a possibility if aided by the development of building material reuse markets and building codes that establish recyclability goals for new buildings. Akanabi et al. 2019 publish a Revit-based tool for predicting the environmental EoL costs of new building designs. They propose the use of this tool for designers, but also imagine it being used by government and planners to evaluate compliance to CE and sustainability building codes, if implemented.

The cost of deconstruction projects is another topic found in literature. Dantata et al. 2005 analyze the cost and duration of deconstruction compared to demolition for residential buildings in Massachusetts. For the buildings in the scope of the study, deconstruction is 17-25% more costly than demolition. Labor costs impact total cost the

most. The resale value of the deconstructed materials is included as an offset to the deconstruction costs. Kin Pun et al. 2006 conduct a very similar empirical study in Victoria, Australia, but find that deconstruction actually has the greatest economic performance. However, they argue that deconstruction is not popular because of increased project complexity and risk. Tatiya et al. 2018 develop an artificial intelligence based technique to predict the cost of a deconstruction project for a given building. The results indicate prediction accuracy over 95% in historical data. Furthermore, the model predicts that deconstruction outperforms demolition economically with recovered material resale. However, the study is limited by deconstruction dataset size.

Research exists on deconstruction project management activities such as programming, planning, and scheduling. Hübner et al. 2017 reviews a plethora of deconstruction project planning methods. Articles are grouped into two categories: strategic planning which focuses on minimization of the total project duration and operational planning which seeks to minimize a single activity's duration. Overall, this review focuses on decision support methodologies.

Other work focuses on project management from a low-level process optimization perspective. Sanchez and Haas, 2018 study disassembly sequence planning in order to minimize one target at a time, environmental impact or removal costs. The resulting approach finds sequence solutions that consider practical concerns and structural soundness during disassembly. Sanchez et al. 2020 upgrade this methodology to a multi-objective optimization where both environmental impact and costs are concurrently optimized with an objective function. Sanchez et al. 2019 introduces an algorithm for programming the disassembly project once the object removal sequence has been determined.

Decommissioning of Nuclear Power Plants (NPPs) represents a fair amount of articles, since it is one infrastructure class where deconstruction is required. Much of the work is high level, and seeks to understand how project characteristics influence project outcomes. Invernizzi et al. 2019 investigates the effects of project characteristics such as the governance of the NPP's country and the site's onsite radioactive waste capabilities on project cost. A data based approach is used based on

a dataset of 24 European projects. Invernizzi et al. 2020 continue to identify high cost impact project characteristics using 35 interviews with European senior practitioners to generate conclusions. The study finds that some characteristics that affect all infrastructure projects are high impact such as uncertain site conditions, regulatory challenges, funding support, and project planning. Other characteristics that are unique to decommissioning such as clarity level about the project end-state and storage and disposal facility availability are high impact. Hübner et al. 2021 address nuclear decommissioning project scheduling based on optimization techniques such as mixed-integer, constraint programming, and metaheuristics. The approach is capable of finding an exact initial feasible solution to a schedule with 300 activities in less than one second.

In one interesting study, D'Souza et al. 2000 investigates the present value of the future decommissioning costs of an NPP. The study was conducted in response to talk of regulations for utilities to incur the costs of decommissioning on their balance sheet at initial plant commission, which impacts investors. The authors argue that the regulation is unfair as the future decommissioning cost can't be known.

2.4. Intersection of reality data, mixed reality, and decommissioning

Work focusing on the application of reality data capture and MR to nuclear decommissioning planning began in the early 2000s, using relatively primitive approaches. Cragg and Hu, 2003 study the use of a teleoperated robotic platform for nuclear decommissioning very early. However, in the abstract the authors make clear that the technology is only powerful enough to demonstrate a proof of concept, limited by network bandwidth, computing resources, and availability. They state regarding early robotic platforms:

> "...their efficiency is limited. Coming decades will see a substantial increase in decommissioning globally as a large number of nuclear facilities are due to reach the end of their useful life. It is desirable that robot characterisation systems meet this increase in demand by becoming more efficient".

Iguchi et al. 2004 present a type of VR technology to assist in the decommissioning of the Fugen Nuclear Power Station called the Decommissioning Engineering Support System (DEXUS). By modern standards, what they consider VR is closer to what we consider a first person computer game. The simulation is presented on a computer monitor in 2D, and the graphics are based on CAD drawings. However, the simulation includes a component called VRdose, which estimates the dosage of radiation exposed during an activity, and includes radiation visualizations based on a database of radiation levels. Rindahl et al. 2006 claim that the first instance of VR tools for decommissioning was in 1999 at the Norwegian Institute for Energy Technology, supporting this Japanese team to start VRdose. By this time, the idea of using VR for training was emerging in these groups (Sebok and Nystad, 2004). The initial VR tech was also utilized in decommissioning of three intact reactors at Chernobyl.

Bogue, 2011 reviews usage of robots in the nuclear industry, with a focus on decommissioning. Robots are seen as an opportunity to reduce human radiation exposure by participating in decommissioning activities, rather than as data collection devices. At this time, the review cites that, “most current robotic systems employ virtually no autonomy or even programmed motion; invariably there is a human in the control loop and this is likely to continue”. The majority of the robotic systems in this review are construction equipment with task-specific tooling and remote control operation.

Jeong et al. 2014 (1) develop a “digital mock-up system” to simulate NPP decommissioning activities. However there is no user control–the actions of all agents are programmed from the start. Jeong et al. 2014 (2) add worker exposure dose assessment to the simulation. The capabilities do not appear to surpass VRdose.

Chabal and Soulabaille, 2016 detail VR work done by the French Alternative Energies and Atomic Energy Commission (CEA) as part of the R&D arm of their decommissioning efforts. The report cites preceding work such as VR worker training and VRdose, then claims to be the first work to use VR to optimize future decommissioning actions. This work represents a leap forward in VR technology. The

authors develop an immersive and interactive VR experience called the “PRESAGE room”. Visual feedback is delivered by a projector wall which delivers a stereoscopic image that pairs with 3D glasses to decode. Sound feedback is achieved through playback of audio recordings when certain events take place in the simulation. Tactile feedback is made possible with a haptic system that can provide force feedback in all six degrees of freedom for each hand. A motion capture suit is used to track the user’s pose. The VR capabilities built in the study were used to verify processes in two CEA decommissioning projects, as well as additional research and training.

Da Silva et al. 2016 present a literature review on VR techniques applied on nuclear projects, with a focus on Brazilian research. The review demonstrates that Brazilian researchers developed simulation environments for training and radioactive dose assessment in parallel with global researchers. Ergonomic studies is a subject that is unique to Brazilian researchers in this time period. The Brazilian research lacks the VR immersion and hardware sophistication present at CEA in France during this time.

Chao et al. 2017 propose an algorithm for planning minimum radioactive dose navigation paths in radiated environments. The approach is based on the rapidly exploring random tree star algorithm, and outperforms Dijsktra’s shortest path algorithm in cumulative dose by 2.7%, but comes with a 44.1% runtime increase. However, the proposed algorithm still runs in 1.1 seconds.

Nash et al. 2018 develop a simulation of a rectore core disassembly procedure that utilizes a master-slave manipulator. The simulation allows the operator to practice the use of the manipulator to train themselves on its usage. Some of the simulations involve block sorting, and other gamified approaches to developing skills using the manipulator. The dismantling of the reactor core is also simulated. However, the simulation is presented on a 2D monitor. Surveys are collected following usage of the simulator, and results indicate that users found the simulator useful for training.

Vitanov et al. 2021 and Bird et al. 2022 represent the most current robotic platforms developed for nuclear decommissioning applications. Vitanov et al. 2021

present novel human robot interaction techniques such as a remote haptic feedback solution using a vibrating motor, similar to techniques used in gaming controllers. Additionally, a novel teleoperation device that uses a human operator's legs to control a wheeled or walking robot is proposed. It is capable of haptic feedback, and is designed to provide immersion, as humans are used to controlling movement with legs. However, these devices remain proposed but untested and unvalidated. Bird et al. 2022 focuses on an approach for generating maps overlaid with radiometric survey data, however only a planar LiDAR is utilized, limiting the sophistication of the inspection map.

2.5. Research gaps

Deconstruction lacks the level of research focus observed in other infrastructure lifecycle stages. Applications of technologies like mobile robotics in deconstruction lag behind core robotics communities and other civil engineering application spaces such as SHM. Similarly, applications of technologies like VR in deconstruction planning lag behind advancements in other fields such as construction design and safety training. For example, construction planning and management increasingly leverage VR for immersive visualization, risk-free training, and collaborative design processes. However, deconstruction planning seldom harnesses these advanced VR capabilities, resulting in a gap in the application of state-of-the-art VR tools to optimize deconstruction activities.

Some solutions developed in related research of other infrastructure lifecycle stages are applicable to deconstruction, however many are not. Deconstruction requires the modeling of unique interactions in the context of tasks such as cutting and packing. Due to the nature of the cutting process, the exact geometries of pieces removed from an assembly are not regular or predictable, contrary to the underlying assumptions of topics like construction site material tracking. Another example can be found in duration estimation, a topic which has seen considerable research in the context of construction, but can not be directly applied to deconstruction, due to the unique nature of deconstruction tooling and processes.

The shortage of VR applications in deconstruction planning likely stems from the lack of research focus placed on deconstruction in general. Additionally, the interdisciplinary nature of this work requires collaboration across fields such as civil engineering, computer science, and human-computer interaction, further complicating the research efforts.

To address the VR application gaps, researchers have begun to explore VR for construction-related activities, but these efforts are primarily focused on new construction rather than deconstruction. The existing VR simulations typically center on design visualization, safety training, and operational planning, which do not directly translate to the unique challenges of deconstruction. Deconstruction involves distinct activities such as selective dismantling, hazardous material handling, and precise sequencing of demolition tasks, all of which require tailored VR environments and specific planning tools.

Furthermore, the current literature inadequately addresses the potential for human-computer collaboration in VR environments for deconstruction planning. Studies exploring how VR can facilitate interactive and collaborative decision-making among planners are sparse. Additionally, there is a notable lack of research on the automated generation of critical project deliverables, such as critical path method (CPM) schedules, within VR simulations. These gaps highlight areas where further investigation is needed to fully understand and utilize the capabilities of VR in deconstruction planning.

On the topic of nuclear decommissioning specifically, the majority of research is focused on worker training, followed closely by radioactive dose assessment. At the moment, planning has only seen research at an extremely high level, suggesting decision support methodologies for capital project planners and multi-decade scheduling. The only deconstruction planning research that focuses on low-level process optimization exists for disassembly sequence planning and programming. Tasks such as the optimal cutting and packing of a section of radiated infrastructure are not addressed. VR technology to enable planners is missing in the literature.

Furthermore, the use of a gaming environment which uses scores, feedback, and repetition to optimize the plan has not been researched.

Addressing these gaps requires dedicated research efforts to develop and validate VR-based deconstruction planning methodologies. By creating specialized VR environments and datasets, and by focusing on the integration of VR with deconstruction-specific activities, researchers can enhance the precision, safety, and efficiency of deconstruction planning. Such advancements are hypothesized to bridge the observed gaps.

Chapter 3

Gamified Virtual Reality Workflow for Cutting and Packing Planning

Statement of Contributions

The research in this chapter is completed collaboratively with Manolis Katsimpalis under the mutual supervision of Dr. Carl Haas at the University of Waterloo. This work builds upon contributions by Yinghui Zhao, distinguishing itself with the introduction of interactive simulations that are built upon reality data, as well as introducing new forms of interaction and feedback. My contribution includes ideas, data collection, and analysis.

3.1. Introduction

This section addresses two key problems in the context of this research. First, the study addresses the problem of creating realistic, interactive, and manipulable VR simulation environments from reality data. Second, the study addresses the problem of conducting human-computer collaborative planning for deconstruction cutting and waste packing tasks.

In this section, a novel approach to deconstruction cutting and packing planning based on reality capture and VR is presented and demonstrated. First, reality capture is used to develop a point cloud of the asset. Next, a 3D mesh solid representation of the asset is created. Finally, 3D game engines are used to develop gamified VR simulations of deconstruction tasks for cutting and packing experimentation and planning. The 3D gaming engine can provide rich feedback to the user on key performance indicators about the current configuration, enabling one form of human machine collaboration. As a result, deconstruction planners can conduct repeated trials to iteratively improve cutting and packing plans in a safe, realistic, repeatable, low-cost, and automated environment.

3D modeling and computation offer the power to model and simulate plans with minimal risk at a fraction of the cost of physical mockups. However, models can be imperfect, and in high-risk deconstruction situations, the insight of experienced professionals is paramount. Therefore, a human-computer collaborative approach mitigates the shortcomings of imperfect models by leveraging expert judgment and oversight. To this end, reality capture and gamified virtual reality are identified as a pair of technologies enabling the combination of planners' insight and computational power.

Figure 2 presents the sequence of actions of the proposed methodology. These steps are discussed in further detail in the following subsections. In general, the deconstruction assets undergo 3D scanning, are converted to meshes, and brought into a simulation environment developed in this study where the user conducts human-computer collaborative cutting and packing planning.

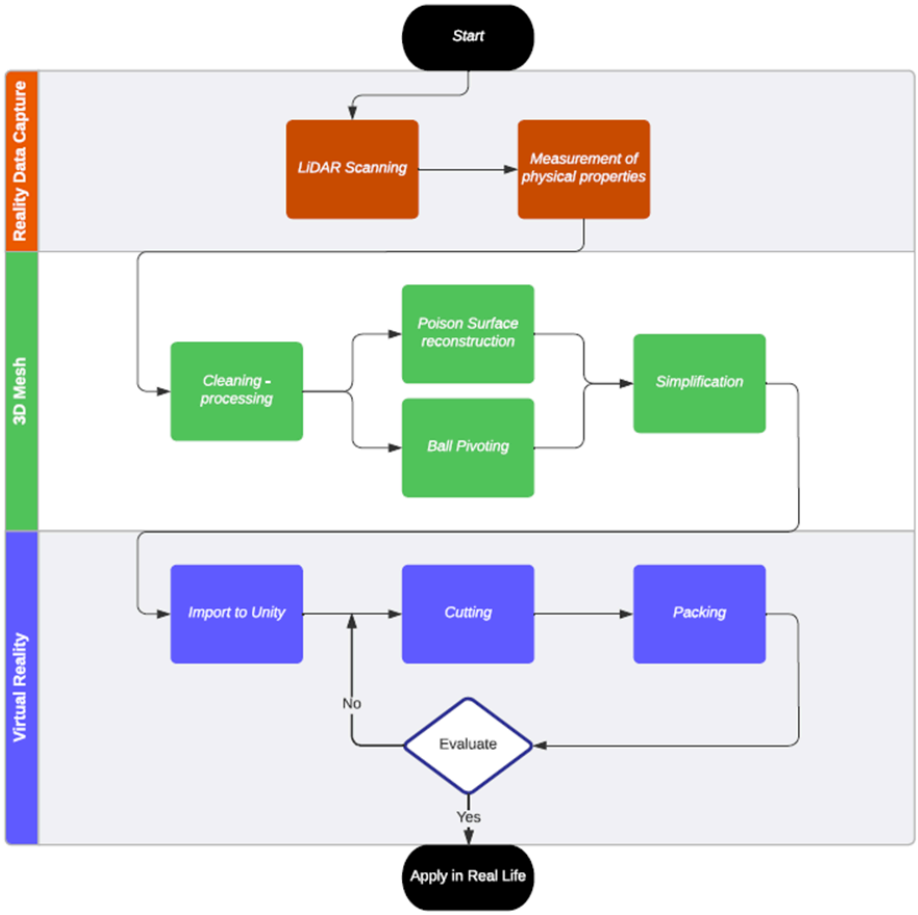


Figure 2. Methodology for cutting and packing planning in VR

3.2. Modeling and Simulation of Reality Data

First, reality data capture is used to develop a point cloud of the asset. The approach for reality data capture can incorporate TLS, handheld scanners, robotic platforms, or SfM. TLS scanning results in high precision, and it is conventionally considered the best ground truth data available for accuracy and reliability. If centimeter or finer precision is required, a TLS is used. Approaches featuring moving sensors can capture massive areas efficiently. However, they fall short of TLS in precision and require the adoption of simultaneous localization and mapping (SLAM) algorithms, which introduces massive complexity. SfM solutions use image sensors only but require computational power to render. This computational step introduces error when the resultant model cannot be viewed in the field. SfM solutions also lack robustness to lighting conditions, corridor effects, and more.

To effectively utilize reality capture data in 3D game engines, a solid representation of the 3D scan is developed. Two main digital representations for reality capture are identified; meshes and BIM. Meshes discretize complex topologies using polygons. Points in a scan can logically be used as the vertices of the polygons, however in practice meshing can amplify errors. Complex meshes are computational burdens in 3D game engines, especially in the context of real time interaction, so mesh decimation and filtering are performed to reduce the number of vertices. Incomplete scans or noisy scans can become unrecognizable after meshing. It is noted that convex surfaces are less error prone than concave surfaces for meshing, and differential surfaces are less error prone than edges. The realism of meshes is enhanced with texturing, wherein the image data is reprojected on the mesh. The shadowing and textures of the image data can be used to convey fine details in the mesh without increasing polygon counts. However, only details represented geometrically by vertices will be included in computational processes such as collision detection.

Alternatively, a scan-to-BIM procedure can be used to develop a digital representation from the scan. In this approach, objects primitives with semantic meanings are fit to the scan. The BIM model captures the geometry of the asset with a vastly reduced level of complexity by using simplified object primitives based on the

expected materials found in infrastructure. The resulting model is extremely well-defined and computationally efficient, but scan-to-BIM is a developing technology, and automated approaches are imperfect. However, the simulation realism of well-made BIM models is outstanding, as demonstrated in section 3.4, validating the approach in scenarios where the labor investment of manual or semi-supervised scan-to-BIM is justified by the project.

3.3. Reality Capture Technique Comparison

In this section, a comparison of three distinct scanning methods is conducted to evaluate their efficacy in the context of the proposed VR workflows. Scanning methods are well studied in existing literature, however one gap is the lack of a comparison that focuses on generating interactive and manipulable 3D reconstructions. Particularly, the comparison seeks to address The methods compared are TLS, iPad with LiDAR, and SfM using iPhone camera images processed with Meshroom software (AliceVision, 2023).

A detailed sculpture is selected as the subject for scanning due to its complex geometry and intricate details, which pose a significant challenge for 3D reconstruction techniques. The sculpture is depicted in Figure 3.

Figure 3. Reality data capture method comparison asset of interest

The candidate scanning procedures are as follows:

1. **Terrestrial Laser Scanning**: The sculpture is scanned using a high-precision TLS device, capturing millions of points to create a dense point cloud. This scan served as the baseline for subsequent comparisons, as similar scanners are seen as the current industry standard. Four scanning positions, each 90 degrees apart on a 3 meter circumference surrounding the sculpture, are utilized.

2. **iPad with LiDAR**: The sculpture is also scanned using an iPad equipped with LiDAR technology. This method, while more accessible and user-friendly, typically generates less dense point clouds compared to TLS.

3. **Structure from Motion**: Using an iPhone camera, 76 images of the sculpture are captured from various angles. These images are processed using Meshroom software with default settings to estimate camera poses and reconstruct a point cloud through photogrammetric techniques.

The point cloud obtained from the TLS is processed in CloudCompare to create a mesh using the default hyperparameters. A BIM model of the sculpture is then composed in Autodesk Revit, using the TLS mesh as the reference model, and visually creating steel beam components that fit the mesh with minimal error. The accuracy of each method is subsequently evaluated by comparing the distribution of signed cloud to mesh distance of each point cloud to the BIM model. Automated approaches for the scan-to-BIM process are emerging in the field, however for the purposes of this study, a manual approach is found to have the best cloud to mesh distance distribution for the baseline model. The TLS scanning procedure is depicted in Figure 4.

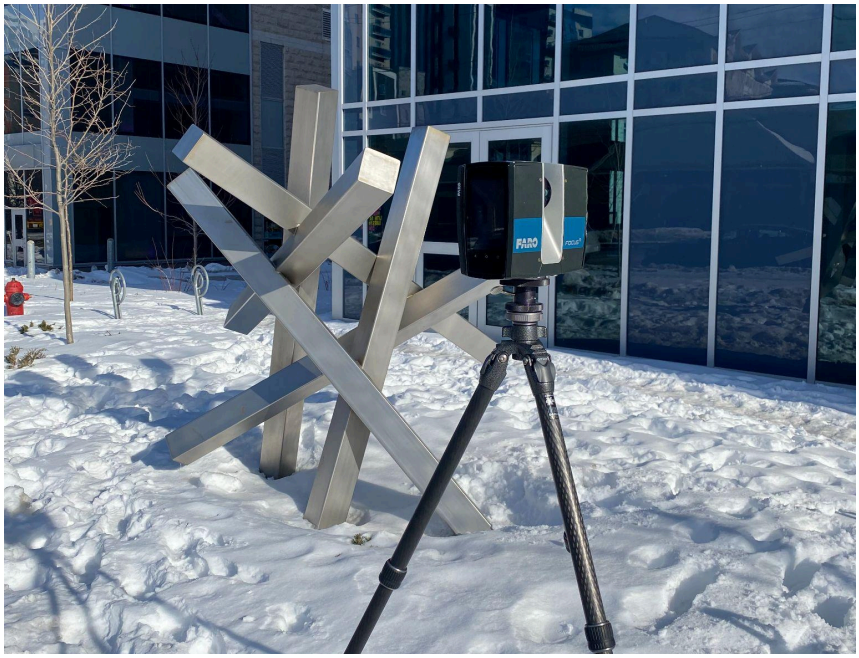


Figure 4. TLS baseline scanning procedure

The point clouds are first converted to meshes in CloudCompare, a software known for its robust processing capabilities. The mesh created from the TLS scan is manually reviewed and used as the reference model in Revit. The BIM model is meticulously built to match the TLS scan, considering it the most accurate representation of the sculpture.

Each point cloud is then compared to the BIM model using the cloud-to-mesh (C2M) distance measurement tool in CloudCompare. This process involves calculating the signed distances from each point in the point cloud to the closest point on an adjacent surface of the BIM model. By using a signed distance metric, the distribution of errors that are outside versus inside the baseline BIM model surfaces can be differentiated. The distribution of these signed distances provides a quantitative measure of the accuracy and deviation of each scanning method relative to the BIM model. The BIM model is depicted in Figure 5 in two levels of rendering realism.

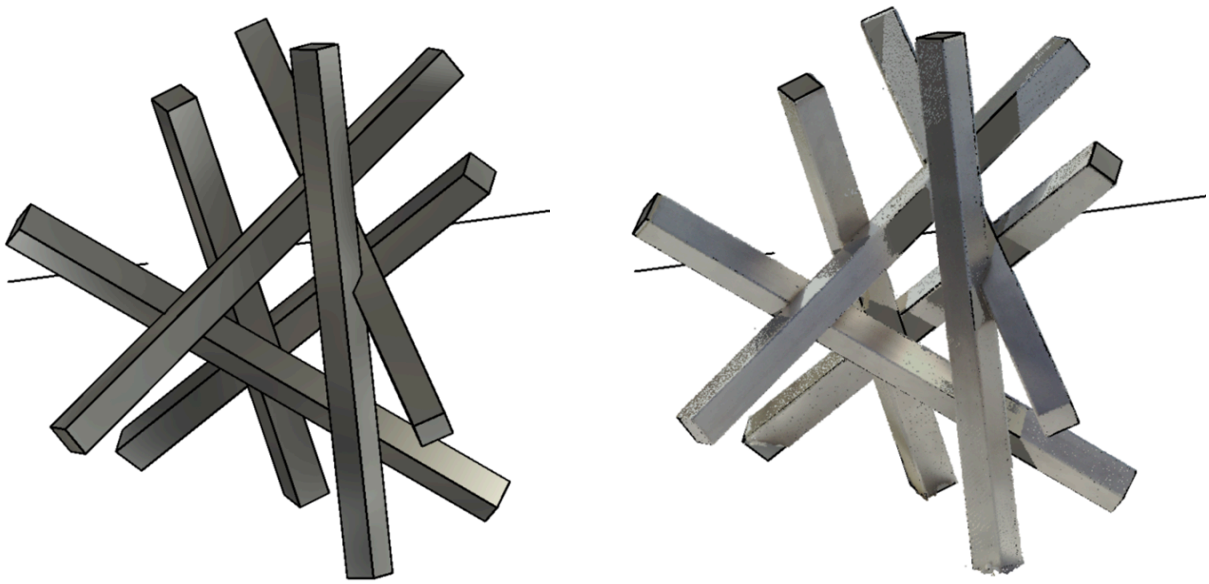


Figure 5. The baseline BIM model depicted in two rendering scenarios

The TLS scan, being the reference for the BIM model, is expected to show the least deviation. However, due to the intrinsic imperfections of the sculpture and the scanning and modeling processes, some errors are still present. Rectangular prisms of best fit are utilized for constructing the BIM model, whereas the sculpture's steel beams may have imperfections due to wear or manufacturing. The iPad LiDAR and SfM methods are expected to exhibit larger deviations, reflecting their lower precision and differences in data acquisition techniques.

The results of the C2M signed distance comparisons are presented in histograms, showing the distribution of deviations for each scanning method. These histograms provide a visual representation of the accuracy and reliability of each technique in replicating the geometry of the sculpture as captured in the BIM model, specifically in the context of the chosen asset of interest. It is important to note that the outcomes of reality data capture methods can be somewhat sensitive to factors such as the specific asset being scanned, the tools and procedures employed, and the hyperparameters set for each method. Consequently, the observations made in this comparison should be viewed as indicative of the general performance characteristics

of each scanning method rather than as definitive assessments. By analyzing these distributions, insights into the strengths and limitations of each scanning method can be derived, informing best practices for selecting appropriate technologies in the context of the needs of individual deconstruction planning tasks.

Figures 6-11 illustrate each reconstruction and the C2M signed distance distributions for each scanning method. The mean, standard deviation, and 95% percentile value for each signed C2M distribution is provided. It is noted that the scale of the horizontal axis on the signed C2M distributions figures is unique for each method, and should be considered for comparison:

TLS

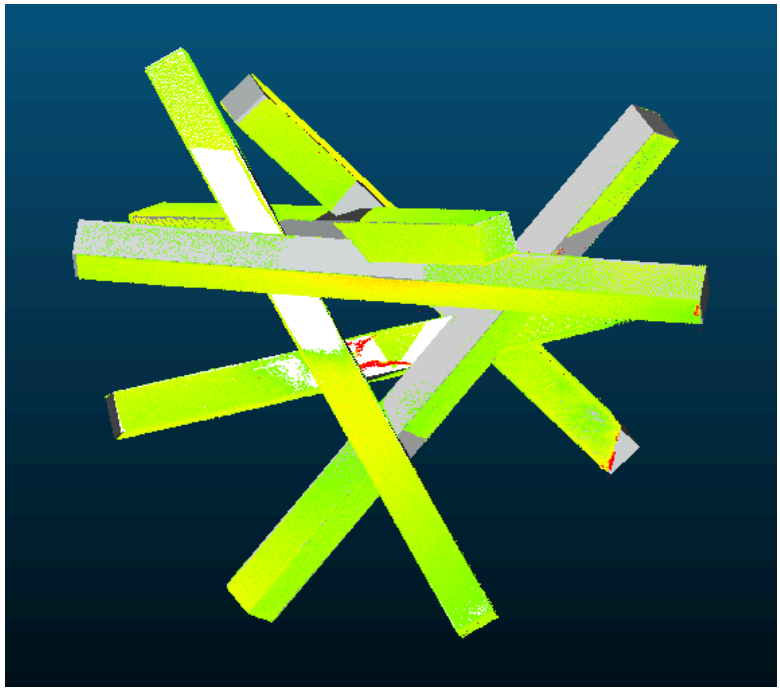


Figure 6. The TLS point cloud overlaid with the TLS-based BIM model

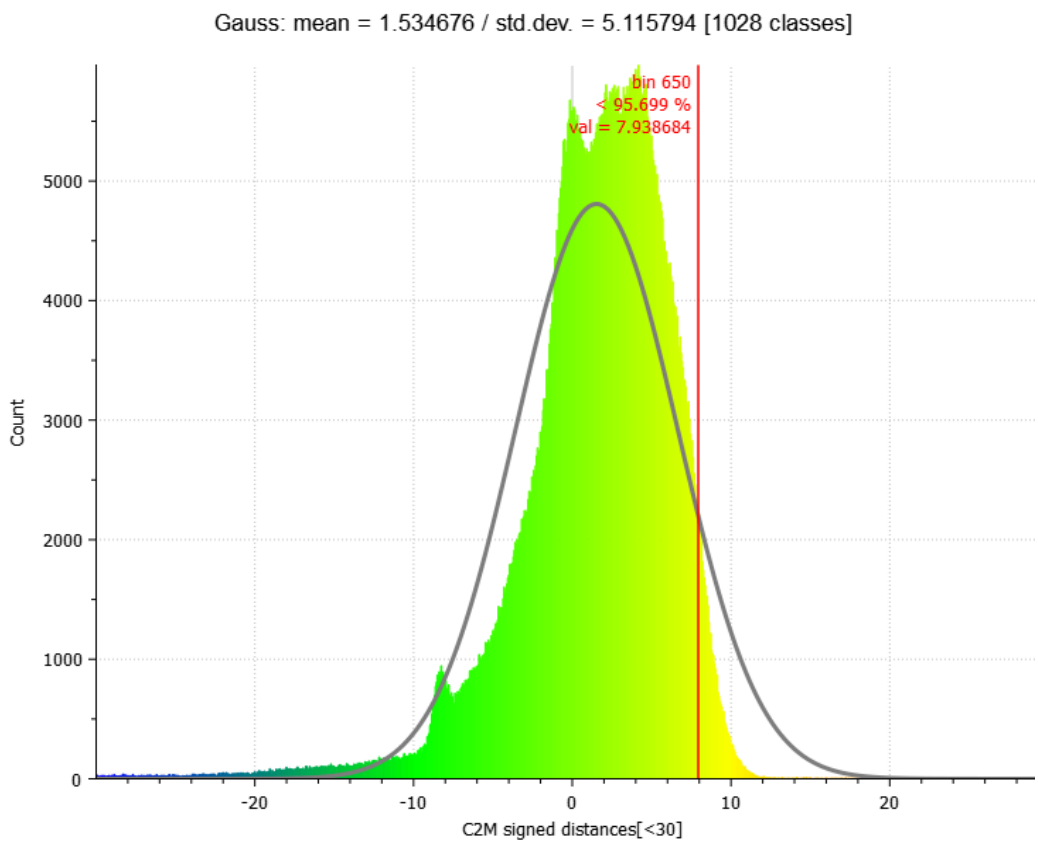


Figure 7. The distribution of signed C2M distances between the TLS scan points and the TLS-based BIM model with the Gaussian distribution of best fit

iPad

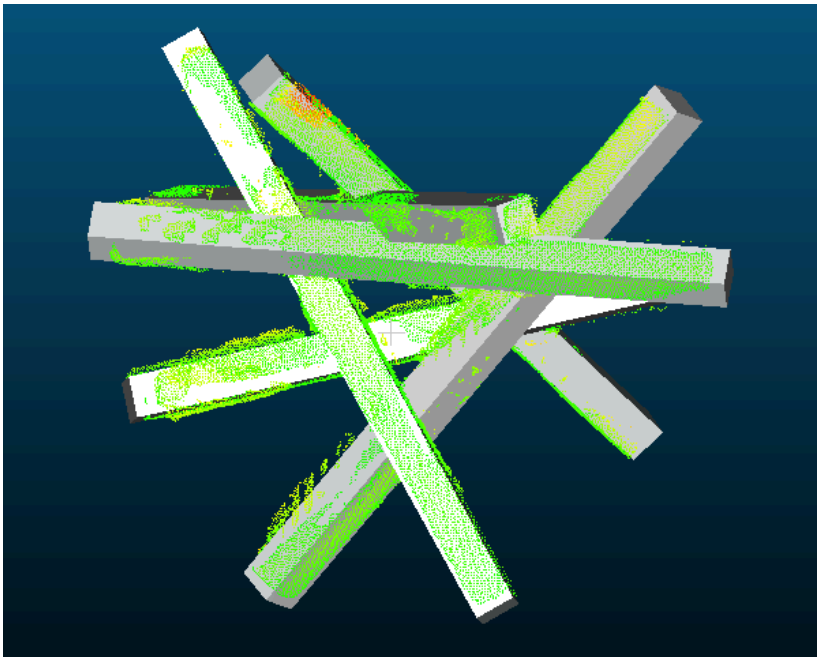


Figure 8. The iPad LiDAR point cloud overlaid with the TLS-based BIM model

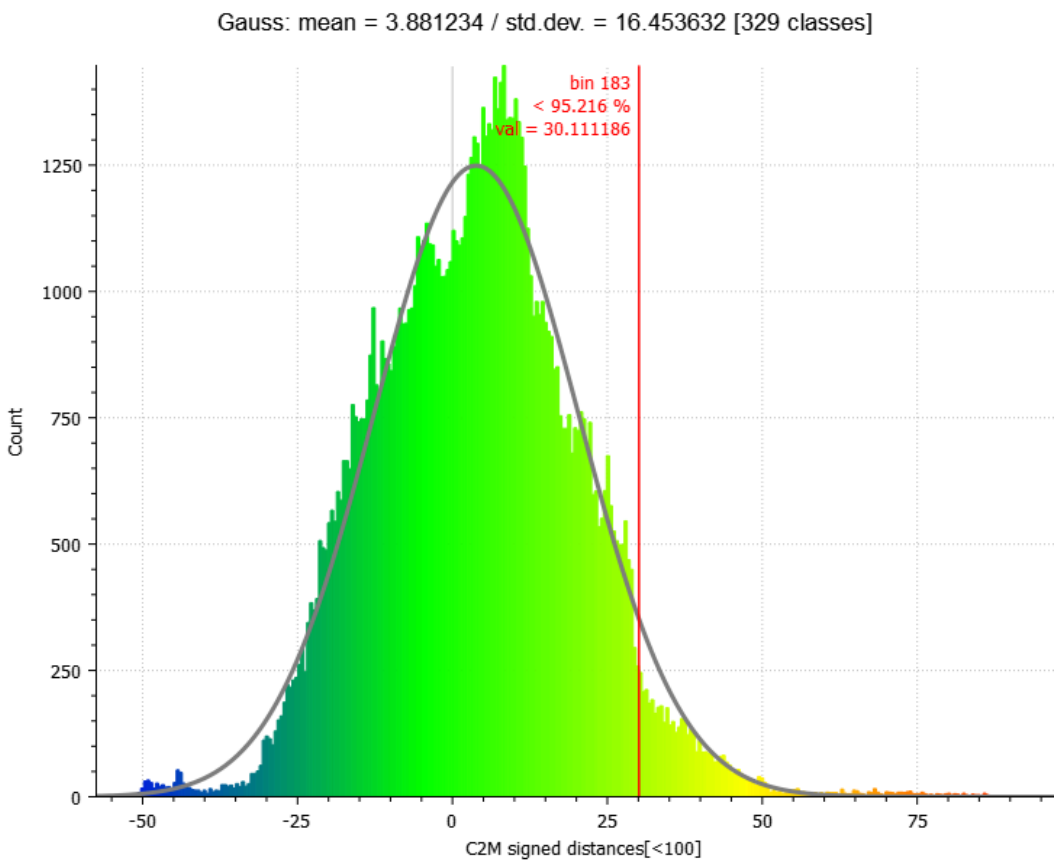


Figure 9. The distribution of signed C2M distances between the iPad LiDAR points and the TLS-based BIM model with the Gaussian distribution of best fit

SfM

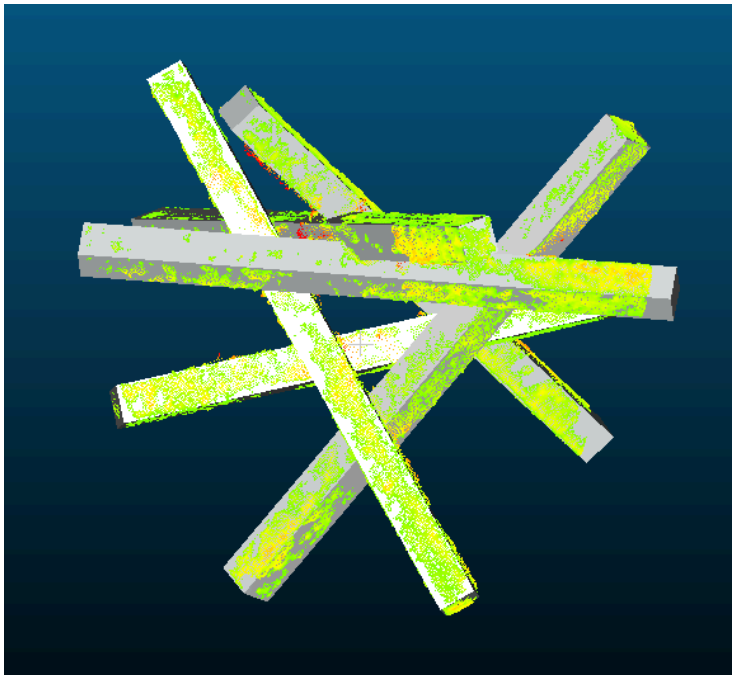


Figure 10. The SfM point cloud overlaid with the TLS-based BIM model

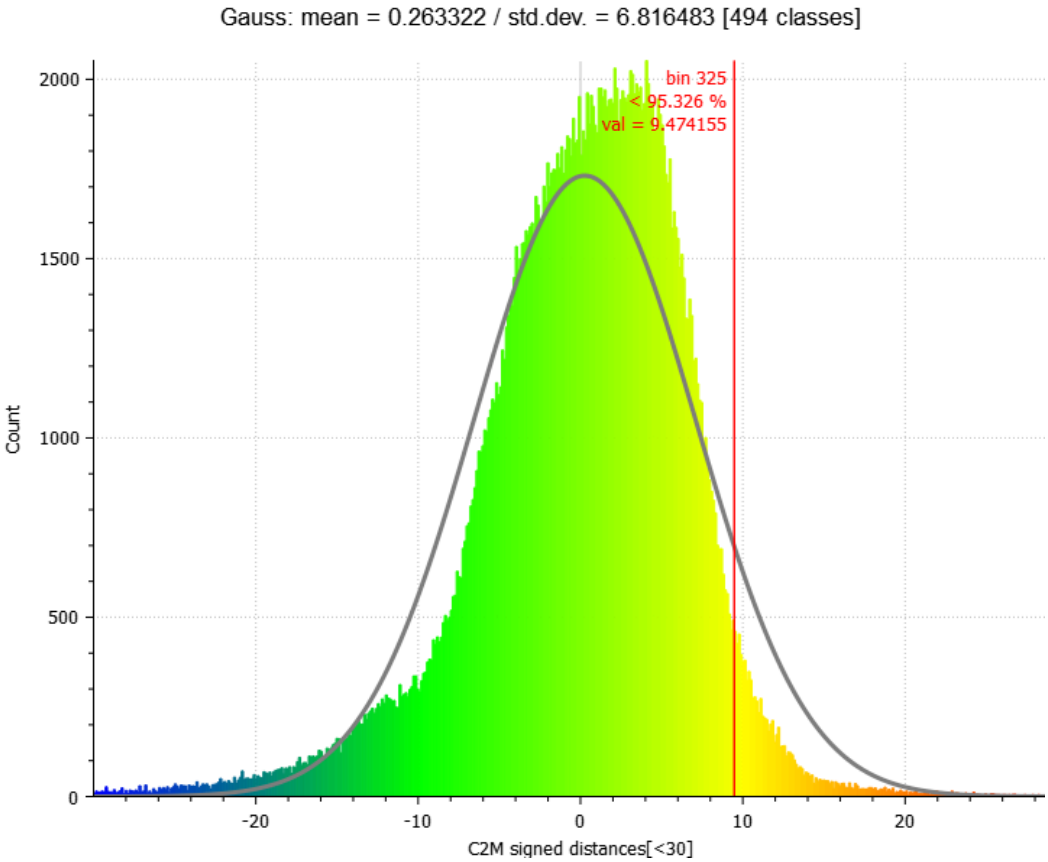


Figure 11. The distribution of signed C2M distances between the SfM points and the TLS-based BIM model with the Gaussian distribution of best fit

A comparison of TLS, iPad with LiDAR, and SfM using an iPhone camera is conducted to assess their effectiveness in generating 3D models suitable for VR simulation in the context of deconstruction planning. The focus on deconstruction-specific tasks, such as cutting and packing, disassembly sequencing, and hazard identification, necessitates a detailed understanding of how each scanning method can contribute to creating accurate and functional digital models for these purposes.

As the industry-standard method for high-precision reality capture, TLS served as the baseline for this study. The distribution of signed C2M distances between the resulting point cloud and the BIM model was fit with a Gaussian distribution having a mean of 1.53mm, a standard deviation of 5.11mm, and a 95th percentile value of 7.94mm. These results indicate that TLS provides a highly accurate and reliable representation of the sculpture, with minimal bias and tight accuracy bounds. In deconstruction, where the exact geometry of components must be known to plan safe and efficient disassembly sequences, TLS provides the necessary accuracy to minimize errors in planning and execution. This precision is particularly crucial in tasks like sequencing cuts on steel structures or determining the optimal packing of disassembled parts into waste containers, where even small deviations can lead to significant safety risks or inefficiencies.

The iPad LiDAR, while more accessible and user-friendly, showed a broader distribution of deviations with a mean C2M signed distance of 3.88mm, a standard deviation of 16.45mm, and a 95th percentile value of 30.11mm. This higher mean suggests a bias in the model's representation, potentially leading to inaccuracies in planning precise operations like cutting or packing. The larger standard deviation and high 95th percentile value point to significant outliers, indicating areas where the model may not accurately capture the true geometry. These inaccuracies could lead to off-target cuts, misaligned disassembly sequences, and unexpected structural challenges, necessitating more on-site adjustments. However, the iPad LiDAR's value lies in its rapid data acquisition and ease of use, making it suitable for preliminary assessments where detailed accuracy is less critical. It is particularly useful in the early

stages of deconstruction projects, where speed and flexibility are prioritized, and a quick, rough model suffices for broad planning decisions.

The SfM method, processed with Meshroom software, showed a mean C2M signed distance of just 0.26mm, with a standard deviation of 6.81mm and a 95th percentile value of 9.47mm. The near-zero mean suggests a very low bias, indicating that the SfM model, on average, closely aligns with the actual geometry of the asset. This is particularly surprising given the typical expectations of SfM performance and highlights its potential for certain deconstruction tasks. However, the standard deviation, while lower than that of the iPad LiDAR, is still significant, reflecting variability in accuracy across different parts of the model. In the context of deconstruction, the relatively low bias means that cut and disassembly plans based on the SfM model are likely to be centered correctly, but the variability in accuracy could still pose challenges. Specifically, areas with greater deviation could result in slightly off-target cuts or misaligned disassembly sequences, requiring adjustments during execution. The 95th percentile value suggests that while most of the model is accurate, there are still some outliers, which could correspond to complex geometries or surfaces with poor texture, potentially leading to localized inaccuracies that must be managed carefully in the planning phase.

The findings of this comparison underscore the importance of selecting the scanning technology that best aligns with the precision requirements of specific deconstruction tasks. For scenarios where accuracy is paramount—such as tasks where even small deviations could lead to significant safety risks or operational inefficiencies—the tight distribution of signed distances from TLS indicates it as the most reliable choice. In particular, contexts like nuclear decommissioning, where the cost of errors is high and worker safety is critical, the minimal bias and low presence of outliers in TLS scans make it well-suited for ensuring precise cut lines and accurate packing plans.

On the other hand, iPad LiDAR and SfM, while exhibiting broader distributions and greater variability, offer benefits in situations where rapid data acquisition and early-stage visualization are prioritized over precise geometry. The results suggest that

these methods can effectively provide preliminary models, particularly in scenarios where the exact fit of components is less critical, and larger tolerances are acceptable. For example, in tasks involving the use of large, inexpensive storage containers, the flexibility and speed of iPad LiDAR and SfM might outweigh the need for the higher precision provided by TLS, allowing planners to quickly develop rough models that inform broader strategy decisions before detailed scanning is conducted.

3.4. Cutting and Packing Workflow

With an understanding of accuracies of the reality capture techniques, 3D game engines such as Unity are used to develop gamified simulations of deconstruction tasks for experimentation and planning. Game engines enable a combination of built-in software, open-source software, and custom software. Game engines like Unity enable the development of universal deconstruction task simulation software that can be applied to many projects. 3D representations of assets such as meshes and BIM can be converted to solid polygon geometries that game engines utilize. Once the new asset of interest is imported into the simulation environment, the software logic developed for the deconstruction task remains the same. Therefore, the cost of developing software simulation for deconstruction tasks diminishes as prior software grows.

Creating a software simulation of a deconstruction task in the game engine involves defining interaction behaviors between the user and the environment. For many common actions, such as moving objects and detecting collisions, software is readily available and just needs configuration. Accurate physics is handled off-the-shelf, if realistic object properties are supplied. Novel actions or actions where proprietary engineering models are required can be programmed. Computational efficiency is one concern with custom or open-source software, especially with complex meshes.

Simulations developed in these game engines are also adaptable to various rendering environments. The same software environment can render a 1st person VR, 1st person desktop, or 3rd person desktop experience, as depicted in Figure 12.

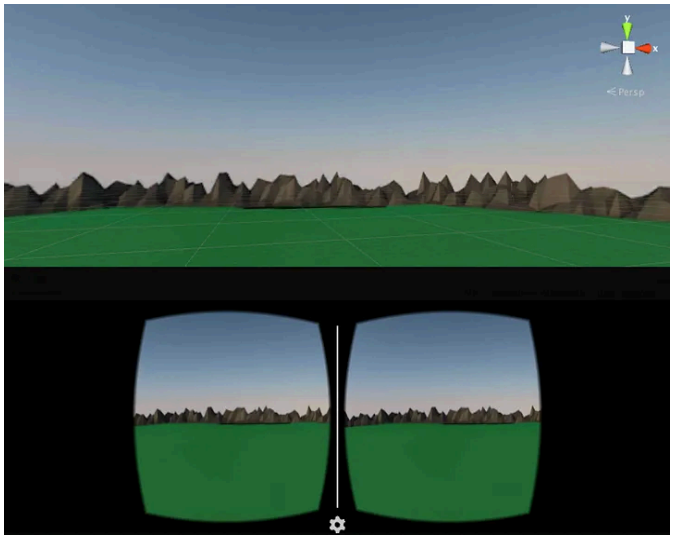


Figure 12. Unity simulation rendered as desktop 1st person (top) and VR 1st person (bottom). Courtesy of https://medium.com/@indiecontessa/how-to-design-vr-skyboxes-d460e9eb5a75

In order to demonstrate the proposed methodology, a complete cutting and packing workflow is implemented. An AISC Steel Sculpture is selected as a hypothetical deconstruction asset, and depicted in Figure 13 below. Its complex and concave geometry highlights challenges observed in this research. The sculpture is scanned with a TLS, then converted to both mesh and BIM representations. Unity, a 3D game engine, is used to develop cutting and packing simulation software. The mesh and BIM models are imported into the simulation environment, and repeated trials of the cutting and packing process are conducted.

Figure 13. University of Waterloo AISC Steel Sculpture

A TLS is used to capture a 3D point cloud of the sculpture. The challenges of the highly non-differentiable and concave surfaces of the steel sculpture begin to emerge. Any scan location for the TLS introduces occlusions from beam to beam, and from flange to web of single beams. In experimentation, a close and a far scan in each of the 4 corners of the sculpture are required to mitigate occlusion in the horizontal plane alone. For flange-web occlusions, multiple scan locations in the vertical axis are required, but left as a limitation of this study. The scans are aligned using iterative closest point registration to create one composite scan, and the background is removed by cropping using Faro SCENE (FARO Technologies, Inc., 2023) scan registration software. Figure 14 depicts three individual TLS scans, while Figure 15 depicts two views of the composite point cloud.

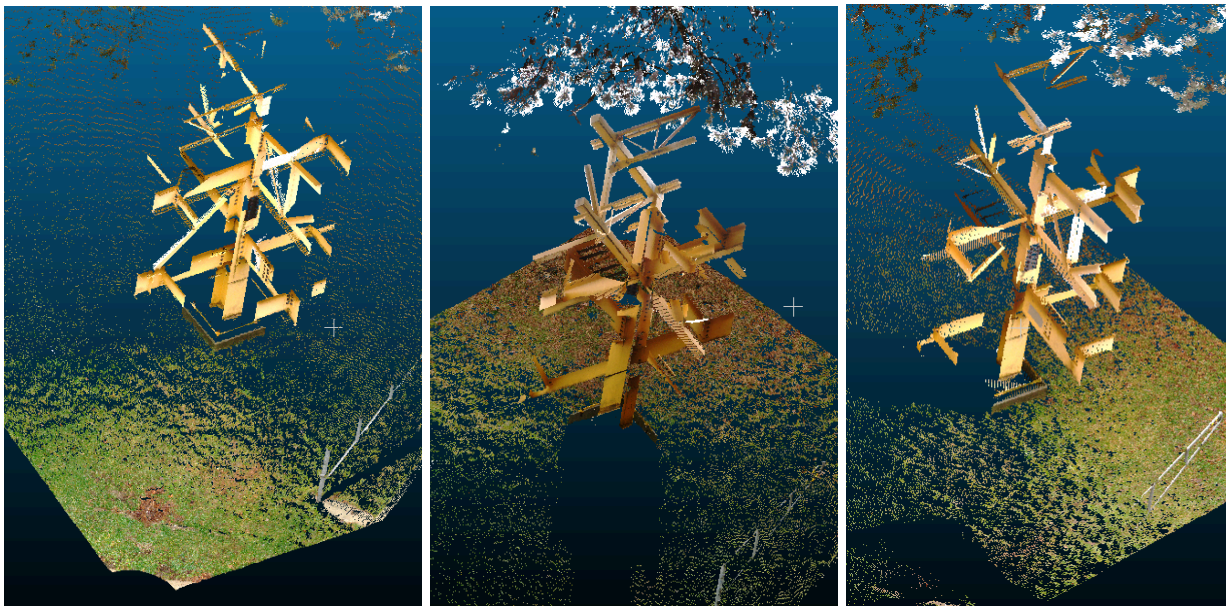


Figure 14. Three individual TLS scans

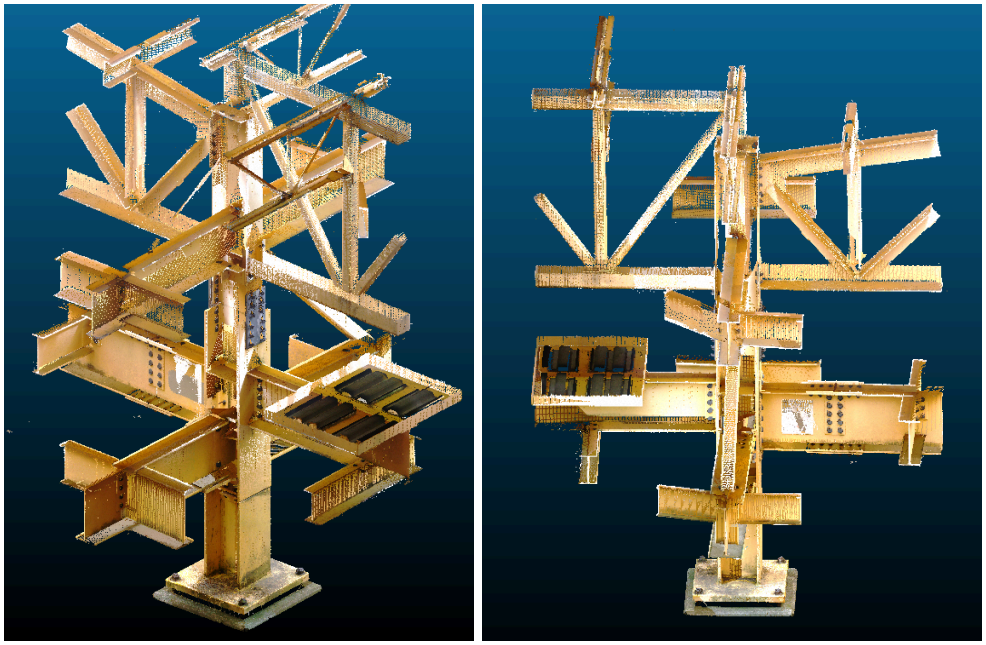


Figure 15. Two views of the composite TLS point cloud

Next, a solid model is extracted from the point cloud. In this demonstration, a textured mesh model and a BIM model are developed. The textured mesh demonstrates the visual deficiencies that can result from reality capture challenges. While the scan is dense and displays the general information correctly, there exist many

small holes that produce large holes when creating a mesh. Furthermore, since the TLS line of sight originates just above ground level, the higher parts of the sculpture are particularly sparse. In Figure 16 below, a close view of the composite TLS point cloud is presented to demonstrate the holes.

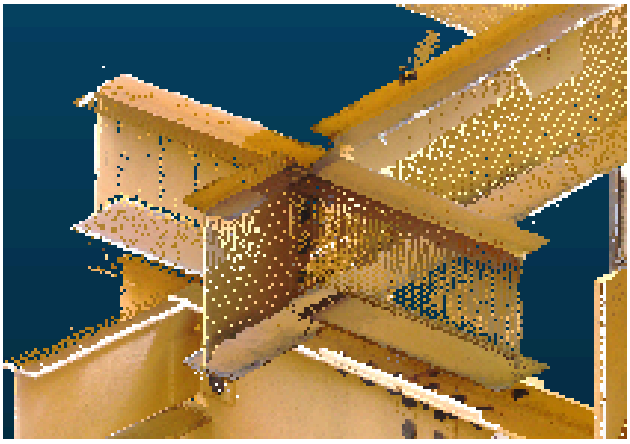


Figure 16. Close view of a sparse section of the composite TLS scan

The BIM model is manually produced in Revit, by matching standard steel beam shapes with scan data. Figure 17 demonstrates two views of the textured mesh model, while Figure 18 depicts two views of the manually developed scan-to-BIM model.

Figure 17. Two views of the textured mesh model

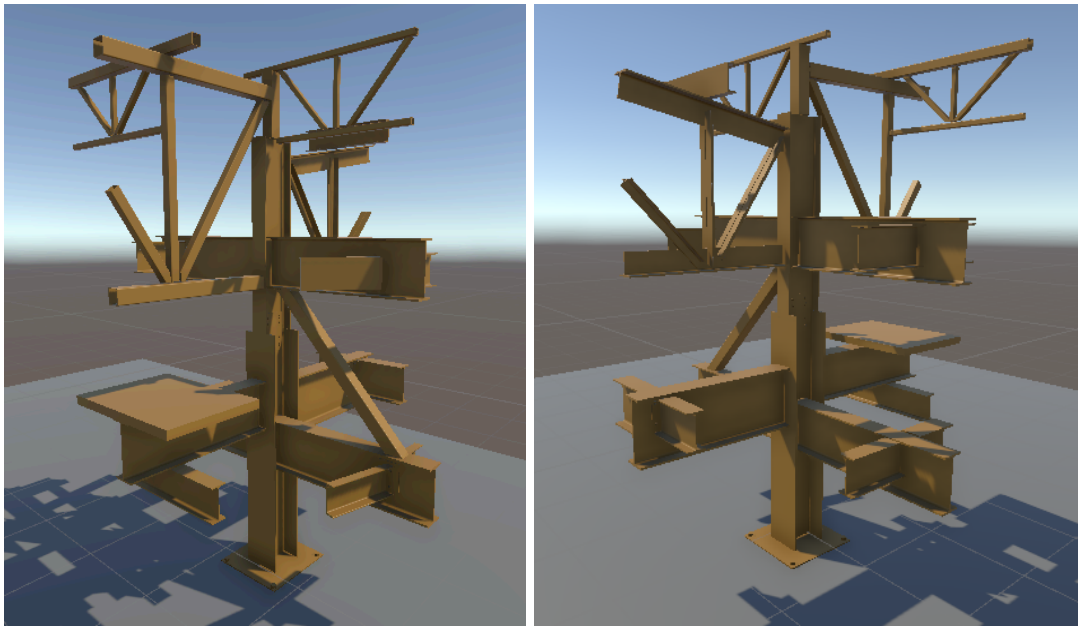


Figure 18. Two views of the manually developed scan-to-BIM model

The models are imported into a 3D game engine. Unity is utilized, as it is free, and it has a vast library of open-source assets, tutorials and online support. A universal cutting and packing simulation is developed in Unity. In the simulation, the VR user is given a gray cutting tool object resembling a hacksaw. The cutting tool can be used to slice the deconstruction asset anywhere with a cutting motion, as depicted in Figure 19.

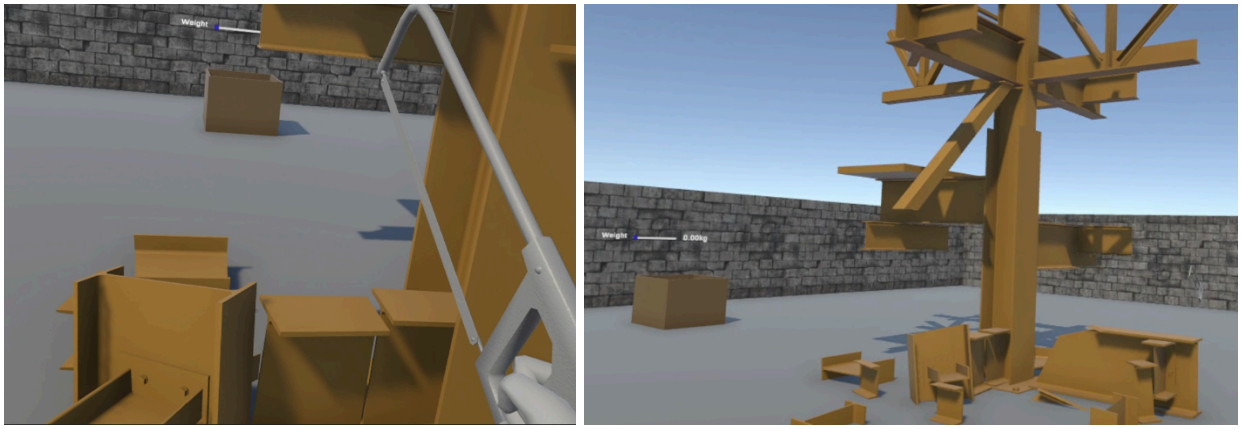


Figure 19. Custom cutting interaction behavior in Unity and the fallen severed pieces

Next, the VR user moves objects into the waste container to test packing configurations, as depicted in Figure 20 below. The user can reset the simulation to try new cutting and packing possibilities until they are satisfied.

Figure 20. VR user bringing a severed piece to the packing container

Finally, the VR user is shown the current weight of the contents of the waste container as a number and as a progress bar indicating the proximity to the waste container's maximum load, as shown in Figure 21 below.. In scenarios such as nuclear decommissioning, feedback like this is critical for meeting waste regulations while optimizing the number of packing containers, which can each cost hundreds of thousands of dollars to store.

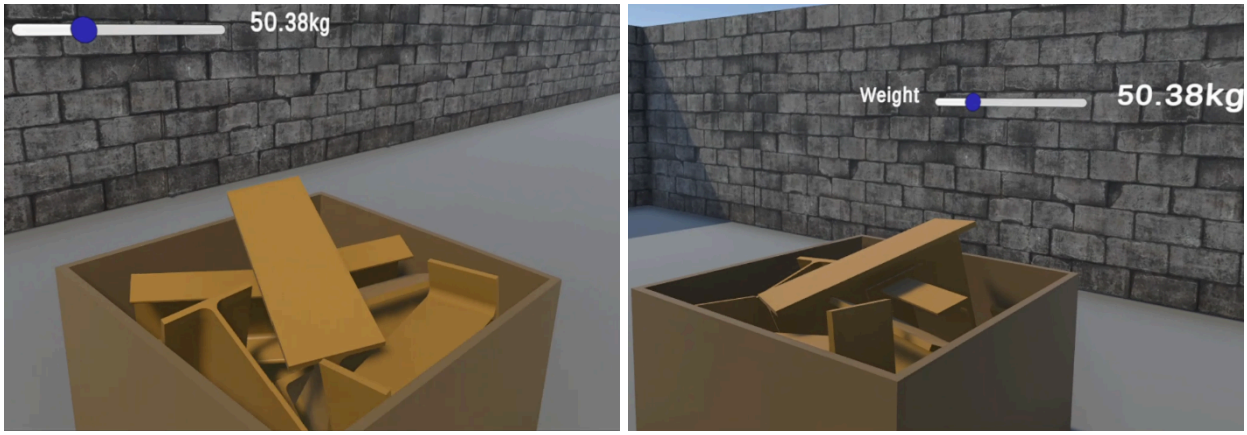


Figure 21. The waste container and the weight indicator

3.5. Discussion

An approach to disassembly planning, specifically focused on cutting and packing workflows, is presented and demonstrated in this study. The key innovation of this methodology lies in its ability to seamlessly integrate cutting interactions and real-time feedback within a VR environment, making these tools instantly applicable to any reality data imported into the simulation. This flexibility allows planners to leverage detailed mesh or BIM models derived from reality capture techniques, such as TLS or iPad LiDAR, and immediately begin optimizing disassembly strategies without the need for extensive reconfiguration or additional programming.

The process begins with the importation of reality data into a game engine like Unity, where the data is converted into solid polygon geometries. What sets this approach apart is the ability to apply pre-developed cutting interactions and packing feedback mechanisms directly to these geometries, regardless of the specific asset being modeled. This capability makes the approach highly adaptable, enabling planners to experiment with different deconstruction tasks across a wide range of projects. By providing real-time feedback on the efficiency and feasibility of various cutting sequences and packing arrangements, the simulation environment facilitates a human-computer collaborative process, where the planner can interactively refine strategies with the support of computational insights.

Occlusions remain a significant challenge in reality data capture, particularly when dealing with complex geometries like structural steel components. These occlusions can result in incomplete data capture, leading to potential inaccuracies in the generated models. However, the instant applicability of cutting interactions and feedback within the VR environment helps mitigate some of these risks. By allowing planners to quickly visualize and adjust for any missing data in real time, the approach ensures that even models with some level of occlusion can still be used effectively for planning. For example, if an occlusion leads to an incomplete scan of an I-beam's flange, the real-time feedback in the simulation can alert the planner to potential issues, allowing for on-the-fly adjustments to cut paths and packing strategies.

Looking forward, the focus should shift towards expanding the library of predefined interactions and feedback mechanisms available within the simulation environment. By developing a broader set of tools that can address a wider variety of materials and structures, the approach can become even more versatile and applicable to more complex deconstruction scenarios. Additionally, integrating more advanced analytics within the feedback loop, such as predictive models for material behavior or automated error detection, could further enhance human-computer collaboration, allowing for even more sophisticated planning and optimization. Studies are required to empirically validate the potential of this approach as well.

Chapter 4

Gamified Virtual Reality for Building Material Reuse Planning

Statement of Contributions

The research in this chapter was completed collaboratively with Manolis Katsimpalis under the mutual supervision of Dr. Carl Haas at the University of Waterloo. The design of the participant study herein and participant study logistics include assistance by Brandon Byers at ETHZ under the supervision of Catherine De Wolff. My contribution specifically includes participating in the design and iterative development of the simulation and leading the design and organization of the participant study, the collection and analysis of participant data, and manuscript writing.

4.1. Introduction

Material reuse offers the construction industry a chance to massively reduce the natural resources it consumes and landfills. However, adopting a “circular economy” of building materials requires many new workflows. This section presents a virtual reality approach for building material reuse planning based on reality capture and gamified VR. Using 3D data captured from real assets a simulation is developed where users deconstruct and rebuild structures in an engaging, realistic, and risk-free environment. Users simultaneously conduct deconstruction planning and reuse-based architectural design. As part of this research, a workshop was conducted to test the simulation with an audience of multi-disciplinary professors, students, and non-academics. Qualitative observation and surveys are used to observe the way that users of different demographics engage and react to the simulation. In particular, users either struggle or excel with the lack of structured objectives in the simulation. Additionally, users disagree on whether the simulation should be more technical and precise or more intuitive and creative. It is proposed that future simulations can increase material reuse by empowering project planners to experiment and imagine effective configurations.

This section delves into a critical aspect of CE in construction: how planners might envision and design with reused materials. Addressing this multifaceted challenge requires more than analytical methods; it calls for human planners empowered with 3D design tools to generate initial designs, later refined for precise deconstructability and structural integrity.

We introduce a VR simulation that enables users to visualize, deconstruct, and reconstruct structures using real 3D data in an immersive, risk-free environment. A workshop was held to evaluate the simulation's effectiveness, gathering multi-disciplinary participants, as shown in Figure 22. Through qualitative observation and surveys, how users from diverse backgrounds interact with and perceive the simulation is analyzed.

Figure 22: Users engaging in the VR building material reuse planning workshop

4.2. Material Reuse Planning Methodology

To bridge the gap between Circular Economy (CE) principles in construction and their real-world application, an exploratory study using a VR simulation is presented. This study aimed to understand how future building planners might approach (1) deconstruction, (2) material recovery, and (3) the reassembly of recovered materials, focusing on wood, steel, and concrete due to their prevalence in construction. The research described in this section followed the procedure depicted in Figure 23.

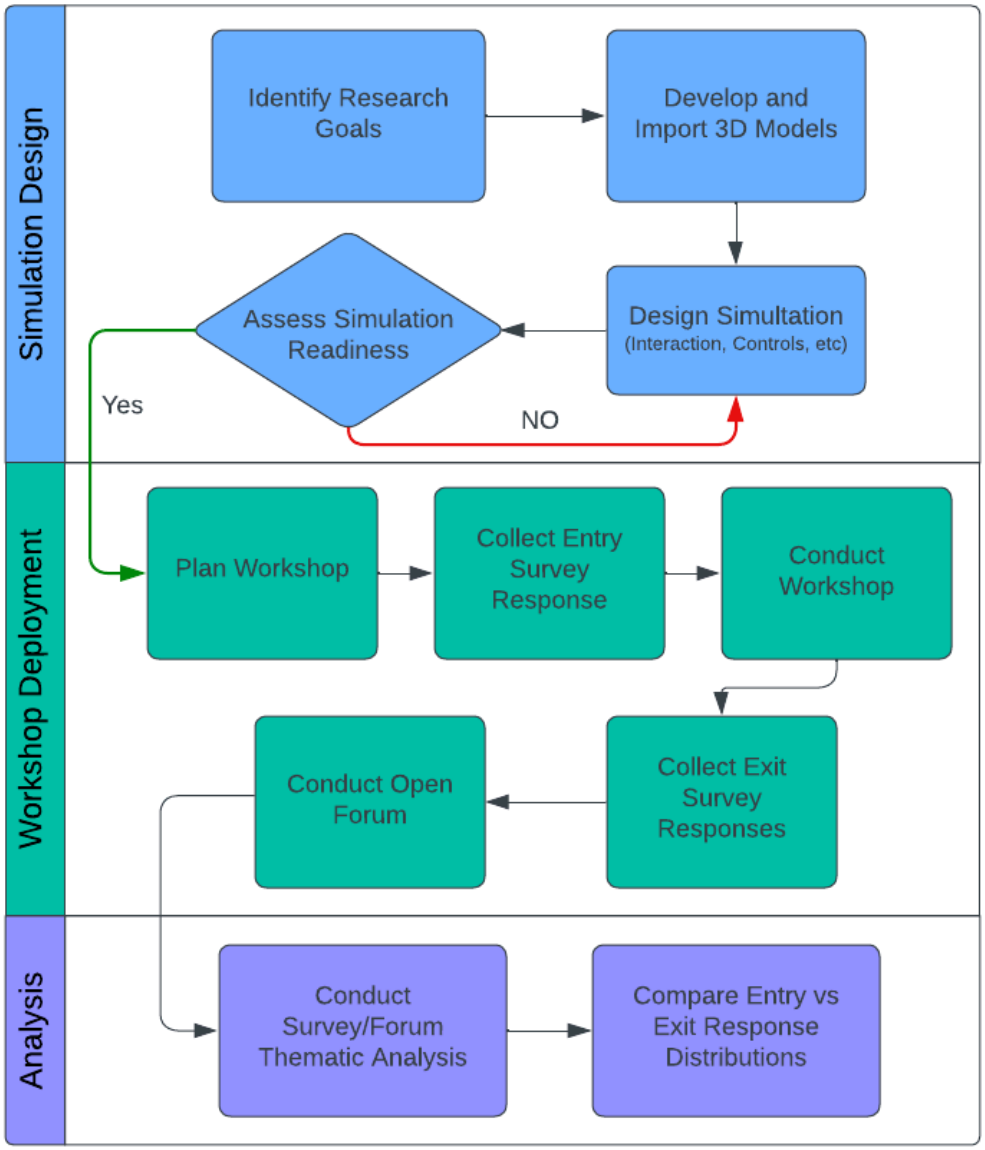


Figure 23: Material reuse simulation and workshop research procedure

4.2.1. VR Simulation Design & Development

Unity 3D, recognized for its robust VR features and compatibility with various VR hardware, served as the core platform for the simulation, which incorporated objects sourced through reality data capture and 3D modeling. The modeling process involved a Faro scanner, Autodesk Recap, and Revit, presenting users with diverse structures like wooden pavilions, concrete slabs, and steel sculptures. The simulation environment enabled dynamic interactions, allowing participants to slice, manipulate, and recombine materials in a VR setting. While the simulation integrated elements of realism, such as gravity and basic physics, it also included gamified aspects. For example, users could effortlessly cut through substantial concrete slabs with a hand saw, emphasizing ease of interaction over material mechanics fidelity.

The model data used in the simulation was meticulously sourced from a blend of reality data capture, creative commons stock 3D models, and architectural models with contextual significance. Reality data, captured using a Faro scanner and processed through Autodesk Recap and Revit, included a detailed scan-to-BIM model of the AISC steel sculpture. This model was scaled to various sizes, providing users with steel materials featuring distinctive connections and complex geometry to interact with. Additionally, creative commons stock 3D models were integrated to offer a wider range of materials, including wood and concrete. A key inclusion was the Hubner Pavilion, an architectural model from ETH Zurich's campus, directly relevant to the workshop attendees due to its ongoing material reuse operations. The incorporation of wood, steel, and concrete elements ensured a comprehensive engagement with different material properties, aligning with the diverse scenarios participants might encounter in real-world deconstruction projects.

During the initial development, perfecting the simulation's physics, including collision, cutting, and reattachment, was challenging. Users needed to interact with materials that authentically mimicked real-world steel and concrete. Initial versions had issues like mismatches between intended cuts and actual results and unconvincing material dynamics, undermining the VR experience's authenticity. However, after several iterations, feedback, and adjustments, leveraging Unity 3D's physics and

custom scripting, these mechanics were refined. The final version offered users a realistic interaction with materials, closely emulating their real-world properties. Figures 24-27 depict screenshots of the final simulation environment in use.

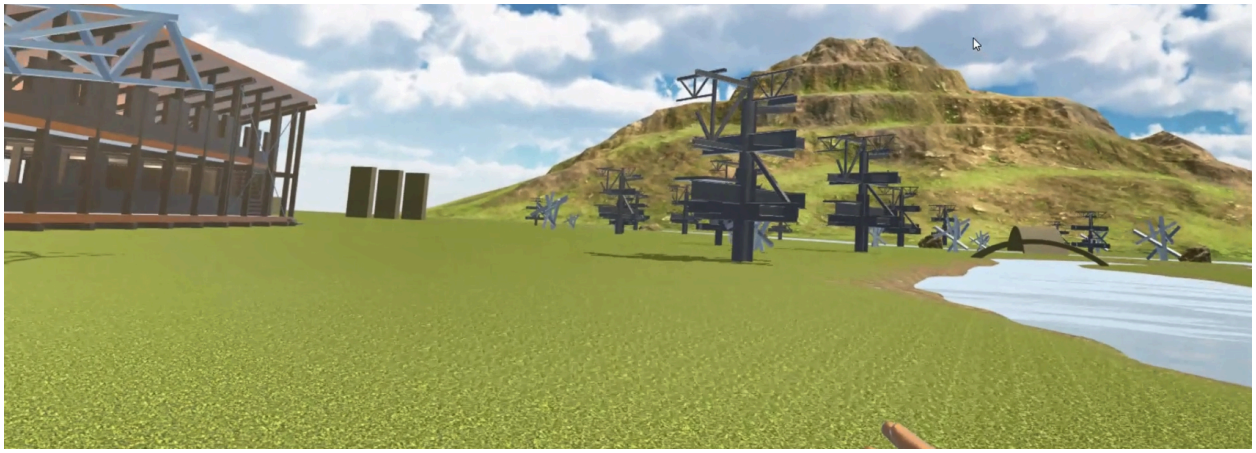


Figure 24. A simulation view including an architectural model (left) and AISC steel sculptures (middle-right)

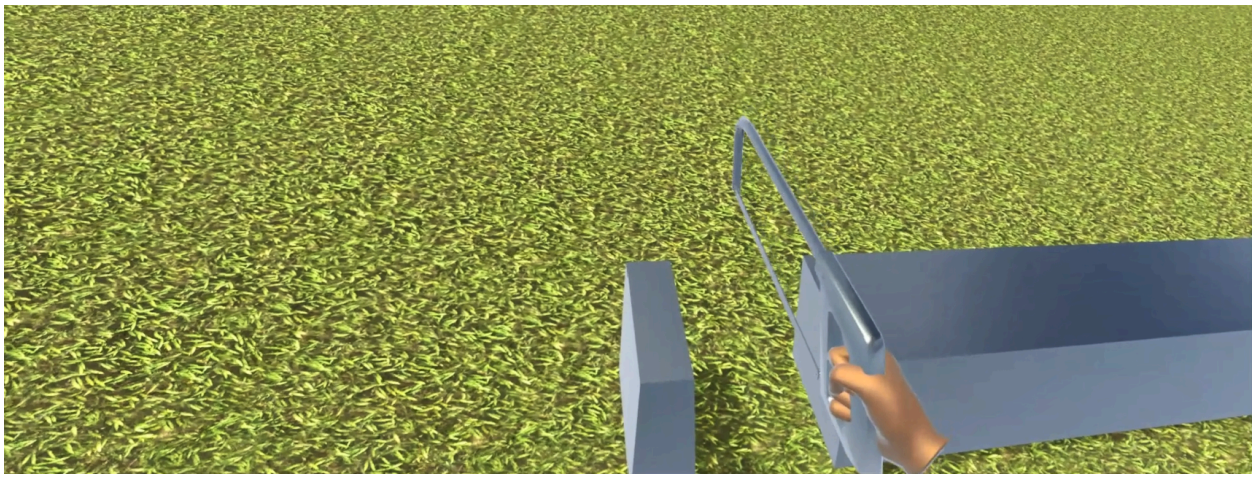


Figure 25: A simulation view depicting a VR user cutting a small end cap off of a steel section with a rectangular cross section

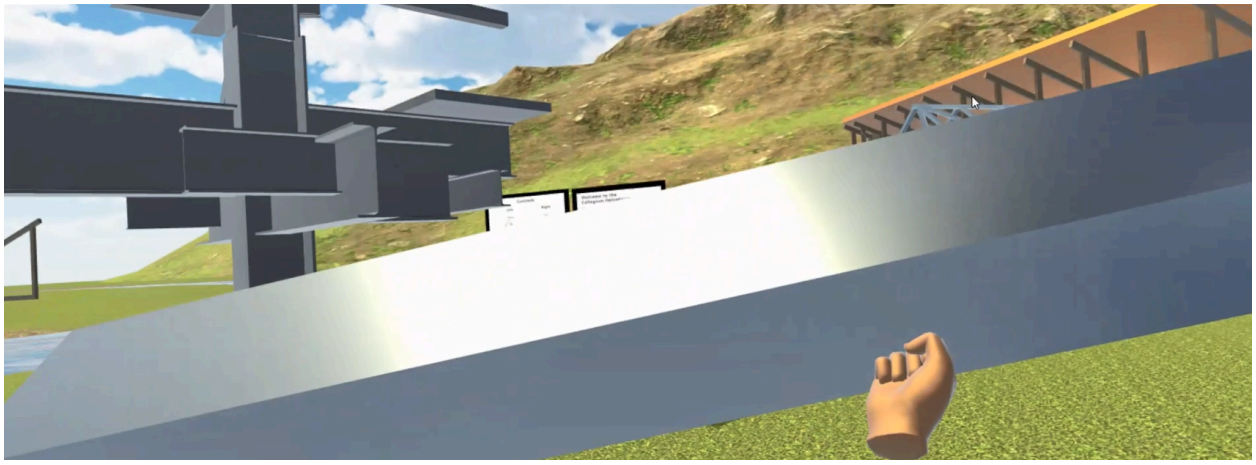


Figure 26: A simulation view depicting a VR user grabbing and moving a steel section that was previously cut

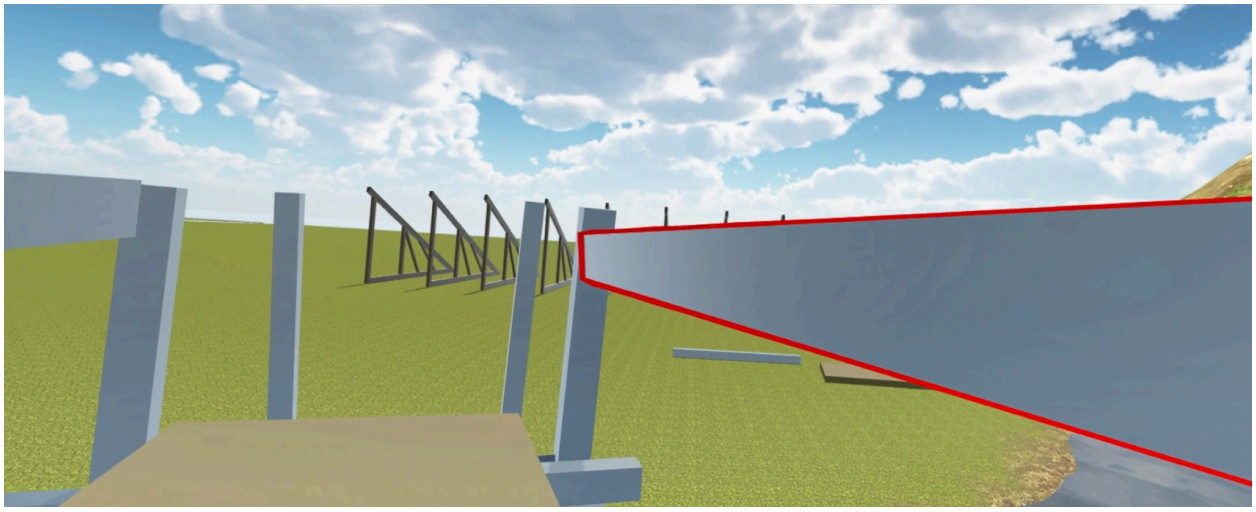


Figure 27: A simulation view depicting a VR user fixing a steel section to a frame assembly

Refining the control scheme was crucial for an intuitive user experience. Initially, the simulation had many controls, making it complex and less immersive. Aiming for simplicity to let users focus on creative design rather than controls, a bifurcation paradigm was introduced: the left hand for cutting, the right for building. This approach streamlined interactions and fostered an intuitive mental model, as confirmed by user feedback, enhancing the immersive and creative aspects of the simulation.

Once the core functionality of the simulation design was deemed effective through internal review and refinement, the simulation was augmented with information to help its users navigate its capabilities and controls. Figure 28 demonstrates an early prototype of the information billboards rendered in the simulation environment.

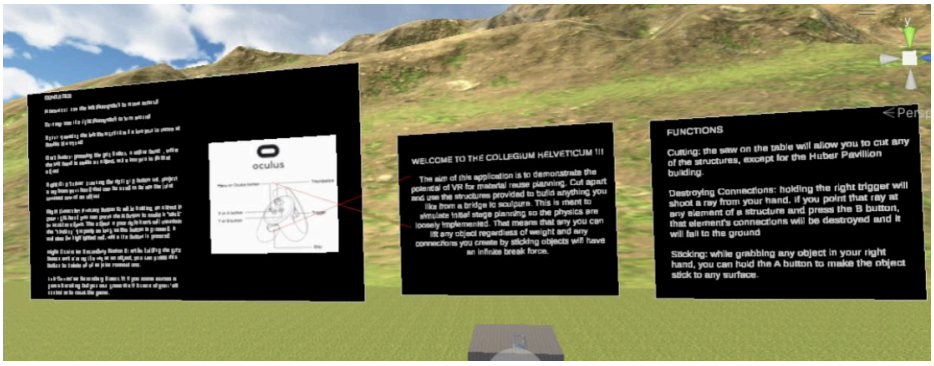


Figure 28: Initial prototype of information billboards presented to simulation users

However, it was clear that the amount of information and its presentation as depicted in Figure 28 was not effective, due to being disorganized and overwhelming. Iteration was performed to improve the effectiveness of the communication. The main focus of the educational content was communicating the control scheme. This was deemed a critical feature of the simulation based on the lack of experience using VR and game controllers of some of the intended participants. Figure 29 depicts the improved overview presented to the users.

Welcome to the Collegium Helveticum.

The aim of this experience is to demonstrate the potential of VR for material reuse planning. Grab the saw in front of you. Pass it through materials from the world around you to deconstruct them. Grab the pieces, and stick to them together to build something entirely new.

Physics are loosely enforced -- you can lift any weight, and make unbreakable connections. Use your right hand to build. Grab with triggers and place with A. Use your left hand to destroy. Target with triggers and break with X.

Figure 29: The introductory message displayed to workshop participants in VR

Figure 30 depicts the visual approach to communicating the VR controls that was implemented to replace the initial text based approach. The visual approach was found to be more intuitive based on feedback from the internal project team.

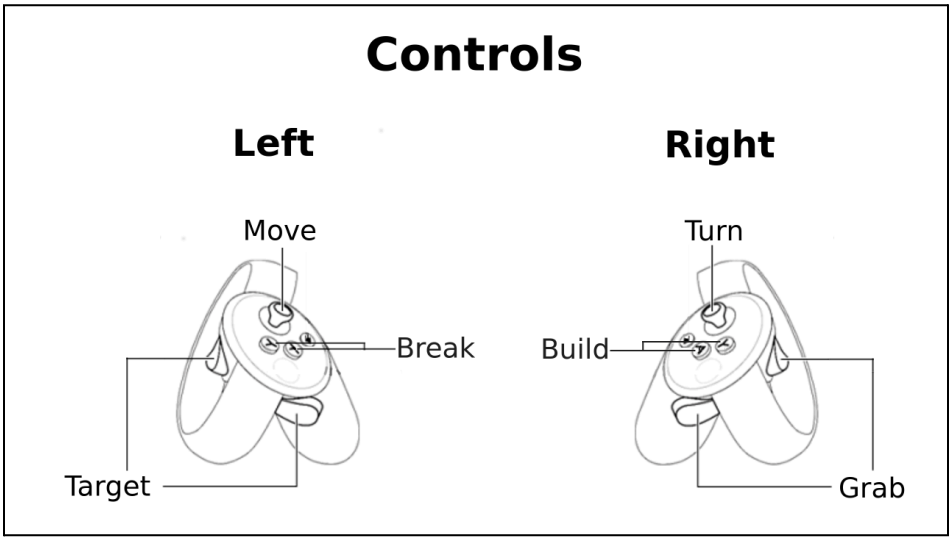


Figure 30: VR control scheme explanation as displayed to VR participants

4.2.2. Workshop Deployment and User Engagement

The refined VR simulation was introduced at a workshop for evaluation. The attendees of the workshop had many different levels of experience in architecture, engineering, and construction (AEC), roles in the AEC industry, and levels of confidence in using VR, as demonstrated in Table 1 below. There were a handful of participants from other disciplines. Upon entrance, the attendees were given a pen and paper survey with 2 qualitative and 6 quantitative questions. A few of the self-assessment responses of the 15 workshop attendees are presented in Table 1.

Table 1. Demographics of the building material reuse workshop participants

Participant	Type	How many years of experience do you have in AEC?	What is your role, if any, in the AEC industry?	How confident are you with using VR in general? (From 1-5, 5 being highest)
A	General Public	0	-	4

B	General Public	0	-	4
C	Professor	10	Researcher	4
D	Lecturer	2.5	research in sustainability and digitalization in construction	3
E	Professor	25	Professor/consultant	1
F	Grad Student	8	Academic researcher on re-use	1
G	Grad Student	10	Academic	2
H	Grad Student	10	PhD Researcher	4
I	Postdoc	Unknown	Unknown	Unknown
J	Professor	18	Structural engineer, researcher	4
K	Professor	21	Professor	3
L	Grad Student	13	Architect, PhD Student	4
M	Professional	6	Architect, Deconstruction, re-use consultant	2
N	Professional	22	Architect	2
O	Professor	40	designer/academic	2

4.2.3. Feedback Collection

Upon concluding their interactions with the VR environment, attendees were encouraged to share their experiences and insights in an exit survey followed by an open forum. The exit survey was designed to capture specific responses, while the forum included open-ended discussions that induced a more in-depth exchange of

ideas and critiques. This approach of both quantitative and qualitative methods fostered a robust collection of feedback to inform the understanding of the simulation's impact. The exit survey included all of the questions from the entry survey a second time, as well as additional questions based on the System Usability Scale (SUS) (Brooke, 1986) regarding the participant's experience with the VR simulation.

4.3. Results

Subsequent to the workshop, the amassed data—encompassing both quantitative metrics from questionnaires and qualitative insights from discussions—underwent methodical analysis. Quantitative data was analyzed statistically for a within-subject comparison before and after the workshop of their belief in the utility of VR. Additionally, qualitative feedback from the workshop and the following open forum was explored through thematic analysis, aiming to derive overarching patterns and insights about the VR simulation's implications in the context of CE-based construction planning. Overall, the methodology was directed toward facilitating an immersive, exploratory experience that spotlighted the potential of CE in construction planning via the medium of VR, ensuring that the simulation was polished through internal iterations and then critically assessed by a varied set of workshop attendees.

4.3.1. User Feedback Thematic Analysis

Participants' feedback from the workshop was collated from two primary sources: structured questionnaires, which provided quantitative metrics, and open-ended discussions, yielding qualitative insights. This combined feedback facilitated a comprehensive understanding of user experiences and the VR simulation's efficacy. Thematic analysis of user feedback is shared in Table 2.

Table 2. Thematic analysis of workshop participant survey and forum feedback

Theme	Frequency	Demonstrative Comment

1. Experience with Simulation		
Positive Engagement	4	"Immersive and engaging, it made me rethink construction processes."
Struggle with Unstructured Nature	5	"Felt lost at times due to the lack of clear objectives."
Desire for More Technical Precision	3	"Would appreciate more detailed and precise control options."
Enjoyment of Creative Freedom	3	"Loved the freedom to experiment without rigid guidelines."
2. Physics Engine Quality		
Realism in Material Interaction	4	"The realistic behavior of materials added depth to the experience."
Issues with Responsiveness	3	"Encountered some lag and unresponsive controls at times."
3. Future Evolution of Simulation		
Expansion to Other Industries	3	"Can see this being useful in urban planning or even game design."
Technical Improvements Needed	4	"The simulation needs to be more user-friendly and intuitive."
Potential as an Educational Tool	3	"This could be a great tool for training future engineers and architects."

4.3.2. Comparison of Entry versus Exit Survey Results

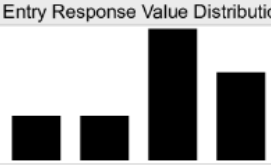
To gauge shifts in participants' perspectives before and after experiencing the VR simulation, both entry and exit surveys were conducted. These surveys aimed to capture the change in participants' understanding, beliefs, or opinions regarding construction material reuse. Table 3 demonstrates the change in survey question responses before and after the workshop experience. Each number represents the delta between the participant's exit and entry responses on a 5 point Likert scale. Each row represents one participant. The participant selection is limited to those with both valid entry and exit survey data. As the entrance survey was voluntary, many participants did not complete it. For those that did, Table 3 shows that the majority of question-participant pairs showed no change. Surprisingly, a decline in sentiment was the second most likely outcome. Cells shaded in green represent a positive change in sentiment towards VR, while cells shaded in red represent a negative change in sentiment.

Table 3. Difference in entry vs exit response values for select workshop participants

Participant	Do you believe VR is an important part of the AEC industry at present?	Do you believe VR will be an important part of the AEC industry?	Do you believe VR is currently important for circular construction?	Do you believe VR will be important for circular construction?	Do you believe XR based approaches generally outperform traditional methods?
B	0	2	2	-1	0
E	0	0	0	-2	0
K	0	0	0	0	0
L	0	0	-1	0	-1
M	-1	-2	0	0	0
N	-2	-2	0		

Table 3 demonstrates a limited view of the trends in the survey data, as only 6 out of 15 participants completed both surveys and the exit survey had more questions. A more detailed view of the survey results is presented below. In general, people thought the simulation was unnecessarily complex, inconsistent and cumbersome but easy to learn and use without the need of a technical person's assistance. Our results indicate that participants don't believe in the value of VR now but think it will be valuable in the future.

Table 4 demonstrates the distribution of each question's responses before and after the workshop. Each row represents one survey question. The middle column corresponds to the entry survey and the right column corresponds to the exit survey. Each chart is a histogram showing the distribution of Likert scale response values for each question, from 1 to 5. Each histogram demonstrates a trend in participant sentiment, and the entry and exit distributions can be compared to gauge the impact of the VR workshop experience.

Question	Entry Response Value Distribution	Exit Response Value Distribution
How confident are you with using Virtual Reality (VR) in general?		
Do you believe VR is an important part of the AEC industry at present?		
Do you believe VR will be an important part of the AEC industry?		
Do you believe VR is currently important for circular construction?		
Do you believe VR will be important for circular construction?		

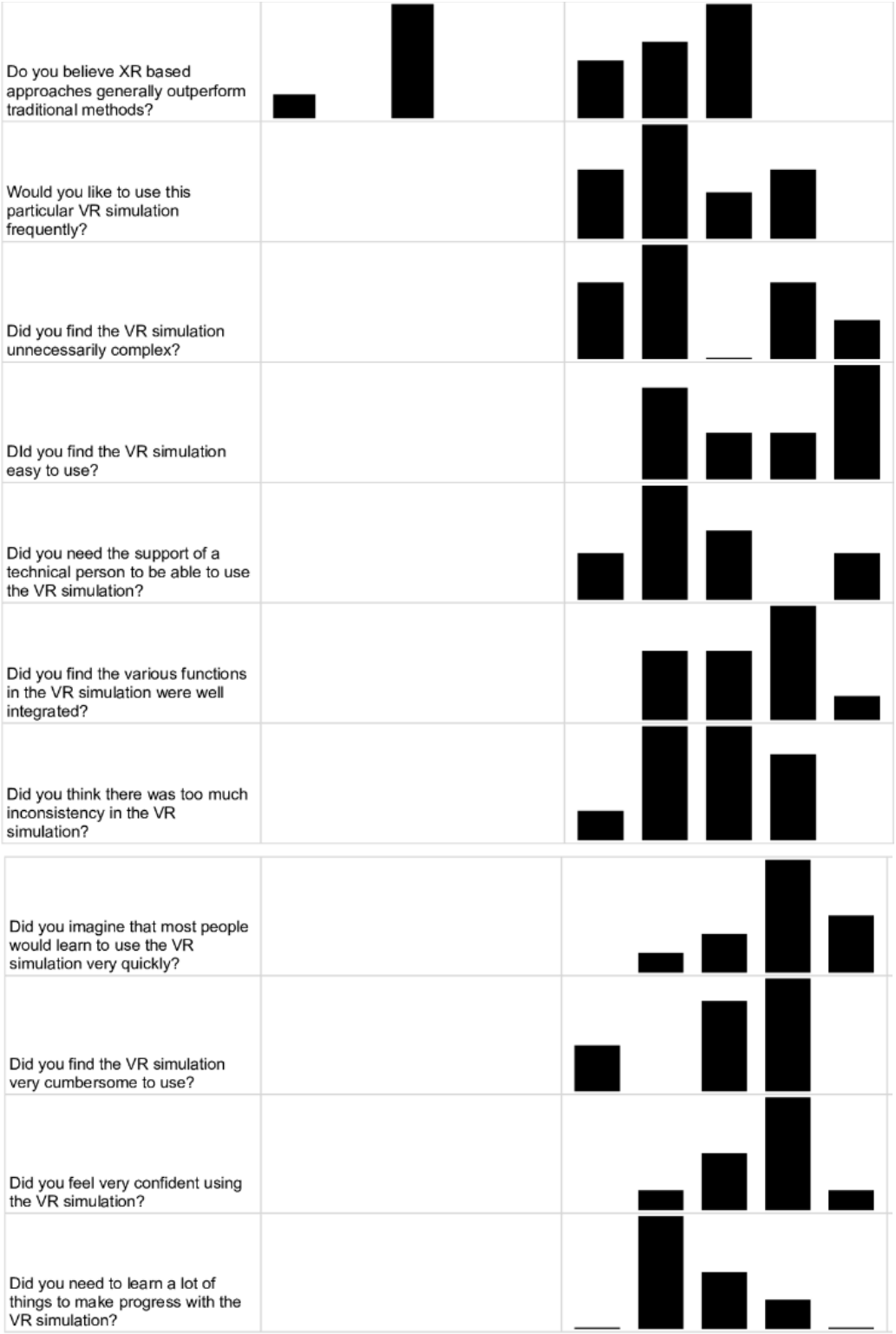


Table 4. Comparison of entry vs exit response distribution across all participants

4.3.3. Workshop Participant Creations

Selected workshop participants' creations are displayed to add insight. The creation depicted in Figure 31 was selected as it demonstrates the outcome of a participant who felt lost in the simulation given the lack of structured objectives.

Figure 31. Remains of an attempted bridge in VR

The creation depicted in Figure 32 was selected as it demonstrates what most participants created. The majority of users found some level of competency, and generally assembled a mass of reused construction materials with some useful properties.

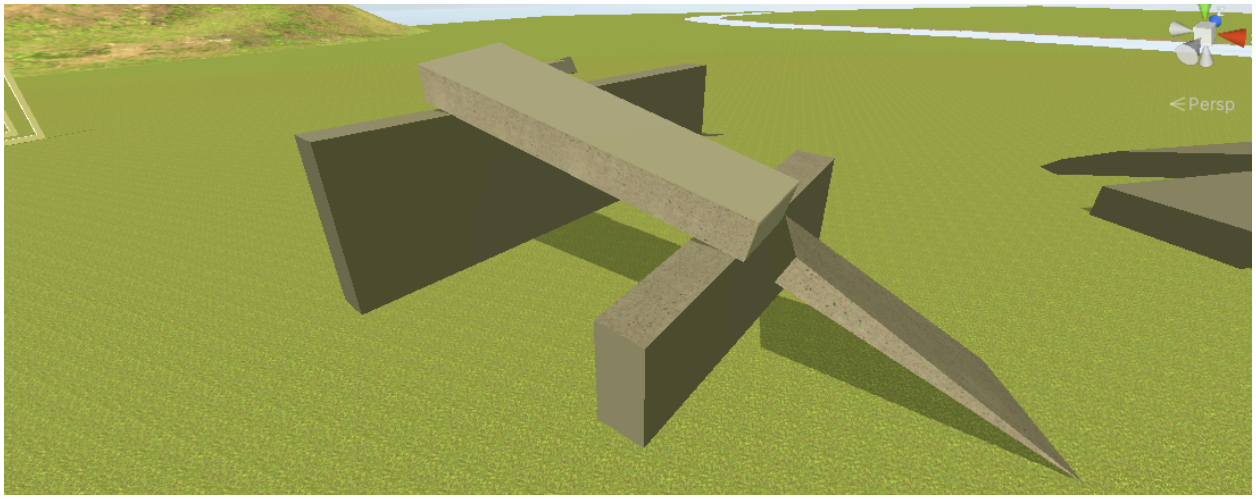


Figure 32. A pair of abutments, truss, and an on-ramp made of reused concrete in VR

The creation depicted in Figure 33 was selected as it demonstrates a participant who demonstrated high competency in the simulation. This participant went as far as concerning themselves with aesthetics, and made sure to source only white powder-coated steel from the bank of reusable materials for their structure, despite a bank of raw steel next to the construction site.

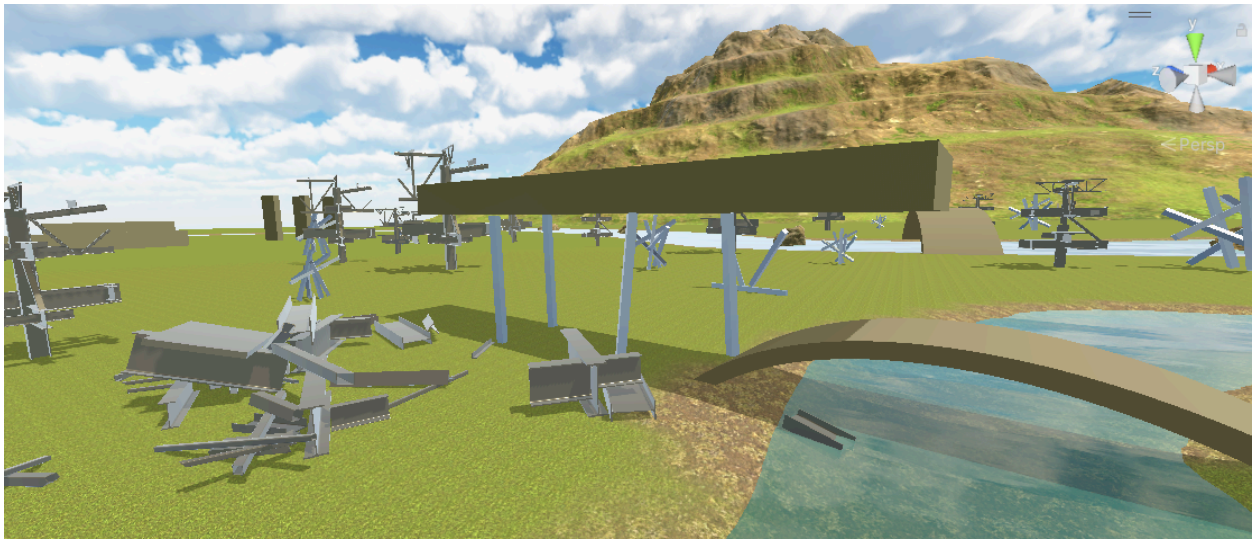


Figure 33. A floating bridge, and a bridge over a river in VR

4.4. Discussion

The intersection of construction engineering, sustainability, architectural design, and virtual reality holds immense potential, particularly for infrastructure planning in a CE. The VR simulation is a step towards this, highlighting technology's role in promoting sustainable construction through material reuse. Yet, this exploratory study has its constraints, including limitations in simulation accuracy and user-reported VR discomfort, alongside challenges in participant number and data collection during the live workshop. These issues provide direction for refining the VR environment and its applications.

While some users questioned the simulation's utility in actual construction projects, appreciating its creative aspect instead, these insights suggest its suitability for early design or collaborative planning rather than advanced stages. Despite the

absence of statistical evidence on VR's effectiveness for CE, the positive feedback received paves the way for further development and objective refinement.

In conclusion, this study reveals VR simulations' potential to revolutionize construction material reuse, with feedback from a diverse participant group shaping future research directions. As CE principles gain traction in the industry, tools like the VR simulation are poised to bridge knowledge gaps, spur innovation, and foster a sustainable construction landscape.

Chapter 5

Automated Critical Path Scheduling Through Virtual Reality

Statement of Contributions

The research in this chapter was completed collaboratively with Manolis Katsimpalis under the mutual supervision of Dr. Carl Haas at the University of Waterloo. I am the primary contributor of the schedule generation methodology, precedence relationship algorithms, schedule estimation algorithms, all pseudocode, and the Python code implementation.

5.1. Introduction

This section addresses the problem of distilling deconstruction planning simulation results into key planning deliverables that are useful and recognizable to the greater project team. To this end, a paradigm is proposed where construction planners interact with a VR environment and a comprehensive critical path schedule is automatically generated from their actions alone. This workflow allows planners to conduct repeated trials of construction activities in a risk-free and low-cost human-computer collaborative environment, and generate a key planning deliverable that allows them to communicate their plan to the project team with minimal additional work.

The main contribution of this chapter is a methodology for the automated generation of recognizable critical path schedules and deliverables using only logs from a VR project simulation. The modular capabilities of modern VR engines are leveraged to create a detailed ledger of all user interactions in the simulation. Then, a system of algorithms, heuristics, basic assumptions, and a workflow is described for inferring the occurrence, dependencies, and duration of construction-centric actions from an arbitrary sequence of event logs collected by the engine.

In an effort to generate schedule deliverables that are recognizable to current construction industry players, a complete and standardized critical path schedule is targeted. To this end, the first sub-contribution is an algorithm to recover real-world precedence relationships from information in the virtual reality event logs. The algorithm applies pre-defined deductive reasoning logic to the event log entries to deduce dependencies. The resulting precedence information can be used to determine a parallelization strategy for the schedule. The second sub-contribution is a series of algorithms for estimating the real-world durations of actions detected in the virtual reality event logs.

Based on the framework suggested by Peffers et al., the research begins with formulating specific questions from a thorough literature review on VR applications in construction. The usage of VR simulation environments to automate the generation of deliverables, specifically critical path schedules, is identified as a key real-world challenge unaddressed by the literature, as discussed in Section 5.1.3. A VR-based planning process is then developed and implemented to validate its efficacy in real-world scenarios.

Following the formulation of the proposed methodology, two case studies based on key use cases are presented. The methodology is validated through functional demonstration on these two test cases. The first case study is based on a straightforward task wherein an operator must cut a machine into pieces in place and efficiently pack the pieces in a waste container. The task depicted in the first case study takes around a dozen actions (moving, cutting, extracting from a confined space, etc) and one minute to plan in the simulation environment, with the corresponding real-world execution duration being a few orders of magnitude longer. In the second study, a much larger process in a nuclear decommissioning context is depicted. The VR operator must take apart a large portion of a reactor core in an NPP based on the Canada Deuterium Uranium (CANDU) design, which takes around thirty minutes to plan in the simulation environment, with the corresponding real-world execution duration being several orders of magnitude larger. The size and scope of the project illuminates the methodology in a more complex environment, with actions required for creating

temporary bracing and platforms for work access. In both case studies, the generated schedules are closely verified against the VR operator's actions to validate the methodology.

5.1.1. Terminology

To be precise, throughout this chapter, construction planning and scheduling terminology is defined in the following way:

- **Groups:** Depending on the project planning and scheduling software being used, tasks or activities can be grouped into aggregate entities for categorizing and reporting project information in a more manageable manner. Groups are beyond the scope of the research described here.
- **Activity:** An activity is defined as the coarsest subdivision of a construction project. The boundaries of each activity are the jurisdiction of the project's planners, however, common practices as well as logical features such as type of work, timing, and location within the project inform the decision.
- **Task:** A task is defined as a subdivision of an activity. Similarly, the boundaries of each task are the jurisdiction of the project's planners, however, it is common to identify tasks based on repeatable chunks of work within the scope of the activity. For example, if the activity involves driving all of the piles for a foundation, driving each singular pile can be a task.
- **Action:** An action is defined as a single human-interpretable state change enacted within a construction project. An action is a subdivision of a task. For example, the movement of a construction material from one position to another is an action. An action may have meta-data associated with it, as defined later in this chapter.

In summary, a construction project is defined here as being composed of groups of discrete activities, which are composed of tasks, which are in turn composed of

actions. In the context of simulations of construction projects, the following additional terminology is introduced as well:

- **Event:** An event is defined as the smallest, most granular subdivision of a construction project simulation, which directly results from the internal mechanisms of the simulation engine. While events are far too granular to represent in a construction plan, they are necessary for interpreting construction planning simulation data, as the flow of data out of the simulation engine occurs at the event level. For example, an event can be a user grabbing an object or a user letting go of an object. Bridging the gap between computer-interpretable events and human-interpretable actions is a key contribution of this chapter, described in Section 5.2.2.

The concept of an “event” is also used in classical DES (Discrete Event Simulation) in construction, and thousands of papers have been written on it. A few seminal works in the area include the development of the CYCLONE method by Halpin, 1977 and the exploration of simulation's role in construction engineering and management by AbouRizk, 2010. In DES for construction, the simulation engine assumes no change in the system being modeled between events, which may occur at a frequency of 1 hertz, for example (so that the system’s state is updated in “discrete” increments every second), and the simulation is run essentially as a batch process. However, in VR simulation, the user is essentially a real-time agent in the system, and the state changes are driven by the user(s) and the game and physics engines. The concept of an “event” is very similar in both environments; however, DES requires expertise to construct a model and run it through simulations, whereas VR is intuitive and accessible to construction planners and experts.

5.1.2. Study Design

Following the methodology framework suggested by Peffers et al., the study begins with the formulation of specific research questions derived from a comprehensive review of existing literature on VR applications in construction, as detailed in Chapter 2 and recalled in Section 5.1.3. The study explores the potential of

VR technology in not only enhancing construction planning through immersive simulations, but also in automating the generation of critical path schedules based on user interactions within the VR environment. Subsequently, the study addresses these questions by developing and formalizing a VR-based planning process, which is demonstrated to validate its efficacy and generalizability in real-world construction project planning.

The demonstration involves the creation of two VR environments tailored to deconstruction planning, incorporating features that allow for the capture and analysis of user interactions to automatically generate project schedules. The approach is demonstrated through two use cases, showcasing the process's ability to produce accurate and comprehensive critical path schedules. The methodology is validated by verifying the generated schedules for accuracy against a video recording of the operator’s simulation run.

5.1.3. Knowledge Gap

The prior literature on automation of planning deliverable generation can be organized into two main categories. The first focuses on fully algorithmic workflows. Amer et al. (2021) presents a comprehensive review tracing this research's origins to the 1980s, highlighting the disconnect between the large body of literature and the limited use of automated planning in practice. The five gaps identified can be distilled into the overarching sentiment that construction firms find the costs of implementing automated techniques unjustified compared to their benefits, mainly due to significant upfront investments and the friction of adapting existing workflows.

In this category, prior research has primarily investigated rule-based and optimization approaches for generating planning deliverables, such as disassembly sequence planning. Sanchez and Haas (2018) developed the Sequential Disassembly Planning for Buildings (SDPB) method, which produces valid disassembly sequences based on a BIM model, a component of interest, and a set of rules. Building on this, Sanchez et al. (2019) extended the methodology with a multi-objective optimization step

to minimize environmental impacts and costs. In such work, once inputs are defined, the sequence generation is deterministic, with constraints and optimization weights being the only controls by which the planner can influence the outcome. This abstraction limits the application of domain knowledge or expert judgment.

The second category, emerging more recently, focuses on AI techniques, particularly large language models (LLMs). Pallagani et al. (2024) review 126 papers in this area, noting greater industry adoption due to the low costs of using publicly available LLMs and their efficiency over traditional methods. However, these methods share drawbacks common to generative AI, including lack of explainability, poor integration of expert judgment, and non-robustness to novel scenarios. In related fields, such as construction project communication, MR has been studied as a bridge between automation and human expertise (Dinis et al., 2021).

MR and VR technologies in construction have been explored, particularly in training, safety, and progress tracking. However, there is a notable gap in using these technologies to create planning deliverables. The literature, reviewed in Chapter 2, predominantly focuses on MR and VR for enhancing training, improving safety, and facilitating progress tracking. For instance, Sacks et al. (2013) showed MR-based training's superiority over traditional methods, and Ali et al. (2021) highlighted MR's potential for real-time inspection feedback in VR environments.

These studies, however, do not address how virtual planning actions can be systematically translated into real-world project deliverables that are actionable and communicable to the broader project team. This gap highlights the need for research that not only advances VR simulations in construction planning but also bridges the divide between virtual experiences and the generation of standardized, recognizable planning deliverables. Such advancements could revolutionize construction planning, moving beyond the current scope of MR and VR applications in the industry, which largely enhance traditional methods rather than creating a new planning and execution paradigm.

5.2. Schedule Generation Methodology

This section proposes a methodology for creating a comprehensive critical path schedule based on detailed event logs from a VR construction planning simulation. The scope of the methodology focuses on low level action sequence planning in order to optimize the predicted early finish of one activity at a time. That is, the methodology focuses on planning each activity individually in isolation, in support of the project as a whole. The schedule that is generated conveys the early finish time of the activity of interest, and each node in the schedule represents one action that has a duration estimate and precedence relationships with other actions.

The methodology includes 4 main phases. The first phase is Simulation Development, where a VR simulation of the project activity is developed in a 3D game engine. The capability to capture detailed event logs of the user's interactions is included in the first phase to enable downstream analysis. The second phase is Analysis Software Development, where a software system is created that can analyze the events logs and create a corresponding critical path schedule. The third and fourth phases, Simulation and Deliverable Generation describe the iterative planning process that is enabled by the pairing of the simulation and analysis software. Various key facets and algorithms relating to the first two phases are described in the following subsections, while the last two phases are demonstrated in the subsequent case studies. Figure 34 presents a high-level overview of the flow of information in the methodology. Many of the algorithms and much of the software generated in phases two through four are reusable in subsequent simulations of different construction and deconstruction activities. It is anticipated that over time, a library of algorithms and functions would emerge and evolve into a flexible construction activity VR planning and analysis environment.

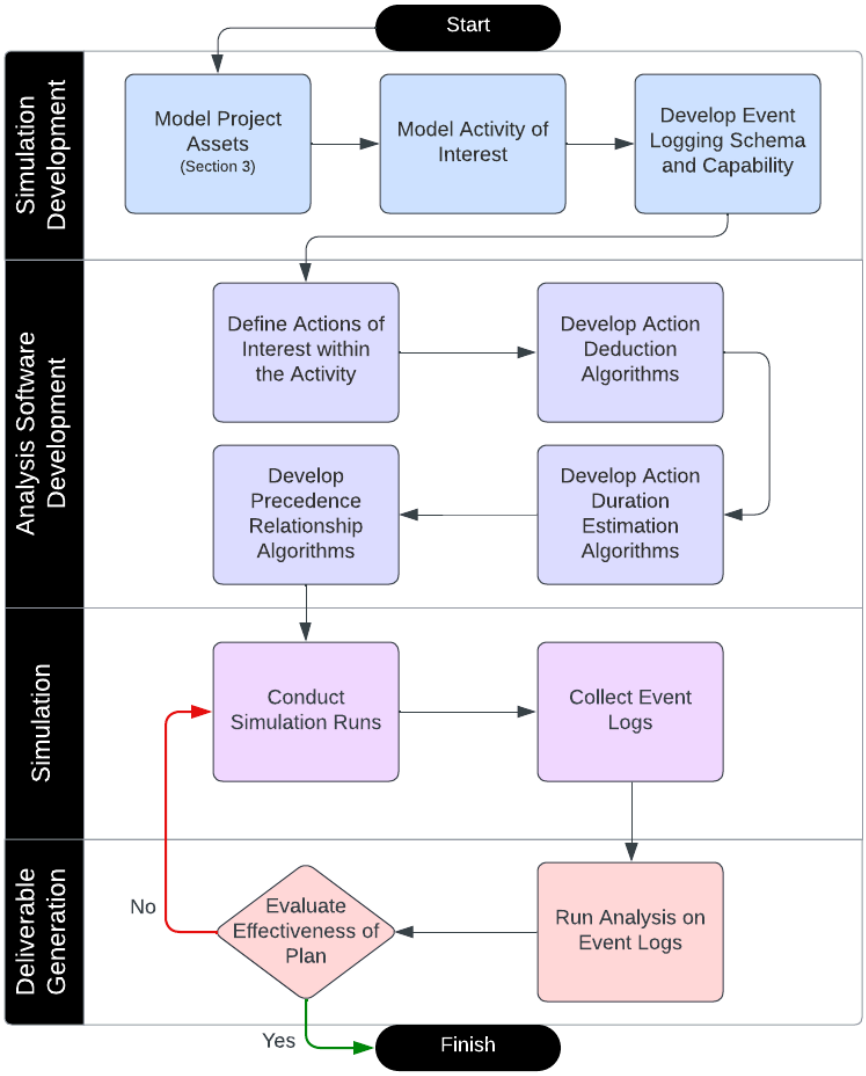


Figure 34. Schedule Generation Methodology Overview

5.2.1. Simulation Development

The first phase of the proposed methodology is Simulation Development, encompassing project asset modeling, action modeling, and event log capability development.

Project asset modeling involves developing a 3D model of the project area for simulation in the chosen game engine. CAD and BIM models can be used to create VR simulations, ensuring smooth integration into existing workflows. Most modeling software can export digital construction site models in the Polygon File Format (.PLY),

compatible with game engines. These engines support VR features, physics simulations, and multi-user capabilities, allowing the development of flexible simulations tailored to planning needs.

A game engine can track the global position of each model component at a high frame rate. The innovation in this approach lies in systematically recording the VR user's interactions—capturing the position, orientation, and time-related data for each component during user interactions. This information is exported into a comprehensive list for further analysis and simulation.

The event logging methodology in the VR environment captures a detailed record of the user’s interactions. This process is crucial for translating dynamic VR planning simulations into actionable data for construction planning and management. By recording relevant events, including object manipulation and user movements, the system creates an event dataset from which construction-centric actions can be deduced and analyzed.

Event logging in the VR system is structured to capture several critical pieces of information for each interaction that occurs within the simulation. For example, this can include:

- Event Type: A descriptor of the nature of the event, such as "GameObject Added," "GameObject Picked Up," or "GameObject Let Go." This classification enables the identification of specific types of interactions, facilitating a more structured analysis of user behavior within the simulation, and eventually leads to the deduction of construction-centric actions as described in section 5.2.2. Similarly, the process for defining the set of event types required by a specific construction activity simulation is further discussed in section 5.2.2. The demonstrations presented in sections 5.3 and 5.4 further illustrate the procedure of defining and modeling a set of event types.
- Object Details: Detailed information about the object involved in the event, including:

- Name: The identifier of the object, often detailed enough to specify the type of construction element (e.g., mechanical equipment, structural components).
- Position: The coordinates of the object within the VR environment at the time of the event, providing spatial context for the interaction.
- Rotation: The orientation of the object, represented as a quaternion or Euler angles, capturing the object's alignment within the virtual space.

- Timestamp: The precise moment an event occurs, down to the millisecond. This granularity allows for the sequencing of events and understanding the temporal relationship between different actions within the planning process.
- Supporting Screenshots: Images captured by the VR engine that depict the action, which can be taken from various angles as needed. The screenshots can accompany downstream deliverables to assist in team communication.

Figure 35 depicts an example of 2 logs from an event log with a data structure that was designed to support the case study further described in section 5.3.


```
{
  "Timestamp": "2024-06-11 17:27:17",
  "EventType": "GameObject Picked Up",
  "ObjectDetails": {
    "Name": "Left Custom Plate North Side",
    "Position": "(-18.41, 2.67, -4.90)",
    "Rotation": "(-18.41, 2.67, -4.90)",
    "Scale": "(1.00, 1.00, 1.00)"
  }
},
{
  "Timestamp": "2024-06-11 17:27:32",
  "EventType": "GameObject Let Go",
  "ObjectDetails": {
    "Name": "Left Custom Plate North Side",
    "Position": "(7.96, 2.87, -1.42)",
    "Rotation": "(7.96, 2.87, -1.42)",
    "Scale": "(1.00, 1.00, 1.00)"
  }
}
```


Figure 35. Deconstruction simulation event log data structure example

This structured approach to event logging not only captures the discrete actions taken by users but also records the spatial and temporal context of these actions. Such detailed data collection is pivotal for several reasons:

- Analyzing User Behavior: Understanding how users interact with virtual objects and navigate the VR environment can offer insights into planning preferences and potential efficiencies or bottlenecks in the planning process. For example, a team could use detailed movement path data captured by the event log to visualize and identify inefficiencies in the resulting plan.
- Action Deduction: By analyzing patterns and sequences of events, it is possible to deduce specific construction-centric actions, such as the movement of equipment. This deduction process is crucial for translating virtual events into meaningful planning actions, which is discussed in detail in section 5.2.2.
- Schedule Generation: The detailed event logs serve as the input for algorithms designed to generate construction schedules. The timestamp and sequence of events allow for the establishment of precedence relationships (section 5.2.3), while the spatial information aids in optimizing the layout and logistics of construction actions.
- Repeatability and Risk Mitigation: Capturing detailed logs of VR interactions facilitates the repeatability of planning exercises and the identification of potential risks in project execution. By reviewing and analyzing these logs, planners can refine their strategies and approaches to mitigate identified risks before ground is broken. For example, the supporting screenshots captured alongside the event log data could be inspected by a construction safety expert to visually identify risks in the proposed plan. Details in the event log data such as timestamp allow the safety expert to communicate back to the planning team the exact moments that the plan deviates from safety standards.

5.2.2. Action Deduction

In the proposed methodology, “action deduction" is defined as the process of translating events, or the user’s low-level simulation interactions, into recognizable construction-centric actions. This process occurs at a higher level of abstraction than the granular event logs, as it seeks to identify and categorize the occurrence of a coherent action relevant to construction from the occurrence of one or more simulation events. Actions require the context of one or more events to be fully described and understood, necessitating a deduction process to recover action data from event logs.

The methodology for deducing actions from the event log hinges on the premise that actions represent a structured sequence of events that, together, signify a meaningful action within the construction planning process. For example, moving an object, a common action in construction planning, is somewhat trivial to deduce in the VR environment, however it exemplifies the deduction process. A “move” action encompasses a sequence of events: the object's initial pickup, the potential movement or manipulation of the user while the object is held, and the final action of releasing the object at a new position and orientation. The object could be a brick, a pipe spool, or any other construction object, and the lifter could be a worker or a piece of equipment. This sequence of events, when viewed together through the lens of action deduction, constitutes an action, reflective of the planner's intention to reposition a construction object (or element) within the project layout.

The action deduction process starts by defining a “template” or event sequence pattern for each action that is present in the activity of interest and that the planner wishes to represent in the plan. Together, these templates and the recorded event log form premises by which deductive reasoning is applied to make sound conclusions about the occurrence of actions. In practice, action templates are implemented in software, as demonstrated in sections 5.3 and 5.4. However, for illustrative purposes, the following hypothetical example verbally demonstrates the action deduction process:

> “An object-move action is defined as the occurrence of the following temporal event sequence without interruptions: 1) a single object-grab event, 2) an arbitrary number of non-interrupted user movement events, and 3) a single object-release event of the grabbed object. The recorded event log contains the following sequence: one object-grab event immediately followed by three user movement events immediately followed by an object-release event of the originally grabbed object. Therefore, an object move action occurred.”

In order to systematically perform this action deduction process, the methodology employs a stateful pattern detection approach. The approach is stateful, because the event log is processed iteratively in temporal order, and while a sequence of events continues to match a template, the sequence is stored in approach’s state (Gamma et al, 1994). The approach’s state consists of a stack data structure (Cormen et al, 1989) for each action template defined in the activity.

First, the action templates for the current activity must be defined. Each template has an event type that initiates it, one or more event types that occur within its duration, and event types that conclude it. Next, the event log is iterated through in temporal order. For each event, the action templates are iterated through in an arbitrary order. The following conditional logic is applied to each event and action template in order to perform pattern detection:

1. If the event’s type matches the initiating event type for the template, the templates’ stack is emptied and the event is stored as the new first element of the stack.

2. If the event’s type matches an intermediary event type for the templates, and the template’s stack is not empty, the event is added to the stack. The template may also define additional logic based on other event details to condition whether events are added to the stack. For example, a template may define that an intermediary event must have the same affected object as the initiating event of the stack to be added.

3. If the event's type matches the concluding event type for the template, and the template's stack contains the requisite preceding events, the event is added to the stack. The completed stack is analyzed to confirm that it sufficiently fulfills the action template. If so, the occurrence of an action is deduced. All of the events in the stack are used together to determine the resulting action's metadata such as its precedence relationships and duration estimate. The determination of these parameters is the central discussion of sections 5.2.3 and 5.2.4. The action is added to the action log for downstream processing. Following the detection of a concluding event, the stack for the template is reset regardless of a valid action detection.

For example, consider the case of designing a template to detect the action of moving a construction material. The template's initiating event is an object being picked up. Intermediary events describing user movement are stored during the duration of the action. The completion of the template is signified by an event describing the object being released. At the time of completion, a move action can be described in detail as a function of all of the composing events. The net displacement of the object can be observed by the change in the object position between the initiating grab event and the concluding release event. On the other hand, the object's complete path of movement can be found by tracking the user's position throughout the intermediary user movement events.

It is noted that for event types that occur in the middle or end of an action template (conditions 2 and 3), if the expected prior events are not found in the template's stack, it is concluded an action matching the template did not occur, and nothing is done. This does not necessarily represent an error, as events may reasonably occur in isolation, and not exclusively in the context of an action template. Take for instance, user movement in the context of the construction material movement example above. User movement events while a move action is ongoing are relevant to the current move action, and user movements while a move action is not ongoing are not relevant to any move action. The presence of an object grab event in the first

position of the template's stack signifies whether a move action is ongoing, and whether storing the user's movements is needed.

Once the occurrence of an action is deduced, the temporal sequence of events, the spatial relationships between objects, and the contextual significance of the events can be used to infer key insights about the action. The deduced actions can be enriched with metadata, such as the start and end positions of moved objects, the duration of actions based on the movement distance or complexity of the task, and dependencies between actions. The metadata needed for each action template is defined by the project team. The demonstrations in section 5.3 and 5.4 provide examples of action definitions, including templates and metadata. This metadata is crucial for translating the virtual planning experience into actionable project deliverables, ensuring that the generated schedules are not only comprehensive but also deeply rooted in the practicalities and nuances of construction project management.

Pseudocode 1 depicts an example action deduction script that includes "move" and "slice" events. The variables initialized in the first statement implement the stateful approach described. The functions "newSliceAction" and "newMoveAction" represent the process of inferring additional insights about the action by comparing the details of the events that compose the action, which are described in more detail in sections 5.2.3. and 5.2.4.

```
initialize moveStack;
initialize sliceStack;
initialize actions;

foreach event in log {
    if event has type "GameObject Picked Up" {
        reset moveStack;
        moveStack.push(event);
    }

    if event has type "User Movement" {
        if (length of moveStack > 0) {
            moveStack.push(event);
        }
    }
```

```
    if event has type "GameObject Let Go" {
        if (length of moveStack > 0) {
            moveStack.push(event);
            action = newMoveAction(moveStack);
            if (action is valid) actions.push(action);
        }
        reset moveStack;
    }

    if event has type "GameObject Removed" {
        reset sliceStack;
        sliceStack.push(event);
    }

    if event has type "GameObject Added" {
        if (length of sliceStack > 0) {
            sliceStack.push(event);
            action = newSliceAction(sliceStack);
            if (action is valid) actions.push(action);
        }
        reset sliceStack;
    }
}
```

Pseudocode 1. Stateful algorithm for the detection of move and slice actions

Since each event is considered only once, and the conditional logic applied is relatively simple, the computational power required is minimal, as verified in the subsequent case studies. Regarding the robustness of sorting the event log in temporal order, the edge case of two events having the same timestamp can not occur, as the creation of an event is an atomic event within the context of the program architecture of event-based game engines.

One key premise of the proposed action deduction process, is that within the same framework, different deduction behaviors can be achieved as desired. Depending on the specific event types, action templates, and action deduction algorithm implemented by a project team, various aspects of the nature of the relationship between events and actions can be controlled. These factors influence:

- The ability to detect actions that occurred simultaneously
- The ability for one event to be included in more than one action
- The ability for one event to potentially initiate an action, while continuing another

Action deduction serves as the bridge between the detailed event logs generated by user interactions in VR and the recognizable actions that guide construction activity planning. By abstracting these logs into identifiable and meaningful actions, the methodology provides a robust framework to understand the VR user's actions in terms of recognizable, construction-centric actions.

This approach creates a tractable, robust, and scalable way to detect complex action types using predefined templates. The stateful nature of the approach creates robustness, because it is resistant to irrelevant or erroneous events emitted between related events. In addition, the stateful approach can be utilized in real time or after the fact, as it processes events sequentially, so knowledge of future events is not required to process each event. This property could be utilized to demonstrate the evolution of the critical path schedule to the VR user in real time as they interact with the simulation, however this capability was not implemented in the scope of this study.

5.2.3. Inferring Precedence Relationship

The deduction of actions from the VR event logs, as outlined in the previous section, forms the foundation for one of the most critical aspects of critical path planning: inferring precedence relationships among actions. Precedence relationships are vital for understanding the sequence in which construction actions must occur, which directly informs the creation of a project's schedule. This section delves into how these relationships are determined from the deduced actions, ensuring that the automated schedule generation reflects the logical and necessary order of construction tasks.

In the context of the methodology, precedence relationships are inferred based on the temporal and spatial dependencies captured through VR interactions. These relationships articulate the necessity for certain actions to precede others, a fundamental principle in construction planning that ensures the efficient and logical progression of the project. The inference process leverages the metadata associated

with each deduced action, including timestamps, spatial configurations, and the specific sequence of events leading to each action's identification.

Using the action deduction framework, each action is analyzed to identify dependencies that signal precedence relations. For example, if an action involves moving an object to a location where another object will subsequently be placed, the moving action must logically precede the placing action. These relationships are not merely based on the chronological order of events but also consider the spatial and functional interdependencies between actions, reflecting the complex dynamics of construction planning.

The process of inferring these relationships is algorithmically supported by examining the objects of interest within each action's metadata, as demonstrated in the code snippet provided. These fields point to the specific simulation objects that were involved in a given action, either directly or indirectly. Direct dependencies may involve physical interactions, such as the need to remove a floor panel before the supporting beam that supports it. Indirect dependencies might stem from safety or accessibility considerations, necessitating the completion of certain tasks before others can safely or practically commence.

It is the role of the construction experts on the project team to determine the conditional logic by which precedence relationships are formed, and it is the role of the programmer to implement these conditions. Therefore, the process for inferring precedence relationships is not physically verifiable, but rather contextual and rule-based. Future work can include the creation of a library of rules that are common to many or all projects. For example, no matter the project, a move action should be dependent on a preceding move action of the same object. Other rules are project specific.

Pseudocode 2 depicts an example precedence relationship script. The script infers the precedence relationships for a “newAction” before it is added to the graph of actions after it has been detected. In this simple example, there are “move” and “slice” actions. Slice actions obtain dependencies from prior actions that created the object

being sliced. Move actions can obtain dependencies in two ways: 1) if the object was moved previously and 2) if the object is colocated close to another object that was moved into its current position. “Epsilon” is provided as an argument that controls the maximum radius around objects to form colocation dependencies. An approach like this could be used to create precedence for objects placed upon other objects in a waste packing container for example (or stacking of masonry units). Overall, the pseudocode provided is one example of the modular nature of the proposed precedence relationship inference process.

```
argument: newAction; // object describing new event of interest
argument: priorActions; // array, with priorActions based on Pseudocode 1
argument: epsilon; // max space between objects for a colocation dependency
initialize currentObject, priorObject;
initialize dependencies; // array to store discovered dependencies

if newAction has type "move" {
    currentObject = newAction.movedObject;
}

if newAction has type "slice" {
    currentObject = newAction.slicedObject;
}

foreach priorAction in priorActions {
    if priorAction has type "move" {
        priorObject = priorAction.movedObject;

        if currentObject equals priorObject {
            dependencies.append(priorAction);
            continue;
        }
        if currentObject.position - priorObject.position < epsilon {
            dependencies.append(priorAction);
            continue;
        }
    }

    if priorAction has type "slice" {
        priorObject = priorAction.slicedObject;

        if currentObject equals priorObject {
            dependencies.append(priorAction);
            continue;
        }
    }
}
```

Pseudocode 2. Precedence relationship inference algorithm

By systematically analyzing these dependencies, the methodology effectively constructs a directed acyclic graph where nodes represent actions, and edges represent the precedence relationships between them. This graph serves as the backbone for the automated generation of the critical path schedule, highlighting the most efficient sequence of tasks that minimizes project duration while adhering to all identified constraints.

Moreover, this inferred network of precedence relationships facilitates the identification of parallelizable tasks, enabling more sophisticated scheduling strategies that optimize the use of resources and time. For instance, actions that do not share direct or indirect dependencies may be performed concurrently, reducing the overall project timeline. In practice, for final derivation of executable realistic schedules, resource constraints (such as the availability of a single piece of lifting equipment) and the judgment of construction experts would be included to revise and edit the derived schedule.

5.2.4. Estimating Action Duration

Estimating the duration of construction actions is a critical component of project scheduling, impacting resource allocation, budgeting, and timeline development. This section introduces a flexible approach for action duration estimation derived from VR simulation event logs.

It is crucial to clarify that the duration estimates derived from this approach are intended to reflect the real-world durations of construction actions, rather than their execution time within the VR simulation. This distinction ensures that the planning outcomes from the VR environment are fully applicable and relevant to real-world construction project management.

The basis of the approach is to design a duration estimation function for each action type of interest in the activity that uses relevant information from the action's associated events to estimate its real-world duration. In other words, a duration

estimation function is defined as a function that predicts the real-world equivalent duration of an action performed in a VR construction simulation, given its associated events. The form of an action duration estimation function is expressed in Equation 1.

$$Duration\ Estimate\ For\ an\ Action\ of\ Type\ T\ = F_T(E_1, E_2, \dots, E_n) \quad (1)$$

Duration estimation functions leverage data and expert knowledge through their design, and they leverage detailed information captured in event logs through their inputs. As such, even for each action detected from the same template, a unique duration may be estimated, since each action consists of a unique set of events. Due to the vast differences inherent between construction projects, duration estimation functions must be defined specifically for each project in order to generate schedules that reasonably predict real-world early finish times. Therefore, the exact definitions are the responsibility of the user of the methodology. The following guidelines and insights are proposed in order to structure the definition process:

- The first step to defining a duration estimation function is to analyze the action of interest to identify the information with the strongest correlation to the action duration. Similarly, an understanding of the nature of each correlation, such as if it is generally linear or exponential is required. For example, for a movement action, it is reasonable that the length of the path of movement will vary linearly with the duration, with a bias term for picking up and setting down the object.
- The level of precision required by the planning effort as a whole dictates the depth of analysis that is required for the duration estimation function.
    - For example, if precision is unimportant, a constant value can be assigned to each action type, and the variation between actions can be assumed to average out.
    - If precision is somewhat important, the single parameter that is likely to have the greatest correlation on the estimate can be studied, such as the linear effect of the path distance on movement action duration as discussed above. Hyperparameters of the estimation functions, such as

coefficients, should be grounded in real-world metrics like data, standards, or expert judgment allowing for a realistic and project-specific estimation. For example, in conventional estimating, travel time estimates for hauling vehicles depend on distance to dump site and average speed expected.

    - As precision requirements increase, more terms can be added to the estimation function in order of their predicted level of correlation with the duration outcome. For example, in the object movement example above, it is reasonable that the weight of the object is the parameter with the next greatest correlation.

    - If precision is paramount, data can be used to computationally optimize a model for duration estimation, ranging in complexity from least-squares regression to training a neural network, depending on the project needs.

- The process of designing the duration estimation functions should be coupled with the process of generating the schema of the event logs, as defined in section 5.2.1, in order to ensure that the information used by the function is captured robustly at the time of simulation. For example, if estimating the duration of cutting an object, it is reasonable that the area of the cross section of the cut will correlate with the action duration. Therefore, the geometry of the object post-slice should be captured within the events of the slice action, to capture the resulting cross section of the cut. Similarly, if it is determined that the material type being cut or the tool being used is an integral factor of the estimation function, it should be captured in the event logs.

- Practical examples of defining action duration estimation functions are provided in the case studies presented in sections 5.3. and 5.4.

The event logs captured in the VR simulations are stored persistently, enabling both live, real-time analysis and post-facto evaluations where more complex computational analysis might be necessary. This dual capability supports immediate

feedback during planning sessions in VR, as well as deeper, more strategic analysis once the simulation is complete. The flexibility to re-analyze the event log with different estimation algorithms post-simulation allows project teams to explore various scenarios and their implications on project timelines and resource needs.

This approach is designed to accommodate a hot-swappable approach to duration estimation algorithms, allowing for a dynamic analysis based on the nature of the events and actions deduced from the VR environment. This adaptability is crucial for tailoring the estimation process to the specific requirements and nuances of each construction project. A key advantage of an approach with hot-swappable algorithms is the capacity for project teams to engage in detailed "what-if" analyses regarding the estimation techniques themselves. By applying different estimation algorithms to the same set of actions, teams can explore various hypotheses about action durations. For instance, they might consider the impact of assigning a constant time to all slicing tasks versus estimating durations proportional to the surface area of a slice versus incorporating material type into duration estimates. This level of analysis not only enhances the accuracy of schedule predictions but also provides valuable insights into potential efficiencies and bottlenecks within the project plan.

Overall, by enabling project teams to design and utilize bespoke estimation techniques, the methodology offers precision and adaptability in project scheduling. This not only improves the reliability of project timelines but also empowers teams to optimize their planning strategies based on detailed, simulation-derived insights and expert knowledge as needed. The flexibility of the estimation framework allows project teams to incorporate as many real-world factors as necessary, from the weight of the objects moved to the material properties of elements being sliced, ensuring that the estimated durations are both accurate and practically applicable.

5.3. Case Study 1 - Machine Cutting and Packing

This section presents the first demonstration of the proposed methodology, implemented within the Unity platform. This demonstration serves as a practical

illustration of the methodology previously described, showcasing its application and validating its effectiveness in facilitating construction project planning.

Following the structured approach of the research methodology, this demonstration serves as both a validation of the innovative VR planning process and an exploration of its generalizability across different project scenarios. The demonstration provides a concrete example of how user interactions within a VR simulation can automatically generate project schedules. This implementation phase is crucial for demonstrating the efficacy of the VR-based planning process in producing comprehensive critical path schedules without manual intervention, as hypothesized in the research methodology.

The demonstration is developed in the Unity engine, chosen for its robust support for VR development and its capacity to simulate complex environments and interactions. While the specific implementation details are tailored to Unity, the underlying principles and processes are designed to be generalizable, highlighting the methodology's applicability across various VR platforms and construction planning scenarios.

The Unity demonstration encompasses the creation of a virtual deconstruction site, where users can interact with a variety of objects and elements reflective of a real-world project. This interactive environment is equipped with mechanisms for capturing user actions as event logs, which serve as the basis for action deduction and schedule generation. The demonstration includes the completion of the four main phases defined in Section 5.2 and depicted in Figure 34:

- **Simulation Development:** The demonstration begins with the setup of the virtual construction site, involving the modeling of project assets and the activity of interest. This phase also includes the development of the event logging schema and capability, ensuring that all possible user interactions, object positions, and timestamps are accurately captured within the VR environment.

- **Analysis Software Development:** Next, the focus shifts to the development of software for analyzing the event logs. This involves defining the

construction-centric actions of interest, developing algorithms for action deduction, estimating action durations, and establishing precedence relationships between actions based on the event data.

- **Simulation:** With the VR environment and analysis tools in place, multiple simulation runs are conducted, during which event logs are collected. These simulations capture real-time user interactions, providing the raw data needed for subsequent analysis and schedule generation.
- **Deliverable Generation:** Finally, the collected event logs are processed using the analysis software to automatically generate a critical path schedule. The effectiveness of the generated plan is evaluated, with the option to refine and rerun the simulations if necessary to optimize the planning outcomes.

5.3.1. Demonstration Background and Motivation

A machine cutting and packing disassembly task is used for the demonstration. Deconstruction is the methodical dismantling of structures to maximize the reuse and recycling of materials, distinguishing itself from traditional demolition by prioritizing the preservation of materials for future use. This approach is increasingly relevant due to the construction industry's shift towards sustainability and the circular economy, where reducing waste and recovering resources are paramount. Deconstruction projects underscore the importance of this method, offering complex scenarios that require meticulous planning and execution due to their intricate action dependencies and the high stakes involved in handling hazardous materials safely.

The focus on deconstruction for the demonstration is twofold. Firstly, it reflects a commitment to exploring sustainable practices within the construction industry. With the increasing global emphasis on sustainability, deconstruction presents a viable, eco-friendly alternative to demolition, reducing the environmental impact of construction projects. This aligns with broader industry and societal shifts towards sustainable development goals, making it a timely and relevant area of study. Secondly,

deconstruction projects, such as nuclear decommissioning, where traditional demolition is not feasible due to safety concerns or environmental risks, present unique challenges.

Deconstruction, particularly in complex settings like nuclear decommissioning, involves intricate action dependencies that must be carefully managed to ensure safety and efficiency. Each step in the deconstruction process can have significant implications for subsequent actions. For example, the removal of structural supports must be carefully sequenced to prevent unintended collapse, and hazardous materials must be handled and disposed of in compliance with strict regulatory standards. These dependencies make deconstruction an excellent case study for demonstrating the effectiveness of VR-based planning. Through VR simulations, planners can visualize and manipulate the deconstruction sequence in a risk-free environment, allowing for the identification and planning of critical paths and dependencies with unprecedented precision.

5.3.2. Demonstration Results

This section presents the results of the implementation and demonstration of the VR-based deconstruction planning methodology, focusing on the event logging in Unity, the analysis of these logs through Python code, and the subsequent schedule generation. The following permanent link leads to a video of the demonstration task being completed to verify the results. https://youtu.be/wZ3tNuM8dhM

The showcased room serves as a sample scenario, using models created in Autodesk Revit, depicted in Figure 36 below. In this virtual setting, the VR user has two basic interaction options. They can grab and move any element in the model or use a "cutting" tool resembling a saw to slice through objects, depicted in Figure 37. The simulation includes collision detection to give feedback on when there's enough space to remove a piece. The task for the VR user is to efficiently remove mechanical equipment from the room. In this initial demo, highly specific rules for interacting with components aren’t specified; for example, there's no requirement to remove bolts before

moving a lid, though that might be added in the future. The strength of VR lies in its ability to let users manipulate virtual environments in a straightforward and realistic way, making it easy to explore planning options step by step. Moreover, the 1:1 perspective and immersive nature of VR could improve decision-making in sequencing. The demo aims to show how experienced planners with minimal VR training can experiment in the simulation and find a practical solution for a disassembly task. To enhance this, the methodology uses a script to track the VR user's hand movements, updating a list whenever they grab, release, or cut a model component. This list also includes additional information like the global position, offering a detailed record of the user's interactions in the virtual space.

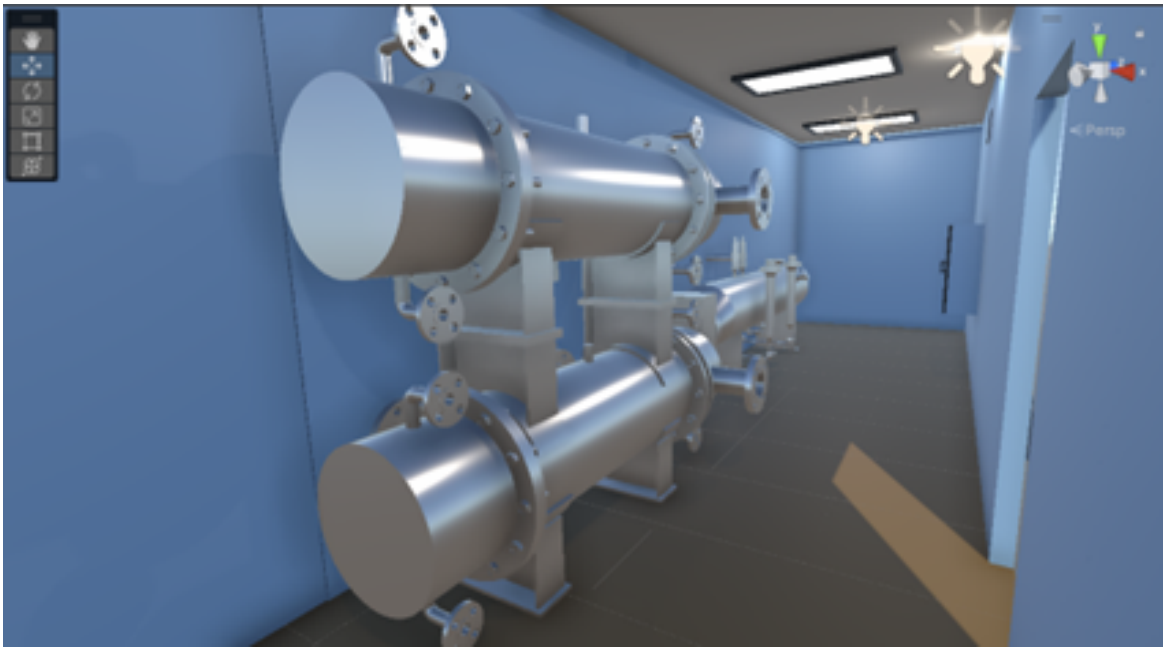


Figure 36: Industrial room developed for demonstration

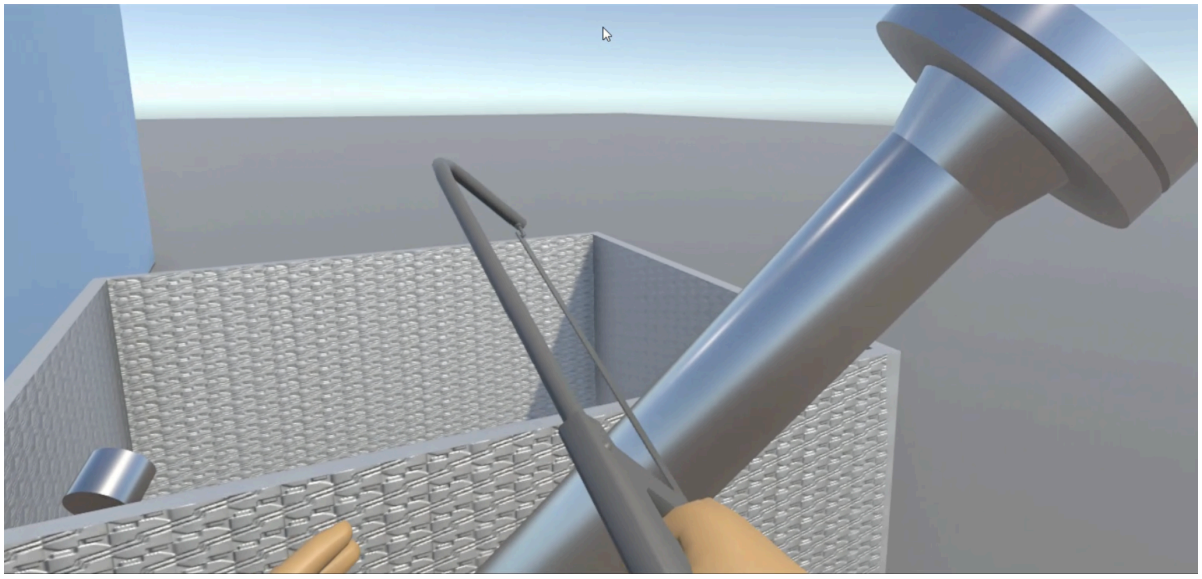


Figure 37: Screenshot of the Unity interface during an event logging session

Following the simulation run, all events that the user conducted are logged to a JSON file for further analysis, as depicted in Figure 38. This step bridges the gap between data capture in Unity and data processing in Python.


```
{
    "Timestamp": "2024-02-06 11:59:05",
    "EventType": "GameObject Added",
    "ObjectDetails": {
        "Name": "Mechanical_Equipment__HVAC_Other_Chromalox_MVSGI-High-Capacity-Steam-Generator__Not_a_Type_-_Load_Type_Catalog!__326873:19_0",
        "Position": "(71.08, 1.53, 22.63)",
        "Rotation": "(0.00000, 0.00000, 0.00000, 1.00000)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
},
{
    "Timestamp": "2024-02-06 11:59:05",
    "EventType": "GameObject Added",
    "ObjectDetails": {
        "Name": "Mechanical_Equipment__HVAC_Other_Chromalox_MVSGI-High-Capacity-Steam-Generator__Not_a_Type_-_Load_Type_Catalog!__326873:19_1",
        "Position": "(70.48, 1.43, 22.71)",
        "Rotation": "(0.00000, 0.00000, 0.00000, 1.00000)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
},
{
    "Timestamp": "2024-02-06 11:59:06",
    "EventType": "GameObject Removed",
    "ObjectDetails": {
        "Name": "Mechanical_Equipment__HVAC_Other_Chromalox_MVSGI-High-Capacity-Steam-Generator__Not_a_Type_-_Load_Type_Catalog!__326873:19",
        "Position": "(68.73, 4.48, 17.58)",
        "Rotation": "(-0.04842, 0.74603, 0.04625, 0.66254)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
},
```


Figure 38: Simulation run event log JSON file excerpt

The analysis phase was conducted using Python, where custom scripts were developed to parse the JSON logs, with a snippet depicted in Figure 39, deduce actions from the sequences of events, and infer precedence relationships essential for schedule generation.

```python
# create and analyze the activity plan using our ActivityPlan class
myPlan = ActivityPlan('./LogFile 1.json')

print ("Activity\t", "Duration\t", "Dependencies\t\t", "Description\t")

counter = 0
for activity in myPlan.activities:
    print(activity["_id"], "\t\t", activity["duration"], "\t\t", activity["dependencies"], "\t\t\t", activity["description"])
    counter += 1
```

Figure 39: Automated schedule generation Python code snippet

The culmination of the demonstration was the generation of a critical path schedule based on the analysis of the VR event logs. First, the list of deconstruction actions that were detected based on analysis of the detailed event log is depicted in Table 5, including their estimated durations and deduced dependencies.

Table 5: Case study 1 deduced actions with duration estimates and dependencies

Action	Duration	Predecessors	Label
A	3.6	[]	Move "Mechanical_Equipment_36"
B	4	[]	Move "Mechanical_Equipment_20"
C	2	['B']	Slice "Mechanical_Equipment_20"
D	1.4	['C']	Move "Mechanical_Equipment_20_1"
E	1.9	['C']	Move "Mechanical_Equipment_20_0"
F	0.3	[]	Move "Mechanical_Equipment_19"
G	4.5	[]	Move "Mechanical_Equipment_35"
H	7.7	['F']	Move "Mechanical_Equipment_19"
I	2	['H']	Slice "Mechanical_Equipment_19"
J	2.2	['I']	Move "Mechanical_Equipment_19_0"

K	0.9	['I']	Move "Mechanical_Equipment_19_1"

Next, an activity on node representation of the critical path for the activity list is presented in Figure 40.

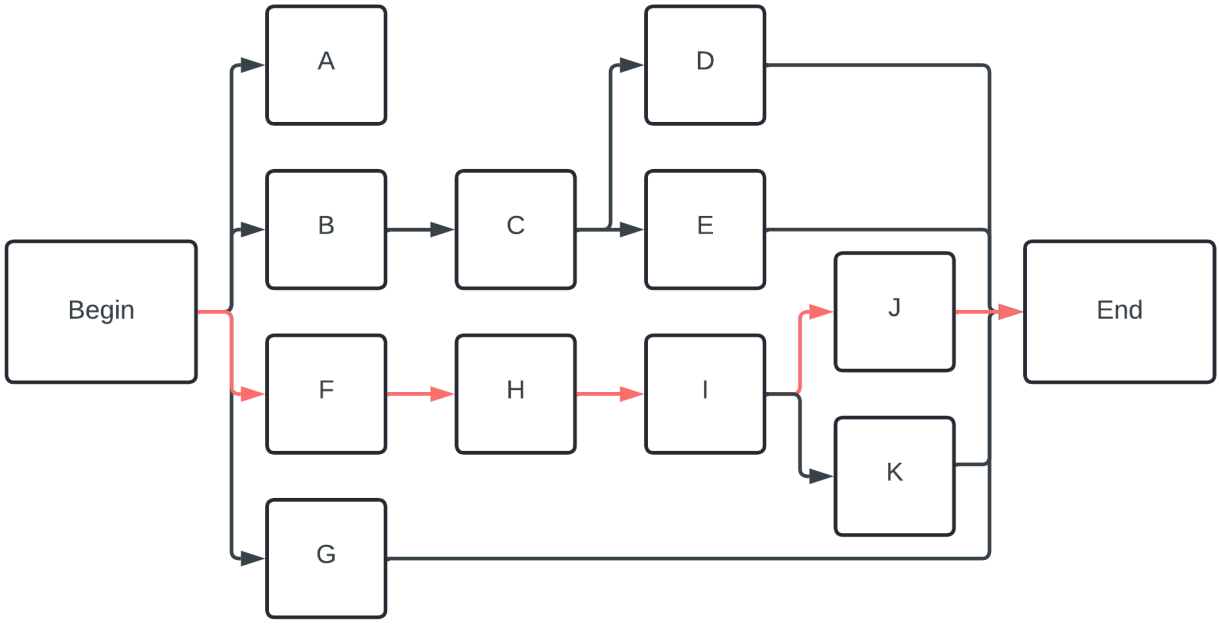


Figure 40: Case study 1 critical path activity on node representation

Finally, all of the information depicted, including the detected actions, corresponding real-world duration estimates, and dependency relationships is assembled into a Gantt chart representation of the critical path using the automated method, and presented in Figure 41.

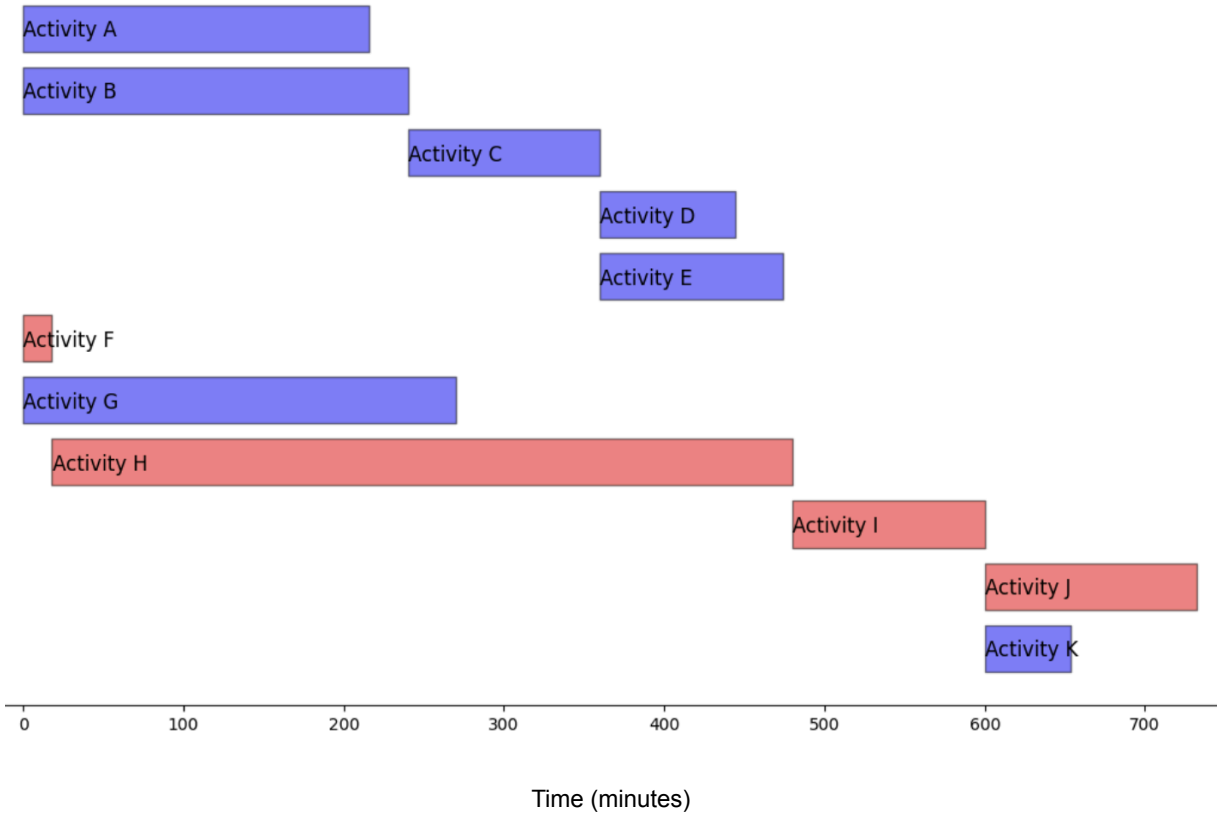


Figure 41: Case study 1 automated critical path Gantt chart representation

The automated CPM schedule demonstrates that the critical path is Actions F, H, I, and J. Verifying the deduced actions against the video recording of the simulation run, the automated approach correctly identifies all action occurrences and their dependencies. The discussion of the results of the both case studies is presented together in section 5.5, following the presentation of the methodology and results of the second case study in section 5.4. The complete code utilized in case study 1 is presented in Appendix B.

5.4. Case Study 2 - Nuclear Reactor Decommissioning

The second demonstration expands the demonstration of the methodology to a more complex deconstruction task: dismantling a large portion of a reactor core based on the Canada Deuterium Uranium (CANDU) design. This task utilizes a detailed 3D

model of Ontario Power Generation's (OPG) Darlington mockup facility in Ontario, Canada, within a VR environment. The Darlington mockup facility's mock react face is depicted in Figure 42. This case study is designed to validate the methodology in a context that demands higher levels of coordination and precision due to the increased complexity and scale of nuclear decommissioning projects.

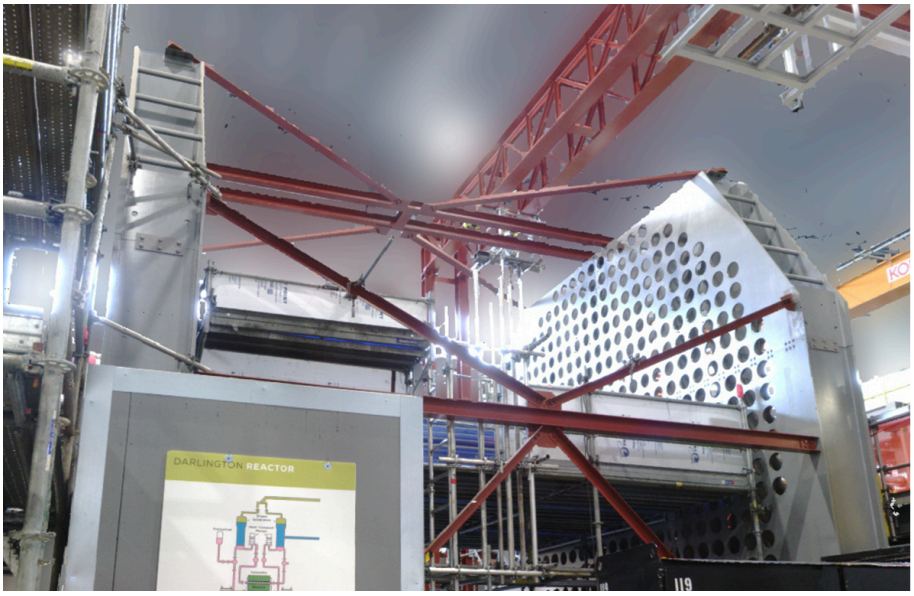


Figure 42: A photograph of the mock reactor core in OPG's Darlington training facility

5.4.1. Demonstration Background and Motivation

The deconstruction of a nuclear reactor involves unique challenges not present in smaller-scale projects. This demonstration requires the VR operator to plan and execute the disassembly of reactor components, addressing additional tasks such as the creation of temporary bracing and access points. For real-world execution, access points are facilitated using equipment such as person-lifts, scissor lifts, and scaffolding, however the capability is partially abstracted to streamline exploration and evaluation of diverse plan options in the VR environment. Similarly, object manipulation is abstracted to some extent in the VR environment and is done based on the judgment of experienced planners in practice with lifting equipment, robotic arms, and other equipment. For this demonstration, planning is not constrained by specific tool choice

(the expert planner using the VR environment may certainly have one in mind), however it is quite possible to import specific tools in a VR environment on a case-by-case basis. The complexity of these tasks, involving multiple interdependent actions, highlights the necessity for advanced planning tools. VR provides an ideal platform for this, allowing for detailed visualization and manipulation of the deconstruction sequence in a controlled, partially abstracted, risk-free setting.

In this demonstration, the VR-based methodology is tested under conditions that simulate the high-stakes environment of nuclear decommissioning. The operator must safely dismantle reactor components, ensuring compliance with strict regulatory standards for hazardous material handling and structural integrity. By capturing the operator's actions and automatically generating a critical path schedule, this demonstration showcases the effectiveness of VR in managing complex deconstruction processes.

Additionally, this case study incorporates new event types to capture the added complexity of the task. Beyond the "move" and "slice" events used in the first demonstration, the VR environment now includes events for creating temporary bracing for portions of the asset that need support as they are dismantled. It also features events for erecting temporary scaffolding or utilizing motorized equipment to access high areas. These new event types reflect the real-world intricacies of deconstructing large and complex structures like a nuclear reactor.

This case study illustrates the scalability of the VR methodology, showing its applicability to larger, more intricate projects. The use of the CANDU reactor model underscores the method's capacity to handle detailed planning and execution tasks in highly regulated environments. The generated schedules are meticulously compared against the VR operator's actions to validate the accuracy and reliability of the proposed approach. This second demonstration reinforces the value of VR in deconstruction planning, particularly for large-scale projects requiring intricate coordination and precision.

5.4.2. Results

The following permanent link leads to a video of the demonstration task being completed to verify the results. https://youtu.be/um0xTgwslQc

The simulation environment for the second demonstration was meticulously created through a detailed scanning process of Ontario Power Generation's (OPG) Darlington mockup facility. Utilizing a TLS, multiple scans were conducted to capture comprehensive and high-resolution data of the facility. These scans were then integrated to form a large-scale, dense, colorized point cloud. The use of TLS ensured precise and accurate data collection, capturing the intricate details and spatial relationships of the facility's components. The dense scan is represented in Figure 43.

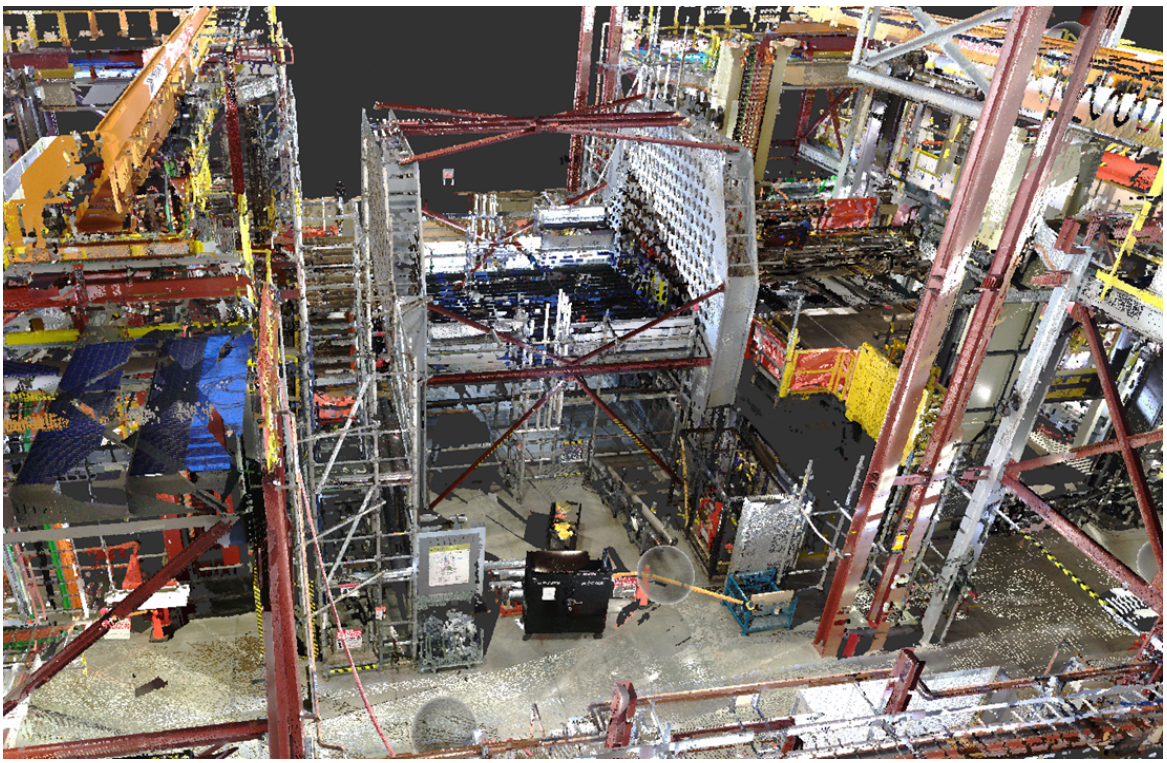


Figure 43: Screenshot of the dense point-cloud reconstruction of the training facility

Following the creation of the point cloud, the data was processed to generate a mesh, providing a continuous surface representation of the scanned environment. This

mesh was then imported into Autodesk Revit, where a manual scan-to-BIM process was performed. By leveraging Revit's mesh overlay feature, BIM elements were visually matched and aligned with the mesh to accurately replicate the physical structure in a digital format. This meticulous process ensured that the virtual environment faithfully represented the physical mockup, providing a robust foundation for the VR simulation used in the deconstruction planning tasks. It also replicates the process followed for most legacy facilities that will be deconstructed in the near future. Figure 44 depicts the BIM representation imported into the Unity game engine.

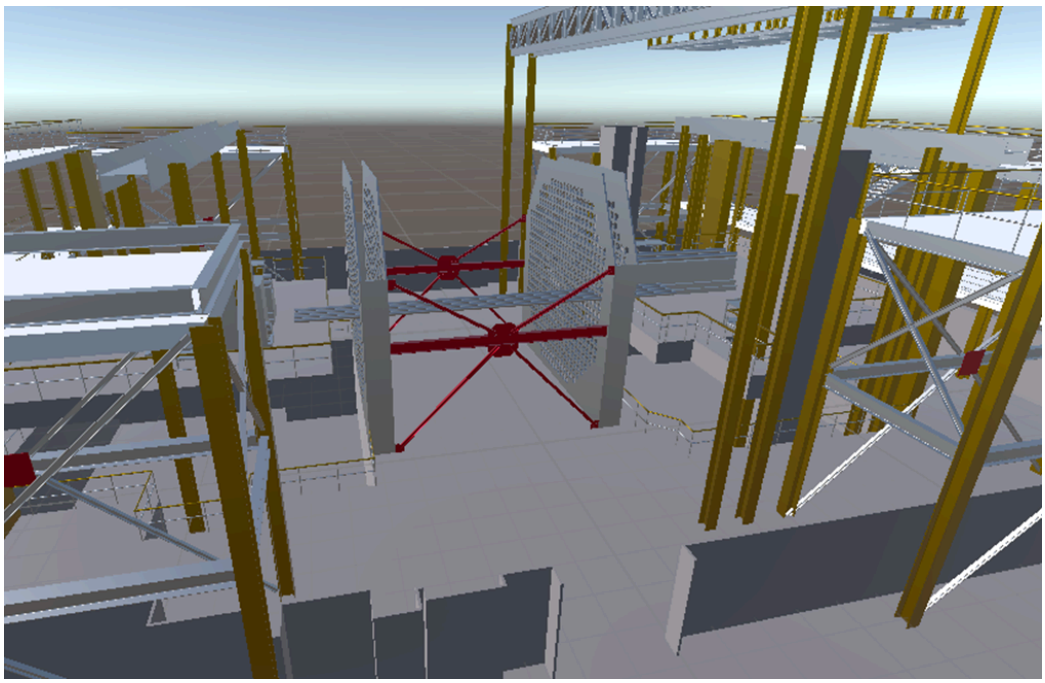


Figure 44: Darlington SMR scan-to-BIM result rendered in the simulation environment

The simulation runs commenced, and the VR users deconstructed the reactor face using the moving, slicing, temporary support, and temporary access capabilities built into the simulation. Screenshots from various phases of the simulation run are depicted in Figures 45-47.

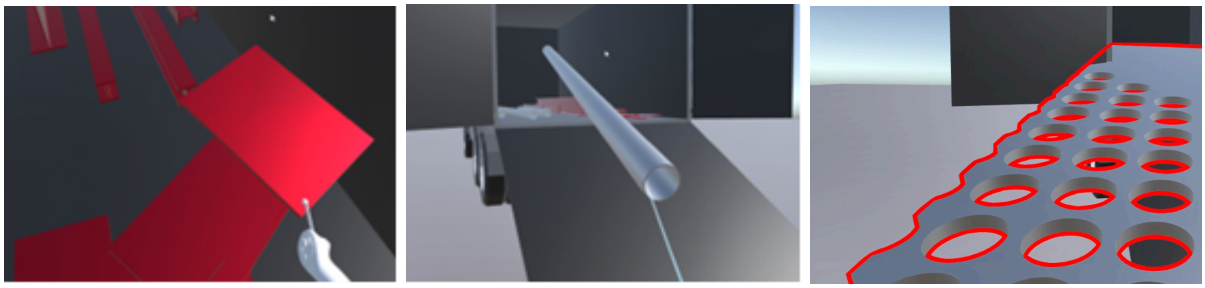


Figure 45: Screenshots from a Darlington SMR decommissioning simulation

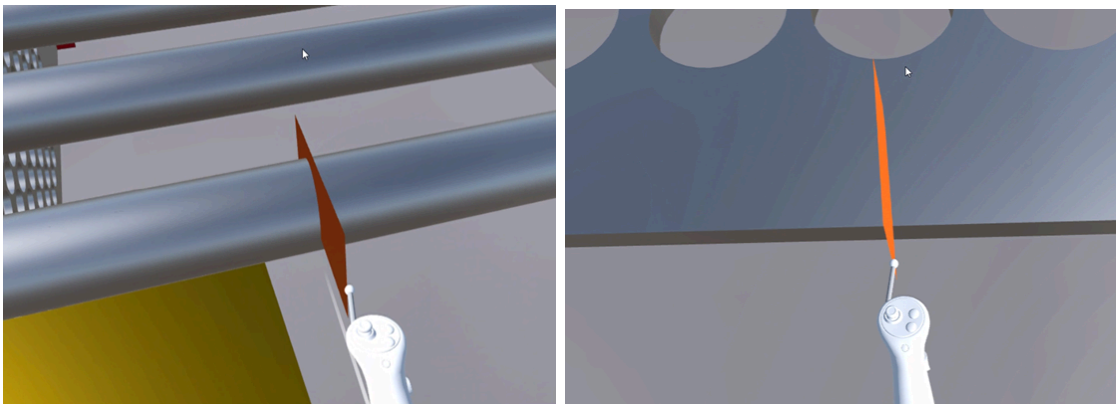


Figure 46: Screenshots of the Unity interface as the user slices reactor components

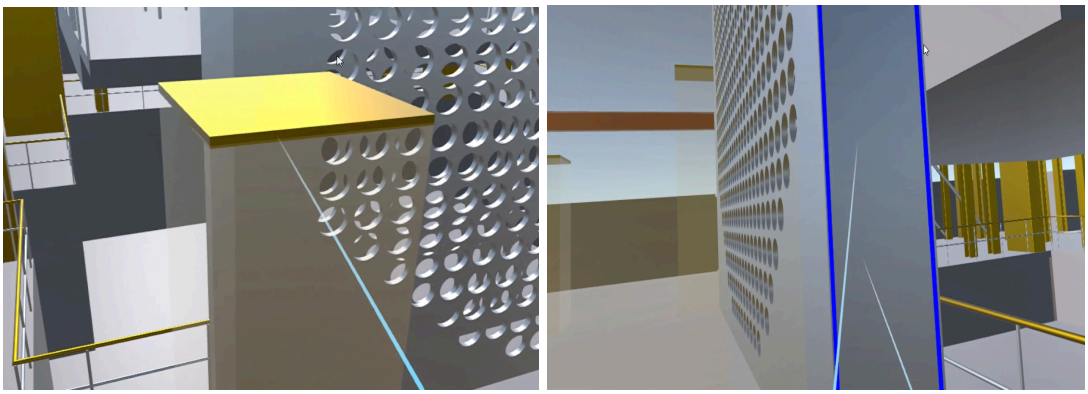


Figure 47: Screenshots of the Unity interface as the creates temporary access (left) and temporarily braces the reactor face (right)

Figures 48 and 49 depict the event log data structure that was designed to support the Darlington mock SMR decommissioning simulation case study. In Figure 48, the data for events associated with “Grab” and “Slice” actions is depicted, while

Figure 49 depicts example event logs for events that are used in “Temporary Support” and “Temporary Fix” action detection.


```
{
    "Timestamp": "2024-06-11 16:59:20",
    "EventType": "GameObject Picked Up",
    "ObjectDetails": {
        "Name": "Frame1Plate3",
        "Position": "(-10.45, 5.20, -4.42)",
        "Rotation": "(-10.45, 5.20, -4.42)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
{
    "Timestamp": "2024-06-11 16:59:27",
    "EventType": "GameObject Let Go",
    "ObjectDetails": {
        "Name": "Frame1Plate3",
        "Position": "(5.39, 1.98, -6.99)",
        "Rotation": "(5.39, 1.98, -6.99)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
```

```
{
    "Timestamp": "2024-06-11 16:59:38",
    "EventType": "Slice Added",
    "ObjectDetails": {
        "Name": "pipe1_0",
        "Position": "(-11.17, 4.13, 0.64)",
        "Rotation": "(0.00, 0.00, 0.00)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
{
    "Timestamp": "2024-06-11 16:59:38",
    "EventType": "Slice Added",
    "ObjectDetails": {
        "Name": "pipe1_1",
        "Position": "(-11.17, 4.13, -5.22)",
        "Rotation": "(0.00, 0.00, 0.00)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
```


Figure 48: JSON event log excerpt for “Grab” and “Slice” related events


```
{
    "Timestamp": "2024-06-11 16:57:28",
    "EventType": "Temporary Support Added",
    "ObjectDetails": {
        "Name": "SupportManager",
        "Position": "(-1.85, -34755.31, 0.48)",
        "Rotation": "(0.00000, 0.00000, 0.00000, 1
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
```

```
{
    "Timestamp": "2024-06-11 17:09:04",
    "EventType": "GameObject Temporarily Fixed",
    "ObjectDetails": {
        "Name": "CoreWall_2_side2",
        "Position": "(-10.47, 2.65, 2.47)",
        "Rotation": "(-10.47, 2.65, 2.47)",
        "Scale": "(1.00, 1.00, 1.00)"
    }
}
```


Figure 49: JSON event log excerpt for “Temporary Support” and “Temporary Fix” related events

Following the simulation run, the events logs were used to generate a critical path schedule. First, an excerpt from the list of deconstruction actions that were detected based on analysis of the detailed event log is depicted in Figure 50 including their estimated durations and deduced dependencies. The excerpt includes creation of

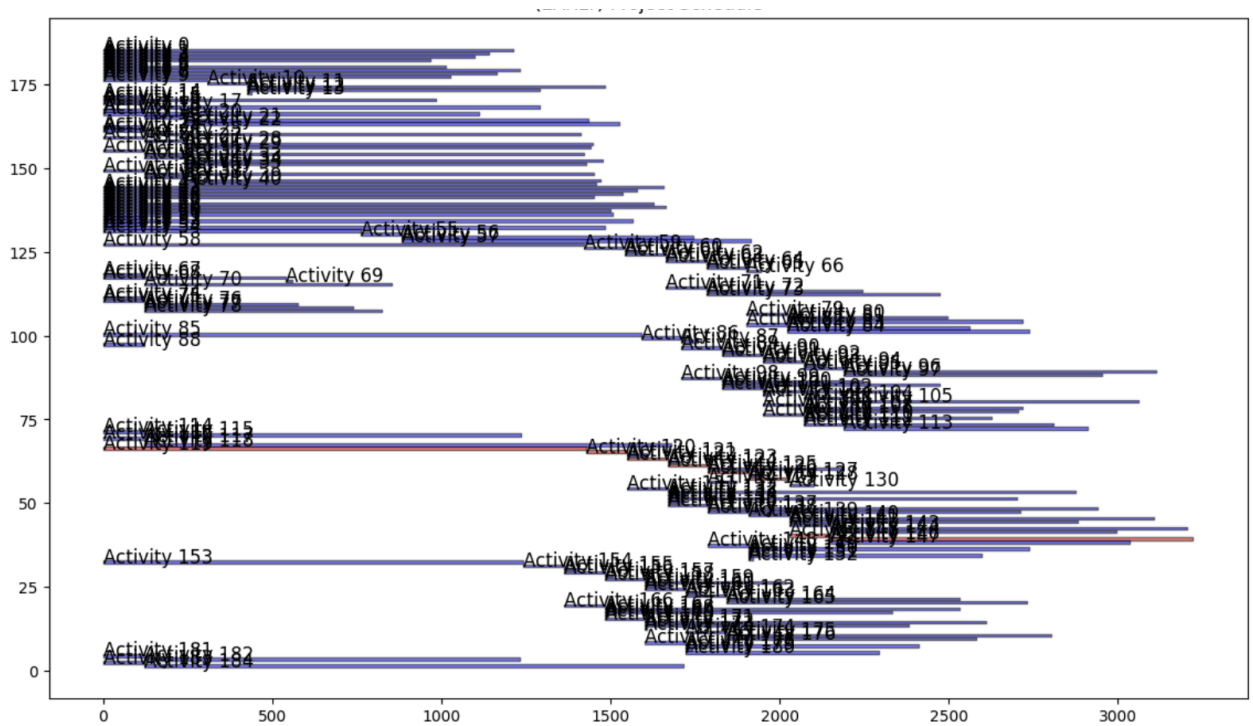
temporary supports to reach the upper reactor sections, and bracing objects to prevent collapse during decommissioning.

Activity	Duration	Dependencies	Description
0	20.2	[None]	Move "Brace1_4UPN"
1	19.0	[None]	Move "Brace1_1UPN"
2	18.3	[None]	Move "Frame1 Plate4"
3	16.1	[None]	Move "Frame1 Plate1"
4	2	[None]	Create a temporary support
5	16.9	[None]	Move "Frame1 Connection Under"
6	20.5	[None]	Move "Brace1_2UPN"
7	19.4	[None]	Move "Brace1_3UPN"
8	17.1	[None]	Move "Frame1 Connection over"
9	5.1	[None]	Move "MainBeam1_HEA"
10	2	['9']	Slice "MainBeam1_HEA"
11	17.6	['10']	Move "MainBeam1_HEA_0"
12	14.4	['10']	Move "MainBeam1_HEA_1"
13	0.2	['10', '12']	Move "MainBeam1_HEA_1"
14	2	[None]	Create a temporary support
15	16.4	[None]	Move "Frame1Plate3"
16	2	[None]	Slice "pipe1"
17	19.5	['16']	Move "pipe1_1"
18	2	[None]	Create a temporary support
19	18.5	[None]	Move "Frame1Plate2"
20	2	['16']	Slice "pipe1_0"
21	19.9	['20']	Move "pipe1_0_1"
22	21.4	['20']	Move "pipe1_0_0"
23	2	[None]	Create a temporary support
...			
182	18.5	['181']	Move "Left Custom Plate South Side"
183	2	[None]	Brace "Left Custom Plate North Side"
184	26.6	['183']	Move "Left Custom Plate North Side"

['Start', '119', '120', '122', '124', '126', '128', '145', '146', 'End']

Figure 50: Case study 2 excerpt of deduced actions

Finally, all of the information depicted, including the detected actions, corresponding real-world duration estimates, and dependency relationships is assembled into a Gantt chart representation of the critical path using the automated approach, and presented in Figure 51. Within the 185 actions detected, the Gantt chart demonstrates a few main chains of dependencies, observed through diagonal structures in the layout of the chart. These dependency chains are related to the different sections of the reactor that were deconstructed over the 30-minute simulation run. For instance, consider the two sets of actions related to the dismantling of each of the two faces of the reactor. Within each set, there are many dependency relationships, but between sets, there are very few dependency relationships due to the structural independence between the two faces.



Time (minutes)

Figure 51: Case study 2 automated critical path Gantt chart representation

The automated approach determined that 185 actions occurred, and that the critical path was the actions 119, 120, 122, 124, 126, 128, 145, and 146. This demonstrates the level of complexity that the automated approach supports in a fraction of a second using only the computational power of a consumer-grade laptop. The complete code utilized in case study 1 is presented in Appendix C.

5.5. Discussion

The proposed methodology seeks to bridge the gap between planning simulations and real-world construction projects by providing a strategy for automatically creating critical path schedules that are standardized, complete, and accurate. The automation efficiency allows planners to explore more alternative solutions with more depth, resulting in more thorough planning and more efficient projects.

By automating this inference process, the accuracy and efficiency of schedule generation is enhanced. And, the plans leverage a more intuitive and detailed understanding of project dynamics, rooted in the actual planning behavior of construction professionals within a VR environment. This approach not only has the potential to streamline the planning phase but also provides a solid foundation for executing construction projects with greater confidence in the schedule's feasibility and reliability.

The methodology developed in this research deduces the precedence relationships using predefined rules and logical constraints, rather than simply the order of occurrence in the simulation, thereby producing a schedule that represents the optimal early finish time under the assumption of unlimited resources. This approach provides a theoretical framework for maximizing parallelization of tasks, as the precedence relationships are determined from first principles rather than being influenced by the sequence of actions performed by the operator in the VR environment. Consequently, the Gantt charts generated reflect the maximum possible parallelization, assuming no resource constraints or workforce availability.

This methodology exemplifies a human-computer collaborative optimization, where the operator's expertise informs the initial action sequences, and the system applies logical rules to optimize these sequences further. This collaboration ensures that the generated schedules benefit from both human intuition and computational rigor, addressing the underconstrained nature of construction planning problems. The resulting schedules offer a theoretically optimal plan for re-sequencing the set of actions from the VR user while respecting logically derived precedence relationships.

This research demonstrates the capabilities of leveraging VR technology for planning and automated schedule generation. By applying the methodology to a complex deconstruction task involving the dismantling of a CANDU reactor core, the effectiveness and efficiency of the approach is validated. A critical path schedule containing 185 actions and an 8-action critical path is generated in a fraction of a second, highlighting significant opportunities for unprecedented efficiency and iterative improvements.

The ability to generate such a detailed and extensive schedule underscores the potential of integrating VR with advanced data analytics in construction project management. This rapid and accurate schedule generation not only facilitates better planning and resource allocation but also enables project teams to respond swiftly to changes and unforeseen challenges. The success of this demonstration emphasizes the impact of VR technology in optimizing deconstruction processes.

These findings suggest that the adoption of VR-based methodologies can impact the field of construction planning by enabling automated, scalable, efficient, and accurate approaches. The significant reduction in time required to produce detailed schedules, combined with the ability to visualize and interact with complex construction scenarios, marks a substantial leap forward in achieving sustainable and safe practices. This research paves the way for further innovations and applications of VR technology in construction and other industries requiring precise and efficient project planning.

5.6. Limitations and Future Work

Limitations exist in the current approach, and can be addressed in future research. One significant limitation is that the scheduling does not include resource constraints. While this allows for the exploration of parallelization opportunities, it means that the results must be further analyzed in a commercial project management software package to achieve the practical usability of the generated plans in real-world scenarios where resource availability is a critical planning consideration. Future work should directly incorporate resource constraints to enhance the realism and applicability of the schedules produced.

The methodology focuses on the scope of one activity. Therefore, the methodology cannot identify opportunities for optimizations or parallelization across activities. Similarly, the methodology does not support optimization of the sectioning of the project into activities itself, although standard practices and logical boundaries generally provide a straightforward solution.

Additionally, both demonstrations in the scope of this study focus on deconstruction tasks. While the principles can be generalized to other types of construction projects, specific adaptations may be necessary to account for different workflows and requirements. Extending the methodology to a broader range of construction activities could validate its versatility and robustness.

The VR environment itself, while providing an immersive and interactive platform for planning, may not fully capture all the nuances of a real-world construction site. Future research should aim to improve the fidelity of VR simulations and explore the integration of AR to provide real-time feedback and updates during actual project execution.

At present, the optimized action sequence generated by the methodology can serve as a comprehensive guide for human workers, ensuring that each task is executed in the most efficient order. In the future, beyond guiding human workers, the rich data obtained in the event logs can be leveraged in various innovative applications. For instance, the optimized sequence can be used to create detailed activity simulations, allowing planners and workers to visualize the action sequence in a virtual environment before actual execution.

Furthermore, the data-rich nature of the event logs enables the integration of AR technologies to provide real-time assistance to workers on-site as future work. By overlaying the optimized sequence onto the physical environment, AR can guide workers through each step with precision, improving accuracy and efficiency. Additionally, as future work, the optimized sequences can be used to instruct robotic workers, automating repetitive and hazardous tasks.

Chapter 6

Conclusion

In Section 1.1, the following thesis is proposed:

> "Deconstruction planning can be reimagined to incorporate reality data capture and VR technologies with the effect of enabling planners to engage with 3D reconstructions of deconstruction assets and leverage simulation environments to optimize and automate aspects of the task such as schedule deliverable generation."

The thesis is substantiated by demonstration in the presented research. The assertion that reality data capture and virtual reality can be incorporated into deconstruction planning in general is supported in Sections 3, 4, and 5, wherein reality data is imported into game engines. The game engine is augmented with software in each section to achieve a unique type of deconstruction planning.

The assertion that incorporation of these technologies enables planners to engage with 3D reconstructions of deconstruction assets is supported in Sections 3, 4, and 5. In each section, the reality data is made interactive through game engine extension software allowing the operator to virtually manipulate the deconstruction assets.

The assertion that the proposed paradigm improves a planner's ability to optimize a plan is substantiated in Sections 3 and 4. In Section 3, the use of real time feedback presents planners with immediate insights on the outcome of their packing configurations. In Section 4, the emergence of a planning workflow that couples disassembly, material recovery, and material reuse design enables many phases of deconstruction and reuse to be co-optimized at once.

Finally, the assertion that VR-based deconstruction enables the automation of aspects of deconstruction planning is supported in Section 5. A methodology for developing simulations that automate critical path schedule generation is presented.

The generated schedules are verified against a manually drafted schedule, and the accuracy of the methodology is validated.

The findings demonstrate that these technologies enable construction planners to engage in interactive planning within a 3D reconstruction of the deconstruction asset, fostering an environment that is both repeatable and devoid of physical risk given its virtual nature. Through the utilization of VR simulation environments, planners have the capability to not only visualize but also iteratively refine deconstruction strategies, optimizing task execution and decision-making processes.

The development and implementation of a methodology for the automated generation of critical path schedules exemplifies the practical application of VR in streamlining construction planning tasks. By analyzing planners' interactions within the VR environment, the system automatically distills these actions into comprehensive schedules, highlighting the potential for significant efficiencies in project planning and execution. Furthermore, the research introduced innovative algorithms for establishing real-world precedence relationships and estimating activity durations from virtual event logs, enhancing the accuracy and applicability of the generated schedules.

This work has extended the boundaries of current construction planning practices by illustrating the benefits of integrating reality data capture and VR technologies into the planning phase. The methodologies developed herein offer a robust framework for conducting deconstruction planning that leverages the full potential of these technologies. The interactive, immersive nature of VR, combined with the precise data captured through reality capture technologies, provides a foundation for informing planning decisions. Moreover, the successful application and evaluation of these methodologies in practical settings, including workshops with multidisciplinary participants and nuclear decommissioning planning underscore the viability and value of this approach.

As an exploratory study, it is important to note the limitations of the presented research and recommendations for future research. The following main categories summarize the limitations of the study:

Industry Information: The presented research is based on an understanding of deconstruction planning that was developed alongside industry advisors, however primarily in an academic setting. The concepts are based on developing technology, algorithms, and methodologies supporting a robust and modular approach for VR-based deconstruction planning, however the case studies within only approximate the way an industry team plans a deconstruction project. Future research stands to have greater implications if it is more closely based on real deconstruction planning efforts, such as in nuclear power, where deconstruction contingency plans must be periodically drafted due to regulations.

Quantitative Validation: This research validates some binary effects of implementing VR-based deconstruction planning. For example, this research investigates whether the implementation of the paradigm achieves or does not achieve the automated generation of an accurate critical path schedule. These binary effects are useful indicators of the capabilities of the paradigm, however, more granular performance data is important validation. Future research can look into directly comparing the proposed methodologies against existing workflows on the basis of quantitative performance metrics. A foreseen difficulty of assessing the performance of multiple plans stems from the lack of ability to implement more than one plan in real life with control of external variables. In other words, you can't deconstruct the same asset twice. However, there exists strategies to control such experiments, especially on a mock scale. Additionally, the plans' performance can be assessed in terms of the predicted efficiencies, for example in the achieved packing efficiency of a cutting and packing plan, or in the early finish time of a critical path schedule.

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Appendix

A. Reality Data Capture Robotics

Statement of Contributions

The research in Appendix A was completed amongst a large cohort of researchers including Alexander Thoms, Nicholas Charron, Steven Phillips, Evan McLaughlin, Jake McLaughlin, and Dirk Friesen as part of the former Sensing and Robotics for Infrastructure Lab at University of Waterloo under the supervision of Dr. Sriram Narasimhan.

The overall research program had a far greater scope than the application of these robotic mapping systems to deconstruction. I contributed to the development of the hardware and software for creating dense 3D reconstructions of assets, with the personal goal of importing these maps into VR simulations in support of the investigation of the research hypothesis presented in Section 1.1. Other contributors were motivated to further the field of robotics itself, or different downstream applications, with infrastructure inspection being the most prominent.

Specifically, I was the primary contributor of sensor integration, system time synchronization, Robotic Operating System (ROS) system design and development, data collection, handheld platform integration, and Unmanned Surface Vehicle platform development. I was a minority contributor to the ideation and software development of the decoupled mapping solution. I am a co-first author on the primary article that the team published on the decoupled mapping solution and Unmanned Surface Vehicle research.

A.1. Introduction

Robotic platforms designed for tasks related to infrastructure have mainly been studied for structural health inspection, disaster recovery, and construction. In this section, guidelines are presented for designing and building robotic data capture platforms suited to deconstruction environments that are capable of quickly producing time-stamped 3D scans of deconstruction environments such as NPPs while protecting humans from radiation exposure. These scans are represented by colorized point clouds and can be augmented with application specific sensor data types. For example, in a NPP project, a radiation level can be associated with each point.

Perhaps most importantly, this contribution includes a novel approach for generating 3D maps, which distinctively separates the simultaneous localization and mapping (SLAM) process from the creation of the final map. Traditional SLAM approaches usually combine the mapping activity directly with path estimation, utilizing sensor data to map the environment and determine the scanning platform's trajectory simultaneously. While these conventional methods are effective for map generation, they encounter limitations in scaling and detail for extensive areas such as NPPs or long-duration mapping due to computational and memory constraints.

A plethora of existing research focuses on 3D reconstruction across disciplines over the past few decades. However, based on the literature review presented in Chapter 2, there remains gaps around its application in deconstruction. Specifically, the emerging demand for deconstruction in the nuclear infrastructure industry necessitates a solution that protects humans from radiation and accommodates large facilities. These two needs are met by robotic infrastructure scanning platforms. The upfront capital costs and highly skilled labor requirements of developing a robotic infrastructure scanning platform prevent some researchers and project owners from participating in smart deconstruction workflows. This research consolidates experimentally validated information on the following facets of robotic reality data capture platforms: mobility, sensing, synchronization, calibration, power electronics, computing, networking, operation, simultaneous localization and mapping (SLAM), map building, and data wrangling. Motivated by the diversity of disciplines present in deconstruction projects, it is presented for an interdisciplinary engineering audience.

This chapter delves into the use of unmanned vehicles (UVs) and the integration of advanced simultaneous localization and mapping (SLAM) technologies to facilitate comprehensive, high-quality volumetric mapping for downstream deconstruction planning tasks. Such capabilities are crucial in environments where traditional methods fall short, either due to accessibility challenges or the need for precision in capturing the structural intricacies slated for deconstruction.

A primary motivation of using SLAM-based scanning platforms to estimate dense 3D reconstructions of assets for downstream deconstruction planning applications is the pursuit of state-of-the-art mapping accuracy for a large asset that can not be captured efficiently with a static scanner like a TLS. Mapping accuracy is essential for downstream planning applications described in subsequent chapters, as inaccuracies in 3D reconstructions result in planning feedback that is ineffective in the real-world. For example, an inaccurate map used in a waste cutting and packing planning simulation could lead the planner to create packing configurations that will not fit in the waste container in the field.

In the realm of construction and deconstruction planning, the process of 3D scanning and reconstruction of environments stands as a critical technological pillar, enabling detailed visualization and analysis crucial for the accurate planning and execution of projects. While the area of 3D scanning and reconstruction is well-explored, with significant advancements facilitating the capture of complex physical spaces in digital formats, the field continues to offer fertile ground for innovation, particularly in the development of more refined, efficient, and versatile mapping techniques.

This work introduces a novel approach to the generation of 3D maps, distinctively decoupling the simultaneous localization and mapping (SLAM) procedure from the generation of the final, comprehensive map. Traditional SLAM methodologies often integrate the mapping process directly, using sensor data to concurrently map the environment and estimate the path of the scanning platform. While effective for creating maps, this integrated approach can impose limitations on the scale and detail of the

mapping, particularly over large areas or extended durations due to computational and memory constraints.

The proposed method reimagines this process by allowing the SLAM procedure to generate a sparse, yet effective map primarily for the purpose of accurate and efficient path estimation. This foundational map supports the navigation and data collection process without necessitating the comprehensive detail and data density required for final project planning and execution. Following the completion of data collection, the amassed sensor data—potentially encompassing a wide range of modalities beyond visual and LiDAR information, such as infrared and nuclear radiation—is densely reprojected onto the map using the final pose estimates derived from the SLAM process. This innovative approach not only enhances the efficiency of the mapping process but also significantly improves the density and accuracy of the final map. Importantly, it allows for the inclusion of diverse data types in the mapping process without directly integrating them into the SLAM procedure, thus broadening the scope of environmental information that can be captured and represented in the final map.

The implications of this methodology are profound for the field of deconstruction planning, particularly in scenarios requiring detailed technical analysis and environmental assessment, such as nuclear decommissioning projects. By decoupling the SLAM and mapping processes, this approach facilitates the creation of highly detailed and accurate environmental models, essential for the meticulous planning and safe execution of deconstruction activities. This chapter aims to elucidate the technical foundations and practical applications of the mapping approach, setting the stage for discussions on the specific robotics platforms developed and implemented to leverage this methodology in real-world deconstruction planning scenarios.

A.2. Decoupled Mapping

Map building refers to the process of developing a final scan using the raw data and the SLAM outputs. While SLAM approaches output a scan of the scene, this map is often sparse and unfiltered. In the map building step, a dense scan is assembled

using the SLAM trajectory, 3D data, and the extrinsic calibrations of 3D sensors. Next, the dense scan is colorized using SLAM trajectory, image data and camera extrinsics. In deconstruction applications, the next step includes adding project relevant fields to the 3D scan, such as radiation imaging data. The dense scan can be filtered and processed using methodologies presented in prior work to create the final map.

In this section, a map building software approach entitled “MabBuilder” for smart deconstruction information pipelines is presented. MapBuilder receives input in the form of extrinsic calibrations, optimized SLAM trajectory, and sensor data. Extrinsic calibrations include the set of rigid transformations relating all sensors to a common frame. SLAM trajectory includes the full set of time-stamped maximum a posterior (MAP) pose estimates, with the option to correct and add high-rate, locally-consistent poses from available odometry subsystems. This feature is particularly useful for keyframe-based SLAM approaches, where non-keyframe poses are excluded during optimization, effectively reducing trajectory granularity. Lastly, 3D sensor data includes time-stamped LiDAR and camera data.

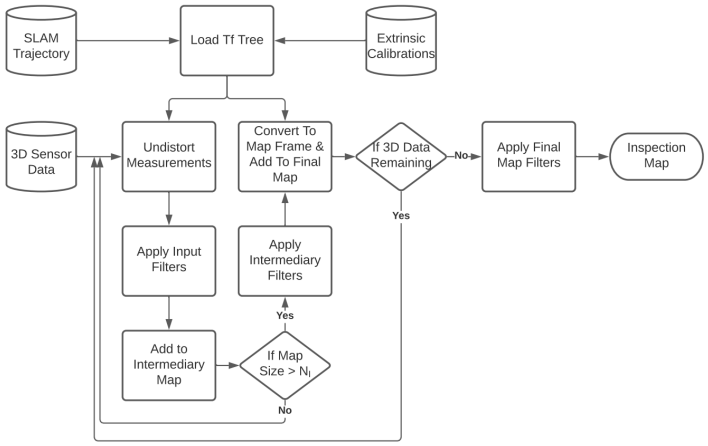

Figure 52: MapBuilder block diagram

First, extrinsic calibrations and SLAM trajectory are combined into a transformation tree (TF Tree) data structure [11]. Conceptually, a TF Tree originates from a single parent node, representing an arbitrarily defined frame common to all sensors, with edges representing time stamped coordinate transformations between frames. Once constructed, the TF tree may be queried at time of 3D sensor data

capture for any sensor, retrieving an estimate of the precise transformation from stationary world frame to sensor frame at that time. If this time does not coincide with an edge of the graph, spherical linear interpolation [50] is used. This interpolation scheme allows use of scans that are asynchronous to SLAM trajectory, which occurs when:

1. Supplementary range sensors are not externally triggered with the range sensor used in the SLAM approach.
2. Range sensors are formulated in the SLAM approach, but do not inform keyframe selection (such as in the case of loosely-coupled approaches [56]).
3. Range sensors are not formulated in the SLAM approach.

Filters may be applied at three stages of the map building process to suit performance needs. First, filters may be applied directly to sensor data, with the Dynamic Radius Outlier Removal (DROR) filter specifically designed to remove outliers from a single LiDAR scan. At this stage, the cropbox filter may also be applied to remove distant, noisy measurements and near measurements of the robot itself. In the second stage of filtering, scans are aggregated into intermediary maps. When filtering is applied to each intermediary map, non-dynamic radius outlier removal (ROR) performance is sufficient, given the denser set of points to discriminate inliers versus outliers. In the last stage, a voxel grid filter may be used to minimally voxelize the final map for space-complexity savings.

The map building performance is essential to the deconstruction application pipeline, as all downstream algorithms and simulations approaches rely on the final inspection map as input. To evaluate MapBuilder, field experiments are conducted near Welland Canal Bridge 13 which is a water-spanning bridge situated in tranquil water. Details on the USV platform deployed for data collection and extrinsic calibrations performed follow in section A.5.

A series of robotic data collection platforms are presented and evaluated through field experimentation. The experiments start with the modular handheld scanning platform. The handheld device incorporates the baseline of sensors required to fulfill

reality data capture needs, but is designed to mount to autonomous vehicles, and expand to additional sensors in alternative usage scenarios. Next, the handheld platform is attached to an unmanned ground vehicle (UGV), and supplemented with additional LiDAR, cameras, and infrared sensors. The infrared data is used to validate the capability to enhance point clouds with application specific data types. Finally, an unmanned surface vessel (USV) is presented. The USV incorporates the handheld baseline sensors, additional LiDAR and camera sensors, and a sonar sensor. The sonar data is used to validate the map building approach, as the sonar data is not a part of the SLAM approach.

A.3. Handheld platform

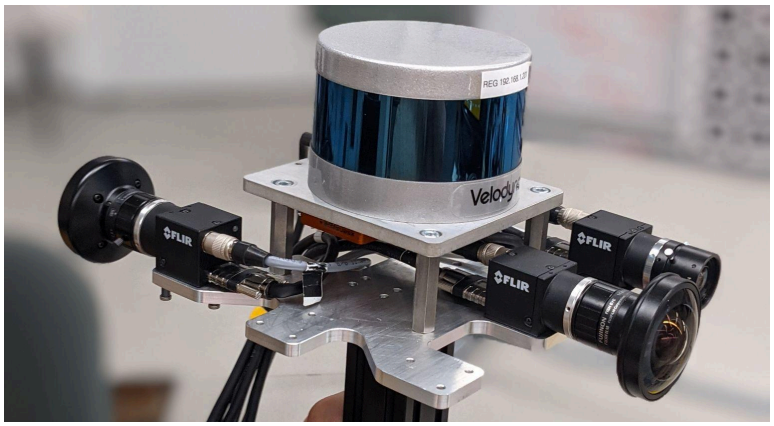

Figure 53: Handheld data capture sensor kit

The handheld platform is the basis of the modular sensing approach. The handheld platform includes a 360 degree FOV LiDAR, a combination of standard and wide FOV cameras, and a high precision IMU. These sensors are capable of robust tightly-coupled LiDAR-visual-inertial (LVI) SLAM, colorized map reconstruction, and inspection imaging. Various supporting hardware is required to enable the platform. A Teensy 3.6 microcontroller is used to relay analog signals to the sensors for triggering and synchronization . An Intel NUC is used as a small form factor computer for integrating the handheld platform. A network switch is used to connect the ethernet enabled sensors and the computer. Figure 54 depicts the handheld platform in use.

The supporting hardware is stored in a backpack worn by the operator, and the laptop in the image demonstrates a live feed from one of the platform's cameras.

Figure 54: Handheld platform in use

To store and protect the supporting hardware as it synchronizes, powers, connects, and controls the sensors, a hardware enclosure is formulated. The hardware enclosure is weatherproof, waterproof, and modular. Interchangeable cable grommets are used to enable sensor connections while ensuring a waterproof enclosure.

Figure 55: Sensor kit and opened enclosure

A.4. Unmanned Ground Vehicle

Figure 56: UGV scanning platform in field

The modular sensor kit is placed on a Clearpath Husky UGV. The Husky provides power and mobility to the sensor kit. A wireless router is used to provide networking from the operator's computer to the hardware enclosure computer. In this configuration, the handheld sensor kit is augmented by a vertical LiDAR and camera for coverage of overhead infrastructure, such as ceilings, pipes, and bridge decks.

Experiments are conducted using the modular sensor kit and the Husky platform to measure the system's localization and mapping accuracy. The Husky conducts a lab-scale scanning mission of a pipe network. To test localization, a Vicon motion capture system with 6 tracking cameras is used to provide ground truth of the Husky's position during a lab-scale scanning mission. The ground truth pose measurements are compared against those output by the LVI SLAM system to measure accuracy. Next, the mission data is used to construct a scan of a pipe network in the lab. Then, the ground truth poses are used alongside the ranging data to construct a ground truth scan

of the pipe network. The two scans are compared to understand how localization errors affect final mapping accuracy.

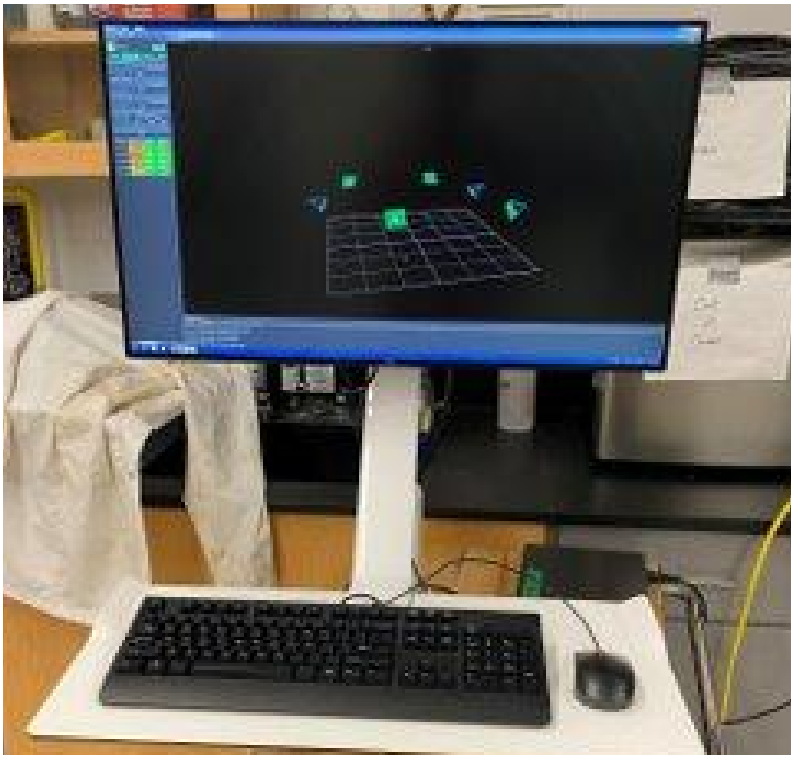

Figure 57: Vicon motion capture software

Next, the UGV platform is used to demonstrate the usage of application specific sensor types. An infrared imaging camera is added to the UGV platform. The infrared camera is calibrated using hand measurements. Coarse accuracy is sufficient in this case, where the infrared measurements are not used in the SLAM process. A scanning mission of a bridge is conducted while collecting infrared images. The LVI SLAM approach is used to estimate the robot's trajectory and the map building approach is used to construct a 3D scan. The scan is colorized using the known robot poses and infrared camera extrinsic calibration.

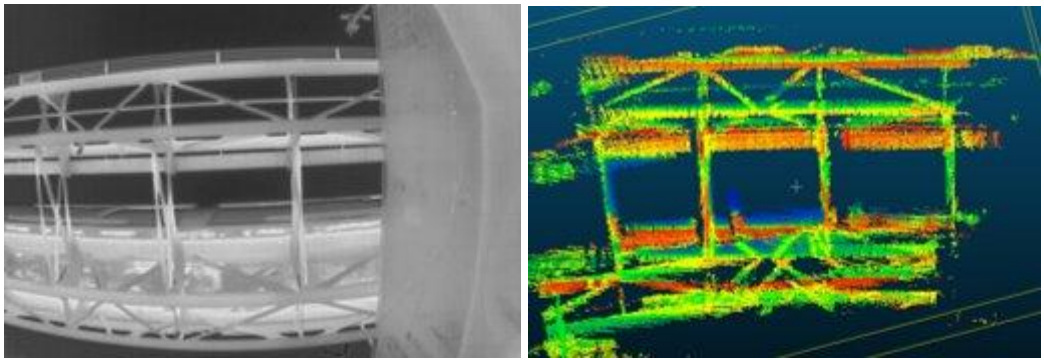

Figure 58: Example infrared image and corresponding scan submap

A.5. Unmanned Surface Vehicle

Figure 59: USV on beach

An unmanned surface vehicle (USV) demonstrates the capabilities of the map building approach. Field experiments are conducted near Welland Canal Bridge 13, which is a water-spanning bridge situated in tranquil water in Ontario, Canada. Details on the USV platform deployed for data collection and extrinsic calibrations performed follow.

Figure 60: Welland Canal Bridge 13 in Ontario, Canada

A Clearpath Robotics Heron platform is outfitted with the handheld sensor kit, an additional LiDAR and camera for bridge deck coverage, and an Imagenex DT100 multibeam sonar. From studies conducted in simulation, the LiDAR remains horizontally mounted, while the IMU has been mounted near the LiDAR to minimize contaminate centripetal forces, given LVI-SAM assumes LiDAR and inertial frames coincide. Cameras are oriented in side-facing directions to maximize the number of tracked features during lengthwise passes of infrastructure.

For volumetric mapping of maritime infrastructure, supplementary sensing is provided by a vertically mounted Velodyne VLP16 LiDAR and an Imagenex DT100 multibeam profiling sonar. The sonar (similar to the one presented in Han, 2018) is mounted to a mechanically adjustable rotational plate to provide coverage up to the water's surface. The sonar is configured to publish at an average rate of 13.8Hz, which corresponds to a set maximum altitude of 40m. Gain is set to 6db for silty sand conditions, with gain equalization and automatic gain control turned off as these parameters tend to over-amplify the signal in testing. In lieu of an external sound velocity sensor, the speed of sound through water is assumed to be 1447m/s, which corresponds to the average reported water temperature at time of field experimentation. All sensors interface with an Aruduino-based Teensy microcontroller, which provides analog signals to start, trigger, and time synchronize sensors to a common clock.

Following the intrinsic calibration of cameras and the IMU described in Section A.5, sensors are extrinsically calibrated according to Figure 61, where calibration methods and their associated transformations are summarized.

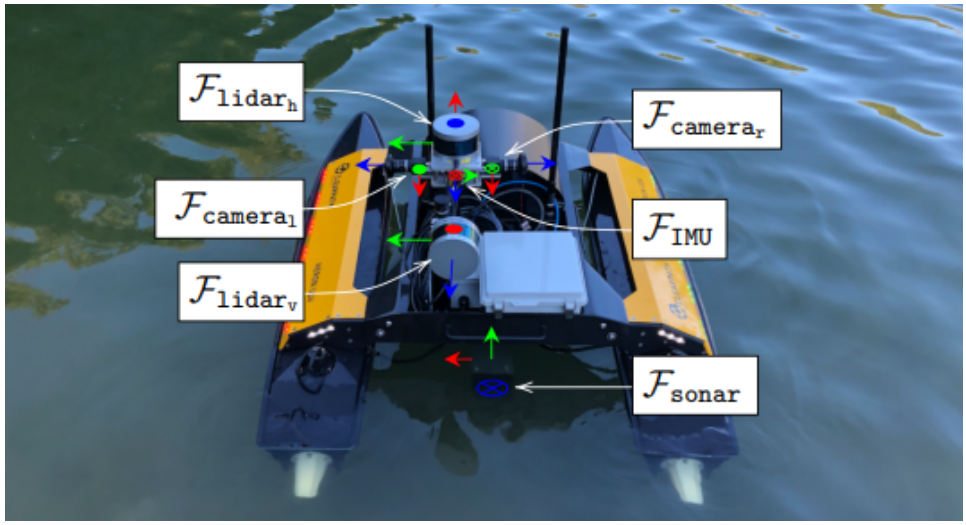

Figure 61: USV sensor coordinate frames

Extrinsic Calibration Method	**Sensor Frame Pair**
Kalibr toolbox	IMU to Left Camera
Zhou et al.	Horizontal LiDAR to Left Camera Horizontal LiDAR to Right Camera
Mapbuilder calibration tool	Horizontal LiDAR to Vertical LiDAR Horizontal LiDAR to Sonar

Figure 62: USV extrinsic calibration methods

The USV platform is deployed for data collection near the right pier of Welland Canal Bridge 13 as illustrated in Figure 63. The USV proceeds to circumnavigate both

bridge piers before reaching a terminal state. The Maximum a Posteriori (MAP) trajectory estimate computed by the adopted LVI SLAM approach is illustrated to scale.

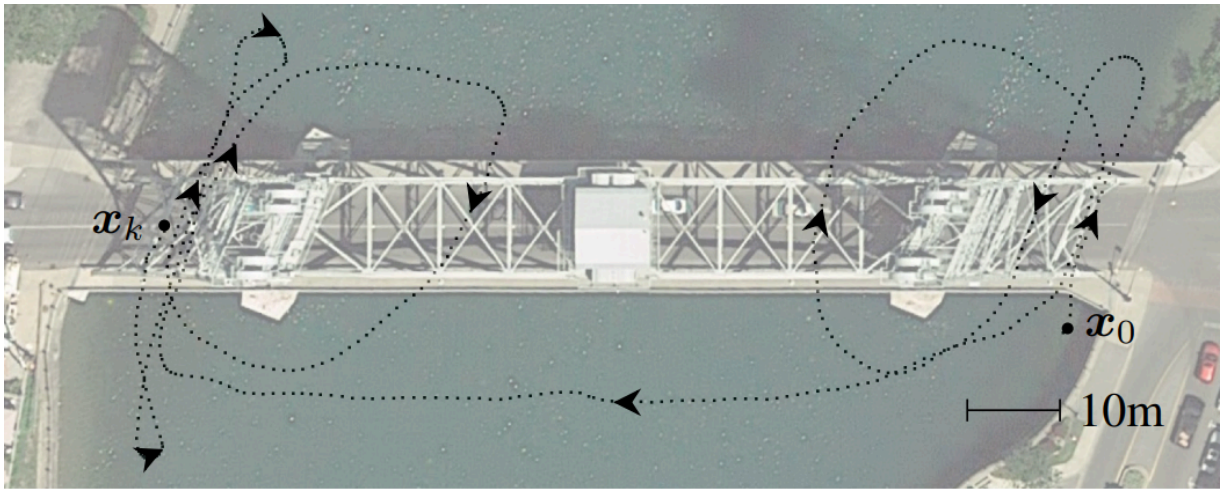

Figure 63: Welland Canal Bridge 13 USV Trajectory

Figure 64 and 65 qualitatively illustrate the differences between SLAM and inspection maps generated for Welland Canal Bridge 13. Figure 64 depicts the global map used by SLAM to register and align LiDAR frames and submaps. Figure 65 depicts the output of MapBuilder, which utilizes all available LiDAR data along with the final output trajectory from the LVI SLAM procedure.

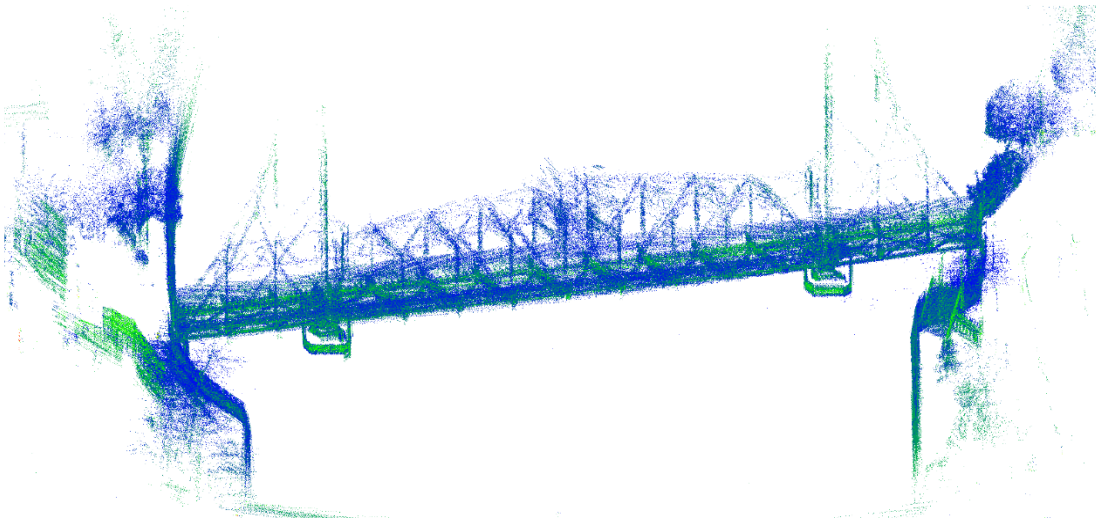

Figure 64: Welland Canal Bridge 13 SLAM map

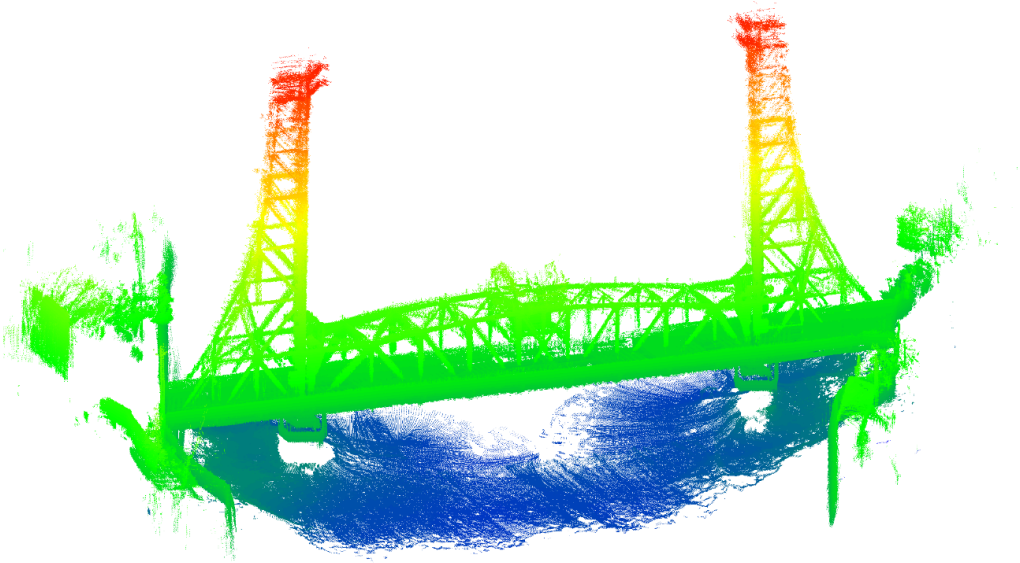

Figure 65: Welland Canal Bridge 13 inspection map

To quantify density, noise, and retention of environmental structure in SLAM and inspection maps, surface density, roughness, and planarity metrics are calculated. Planarity serves as a proxy for reconstructing geometrically accurate models that are Manhattan in nature (Khaloo, et al. 2018), where higher planarity values indicate a higher probability of a volumetric data point being associated with structural elements, which are composed of mainly planar surfaces. Figure 66 summarizes mean metric values for both SLAM and inspection maps, where inspection map performance exceeds SLAM map performance across all metrics.

	SLAM Map	Inspection Map
Surface Density (points per 0.25m radius circle)	337.124	**31986.9**
Roughness (unitless)	3.637e-2	**2.576e-2**
Planarity (unitless)	4.686e-1	**6.546e-1**

Figure 66: Welland Canal Bridge 13 map quantification

B. Complete Schedule Generation Case Study 1 Code

```
# Active our virtual environment and confirm it worked

! source ./venv/bin/activate

! whereis python

# define some helper functions to make our main event loop more readable

import math


def objName(event):

   return event["ObjectDetails"]["Name"]


def objPos(event):

   return event["ObjectDetails"]["Position"]


def stringToTuple(string):

   return tuple(float(x) for x in string[1:-1].split(','))


def moveDistance(start, end):

   return math.dist(stringToTuple(objPos(start)), stringToTuple(objPos(end)))


# define an ActivityPlan class that will allow us to create an activity plan in a
stateful way

import json

from string import ascii_uppercase


class ActivityPlan:
```

```
    def __init__(self, path):

        self.activities = [] # an array that will store the activities in the plan

        self.counter = 0

        self.currentAdd1 = None # temporarily store a GameObject Added event as we
deduce the occurence of slices

        self.currentAdd2 = None # temporarily store a GameObject Added event as we
deduce the occurence of slices

        self.currentRemove = None # temporarily store a GameObject Removed event as we
deduce the occurence of slices

        self.currentGrab = None # temporarily store a GameObject Picked Up event as we
deduce the occurence of moves

        self.currentRelease = None # temporarily store a GameObject Let Go event as we
deduce the occurence of moves

        self.loadEvents(path)

        print("# of events: ", len(self.events))

        self.parseEvents()


    def resetMove(self):

        self.currentGrab = None

        self.currentRelease = None


    def resetSlice(self):

        self.currentRemove = None

        self.currentAdd1 = None

        self.currentAdd2 = None


    def loadEvents(self, path):

        self.path = path
```

```
        with open(path, 'r') as f:

            self.events = json.load(f)



    def parseEvents(self):

        for event in self.events:

            if (event["EventType"] == "GameObject Added") : # Added (could be added due
to a slice or the simulation starting)

                self.resetMove()

                if (objName(event).endswith("_0")):

                    self.currentAdd1 = event

                if (objName(event).endswith("_1")):

                    self.currentAdd2 = event

                self.attemptSliceActivity()



            if (event["EventType"] == "GameObject Removed") : # Removed (could be
removed to to a slice or the simulation ending)

                self.resetMove()

                self.currentRemove = event

                self.attemptSliceActivity()



            if (event["EventType"] == "GameObject Picked Up") : # Picked Up (A game
object was grabbed by the user)

                self.resetSlice()

                self.resetMove()

                self.currentGrab = event
```

```
            if (event["EventType"] == "GameObject Let Go") : # Let Go (A game object
was released by the user)

                self.resetSlice()

                self.currentRelease = event

                self.attemptMoveActivity()



    def attemptMoveActivity(self):

            if (self.currentGrab and objName(self.currentGrab) ==
objName(self.currentRelease)):

                newActivity  = self.computeMove(self.currentGrab, self.currentRelease)

                self.addActivity(newActivity)



    def attemptSliceActivity(self):

        if (self.currentRemove and self.currentAdd1 and self.currentAdd2):

            newActivity = self.computeSlice(self.currentRemove, self.currentAdd1,
self.currentAdd2)

            self.addActivity(newActivity)



    def addActivity(self, activity):

        activity["_id"] = ascii_uppercase[self.counter]

        self.activities.append(activity)

        self.counter += 1



    def computeDependencies(self, new):

        dependencies = []

        for previous in self.activities:

            if (new["object"] in previous["dependentObjects"]):
```

```
            dependencies.append(previous["_id"])
    if (len(dependencies) == 0):
        dependencies = [None]
    return dependencies




def computeMove(self, start, end):
    # print(objName(start), "moved from:", objPos(start), "to:", objPos(end))
    activity = {
        "type": "move",
        "object": objName(start),
        "dependentObjects": [objName(start)],
        "startEvent": start,
        "endEvent": end,
        "startPosition": stringToTuple(objPos(start)),
        "endPosition": stringToTuple(objPos(end)),
        "moveDistance": moveDistance(start, end),
    }
    activity["description"] = "Move \"" + objName(start) + "\""
    activity["duration"] = round(activity["moveDistance"], 1)
    activity["dependencies"] = self.computeDependencies(activity)
    return activity


def computeSlice(self, remove, create1, create2):
    activity = {
        "type": "slice",
```

```
            "object": objName(remove),

            "dependentObjects": [objName(remove), objName(create1), objName(create2)],

            "removeEvent": remove,

            "createEvent1": create1,

            "createEvent2": create2

        }

        activity["description"] = "Slice \"" + objName(remove) + "\""

        activity["duration"] = 2

        activity["dependencies"] = self.computeDependencies(activity)

        return activity

import time

start = time.time()


# create and analyze the activity plan using our ActivityPlan class

myPlan = ActivityPlan('./LogFile 1.json')


# cheche_pm allows us to create a critical path schedule diagram from our ActivityPlan
class

from cheche_pm import Project

p = Project()


print ("Activity\t", "Duration\t", "Dependencies\t\t", "Description\t")

for activity in myPlan.activities:

   p.add_activity(activity_name=activity["_id"], activity_duration = 60 *
activity["duration"],
activity_precedence=[activity["dependencies"][len(activity["dependencies"])-1]],
a_desc=activity["description"], activity_resources=[0])
```

```
    print(activity["_id"], "\t\t", activity["duration"], "\t\t",
activity["dependencies"], "\t\t\t", activity["description"])


try:
    p.CPM()
    print("--- %s seconds ---" % (time.time() - start))
    print(p.get_critical_path())
    p.plot_gantt_cpm(save=True)
except:
    pass
```

C. Complete Schedule Generation Case Study 2 Code

```
# Active our virtual environment and confirm it worked
! source ./venv/bin/activate
! whereis python
# define some helper functions to make our main event loop more readable
import math
import re


def objName(event):
    return event["ObjectDetails"]["Name"]


def parentObjName(event):
    # Use regex to match the base string before any underscores and digits
    match = re.match(r'(.+?)(?:_\d+)?$', event["ObjectDetails"]["Name"])
    if match:
```

```
        return match.group(1)

    return event["ObjectDetails"]["Name"]


def objPos(event):

    return event["ObjectDetails"]["Position"]


def stringToTuple(string):

    return tuple(float(x) for x in string[1:-1].split(','))


def moveDistance(start, end):

    return math.dist(stringToTuple(objPos(start)), stringToTuple(objPos(end)))


# define an ActivityPlan class that will allow us to create an activity plan in a
stateful way

import json

from string import ascii_uppercase


class ActivityPlan:

    def __init__(self, path):

        self.activities = [] # an array that will store the activities in the plan

        self.counter = 0

        self.currentAdd1 = None # temporarily store a GameObject Added event as we
deduce the occurence of slices

        self.currentAdd2 = None # temporarily store a GameObject Added event as we
deduce the occurence of slices

        self.currentGrab = None # temporarily store a GameObject Picked Up event as we
deduce the occurence of moves
```

```
        self.currentRelease = None # temporarily store a GameObject Let Go event as we
deduce the occurence of moves

        self.currentFixed = [] # temporarily store all GameObjects that are fixed

        self.currentUnfixed = None # temporarily store all GameObjects that are fixed

        self.loadEvents(path)

        print(len(self.events))

        self.parseEvents()


    def resetMove(self):

        self.currentGrab = None

        self.currentRelease = None


    def resetSlice(self):

        self.currentAdd1 = None

        self.currentAdd2 = None


    def loadEvents(self, path):

        self.path = path

        with open(path, 'r') as f:

            self.events = json.load(f)




    def parseEvents(self):

        for event in self.events:

            if (event["EventType"] == "Slice Added") : # Added (added due to a slice)

                self.resetMove()
```

```
                if (objName(event).endswith("_0")):

                    self.currentAdd1 = event

                if (objName(event).endswith("_1")):

                    self.currentAdd2 = event

                self.attemptSliceActivity()


            if (event["EventType"] == "GameObject Picked Up") : # Picked Up (A game
object was grabbed by the user)

                self.resetSlice()

                self.resetMove()

                self.currentGrab = event


            if (event["EventType"] == "GameObject Let Go") : # Let Go (A game object
was released by the user)

                self.resetSlice()

                self.currentRelease = event

                self.attemptMoveActivity()


            if (event["EventType"] == "Temporary Support Added") : # Let Go (A game
object was released by the user)

                newActivity = self.computeSupport(event)

                self.addActivity(newActivity)


            if (event["EventType"] == "GameObject Temporarily Fixed") : # Fixed
(removes gravity, simulating temporary bracing)

                self.currentFixed.append(event)
```

```
            if (event["EventType"] == "GameObject Unfixed") : # Unfixed (resumes
gravity for that object, simulating removal of bracing)

                self.currentUnfixed = event

                self.attemptBracingActivity()





    def attemptMoveActivity(self):

            if (self.currentGrab and objName(self.currentGrab) ==
objName(self.currentRelease)):

                newActivity  = self.computeMove(self.currentGrab, self.currentRelease)

                self.addActivity(newActivity)


    def attemptSliceActivity(self):

        if (self.currentAdd1 and self.currentAdd2):

            newActivity = self.computeSlice(self.currentAdd1, self.currentAdd2)

            self.addActivity(newActivity)


    def attemptBracingActivity(self):

        for event in self.currentFixed:

            if (objName(event) == objName(self.currentUnfixed)):

                newActivity = self.computeBracing(event, self.currentUnfixed)

                self.addActivity(newActivity)

                self.currentFixed.remove(event)


    def addActivity(self, activity):

        # activity["_id"] = ascii_uppercase[self.counter]
```

```
        activity["_id"] = str(self.counter)

        self.activities.append(activity)

        self.counter += 1



    def computeDependencies(self, new):

        dependencies = []

        for previous in self.activities:

            if (new["object"] in previous["dependentObjects"]):

                dependencies.append(previous["_id"])

        if (len(dependencies) == 0):

            dependencies = [None]

        return dependencies




    def computeMove(self, start, end):

        # print(objName(start), "moved from:", objPos(start), "to:", objPos(end))

        activity = {

            "type": "move",

            "object": objName(start),

            "dependentObjects": [objName(start)],

            "startEvent": start,

            "endEvent": end,

            "startPosition": stringToTuple(objPos(start)),

            "endPosition": stringToTuple(objPos(end)),

            "moveDistance": moveDistance(start, end),

        }
```

```
        activity["description"] = "Move \"" + objName(start) + "\""
        activity["duration"] = round(activity["moveDistance"], 1)
        activity["dependencies"] = self.computeDependencies(activity)
        return activity


    def computeSlice(self, create1, create2):
        parentObj = parentObjName(create1)
        activity = {
            "type": "slice",
            "object": parentObj,
            "dependentObjects": [objName(create1), objName(create2)],
            "createEvent1": create1,
            "createEvent2": create2
        }
        activity["description"] = "Slice \"" + parentObj + "\""
        activity["duration"] = 2
        activity["dependencies"] = self.computeDependencies(activity)
        return activity


    def computeBracing(self, fixed, unfixed):
        activity = {
            "type": "bracing",
            "object": objName(fixed),
            "dependentObjects": [objName(fixed)],
            "startEvent": fixed,
            "endEvent": unfixed,
```

```
        }
        activity["description"] = "Brace \"" + objName(fixed) + "\""
        activity["duration"] = 2
        activity["dependencies"] = self.computeDependencies(activity)
        return activity


    def computeSupport(self, event):
        activity = {
            "type": "support",
            "dependentObjects": [],
            "startEvent": event,
        }
        activity["description"] = "Create a temporary support"
        activity["duration"] = 2
        activity["dependencies"] = [None]
        return activity
import time


start = time.time()


# create and analyze the activity plan using our ActivityPlan class
myPlan = ActivityPlan('./LogFile 4.json')


# cheche_pm allows us to create a critical path schedule diagram from our ActivityPlan
class
from cheche_pm import Project
```

```
p = Project()



print ("Activity\t", "Duration\t", "Dependencies\t\t", "Description\t")

for activity in myPlan.activities:

   p.add_activity(activity_name=activity["_id"], activity_duration = 60 *
activity["duration"], activity_precedence=activity["dependencies"],
a_desc=activity["description"], activity_resources=[0])

   print(activity["_id"], "\t\t", activity["duration"], "\t\t",
activity["dependencies"], "\t\t\t", activity["description"])



try:

   p.CPM()

   print("--- %s seconds ---" % (time.time() - start))

   print(p.get_critical_path())

   p.plot_gantt_cpm(save=True)

except:

   pass
```