A framework for offsite construction manufacturing process improvement through digitalization and automated real-time data collection

by

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ABSTRACT

This thesis proposes methods to apply real-time data to improve manufacturing operations in offsite construction using a combination of tools such as simulation, machine learning, and exploratory data analysis. These methods are applied to increase flexibility in operations and digitalize the design, planning, and manufacturing phases in offsite construction. Through empirical implementations, the proposed methods provide applications of digitalization to improve offsite construction manufacturing operations by integrating existing information systems while combining and applying design-related and real-time data gathered from shop floors. The proposed framework includes implementation of digitalization strategies in the design, bidding, and procurement phases of offsite construction. The proposed framework also integrates building information modelling with lean-based metrics based on real-time data gathered using radio-frequency identifier sensors logistically installed on a shop floor The proposed method addresses improvement measures using a combination of expert's knowledge and statistical analysis, thus reducing the impact of personal opinions with respect to proposed changes to the shop floor in favor of empirical analysis supported by actual production data. A simulation-based analysis is also introduced to address the impact of the proposed framework in terms of increasing labour flexibility and reducing the average cycle time of projects in offsite construction. The key contribution of this research is the development of a framework and methods to improve manufacturing operations in offsite construction by leveraging digitalization and real-time data.

PREFACE

This thesis is an original work by Béda Barkokébas. The research of which this thesis is a part received research ethics approval from the University of Alberta Research Ethics Boards, project name "Digitalization for process improvement in off-site construction manufacturing", No. Pro00120617, July 11, 2022. This thesis is organized in a paper-based format, and it follows the University of Alberta's guidelines for a paper-based thesis. Five journal papers, eight conference papers, and a book chapter associated with the research developed for this thesis have been submitted or published, as follows:

1. **Barkokebas, B.**, Khalife, S., Hamzeh, F., and Al-Hussein, M. (2021) "A BIM–lean framework for digitalisation of premanufacturing phases in offsite construction." Engineering, Construction and Architectural Management, 28(8), 2155–2175.

A version of the above-noted publication appears as Chapter 2 of this thesis. Beda Barkokebas was responsible for leading the development of the method and carrying out the data collection and analysis, as well as for leading the manuscript composition. Salam Khalife assisted in the development of the analysis and manuscript composition. Dr. Hamzeh and Dr. Al-Hussein were the supervisory authors and were involved with concept formation and manuscript revision.

2. **Barkokebas, B.**, Martinez, P., Bouferguene, A., Hamzeh, F., Al-Hussein, M. (2022). "Digitalization method for process improvement and decision-making in offsite construction." *Automation in Construction* (Under review)

A version of the above-noted manuscript appears as Chapter 3 of this thesis. Beda Barkokebas was responsible for the developing the method, leading the data processing and analysis, as well as for leading the manuscript composition. Dr. Martinez assisted during the data processing stage and manuscript revision. Dr. Bouferguene assisted in implementing the statistical methods during the analysis stage and manuscript revision. Dr. Hamzeh and Dr. Al-Hussein were the supervisory authors and were involved with concept formation and manuscript revision.

3. **Barkokebas, B.**, Al-Hussein, M., Hamzeh, F. (2022). “Assessment of digital twins to reassign multi-skilled workers in offsite construction based on lean thinking.” *Journal of Construction Engineering and Management* (Accepted)

A version of the above-noted manuscript appears as Chapter 4 of this thesis. Beda Barkokebas was responsible for developing the method, carrying out data collection and analysis, as well as for the manuscript composition. Dr. Hamzeh and Dr. Al-Hussein were the supervisory authors and were involved with concept formation and manuscript revision.

4. **Barkokebas, B,** Alsakka, F., Hamzeh, F., and Al-Hussein, M. (2022). Digital Twins to enable flexibility in off-site construction. In *Lean Construction 4.0: Driving a Digital Revolution of Production Management in the AEC Industry* (in press). Taylor & Francis/ Routledge.

A part of the case study in Chapter 4 of this thesis appears in this book chapter. Beda Barkokebas was responsible for leading the development of the proposed method and case studies. Fatima Alsakka participated in discussions and assisted with the literature review and manuscript composition. She also contributed to the research methods and data analysis. Dr. Hamzeh and Dr. Al-Hussein were the supervisory authors and were involved with concept formation and manuscript revision.

In addition to the above-noted works, the research presented in this thesis is described in the following publications.

5. Martinez, P., **Barkokebas, B.**, Hamzeh, F., Al-Hussein, M., and Ahmad, R. (2021). "A vision-based approach for automatic progress tracking of floor paneling in offsite construction facilities." *Automation in Construction*, 125, 103620.

6. **Barkokebas, B.**, Alwisy, A., Bu Hamdan, S., Altaf, M. S., and Al-Hussein, M. (2019). "Framework to evaluate the impact of prefabrication of wood-frame structures for low-rise buildings." Wood Design Focus, 29(1), 18–25.

7. **Barkokebas, B.**, Brown, R., Altaf, M.S., Bouferguene, A., and Al-Hussein, M. (2020). "Evaluation of multi-skilled labor in an offsite construction facility using computer simulation hybrid approach." Proceedings, 37th CIB W78 Information Technology for Construction Conference, Sao Paulo, Brazil (virtual conference), Aug. 18–20, pp. 488–502.

8. Brown, R., **Barkokebas, B.**, and Al-Hussein, M. (2019). "Predicting performance indicators using BIM and simulation for a wall assembly line." Proceedings, Annual Conference of the International Group for Lean Construction, Dublin, Ireland, Jul. 1–7, pp. 853–862.

9. **Barkokebas, B.**, Bu Hamdan, S., Alwisy, A., Bouferguene, A., and Al-Hussein, M. (2018). "BIM guideline review for public post-secondary institutions." Proceedings, International Symposium on Automation and Robotics in Construction, Berlin, Germany, Jul. 20–25, 8 pages.

10. **Barkokebas, B.**, Dias Ferreira, R. C., Secchi, L., Gül, M., and Al-Hussein, M. (2018). "Addressing the impact of industrialized components on the reduction of temporary heating cost in cold-climate regions." Proceedings, 2018 Modular and Offsite Construction Summit, Hollywood, FL, USA, Mar. 22–25, pp. 109–116.

11. **Barkokebas, B.**, Ritter, C., Li, X., and Al-Hussein, M. (2018). "Predictive model for siding practice in panelized construction." Proceedings, 2018 Modular and Offsite Construction Summit, Hollywood, FL, USA, Mar. 22–25, pp. 49–56.

12. Ritter, C., **Barkokebas, B.**, and Al-Hussein, M. (2018). "Evaluation of existing layout improvement and creation algorithms for use in the offsite construction industry." Proceedings, 2018 Modular and Offsite Construction Summit, Hollywood, FL, USA, Mar. 22–25, pp. 93–100.

13. **Barkokebas, B.**, Ritter, C., Li, X., and Al-Hussein, M. (2018). "Predictive model for siding practice in panelized construction." Proceedings, 2018 Modular and Offsite Construction Summit, Hollywood, FL, USA, Mar. 22–25, pp. 49–56.

14. **Barkokebas, B.**, Zhang, Y., Ritter, C., and Al-Hussein, M. (2017). "Building information modelling and simulation integration for modular construction manufacturing performance improvement." Proceedings, European Modeling and Simulation Symposium, Sep. 18–20, Barcelona, Spain, pp. 409–415.

"Because what was old in the North, becomes new in the South"

Fred 04

"Blessed, blessed are the thieves who stole my masks"

Kahlil Gibran

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LIST OF ABBREVIATIONS

BIM	Building Information Modelling
CAD	Computer-Aided Drawing
CNC	Computer Numerical Control
CRISP-DM	Cross-Industry Standard Process for Data Mining
CV	Coefficient of Variation
DS	Dual Skill
DT	Digital Twin
DCB	Direct Capacity Balancing
DSR	Design Science Research
EDA	Exploratory Data Analysis
ERP	Enterprise Resource Planning
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
HB	Hybrid
IQR	Interquartile Range
KM	Key Metric
MEP	Mechanical Electrical and Plumbing
OSB	Oriented Strand Board
OSC	Offsite Construction
RFID	Radio Frequency Identification
RFR	Random Forest Regressor
SPIE	Specific-Purpose Improvement Entity
SVR	Support Vector Regressor
VSM	Value Stream Map
WIP	Work in Progress

CHAPTER 1: INTRODUCTION

1.1. Background and motivation

Offsite construction (OSC) is an approach in which concepts from manufacturing are applied to produce building components in a controlled environment (i.e., shop floor), then transported to the site for installation (Goodier and Gibb 2007). Following this approach results in a significant reduction in construction cycle time while providing increased predictability in terms of schedule and cost of construction projects (van Vuuren and Middleton 2020). Despite its well documented benefits, though, Bertram et al. (2019) argue, in a report commissioned by McKinsey Global Institute, that adoption of OSC has been relatively low, with housing market shares of less than 6% in countries such as China, Australia, the United Kingdom, and the United States.

Several barriers to the adoption of OSC, such as low standardization of operations due to high variability in projects requested from clients, process uncertainty, and increased fixed costs due to factory overhead and personnel, have been identified in the literature (Gan et al. 2018; Killian et al. 2016). These barriers are common characteristics of OSC, and they have also been identified by Zolghadr et al. (2022), who suggest the application of advanced technologies to alleviate the effect of product variability during manufacturing operations and to improve project coordination during premanufacturing phases (i.e., design, bidding, and procurement).

According to Oesterreich and Teuteberg (2016), a number of advanced technologies, such as building information modelling (BIM), computer simulation, and sensor technologies—e.g., radio frequency identification (RFID), barcodes, etc.—by which to digitalize processes, have been applied and reached their maturity in construction. Applications of these technologies in OSC, moreover, such as for quality control, material waste optimization, real-time production control, and the automation of quantity takeoff estimations from BIM models to other information systems, are widely available in the literature (Altaf et al. 2015; Malik et al. 2021; Martinez et al. 2019; Wang et al. 2019). Nevertheless, although these technologies have been successfully applied individually to specific phases (e.g., design, manufacturing, etc.), their integration among the various areas of expertise in OSC enterprises have yet to be explored (Mukkavaara et al. 2018).

A common practice to bridge this gap in OSC has been the application of lean construction as a conceptual framework for process improvement and for the implementation of novel technologies (Innella et al. 2019). Lean construction is highly applicable to OSC, given its roots in manufacturing and the adaptation of concepts and tools from the manufacturing industry (Yu et al. 2013). In this regard, Brown et al. (2019) link multiple BIM models in a discrete-event simulation model to collect lean-based performance indicators and to further leverage this information for production forecasting. In recent studies by Barkokebas et al. (2017) and by Ritter et al. (2020), meanwhile, a combination of value stream mapping (VSM) and Monte Carlo simulation is used to assess process improvements in OSC. Despite the extensive work carried out in process improvement of OSC manufacturing, though, Erikshammar et al. (2013) argue that existing approaches involving the use of simulation are not sufficient for leveraging these tools outside of an academic environment due to the significant discrepancies between input data and actual data, and the time-consuming nature of simulation model development and validation. In practice, in order to achieve efficient manufacturing operations, processes must be improved continuously, with decision-making firmly rooted in actual operational data (Ahn et al. 2022). Hence, it is imperative to collect, process, and apply data regarding both products (e.g., wall and floor panels) and processes to improve OSC manufacturing operations and reduce its fixed costs while accounting for its inherent variability.

According to Björkdahl (2020), digitalization is characterized as the creation, analysis, and use of data to increase an enterprise's internal efficiency while creating value-adding opportunities for its clients through digital platforms. Despite the prominence of digital tools such as spreadsheets, BIM, and other information systems in this paradigm, OSC still lacks a digitalized approach by which stakeholders can work collaboratively with high efficiency. Attouri et al. (2022), based on a comprehensive survey of OSC practitioners, identify low adoption of digitalization strategies as a notable issue. Meanwhile, they also identify digitalization as a strategic lever by which to increase the efficiency of OSC by significantly reducing construction cost and enhancing communication using real-time data combined with BIM models.

Hamzeh et al. (2021) argue that the triad, people–processes–technology, must be at the core of any effort to advance digitalization in construction, while also noting the increased use of sensors combined with artificial intelligence/machine learning and automation as evidence of a trend in this direction. Sjödin et al. (2018) propose a similar triad for the digitalization of manufacturing operations and implementation of Industry 4.0 while providing four levels at which it can be implemented as outlined below:

Connected technologies: This involves mapping existing and applicable new technologies and connecting existing technological applications to create a continuous data flow. It also involves creating an inclusive environment by involving personnel from different hierarchical levels and formalizing a process to develop a connected information platform.

Structured data gathering and sharing: At this level, data-mining processes to support information gathering across departments are created, and production insights are identified based on data gathered from the shop floor. It is also important in this regard to train stakeholders to develop new abilities to exploit the connected data systems, and to establish internal procedures to automate data extraction from different sources.

Real-time process analytics and optimization: At this level, production insights are used as the basis for streamlining operational processes and establishing methods by which to evaluate proposed process improvement measures in manufacturing operations. Moreover, simulation systems are implemented to test and prototype information systems (e.g., digital twins) in order to optimize manufacturing operations in real time.

Smart, predictable manufacturing: Finally, it is critical to create a culture of continuous improvement, creating processes for integrating data visualization into decision-making while implementing systems to monitor critical operational analytics.

In this context, this thesis provides frameworks and methods for process improvement in OSC using a digitalization approach and data gathered in real time or offline (e.g., BIM models, cost databases, and other information systems.). First, a framework to map and evaluate processes and connect different information systems across the design, bidding, and procurement phases in OSC using a lean-BIM approach—i.e., level 1, according to Sjödin et al. (2018)—is presented. As per level 2 above, this thesis proposes structured methods to evaluate proposed process improvement measures using exploratory data analysis, machine learning, data visualization, and statistical analysis (i.e., hypothesis-testing) using large sets of data from RFID antennas installed on an OSC shop floor and project features from BIM models. Corresponding to level 3 above, this thesis evaluates in real time the impact of digital twins (DT) in improve manufacturing operations using a combination of discrete and continuous simulation as a surrogate system. (Due to the novelty of this topic, maturity level 4 as described in Sjödin et al. (2018) is outside the scope of this thesis.) In this manner, this thesis contributes to the application of digitalization approaches to improve manufacturing operations in OSC.

1.2. Hypothesis and Research Objectives

This research is built upon the following hypothesis:

"Digitalization and the use of real-time data can be applied to improve offsite construction operations by reducing cycle times and process waste"

Hence, the primary goal of this thesis is to develop frameworks and methods to improve OSC operations through digitalization and the application of real-time data combined with expert knowledge and data generated offline (e.g., BIM models). To meet this primary goal, this research pursues three specific research objectives (O*x*):

O$_1$: propose a BIM–Lean framework to map currently available innovative technologies that are applicable to OSC in order to establish formal linkages among different information systems for the digitalization and process improvement of the premanufacturing phases of OSC;

O$_2$: develop methods for evaluating proposed process improvement measures that combine manufacturing and data science expertise in OSC using real-time data and a digitalization approach; and

O_3: evaluate the impact of novel technologies such as DT to digitalize manufacturing operations and reduce waste in OSC.

Table 1.1 shows the relationship between the research objectives and the maturity levels as proposed by Sjödin et al. (2018) within the context of this thesis. As observed in the table, each objective is related to a digitalization maturity level that Industry 4.0 must achieve to improve their processes leveraging their own data.

Table 1.1: Relationship between the digitalization maturity level and research objectives.

Maturity level	**Research objectives (O_x)**
Level 1: Connected technologies	**O_1:** Framework for the digitalization of the premanufacturing phases of OSC
Level 2. Structured data gathering and sharing	**O_2:** Methods to evaluate manufacturing operations using real-time data through a digitalization approach
Level 3. Real-time process analytics and optimization	**O_3:** Evaluate the impact of digital twins to leverage manufacturing operations in OSC

1.3. Thesis Organization

This thesis is composed of seven chapters. Chapter 1 provides the background and motivation, culminating in the formulation of a hypothesis and corresponding research objectives to address the identified gaps in the literature. Chapter 2 provides a review of the main topics relevant to the research presented in this thesis. As such it provides the state of the art on digitalization strategies and the impact of BIM on the OSC premanufacturing phases, reviews relevant research on the application of real-time data in OSC manufacturing operations, and provides a summary of the use of DT in construction. Chapter 2 also identifies the main gaps related to this research and the point of departure for Chapters 4, 5, and 6. Chapter 3 describes the main research methods and the underlying approach applied to achieve each of the specific objectives. This chapter also characterizes the linkages among the various research objectives and the contributions of each toward meeting the overarching research goal described in Chapter 1.

Chapter 4 presents the development of a framework to address the impact of digitalization in OSC premanufacturing (design, bidding, and procurement) phases, with BIM and lean principles being the main drivers (O_1). The framework uses design science research (DSR) while also applying VSM and simulation to identify existing sources of process waste and to quantify process uncertainties, respectively. The proposed framework is tested and validated through empirical implementation, being found to result in a reduction of up to 23.33% in total time during the design and procurement phases of projects as a result of waste minimization and digitalization of processes. The impact of digitalization in the premanufacturing phases and a formal framework for identifying the necessary connections between BIM and other information systems having been established, this research then evaluates the impact of digitalization in OSC manufacturing operations as presented in Chapters 5 and 6 (i.e., O_3 and O_4, respectively).

Chapter 5 describes the development of a method that leverages exploratory data analysis, machine learning, and digitalization to develop novel procedures for validating proposed process improvement measures on an OSC shop floor (O_2). Using the cross-industry standard process for data mining (CRISP-DM), the research takes a structured approach leveraging machine-learning algorithms to identify production insights in semi-automated workstations by combining insights from experts, project features from BIM models, and actual durations of wall panel fabrications collected via RFID. This chapter also evaluates the efficiency of approaches adopted on the shop floor to deal with variability in production using statistical analysis. As notable contributions of the research presented in this chapter, the proposed method provides a number of different procedures for applying project- and production-related data for process improvement in OSC. Additionally, it provides novel insights regarding the impact of product variability as well regarding the process wastes associated with the use of semi-automated framing machines.

Chapter 6 presents empirical evidence by which to evaluate the impact of digitalization (leveraging a DT) as a means of increasing flexibility on the shop floor by reassigning multi-skilled workers dynamically and reduce waiting waste on an OSC shop floor (O_3). Using simulation as a surrogate system, this study emulates a shop floor (leveraging actual production data collected in real time) to improve manufacturing operations via the proposed DT. In this respect, this research emulates a DT that reassigns multi-skilled workers to deal with project fluctuations and uncertainties in different scenarios. The proposed approach simulates relevant aspects of production such as the important features of multi-skilled workers (learning effect, multi-skilling strategies, cost, etc.), the impact of DT in increasing productivity, and the average waiting time per module. The practical application of the proposed system demonstrates a significant decrease in waiting waste in manufacturing operations in comparison with the current baseline for a case OSC operator.

Finally, Chapter 7 summarizes the research, outlining the conclusions drawn, the study limitations, and the recommendations for future research in this area.

CHAPTER 2: LITERATURE REVIEW

Applying real-time data and digitalization to improve manufacturing operations in offsite construction (OSC) is a major challenge in both industry and academia. In the context of this thesis, it should be noted, OSC manufacturing operations refers to the processes involved in transforming raw materials or components into OSC projects, including the management of labour, materials, and data. To conduct OSC manufacturing operations, a number of different information systems need to be put in place and integrated, given the multi-disciplinary nature of OSC whereby different stakeholders (e.g., designers, estimators, builders, etc.) must interact in a coordinated manner to efficiently deliver projects. In this regard, there is a lack of methods by which to integrate and apply real-time data on the shop floor using a digitalization approach. Accordingly, this thesis explores three main areas within the literature so that the barriers to implementation of digitalization can be identified and addressed in order to better leverage the value of OSC manufacturing operations. This research endeavors to reduce the adverse effects of these barriers and bridge the gap between the gathering of real-time data and its application for data-driven improvements in OSC.

2.1. Digitalization strategies at premanufacturing phases of OSC projects

The premanufacturing phases (i.e., design, bidding, and procurement) in OSC are characterized by uncertainty, given that projects vary considerably depending on client requirements and inherent market fluctuations (Sutrisna et al. 2019). Meanwhile, uncertainty in the form of varying productivity of designers and estimators results in significant process waste due to inadequate data exchange and inadequate tools for performing premanufacturing tasks. Given the complexity of OSC projects, Bakhshi et al. (2022) argue that current strategies to design and deliver OSC projects lack the requisite flexibility to accommodate client requests in an efficient manner. Arashpour and Wakefield (2020) voice similar concerns, while attributing inefficiencies in the OSC premanufacturing phases to inadequate data or improper data exchange among stakeholders (e.g., designers, estimators, plant managers, etc.). Indeed, OSC stakeholders often disregard data generated at earlier phases due to inaccuracy of the data, while in other cases they may be entirely unaware of its existence, and these deficiencies ultimately result in various forms of process waste. In this regard, Wang et al. (2020) conclude that productivity in OSC manufacturing is inhibited by inadequate data exchange due to a lack of digitalization, a shortcoming that results in a number of issues such as information delays and a lack of consistency and accuracy in data.

Gartner Analytics (2022) defines “digitization” and “digitalization” differently, where the former deals with transformation of processes from analog to digital (without changing the process itself), while the latter is defined as an approach to generate, analyze, and apply data to improve internal processes while creating new opportunities for further improvement. In this context, Assaad et al. (2022) point out that OSC can significantly leverage digitalization through the generation of information pertaining to the feasibility of alternative construction methods and by providing data to be used in the future as part of a continuous improvement program. In fact, digitalization strategies and a greater degree of adoption of advanced technologies are often acknowledged as being strategically advantageous for contractors (Biggs 2018). Nevertheless, OSC operators are hesitant to invest in new technologies or digitalization initiatives without a clear picture of the trade-off between the investment needed and the inherent uncertainties in the process, such as in the case of the considerable initial investment in software and training, and without a clear path to implementation of these technologies (Kumar and Kaushik 2020).

In light of this, Ghaffarianhoseini et al. (2017) identify building information modelling (BIM) as a key technology for digitalizing the OSC industry, as BIM models provide accurate project information in a structured manner that can be automated. Meanwhile, Jin et al. (2018) argue that the integration of BIM with other information systems is the cornerstone of any effort to increase productivity in OSC. Despite the benefits of BIM in the design phase (which have been widely recognized by industry practitioners and academia), though, Mostafa et al. (2020) argue that frameworks by which to integrate BIM with other information systems in OSC are lacking, and that this hinders further collaboration with other premanufacturing phases. To bridge this gap, Pan and Pan (2022) point to the integration of lean thinking with BIM in OSC-centric frameworks as a way to systematically reduce process waste, while Marte Gómez et al. (2021) argue that combining lean concepts with the digitalization features of BIM can improve communication and reduce costs compared to current frameworks.

Nascimento et al. (2017) propose a BIM–lean framework to improve the constructability of prefabricated building components, the focus of this framework being on increasing the degree of digitalization in the workflow of data being exchanged between different stakeholders. Popovic et al. (2021), meanwhile, develop a digitalization-based framework to increase the design flexibility of OSC projects by identifying the key information required at each stage of project development. Despite recent developments, though, Herrera et al. (2021) argue that, even as they necessitate investment in other advanced technologies, quantitative evidence of the advantages of BIM–lean frameworks is still lacking. Strategies by which to formally identify new technologies and connect different information systems are currently missing in the literature, and this hinders the digitalization of the premanufacturing phases of OSC.

2.2. Advanced technologies and the application of real-time data in OSC manufacturing operations

Various technologies are applied to improve processes in the context of OSC, and technologies such as BIM and computer simulation have been explored extensively within academia (Oesterreich and Teuteberg 2016). Despite not having a clear definition on the term, Li et al. (2021) point to a lack of research specifically pertaining to OSC and the application of advanced technologies such as work-monitoring systems leveraging sensors, data analytics, and the automation of processes in shop floors. Therefore, in the context of this thesis, advanced technologies are characterized as technologies where methods for their implementation in the construction industry are still under development. Within the context of OSC in particular, advanced technologies capable of leveraging large volumes of data are required due to the dynamic and multi-disciplinary interactions between the shop floor and the site where installation occurs (Wang et al. 2020c). In a study exploring the deployment of various advanced technologies, Assaad et al. (2022b) identify sensors, machine learning, and data analytics applications as the technologies with the greatest potential for use in OSC projects. As an example of the application of such a technology to OSC, Zhou et al. (2021) propose a cloud-based platform to improve the onsite assembly of volumetric OSC projects by leveraging data from BIM models, mobile applications, and location-based sensors. Meanwhile, Martinez et al. (2022) apply vision-based algorithms coupled with statistical tools to assess the non-conformity of manufactured components on OSC shop floors and generate predictive maintenance models for the equipment used.

Wang et al. (2020b), in their review of various work-monitoring technologies in OSC, identify RFID as the advanced technology that is most commonly used in combination with BIM models for this purpose. As noted in other studies, RFID has been deployed in OSC in applications ranging from near-real-time material tracking to scheduling and real-time retrieval of building component information (Li et al. 2018, 2020; Zhai et al. 2019). Moreover, Forsythe et al. (2019) highlight the ability of RFID to integrate the supply chain of prefabricated components (i.e., supply, transformation, transportation, and installation of raw materials). Meanwhile, Mohsen et al. (2022) develop comprehensive machine-learning applications to predict the performance of the shop floor under different scenarios, combining the cycle time duration of manufactured panels with design and shop floor features extracted from BIM models and by inferring information from data gathered on the shop floor, respectively. Similarly, Ritter et al. (2018) propose the use of RFID data in combination with design features extracted from BIM models to balance and forecast production in OSC.

However, Barkokebas et al. (2018) argue that, despite its successful application to locate and calculate the cycle times of components being produced in OSC, RFID technology is not capable of identifying whether work is actually being performed on components that are in-between antennas (i.e., it is not able to distinguish between process times and idle times). To account for this limitation, they propose to subject the RFID data to a series of statistical analyses based on manual time studies performed on selected workstations. To address the same limitation, Rashid and Louis (2021) install inertial measurement sensors to detect process times and idle times at workstations in an OSC facility. Martinez et al. 2021 employ a similar approach to identify process times and idle times in an OSC shop floor by applying vision-based algorithms. These examples demonstrate that a combination of multiple advanced technologies must be applied in careful consideration of the characteristics and limitations of the given OSC shop floor in order to increase manufacturing efficiency.

In this regard, Hou et al. (2020) assert that applications leveraging artificial intelligence and sensor monitoring can result in increased productivity and can yield useful production insights to improve OSC operations. Nevertheless, Ahn et al. (2022) argue that the effective implementation of these applications has yet to be achieved due to the lack of a systematic approach to gather, process, evaluate, and apply data for process improvement in OSC. To implement such applications, approaches must be developed that take into consideration the nature of the operations to be optimized, followed by extensive preprocessing of the raw data collected from different sources. However, Wu et al. (2020) point out that the current paradigm of data preprocessing is heavily reliant on the experience of experts and is time-consuming, error-prone, and largely manual.

Wang et al. (2020b), meanwhile, argue that the lack of empirical validation and case studies restricts the use of real-time data applications in OSC, particularly at the conceptual level, thus hindering the development of digitalization methods to improve OSC operations. Indeed, there is a lack of expertise in data analysis in the context of OSC operations, which requires a combination of knowledge of the operations conducted on the OSC shop floor and data science skills to analyze data and develop machine-learning models for process improvement. Therefore, data-mining approaches must be developed that are tailored to accommodate the unique nature of OSC manufacturing operations.

2.3. Digital twins in construction

The construction industry is characterized by a high level of customization, where clients are given a wide range of options related to dimensions and building specifications (Smith 2018), resulting in a high degree of product variability on OSC shop floors. Additionally, the inherent uncertainty of manual tasks increases variability on the shop floor, thus introducing even more complexity to overall production in OSC. According to Bataglin et al. (2020), the complexity involved in managing several projects concurrently with short lead times and accommodating different clients' requests is the principal challenge in OSC. In light of this, Ding et al. (2019) propose the application of novel technologies leveraging real-time monitoring and automated systems such as digital twin (DT) to account for production variability and allow for a flexible manufacturing system on the shop floor.

In their seminal work, Grieves and Vickers (2017) define DT as an informational construct describing a physical system, object or process, while providing its virtual counterpart in real-time. They go on to argue that three elements are required in order to develop a DT: (1) a physical system, (2) its virtual counterpart (i.e., virtual system) generated from data gathered in the physical system, and (3) a seamless connection between both systems in real time. In manufacturing, DT has been applied to increase the flexibility of shop floors while considering the influence of external factors such as fluctuations in demand and the need to accommodate individualized demand from clients (Zhang et al. 2022). In this regard, Fera et al. (2019) apply DT to monitor and balance manual operations on a shop floor considering the pace of manual and automated workstations, while Arnarson et al. (2022) develop a DT to adapt and increase the flexibility of a shop floor, thus shifting the manufacturing paradigm of mass manufacturing to customized production in small batches. It should be noted that in the current paradigm of OSC, clients expect customized products (e.g., single-family houses, condos, etc.) at a low number of units per product type, rather than large volumes of uniform products.

Correa (2018) argues that OSC shop floors are more likely to implement advanced technologies such as DT than are traditional construction jobsites, given the controlled environment (and the relative ease with which sensor infrastructure can be installed) in OSC. Indeed, a critical factor in the future course of OSC will be the uptake of various methods to process data from sensors and BIM models and the successful application of these methods to improve construction processes using advanced technologies such as automation and DT (Baduge et al. 2022). Jiang et al. (2022) apply DT to improve the coordination of operations between the shop floor and the site where products are installed. Rausch et al. (2020) develop algorithms to support DT in order to optimize the production and quality of manufactured components. Rausch et al. (2021) also apply DT to verify the geometric compliance of manufactured components by comparing actual geometrics gathered by laser scans against a virtual counterpart in the BIM model.

In this regard, a considerable amount of data is generated by sensors on the shop floor that could be used to improve production in real or near-real time. In the present research, DT is used to gather and process real-time data from sensors in order to increase the flexibility of manufacturing operations in OSC. Despite promising results in the literature, practitioners remain reluctant to adopt DT to assist in managing their manufacturing operations, and more case studies are needed in order to validate its impact and applicability in OSC (Qi et al. 2021). Neto et al. (2020), in a study addressing issues related to the implementation of DT in shop floors, argue that there is also a lack of studies quantifying the impact of DT in manufacturing. To bridge this gap, Glatt et al. (2021) apply simulation as a surrogate system to quantify the impact of DT in shop floors identifying and simulating important factors for its implementation. Meanwhile, Zhou et al. (2021b) conclude that a comprehensive study identifying the key features and issues in the implementation of DT on a project basis is needed. Moreover, Dittmann et al. (2021), in a study in which they propose open source standards for data exchange in DT implementation, argue that generic and scalable approaches for DT implementation in OSC have yet to be developed. In fact, despite its potential benefits, DT technology is still in the early stages of development, and further research is needed concerning its implementation in OSC that considers such factors as: (1) the variable production rate of automated and manual workstations, (2) the impact of human behaviour during production, and (3) the significant variability and customization of products based on client requirements.

2.4. Identified gaps in the literature and point of departure

Based on the literature review, three gaps are identified: (1) there is no digitalization approach for the premanufacturing phases in OSC that considers the formal connection between different information systems and the multi-disciplinary nature of OSC, (2) a digitalization method is needed to integrate real-time data with expert knowledge for process improvement, and (3) there is a lack of sound methods and quantitative evidence by which to evaluate the impact of DT on OSC. Hence, this thesis aims to address these gaps (and thereby improve manufacturing operations in OSC) through the development of frameworks and methods rooted in digitalization and the use of real-time data.

CHAPTER 3: METHODS

This chapter summarizes the research methods employed to address the identified research problems. This research takes an inductive reasoning approach whereby hypotheses are developed based on field work and observations (Williamson 2013).

Figure **2.1** illustrates the methodologies applied as well as the inputs and outputs corresponding to each research objective. To develop a framework for digitalization in offsite construction (OSC) premanufacturing phases (O_1), design science research (DSR) is applied, as it involves the creation and testing of a research artefact (i.e., the proposed framework). According to Hevner et al. (2004), DSR is a methodology focused on developing a research artefact (e.g., framework, forecast model, etc.) to solve an identified problem, where the effectiveness and contribution of the research artefact must be rigorously demonstrated and explained. DSR is selected as a suitable methodology for achieving O_1 based on its popularity among researchers as a means of developing and evaluating frameworks within the information systems domain (Nimmagadda et al. 2019). The framework having been completed, implemented, and tested; it serves as an input to the second research objective (O_2), which is to devise digitalization methods leveraging real-time data, expert knowledge, and design features from BIM models. These methods are devised through a Cross-Industry Standard Process for Data Mining (CRISP-DM), where the development of the proposed methods constitutes an exploratory study on large sets of data aimed at improving manufacturing processes in OSC based on expert input. CRISP-DM is applied in this case because it is the standard methodology for analyzing large sets of data in industrial applications (Huber et al. 2019). The expected impact of applying these advanced technologies (e.g., DT) is then assessed by using simulation as a surrogate system to test different scenarios involving the use of multi-skilled workers to increase labour flexibility in OSC. Due to the significant risk and complexity involved in the implementation of DT on a shop floor, Al Hattab et al. (2018) argue that simulation can be a useful approach to employ prior to implementation, since significant aspects of a system (in this case, the OSC shop floor) can be modelled and forecasts performed accordingly with a reasonable level of certainty. Hence, for the present study, simulation is selected as a suitable method for assessing the impact of DT in increasing labour flexibility in OSC (i.e., O_3).

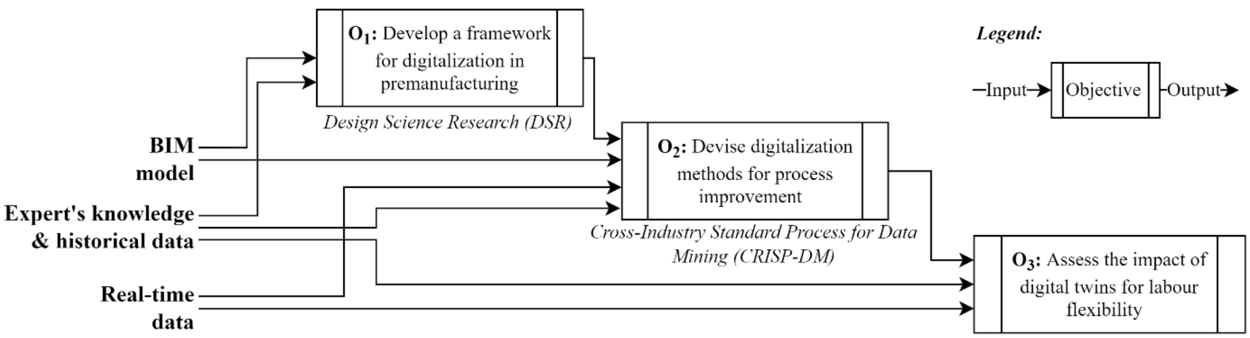


Figure 2.1: Methods applied and linkages among research objectives

Figure 2.2 illustrates the procedure followed in this research, including the inputs, criteria, and outputs. For O_1, a framework is required for the establishment of a repository of project-related data by which to formally develop digitalization approaches for the premanufacturing phases of OSC. This framework is based on the current-state assessment of OSC premanufacturing tasks developed from a combination of discrete-event simulation and value stream mapping (VSM). The current-state assessment having been validated, measures to improve the mapped processes are proposed, while the expected impacts of these measures are forecast using the same methods (i.e., discrete-event simulation and VSM).

Using the proposed framework, a repository containing project-related data from the BIM models is linked with data gathered by sensors on the shop floor, while methods by which to assess potential process improvement measures are proposed based on a combination of input from OSC experts and exploratory data analysis (EDA) techniques (i.e., O_2). A hypothesis is developed for each of the improvement measures formulated based on expert input, and machine learning techniques and statistical analysis are applied to assess the feasibility of each improvement measure at the early stages of its implementation. Furthermore, a simulation-based approach for the near-real-time assessment of the potential impact of DT (in both industrial and academic contexts) in improving manufacturing operations is implemented (i.e., O_3). The proposed assessment will assist practitioners and researchers in assessing the impact of DT in increasing labour flexibility in OSC manufacturing operations.

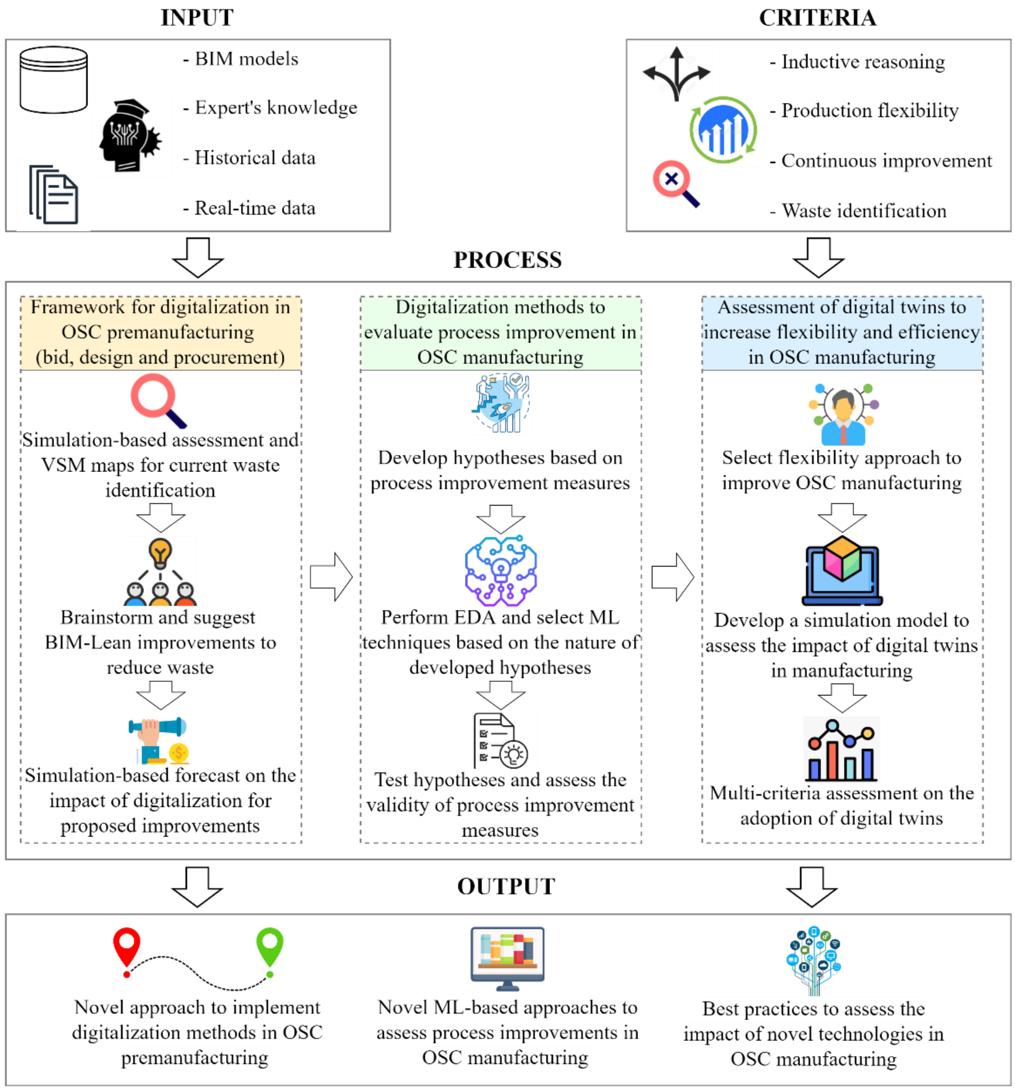


Figure 2.2: Overview of the research

In summary, this thesis provides a framework to implement digitalization approaches in the premanufacturing phases of OSC; describes the development of novel methods to apply large sets of BIM data and real-time production data for process improvement in manufacturing operations; and proposes a novel approach to evaluate the impact of DT in terms of production efficiency and flexibility, taking into account various aspects of production, including, but not limited to, the trade-off between average process times and waiting times during production.

CHAPTER 4: A BIM–LEAN FRAMEWORK FOR DIGITALIZATION OF THE PREMANUFACTURING PHASES OF OFFSITE CONSTRUCTION[1]

4.1. Introduction

Offsite construction (OSC) is an approach that reduces construction time, defects, and risks by manufacturing building components in a factory-like environment and installing them at their final destination on site (Mostafa et al. 2016). In spite of the recognized benefits, OSC still faces several challenges as researchers discuss these issues and suggest ways to overcome them. Bataglin et al. (2020) argue that the short lead times required in order to accommodate clients' requests and the complexity involved in managing different projects being manufactured at the same time are the main challenges in OSC projects. By providing an integrated solution (design, procurement, manufacturing, and installation) based on the client's requirements, offsite contractors take on the majority of the risk while dealing with a range of different professionals such as consultants, suppliers, plant managers, and construction personnel. Information transmitted by the client that is translated into drawings, commercial proposals, and design specifications must be consistent and shared throughout the process to avoid waste, such as cost overruns, and product nonconformity (Li et al. 2018). Building information modelling (BIM) has been used to streamline the flow of information while facilitating the use of digital technologies in OSC even though its implementation has not received widespread attention (Luo et al. 2020). However, despite

[1] The manuscript appearing as Chapter 2 of this thesis is published as Barkokebas, B., Khalife, S., Hamzeh, F., and Al-Hussein, M. (2021) "A BIM–lean framework for digitalisation of premanufacturing phases in offsite construction." *Journal of Engineering, Construction and Architectural Management*, 28(8), 2155–2175.

evidence of the benefits of using BIM to digitalize and enhance design and procurement processes in OSC, Razkenari et al. (2020) argue that most benefits are not yet measured or quantified.

Seamless data flow and the integration of different information systems is crucial for efficient product development and management (Caldas et al. 2005). In this context, Grieves (2006) pointed out that there is a substantial cost associated with the rework required to deal with information isolated between departments (e.g., sales, engineering, estimation) and the re-creating or reconstructing of missing/ incomplete information in inter-departmental work. Similarly, Agarwal et al. (2016) attribute the construction industry's low productivity to a lack of timely information sharing, which results in stakeholders often working on different versions of documents creating disagreements and additional cost. Agarwal et al. (2016) accordingly recommend the adoption of digitalization, which they define as the transformation to an environment in which information is digital, updated in real time, and transparent, resulting in improved and more reliable outcomes. Moreover, Ghaffarianhoseini et al. (2017) claim that continued digitalization will allow the construction industry to reinvent project design and delivery processes and position BIM as a key technology in this initiative. In this context, BIM has been used to bridge information gaps in various areas such as schedule and project coordination between stakeholders (Ocheoha and Moselhi 2018).

Moreover, OSC has benefited from concepts derived from other domains, such as lean manufacturing. Through its premise of minimizing waste and adding value to the process, lean construction provides tools to identify and minimize wastes in offsite operations (Innella et al. 2019). Lean philosophy provides a comprehensive framework to propose and quantify improvements in construction-related processes, such as the implementation of BIM or its integration with different information systems.

Despite relevant work in the area, Yin et al. (2019) argue that researchers have yet to establish criteria by which to quantify the improvements achieved by BIM adoption and thereby encourage its wider adoption in OSC. Organizations acknowledge the benefits inherent to the integration of BIM with other information systems to harness their advantages, yet further research is required at the organizational level to quantify the benefits from these implementations (Lu and Korman 2010). Additionally, the adoption of the lean approach in offsite companies shall be guided early on from the design phase, and research needs to examine the help of advanced technology to support lean techniques in achieving its full potential (Innella et al. 2019).

Accordingly, this chapter proposes a framework to introduce digitalization in OSC premanufacturing phases (pre-bidding, design, and procurement) using a BIM–Lean approach where BIM is characterized as the main source of project-related information; while lean philosophy is applied as a guiding principle to identify and minimize wastes in current and future processes. The proposed framework integrates BIM and other information systems to improve inter-departmental communication focusing on three organizational needs: improved planning, improved information exchange, and quantification of improvements. The motive behind this research is to provide OSC companies with a roadmap for improving their performance during premanufacturing phases while also providing methods to quantify improvements due to digitalization. This study contributes to the body of knowledge by providing a well-defined reproducible approach that serves as a guide to digitalize and improve processes in the offsite sector using BIM, lean principles, and other tools. Additionally, the suggested measures for tracking the improvements will benefit practitioners by having recorded evidence of improvement while establishing a culture of continuous improvement at their organizations.

4.2. Background

Gartner (2020) defines digitization as the process of transforming analogue information to digital without changing the process itself, whereas digitalization (or process digitization) refers to the use of digital technologies to transform processes and produce value-adding opportunities. Therefore, premanufacturing processes in OSC are highly digitized given the predominant use of spreadsheets, digital construction drawings, and the use of enterprise resource planning systems (ERP) to design, estimate, and bid projects. In fact, despite advancements of BIM in OSC and growing demands for customization in the industry, premanufacturing may become a future bottleneck since its processes are still carried out manually and rely heavily on experience (An et al. 2020). Hence, OSC lacks digitalization as it continues to conduct its processes in an analogue manner with digitized tools. While BIM research has been focused on methods and tools at the practical level (Santos et al. 2017), Yin et al. (2019) argue that researchers must establish criteria and quantify the improvements attributable to BIM in OSC to further its adoption. In this regard, Al Hattab and Hamzeh (2018) assert that the full implementation of BIM is inhibited by traditional management strategies and short-term goals, where the lack of guidance and assertive procedures constitute a significant barrier to BIM implementation. To bolster the use of BIM and digitalization at an organizational level in OSC, this research applies lean philosophy given its origins in manufacturing and previous applications in OSC.

Many studies offer frameworks and approaches to incorporate lean philosophies into OSC, as continuous efforts are made to transform the industry into a highly efficient and cost-effective one

(Zhang et al. 2020). Value stream mapping (VSM) techniques have been fundamental lean tools used to identify the current state and its areas of improvement, then redesign processes to maximize performance by identifying and quantifying waste (Howel and Ballard 1998). Three different types of waste are found in activities: value adding, necessary waste (i.e., non-value adding but necessary activities to the process), and pure waste, which are non-value adding activities and can be eliminated from the process (Lee et al. 1999). Discrete-event simulation is another tool applied successfully by lean practitioners in OSC to forecast different scenarios and establish measures for future-state scenarios (Goh and Goh 2019). Furthermore, simulation has helped in providing a means of test the concepts of lean in construction simulation, and templates have been suggested to quantify the impact of implementing such concepts (Farrar et al. 2004). Other studies focus on implementations for process improvement by developing measures to evaluate current and future states of shop floors (Karim and Arif-Uz-Zaman 2013). Regardless of the tools applied, Innella et al. (2019) points out that the full potential of OSC will be achieved once lean principles are used with the support of technology to integrate knowledge across different phases of the project. Hence, there is a need for a framework to promote the digitalization of OSC organizations during early stages taking into consideration differences inherent to each company and the inherent uncertainties in applying predetermined measures to quantify its impact.

Several studies have investigated the combination of BIM and lean methods to improve processes in the OSC sector. For instance, Moghadam (2014) offers an integrated BIM–Lean framework for offsite manufacturing operations mapping the current state and proposing improvements through simulation while generating data and shop drawings for modular projects. Gbadamosi et al. (2019) propose a framework to optimize the constructability of prefabricated building components by applying lean principles and optimization algorithms in BIM models to leverage the design of building envelope components. The literature acknowledges the benefits of both lean principles and technologies such as BIM that emphasize the necessity of incorporating these concepts into the curricula (Li et al. 2018). For instance, Jin et al. (2018), in their literature review of various OSC topics, identify the integration of BIM and lean with technological applications as a prominent research trend.

However, even with the implementation of information technologies (BIM) and lean frameworks into OSC processes, factories still encounter major challenges as the whole sector remains behind (Fenner et al. 2018). This is likely the result of a disconnect between current studies and current practices where BIM–Lean approaches are in dire need of being integrated with other digital technologies (Hosseini et al. 2018). Additionally, Al Hattab and Hamzeh (2017) claim that the impacts attributable to the integration of lean practices and BIM in the flow of design-related information and communication between different departments has not yet been realized, nor have measures been proposed to quantify the benefits. As such, more studies are needed to evaluate the combination of BIM, lean, and other tools to improve OSC through the digitization of its processes and to provide empirical case studies of implementation to demonstrate applicability.

In summary, this research identifies the following problems and gaps in the literature: (1) the misuse of digital strategies in premanufacturing phases of OSC companies, where BIM and other digital technologies are not fully implemented, (2) the lack of quantitative measures that facilitate the assessment and implementation of these digital strategies, and (3) the little attention in the literature given to premanufacturing phases when compared to the fabrication phase. Consequently, this chapter herein presents a tested framework to leverage digitalization in the premanufacturing phases of OSC using a BIM–Lean approach, predetermined measures, and simulation.

4.3. Research Methodology

This chapter implements the design science research (DSR) methodology to propose a framework for improving premanufacturing processes in OSC. DSR involves the development of an artefact to resolve a relevant problem identified in a specific environment, for which the effectiveness and contribution should be demonstrated and rigorously explained (Hevner et al. 2004). In the present research, the artefact is a BIM–Lean framework to improve premanufacturing processes in OSC using digitalization. The development of the framework follows a six-step process (Peffers et al. 2007), as follows:

1. identify the problem under study and main motivation;
2. define specific objectives to address the specified problem;
3. design and develop the proposed artefact;
4. test and demonstrate the artefact's implementation through established metrics in a specified environment;
5. evaluate the artefact's effectiveness based on a proposed experiment; and
6. communicate the artefact through publications.

In step one, the major challenges in OSC were identified by reviewing the state-of-the-art literature and engaging in discussions with practitioners. Step two focused on identifying the objectives in consultation with four different OSC companies and based on the extensive review of common challenges found in these organizations. The objectives of this research were thus determined to be the quantification of improvements from digitalization and integrating data exchange in the context of the use of BIM in OSC companies. In step three, the framework was carefully developed by applying lean principles to account for the possible differences in offsite companies while serving as a generic guideline for proposing and implementing improvements step by step.

Multiple lean principles are adopted in this framework. Mainly, the framework uses VSM to identify current wastes and then forecasts future processes after minimizing wastes. The objective of the mapping exercise is to minimize waste and improve the existing workflow by digitizing processes when applicable and by using the measures proposed in this research. Two types of variation are encountered in OSC premanufacturing processes: (1) variation caused by internal processes at the organization, and (2) variation caused by the range of project specifications offered to clients. While the first type of variation should be minimized using different approaches ranging from low-tech solutions to the implementation of digital solutions, digitalization is applied to minimize the effects from the second type of variation. The latter is due to the fact that external customers value the high range of options OSC offers to them.

The framework takes into consideration the voice of the customer being the internal customer (different teams within the organization) or the external customers (OSC clients). Forecasting is part of this exercise to promote pull from the customer. Moreover, the framework advocates continuous improvement (i.e., kaizen) of current processes by constantly repeating the framework to identify new improvement opportunities. The overall objective is to have continuous flow of information. Furthermore, it calls for implementing *genchi genbutsu*, a lean principle that is helpful in identifying the unique features of a given organization but that requires being physically present to investigate and understand the process. Lean construction calls for releasing work by achieving flow where you can, pull where you cannot, and push where you must.

To this end, the process of developing the framework is iterative. The proposed framework specifies the required input and data from the company while providing details to identify and account for variations in each company, i.e., the framework highlights the practices needed in order to develop the context-specific improvements. By applying simulation and statistical tools expressed in the framework, the current state of premanufacturing processes is quantified while the impact of future digitalization is forecast at the company under study. At step four, test stage, an empirical implementation was used to: (a) help in establishing the instructions or steps in the framework, and (b) demonstrate the effectiveness of the framework. A detailed explanation of the implementation is provided in Section 5. Step five included the evaluation of the proposed framework by recording the observed results. Lastly, the present study communicates the importance of the problem and the effectiveness of the artefact as part of step six of the DSR. The framework targets different departments working at premanufacturing phases in OSC companies to improve their processes by digitizing their work while providing quantitative evidence so the upper management can make the required investment for the proposed digitalization plan. The detailed explanation of the framework is clarified in the next section.

4.4. Proposed BIM–Lean Framework

The proposed framework, presented in Figure 4.1, includes the methods employed to quantify the impact of digitalization achieved by automating and integrating BIM and other information systems in OSC companies. The guiding principles of this framework are presented taking into consideration characteristics identified in each area (OSC, lean and digitalization) at earlier sections. The specific context of OSC- where an integrated solution (design, procurement, and construction under the same company) is presented following standardized construction methods under short lead times- is a determining factor for mapping premanufacturing processes. Moreover, lean is applied to align OSC practices and digitalization features through the lean principles mentioned earlier such as conducting *in situ* observation (i.e., *genchi genbutsu),* mapping of activities, achieving continuous flow of information, and applying continuous improvement (i.e., *Kaizen*) to identify and minimize waste in the process. The digitalization of design and procurement of building components is proposed by using BIM as means to generate, store, and transform project-related data. By working with BIM-based tools, the digitalization of premanufacturing tasks is proposed by connecting different systems (e.g., BIM, ERP), automating processes and sharing data between departments in real-time.

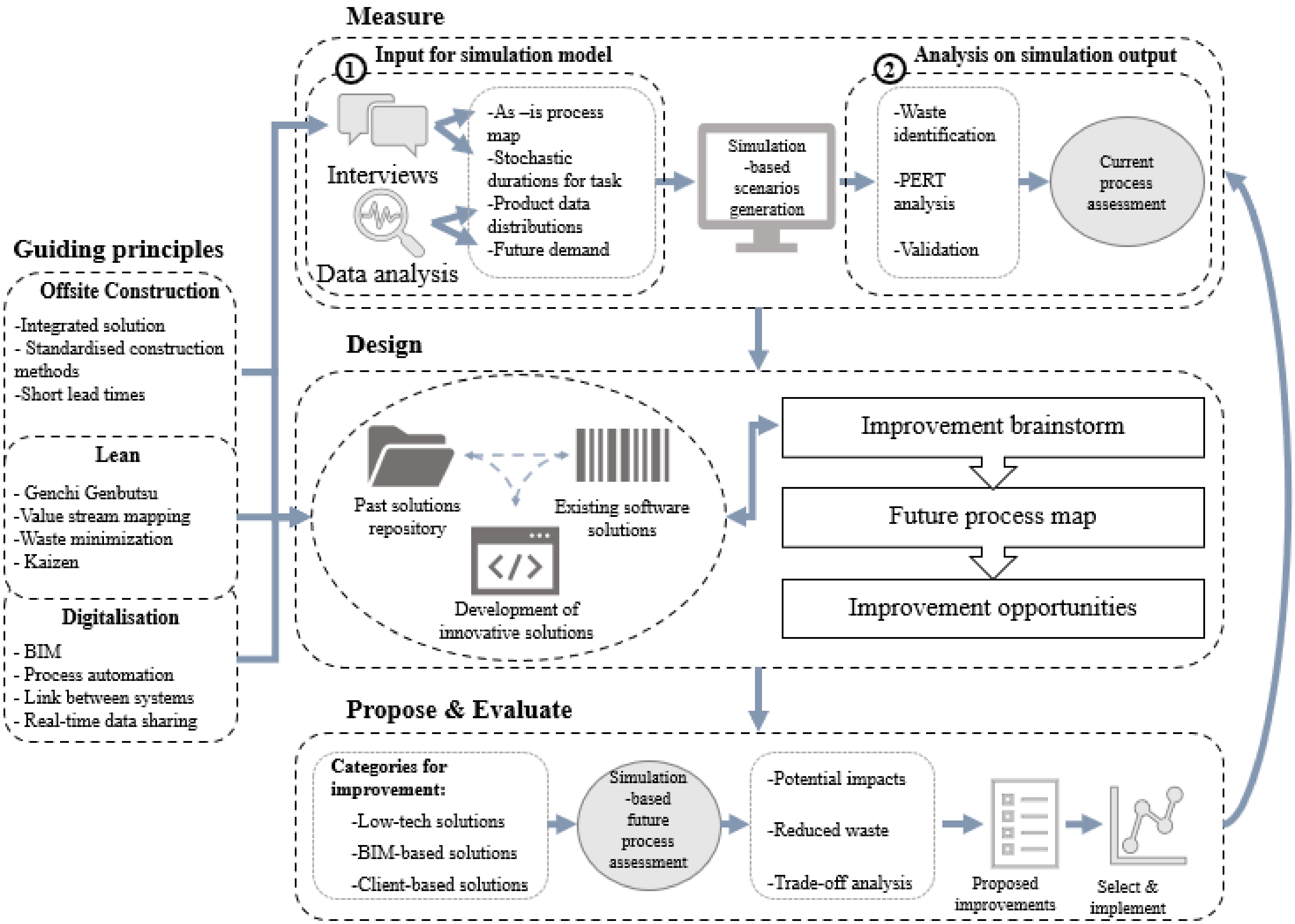


Figure 4.1: Methods employed in the proposed framework.

Lean philosophy is applied as the guiding principles to measure, identify, and implement opportunities for improvements. This framework is therefore divided into three stages as demonstrated in Figure 4.1: stage (1) is *measure*, which involves measuring the current processes observed at the organization, stage (2) is *design*, which involves identifying and designing opportunities for improvement based on the previous assessment, and stage (3) is *propose and evaluate*, which involves proposing opportunities and forecasting the impact of implementing the identified opportunities at the design stage. In summary, the measure stage maps and quantifies the current situation of the addressed offsite organization, whereas the remaining stages suggest improvement opportunities (i.e., design stage) while proposing these opportunities based on simulation models that forecasts their impact on the same organization (i.e., propose and evaluate stage).Simulation is applied at the first and third stages to estimate durations and variations in the process taking the inherent identified uncertainties into account. The proposed framework must be replicated after a testing phase of improvements to allow company experts to measure the impact of the implemented changes and propose new ones, thus creating a culture of continuous improvement around the digitalization of premanufacturing processes.

Table 4.1 summarizes which lean and BIM-based principles were applied to the steps of the proposed framework. Lean philosophy is applied at every stage of the framework while the digitalization of processes acts as an enabler for improvements at the addressed company and is only present at the later stages of the process. Hence, while lean principles such as *genchi genbutsu* and VSM are applied for data collection and analysis, kaizen and waste minimization are applied concurrently with digitalization principles to plan and improve future processes. During the development and implementation of the proposed framework, it is important to understand how the impact of parametric modelling from BIM differs from processing real-time data from different information systems (e.g., BIM, ERP systems, etc.). While the first enhances the quality and speeds the process of design and drafting, the second may change the way and the sequence of present tasks since information between departments is shared continuously (e.g., real-time unit costs for bid proposals and current production status at the shop floor). Hence, BIM-based digitalization principles will play a decisive factor in how tasks will be performed in the future, while lean principles will help forecast and address its actual impact (i.e., kaizen).

Table 4.1: Guiding principles applied to proposed framework steps

		Measure		**Design**			**Propose & Evaluate**	
		1	**2**	**3**	**4**	**5**	**6**	**7**
Lean	Genchi Genbutsu	X		X				
	Kaizen			X				X
	VSM	X			X			
	Waste minimization		X	X		X	X	
BIM-based digitalization	Parametric modelling			X		X		X
	Real-time data processing			X	X	X		X

1: Input for simulation model; 2: Analysis on simulation output; 3- Improvement brainstorm; 4- Future process map; 5- Improvement opportunities; 6- Opportunities selection; 7- Implementation and re-evaluation

4.4.1. Stage 1: Measure

This stage is divided into two procedures: (1) data collection used as an input for the simulation model, and (2) analysis on simulation output to measure current process performance at the company under study. The measures calculated at this stage are used as a benchmark and indicate the current state of process digitization at the company taking into consideration both performance and uncertainties forecast by the simulation model.

4.4.1.1. Input for the Simulation Model

Based on a combination of semi-structured interviews and analysis of historical data provided by the case company, current-state VSM was developed using lean techniques, and sales forecasts were established accordingly. The resulting current-state maps, containing task durations estimated by the organization's experts (e.g., engineers, managers, etc.), and forecasts are used as inputs for the simulation model to estimate different scenarios. At this stage, the organization must appoint experts that directly oversee or perform the mapped tasks to indicate the current situation as close to reality. The semi-structure interviews are carried until both parties (i.e., the organization and research team) are satisfied with the level of details mapped, and their duration is dependent upon the length of the mapped tasks. Tasks are grouped into two main phases: (1) pre-award, including all of the work involved in preparing bid documentation; and (2) post-award, including all of the work performed after submitting the bid (in the event that the project is awarded to the given proponent). Due to the uncertainties inherent in the development of offsite projects, task durations are estimated by experts, since these durations depend on factors such as project size, the complexity of the project, and the inherent uncertainty of the process (e.g., low productivity, changes from client, etc.). For instance, if a task duration is collected and mapped as a range (e.g., 16 h to 24 h) or as discrete values (16 h, 24 h, and 30 h), it is modelled as either a uniform or triangular distribution in the simulation model, respectively.

Besides mapping the process, the research team also classifies each task as value-added, necessary waste, or pure waste. This classification is based on the nature of the work, i.e., whether it is directly affecting the end-product, whether it is merely related to the processes needed to manage the work, or whether it can be removed or replaced. Likewise, event occurrences such as changes in design, rework, and sales forecast are estimated in the form of likelihoods and scenarios. The simulation input combines data from the organization's historical data (e.g., number and size of projects developed in a year, sales forecast, etc.) with information based on the company experts experience. Together with the current-state VSM, sales forecast is an input to the simulation model to estimate the volume of work the organization under study will undertake in the future and whether the investment in process digitization is justified.

4.4.1.2. Data Analysis on Simulation Output

The developed simulation model reports the maximum, average, and minimum durations for each task followed by a sales estimate of how many proposals are rejected (J) and awarded (A) per year. These durations and volume of work are assigned to each phase and presented as pessimistic (P), realistic (R), and optimistic (O) scenarios. This framework applies the program evaluation and review technique (PERT) to calculate the expected duration (E) and coefficient of variation (CV) of pre- and post-award phases under project-related uncertainty (e.g., durations of tasks, project features, etc.) as per Equations (4.1) and (4.2), respectively. Equation (4.3) incorporates uncertainty that falls outside the engineering team scope such as the yearly number of rejected and accepted bids provided by the sales forecast. The equation is used to calculate the total number of hours (H) spent by the organization, thus indicating the volume of work expected from the company. Validation from the team of experts is required at this point to address the current situation of premanufacturing tasks and suggest impactful solutions. This can be done using different methods such as Delphi, nominal group, and face validation by a third party with relevant knowledge of the process. After the analysis is validated, the design stage of the proposed framework is initiated to identify potential solutions based on the measures derived from Equations (4.1), (4.2), and (4.3).

$$E = \frac{P + 4 \times R + O}{6} \tag{4.1}$$

$$CV = \frac{P - O}{6 \times E} \tag{4.2}$$

$$H = (A + J) \times E_{pre} + A \times E_{post} \tag{4.3}$$

where:

E: Estimated duration from different simulated scenarios

P: Simulated duration for the pessimistic scenario

R: Simulated duration for the realistic scenario

O: Simulated duration for the optimistic scenario

CV: Coefficient of variation

H: Total hours spent on mapped tasks by the team in a year

E_{pre}: Estimated duration per project at pre-award phase

E_{post}: Estimated duration per project at post-award phase

A: Accepted bids in one year

J: Rejected bids in one year

4.4.2. Stage 2: Design

At the design stage, solutions for improvement are identified and developed based on the analysis from the simulation model output and based on whether the tasks are value-added or not. The specific context of design development and procurement in OSC is a primary factor at this stage. Given the low number of OSC companies and documented case studies in the area, this framework becomes a repository of solutions and improvements for OSC premanufacturing phases that is expanded according to the number of companies addressed. Combined with this repository, existing software solutions (e.g., BIM-based software, ERP systems, database management systems, etc.) are tested while the development of further innovative solutions not available for the context of OSC are suggested as means to fill a gap identified at the measure stage. An improvement brainstorm is performed by the research team to identify possible improvement suggestions based on the mapped tasks and internal expertise. Besides what was previously mentioned, expertise requires knowledge in different areas such as project management, design development, and software development in case some solutions can be developed specifically for the company under study. After the brainstorm session, a list of possible improvements is developed considering potential impact on task durations at the current state. The improvements are classified under one of the following three categories: (1) low-tech solutions, where changes are proposed by improving processes without the introduction of new technologies; (2) BIM-based solutions, where processes are digitized by commercially available software; and (3) client-based solutions, in which solutions are designed specifically for the addressed company taking into consideration tasks mapped at the measure stage. By following lean principles, the proposed framework prioritizes low-tech solutions over the remaining categories when its forecast improvements are not significantly higher according to the simulation models. This decision is made to improve current premanufacturing phases in OSC by improving the flow in their processes without investing heavily in digitalization (e.g., software, hardware and training), but rather focusing on the existing personnel and current practices applied at the addressed company. In this regard, any effort to digitalize premanufacturing phases in OSC must address the significant wastes at the current processes to be effective and pursued by the organization.

Future-state VSMs are developed based on each improvement category. These maps address changes in the process regarding the duration of tasks and the impact of adding and/or removing tasks from the mapped workflow. In the present study, future-state VSM is used to evaluate the proposed changes with the team and identify the validity of these changes in terms of practical implementation at the company under study. After discussing these changes internally and with the organization, a list of improvement opportunities for the mapped tasks is provided, taking into consideration the projected impact of the proposed improvement measures on the total duration and current workflow as identified in the previous stage. The work performed during this stage is used to provide input for the future-state simulation model to determine the impact of process digitization for each improvement category.

4.4.3. Stage 3: Propose and evaluate

The "propose and evaluate" stage presents changes in mapped processes in each improvement category as forecast by the future-state simulation model. By replicating the post-simulation calculations for each improvement category, the potential improvement is presented taking into consideration the organization's own data and the inherent uncertainties mapped in the process. During the analysis, the quantification of the estimated improvement is approached three ways: (1) average duration per project as per Equation ((**4.1**); (2) wasteful tasks in the process (value-added, necessary waste, and pure waste); and (3) coefficient of variation as per Equation ((**4.2**). Meanwhile, the average duration per project is often the primary metric employed to measure process improvement. The proposed framework acknowledges the team's current waste and variation as equally important in determining the rate at which the team generates value and how the duration of a project varies.

Moreover, Equation ((**4.3**) calculates the total hours saved in a year in each improvement category to provide company experts with the overall impact of the proposed improvements. The results from current and future states are compared, and options for process improvement (including a quantitative projection of their expected impacts) are proposed to the organization. Then, a qualitative assessment of the improvements is undertaken to identify intangible outcomes such as improved communication. Once a complete analysis is performed, the organization must choose which process improvement suggestions will be selected for implementation and tested for a period of time. After this period, the proposed framework must be applied once again to determine the impact and identify new opportunities for improvement.

4.5. Empirical Implementation

The empirical implementation of the proposed framework involves one of the largest modular contractors in Brazil specialized in temporary and permanent construction of commercial projects. While the commercial department is decentralized in nine different branches for wider sales coverage across the country, all estimation and engineering work is centralized at the company's main headquarters and at their factory, which are approximately 700 km apart from one another. This geographical limitation requires the company to rely on emails and a commercially available ERP system for all inter-departmental communications while relying on computer-aided design (CAD) systems for design development. Here, all project-related information is manually interpreted in the form of text or schedules from quantity take-offs. This section is divided according to the proposed framework in Figure 4.1 where the current state at the company is measured, and solutions for improvement are designed, and then proposed.

4.5.1. Implementation of Framework: Stage 1 (Measure)

4.5.1.1 Input for Simulation Model

For two months, nine semi-structured interviews were conducted on weekly basis with experts in each department to identify and determine durations for each task. A total of four experts were interviewed to map all tasks required according to each expert's expertise and practical experience in the addressed phases. Table 4.2 depicts all the mapped tasks identified during the semi-structured interviews and the likelihood of event occurrences, stochastic durations, and the task type (value-added, necessary waste, or pure waste). A likelihood lower than 100% means the mapped task may not occur depending on requirements from the client or the nature of the project. These tasks, combined with durations dependent upon project features, are the main drivers of process uncertainty that reduce the ability of managers to plan available resources during the year. As previously mentioned, stochastic durations are applied to allow experts a more representative duration of their tasks and to acknowledge the uncertainty of design, bidding, and procurement phases at the company. These durations represent the time experts spent working on each task, but they do not take into account time that is out of their control, such as the duration of the entire bid event conducted by the client or time spent waiting for quotes from suppliers.

As demonstrated in Table 4.2, the major uncertainties in pre-award tasks depend on the occurrence of events that are most often related to interactions with the client. These include, for instance, providing extra documents, such as renderings, for better clarification of the project. Uncertainty in post-award tasks is driven by a project's features such as its complexity and number of modules to be designed. Project complexity at the company under study is quantified according to the number of special items in the project that are customized items and that have never used by the company before. These items must be outsourced, registered at the organization's ERP system, then purchased and installed at the factory while complying with an unknown delivery time from suppliers. After collecting all data required during interviews, current-state VSMs are prepared, and then validated through consensus and face validation by the company's experts and managers.

Table 4.2: Information of tasks collected during interview process.

Phase	Task name	Type	Likelihood	Task duration (hr)			Observation
				P	R	O	
Pre-award	More information from client	PW	30%	16–24	8	1.5–2	
	1st Layout development	VA	100%	5		4	
	3D model development	NW	15%	6–8		2	
	Rendering	VA	15%	6–8		2	
	Commercial to respond client	NW	60%		1		
	Engineering to respond client	NW	12%	1.5		1	
	Project quantity take-off	VA	100%	10–20	20–40	40–60	min per module as project complexity
	Client adaptations on 1st revision	NW	S:65% R:30%	8		0.17–0.33	
	Client adaptations on 2nd revision or more	NW	S:30% R:15%	40% of previous revision			
Post-award	Special items and quantity take-off	NW	100%	8	4	2	as per project complexity
	Special items to ERP	NW	100%		7 min		per special item
	Electrical design	VA	100%		1.3		per module
	Plumbing design	VA	100%		1		per module
	Electrical design rework	PW	7.5%		2.5		
	Plumbing design rework	PW	5%		2		
	Openings and partitions design	VA	S:90%	2	5	9	1–10 modules
			R:10%	5	10	15	11+ modules
	Revised quantity take-off	NW	100%	10	20	40	as per project complexity
	Registry to ERP system	NW	100%	10–20	20	40	as per project complexity

In addition to the information provided during the semi-structured interviews, other data are collected by analyzing historical data from the company in two areas: (1) estimated number of modules per project to indicate project size, and (2) sales forecasts indicating the number of projects the company expects to bid and award during the year. The number of modules per project is acquired by analyzing and curve-fitting historical data containing past projects awarded by the company for two years containing a dataset of 235 projects. Through multiple interactions and addressing the goodness of fit by visual assessment and Pearson's chi-squared method, the best distributions that match the dataset are found by splitting the data by project negotiation (i.e., sales and rental which indicates whether the commercial proposal contains modules that will be sold or rented) and subsequently splitting the rentals dataset into projects with 15 modules or more, and less than 15 modules, as per Equations (4.4) and (4.5). Those distributions are added to the simulation model to calculate the duration of tasks dependent on the project size and to estimate the yearly production volume. Equation (4.6) is a distribution for the quantity and likelihood of special items per project determined through the analysis of historical data and consensus from the engineering department.

$$N^o of\ modules\ in\ Sales\ prjects = LogLogistic(1.32, 2.01) \tag{4.4}$$

$$N^o of\ modules\ in\ Rental\ projects = \begin{cases} Weibull(1.23, 2.99), if\ Exponential(3.93) < 15 \\ Logistic(1.23, 2.99), if\ Exponential(3.93) \geq 15 \end{cases} \tag{4.5}$$

$$Quantity\ and\ likelihood\ of\ special\ items\ per\ project: 0 - 5 = 50\% |\ 6 - 19 = 30\% |\ 20 - 30 = 20\% \tag{4.6}$$

Moreover, sales forecasts provided by the commercial department are shown in Table 4.3 and reveal the expected number of bids their sales team intends to bid followed by the conversion rate (i.e., number of bids awarded divided by total bids) on scenario-basis during a year. With the information described in Table 4.2 and Table 4.3, and with Equations (4.4), (4.5), and (4.6), a simulation model is developed in Simphony.NET to generate different scenarios for premanufacturing tasks, including the number of projects to bid on each year and the number expected to be awarded at the company under study based on the optimistic, realistic, and pessimistic scenarios extracted from the simulation model.

Table 4.3: Yearly sales forecast from commercial department.

	Sales		Rentals	
	Number of bids	**Conversion rate**	**Number of bids**	**Conversion rate**
Pessimistic	174	10%	435	8%
Realistic	196	20%	490	15%
Optimistic	225	15%	563	12%

4.5.1.2 Analysis of Simulation Output

Figure 4.2 depicts the performance of the company during the pre- and post-award phases by indicating the man-hours required to perform tasks according to each scenario and categorized by value-added, necessary waste, and pure waste as per the lean principles previously discussed. In the pre-award phase, wasteful tasks are driven by uncertain information exchanged between the company and the client wherein more information is required to fulfil the client's scope or questioned by the client during the bidding process. According to company experts, questions from clients are a common occurrence in practice since some of them lack an engineering/architectural background or are not experienced in modular construction projects. Besides sales representatives seeing this as an opportunity to explore future business opportunities with the client, the engineering department indicates a lack in procedure to receive complete information from the start, as one sales representative may be more experienced than another in gathering this information. Hence, rework is required to complete the information prior to starting a new project, and this may take days or may preclude the company participating in bidding due to deadlines imposed by the client.

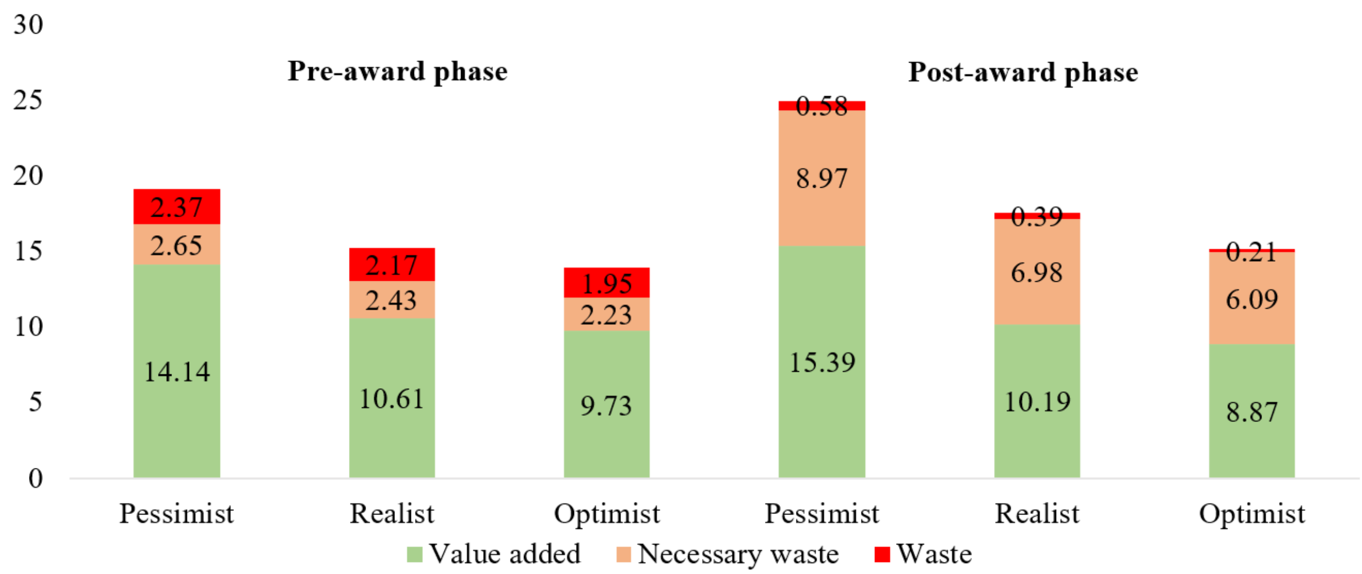


Figure 4.2: Pre- and post-award average man-hours per project according to scenario and performance.

In the post-award phase, necessary and pure waste occur for different reasons. Necessary waste occurs due to the changes in the project and the manual interaction with the existing ERP system, while pure waste occurs due to manual quantity take-offs and registry of special items required by the client (e.g., panic doors, curtain walls, etc.). Pure waste is significantly lower at this phase due to the experience of the engineers and since most of the project-related uncertainties are solved during the bid event. Table 4.4indicates a higher coefficient of variation at the post-award phase where the durations are predominantly determined by project features, thus indicating that a high level of product flexibility has an impact on premanufacturing at the company under study. Additionally, in Table 4.4, the total times of phases are presented according to each scenario (P, R, or O), while estimated times and coefficient of variations are calculated based on PERT analysis as per Equations (4.1) and (4.2). The total estimated time of the pre-award phase is found to be slightly lower than post-award, which is a positive result since it is not in the company's interest to focus on projects that may not be awarded. It is expected that, by digitalizing and automating processes, wasteful tasks can be reduced or eliminated to decrease durations and variation in each phase.

Table 4.4: PERT analysis on simulation results.

		Scenarios			PERT analysis	
		P	**R**	**O**	**Estimated total**	**Coefficient of variation**
Simulated total man-hours	Pre-award	19.16	15.21	13.91	15.65	5.59%
	Post-award	24.94	17.56	15.17	18.39	8.85%
Total bids processed	Accepted bids	50	87	133	-	-
	Rejected bids	520	606	708	-	-
Hours spent in a year		9,842	12,448	15,610	-	-

Moreover, Table 4.4 presents the simulation results using the information provided by the commercial department indicating the expected number of bids accepted and rejected during a year according to information provided in Table 4.3. Table 4.4 shows a high volume of bids processed, where the conversion rate is more dependent on external factors such as market conditions and competitiveness. Although the operational staff (e.g., engineers, architects, and estimators) understand the value of upgrading and connecting their information systems by using BIM and ERP, managers are often unsure of the required investment given the short duration of projects and the low conversion rate between pre- and post-award phases. Therefore, Table 4.4 presents the total number of hours spent by the engineering team during the year as calculated by Equation (4.3), which is used as a benchmark to measure the impact of the proposed improvements at the company. This information is very important since it quantifies the overall impact and assists managers to better plan resources for future demand.

4.5.2. Implementation of Framework: Stage 2 (Design)

With the current process assessment evaluating the efficiency of mapped tasks, improvement solutions are formulated in consideration of their projected impact on task durations and expected role (or lack thereof) in reducing waste and variation in the overall process. Different improvements were suggested and discussed during internal brainstorming sessions then mapped in the future-state map to better understand its impact on the overall workflow. After reaching consensus, suggestions were listed as improvement opportunities in three categories: (1) low-tech solutions, (2) BIM-based solutions, and (3) client-based solutions. These opportunities refer to improvements in the existing tasks listed in Table 4.2 that provide an estimated impact measured in saved hours or likelihood of an event occurring. Table 4.5 includes the improvement opportunities in each category starting from low-tech improvements and moving to the introduction of commercially available BIM software and BIM add-ons to address the specific needs of the company. For the low-tech solutions category, a checklist to capture client requirements at early stages was recommended for two reasons: (1) to help the sales team from different branches use methods to collect client requirements, and (2) to save a considerable amount of the effort required by engineering staff to acquire the information needed to fulfil the intended scope.

Table 4.5: Improvement opportunities for the company under study.

Improvement category	Affected task	Task type	Proposed improvement	Estimated improvement (hr)
Best practices	More project information	Pure waste	Checklist to collect most frequent missing information from client's expectations during pre-award phase	Reduced time resulting from 50% reduction in clients questions
Best practices	3D model and rendering development	Value-added	Acquiring a computer for renderings	50% reduced time in rendering
BIM-based	Develop 1st layout as per project specs	Value-added	Model development in BIM authoring software	0
BIM-based	3D model development	Necessary waste	Modify 3D geometry from the BIM model for rendering	1.5
BIM-based	Identification of special items and quantity take-off	Necessary waste	Create automatic schedules in the BIM model	2
BIM-based	Rework	Pure waste	More assertive modelling will reduce rework	1
Client-based	Project quantity take-off	Value-added	Add-on for generation of take-offs and company forms	4
Client-based	Revised quantity take-off	Necessary waste	Add-on for generation of take-offs and company forms	4
Client-based	Registry to ERP system	Necessary waste	Connection between BIM and ERP systems	2
Client-based	Electrical design	Value-added	Add-on for automated drawings for electrical design	1
Client-based	Plumbing design	Value-added	Add-on for automated drawings for plumbing design	1
Client-based	Openings and internal partitions design	Value-added	Add-on for automated drawings for internal partitions design	1

Under the BIM-based solutions category, the author suggests the implementation of a BIM authoring software to enhance the design process and streamline quantity take-off for estimation and procurement is suggested. It was determined that the use of Autodesk Revit instead of using a traditional CAD software will not affect the time required to develop the initial drawings given the time saved on later stages such as providing renderings, easier revisions, and automated schedules for quantity take-off. Apart from creating automated schedules, Revit does not provide sufficient information for modular construction practitioners and does not connect the required information with existing ERP systems. Therefore, manual work still must be done by engineers to provide the take-off required for estimation and procurement processes.

Changes in the client-based solutions category are introduced by the development of add-ons in Autodesk Revit to automate and connect the BIM model to different information systems, including the existing ERP system, and digitalize the quantity take-off exercise. These add-ons are conceptualized and developed using Dynamo, while others are automated by programming directly into Revit's application programming interface. These opportunities are focused on digitalizing the premanufacturing processes by providing a seamless exchange of data between different design options while accelerating the procurement of special items. Other improvement opportunities in this category deal with the digitalization of the development of fabrication drawings by automating routing paths and drawing generation according to constraints provided by designers in each discipline (Table 4.5).

In terms of the implementation of the identified improvement opportunities, reduction of wasteful tasks is given priority to increase efficiency in the overall process. By automating these tasks, engineers no longer have to perform tedious and error-prone activities, instead, they will have more time to dedicate themselves to value-added tasks and even work on a higher number of projects. After running the updated simulation model with the proposed changes in Table 4.5, quantitative measures are recalculated and benchmarked for each improvement category.

4.5.3. Implementation of Framework: Stage 3 (Propose and evaluate)

With results from the simulation model for the improvement opportunities proposed at the design stage, the updated measures in Equations (4.1), (4.2), and (4.3) for each improvement category are benchmarked with values from the measure stage. Figure 4.3 shows the estimated durations and coefficient of variation at the pre- and post-award phases for each improvement category where all proposed categories outperformed the company's current state. Whether by reducing the variation in the process or the duration of wasteful tasks, significant improvements were estimated by digitizing premanufacturing processes. While the low-tech solutions category reduced significantly the variation of pre-award tasks, BIM-based solutions demonstrated a significant improvement for the post-award task durations where only accepted bids are processed. The significant benefits of digitalization were demonstrated for the client-based solutions category by automating repetitive tasks and connecting the model to the existing ERP system. The automation of quantity take-off and its connection to the ERP system reduced the duration of value-added tasks by 22% in pre-award, and the duration of necessary waste tasks by 47% in post-award, thus demonstrating significant improvements in both phases.

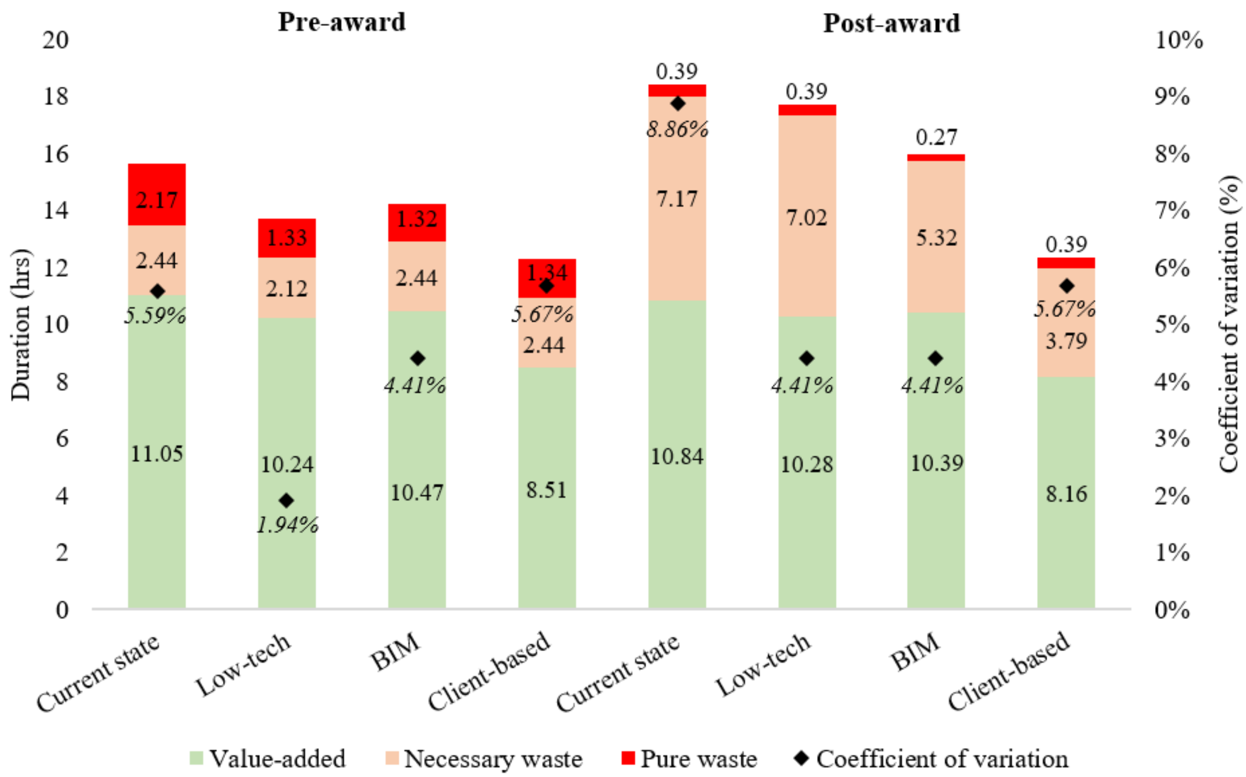


Figure 4.3: Estimated duration according to each improvement category and phase.

Moreover, Figure 4.4 demonstrates the overall number of hours saved in a year by improvement category in comparison with the current state for the pessimistic, realistic, and optimistic scenarios, which are a function of the company's sales in a given year. This analysis is meant to quantify the potential benefits of the proposed improvements while taking into consideration uncertainties that are outside the scope of the engineering department, such as the market conditions and number of awarded proposals. As shown in Figure 4.4, all categories indicate a significant reduction in hours worked, varying between 9.45% and 23.33% for the various improvement categories and scenarios. Among the improvement categories, client-based provide a significant increase in the savings compared to other categories by developing add-ons to digitize BIM processes and connecting BIM models to ERP systems. In addition to the quantitative assessment, a qualitative assessment was provided to the company that enumerates the benefits to the team such as improved communication, and readily available and easily accessible information and drawings produced by the engineering department. After the assessment was complete, the company under study selected which proposed process improvement suggestions to implement. After a period of implementation and testing, the proposed framework can be applied once again to evaluate the actual benefits of the proposed changes.

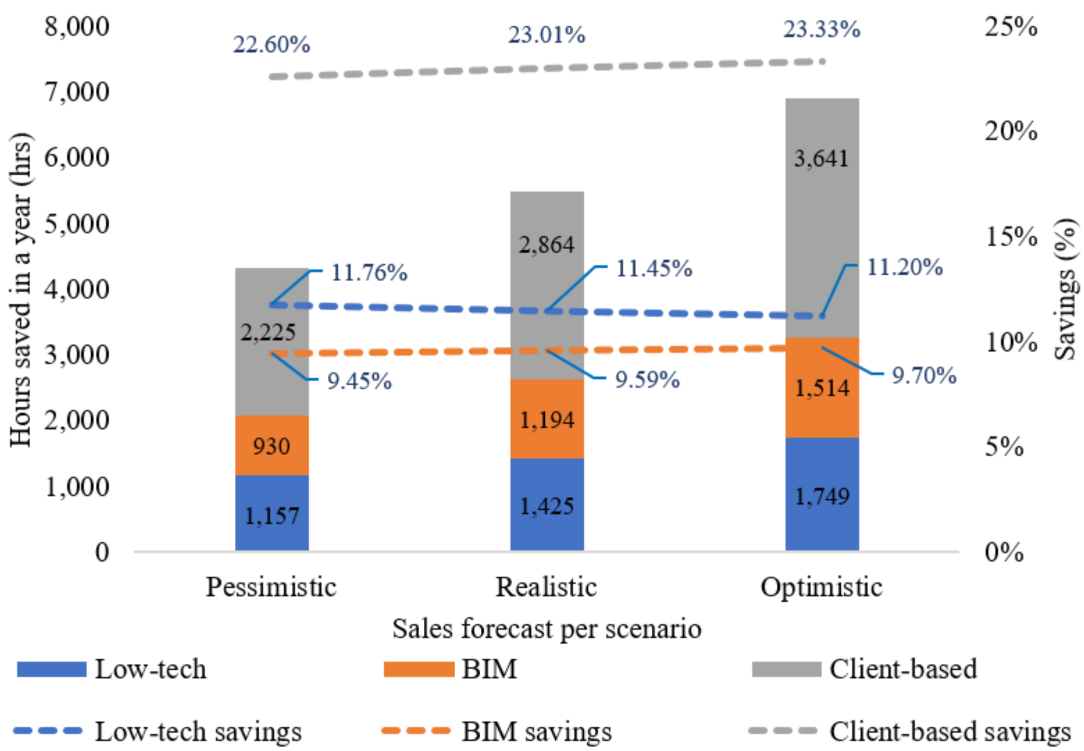


Figure 4.4: Yearly estimated savings from proposed improvements.

4.5.4. Framework Evaluation and Assessment

According to the DSR methodology, the evaluation of an artefact (the framework, in this case) is achieved by demonstrating its utility, quality, and efficacy using carefully selected methods. The assessment could be done through quantitative performance measures which can be results of satisfaction surveys (Peffers et al. 2007). Accordingly, the framework and its steps are assessed using a survey administered to the experts and managers who participate directly in practical implementation at the company. The survey requested feedback tackling the following: (1) the effectiveness of the framework to improve processes, (2) its easiness to understand and implement, (3) the sufficiency of the steps and the completeness of the framework, and (4) its applicability to other OSC companies. A five-point Likert scale was used to capture responses with 1 being 'strongly disagree' and 5 being 'strongly agree'. The survey had a total of five responses, with all of the key company experts involved in the empirical implementation of the proposed framework being represented among the respondents, including the head of the engineering team, the project manager, and the parties responsible for developing all of the pre- and post-award tasks mapped. Figure 4.5 demonstrates the questions, the answers from respondents, and the average of responses for each question.

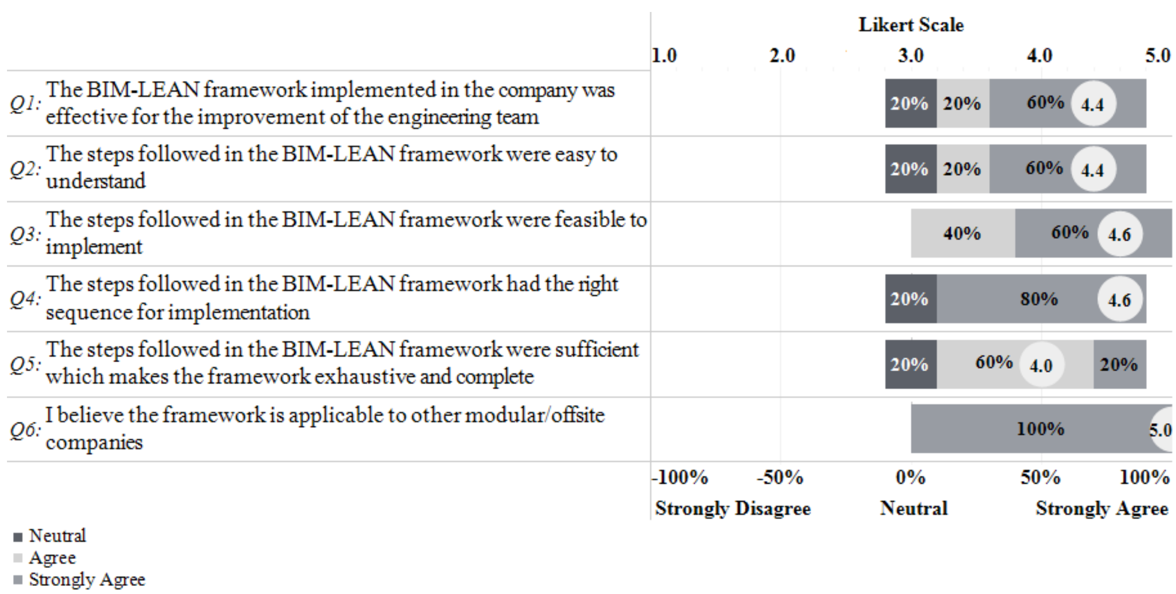


Figure 4.5: Survey questions and results from the proposed framework evaluation

Results reveal that respondents saw that the framework implementation in the company was effective for the improvement of the engineering team (average answer was 4.4). As for the steps presented in the framework, respondents scored their agreement with the steps being easy to understand, feasible to implement, and in the right sequence for implementation as 4.4, 4.6, and 4.6, respectively. When asked about the completeness of the framework and the sufficiency of the steps to make the framework exhaustive for applying digitalization and improvements in premanufacturing sequence, the average reply was reported as 'agree'; this indicates the framework should comprehend a wider scope to digitize processes in OSC premanufacturing operations. Following the continuous improvement approach, the failure to receive a 'strongly agree' for this entry would constitute an opportunity for future investigation on other case studies. In this case, though, all respondents indicated strong agreement with the statement that the framework is applicable to other modular and OSC companies, supporting the conclusion that the proposed framework is replicable to the OSC industry.

In addition to validating the framework applicability and efficacy with the selected experts, informal discussions were held out while and after the implementation. Although improvements in information exchange and engineering processes have been reported, some resistance towards the multiple simultaneous changes were recorded. This indicates the need for gradual implementation of the suggested improvement measures for easier transition and adoption on the part of practitioners and management. Accordingly, it is recommended that each company additionally take into account time considerations when evaluating a given set of proposed improvement measures.

4.6. Conclusions

This study introduces a framework to evaluate processes and leverage digitalization during the premanufacturing phases in OSC companies. The framework was developed to address the following main problems: (1) the misguided use of digital technologies in premanufacturing phases, where OSC companies are not applying the full potential of BIM and other digital technologies due to insufficient implementation procedures and guidance for connections with existing systems, (2) the shortage in measurements and quantifications of benefits and proposed improvements; and (3) the poor focus of OSC literature on the earlier phases, where the major attention is given to the fabrication phases and production lines.

Accordingly, this study promotes the use of a stepwise framework to measure, analyze, design, propose and evaluate processes of premanufacturing phases in OSC companies. The novelty of this framework lies in the detailed steps and guidance provided to enhance these phases using (a) BIM potentials and (b) Lean principles, in addition to the development of methods based on (c) statistical analysis and (d) simulation for quantifying the suggested improvement measures. Specifically, this framework helps practitioners to quantify the benefits of integrating BIM and other information systems (e.g., ERP), thus expanding the use of BIM beyond the design stage in a practical manner based on quantitative evidence. This is achieved by providing replicable methods to promote digitalization in OSC companies while providing measures to assist in its implementation and establishing a continuous improvement cycle at the offsite company. Thus, the proposed framework provides practitioners with quantitative assessment so they can discover different opportunities to improve processes through digitalization in a structured manner. In addition to providing a quantitative assessment using the proposed measures, a qualitative assessment is also presented where intangible benefits are highlighted such as improved communication between departments and more readily available information through BIM models. Moreover, it allows processes for each OSC company to be evaluated while considering the unique features of each organization individually.

Based on the results of a case study undertaken in a modular construction facility, 22% and 47% of the task durations in the pre-award and post-award phases, respectively, were reduced through the use of digitalization and various different improvements methods. These methods were categorized into 3 types: low-tech solutions, BIM-based solutions, and client-based solutions. Companies invest in different methods based on the different considerations, primary their budget and the level of improvements obtained from the diverse suggested solutions. An important understanding of this framework is the connection to lean principles that endorse solutions based on the feedback of internal and external customers to digitize processes. Simulation-based trade-off analysis and potential impacts are important considerations in the evaluation phase before selecting and implementing the improvements. The need for a learning loop and continuous improvement is highlighted in the framework.

The practical implication of the framework was also observed in a survey distributed to the main experts involved at the empirical implementation of the proposed framework. The survey demonstrated that the majority of respondents find the proposed framework easy and feasible to implement at their context with averages of 4.4 and 4.6 in a 5-point Likert scale. Moreover, all respondents strongly agree that the proposed framework is applicable to identify and propose digitalization-driven improvements at OSC companies. This indicates the readiness of the framework and its practical implementation to assist OSC companies to improve its premanufacturing tasks.

On a final note, the successful implementation of the framework depends on acquiring accurate information from experts working at the company. This could be a potential limitation since imprecise information will provide an inaccurate baseline for the assessment of current and future states. Hence, further work is recommended to evaluate the use of automated methods for data collection followed by methods to estimate the negative impact of inaccurate data used in premanufacturing phases in OSC.

CHAPTER 5: DIGITALIZATION METHOD FOR PROCESS IMPROVEMENT AND DECISION-MAKING IN OFFSITE CONSTRUCTION[2]

5.1. Introduction

Offsite construction (OSC) is an approach in which the majority of the building components are fabricated in a controlled environment (i.e., shop floor) and subsequently installed on site (Joo et al. 2007). The benefits of OSC manufacturing can be summarized as follows: (1) it allows for the establishment of a culture of process improvement and for added value to be identified in the overall process (Nahmens and Ikuma 2012), (2) it promotes the use of automation to increase production (Linner and Bock 2012), and (3) it provides a fruitful environment for the adoption of new technologies such as sensors—in combination with data analysis, machine-learning applications, and digitalization—for process improvement (Correa 2020). Indeed, working in a controlled offsite facility is highly conducive to both process improvement and the adoption of the requisite technologies and methods for digitalization. *Nevertheless, strategies and decision-making with respect to process improvement are often based on personal experience rather than empirical evidence.* This poses significant risks considering the financial or productivity loss that could result from an unsuccessful process improvement program.

Various approaches, such as the application of lean philosophy and simulation, are used for process improvement in OSC. Lean philosophy is highly applicable to OSC, given its origins in manufacturing and the tools it offers to minimize the effect of variability and waste. Simulation, meanwhile, is widely used in

[2] The manuscript appearing as Chapter 3 of this thesis has been submitted for publication in Automation in Construction as of the time of writing of this thesis as Barkokebas, B., Martinez, P., Bouferguene, A., Hamzeh, F., and Al-Hussein, M. "Digitalization method for process improvement and decision-making in offsite construction".

combination with lean to improve processes in OSC. Goh and Goh (Goh and Goh 2019) present a discrete-event simulation model for identifying and addressing process waste in OSC based on indicators such as cycle time, labour productivity, and process efficiency. Despite significant efforts in the area, the current paradigm for the practical implementation of simulation is not sufficient to leverage the tools being developed in academia due to discrepancies between actual data and input to current simulation models (Erikshammar et al. 2013). The effective application of lean principles in combination with simulation tools for process improvement in a real-life setting requires (1) the use of reliable real-time data gathered by work-monitoring technologies (i.e., sensors) as inputs, and (2) large enough sample sizes to avoid biased results.

In addition to providing real-time production status, sensor-monitoring systems generate large volumes of useful data. However, this data is not typically put to use for process improvement purposes (Buer et al. 2018; Gantz and Reinsel 2011), despite the fact that having large volumes of data is fundamental to improving operations through digitalization, wherein decisions are made on the basis of both the personal domain knowledge of experts and actual data gathered from operations. Furthermore, the implementation of frameworks to apply machine learning for process improvement must be tailored to the type of data available and the problem at hand (Chien et al. 2007). In the context of OSC, the most notable knowledge gap lies in the lack of methods to evaluate process improvement measures leveraging empirical evidence gathered by work-monitoring technologies, e.g., radio-frequency identification (RFID), bar code, etc. (Razkenari et al. 2018). Although aware of the potential value real-time data can provide as the basis for improving current operations, operators are hesitant to digitize their processes due to a lack of robust methods and frameworks to incorporate production insights derived from data-mining experiments and apply its findings into managerial decisions (Lundkvist et al. 2010). Moreover, limited research is available regarding the implementation and efficiency of automation in OSC (Bowmaster and Rankin 2019), whereas strategies to increase flexibility in manufacturing systems are rarely discussed or evaluated. Therefore, studies are needed to develop methods that combine the operational expertise from experts and the robust data analysis techniques to evaluate process improvement measures in OSC manufacturing operations.

To address this gap, the present study develops a novel method for evaluating proposed process improvement measures by combining real-time production data collected from sensors and design features (e.g., surface area, number of components, etc.) of projects manufactured on OSC shop floors. This method takes a hybrid (qualitative and quantitative) approach leveraging digitalization to evaluate the validity of proposed process improvement measures using statistical and machine-learning applications while gathering production insights. This method is tested in a case study using two years of data drawn from building information modelling (BIM) and from RFID sensors installed at workstations on an OSC shop floor to measure production durations. Hence, the large volume of data employed helps to mitigate the risk of bias in the results.

5.2. Literature Review

5.2.1. Automation and Process Improvement in OSC

The use of automated and/or semi-automated machines in OSC adds more flexibility in the fabrication of building components (e.g., wall and floor panels) by reducing process variation regardless of the size of component (Ritter et al. 2020). Indeed, automation has been implemented extensively to improve productivity and performance in OSC, as in other industries (Chen et al. 2018), while also enabling the introduction of innovative construction methods to increase operational efficiency. The multi-panel approach as an example is an innovative method in which a combination of smaller panels (i.e., single panels) are framed together by a framing machine as a "multi-panel" to reduce set-up times. These multi-panels are separated into single panels later in the process and finished at different workstations according to their features (Ajweh 2014). Single panels are combined into multi-panels in a particular manner taking into consideration all the panels required for a given project. For this purpose, designers must extract the panel geometries (widths, heights, and lengths) from BIM models and implement a greedy algorithm in which panels are optimally sequenced in such a way as to span the full length of the top and bottom tracks of the framing machine (e.g., 12 m) in order to minimize material waste (Zhao 2015). In other words, the multi-panel approach leverages principles of both automation and manufacturing to reduce variation in the process times and material waste based on the extraction of design data from BIM models and the creation of optimized computer numerical control (CNC) files (which are used as inputs to framing machines). This synergy allows designers, production planners, and automation experts to develop new methods of construction that can be later adapted to traditional construction on site.

Despite the significant improvements in industry practice, the uptake of automation in OSC is still very limited and has drawn little interest from practitioners (Delgado et al. 2019; Razkenari et al. 2020). Mao et al. (2016) argue that practitioners struggle to adopt more automated processes due to various obstacles such as the lack of skilled labour, lack of expertise to develop automated processes in OSC, and high initial cost (including purchase of machinery, and factory setup). Despite the growing trend toward improving construction productivity through a manufacturing approach, the capital-intensive investment required to adopt automated processes increases the risk to practitioners, especially when the trade-off between productivity gains and capital investment is not easily identified (Taylor 2010). The impact of semi-automation in OSC, for instance, where some workstations are assisted by machines while others are dependent on manual work, is limited due to a natural imbalance in production between the manual and automated workstations. In this regard, the impact of automation in the context of other aspects of production in OSC, such as utilization of resources and inventory, still needs to be evaluated (Zhang et al. 2020), since the available literature in this domain is limited to evaluating the effect of automation on production rates at automated workstations. In reality, the automation of some processes in OSC can have adverse effects such as production imbalance brought to bear by the increased rate, resulting in reengineering and production waste (Razkenari et al. 2019). To better leverage the use of automation in OSC, Zhang et al. (2016) suggest the use of sensors to enable process improvement analysis based on actual data. It has also been noted that the use of work-monitoring technologies and information modelling must be prioritized to improve operations and increase the adoption of OSC (Taylor 2020). In this regard, a method leveraging digitalization in which data from sensors is collected, combined with other information systems (e.g., BIM models), and applied to improve current manufacturing operations is required.

5.2.2. Digitalization and Real-time Work-monitoring Technologies in OSC

Digitalization (or "process digitization") is defined as the use of digital technologies to transform processes and generate value-adding opportunities to current operations (Gartner 2020). In other words, digitalization focuses on the increased use of data to improve internal efficiency while adding value to processes by moving them from analog to digital platforms (Björkdahl 2020). Despite the increased use of digital platforms such as BIM and the use of sensors to collect production data, OSC is lagging behind other industrial sectors in terms of the adoption of digitalization methods and the integration of different information systems to improve internal processes (Barkokebas et al. 2021). That being said, various data collection methods, ranging from sensor-monitoring (e.g., RFID and audio signals) to image capture, can be used to capture the progress and location of elements on a shop floor. Meanwhile, machine-learning algorithms can be applied to extract meaningful information from the data collected as discussed below.

For instance, a production control system that uses various sources of information (e.g., BIM models, barcodes, and RFID sensors) and spans the design and procurement phases has been proposed as a means of facilitating just-in-time procurement of materials and mitigating the risk of shortages or excess inventory during production (Wang et al. 2018). Elsewhere in the literature, a production control system has been applied to manage materials on the shop floor during production in accordance with project specifications while facilitating ready communication within the team using mobile devices (Yin et al. 2009). To accommodate process uncertainty, an approach combining RFID data and information inputted to mobile devices to monitor quality and manage the schedule while proposing further usage of this information during the product's lifecycle has been proposed (Min and Junyu 2013). Moreover, Altaf et al. (2015) proposed a tool that provides production managers with real-time feedback regarding the production rate by comparing the planned production schedule against data from sensors capturing the actual production rate.

Martinez et al. (2021) applied convolutional neural networks to identify tasks in, and evaluate the efficiency of, OSC operations using video data from security camera footage. Their study achieved an accuracy of 92% in a case study involving the manufacturing of floor panels in a semi-automated production facility. Other machine-learning algorithms, such as support-vector machines, have been applied to automatically identify common tasks (e.g., hammering, sawing, and nailing) using audio signals from cameras installed on an OSC shop floor (Rashid and Louis 2020). This approach was found to yield similar accuracy in its results to the previous study, and a case study was presented that generated relevant production insights. Another recent study used historical data to predict future performance, with RANdom Sample Consensus (RANSAC) being applied to predict performance using a large dataset of historical data combining information from BIM models (i.e., project specifications) and RFID sensors (i.e., workstation cycle times)

(Altaf et al. 2018). The authors of that study noted that predictions are subject to a high degree of variability, not only due to the variability of project features in OSC, but also due to the uncertainties of production itself.

To address issues with product variability, Kalman filters have been applied to predict cycle times of identical panels manufactured in an OSC setting (Wen et al. 2017), with the results of that particular study demonstrating that: (1) only 1% of panels were repeated more than 10 times, indicating a low degree of repetition of identical panels, and (2) predictions of cycle time are not reliable due to significant variation in the manufacturing process. Mohsen (2021), meanwhile, used the location of panels in the RFID system in combination with its features (e.g., length) to calculate the work-in-progress (WIP) at downstream workstations as a way of increasing the accuracy of prediction models. After applying different machine-learning algorithms such as linear regression and random forest regressor, Mohsen concluded that the accuracy of regression models in predicting workstation cycle times is governed largely by production-based features (i.e., WIP). Despite significant research in the area, further investigations are required in order to address the impact and increase the use of machine-learning applications in OSC using data from work-monitoring technologies (Elghaish et al. 2021). Moreover, further study is needed to develop methods and procedures to analyze, process, and apply data from work-monitoring technologies to achieve operational improvements in OSC.

5.2.3. Identified Gaps in the Literature and Point of Departure

Based on the above literature review, three gaps are identified: (1) research is needed to address the use of automation in OSC considering its impact on the overall productivity of the shop floor, (2) there is a lack of methods to leverage digitalization and evaluate proposed process improvement measures based on both qualitative and quantitative evidence in OSC, and (3) more studies are needed to develop and implement machine-learning applications to achieve operational improvements in OSC. Accordingly, the present study proposes a structured method to leverage digitalization in the evaluation of proposed process improvement measures for OSC. In this method, qualitative data in the form of inputs from OSC experts and quantitative data from sensors and BIM models are combined, thus creating a synergy between expert input and data analysis. The proposed method is then tested using actual data collected from RFID antennas and BIM models from projects manufactured over a period of almost two years on an OSC shop floor. An important aim of the present study, then, is to provide extensive evidence on the validity of proposed process improvement measures developed in collaboration with OSC experts while providing a structured stepwise procedure to address them.

5.3. Methodology

The present study applies cross-industry standard process for data mining (CRISP-DM) as the methodology for assessing the validity of proposed process improvement measures in OSC. CRISP-DM is the most common methodology for conducting data-driven improvements in the context of Industry 4.0, where high volumes of production data are generated (Martinez-Plumed et al. 2021; Schröer et al. 2021). Even twenty years removed from its introduction, CRISP-DM remains the de-facto method due to its flexible and reliable structure for conducting data-mining projects, the explainable data it generates, and the robust modelling and evaluation it provides (Martinez-Plumed et al. 2021; Schröer et al. 2021). The present study also applies an inductive approach that can be characterized as data-driven and exploratory to develop, test, and subsequently generalize on the basis of hypotheses formulated based on observation (Woo et al. 2017). It should be noted in this regard that hypotheses are not required in order to initiate inductive research, as they are a by-product of exploration emerging from the interactions between data and participants (Antwi and Hamza 2015). This chapter also applies exploratory data analysis (EDA) as a set of tools and techniques to explore, find patterns, and draw conclusions from the data (Sharma et al. 2021). Using well-known EDA techniques, such as visualization and statistical analysis, a hypothesis is prepared for each proposed process improvement measure based on consultation with experts and actual production data collected by sensors. The steps in CRISP-DM applied in this research are presented as follows:

1. Business understanding: assess the current business situation and define the project goal to be transformed into a specific data-mining problem.

2. Data understanding: explore the data collected and develop hypotheses based on the data, experience, and expert input.

3. Data preparation: clean, process, and combine the data by applying data-mining techniques to create meaningful datasets for the testing of the developed hypotheses.

4. Modelling: select which machine-learning algorithms (e.g., *k*-means, linear regression, among others) to use based on the given problem and build/train models as required to test the developed hypotheses.

5. Evaluation: evaluate and present the results from the developed models so that the next steps can be determined.

6. Deployment: in the case that the project is approved, plan the deployment of the developed models in consideration of the monitoring and maintenance requirements in a real-world setting.

Since data-mining projects must followed a tailored approach that considers the type of data and the problem at hand (e.g., predictive maintenance, process improvement, quality management, etc.), CRISP-DM provides a structured yet flexible approach (Ribeiro et al. 2020). Meanwhile, an inductive approach allows the researcher to identify counterintuitive patterns (Faems 2020) in data, while EDA methods provide a statistical foundation for interpreting results and drawing conclusions. The present study applies these paradigms in a semi-automated wall panel production facility by collecting project specifications from BIM models and RFID timestamps from the panels manufactured. To apply CRISP-DM in the context of digitalization in OSC manufacturing, a case study is used to develop the proposed method. Given that this is an exploratory study, the final step of CRISP-DM (i.e., step 6 in the previous list, 'deployment') falls outside the scope of this chapter.

5.4. Development of the Proposed Digitalization Method Using a Case Study

This research presents a case study of a semi-automated OSC operation in Alberta, Canada, in which wall, floor, and roof panels are manufactured in distinct areas of the shop floor and then loaded onto trailers to be transported to the site for assembly. The wall panel area is selected for the present case study. Some of the wall panel workstations are furnished with semi-automated machines that are continuously monitored by RFID antennas that collect location information and timestamps for each panel in production. Figure 5.1 provides an overview the manufacturing process, which begins at the framing workstation (listed as W01), where multi-panels (single panels combined together in 12 m sections, as described in Section 5.2.1 above) are framed by a semi-automated machine according to the specifications in a CNC file extracted from a BIM model. At the beginning of the framing process, an RFID tag is affixed to the first stud of each single panel within the multi-panel. The sheets of oriented strand board (OSB) are placed manually and then nailed automatically by a CNC machine at workstations W03 and W04, respectively, whereas interior panels bypass these workstations since they do not require OSB sheathing. The multi-panels are then separated into single panels at workstation W05, from where they are directed to different workstations according to wall panel type (exterior or interior).

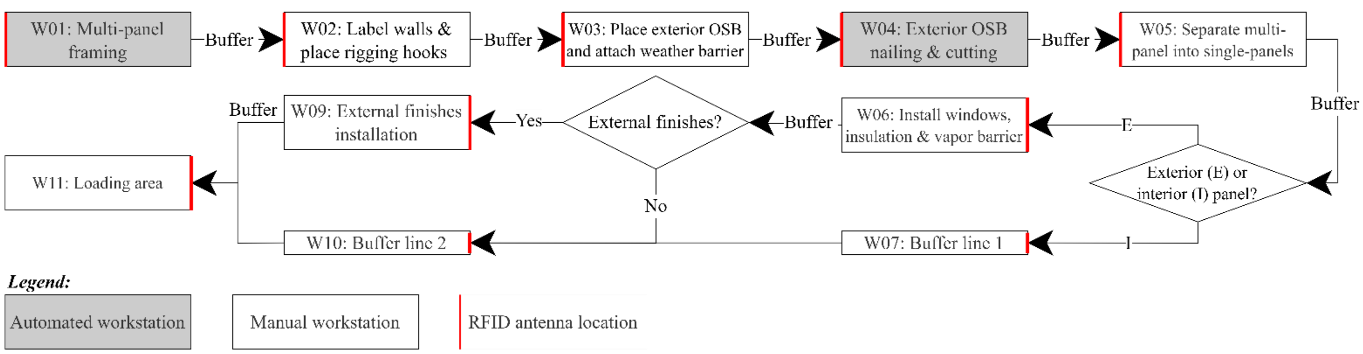


Figure 5.1: Wall manufacturing tasks according to current workstations layout at the shop floor under study and locations of RFID antennas.

Windows, insulation, and vapour barrier are installed in exterior walls at W06 and then sent to either workstation W09 or workstation W10 depending on whether or not the project requires exterior finishing to be installed on the shop floor (as opposed to being installed on site). Interior panels, meanwhile, are sent from W05 to one of two buffer lines (stations W07 and W10) and then loaded onto the trailers together with the exterior panels. Buffers are also provided between each workstation throughout the shop floor, while RFID antennas are installed at the start of each workstation, as indicated in Figure 5.1. A significant portion of the work being carried out at workstations W01 and W04 is semi-automated, and this increases the production rate significantly. The present research evaluates the effect of this automation on production balance and flexibility. The following subsection are divided according to the steps in the CRISP-DM methodology as indicated in Figure 5.2.

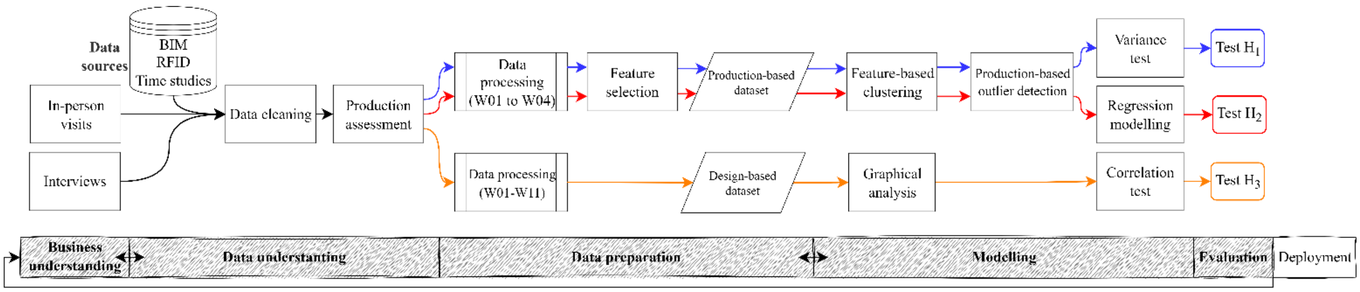


Figure 5.2: Study procedure and methods.

5.4.1. Business Understanding

To better understand the current process and define the goals for a data-mining project, several in-person observations of the shop floor are conducted, followed by consultations with experts from the case company. On this basis, three conclusions are drawn at this juncture: (1) there is a high degree of variability in demand over the course of the year due to market fluctuations (e.g., more projects are manufactured during the summer); (2) there is a discrepancy in productivity between manual and semi-automated workstations, given the higher pace of production of semi-automated workstations over manual ones; and, (3) the initial workstation, W01—which features a semi-automated framing machine—dictates the pace of production throughout the shop floor and is often referred to as the benchmark for overall production.

Although the automation of workstations increases the overall wall production significantly, any adverse effects on overall production have yet to be investigated and quantified. A notable challenge concerning any effort to improve operations is the varying demand over the course of the year and thus the lack of a fixed production target. In other words, the shop floor must be flexible enough to accommodate significant market fluctuations throughout the year despite there being various fixed overhead costs such as the cost of factory space and the cost of idle machinery at semi-automated workstations.

To account for variable demand and deadlines imposed by clients, the management team applies two strategies to increase operational flexibility are considered in the case study: (1) irregular days, and (2) work beyond hours. Irregular days are extra working days added into a week during a period of unusually high demand, with all workers at their workstations as they would be on a regular working day. Work beyond hours, on the other hand, occurs when workers work slightly before or after hours (e.g., 5 to 10 minutes) to finish the remaining portion of their work or to compensate for an unscheduled break. This typically results in a few workers either remaining at their workstation after their shift or arriving early for a shift. In the case that workers extend their shift beyond a reasonable limit (e.g., 30 minutes), the management team creates issues to production such as loss of productivity due to fatigue and increased factory overhead (since the shop floor must remain open beyond planned hours). The RFID system can identify instances of both flexibility strategies (irregular days and work beyond hours by detecting when panels are entering workstations (based on the RFID timestamps).

The impact of product variability (i.e., differing panel features) on production is also a matter of interest in the case study, especially at the initial workstations (W01 to W04), where automation is more prominent. Panel features such as panel length, panel type (exterior or interior), and number of studs are extracted directly from BIM models used to produce the CNC files that are inputted to the semi-automated workstations. After consultation with production managers at the case company to obtain information concerning regular working hours (Monday to Thursday from 7:00 a.m. to 5:00 p.m.) and scheduled breaks, various assumptions are adopted accordingly for the purpose of the study as listed below.

- The wall framing station, W01, operates at an increased pace and provides reliable durations for the manufacturing of multi-wall panels.

- Wall surface area (in m^2) is the common metric for input and output production.

- In current practice at the case company, there are two flexibility strategies in use (as described above): (1) work on irregular days, and (2) work beyond hours.

- Work on irregular days (Fridays, Saturdays, and Sundays) is a common strategy to make production more flexible and to accommodate occasional high demand. The use of this strategy is detected by observing the day of the week in the RFID timestamps when panels are moved from one workstation to another.

- Work beyond hours is another common strategy to make production more flexible and to accommodate occasional high demand. For the purpose of the present study, "work beyond hours" is deemed to have occurred any time a panel is moved between workstations more than 30 minutes prior to or more than 30 minutes after regular working hours. The management team will evaluate the effectiveness of this strategy and determine whether its application on the shop floor should continue.

As determined in consultation with production managers from the case company, the objective of the data-mining project is to evaluate the impact of automation, as well as the impact of the two strategies employed in current practice to increase operational flexibility, on production. Accordingly, hypotheses are formulated to evaluate: (1) the impact of automated machinery on production, taking into account both the production rate and the capacity to accommodate different panel features, and (2) the effectiveness of existing flexibility strategies (working on irregular days and beyond hours) in enabling a flexible manufacturing process and accommodating varying demand.

5.4.2. Data Understanding

RFID data (i.e., timestamps and locations of panels, as described in Figure 5.1) and information about panel features available in BIM models are collected for the purpose of the initial investigation of the current state of production. The data is combined, processed, and visualized using Python scripts various data science libraries (e.g., Pandas, Pyplot, Scikit-learn, etc.) to identify initial patterns in production and to investigate the capacity of the shop floor throughout the period under study. In this period, no significant changes are made either to the manufacturing process or to the shop floor layout. As an initial investigation, the daily input and output productions are measured by identifying the total surface area (in m^2) of panels entering and leaving production (entering W01 and leaving W11, respectively, as per Figure 5.1) based on the RFID readings. Additionally, the average production output is calculated using a 14-rolling window to quantify the variation in production over the course of the year, and production days are then labelled in accordance with assumptions developed in the "business understanding" step of the research (described above).

Figure 5.3 shows the daily production output according to the flexibility strategy employed (irregular day, work beyond hours, both strategies, or neither strategy). The average daily production output using a 14-rolling window is also displayed to visualize varying demand. Figure 5.3 demonstrates that the flexibility strategy of working beyond hours (thirty or more minutes before or after regular hours) is commonly employed at the case company, while the strategy of working irregular days is only employed during periods of high demand, as indicated by the rolling mean. The use of both strategies on the same day, meanwhile, is relatively rare. It is also clear that the production output is highly variable over the course of the year, as indicated by the rolling mean.

In this regard, Table 5.1 shows that the rolling mean production output varies by 230%, 264%, and 230% across 2016, 2017, and 2018, respectively (when long holiday breaks such as Christmas and Easter are excluded). In other words, the case company must accommodate a significant variation in production, thus requiring a high degree of flexibility in its operations. The variation in the rolling mean is the result of a combination of factors, such as season (e.g., summer period is a high season for construction), inherent market fluctuations, and low productivity due to material shortages, skilled labour shortages, machine breakdowns, etc. It should be mentioned that these inferences regarding the causes of variation are made on the basis of consultation with the case company's production managers due to the unavailability of quantitative data concerning the production capacity and demand. Nevertheless, the available data confirms that the shop floor must be flexible to accommodate different output demands, especially when dealing with fixed overhead costs, such as lease, utilities, and equipment depreciation and maintenance.

Table 5.1: Minimum and maximum daily rolling mean production at the case shop floor

Year	Minimum production (m2)	Maximum production (m2)	Variation
2016	240	557	230%
2017	251	665	264%
2018	137	322	230%

Figure 5.4 shows the daily production output (in m2) according to the status of the framing station (operating or shut down) and the work-in-progress (WIP) (i.e., total area of walls being produced between W01 and W11) while also displaying capturing the work performed on irregular days. Ideally, the production output will be relatively uniform, indicating balanced production; however, Figure 5.4

demonstrates that this is not the case. Instead, Figure 5.4 shows that production is imbalanced and that there is a high variation in WIP. The figure also shows that the framing station is shut down on several days across the year, particularly when there is a significant WIP. (The framing station, W01, is shut down on occasion to suspend the input of new panels so that downstream workstations can clear a backlog of panels in progress.)

To better illustrate the operations at W01, a callout from the one of the busiest periods of production is included in the figure. The callout shows the work being performed on irregular days to accommodate the increased demand during the period where the framing station is shutdown to reduce current WIP. As can be seen, the framing station's high speed of production causes overproduction, and strategies such as temporarily suspending the operation of W01 or working on irregular days are used to reduce current WIP and accommodate increased production demand. The initial assessment of the data demonstrates that the case company must maintain a flexible operation, given the variable demand throughout the year that must be met with fixed resources and factory space.

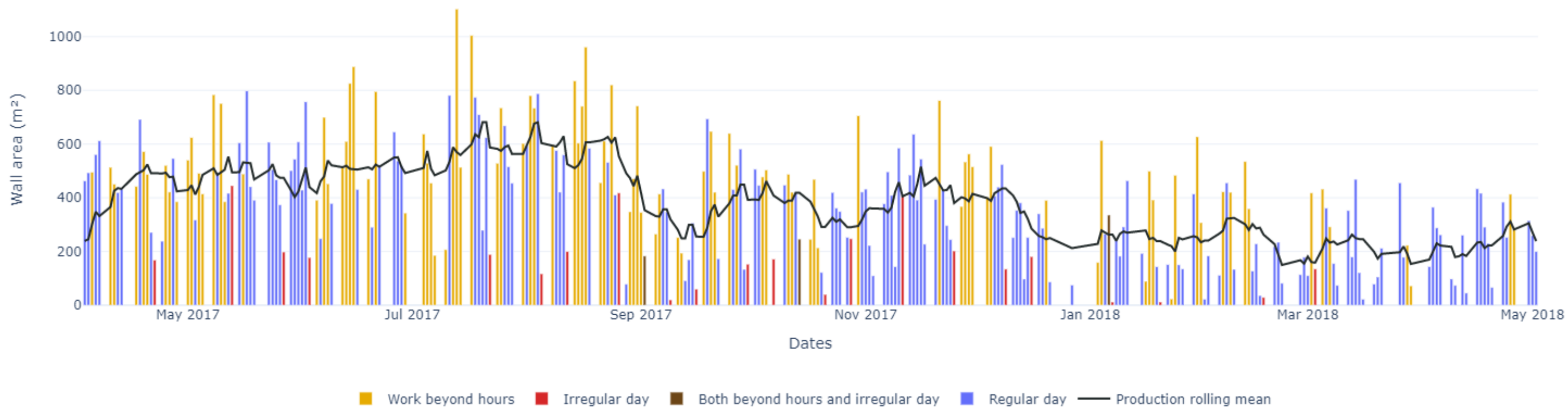


Figure 5.3: Production rolling mean with a window of 14 days and daily production output according to approaches to maintain flexibility on sample data gathered on the shop floor

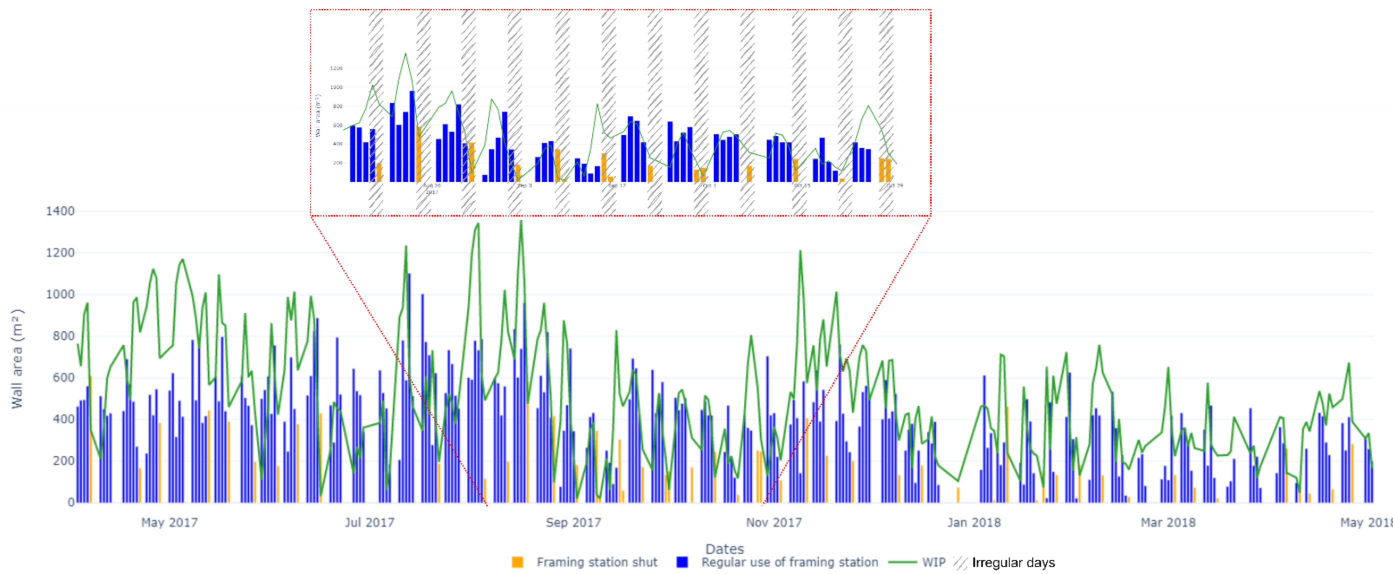


Figure 5.4: Production output according to WIP, framing station status, and irregular days

Based on the initial assessment and consultation with the case company's production managers, three proposed process improvement measures with corresponding hypotheses are developed as presented in Table 5.2. Each hypothesis is tested to verify the feasibility of its practical application based on actual data collected from the shop floor. If a given hypothesis is accepted, then additional efforts are to be made on the development and deployment of the corresponding process improvement measures, whereas, if the hypothesis is rejected, the given process improvement measure must be modified or discarded, as the rejection of the hypothesis means that the actual production data shows that the improvement measure is not feasible under the existing shop floor conditions. As previously mentioned, the framing machine is given special attention in the study since it is at the first workstation (i.e., W01) and its production capacity is often cited by the case company's production managers as being synonymous with the production capacity of the shop floor overall. Moreover, the hypotheses developed in this study are categorized as either design- or production-based depending on the nature of the given process improvement measure. The design-based hypotheses are tested based on the design features of multi-panels, while the production-based hypotheses are tested based on the panel production data. Hypotheses 1 and 2 (H_1 and H_2, respectively) are formulated based on the process improvement measures proposed to increase the flexibility and improve the operations of the framing machine at W01.

Table 5.2: Proposed process improvement measures and hypotheses developed for the present study

ID	Proposed process improvement measure	Hypothesis
H1	Combine different panel types (exterior and interior) at W01 and separate them at W02	The panel cycle time at W01 is not affected by panel type
H2	Combine multi-panels at W01 according to a predetermined takt time in order to balance overall production	The panel cycle time at W01 is directly related to the features of the given panel
H3	Add extra shifts and allow for extended working hours to meet production targets	Working on irregular days and beyond work hours is an effective strategy for meeting production target

The first process improvement measure proposes to alter the existing layout of the shop floor, shifting the separation of multi-panels into single panels from W05 to W02 (as per Figure 5.1). In this alternative layout and workflow, exterior single-panels continue along the same path as before, whereas interior single-panels are moved directly from W02 to W07 as indicated in Figure 5.1. As a result, workstations W03 and W04 (only applicable to exterior panels) will be less congested, and operations may improve since there are no interior panels occupying buffer space unnecessarily. Since multi-panels are combined primarily based an algorithm that considers panel type and other features extracted from BIM models, three steps are needed in order to test and deploy this process improvement measure: (1) verify whether W01 manufactures exterior and interior panels at a similar pace, (2) modify the current algorithm to combine multi-panels according to this process improvement measure so that the CNC files that serve as inputs to the semi-automated machine can be generated accordingly, and (3) alter the layout to accommodate this change to the workflow. Since implementing these changes would entail a significant investment of capital and effort, H_1 is tested to determine whether the cycle time of W01 is significantly affected by panel type (i.e., interior versus exterior).

The second process improvement measure proposes to create multi-panels at W01 according to a predetermined takt time in order to balance overall production. Accordingly, the semi-automated framing machine should manufacture multi-panels at a slower pace to avoid congestion in downstream workstations and thereby decrease WIP without having to further alter the plant layout. According to consultation with the case company's production managers, the framing machine is very reliable and predictable in its operation, so the process time for a multi-panel is governed largely by its features (e.g., surface area, number of openings, etc.) rather than by the performance of the framing machine. Hence, the algorithm used to lay out the single panels to form multi-panels must be revised to change its objective function from material waste minimization to achieving a predetermined takt time and balancing production. To address the practical feasibility of this process improvement measure, then, H_2 determines whether the cycle times at W01 are directly governed by the multi-panel's features or there are other inherent uncertainties during production that are having a significant effect.

The third process improvement measure addresses the existing strategies in use for achieving operational flexibility and meeting production targets. Figure 5.3 and Figure 5.4demonstrate that working beyond hours and on irregular days are commonly used strategies to employ when needed for accommodating variation in demand and meeting production deadlines. Despite being effective in these respects, these strategies do not take under consideration other aspects, such as production efficiency and balance. In this context, it should be noted that a production target is considered to have been met when the output is within a 25% range of the input during the same period (e.g., day or week). As determined based on consultation with production managers from the case company and shown in Figure 5.4, the production target is set on a weekly rather than on a daily basis, since there are minor fluctuations between days in the week. Based on the three hypotheses formulated, data is prepared, modelled, and evaluated as described in the following sub-sections.

5.4.3. Data Preparation

This subsection describes the creation of datasets to test the hypotheses proposed in Section 5.4.2. The initial dataset consists of design specifications and production data for 27,680 multi-panels drawn from BIM models and RFID readings spanning the period, September 2015 to October 2018. To ensure consistency, the data cleaning phase is performed in three steps: (1) removal of data for panels manufactured before June 1, 2016 due to significant changes to the shop floor layout; (2) removal of data for panels manufactured before September 18, 2016 due to a detected malfunction in the RFID system before this period; and, (3) removal of custom panels built manually on the shop floor (mainly due to having an abnormally short height or length).

After the initial cleaning, the data is processed in order to calculate the cycle times of panels at each workstation. Since each multi-panel is actually a combination of multiple single panels, each with an RFID tag affixed to the leading study, each multi-panel has multiple RFID tags according to the number of single panels it comprises. To avoid having multiple cycle time readings for the same multi-panel, only the RFID tag from the first single panel of a given multi-panel is considered, as this will be the first one to enter the workstation. As a result of the data cleaning process, the number of multi-panels is reduced from 27,680 to 7,819. The most significant portion of panels discarded is at the first step as 16,679 multi-panels were manufactured before June 1, 2016. Furthermore, the RFID data is prepared differently according to the nature of each hypothesis. Cycle times are calculated for each panel at W01 for the design-based dataset in order to evaluate H_1 and H_2, whereas the production-based dataset is used to evaluate the weekly production and address the efficiency of flexibility strategies, as stated in H_3.

5.4.3.1 Design-based Data Preparation for H_1 and H_2

Figure 5.5 shows the configuration of RFID antennas at a given workstation, as well as how the durations are interpreted from the data collected by these antennas. Equation (5.1), meanwhile, demonstrates how the cycle time $CT_{p,n}$ (in minutes) for panel p at workstation n is calculated by subtracting the timestamp of when the panel entered the workstation from the timestamp of when the subsequent one did ($t_{p,n}$ and $t_{p,n+1}$, respectively). Due to the arrangement of antennas at the workstations, only cycle times can be extracted from the timestamps, whereas the processing ($PT_{p,n}$) and waiting times ($WT_{p,n}$) cannot be calculated based on the RFID data. The lack of processing and waiting times hinders more in-depth analysis of the manufacturing process, since we cannot discern based on the cycle times alone whether the panel is being processed or is idle (Barkokebas et al. 2018). Nonetheless, in some cases, the panel cycle times can be adjusted to give a clearer picture of actual production. For instance, in the case that a panel has remained at a workstation during non-working hours (e.g., scheduled breaks, weekends, etc.), time is deducted accordingly. To give a specific example, if a panel has remained at a workstation between 9:20 a.m. and 10:00 a.m., fifteen minutes will be deducted from its cycle time since the shop floor has a scheduled break between 9:30 a.m. and 9:45 a.m.

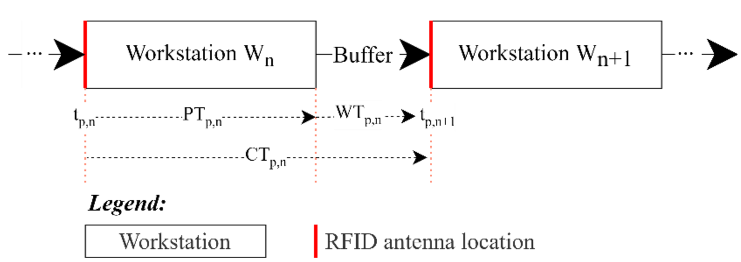


Figure 5.5: Data collected from the RFID system

$$CT_{p,n} \rightarrow t_{p,n+1} - t_{p,n} = PT_{p,n} + WT_{p,n} \tag{5.1}$$

Since H_1 and H_2 are focused on the duration of W01, multi-panel's features are combined with data from BIM models and cycle times calculated for this workstation. As indicated in Figure 5.6, there is a significant number of panel features extracted from BIM models that are dependent on one another (e.g., length and number of studs) and that may not be relevant for the prediction of cycle times at W01. These interdependent features can cause two problems during analysis: (1) overfitting due to the high number of input variables, and (2) skewed and misleading results due to multicollinearity. Therefore, multi-panel features are selected according to validated time studies to predict the process times at W01 performed by (Shafai 2012). Figure 5.6 lists the selected features. The selection of features having been performed, the design-based dataset is ready to be deployed for the training of the machine-learning models to be used to test H_1 and H_2.

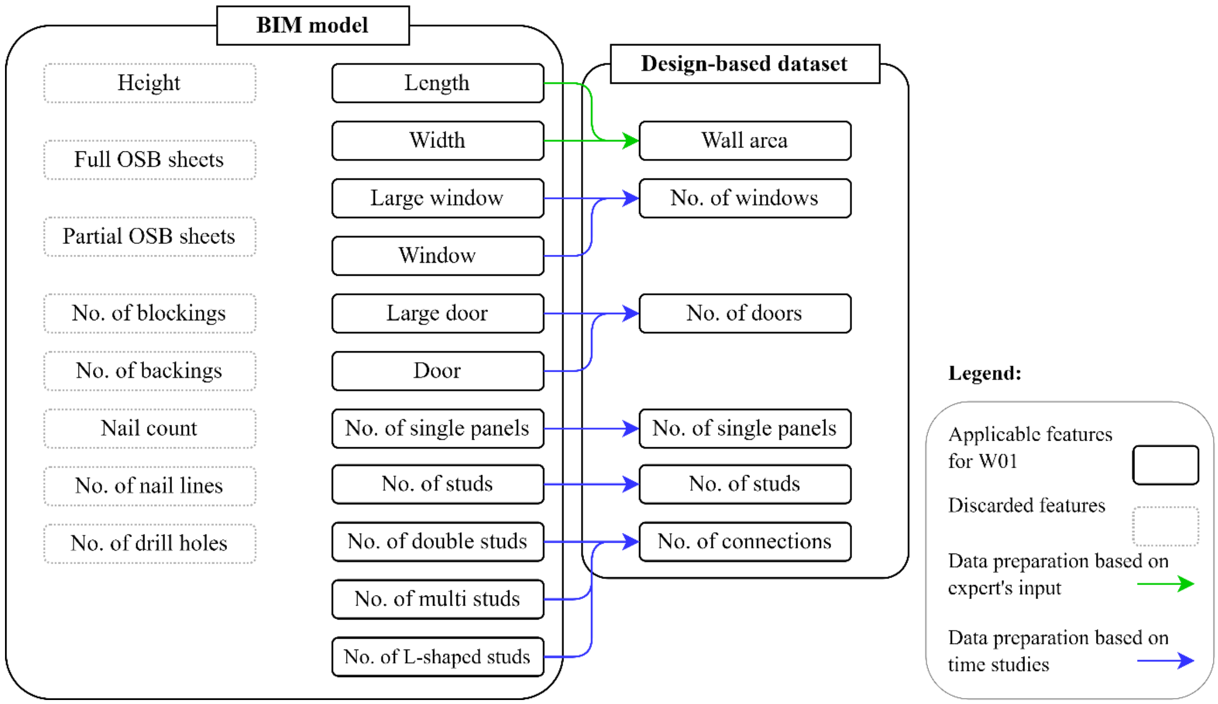


Figure 5.6: Design-based dataset on multi-panels

5.4.3.2 Production-based Data Preparation for H_3

Since H_3 addresses the efficiency of the flexibility strategies currently in use, the initial dataset is created from the data from the RFID system, organized according to the initial date of the panels manufactured. According to the assumptions determined in Section 5.4.1, the data is organized by labelling each working day (1 for yes and 0 for no) according to the following criteria: (1) whether any work was performed more than 30 minutes before or after the scheduled work shift (i.e., work beyond hours) according to the earliest and latest timestamps of the day; (2) whether work was performed on an irregular day based on the days of the week given in the timestamps; and (3) daily production input and output (in m^2). Once the daily production data has been prepared, it is grouped into weeks of the year and includes the following: (1) number of days when work beyond hours occurred; (2) amount of work on irregular days in the week; and (3) weekly production input and output. In addition, an indication of whether the production target was met or not in a given week is also included in the dataset following the criteria defined in Section 5.4.2. As per Equation (5.2), the production target (P_{met}) is met if the weekly production output (O_w) is within a 25% range of the weekly production input (I_w). Finally, the dataset is ready to be used in testing H_3.

$$P_{met} = \begin{cases} 1, & O \quad \geq 0.75 \times I_w \wedge O_w \leq 1.25 \times I_w \\ 0, & O_w \leq 0.75 \times I_w \vee I_w \geq 1.25 \times O_w \end{cases} \tag{5.2}$$

5.4.4. Modelling

This subsection describes the selection of the machine-learning models and other methods to be deployed in addressing the proposed hypotheses according to its nature. Since H_1 and H_2 deal with the influence of panel's features to predict its cycle time at W01, a design-based analysis is performed in which a series of machine learning and statistical methods are applied to test the proposed hypotheses. Furthermore, given that H_3 has to do with the ability of existing flexibility strategies to accommodate variability in demand, a production-based analysis is performed in which Pearson's correlation algorithm is applied in order to identify and characterize the correlation between the application of these strategies and production targets being met. In other words, the purpose of testing H_3 is to determine whether working beyond hours and/or on irregular days are effective strategies for meeting production targets under the current production. The different modelling approaches employed for this purpose are described in the following subsections.

5.4.4.1 Design-based Data Modelling for H_1 and H_2

As previously discussed, OSC is characterized by significant variation in both products and processes. Hence, a series of models is implemented combining and testing different machine-learning algorithms to identify design-related patterns in the manufactured multi-panels and evaluate cycle times at W01 accordingly. Figure 5.7 depicts the steps and machine-learning algorithms applied in the present study to test H_1 and H_2. Initially, multi-panels from the dataset prepared as described in Section 5.4.3.1 are clustered according to their features under the assumption that similar multi-panels will have similar cycle times. Due to the lack of scholarship specifically pertaining to the clustering of wall panels according to their features, popular algorithms from each clustering category are selected. Hierarchical density-based spatial clustering of applications with noise (HDBSCAN), an improved version of density-based spatial clustering of applications with noise (DBSCAN), is selected due to its popularity as a density-based clustering algorithm (Campello et al. 2013). It offers the advantage of being able to automatically select the number of representative clusters based on a relatively small number of samples from each cluster, while it can also identify noise in the dataset so that it can be addressed accordingly. *k*-means and agglomerative, meanwhile, are selected due to their popularity as density-based and hierarchical clustering algorithms, respectively (Ahmed et al. 2020; Naeem et al. 2019).

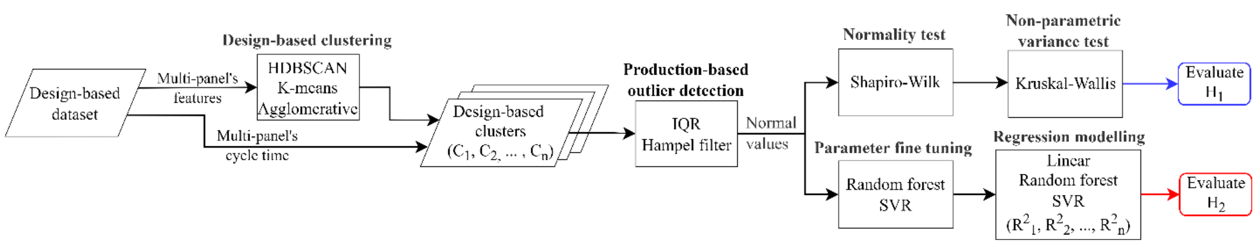


Figure 5.7: Machine-learning modelling to test H1 and H2

In contrast to HDBSCAN, the latter-mentioned algorithms require the user to specify the desired number of clusters beforehand, since there is not an initial indication of what that number might be. For this reason, HDBSCAN is first performed to obtain a possible number of clusters in the design-based dataset, and this number of clusters is found to be 4 based on a minimum of 700 multi-panels per cluster as the input parameter. This number is increased to 5 in order to gain a better understanding of the variation in features, and the same number of clusters is used for the other algorithms as well. The multi-panels having been clustered according to their design features, the cycle times are filtered through outlier detection algorithms to exclude abnormal durations that may have occurred due to unforeseen events such as machine breakdown, low productivity, or lack of material. Interquartile range (IQR) is used for this purpose as a classical statistical method for detecting outliers, while a Hampel filter is also employed due to its good performance in detecting outliers in manufacturing cycle times in particular (Nishigaki et al. 2020).

Various approaches are then applied in order to test H_1 and H_2. To test H_1, samples from each cluster are grouped into interior and exterior panels so that a statistical test can be performed to evaluate whether the cycle times of exterior and interior panels are significantly different. To select which test to use (parametric or non-parametric), a Shapiro-Wilk test is applied to the cycle time samples in each cluster to determine whether they behave as Gaussian or non-Gaussian distributions. The distributions of both exterior and interior multi-panels having been found to exhibit non-Gaussian behaviour, the Kruskal-Wallis test—a popular non-parametric method to evaluate means of durations in manufacturing (Chien et al. 2007)—is applied to test H_1. To evaluate H_2, three regression algorithms—linear regression, random forest regression (RFR), and support vector regression (SVR)—are applied, and the R^2 value (also known as coefficient of determination) from each regression is calculated in order to determine the degree design-related features of multi-panels explain the variation in the forecast of its cycle-times. Given that the efficiency of regression algorithms such as RFR and SVR is dependent on the parameters used during regression, the parameters are fine-tuned according to the sample in each cluster using a GridSearchCV algorithm. GridSearchCV, it should be noted, performs an exhaustive search over a range of predefined parameters to identify the best set of parameters to be used in a regression model based on the training set provided in each cluster. A two-fold cross-validation using a

90%/10% ratio is applied in each cluster for training/testing to ensure the models are not over-fitted.

5.4.4.2 Production-based Data Modelling for H_3

As indicated in Figure 5.3 and in Table 5.1, there is significant variation in output production, and different flexibility strategies (i.e., working beyond regular hours and/or during irregular days) are used to make production more flexible when needed. To capture this aspect, graphical tools are applied to visualize when these flexibility strategies are being applied and whether production targets are being met when these strategies are applied. Following the visual assessment, Pearson's correlation method—a method to evaluate the linear relationships among productivity parameters in manufacturing (Charaniya et al. 2010)—is applied to determine the extent to which there is a correlation (measured by the covariance factor) between these flexibility strategies being applied and the weekly production targets being met.

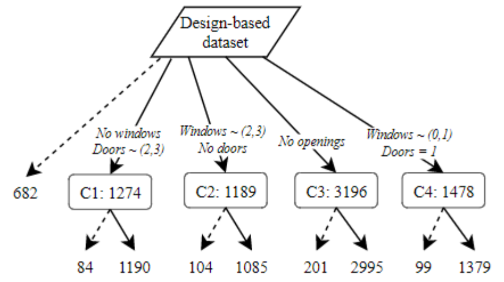
5.4.5. Evaluation

In this subsection, the results of the modelling are evaluated and presented. The data is presented visually to demonstrate the function of the developed models and to illustrate the results of the design-based assessment. The figures below aid understanding of the important design features in the multi-panels and the sample sizes in each clustering algorithm. Moreover, the graphs indicate the number of weeks during which flexibility strategies have been used, followed by the number of weeks during which the production targets have been met, as determined in the production-based assessment. These graphs aid understanding of the results and shed light on the determinations made to either accept or reject the proposed hypotheses. Each hypothesis is evaluated separately according to its nature and the type of testing. For the design-based hypotheses (i.e., H_1 and H_2), the multi-panels are grouped into clusters according to their design features. The *p*-values from the Kruskal-Wallis test can then be used to evaluate whether there is a significant difference in cycle times between exterior and interior panels (H_1). To address H_2, the R^2 values from the regression models are used to evaluate the extent to which the design features can explain the variance in the cycle times of the multi-panels in a given cluster. To address the production-based hypothesis, H_3, Pearson's correlation method is applied to determine the linear relationship between the existing flexibility strategies being used and the production targets being met.

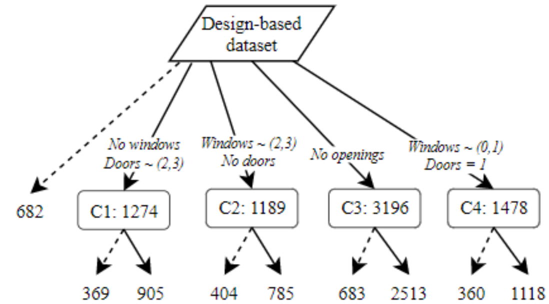
5.5. Computational Results

5.5.1. Design-based Assessment

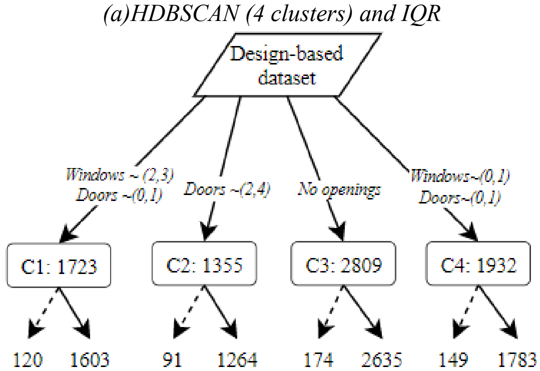
Figure 5.8 depicts the results of each model according to the number of multi-panels per cluster and outliers detected using IQR and Hampel filter. As can be observed in the figure, the number of openings (windows and doors) is the determining feature used to cluster the multi-panels. Furthermore, the number of single panels in each multi-panel appears in some models as a secondary feature when using HDBSCAN and agglomerative with five clusters. This is attributable to the influence that the number of openings has in determining the process times at the framing station, as noted in previous studies performed at the particular shop floor under study(Altaf 2016; Shafai 2012). Figure 5.8 also demonstrates that more cycle times are identified as outliers when applying the Hampel filter method compared to when applying IQR, since the Hampel filter provides narrower acceptable ranges compared to IQR (Domanski 2020; Falkowski and Domanski 2020). The models having been obtained, normal values in each cluster are saved to new datasets that can be used in the calculations performed for the purpose of testing H_1 and H_2.



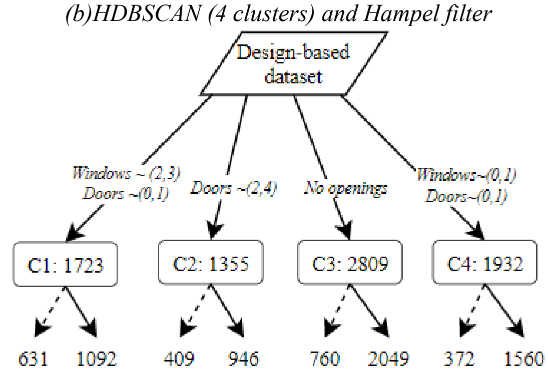
(a)HDBSCAN (4 clusters) and IQR



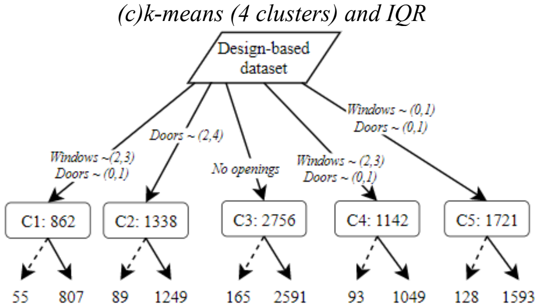
(b)HDBSCAN (4 clusters) and Hampel filter



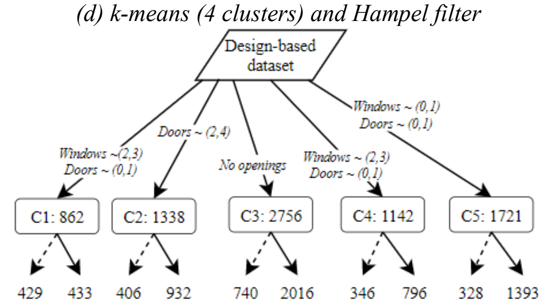
(c)k-means (4 clusters) and IQR



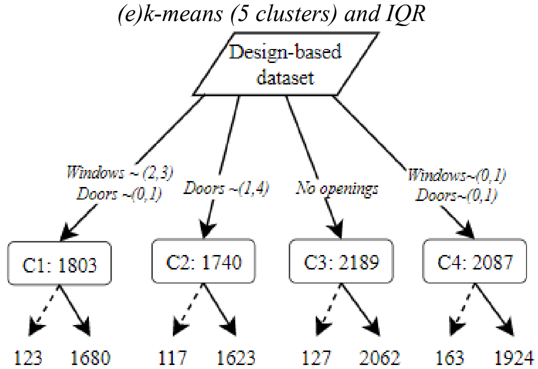
(d) k-means (4 clusters) and Hampel filter



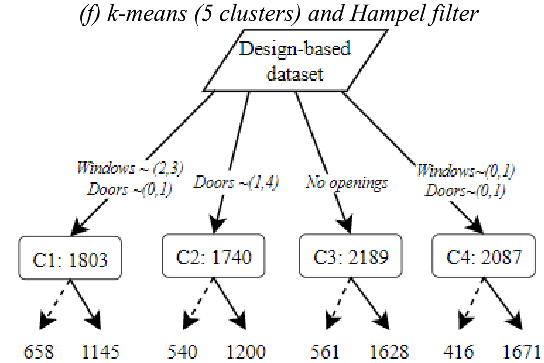
(e)k-means (5 clusters) and IQR



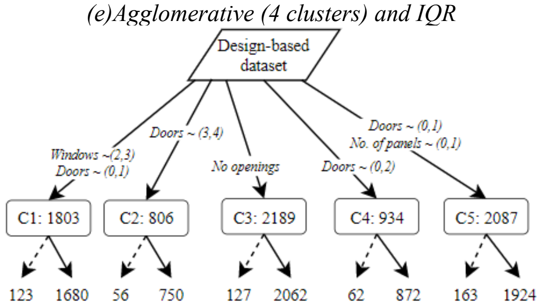
(f) k-means (5 clusters) and Hampel filter



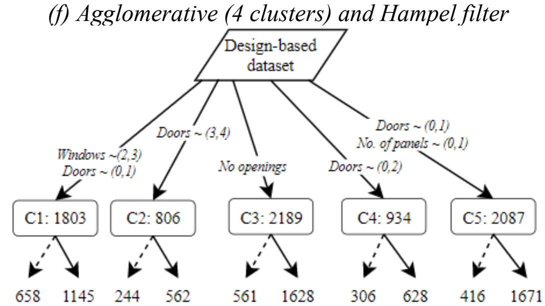
(e)Agglomerative (4 clusters) and IQR



(f) Agglomerative (4 clusters) and Hampel filter



(e) Agglomerative (5 clusters) and IQR



(f) Agglomerative (5 clusters) and Hampel filter

Figure 5.8: Clusters and outliers created from the design-based dataset according to the proposed models.

5.5.1.1 H_1: The panel cycle time at W01 is not affected by panel type

Table 5.3 lists the *p*-values of each cluster, where the cycle time samples of exterior and interior panels are compared according to the Kruskal-Wallis test based on a significance of $p = 0.05$ after excluding outliers. This analysis is performed in order to evaluate H_1 and determine whether there is a significant difference in cycle time at the semi-automated framing station between different panel types. The *p*-values are found to vary considerably within each cluster, where the values obtained by the models using the agglomerative algorithms show the widest variation, ranging from 0.06 up to 0.98. The models using *k*-means, meanwhile, are found to vary in terms of the range of *p*-values depending on the number of clusters, with the models with four clusters exhibiting the narrowest range between clusters (0.28 to 0.57), and the models with five clusters exhibiting similar ranges to the agglomerative models. These ranges indicate that cluster samples (e.g., C1, C2, etc.) with higher *p*-values overall show more similarity in cycle time between exterior and interior multi-panels than the cluster samples with lower *p*-values. Moreover, all the *p*-values in Table 5.3 exceed the significance level of 0.05, meaning that cycle times at the semi-automated workstation are not affected by wall panel type (i.e., interior versus exterior), and that H_1 should be accepted. These results are aligned with the findings of previous time studies performed at the shop floor under study, wherein wall type (noting that garage walls were excluded from these time studies since they are not tracked by the RFID system at the case company) was deemed to not be a significant feature to consider in determining the process times of wall panels at the framing station (Altaf 2016; Shafai 2012).

Table 5.3: P-values between exterior and interior multi-panels cycle times for each cluster according to the Kruskal-Wallis test

Model	**C1**	**C2**	**C3**	**C4**	**C5**
HDBSCAN + IQR	0.87	0.26	0.11	0.89	-
HDBSCAN + HF	0.87	0.26	0.11	0.89	-
k-means (4) + IQR	0.28	0.57	0.39	0.47	-
k-means (4) + HF	0.28	0.57	0.39	0.47	-
k-means (5) + IQR	0.08	0.42	0.27	0.99	0.79
k-means (5) + HF	0.08	0.42	0.27	0.99	0.79
Agg. (4) + IQR	0.06	0.81	0.98	0.66	-
Agg. (4) + HF	0.06	0.81	0.98	0.66	-
Agg. (5) + IQR	0.06	0.61	0.98	0.66	0.73
Agg. (5) + HF	0.06	0.61	0.98	0.66	0.73

Note: HF = Hampel filter, Agg. = Agglomerative

H_2: The panel cycle time at W01 is directly related to the features of the given panel

Table 5.4 lists the R^2 values from the regression analysis performed on each cluster using various regression algorithms (as described above) to predict cycle times at the framing station (W01) according to multi-panel features. Table 5.4 shows that the values of R^2 obtained are very low, meaning that variation in multi-panel cycle time is not significantly attributable to variations in panel design features. At first consideration, these results seem to contradict two of the assumptions underlying the present study: (1) multi-panel features are accurate predictors of cycle times, according to previous time studies carried out at the shop floor presently under investigation (Altaf 2016; Shafai 2012); and (2) the automation at the framing station should allow for a more predictable manufacturing process. To explain the seeming contradiction with respect to the first assumption, we simply note that time studies are mainly focused on the process times of activities, and thus waiting times are not taken into account. Time studies are also limited in sample size, whereas the present study considers production data for a period spanning approximately two years. Regarding the seeming contradiction with respect to the second assumption, we note that the increased production rate of the semi-automated framing station in the process predictability surpasses the variation imposed by the features in the multi-panels. Furthermore, the variation in production caused by the dynamic environment of the shop floor also contributes to the decrease in significance of the design features in explaining the multi-panel cycle time at W01.

Table 5.4: R^2 values from different regression analyses performed for each cluster

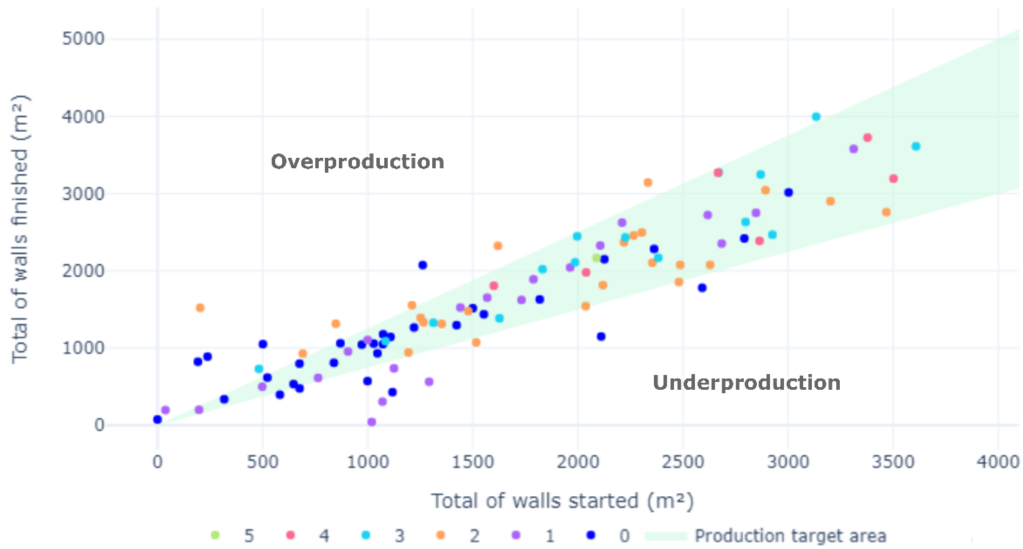
	R^2 value														
Model	**C1**			**C2**			**C3**			**C4**			**C5**		
	LR	**RFR**	**SVR**	**LR**	**RFR**	**SVR**	**LR**	**RFR**	**SVR**	**LR**	**RFR**	**SVR**	**LR**	**RFR**	**SVR**
HDBSCAN + IQR	0.05	−0.01	−0.22	0.03	0.00	0.03	0.07	0.07	0.07	0.02	0.06	0.03	-	-	-
HDBSCAN + HF	0.08	0.15	0.07	0.13	0.03	−0.07	0.09	0.17	0.12	0.19	0.18	0.06	-	-	-
k-means (4) + IQR	0.12	0.13	−0.04	0.03	0.05	−0.02	0.10	0.08	0.05	0.02	0.10	−0.07	-	-	-
k-means (4) + HF	0.05	0.23	0.19	0.14	0.10	−0.05	0.09	0.15	−0.01	−0.01	−0.02	−0.05	-	-	-
k-means (5) + IQR	0.20	0.18	0.05	0.00	0.05	−0.06	0.06	0.12	0.02	0.12	0.12	0.01	−0.03	0.11	−0.12
k-means (5) + HF	−0.02	0.06	−0.07	−0.09	0.13	0.09	0.12	0.19	0.05	0.22	0.17	0.09	0.04	0.13	0.03
Agg. (4) + IQR	0.11	0.20	−0.01	0.01	0.01	−0.04	0.01	0.13	−0.03	0.04	0.10	−0.09	-	-	-
Agg. (4) + HF	0.20	0.13	0.00	0.00	0.03	0.00	0.05	0.04	0.09	0.06	0.06	0.05	-	-	-
Agg. (5) + IQR	0.12	0.16	−0.03	0.08	0.02	−0.03	0.09	0.05	−0.02	−0.01	0.13	−0.06	0.00	0.10	−0.08
Agg. (5) + HF	0.18	0.09	0.10	0.11	0.09	0.12	0.13	0.11	0.03	−0.09	0.09	0.17	0.05	0.12	0.04

Note: HF = Hampel filter, Agg. = Agglomerative, LR= Linear regression, RFR = Random forest regression, SVR = Support vector regressor

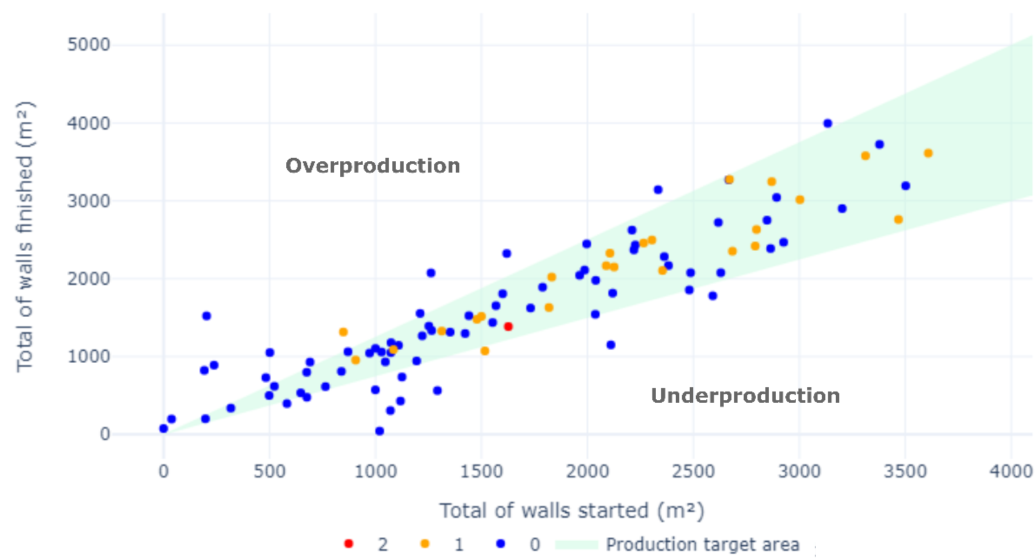
Despite these seeming contradictions, the results of the present study are aligned with the findings of previous machine-learning studies carried out using the same RFID dataset (Mohsen 2021; Wen et al. 2017). As described in Section 5.2.1, Mohsen (2021), using the same dataset from the same shop floor as the present study, similarly found that multi-panel design features were not an accurate predictor of cycle times. Wen et al. (2017) drew a similar conclusion, finding that production variability is high on the shop floor under study, and that this variability impedes the accurate estimation of cycle times of identical multi-panels at W01. Since the existing RFID system employed by the case company captures the total time each multi-panel spends at W01 and at the buffer, we similarly conclude that more granular data that clarifies the production status must be obtained before multi-panel design features can be used as an accurate predictor of cycle times at W01. In other words, more production-related data is needed in order to assess the variability of the manufacturing process itself as a predictor of cycle times at the framing station under investigation. Hence, we reject H_2, as it is concluded that multi-panel features do not explain the variation in cycle times.

5.5.2. Production-based Assessment

Figure 5.9 illustrates the production balance—e.g., total surface area of walls started versus finished—for every week of the period under study, as well as identifying the flexibility strategies used in a given week (if any). In the figure, the regions highlighted in green show where weekly production targets have been met as determined using the approach described in Section 5.4.2. As shown in the figure, for most weeks, production targets have been met, while a similar number of weeks are characterized by either over- or under-production. As can be seen, production targets have been met in over 71% of the weeks under study, with work beyond hours being found to be common in these weeks, whereas working on irregular days is found to be less common (Figure 5.9a and Figure 5.9b, respectively).



(a) Production target according to the number of days with work beyond hours per week



(b)Production target according to the number of irregular days per week

Figure 5.9: Production status according to existing flexibility strategies

5.5.2.1 H_3: Working on irregular days and periods will assist to meet production target H_3: Working on irregular days and beyond work hours is an effective strategy for meeting production target

As previously described, this hypothesis is tested by applying Pearson's correlation method to evaluate the correlation between the flexibility strategies being used and the production targets being met in a given week. Table 5.5 lists the occurrence of each flexibility strategy and indicates whether the production target has been met; the corresponding Pearson's correlation coefficient is also given in the table. As illustrated in Figure 5.3, in Figure 5.9a, and in Table 5.5, the strategy of working beyond hours is commonly employed to make production more flexible. It is important to note that the use of this strategy can be identified based on the RFID timestamps, which imply that an unknown number of workers are continuing on the shop floor. Allowing extended work beyond hours such as 30 minutes or more exposes the shop floor to increased factory overhead cost and decreased productivity by workers. Hence, the management team would like to address if this flexibility approach is efficient to meet the weekly production target. Despite the high occurrence of working beyond hours (68% of the weeks under study), the Pearson's correlation coefficient for this strategy is quite low, meaning that the ad hoc use of this strategy in individual workstations does not contribute significantly to production targets being met.

The strategy of working on irregular days (Fridays, Saturdays, and Sundays), on the other hand, is applied to all workstations and is often used at times throughout the year when demand is high. This strategy is found to be used less frequently compared to the strategy of working beyond hours (i.e., in only 25% of the 99 weeks under study); meanwhile, as with the other strategy, there is not a strong linear correlation between its use and the achievement of the production target for the given week. This result provides an interesting insight, as it indicates that working extra shifts does not guarantee that the shop floor will be able to meet demand. On the other hand, it results in the company incurring extra expenses such as overtime-labour pay and higher expenditure on utilities (heat, electricity, etc.) due to the extra working days. Meanwhile, Table 5.5 shows that the framing station is often shut down, and this is indicative of imbalanced production (i.e., the framing station is being shut down to allow other stations to clear their backlog). In conclusion, the Pearson's correlation analysis indicates a low linear correlation between the use of the flexibility strategies and the ability to meet production targets. Therefore, we reject H_3.

Table 5.5: Flexibility strategies and correlation between their use and production targets being met

Flexibility strategy	Occurrence	Pearson's correlation coefficient
Work beyond hours	68%	9.3%
Work on irregular days	25%	21.0%
Production target met	72%	N/A

5.5.3. Summary of Computational Results

The aim of the case study is to test the proposed method leveraging digitalization, which evaluates proposed process improvement measures based on a series of hypothesis-testing methods and using a large dataset containing cycle times and multi-panel design features, the data having been gathered from an RFID system installed on the shop floor and from BIM models spanning a period of two years. For this purpose, a series of visualization methods, machine learning, and statistical methods are applied in a case study involving the production of wall panels in order to evaluate the impact of automation and of the case company's existing flexibility strategies. Hypotheses formulated for this purpose are tested using a combination of machine learning and statistical methods. Initially, the impact of the semi-automated machine is characterized by an increased pace of production but also interruptions to production due to increased WIP throughout the shop floor. In the design-based analyses as described above, the acceptance of H_1 and the rejection of H_2 confirm that the impact of design features is not significant in explain the variability in cycle times at the semi-automated framing station. H_1 is accepted, as noted above, by virtue of the fact that the Kruskal-Wallis test shows that all clusters have *p*-values higher than the 0.05 significance level (in fact, the overall values in each cluster are above 50%). Meanwhile, H_2 is rejected by virtue of the fact that the R^2 values are well below 0.70 in each cluster (looking at the values in the models combining different approaches of clustering, outlier detection, and regression analysis). H_3, a production-based hypothesis, is rejected by virtue of the fact that the Pearson's correlation coefficients show a low linear correlation (9.3 and 21%) between the weekly production target and the respective flexibility strategies.

5.6. Conclusions

The aim of this study was to propose a method to evaluate proposed process improvement measures based on production insights from experts and data gathered from RFID sensors and BIM models leveraging a digitalization approach. Additionally, this study addresses the impact both of automation and of the strategies used to increase operational flexibility based on data-mining techniques applied using the gathered data. By following the steps in the CRISP-DM methodology and the principles of inductive research, the proposed digitalization method is implemented to gain understanding of, prepare, model, and evaluate data as the basis for testing hypotheses on process improvement measures. The proposed method applies various EDA techniques on a large dataset that includes the cycle times of semi-automated framing station and design features of multi-panels gathered from BIM models.

The novelty of this study lies in its development of a method to apply digitalization to process improvement in OSC using real-time RFID data in combination with design features of multi-panels gathered from BIM models. In the case study used to develop and test the proposed method, the design-based hypotheses (H_1 and H_2) are focused on the impact of the semi-automated framing station (i.e., W01), as well as of the design features of the multi-panels being manufactured, in determining cycle time. H_1 is accepted based on a Kruskal-Wallis test in which interior and exterior panels are found to have similar manufacturing durations at the semi-automated framing station. H_2, on the other hand, is rejected, as an extensive analysis using a combination of machine-learning models indicates that design-based features do not explain to a significant degree the variability in manufacturing durations at the semi-automated framing station under study. H_3 is also rejected, as there is not a strong correlation between the use of strategies to increase operational flexibility (i.e., working beyond hours and on irregular days) and weekly production targets being met. Two notable inferences are derived from the present study: (1) variability poses a great challenge with respect to production control, as many of the resources used in production (e.g., semi-automated machines and factory space) are fixed throughout the year, and (2) the use of automation or semi-automation is not sufficient to eliminate the effects of variation in the manufacturing process. In this respect it is clear that the increased pace of W01 in the present case creates a push system in which downstream workstations become overloaded with panels. Hence, process improvement efforts should be focused on achieving balance in production between semi-automated and manual workstations in order to ensure the needed flexibility to respond to changing production targets over the course of the year.

Despite providing a structured, inductive method for process improvement in OSC leveraging digitalization, more case studies are needed to improve upon the proposed method in consideration of different contexts (e.g., smaller datasets, structured methods to gather qualitative data, etc.). Moreover, although the proposed method can be used to test the validity of proposed process improvement measures, the present study does not evaluate the potential impact of, or otherwise address, the implementation of these measures. As such, future research is needed in order to develop the proposed method into a framework in which proposed process improvement measures are assessed in terms of both their validity and their potential impact on OSC operations.

CHAPTER 6: ASSESSMENT OF DIGITAL TWINS TO REASSIGN MULTI-SKILLED WORKERS IN OFFSITE CONSTRUCTION BASED ON LEAN THINKING

6.1. Introduction

Offsite construction (OSC) has become increasingly popular among construction practitioners due to its high productivity and efficiency compared to traditional construction, achieved by shifting operations from the construction site to an offsite factory (Modular Building Institute 2010). In OSC, projects are divided into building components (e.g., wall panels, modules), manufactured on a shop floor, transported to and installed on site. In spite of the numerous benefits of OSC, Goulding et al. (2015) identified the lack of production flexibility in OSC as one of the major challenges to overcome in order to accommodate customer needs and different economic scenarios. Indeed, OSC has a characteristic of offering a large selection of design options, thus introducing a high degree of variability to the manufacturing process, since each product (e.g., module, panel) is unique, and since the manufacturing operations, even with the use of semi-automated or fully automated machinery, still rely on labour-intensive tasks and human supervision. The significant variability in the product combined with the static production capacity of fixed workers in their workstations causes bottlenecks across the shop floor while making future performance difficult to predict without significant cost and time deviations. Hence, workstations with a static production capacity cannot manufacture different products at a similar duration, and this results in production waste that typically goes undetected on the shop floor. This study addresses the latter problem whereby OSC manufacturing operations must increase their flexibility to optimize the shop floor dynamics to reduce production waste. In summary, a shop floor that lacks flexibility is unable to manufacture projects efficiently and is susceptible to low performance due to product variation and process uncertainty from labour-intensive tasks.

In light of this, Widfeldt et al. (2008) argued that labour flexibility must be a priority in OSC while pointing to the lack of available approaches to develop a more flexible manufacturing system while Goh and Goh (2019) proposed the use of multi-skilling as a strategy to increase labour flexibility in OSC. Despite promising results, Zhang et al. (2020) pointed out that multi-skilled workers can lead to waste activities, delays, and interrupted production while also resulting in ineffective labour resource allocation due to the traditional management practices in OSC. Clarke and Wall (2000) point to the negative psychological effects affecting multi-skilled worker's productivity due to the confusion regarding the overlap between different trades and their management during operations. Furthermore, multi-skilling is regularly associated with increased cost and reduced productivity as multi-skilled workers cannot be equally productive in two or more trades and due to learning and forgetting effects while requiring more training from employers (Ahmadian Fard Fini et al. 2016, 2017; Goh and Goh 2019; Hegazy et al. 2000). Qin et al. (2015) attributes the lack of consensus to apply multi-skilling in construction due to the absence of in-depth studies involving their negative effects on workers and the complexity involved to perform these studies. Therefore, it is clear that trade-off analyses must be developed to evaluate the actual benefits of using multi-skilled workers considering various aspects of production and management practices particular to OSC shop floors. Additionally, more research is needed to address if the application of innovative technologies will cause a significant impact in manufacturing operations by improving the management of multi-skilled workers, reduce production waste and optimize shop floor dynamics. In the context of the research presented in this chapter, labour flexibility is defined as the ability workers have to adapt shop floor processes in a timely manner in response to events that are inherently uncertain and variable, such as product and production variation due to market demands, client requirements, and task durations.

Initially proposed by Michael Grieves in 2002, a digital twin (DT) is a digital informational construct that describes a potential or actual physical system to perform real-time simulations composed of three elements: (1) real space containing the actual system, (2) virtual space containing the system's digital representation, and (3) the seamless information flow between the real and virtual spaces in real time (Grieves and Vickers 2017). The current focus of DT revolves around the design of products, whereas research in manufacturing is considered an evolution of an ongoing research stream (Zhang et al. 2019). Commonly mistaken with cyber-physical systems, a DT distinguishes itself in that it is a data-driven approach that leverages data collected from sensors, whereas cyber-physical systems involve real-time actuation in the physical environment leveraging sensor-monitoring data (Tao et al. 2019). Due to it having been only recently introduced in the manufacturing and construction industries, the application of DT in OSC is still in its early stage wherein various applications and approaches must be developed to facilitate its wider adoption.

Sacks et al. (2020) conceptualize the use of a DT in construction as an innovative approach to manage production by acknowledging both products and processes in an inter-exchangeable manner through real-time data streaming to provide updated production status and to proactively optimize design, planning, and production processes. In the context of OSC shop floors, DT is proposed as a solution to monitor and improve labour flexibility since it provides a robust analysis using the actual status of production on the shop floor, which is influenced by production variability and uncertain manufacturing operations. Despite promising results, Zhang et al. (2020) argue that OSC is still labour-intensive, given that planning and control are dependent on personal experience and few technology-driven or digitalized methods are used to improve production. Therefore, DT is a suitable technology to manage multi-skilled workers as it receives, processes, and analyzes real-time data to improve manufacturing operations at the shop floor without requiring any automated actuation in the physical environment such as in cyber-physical systems. In fact, DT can assist the management team by reassigning multi-skilled workers dynamically in near-real time to avoid bottlenecks based on updated production information from sensors. Hence, the investigation of DT applications is crucial for the development of approaches using real-time data to optimize shop floor operations in OSC while accounting for aspects such as production flexibility, productivity, cost, and information flow between systems. Align to that, lean thinking provides a strong theoretical background to quantify improvements, identify wastes and evaluate operations within the context of OSC (Koskela et al. 2013). However, despite its importance, few studies are found in the literature with the primary objective to increase labour flexibility in OSC regardless of being supported by a DT or any type of autonomous system at all. Consequently, this study aims to answer the following research questions: (1) are multi-skilled workers a feasible approach to improve OSC manufacturing operations despite their reduced productivity and increased cost?, and (2) is DT impactful in managing multi-skilled workers to reduce manufacturing cycle times in OSC?

Therefore, this research proposes to improve the dynamics of manufacturing operations on OSC shop floors by increasing labour flexibility through multi-skilled workers and by applying a DT to leverage real-time data. Using simulation as a surrogate system, a novel approach is presented to quantify the impact of applying a DT to manage multi-skilled workers to increase overall productivity in OSC while simulating the interactions between the physical/virtual environments and the information flow between them. Using a practical application, the present study emulates the shop floor where multi-skilled workers are managed by a DT under different scenarios such as different multi-skilling configurations (e.g., dual-skill, direct capacity balancing, etc.), the loss in productivity due to the learning effect, and the increased cost as indicated by the literature. Therefore, the academic contribution of the present study is two-fold: (1) the present study provides a trade-off analysis on the application of multi-skilling to increase labour flexibility on OSC shop floors considering different aspects of production such as cost, production time, and gained productivity based on a lean thinking perspective; and (2) the present study addresses the impact of DT to manage multi-skilled workers and increase labour flexibility in the context of OSC shop floors.

6.2. Background

The construction industry provides clients with a wide range of options and specifications during the design phase, making it one of the largest engineer-to-order sectors (Jansson 2013). Bataglin et al. (2020) point out that the complexity of engineer-to-order is further amplified in OSC due to the short lead times and the fact resources must be shared between different projects being produced concurrently on the same shop floor. This imposes a great variability in the manufacturing process since each product (i.e., module or panel) is unique, and its manufacturing process is still labour-intensive and prone to a high degree of uncertainty. In this regard, Altaf et al. (2018) indicate that the high level of variability in production is not only due to project attributes but also due to the uncertainties inherent to the production itself on a semi-automated OSC shop floor. Likewise, Goulding et al. (2012) argue that OSC enterprises must embrace methods for mass production; however, given the customized nature of construction, manufacturing processes must be flexible enough to accommodate design changes and process uncertainties.

6.2.1. Multi-skilling in Offsite Construction

First introduced by Burleson et al. (1998), multi-skilling is a labour utilization strategy used in the construction industry to reduce cost, to increase productivity, and to reduce ergonomic risks (Otto and Scholl 2013; Leider et al. 2015). Multi-skilling is a widely recognized solution employed to deal with production fluctuations and to improve efficiency in operations (Satta et al. 2019). In the context of OSC, where there is a significant variability in processes due to the high customization of products and labour-intensive tasks, multi-skilling is a highly requested feature capable of bridging skilled labour shortages and providing a significant reduction in retention costs by increasing production line efficiency (Warszawski 2003; McGuinness and Bennett 2006). In the context of a typical OSC shop floor, project management assigns workers with individual specializations to each workstation. Workers do not migrate away from their assigned workstations, which results in bottlenecks at workstations with higher demand; this, in turn, can negatively affect the progress rate of projects (Arashpour et al. 2015). To solve this problem and add more flexibility to the production facility, Wongwai and Malaikrisanachalee (2011) propose applying multi-skilled workers to reduce project duration, increase job stability for workers, and allow for a higher degree of flexibility in task assignment. The use of multi-skilled workers is suitable for solving issues related to the lack of flexibility in OSC, as they can be assigned to different workstations to balance production according to the required customizations from clients while proactively eliminating bottlenecks on the shop floor. Despite relevant work published in construction, Nasirian et al. (2019a) found that only six papers, out of a total of 61 papers in their review, describe research that applies multi-skilling in an OSC context, which demonstrates that research is lacking in this area.

Table 6.1: Multi-skilled labour modelling in offsite construction.

References	Method	Variables considered									Observed outcomes		
		PR	PU	PL	TC	SC	RC	FO	SA	LE	ET	EC	RU
Arashpour et al. (2015b)	DES	X	X								X		X
Arashpour et al. (2018a)	MCDM			X*	X				X*			X	
Arashpour, et al. (2018b)	Linear and integer optimization		X		X	X	X				X	X	X
Avva and Chamberlin K. (2020)	MCDM	X			X	X	X			X*	X	X	
Barkokebas et al. (2015)	DES & CS	X		X							X		X
Barkokebas et al. (2020)	DES & CS	X		X		X		X			X	X	
Nasirian et al. (2019)	MCDM	X			X	X	X		X*	X*	X		
Present study	DES & CS	X	X	X	X	X		X		X	X	X	

Note: DES = Discrete-event simulation; MCDM = Multicriterion decision-making; CS = Continuous simulation; PR = Productivity; PU = Production uncertainty; PL = Production layout; TC = Training cost; SC = Salary cost; RC = Retention cost; SA = Safety; LE = Learning effect; FO = Factory overhead; ET = Effect in time; EC = Effect in cost; RU = Resource utilization; *=Qualitative variable

Table 6.1 presents the relevant literature where the use of multi-skilled labour in offsite OSC is modelled and forecast using different methods. It can be observed in Table 6.1 that multi-criterion decision-making methods are successfully applied by combining quantitative and qualitative criteria to investigate best strategies for multi-skilling implementation in OSC facilities. When applying discrete-event simulation, Arashpour et al. (2015b) indicate the limitations of this method with respect to modelling multi-skilled resources and their productivity. To address this issue, Barkokebas et al. (2020) propose a combination of discrete-event and continuous simulation, so the duration of continuing tasks is dynamically updated according to traditional and multi-skilled resources. As shown in Table 6.1, the majority of studies examine the productivity of tasks performed while taking into consideration the loss of productivity from multi-skilled workers due to lack of experience or ongoing training (Arashpour et al. 2018). Production uncertainty is also considered in the analysis by assuming stochastic values in the product's man-hour requirements while the facility layout is considered either qualitatively or as a quantitative metric such as the maximum number of workers allowed per station (Barkokebas et al. 2020). Cost is evaluated from various perspectives whether addressed directly through training, through the increase of salaries, and the retention of multi-skilled workers, or indirectly by addressing the impact of multi-skilled workers on the factory's overhead. Other variables considered qualitatively are safety and learning effects, which affects productivity and the choice as to which multi-skilled strategy is applied. Most studies indicate a positive effect on production time due to using multi-skilling on OSC shop floors while also accounting for the financial impact of these strategies and their utilization at the workstations under study. Nevertheless, Arashpour et al. (2015b) points out to the lack of quantitative evidence involving human behavior while recommending the application of learning curves to forecast the learning effect of multi-skilled workers and the impact on productivity over time. Despite the significant number of variables considered, none of the studies in Table 6.1 provides a multi-criterion analysis on the trade-off involving the application of multi-skilling in OSC. In turn, these studies are mainly focused on demonstrating the benefits of multi-skilling to increase the flexibility of production and reduce manufacturing times, whereas trade-off analyses evaluating the adverse aspects of such strategies are lacking. Indeed, all of these studies rely on the assumption that multi-skilled workers are successfully managed to assist workstations when needed without the assistance of any proactive system or any delay. As already pointed out by Zhang et al. (2020), this is not the case in OSC shop floors where resources are poorly allocated and based on personal experience with minimal use of real-time data to perform decisions. Table 6.1 demonstrates the present study combines a comprehensive number of important variables identified in past studies to quantify the impact of multi-skilling, presented here as the main driver of labour flexibility in OSC. Moreover, Table 6.1 shows that only human behaviour aspects such the learning effect have been addressed qualitatively in previous studies, whereas the present study is the first to apply learning curve models to quantify the reduced productivity of multi-skilled workers as an input in the proposed trade-off. In addition, this study evaluates the impact automated systems (e.g., DTs) could have if used to automate the reassignment of multi-skilled workers based on real-time data gathered on the shop floor to balance production and increase the flexibility of OSC shop floors.

6.2.2. Digital Twin Applications in Manufacturing and Offsite Construction Shop Floors

Traditionally, manufacturing facilities control their production using card systems (e.g., Kanban) and/or by way of expert knowhow, such as a foreman walking up and down the production line and assigning workers to workstations as needed (Bagni et al. 2020). Ghanem et al. (2018) point out that traditional control systems in construction are push-driven wherein labour is moved to attend to short-term milestones with little attention given to productivity and future demand. Meanwhile, Innella et al. (2019) argue that labour management is more complex on OSC shop floors due to the dynamic environment wherein teams of workers with different skills work concurrently on multiple projects. Indeed, production in OSC facilities is heavily influenced by a level of variability that is beyond management's control, since each project's specifications are unique due to client requests and because processes rely on labour-intensive operations. In light of this, Zhang et al. (2016) suggest the implementation of simulation-based systems that use real-time data to balance production in OSC facilities and to enhance decision-making in terms of long-term strategies regarding inventory and labour utilization. A DT is proposed to increase labour flexibility on OSC shop floors by employing a proactive approach in which data is seamlessly exchanged and manufacturing operations are improved in near-real time. By adopting this approach, a DT is expected to improve labour flexibility and considerably reduce total production time.

In the manufacturing industry, various frameworks for the implementation of a DT in the context of a shop floor are proposed in which data extracted from sensors are used to create a high-fidelity model and to improve both physical and virtual environments simultaneously (Tao and Zhang 2017; Zhuang et al. 2018). Several applications of DT have been found to leverage planning in a manufacturing environment, such as layout optimization (Guo et al. 2021) and evaluating the performance of machine operations (J. Liu et al. 2019). Production control is also a widely studied application, where recent research on preventive maintenance of equipment and disturbance detection on the shop floor has resulted in several useful models (Zhuang et al. 2018; Zhang et al. 2021). Despite significant progress, Melesse et al. (2020) argue that the application of DT for industrial production is still in its early stages as more research is needed to present feasible solutions for complex manufacturing systems. Furthermore, significant gaps still need to be addressed such as the consideration of human interactions and DT during the manufacturing phase as humans are prone to uncertainty and loss of productivity (Liu et al. 2020).

In the construction industry, Opoku et al. (2021) identify only 22 publications on DT in their review of literature published between 2017 and 2020 of which more than half are focused on the design and engineering phase of projects. This slow rate of adoption is expected since the concept of DT in manufacturing is in its infancy and is still being adapted to other domains such as construction. Despite the many particularities that need to be addressed, Correa (2020) argues that OSC shop floors have the potential to incorporate DT technologies more rapidly than traditional construction settings due to their factory-like environment, use of automation, and the relative ease with which sensor instrumentation can be implemented. In this regard, Rausch et al. (2020) develop algorithms to solve complex geometry challenges to minimize material usage and automate quality checking in OSC projects ready for implementation on a DT. Moreover, Lee and Lee (2021) propose a DT approach for supply chain coordination to optimize transportation routes for modular construction. In addition to these interesting applications, Gerhard et al. (2020) argue that data transformation procedures must be analyzed using an integrative approach in the building of a DT tailored to the requirements of OSC while exploring information exchange standards in both construction and manufacturing industries. In their seminal paper, Sacks et al. (2020) provide a holistic approach to collect, transform, and apply data in construction-centric DT considering both product and processes. Moreover, they proposed data to be transformed and distinguished in four different dimensions considering the physical/virtual environments and the planned/actual status relative to information provided and processed by the DT., Xie and Pan (2020) identify the lack of empirical evidence related to the benefits of leveraging data by employing a DT as a significant barrier to the wider adoption of DT, notwithstanding the recent interest DT has garnered. Furthermore, Anderl and Fleischer (2016) indicate that practitioners are still reluctant to incorporate novel technologies such as DT due to the lack of internal expertise and the risk involved in the initial investment and associated benefits from its implementation. According to Uhlemann et al. (2017), this reluctance is augmented in shop floors that have a low level of automation, as is typically the case in OSC, thus encouraging alternative approaches to evaluate the impact of these novel technologies. In this regard, Razkenari et al. (2020) suggest the use of simulation for the reliable assessment of the performance of new technologies while indicating a DT may be used to improve flexibility on OSC shop floors.

In summary, the main identified gaps in the literature are: (1) the lack of in-depth trade-off analysis regarding the actual benefits of increasing labour flexibility (i.e., multi-skilling) on OSC shop floors, (2) the lack of studies addressing the impact of automated systems (i.e., DT) to manage multi-skilled workers and increase flexibility on OSC shop floors, and (3) the need for approaches to measure the impact of DT tailored for the OSC and its contexts of high variability in both product and production. These gaps are addressed in the sections below.

6.3. Methodology and Research Methods

6.3.1. Methodology

Due to the excessive risk involved and investment required to implement a DT at full scale, simulation is used as a surrogate system to forecast the impact a DT will have in terms of increasing labour flexibility in OSC. Discrete-event and continuous simulation are common approaches used to forecast the future performance of complex systems, such as that of an OSC shop floor, and to forecast the impact of a DT on overall production (Afifi et al. 2020; Jiang et al. 2021). Given the complexity of actual systems, simulation is a reductionist approach where only significant aspects of the system under study are modelled and evaluated (Al Hattab et al. 2018). Therefore, significant aspects of a DT (physical and virtual environments, and their interconnectivity) and its virtual domains are modelled according to production metrics, constraints, and the information provided in the practical application. The developed simulation addresses production improvements that result from interventions made by the proposed DT. In this chapter, an intervention is defined as occurring when the DT suggests a modification to the multi-skilled worker assignment to improve production based on data from sensors on the shop floor. For each simulated scenario, production on the OSC shop floor is evaluated according to the number of interventions the proposed DT will perform during the work shift. The time period during which the DT will intervene is set as equal to the duration of the work shift. For example, if the DT is set to intervene in production four times during a work shift of eight hours, its intervention period will be 2 h (i.e., the DT will intervene every two hours).

Figure 6.1 demonstrates the flow of information processed by the proposed DT according to its inputs and criteria, and the figure also shows how the information is transformed in the developed simulation model across physical and virtual environments considering the planned and actual status of tasks. Initially, the DT must have a clearly stated goal to determine how key metrics (KM) can be used to quantify the system's performance. Relevant information pertaining to the shop floor layout and production resources are identified and modelled according to the model's practical application information to accurately represent the facility and its limitations in terms of improvement. Moreover, multiple labour utilization strategies are considered in determining which strategy will be used, where the proposed DT intervenes a number of times throughout the work shift and production performance is recorded accordingly. Once the simulation model has been developed, it is validated and tested by comparing different scenarios. This process is iterative as the model is adjusted during the validation and testing/comparing processes.

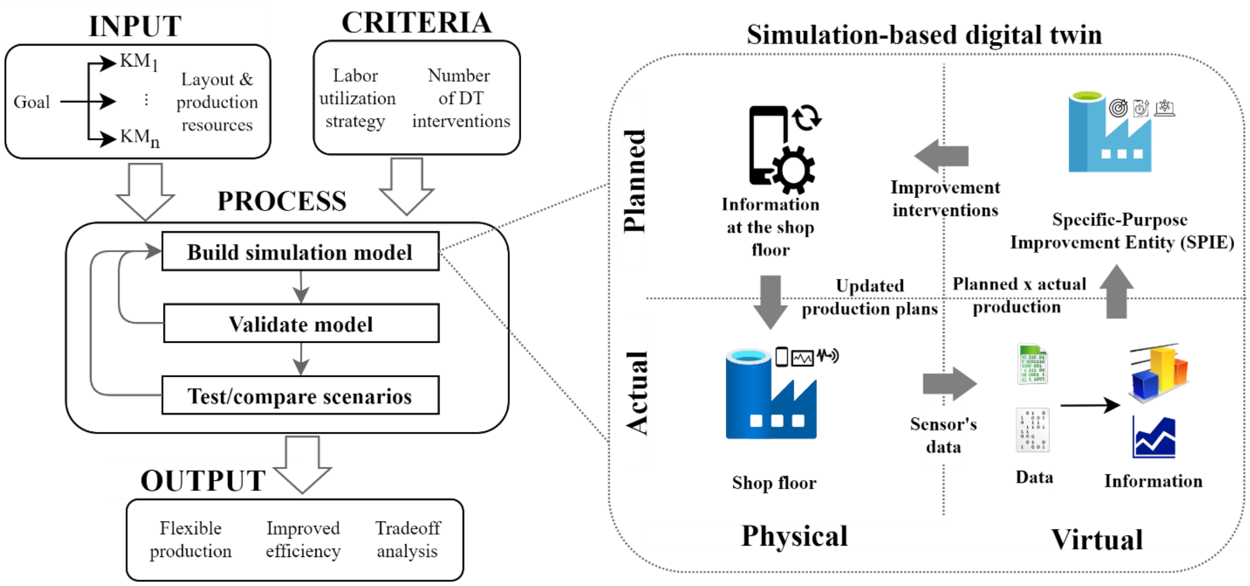


Figure 6.1: Information flow in the proposed DT.

Built upon the concepts proposed by Sacks et al. (2020), the simulation-based DT processes information in four domains: (1) planned-physical, where project and process-related information is updated and sent to the shop floor; (2) actual-physical, where the locations of components (modules or panels) and workers are monitored by sensors; (3) actual-virtual, where data collected on the shop floor is converted into information regarding the actual state of production; and (4) planned-virtual, in which improvement interventions are simulated and selected based on the latest production status. This process occurs according to the desired number of interventions of the DT on the shop floor throughout the work shift and ends after all projects in the schedule are manufactured. At the end of simulation, a trade-off analysis is performed considering the additional cost incurred from having a more flexible shop floor and the improved efficiency at overall production.

The planned-virtual domain is a cornerstone of the DT because it acts on the shop floor according to the established goal and its key metrics. By leveraging the actual data collected by sensors and the production information (e.g., shop drawings, production schedules, etc.), the Specific-Purpose Improvement Entity (SPIE) is a proposed decision-support system that simulates different scenarios and decides how to best increase labour flexibility for the next given period according to the DT's intervention period (i.e., the duration during which the DT intervenes on the shop floor before the next interaction). In the present study, multi-skilling is the labour utilization strategy selected to increase production on OSC shop floors. Therefore, the goal for the proposed DT is to improve production by reassigning multi-skilled workers according to actual production status in near-real time. The SPIE will simulate different scenarios considering current productivity of multi-skilled workers and the latest production status as given by sensors in order to reassign multi-skilled workers in near-real time. The developed simulation model emulates a shop floor on which sensors are used to track projects and multi-skilled worker locations and the DT intervenes in production according to decisions supported by the proposed SPIE. The simulation model and its modules are described in the following subsections.

6.3.2. Simulation-based digital twin applied for multi-skilled worker reassignment

To accommodate the specific characteristics in OSC such as the significant variability in task durations due to manual operations and highly customizable products to accommodate client's request, a simulation model is developed using a combination of discrete and continuous simulation to increase production flexibility on the shop floor. Hence, the proposed model emulates the shop floor where multi-skilled workers are reassigned according to the proposed DT to accommodate the inherited uncertainties in manufacturing operations while overall production performance is forecast based on different scenarios. Considering the nature of manual operations in OSC, the effect of human behavior and its impact in the productivity of multi-skilled workers is emulated using learning curves based on previous productivity studies in construction followed by the transportation time workers spend moving between workstations. Space limitations are also critical in OSC shop floors where the sequence of workstations and space constraints are critical to accurately simulation the work performed. In light of that, Figure 6.2 demonstrates how the modules simulate various aspects of production and their interactions using input data, data produced within the DT, and outputs that include key performance metrics for production. Additionally, Figure 6.2 relates each module according to its original three key elements (physical environment, virtual environment and a seamless connection between the first two) while demonstrating its conceptualization to the construction industry and its domains (planned-physical, actual-physical, actual-virtual and planned-virtual) according to Grieves and Vickers (2017) and Sacks et al. (2020), respectively. The developed simulation model emulates the key elements of DT, while workstations are continuously monitored by sensors in the physical environment, and data is processed in the virtual environment and sent back to the physical environment so that multi-skilled reassignments can be implemented in near-real time. The various modules are discussed in detail in the following sections.

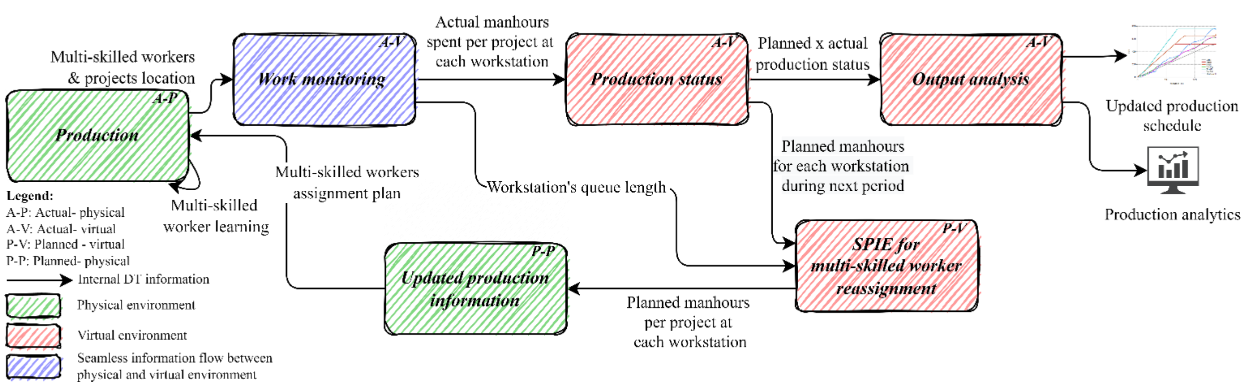


Figure 6.2: Developed simulation model to forecast performance under DT interventions.

6.3.2.1 Production module

Simulated in a discrete-event environment, information in this module belongs to the DT's actual-virtual domain, which simulates the actual production on the physical shop floor. This module also simulates significant multi-skilling criteria, as described in the Background section above. The shop floor is modelled to take into account two key aspects: (1) physical features, including the shop floor layout, workstations sequence and space limitations; and (2) significant resources used in production, such as fixed and multi-skilled workers, workstation production capacity, and data obtained by sensors. Data obtained by sensors is simulated providing information such as the location of project components and multi-skilled workers in the form of timestamps.

To simulate the actual impact of multi-skilling in a shop floor environment, this module simulates the productivity of multi-skilled workers that decreases for two reasons: (1) the training of multi-skilled workers using learning curve models, and (2) the time multi-skilled workers spend moving between workstations as needed. Learning curve models are widely used in construction and aim to forecast the reduction in the amount of time required to complete a specific task based on the repetition of the task in question. In the developed simulation, a learning curve model emulates the productivity of multi-skilled workers as a variable affecting the workstation's overall productivity based on how many multi-skilled workers are used and how often the work was previously performed by them. The improved S-curve model is selected due to its previous success in the construction industry and because it accounts for previous experience, mechanization of tasks, and a productivity plateau when learning is reached (Srour et al. 2016).

Equation (6.1) is employed to determine the productivity of multi-skilled workers according to the number of repetitions they complete at each workstation and based on which multi-skilling configuration (e.g., direct capacity balancing, dual-skill, etc.) is being used. The number of work shifts performed ($x_{t,w}$) in this equation is only updated by the simulation model once multi-skilled workers complete a task for a combined duration equivalent to a complete work shift. Therefore, if the DT intervenes in production every two hours during an 8-hour work shift, $x_{t,w}$ is only updated after multi-skilled workers performed the task at the workstation four times. $B_{t,w}$ is assumed to be the same as $x_{t,w}$ in the present study, meaning that in terms of quality, multi-skilled workers perform the same as fixed workers. The remaining inputs variables in Equation (6.1) are provided in the model practical application section. The transportation time of multi-skilled workers is determined according to the shop floor limitations.

$$p_{t,w} = A_{t,w} \times M_w + C_{t,w} + \left[A_{t,w}(1 - M_w) - C_{t,w}\right]\left(x_{t,w} + B_{t,w}\right)^{-log_2 L_{t,w}} \tag{6.1}$$

where:

t: Multi-skilling configuration

w: Addressed workstation

$p_{t,w}$: Productivity factor of multi-skilled workers of configuration t at workstation w

$A_{t,w}$: Initial productivity factor of configuration t at workstation w

M_w: Mechanization factor at workstation w

$C_{t,w}$: Productivity factor performed under perfect conditions of configuration t at workstation w

$x_{t,w}$: Number of work shifts performed under configuration t at workstation w

$B_{t,w}$: Number of acceptable work shifts performed under configuration t at workstation w

$L_{t,w}$: Learning factor of configuration t at workstation w

6.3.2.2 Work-monitoring module

The proposed work-monitoring module uses continuous simulation to model how information is processed once it is received by sensors employed on the shop floor. Since information is provided continuously to the system and the productivity of each workstation is dependent on how many multi-skilled workers are used based on the data provided, continuous simulation is applied as it allows the simulation model to track and adjust workstation productivity without interrupting the work in progress. This module processes actual production data provided by the production module into the actual-virtual domain to determine whether there is a queue of projects waiting to enter workstations. Various types of sensors (e.g., bar codes, radio-frequency identification, etc.) can be used in this module, provided the location of projects and multi-skilled workers are registered in real time.

The work-monitoring module calculates the actual man-hours spent in each workstation in the last time period before the DT is activated again as per Equation (6.2). Output values from Equation (6.2) are used by the production status module on two occasions: (1) to compare performance against the estimated values (e.g., planned versus actual), and (2) as an input for the estimated remaining duration of projects at each workstation. This equation also quantifies the impact in terms of the duration of time multi-skilled workers spend moving from one workstation to another as indicated by the sensors. Moreover, this work-monitoring module identifies bottlenecks on the shop floor by informing the SPIE module if workstations have a queue of projects waiting to be processed.

$$h_{p,w}^{a} = \left(F_w + \sum_{t=0}^{i} M_{t,w}\right) \times r - tr \times M'_w \tag{6.2}$$

where:

$h_{p,w}^{a}$: Actual man-hours spent by project p at workstation w during period r

p: Project under production

F_w: Number of fixed workers at workstation w

$M_{t,w}$: Number of multi-skilled workers under configuration t at workstation w during period r

i: Number of labour utilization strategies simulated at the proposed model

r: DT's intervention period in hours

tr: Transportation duration of multi-skilled workers between workstations

M'_w: Number of multi-skilled workers that arrived at workstation w for period r

6.3.2.3 Production status module

The production status module is developed using discrete-event simulation and processes data for both the SPIE and output analysis modules every time the DT intervenes. By processing data in the actual-virtual domain, the production status module's contribution to the proposed DT is three-fold: (1) workstation durations are forecast for projects that have not yet started based on current production variation on the shop floor and the project's attributes as per Equation (6.3); (2) planned man-hours are forecast for each workstation for projects yet to be manufactured as per Equation (6.4); and (3) data are provided by the module in order to evaluate the system by way of a comparative analysis of the output and the key metrics. The first two contributions are inputs to the SPIE module used to assign multi-skilled workers over the next period, while the third contribution assists in determining the impact the DT has on production.

Equation ((6.3) estimates the man-hours for projects that have not yet started at a workstation based on the project's attributes ($m_{p,w}$) that are defined during the design stage (e.g., wall lengths, number of openings, finishes, etc.) and based on previous project performance at each workstation (l_w and u_w). The value for $m_{p,w}$ can be calculated by using various methods, such as from previous time studies conducted at each workstation, from regression models using sensor data, or even through practical experience from experts such as assigning a determined number of man-hours based on the square footage of a wall. The remaining values in the triangular distribution in Equation (6.3) are based on previous project performance of a workstation w as recorded by the DT and calculated using Student's distribution considering a 5% interval in variation. Once the project is started at the workstation, the remaining planned man-hours are reduced as the actual man-hours are accrued during past production.

$$h_{p,w}^{e} \sim Triangular(l_w, u_w, m_{p,w}) \tag{6.3}$$

$$h_{p,w} \rightarrow \begin{cases} h_{p,w}^{e}, if\ project\ has\ not\ yet\ started \\ h_{p,w} - h_{p,w}^{a}, if\ project\ is\ under\ production \end{cases} \tag{6.4}$$

where:

$h_{p,w}^{e}$: Estimated man-hours of project p about to enter workstation w

l_w: Lower bound for recorded man-hours at w using Student's distribution

u_w: Upper bound for recorded man-hours at w using Student's distribution

$m_{p,w}$: Estimated man-hours of project p at workstation w based on project attributes

$h_{p,w}$: Planned remaining man-hours for project p at workstation w

6.3.2.4 SPIE module for multi-skilled worker reassignment

The SPIE module uses discrete-event simulation to implement a heuristic approach and determine which of the multi-skilled workers should be assigned to each workstation (i.e., a multi-skilled work assignment plan) when the DT next intervenes. Located in the DT's planned-physical domain, the SPIE module calculates the remaining duration of the projects that are in-progress at each workstation based on information provided by the preceding modules and based on the simulated productivity of multi-skilled workers, which is determined using the improved s-curve learning model as shown in Equation (6.5).

$$D_{p,w} = \frac{h_{p,w}}{F_w + \sum_{t=0}^{i} p_{t,w} \times M_{t,w}} \tag{6.5}$$

where:

$D_{p,w}$: Planned remaining duration of project p at workstation w

The criteria for the multi-skilled worker assignment in the proposed DT are demonstrated in the pseudocode available in Appendix A. Considering the location of projects and multi-skilled workers on the shop floor, the SPIE module aims to balance production by reducing the queue length at workstations. Many aspects of production are considered such as the physical limitations of workstations in terms of its maximum worker capacity, C, the various labour utilization strategies in terms of employing multi-skilled workers, and the information generated by the preceding modules. Moreover, the SPIE module also considers whether there is already a multi-skilled worker assigned to the workstation in order to reduce the movement of multi-skilled workers between workstations. Other approaches, in addition to a heuristic approach, are likely suitable in terms of implementing the reassignment algorithm; however, a heuristic approach offers an easy implementation with significant improvements in production by reassigning multi-skilled workers in to low-automated shop floors (Campana et al. 2021; Lian et al. 2018).

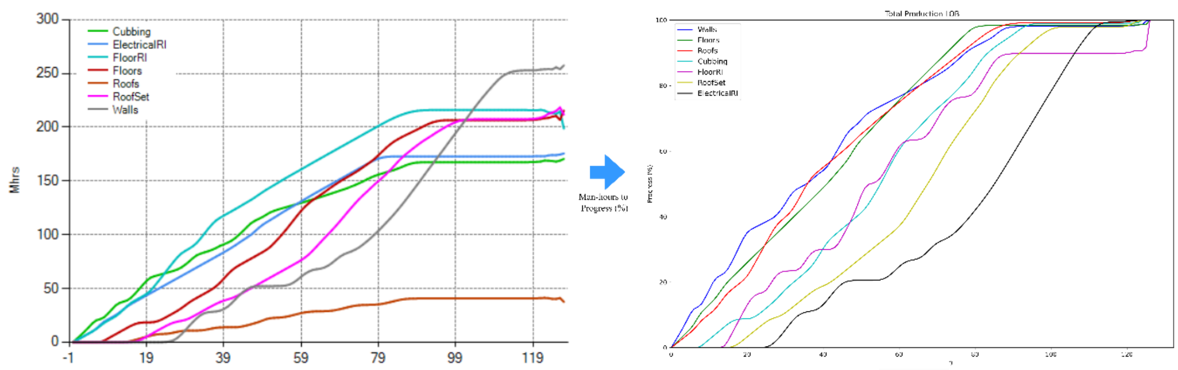
6.3.2.5 Updated production information module

Developed using discrete-event simulation and using information pertaining to the planned-physical domain, the updated production information module simulates the interface between the virtual and physical environments. Based on information processed by preceding modules, this module updates production information (e.g., multi-skilled worker assignment plans, production schedules, etc.) to workers on the shop floor. Information that is conveyed to workers on the shop floor can be transmitted in various ways such as alerts on smartphones, or smart screens, etc. The multi-skilled worker assignment plan that indicates how multi-skilled workers should be assigned to workstations on the shop floor is updated with a frequency that corresponds to the number of interventions the DT is set to perform in each simulated scenario.

6.3.2.6 Output analysis module

The output analysis module determines the impact of the proposed DT on the shop floor under study. By processing actual data from production, this module performs a series of benchmark analyses by comparing the baseline, i.e., a scenario in which the DT does not assign multi-skilled workers to workstations on the shop floor, against scenarios where multi-skilling is the labour utilization strategy leveraging the proposed DT. Four key metrics are used in the present study: (1) production balance, (2) production total duration, (3) production cost, and (4) average processing/waiting time per component in production. Hence, the analysis performed by this module uses the abovementioned key metrics to evaluate whether the proposed DT achieves its goal to improve production by way of reassigning multi-skilled workers in near-real time.

Production balance is a product of the features of each different project in production on the shop floor and how workers are assigned to workstations. Hence, production balance is processed by the output analysis module and represented visually by line of balance graphs as shown in Figure 6.3. Since the progress at each workstation is measured in man-hours and the total value is different for each workstation (i.e., the total required man-hours to perform the work at the wall station differs from that required at the floor station due to the nature of the work), raw data from the simulation model, represented In Figure 6.3a, is normalized through a python script and converted from man-hours to progress (expressed as a percentage of completion for each workstation) such that the slopes for each workstation can be readily compared, as shown in Figure 6.3b.



(a) (b)

Figure 6.3: Line of balance conversion from workstation man-hours to progress.

Moreover, the present study addresses production efficiency by identifying and quantifying operation waste using a lean thinking approach. Ohno (1988) identifies overproduction (i.e., more parts being manufactured than needed at the time) and waiting (i.e., idle workers) as primary wastes, among a total of seven wastes, to be addressed in manufacturing operations. With that in mind, the output analysis module quantifies key metrics of production cost and average processing/waiting times using Equations (6.6) and (6.7), and Equations (6.8), (6.9) and (6.10), whereas the total duration is provided by the production status module at the end of production. The man-hours associated with fixed and multi-skilled workers are recorded separately, since the hourly wage may differ. The indirect cost considers the factory overhead cost ($\$_o$) including amenities, ownership of equipment, and rental of the space. Total production cost is also quantified by adding both direct and indirect costs wherein the direct cost is based on the number of hours worked by fixed or multi-skilled workers. As final output, the output analysis module provides a time and cost trade-off analysis indicating the expected impact the proposed DT will have on production by reassigning multi-skilled workers.

$$\$_D = MH_f \times \$_f + MH_m \times \$_m \tag{6.6}$$

$$\$_I = T_{sim} \times \$_o \tag{6.7}$$

$$W = \frac{\sum_{p=1}^{j} {W_p}/{T_p}}{j} \tag{6.8}$$

$$P = \frac{\sum_{p=1}^{j} {P_p}/{T_p}}{j} \tag{6.9}$$

$$W_\$ = W \times \$_m \tag{6.10}$$

where:

$\$_D$: Direct production cost

MH_f: Total man-hours worked by fixed workers during production in hours

$\$_f$: Hourly cost for fixed workers in Canadian dollars

MH_m: Total man-hours worked by multi-skilled workers during production in hours

$\$_m$: Hourly cost for multi-skilled workers in Canadian dollars

$\$_I$: Indirect production cost

T_{sim}: Total duration for the manufacturing of all projects

$\$_o$: Shop floor's overhead cost in Canadian dollars

W: Average waiting time during production

j: Total number of projects manufactured

W_p: Waiting time of project p during its production

T_p: Total duration of project p during its production

P: Average processing time during production

P_p: Processing time of project p during its production

$W_\$$: Average waiting cost per module

6.4. Practical application of the proposed system

To address the impact of the DT in terms of increasing labour flexibility in OSC, a practical application of the proposed system using production data from an actual OSC shop floor is presented. The application of the system is contextualized for the scope of the present work while the simulation model is demonstrated and validated using input values provided in the case study information.

6.4.1. Problem description

The model is applied in the context of the workstations of a modular construction shop floor where residential projects are produced with a high degree of customization for clients in Alberta, Canada. Modular construction is an OSC method wherein projects are divided into volumetric modules that are manufactured and finished on the shop floor, then shipped to the site for assembly (Moghadam 2014). Data pertaining to both the production line and its projects were extracted from the data provided in a study by Moghadam (2014), who developed and validated a simulation model to evaluate the current production cycle. Figure 6.4 presents the layout of the shop floor under study and the number of fixed workers (i.e., workers who do not move between workstations) at each of the seven workstations that require two skills: (1) carpentry, shown in orange; and (2) mechanical, plumbing and electrical (MEP) rough-in, shown in purple. The shop floor does not make use of automation to leverage its production making its workers the main drivers of production capacity. Currently, a total of eighteen fixed workers are distributed at their respective workstations, thus creating bottlenecks on the shop floor in various circumstances (depending on the attributes of the project being manufactured at the time). From lean thinking perspective, the shop floor under study is a push system where modules are completed as soon as possible and pushed downstream by each workstation, resulting in overproduction of modules and frequent instances of workers waiting for work throughout manufacturing operations. The dynamic reassignment of multi-skilled workers by the proposed DT will allow for a more flexible production system by balancing the production capacity of each workstation in near-real time according to production constraints and the particularities of the projects being manufactured at any given time.

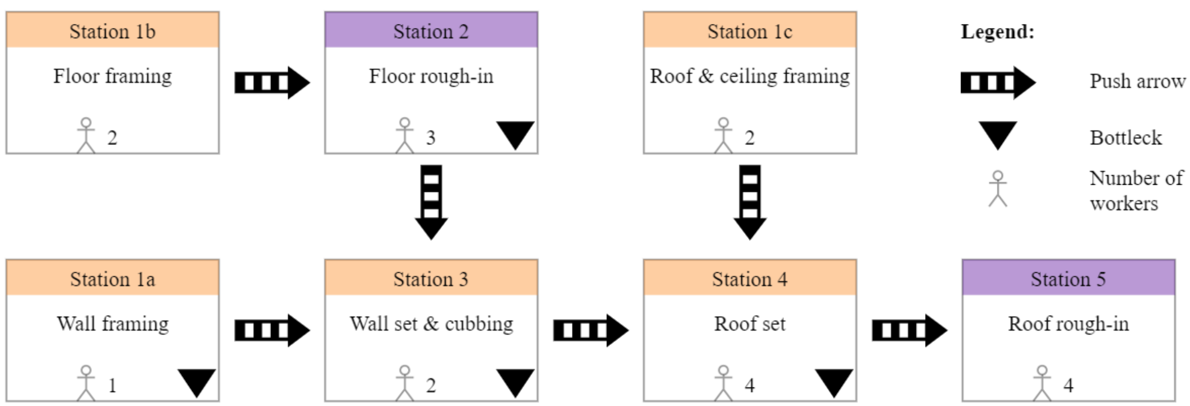


Figure 6.4: Shop floor under study.

6.4.2. Simulation inputs

This section describes the inputs to the simulation model used to evaluate the impact of proposed DT on the OSC shop floor under study.

Table 6.2 presents the estimated man-hour requirements ($h^{e}_{p,w}$) for projects at each workstation on the shop floor under study, as well as the coefficient of variation (CV) based on varying project attributes. The forecast man-hours per project were determined by Moghadam (2014), who developed a regression model based on project attributes and time studies conducted at each workstation on the shop floor under study. There is significant variation in the man-hours at those workstations where the coefficient of variation reaches values higher than 90% in some cases. The high variation in product demand, as indicated by the high CV, when combined with a workstation's fixed capacity due to the lack of multi-skilling in current production, leads to the observed bottlenecks. These variations imposed by the different project attributes must be addressed during the planning stage when workers are being assigned to each workstation.

Table 6.2: Estimated man-hour requirements per project for the workstations under study. Adapted from Moghadam (2014).

Module ID	Total Area (m^2)	Forecast man-hours of projects p per workstation w ($m_{p,w}$)						
		1a	**1b**	**1c**	**2**	**3**	**4**	**5**
420A	65.59	18	17	16	0	18	20	28
420B	64.85	16	16	18	7.5	16	20	24
432	147.16	24	22	46	3	32	32	16
433	122.63	21	18	32	3	31	28	16
434	147.16	22	20	54	9	30	32	16
442A	61.78	10	14	13	0	12	16	20
442B	61.78	12	14	14	6	16	12	28
443A	61.78	7	14	12	0	12	12	20
443B	61.78	11	12	15	6	15	12	28
431A	61.32	12	14	12	0	12	12	28
431B	56.58	14	11	26	6	11	12	28
CV	**44%**	**36%**	**21%**	**55%**	**92%**	**44%**	**43%**	**24%**

Table 6.3 shows the data related to the layout and cost analysis in the context of the present case study. For simulation purposes, multi-skilled workers are paid the same hourly rate as fixed workers. However, a sensitivity analysis is conducted to evaluate the weight of premiums in multi-skilled worker wages on production cost. The rate for factory overhead is assumed to be $700 per hour. In addition, a maximum of seven workers are allowed to work in the same workstation due to insufficient physical space. Although the present study establishes a maximum number of simultaneous workers in each workstation to account for space restrictions, the simulation model does not account for productivity fluctuations due to the increased number of workers at workstations. These data serve as inputs to the output analysis module in the proposed simulation model.

Table 6.3: Cost and layout data for production line under study.

Description	Value
Fixed worker hourly wage ($\$_f$)	$25/h
Multi-skilled worker hourly wage ($\$_m$)	$25/h*
Factory overhead ($\$_o$)	$700/h
Maximum number of workers allowed per workstation (C)	7 workers
Work shift duration	8 h

*Hourly wage will increase until it doubles for cost sensitivity analysis

Table 6.4 includes the various combinations of workers used as inputs to the simulation model based on the number of fixed and multi-skilled workers at each workstation and the multi-skilling strategies employed. The baseline combination represents the current state on the shop floor in which multi-skilling is not applied. In addition to the baseline, other combinations of workers are created wherein fixed workers are trained to be multi-skilled according to different multi-skilling strategies in an attempt to increase labour flexibility while keeping the same number of workers on the shop floor. According to Nasirian et al. (2019), direct capacity balancing (DCB) is a multi-skilling configuration where workers are trained to cover bottlenecks at overloaded workstations based on their skills and affinities, whereas dual skill (DS) does not consider workers' skills and affinities, and training is based instead on idle trades that can be reassigned to overloaded workstations. In the context of this practical application, DCB is applied to workers that will move between workstations requiring the same skill (i.e., carpenters will work only in carpentry workstations), whereas DS is applied such that multi-skilled workers are able to work at workstations regardless of the skills required. In other words, according to the DS strategy, carpenters can work at both carpentry and MEP rough-in workstations. Moreover, a hybrid scenario (HB) considers multi-skilled workers under both multi-skilling strategies. The process of selecting which fixed workers should be trained to be multi-skilled is performed interactively by running the simulation model and identifying which workstations are the most imbalanced through line of balance graphs.

Table 6.4: Number of workers according to each multi-skilling configuration in the simulation model.

Worker combination label	Fixed workers at workstations (F_w)							Direct capacity balancing (DCB)		Dual skill (DS)
	1a	1b	1c	2	3	4	5	Carpentry	MEP	Multi-skilled
Baseline	1	2	2	3	2	4	4	0	0	0
DCB-1	1	2	2	2	2	3	4	1	1	0
DCB-2	1	2	2	1	2	2	4	2	2	0
DCB-3	1	2	2	1	2	1	3	3	3	0
DS-1	1	2	2	2	2	3	4	0	0	2
DS-2	1	2	2	1	2	2	4	0	0	4
DS-3	1	2	2	1	2	1	3	0	0	6
HB-1	1	2	2	2	2	3	4	1	0	1
HB-2	1	2	2	1	2	2	4	2	0	2
HB-3	1	2	2	1	2	1	3	3	0	3

In addition to the baseline, which does not have multi-skilled workers, four scenarios are simulated for every combination of workers shown in Table 6.4. These scenarios are developed based on the number of times the DT will intervene during the work shift to determine the impact of the DT in labour flexibility on the shop floor regardless of which multi-skilling configuration is used. Therefore, the simulation-based DT emulates the shop floor and the DT will intervene 1, 2, 4, or 8 times during the work shift at intervention periods (r) of 8 h, 4 h, 2 h, or 1 h, respectively.

Table 6.5 shows the learning rates (L, in Equation 4.1) adapted from Hijazi et al. (1993) for the required skills (carpentry and MEP rough-in) followed by the assumed initial productivity factor

(A, in Equation (6.1)) for DCB and DS strategies, respectively. A higher productivity factor is assumed for DCB since the in-training multi-skilled worker is not learning a new skill but working on a different workstation that requires he use his existing skill (e.g., a carpenter working in both wall and floor framing). However, if this carpenter starts working at a workstation that requires a different skill (e.g., insulation rough-in), it is assumed he is half as fast as the skilled worker the first time he performs this work.

Table 6.5: Input parameters applied in the learning model.

Learning rate (L)		Initial productivity (A)	
Skill	**Value**	**Multi-skilling**	**Value**
Carpentry	80%	DCB	70%
MEP	90%	DS	50%

6.4.3. Baseline calibration

The developed simulation model is calibrated by obtaining similar results from previously validated models where results were compared according to validation techniques proposed by Sargent (2010). As previously mentioned, Moghadam (2014) developed a simulation to forecast the current production capacity for the shop floor under study and validated her model using face validation from experts and by comparing simulation results with actual historical data. The proposed simulation model replicated the same conditions as Moghadam (2014): (1) only fixed workers performing activities ($M_{t,w} = 0$), and (2) fixed workstation man-hours according to

Table 6.2 ($h^{e}_{p,w} = m_{p,w}$). By running both models one thousand times and applying the comparison between models technique proposed by Sargent (2010), the results between the proposed simulation model and from Moghadam (2014), differed 1% and 2.06% in the total production time and average cycle time per module, respectively. Another validation was performed using a simulation model from Barkokebas et al. (2020) who simulated the use of multi-skilling at the initial workstations of the addressed shop floor considering the productivity of multi-skilled workers the same as fixed workers (i.e., not considering the impact of learning in production) ($p_{t,w} = 1$) and fixed workstation durations as per

Table 6.2 ($h^{e}_{p,w} = m_{p,w}$). Since both the present study and Barkokebas et al. (2020) address the impact of multi-skilling, the results from similar scenarios considering the application of multi-skilled workers (Baseline, DCB-1 and DCB-2) were compared following the approach described in Sargent (2010). By running models one thousand times, both models presented similar results considering the same stated conditions with a difference of 1.05, 1.01, and 3.05% for total production time in the Baseline, DCB-1 and DCB-2 scenarios, respectively. Moreover, the average cycle per module from both models differed 0.02, 3.11, and 5.13% for the Baseline, DBC-1 and DCB-2 scenarios, respectively. Furthermore, an event validity test suggested by Sargent (2010) was performed to evaluate if both models behave in a similar manner by comparing the queue length of the addressed workstations. The average queue length in the addressed workstations differed 7.3, 3.94, and 3.89% for the Baseline, DBC-1 and DCB-2 scenarios, respectively. These differences are explained by the different logic applied in the respective studies, where Barkokebas et al. (2020) applied multi-skilled workers to give preference to specific workstations, while the present study applies multi-skilled workers to reduce the waiting time per module on the shop floor. Nevertheless, differences in the presented results are acceptable to simulation efforts involving OSC operations and uncertain events (Alvanchi et al. 2012). In summary, the proposed simulation model incorporates more aspects of production (the use of multi-skilled workers to balance production, their decreased productivity due to the learning effect and uncertainty regarding workstation durations), thus removing assumptions present in the mentioned previous studies. Therefore, the model developed in the present study to assess the impact of the simulation-based DT is calibrated through a comparison with the previously validated models.

6.5. Results and discussion

Results from the developed simulation model are presented herein to determine the impact of on production on the OSC shop floor under study of reassigning multi-skilled workers. The results are presented in terms of the predetermined key metrics for each of the simulation scenarios and in terms of a sensitivity analysis of the hourly wages paid to multi-skilled workers. In Table 6.6, scenarios are labelled according to the multi-skilling configuration (DCB, DS or HB), worker combination (as described in Table 6.4), and number of DT interventions during the work shift. As an example, DCB-1-8 is the scenario where multi-skilled workers perform tasks using the multi-skilling configuration direct capacity balance (DCB), under the first worker combination and the proposed DT intervenes a total of eight times during the work shift.

Table 6.6: Simulation results according to key metrics.

Scenario	Total production time (T_{sim}) in hours	Average processing time per module (P) in hours	Average waiting time per module (W) in hours	Total fixed worker man-hours (MH_f)	Total multi-skilled worker man-hours (MH_m)
Baseline	182.55	54.01	56.22	1,266	0
DCB-1-8	137.28	49.46	27.53	1,166	265
DCB-1-4	135.24	49.26	27.46	1,162	259
DCB-1-2	133.82	49.01	27.13	1,157	256
DCB-1-1	132.22	48.77	25.93	1,152	253
DCB-2-8	129.52	48.35	24.56	1,063	496
DCB-2-4	125.40	48.43	19.28	1,066	480
DCB-2-2	122.82	48.39	16.87	1,066	471
DCB-2-1	121.27	48.33	16.19	1,066	465
DCB-3-8	137.20	49.06	33.49	938	779
DCB-3-4	132.04	49.52	24.06	948	753
DCB-3-2	129.20	49.74	20.83	954	741
DCB-3-1	128.08	49.69	19.95	954	736
DS-1-8	129.58	48.36	21.76	1,147	258
DS-1-4	128.22	48.46	20.49	1,148	254
DS-1-2	127.92	48.68	20.52	1,152	252
DS-1-1	127.32	48.55	20.19	1,149	250
DS-2-8	123.14	48.19	23.11	1,039	489
DS-2-4	119.19	48.68	17.05	1,048	471
DS-2-2	118.21	49.04	14.61	1,057	465
DS-2-1	117.53	49.17	14.11	1,061	460
DS-3-8	127.13	48.78	29.97	919	757
DS-3-4	124.37	49.60	20.57	934	737
DS-3-2	124.53	50.11	19.07	944	734
DS-3-1	124.92	50.40	18.67	950	733
HB-1-8	129.28	47.48	22.03	1,133	255
HB-1-4	125.43	47.39	18.72	1,132	236
HB-1-2	122.75	47.18	16.60	1,130	230
HB-1-1	121.14	46.99	15.94	1,126	226
HB-2-8	117.21	46.81	23.01	1,037	428
HB-2-4	116.94	46.82	16.97	1,017	439
HB-2-2	114.21	46.80	14.74	1,018	428
HB-2-1	112.45	46.28	14.55	1,009	421
HB-3-8	124.14	46.66	28.36	890	685
HB-3-4	121.78	46.87	22.07	893	673
HB-3-2	118.47	47.09	19.12	897	659
HB-3-1	116.14	46.68	18.24	891	648

Figure 6.5 shows, for all of the simulated scenarios, the total production duration and a sensitivity analysis that compares the total cost reduction to the baseline in which neither a DT nor multi-skilled workers are used on the shop floor. Since multi-skilling is the strategy employed to increase labour flexibility, a sensitivity analysis is conducted to evaluate the impact multi-skilled workers have on the total cost of production. The variable in this sensitivity analysis is the hourly wage for multi-skilled workers, which varies from the value paid to fixed workers to an amount that is doubled (i.e., $25 and $50 Canadian dollars per hour, respectively). All simulated scenarios indicate a significant reduction in total production duration of almost 38% in comparison to the baseline, while seven out of the ten shortest simulated production durations have four or more DT interactions during each work shift. These results are consistent with previous publications where the simulation of multi-skilled workers leads to reductions of 21%, 22%, and 32% in total production time while not using any autonomous system to reassign multi-skilled workers (Arashpour et al. 2015; Barkokebas et al. 2015; Barkokebas et al. 2020).

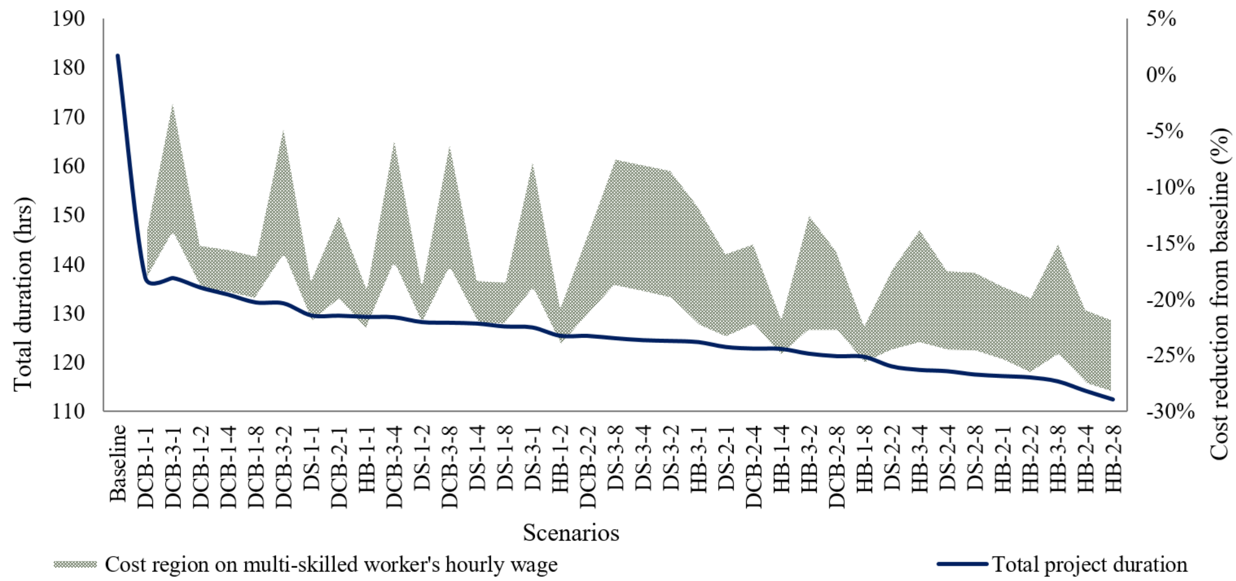


Figure 6.5: Total duration and cost reduction considering the total cost from baseline.

Moreover, Figure 6.5 demonstrates the total cost of production can be reduced in the range of 21% to 28% depending on how much the multi-skilled workers are paid in comparison to fixed workers, whereas the number of DT interactions are not directly correlated to lower production costs. Although similar results are found when the hourly wage of multi-skilled workers is similar to the fixed worker hourly wage, the total production cost (i.e., direct and indirect cost) of using multi-skilled workers varies by a significantly higher amount in comparison to the sensitivity analysis developed by Barkokebas et al. (2020) that presented a range of 27% and 29%. This is explained by the difference between the criteria adopted by the respective studies: the proposed simulation-based DT aims to reduce queue lines at workstations, while Barkokebas et al. (2020) proposes multi-skilled workers work at delayed workstations paying little attention to queue lines at workstations. Another impact factor leading to a wider range of total production cost is the adopted multi-skilling configuration. Figure 6.5 depicts a lower range in the sensitivity analysis is more related to the multi-skilling configuration where DCB (i.e., direct capacity balancing) provides lower cost ranges despite having higher durations in comparison to other multi-skilling strategies.

Still regarding the adoption of multi-skilling configurations, these results are consistent with previous studies where hybrid (HB) and dual-skill (DS) demonstrate lower total production times compared to DCB (Avva and Chamberlin 2020; Nasirian et al. 2019b).

6.5.1. Production assessment

To illustrate the impact on production efficiency, Figure 6.6 depicts the key metrics: the average cycle time per module (further divided between process time and waiting time), and the average waiting cost per module according to a similar sensitivity analysis as that shown Figure 6.5 where multi-skilled hourly wages vary between \$25 and \$50 per hour. Figure 6.6 demonstrates that the average cycle time per module is reduced 37% depending on the number of DT interactions and multi-skilling configurations. As observed in a study authored by Arashpour et al. (2015), who presented a reduction in production cycle time of 8% and 18% using direct capacity balancing (DCB) and hybrid (HB) multi-skilling configurations, Figure 6.6 presents a similar trend with reductions of 33% and 40%, respectively, using the same configurations.

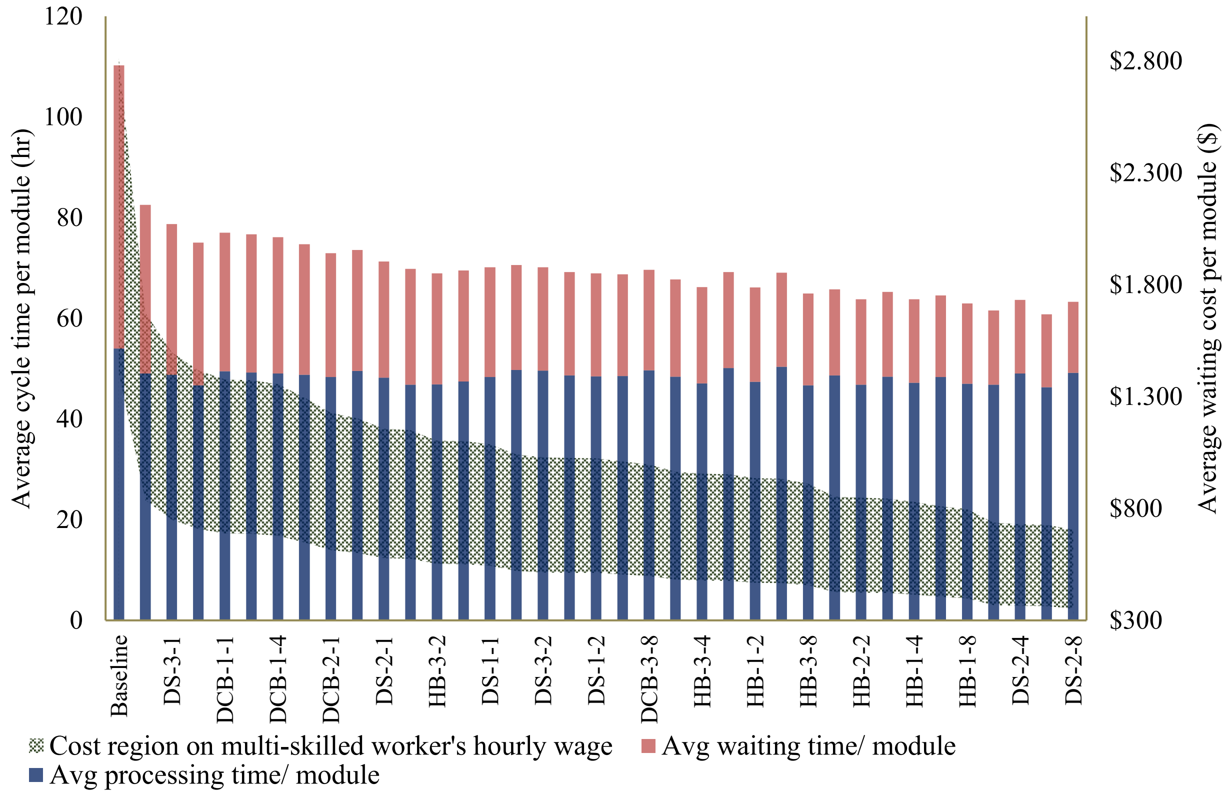


Figure 6.6: Production efficiency assessment and average waiting cost per module.

Based on Figure 6.5 and Figure 6.6, the present study presents improved results compared to previous studies where production on shop floors is simulated using multi-skilled workers. These results can be explained by the increased number of interactions the proposed DT makes, which makes production more flexible as needed. Scenarios in which the proposed DT intervenes more frequently have a lower average cycle time per module, this being driven by a significant reduction in the waiting time (considered as waste) between modules. Figure 6.6 shows the average waiting time per module using multi-skilled workers reassigned by the DT, which is, on average, 62% lower compared to the baseline despite some scenarios presenting slightly higher average process time. This is due to the learning effect and the time multi-skilled workers spend moving between workstations as needed. Moreover, the average waiting cost per module varies significantly with variations in the hourly wage paid to multi-skilled workers since its value is calculated directly from the total number of multi-skilled man-hours spent on production. From a lean thinking perspective, the use of multi-skilled workers causes the increase of over-processing and transportation wastes (wastes also listed by Ohno 1988). Indeed, multi-skilled workers perform inefficient operations due to the learning effect and movement between workstations, followed by a decrease of waiting waste as they are assigned to workstations by the proposed DT. As demonstrated in Figure 6.6, the decrease of waiting waste greatly compensates the increase of other wastes caused by the learning effect and transportation of multi-skilled workers between workstations. Hence, over-processing and transportation wastes are considered in this present study as necessary wastes for an improved production performance.

To assess the impact of the proposed DT in terms of increasing labour flexibility on the shop floor, Figure 6.7 shows the average waiting time per module for each scenario represented by the worker combination (as defined in Table 6.4), multi-skilling configuration, and number of DT interventions on the shop floor. As depicted in the figure, an increased number of interventions leveraging the DT reduces the average waiting time per module by 29%, on average, regardless of the worker combination and multi-skilling configuration adopted. A negative correlation between the average waiting time per module and the number of DT interactions is expected since an increased number of interactions during the work shift allows the DT to reassign multi-skilled workers more frequently and more responsively, thus minimizing queues and bottlenecks at their very beginnings. Therefore, the application of a DT to reassign multi-skilled workers and increase labour flexibility is validated since a traditional approach (e.g., a foreman is responsible for controlling production and reassigning multi-skilled workers based on his experience and personal judgement) is not feasible. Typically, the foreman would have to dedicate himself solely to the task of assigning rotating multi-skilled workers, and even in this case, such a manual system would be prone to human error. Sensors must be installed to monitor the location of each module and each multi-skilled worker, while the proposed DT processes the generated data and automatically reassigns multi-skilled workers to workstations according to the proposed method described in the present study.

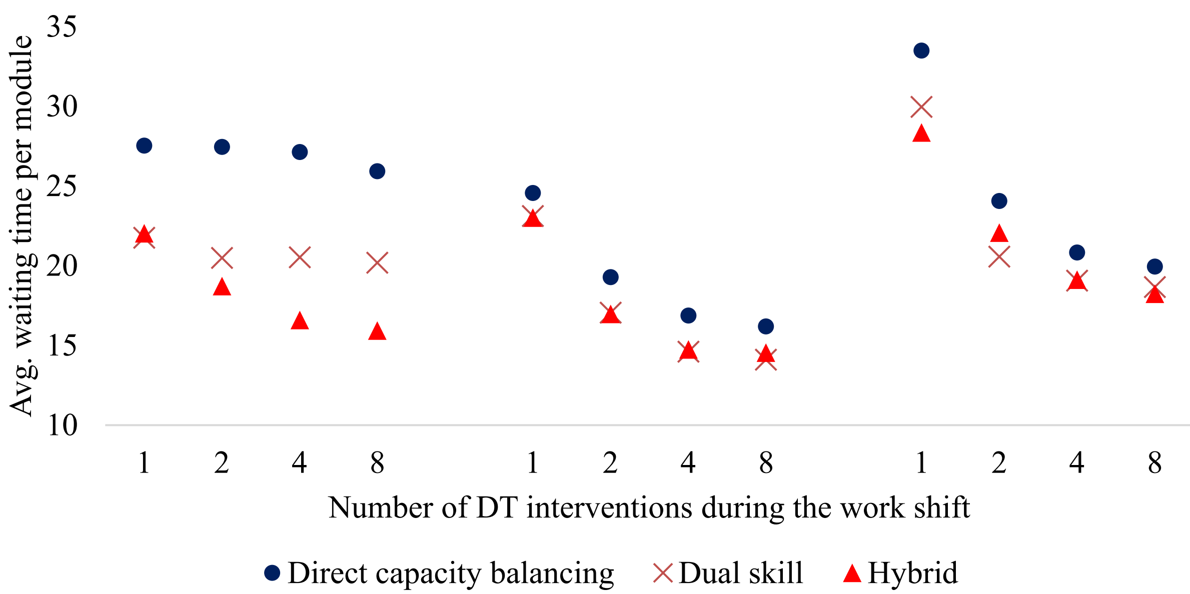


Figure 6.7: Average waiting times per module as per proposed combinations and rotation intervals.

6.5.2. Schedule comparison

Based on the results presented herein, the recommended multi-skilling configuration for the shop floor under study is scenario HB-2-8 (i.e., the second worker combination using a hybrid multi-skilled configuration with eight DT interventions during the work shift) due to its superior performance in terms of total production duration, and due to the fact this scenario resulted in the lowest production cost, as shown in Table 6.6, Figure 6.5, and Figure 6.6. As demonstrated in Figure 6.8b, production at the workstations in the proposed scenario is significantly more balanced in comparison to its baseline (Figure 6.8a), which results in a reduction in the total production duration of approximately 40%. As previously mentioned, the production is balanced by reducing the waiting time between workstations by reassigning multi-skilled workers among the workstations under study. It can also be observed in Figure 6.8b that production at the walls workstation, which is the main bottleneck in the baseline scenario, is significantly improved by the addition of multi-skilled workers.

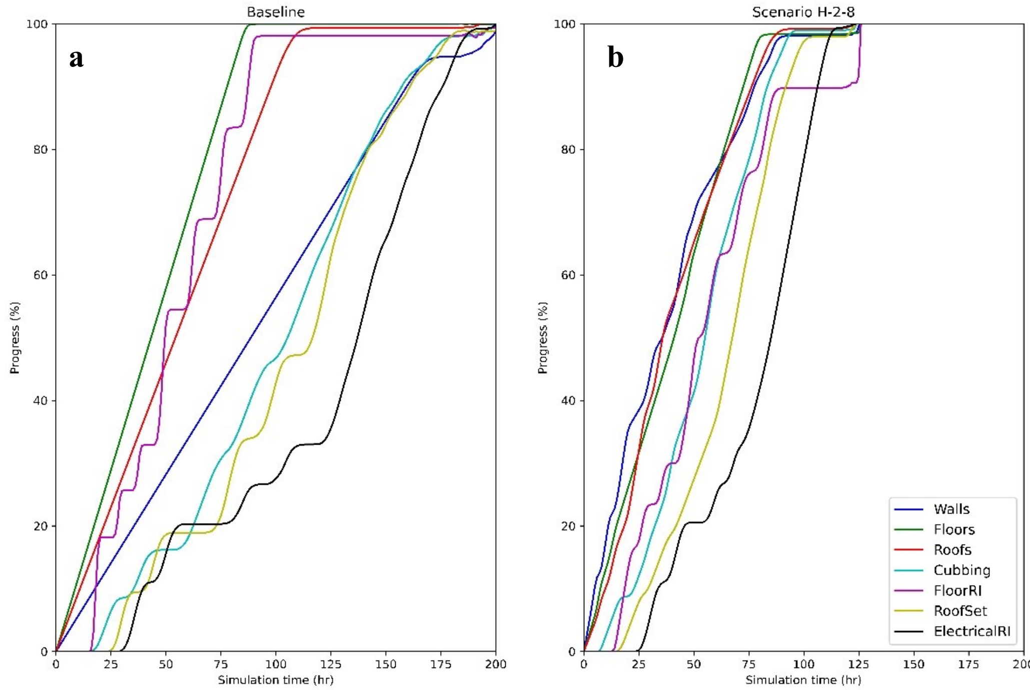


Figure 6.8: Line of balance comparing the production between the baseline and scenario HB-2-8, respectively.

6.6. Conclusion

To answer the research questions related to the feasibility of increasing flexibility (i.e., multi-skilling) and address the impact of automated systems such as DT in OSC, the present study proposes a simulation-based application of DT to manage multi-skilled workers to address the inherited variability from customized products and manual operations in OSC. To address the first research question related to the feasibility of multi-skilled workers despite their reduced productivity and increased cost, the present study sets its first contribution by performing an in-depth trade-off analysis considering main variables identified in previous studies. Indeed, the present study provides evidence that, despite increasing transportation and over-processing wastes due to the dynamic reassignment of multi-skilled workers, the reduction in waiting waste greatly improves manufacturing operations on the shop floor. In addition, the gains from the production's indirect cost due to the reduced production time surpasses the impact of increased wages for multi-skilled if needed. In summary, the performed in-depth trade-off analysis indicate that the increased flexibility improved the shop floor dynamics while reducing its cost despite the perceived reduced productivity of multi-skilled workers. Meanwhile, to address the second research question related to the impact of DT on the shop floor considering different multi-skilling configurations and inherited uncertainties of manual operations, the present study proposes its second contribution by demonstrating that the average waiting time per module (waiting waste according to lean thinking) is significantly reduced according to the number of DT interventions and despite the different stated conditions. The implementation of DT to increase flexibility in OSC shop floors is derived by the particular characteristics of OSC manufacturing where products are highly customizable and operations are still labour-intensive. Hence, different bottlenecks are created in shop floors since traditional workstations have a static production capacity that cannot accommodate the inherited variability caused by these characteristics. Therefore, the proposed model is developed to address the following main research gaps: (1) the lack of trade-off analyses related to the impact of multi-skilling on OSC shop floors, (2) the absence of studies pertaining to the application of a DT on OSC shop floors, and (3) the need for approaches to evaluate the impact of DT in OSC.

The present study employed simulation to emulate the implementation of a DT that is designed to improve production rates in OSC by increasing labour flexibility, which involves reassigning multi-skilled workers to balance production while taking into account the following information: (1) production uncertainty, (2) physical space limitations and shop floor layout, (3) learning effect, (4) production cost, and (5) the number of DT interventions during the work shift. The present study determines the impact the proposed system will have on production by providing practical application of the beneficial impacts attributable to the use of a DT, supported by real-time data, while addressing labour flexibility as a key subject of interest in OSC. This is accomplished by developing a simulation model based on actual information from the model's practical application.

The results of the practical application indicate that the average waiting time, total production duration and production cost are reduced by approximately 62%, 40% and 25%, respectively, compared to the baseline, while the findings show a positive correlation between the reduced average waiting time per module and the number of times per shift the DT intervenes on the shop floor. Moreover, the application of the proposed DT provides beneficial outcomes to OSC manufacturing operations regardless of any multi-skilling configuration applied or duration uncertainties caused by labour-intensive tasks. While these results are promising, the proposed method requires a significant modelling effort to develop the simulation, thus requiring constant monitoring of physical changes (e.g., layout and workstations sequence) and shop floor conditions (e.g., number of workers on production), which can be considered a limitation. Despite accounting for the loss of productivity due to the learning effect and establishing a maximum number of workers working simultaneously in the same station, the simulation model does not account for other productivity fluctuations due to space limitations (e.g., works in congested areas) which is another limitation of the present study. Moreover, additional practical applications, in a real setting, are needed to validate the positive impact a DT can have by reassigning multi-skilled workers on OSC shop floors considering similar assumptions. Nevertheless, broader application of these methods, such as the implementation in real-scale and the addition of other significant aspects of production such as quality management and worker absence, is recommended. The use of recursive algorithms to better assign multi-skilled workers in consideration of the production schedule, as well as the use of DT to increase flexibility in other areas of production such as scheduling and design of OSC projects, is also recommended. Finally, the present study contributes to the body of knowledge by providing a novel method to determine the impact of a DT in terms of dynamically reassigning multi-skilled workers using a set of methods to acquire, transform, and apply data to increase labour flexibility on OSC shop floors.

6.7. Data availability statement

Some or all data (simulation model, simulation model input data) that support the findings of this study are available from the corresponding author upon reasonable request.

6.8. Acknowledgments

The technical writing assistance of Kristin Berg and Jonathan Tomalty is appreciated. Gratitude is also extended to Mana Moghadam for her guidance and insights concerning this research.

CHAPTER 7: CONCLUSIONS

7.1. Research Summary

Offsite construction (OSC) is gaining significant attention from industry and academia due to the increased productivity achieved in controlled environment compared to in traditional construction. Nevertheless, significant variability is observed on OSC shop floors due to various product- and process-related factors. To allow for a more flexible manufacturing system, this thesis proposed the use of design-related data generated from the premanufacturing phases combined with real-time data gathered from sensors on the shop floor to improve manufacturing operations and provide valuable production insights.

The research described in Chapter 4 involved the development of a framework to identify existing and prospective new technologies to improve processes and to link different information systems employed in the OSC premanufacturing phases into a centralized system containing all relevant project features. This system can later be connected to real-time data from sensors on the shop floor and used to improve operations. To account for the inherent uncertainties and process waste associated with premanufacturing processes, a combination of discrete-event simulation and value stream mapping (VSM) is embedded in the proposed framework to allow for the participation of company experts in identifying existing forms of waste and prospective new technologies to reduce them. The proposed framework was tested and validated by company experts, and was found to provide a robust foundation for the development of a centralized system containing relevant design features (wall area, volume, material specifications, etc.) of OSC projects.

Chapter 5 described the development of a structured method for performing data science analyses on design-based data gathered by deploying the system proposed in Chapter 4 together with production-based data in the form of timestamps extracted from RFID sensors installed on the shop floor. This culminated in a hybrid method (qualitative and quantitative evidence) by which to preprocess and analyze the data focusing on process improvement of manufacturing operations in OSC. This method provides production insights on the empirical implementation while allowing for the evaluation of proposed improvement measures using statistical analysis.

Chapter 6 discussed the impact of automated systems in terms of achieving dynamic operational improvements, as well as and to account for the inherent variability in manual manufacturing operations in near-real time. As per the description of the practical application in that chapter, DT and deployment of multi-skilled workers were selected as the applicable automated system and strategy to account for variability in production, respectively. Using simulation as a surrogate, a DT performs simulations leveraging real-time data to reduce the identified production bottlenecks by reassigning multi-skilled workers between workstations to balance production among stations was represented. By simulating different scenarios in consideration of several factors (physical limitations on the shop floor, learning effect of multi-skilled workers, fluctuations in production, DT intervention interval, and production cost), the DT was found to present significant improvements using real-time data in terms of production time and cost. Moreover, this application provided significant evidence of the potential impact of DT in reducing process waste in the form of waiting times in OSC.

7.2. Research Contributions

Although relatively little research has been carried out in this area, the application of data is highly relevant and practical as a means to improve efficiency in OSC manufacturing. The principal contributions of the research speak directly to the fundamental question underlying this topic as to how data can be organized and applied to improve manufacturing operations in OSC. The research described in this thesis addressed three significant challenges pertaining to this question by applying a combination of different techniques (e.g., simulation, machine learning, BIM, VSM, etc.) while using lean philosophy as the theoretical framework. The notable contributions to academic study in this area and to industry practice are presented below:

7.2.1. Academic Contributions

1) Proposed a framework to identify wastes, connect different systems, and improve premanufacturing processes in OSC (O_1). This framework provides hybrid methods, based on qualitative and quantitative evidence, that can be employed by practitioners as part of a company's digitalization strategy and that takes into consideration the inherent uncertainties related to design, bidding, and procurement in OSC projects.

2) Combined simulation, VSM, and statistical analysis as the basis for a decision support tool to aid OSC enterprises in adopting and implementing new technologies and in evaluating the potential impact of linking different information systems (BIM and ERP) in a central platform.

3) Proposed a novel method for evaluating proposed process improvement measures for OSC manufacturing using real-time data and digitalization processes (O_2). This method allows for a structured analysis of proposed process improvement measures based on statistical analysis.

4) Developed novel approaches using machine-learning algorithms to identify patterns in design features of manufactured products, perform outlier detection, and

evaluate the impact of design features on the manufacturing durations for wall panel fabrication at semi-automated stations (O_2).

5) Adapted digital twin (DT) implementation methods to the OSC manufacturing context (O_3), thereby providing empirical evidence of the potential impact of DTs in terms of reducing the adverse effect of variability on production while reducing total duration and cost on OSC shop floors.

6) Developed a novel approach for evaluating the potential impact of DT based on a series of production constraints while proposing methods to acquire, transform, and apply real-time data to increase labour flexibility on OSC shop floors (O_3).

7.2.2. Contributions to Industry Practice

1) Developed methods to quantify the benefits of integrating BIM with other information systems (e.g., ERP) and to expand the use of BIM beyond the design phases.

2) Developed replicable methods to implement digitalization in OSC companies while providing quantitative metrics to assist in the implementation and to promote a culture of continuous improvement in OSC companies.

3) Developed a method for evaluating proposed process improvement measures in OSC manufacturing using real-time data and machine learning through digitalization. This method demonstrates how to apply data—data that, in current practice, would often go unused by OSC companies—to monitor the current production status and evaluate proposed process improvement measures accordingly on a quantitative basis.

4) Provided empirical evidence of the impact of semi-automation on overall shop floor production while demonstrating its ability to accommodate design variability.

7.3. Limitations and Future Research

Notwithstanding the successful achievement of research objectives, the research presented in this thesis was subject to the following limitations, which will be addressed in future work:

1) The effectiveness of the developed framework for the digitalization of the premanufacturing phases depends on the accuracy of the information gathered from experts, which is often qualitative, anecdotal, and based on personal experience. This is a potential limitation since inaccurate input information will lead to an inaccurate baseline for the digitalization of future states. Two courses of action are recommended to address this limitation: (1) incorporate proven methods for collection of qualitative data (e.g., delphi) into the framework to improve the precision and accuracy of the information collected, and (2) incorporate automated data extraction procedures from ERP system as a way of gathering information pertaining to the premanufacturing phases of OSC, such as the volume of commercial proposals per year, bid conversion rates, and average duration of activities.

2) Several research limitations posed by low-quality data (e.g., inconsistent, flawed, small sample sizes, etc.) are identified with respect to forecasting and data analysis. However, no method by which to quantify the impact of using low-quality data in OSC is available in the literature. Therefore, the development of a framework to quantify the impact of using low-quality data as a way of alerting practitioners of

the importance of using reliable methods for data collection in OSC manufacturing is suggested as a direction for future research.

3) The proposed method for evaluating proposed process improvement measures in OSC manufacturing operations should be further validated using case implementations in different production scenarios (e.g., different sample sizes, production constraints, and automation levels). Moreover, although the proposed method assesses the validity of proposed process improvement measures, it does not evaluate their potential impact on production. Hence, the development of a framework for applying the proposed method that incorporates the use of simulation to evaluate the potential impact of validated process improvement measures is recommended.

4) In the implementation of the proposed DT, a greedy approach was used for the reassignment of multi-skilled workers on the shop floor, and this approach prevented further optimization of the reassignment. Hence, the testing and implementation of different algorithms, such as recursive, are recommended as a way of allowing for further optimization leveraging DT.

5) While significant improvements were observed in the case study, an application in a real-life setting is recommended as further proof of concept of the use of DT in OSC.

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APPENDIX A

Figure A.1 presents the pseudocode used for the objective function applied in the proposed DT.

```
Mt: Number of available multi-skilled workers under labor utilization strategy t
t: Number of available labor utilization strategies available for simulated scenario
WQ>0: Set of workstations with queue length > 0
Dp,w: Planned remaining duration of project p at workstation w
C: Workstation total workers capacity

Condition 1: Total number of workers (fixed and multi-skilled) in workstation <= C
Condition 2: There is a multi-skilled worker already at the selected workstation

For  each labor utilization strategy in t:
    For each multi-skilled worker in Mt:
        Select workstation in WQ>0 with highest value Dp,w
        If  Condition 1& Condition 2 are met:
            Assign multi-skilled worker to workstation
        ElseIf:
            Select workstation in WQ>0 with the next highest value Dp,w until Condition 1 & Condition 2 are met
        End if
    Next multi-skilled worker in labor utilization strategy
    Update Dp,w values
Next labor utilization strategy
```

Figure A.1: Pseudocode for multi-skilled worker assignment.