TRANSPORTATION FRAMEWORK IN PANELIZED CONSTRUCTION FOR RESIDENTIAL BUILDING

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in
Construction Engineering and Management

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ABSTRACT

Transportation operations, in connecting the factory with the construction site through the delivery of prefabricated building components (e.g., panel) using transportation equipment (e.g., trucks and trailers), play a significant role in determining the efficiency of overall panelized construction operations. However, several issues surrounding transportation operations have been identified, including the fact that operations planning and decision making are typically carried out in an experience-based manner in the absence of a systematic approach to transportation management, while existing construction transportation planning approaches are based on a material flow and information flow that are ineffective for offsite construction. Thus, this research proposes the development of an automated transportation planning approach tailored to panelized construction, the framework for which can provide better transportation planning and decision making based on collected data from actual logistics operations. In developing the framework, various tools for logistics planning are considered. First, a projection based augmented reality (AR) is applied to improve potential transportation quality issue during panel manufacturing processes at offsite facility. Second, an extensive data collection system using quick response (QR) codes and global positioning system (GPS) is proposed to improve the transparency of logistics operations as well as to validate the optimized fleet-dispatching plan from the simulation. Third, machine learning (e.g., SVM) and rule-based algorithms are utilized to extract key information the collect data and perform estimations on durations and costs. Fourth, fleet-dispatching discrete-event simulation (DES) is established in order to determine the optimum fleet management schedule and construction job schedule based on construction site locations. The proposed framework addresses existing issues while providing optimized, data-driven planning and decision support. Potential contributions include efficiency improvement in transportation operations for panelized construction, reduced transportation costs, and improved transportation data collection and utilization.

Preface

This thesis is the original work of the author, Sang Jun Ahn. One (1) journal paper and one (2) conference papers. The projection-based AR method has been published in *the Journal of computing in civil engineering*, as Sang Jun Ahn, SangUk Han, and Al-Hussein M "A 2D drawing visualization framework for applying projection-based augmented reality in a panelized construction manufacturing facility: Proof of concept.". Mr. Sang Jun Ahn was responsible for designing methodology and conducting both lab and field test to investigate its feasibility in offsite manufacturing facility. For the conference papers, the transportation cost estimation using a machine learning approach and the fleet dispatching discrete event simulation (DES) model have been published in *the Modular Offsite Construction* and *the Winter Simulation Conference*, respectively. Mr. Sang Jun Ahn was the main investigator for the conference papers with advising from Dr. SangUk Han and Dr. Al-Hussein.

Acknowledgements

First of all, I would like to express my sincere appreciation and gratitude to my co-supervisors, Dr. Mohamed Al-Hussein and Dr. SangUk Han, for their continuous support and encouragement throughout my Ph.D. studies. Dr. Al-Hussein always provided me new opportunities and inspired me to pursue new directions of research in many areas, and his profound knowledge and direction helped me to find new answers. Dr. Han always dedicated his time to support research and to provide me with insightful comments, and I could not have achieved what I have without his patience and support.

I would also like to express my appreciation to all my colleagues at ACQBUILT Inc. (especially Kurt, Sadiq, Chris, Tony, Mike, Rita, Rick, and Suhki) who have supported my research and provided me with valuable insights. They inspired me to find a new direction of research that could be valuable knowledge for both academia and industry. Without their support and open-mindedness to new research, I would not have finished my studies.

Last but not least, I would like to thank my parents and mother-in-law who supported me to finish my studies, and my deepest gratitude is given to my family, Yunga, Jay, and Alice who have been my motivation to pursue a new direction in my life.

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DES	Discrete-event simulation
AR	Augmented reality
SQL	Structured query language
NOSQL	Not only structured query language
QR code	Quick response code
GPS	Global positioning system
GUI	Graphical user interface
ML	Machine learning
SVM	Support vector machine
DOF	Degree of freedom
UI	User interface
KPI	Key performance indicator

1. Chapter: Introduction

1.1. Background

In recent decades, the construction industry has been transitioning toward the offsite construction paradigm in an effort to overcome the labour supply and productivity issues characteristic of traditional construction (Assaf and Al-Hejji 2006). Offsite construction, also known by other terms such as industrialized construction, has been regarded as a promising construction approach with various advantages over traditional on-site construction, and with the potential to overcome productivity and labour issues. In efforts to promote adaptation of offsite construction, the following benefits are commonly identified: better safety performance, lower project cost, shorter project duration, improved efficiency, and reduced environmental impact. Considering today's competitive construction market conditions, project owners are highly motivated to adopt offsite construction over traditional methods due to the various advantages offered by the offsite approach. However, despite the benefits offered by offsite construction, the adoption of offsite construction methods by the construction industry has not increased significantly, even though government-initiated programs exist in both developed and developing nations (Goulding et al. 2015). The main reasons for the lag in uptake can be largely divided into technical aspects (e.g., information collection and scheduling optimization) and non-technical aspects (e.g., maturity of market, perceptions toward offsite construction, and period of warranty), and this study will focus on the technical barriers identified in previous research (MBI 2015). Among these barriers, transportation operations are an area of particular focus in the present research due to its large impact on the overall performance of offsite construction. Issues in transportation operations in offsite construction (e.g., panelized residential construction) are introduced in the following section, and are discussed in greater detail in Section 3.2 of Chapter 3.

1.2. Challenges for transportation operations in panelized off-site construction

In panelized offsite construction projects, there is a deficiency in understanding surrounding logistics for transportation operations, which continues to be inefficiently managed and to show little improvement when compared to other operations such as manufacturing and site operations (Hill and Ballard 2001). Key causes of inefficient management have been identified in previous studies (MBI 2015), one of which indicated that the short-term, fragmented nature of construction projects causes difficulties in establishing a standardized management system for transportation operations such as that employed in the automobile manufacturing industry (Shakantu et al. 2008; Wegelius-Lehtonen 2001). Once automobiles are manufactured, the finished products are loaded into a car carrier to be delivered to retail centres. Since the manufactured cars are completed products, no further processes are required, and all that remains after they leave the production floor is delivery to the customer. Most manufacturing sectors follow a similar process with a simple product delivery process. However, panelized offsite construction is a unique combination of two different industries (i.e., manufacturing and construction), and a complex and creative approach is necessary in order to properly manage transportation operations. To be specific, panelized offsite construction involves additional site assembly processes to complete the project. Unlike in traditional manufacturing, in panelized offsite construction additional work is required on site (after delivery of prefabricated components) in order to arrive at the finished product. Thus, in order to keep costs minimal while satisfying factory operation and site delivery schedules, proper planning and management of transportation through effective cost estimation, trailer delivery and pick up scheduling, and operational data collection have emerged as critical processes that have a significant impact on overall project performance.

Due to the heavy reliance on transportation operations in panelized offsite construction, any improvements in overall productivity resulting from the use of panelized offsite construction methods tend to be offset by the inefficiencies resulting from the insufficient planning and management of logistics operations (e.g., incorrect sequence of delivery) (Assaf and Al-Hejji 2006; Navon and Sacks 2007). Therefore, it is important to improve the efficiency of transportation operations in order to fully realize the potential benefits of panelized offsite construction; furthermore, in order to improve operational efficiency, advanced planning and management approaches are required.

The principal feature of transportation planning and management is an integrated framework that connects the fragmented operations of a construction project, while coordinating the transportation of materials and other resources to required locations according to a scheduled timeline. Considering the interdependencies among various operations (e.g., manufacturing, transportation, and site operations), transportation planning in construction has proven effective in reducing logistics costs by as much as 10% to 30% (BRE, 2003). However, previous construction transportation planning studies have focused on the traditional construction method, which has a different flow of materials and information compared to offsite construction (Jang et al. 2003; Said and El-Rayes 2014). For example, traditional construction requires all building materials to be delivered to the construction site from various suppliers, whereas offsite construction requires the transportation of prefabricated building components, such as module or panels, to the site. Therefore, a new transportation planning and management approach needs to be developed to improve the efficiency of transportation operations in panelized offsite construction in order to leverage the benefits of panelized offsite construction.

1.3. Problem statement, hypothesis and research objective

Adoption of the panelized offsite construction method in today's construction industry is the most viable way to boost the competitiveness of the industry and alleviate issues such as skilled labour shortages and project cost and schedule pressures. Transportation operations are essential to panelized offsite construction, and the potential impacts of transportation operations on both cost and schedule are more pronounced than in traditional construction. Although the development of construction transportation planning has led to improvements in the efficiency of transportation operations in traditional construction, this planning approach cannot be directly applied to panelized offsite construction due to several differing material and data flow structures between the two construction paradigms. Therefore, a novel transportation planning and management framework is necessary in order to resolve a number of transportation-related issues in offsite construction: (1) in experience-based logistics decision making, since no transportation plan is available to workers, all transportation decisions are made based on the worker's expertise gained through previous work experience; (2) no formal data collection framework is available to collect extensive transportation operation data—current practice is mainly focused on GPS fleet data, which cannot provide details of logistics operations; (3) no systematic transportation quality assurance tool is available; and (4) there is a lack of control in transportation operation cost, such that the transportation cost is inaccurately estimated for different types of house projects (i.e., the cost is considered part of overhead, and this potentially leads to over- or under-estimation of cost). In light of these issues, particularly in the context of panelized offsite construction, knowledge-based logistics planning and management are essential to improving operational efficiency and cost performance.

The proposed research is based on the following hypothesis:

> *"Collection of both real-time and historical transportation operational data with detailed project specifications will reduce cost and duration of the panelized residential construction."*

In order to validate the above hypothesis, the following research objectives will be pursued:

1. Application of the projection-based AR method to reduce transportation risk during operations.

2. Development of an extensive mobile app-based logistics operations data collection framework.
3. Investigation of the logistics operation and cost impacts on different projects and development of cost and duration models.
4. Automated generation of a fleet dispatching sequence by developing a discrete event simulation model using the collected data.

As the basis for the development of a panelized offsite construction-oriented transportation planning and management approach, a simulation-based planning framework is proposed that utilizes a comprehensive live-data collection method employing quick response (QR) codes and global positioning system (GPS) data. Based on the collected transportation operation data, the simulation model provides the estimated cost and duration of transportation operations. Following completion of the simulation model, a transportation supply-demand graph is developed and used to visualize and manage the transportation schedule (i.e., fleet-dispatching sequence), while the real-time logistics data is used to improve communication among various operational units as a means of validating the transportation plan. Finally, the proposed study is implemented in actual panelized construction project—which is the most rapidly growing offsite construction method for residential construction in Canada (FMI 2018)—in order to identify potential improvements in transportation operations.

1.4. Organization of the thesis

This thesis is organized into the following chapters: Chapter 1 (Introduction), Chapter 2 (Literature review), Chapter 3 (Methodology), Chapter 4

(Implementation and case studies), and Chapter 5 (Conclusion and future works).

The introduction (Chapter 1) presents current transportation issues in offsite construction and defines the main objectives of this research. The literature review (Chapter 2) provides an overview of the state of the art in offsite construction operations, including transportation operations in offsite construction, transportation equipment data collection (real-time) and analysis, proactive transportation quality improvement, DES in offsite construction transportation operation, and transportation cost estimation. The methodology section (Chapter 3) explains the framework developed in this study, including the projection-based augmented reality (AR) approach to improve transportation operation accuracy, advanced equipment operation data collection (GPS and smartphone application), operation data analysis using the rule-based algorithm, fleet-dispatching optimization using DES simulation, and real-time fleet operation monitoring. The implementation and case studies (Chapter 4) encompass the demonstration processes of the proposed framework at the selected panelized construction projects. Here the framework is deployed on several actual residential construction projects in order to measure performance metrics as well as validate the methodology. Finally, Chapter 5 summarizes the outcomes from the case studies and potential contributions to the body of knowledge as well as limitations. Moreover, future research directions in transportation research for offsite construction are also suggested.

2. Chapter: Literature Review

This section focuses on five theoretical bases: (1) offsite construction operations; (2) logistics planning and management in offsite construction; (3) proactive (preventative) transportation quality management; (4) construction operation data collection; (5) discrete-event simulation (DES) in construction; and (6) a machine learning application in logistics cost prediction

2.1. Offsite construction operation and management

In recent decades, the number of studies in the area of offsite construction has rapidly increased due to the benefits associated with this construction method (Hosseini et al. 2018). In addition to its frequently cited benefits in terms of cost, time, and quality, environmental and social benefits have also been identified (Jaillon and Poon 2008; Kamali and Hewage 2016). However, a recent review of papers on the subject of offsite construction revealed that past research has been skewed toward specific areas, such as centering on a specific product (e.g., pre-cast concrete), rather than looking at offsite construction operations in general (Hosseini et al. 2018; Li et al. 2014). Once products have been manufactured in an offsite facility, they require transportation and delivery to a construction site in order for the assembly to proceed; these operations and processes entail complex interrelationships between the manufacturing facility and the construction site. Unlike other, more traditional, sectors of manufacturing (e.g., automobile industry), in construction manufacturing, the final product is not generated in the factory but at the construction site. Thus, a clear understanding of these complex interrelationships is key to improving overall operations (Yuan and Shen 2011);

however, this aspect has been disregarded in most offsite construction studies (Marasini and Dawood 2006). In order to improve the understanding of these interrelationships, a dynamic simulation software, SIMPROCESS, was developed for a precast bridge construction project (Pan et al. 2008). This software provides overall operations of the construction process, including production, transportation, and installing a precast. The outcomes of SIMPROCESS simulation reveal that this tool can provide accurate productivity calculations for real-world operations. However, their study focuses on transportation operations, while the details of processes such as loading, unloading of precast components, the facility operations at the yard, and other details have yet to be discussed.

2.2. Logistic operations management in the offsite construction

A study by Chan et al. underscores the important role of logistics operations in manufacturing, estimating that these activities account for as much as 30%–40% of manufacturing costs (Chan et al. 2001). In offsite construction manufacturing in particular, logistics operations play a critical role given that 80% of all construction activities are directly affected by logistics operations (Browne, 2015). The definition of the logistics operations can vary by industry, but in construction logistics operations include transportation of all resources (e.g., labour, equipment, materials, and information) involved in construction activities. In the offsite construction process, logistics operations are required throughout, beginning with the transportation of building materials to the prefabrication facility, and, in turn, the transportation of fabricated building components to the construction site for assembly. Furthermore, other essential resources, such as site crews and mobile cranes, also need to be transported to the site, in order to complete the construction project. In addition to the general reliance on, and high cost of, logistics operations, it is also worth noting that offsite construction operations are particularly dependent on logistics due to the unique requirements for the transportation of prefabricated components to a construction site. Without careful planning of logistics operations between a site and a facility, panelized construction will not be able to utilize advantages of using the panelized construction. Furthermore, the reliability of logistics operations is critical in panelized construction due to the unique design of prefabricated building components and their fixed assembly sequence. Each component is designed for an individual purpose and cannot be replaced by other components, such that the assembly process of building components on the construction site is a fixed sequence that cannot be changed. Thus, any logistics issues such as missing or incorrect components, or delayed deliveries, can lead to significant negative impacts on cost and schedule. However, in current practice, logistics operations in panelized construction are often managed intuitively or manually based on past experience rather than on actual data.

In recent years, implementation of offsite construction methods (e.g., preassembly, offsite multi-trade fabrication, modularization) has been increasing due to its various benefits over traditional construction such as reducing cycle time and cost. Among these methods, prefabrication has been the most widely used. However, a survey conducted in 2018 indicated that the majority of construction enterprises have not adopted offsite methods, with 62% of construction company executives reporting hesitancy to make such a change. The primary cause of this prevalent mentality is difficult to identify, but in any case, a lack of understanding of logistics operations and management aspects of offsite construction presents a major challenge (FMI 2018).

2.3. Proactive transportation quality assurance in offsite construction

In offsite construction, prefabricated panels from a manufacturing facility are transported to a construction site for final assembly processes. In this regard, it is important to maintain the quality of prefabricated building component before shipping. Once the panels arrive at a construction site, any defective panels can have significant negative impacts on both cost and schedule; quality issues could halt entire site construction due to the time needed for re-assembly and re-delivery of defective panels when the issues cannot easily be resolved at the site. For example, a panel may need to be transported back to the manufacturing facility to resolve the issue, and this rework may require additional logistical cost and time. The preliminary investigation conducted in the present study—in which the quality controllers at two panelized construction companies in Edmonton, Canada were interviewed—revealed that approximately CAN$270,000, including 84 working days, were additionally spent to resolve panel quality issues over three years. Causes for the quality issues include the method of quality control, which is dependent on a random visual check performed by an employee (the quality controller). The random visual check can be considered as the passive quality control that can only detect quality issues after they occur. Also, the quality data of the two companies revealed that the quality issues such as missing parts or dimension errors were often found on a job site during field assembly processes.

To facilitate the proactive quality control which is opposed practice to the passive quality in the visited companies, augmented reality (AR) approaches have applied in the construction industry to improve potential quality issues. Augmented Reality (AR) is a technique for superimposing computer generated information (e.g., an image) into a real-life setting using a device (e.g., head-mounted display), which allows a user to recognize the composite views of the generated information and the surrounding environment simultaneously (Barfield 2015). As AR technologies and devices become more accessible and popular due to recent advancements in software and hardware, AR is being adopted in various industries as a means of improving productivity and quality in the workplace (Chi et al. 2013). For example, in automobile manufacturing, welding spots are projected onto surfaces of vehicles to assist welders in determining the correct welding locations; the results indicate that welders are able to recognize the correct welding locations in a shorter time and with greater accuracy (Zhou et al. 2003; Zhou et al. 2012), resulting in a 52% reduction in welding location errors (Doshi et al. 2016). Funk (Funk et al. 2016) also argues that AR technologies could reduce cognitive demands while improving performance in terms of speed and accuracy.

Table 1 Overview of recent information for projection-based AR studies in various industries

Authors (Year)	Industry	Applied Task	Projection Distance	Illumination	Method of Alignment	Device	Etc.
Yeh et al. (2012)	Construction	On-site construction drawing (2D) retrieval	1.5 m–2.5 m	N/A	N/A	LCD mobile Projector	Construction site application
Zhou et al. (2012)	Automobile Manufacturing	Guiding welding inspector for checking	Approximately 2 m–3 m	N/A	Manual	LCD Projector & HMD	Manufacturing site application

		spot welding points					
MacIntyre (2005)	Agriculture	Guiding poultry cutting instruction	N/A	N/A	Manual	Laser Projector	Production line application
Funk et al. (2015)	General Manufacturing	Guiding a worker to pick-up correct item from inventory	Approximately 2 m–3 m	N/A	Optical marker	LCD Projector	Warehouse application
Büttner et al. (2016)	General Manufacturing	Comparison cognitive demands between HMD and projection	Approximately 2 m–3 m	Natural + artificial light (approx. 500 lux)	Manual	LCD Projector	Assembly line application
Tabrizi et al. (2015)	Medical Industry	Guiding surgeon to location brain tumor	Approximately 2 m–3 m	N/A	Optical marker	LCD Projector	Medical operation room
Wen et al. (2013)	Medical Industry	Guiding surgeon to visualize surgical plan	Approximately 2 m–3 m	N/A	Optical marker	LCD Projector	Medical operation room

In implementing AR, three visualization approaches, such as head-worn, hand-held, and spatial, have been applied as visual display and positioning techniques. Krevelen et al. (2010) and Carmigniani et al. (2011) compared the advantages and disadvantages of the three approaches from technical perspectives, as presented in Table 1 (extracted from (Van Krevelen and Poelman 2010; Carmigniani et al. 2011)). In general, the head-worn and the hand-held are the most popular visualization types and are commercially available. Google Glass and Microsoft HoloLens are examples of head-worn AR, and a smartphone or tablet are examples of a typical medium for hand-held applications. On the other hand, the spatial AR directly visualizes information onto a designated object without requiring a user to wear any devices (Bimber and Raskar 2005), examples of which include a head-up display (HUD) and an interactive wall and floor using a projector.

The comparisons presented in Table 1 show that the head-worn and the hand-held methods may allow for relatively higher mobility and outdoor usability than that of spatial, which is generally used in a fixed location. However, the spatial approach does not require a user to carry or wear a device, which allows the user to freely move around using both hands and to easily collaborate with multiple users by which the same views can be seen. For the recent applications of AR in construction, both head-worn and the hand-held have been actively studies as in Table 1 but limited number of the spatial AR has been applied. Due to the mobility issue in the spatial AR, most of the studies have examined the head-worn and hand-held to visualize information during construction site operations that require constant changing locations. But considering the main focused area of this study which is the industrialized construction that prefabrication of building components at the factory are considered as main processes, the spatial AR with a projector can be efficiently applied to provide a visualization of information to manual assembly workers rather than using other AR devices. In addition, the previous AR studies in the head-worn and hand-held devices had lack of proactive quality management feature that an error can be prevented during manufacturing processes.

The other AR methods such as head-worn and hand-held can also assist workers to visualize information but the spatial AR is considered as the best match for purpose of this research and practices of the panel manufacturing. The head-worn AR devices can effectively provide information to users in real world environment, but their high costs and limited battery life are critical issue in the practice. For example, the panel manufacturing factory often runs 10 hours excluding over-time and the panel assembly lines require 3 to 5 workers to perform together. The HoloLens from Microsoft is roughly cost over $3,000 USD with 5.5 hours of battery life with average use, and the cheaper Google Glass is still cost over $1,500 USD with similar 5 hours of battery life. To implement the head-worn devices, the cost would be significant and the limited battery life requires additional set of the devices. The most of prefabricated construction companies in North America is small-to-medium companies that such large investment in the information technology may not be feasible. If the head-worn devices can significantly improve accuracy and productivity of workers then the investment can be considered as reasonable, but the previous studies (Wille and Wischniewski 2014; Büttner et al. 2016) showed that the head-worn devices did not significantly improve performances of workers. On the other hands, the spatial AR with a projector can provide visualization of information in real world environment with far less financial investment without any battery life issues as in the head-worn devices. The utilized projector in this study was roughly cost $700 USD. Unlike the head-worn devices that require a device per a worker, the projector can be shared by all workers. In addition, use of the head-worn devices may entail a learning curve to adapt to new information display system, but the projection provides more simple and intuitive visualization of the information to workers. Thus, this study focuses on the spatial approach, which is considered suitable for panelized construction where (1) manual assembly tasks are performed in a fixed position; (2) workers need to use both hands to perform manual activities such as lifting, squaring, and laying; and (3) multiple workers often work together to produce one panel. In addition, when instructions were provided through a spatial AR approach, the workers significantly outperformed those who were administered paper-based instructions in terms of productivity and quality (Bosch et al. 2017).

Spatial AR using a projector has been proposed and examined in various areas where complex manual tasks are involved (Table 2). For instance, in the agriculture industry, MacIntyre and Wyvill (2005) applied this type of projection to help workers at a meat packing factory to visualize cutting points for the improvement of productivity and accuracy of meat cutting. In the medical field, Tabrizi et al. (2015) proposed to project the accurate surgical points (e.g., brain tumor) using a projector on the surface of a patient's skull during an operation; this particularly helped physicians to recognize tumors that were difficult to see without the projection. Wen et al. (2013) also projected the surgical plan on specific areas of a patient's body to visualize detailed operations. In manufacturing, Zhou et al. (2011 and 2012) applied a projector to visualize spot welding points to both welders and inspectors in order to reduce the amount of time necessary for finding welding locations.

In construction, however, the spatial approach has seldom been applied due to its lower mobility than other approaches. Although Yeh et al. (2012) proposed a portable projector mounted onto a hard hat for construction applications, the authors pointed out as a limitation the negative impact wearing a helmet with a projector may have on the user's comfort and attentiveness. Furthermore, the spatial AR methods proposed in other industries, as presented in Table 1, cannot merely be applied to panelized construction due to the following challenges:

(1) The use of a projector in the offsite construction facility would require larger-scale projection due to the large size of building material; in general, the size of construction modules would be greater than the objects onto which an image is being projected in the manufacturing and medical industries. This may require a longer distance between a projector and a target object, but the distances in the previous studies provided in Table 2 are approximately less than 3 m, which may not be sufficient to project a construction drawing onto the target surface in an offsite construction facility. For example, the preliminary experiment presented in the current study indicates that at least 7 m are required to project a drawing of one wall in a residential home manufacturing facility.

(2) The projection alignment between a virtual model and an actual target area is critical in spatial AR and is directly related to the quality of a product. For example, in the previously mentioned brain surgery application (Besharati Tabrizi and Mahvash 2015), even a minor misalignment of the projection could lead to serious consequences for the patient. As a method of projection alignment, two methods (i.e., manual and marker-based) have been applied in previous studies (Table 1). If a projection distance is short and safely accessible by a user, then the manual adjustment approach offers a more convenient way of performing alignment than the marker-based method. On the other hand, if the distance is not accessible, the marker-based projection alignment would be suitable since the method can provide an automated alignment method using makers. However, previous studies that utilized the marker-based alignment approach have only been applied for short distances (e.g., 2 m–3 m), and operational conditions such as illumination level

were not tested to understand their potential influences on the projection alignment accuracy (Tabrizi and Mahvash 2015; Wen et al. 2013; Funk et al. 2015). Rabii and Ullah (2015) examined the maker-based AR in a large indoor environment but their maximum testing distance was limited in 5 meter by using 0.2 by 0.2 meter size marker.

(3) An illumination condition is another important factor affecting the performance of projection-based AR. Amano et al. (2011) stated that the various illumination level in computer vision is one of the critical problem, and the marker-based AR also need to consider its potential negative impact on quality of tracking accuracy. Specifically, if a constant level of illumination can be maintained throughout working hours, this illumination issue may be ignored. Nonetheless, panelized construction facilities may feature both natural and artificial lighting which can result in brightness changes over time. As presented in Table 2, however, illumination conditions have yet to be fully investigated to apply projection-based AR to offsite construction.

To address the quality issues of industrialized construction, the concept of spatial AR using a projector remains largely unexplored such that further research efforts are required to apply the approach to a field setting. However, issues surrounding the projection scale, alignment method and accuracy, and level of illumination should be tested and resolved to implement the approach in practice.

2.4. Construction equipment operation data collection and analysis

Concerning the methods available to monitor the operations of construction equipment, research efforts have been put forth in the areas of location tracking and action recognition of heavy equipment. Particularly, two major streams of such monitoring methods found through literature review include a computer vision approach using visual sensors (e.g., cameras) that estimates the positions of construction resources on images or classifies equipment's actions into pre-defined ones of interest, and a sensor-based approach using mobile sensors (e.g., GPSs, IMUs) or static sensors (e.g., RFIDs) that attempts to identify the activities of equipment based on the tracked locations on a jobsite; the summary of relevant research is presented in Table 2. The computer vision approaches (Brilaskis et al. 2011; Zou and Kim 2007; Gong et al. 2011; Memarzadeh et al. 2013) mainly focus on computational algorithms that can accurately detect and track objects in the image scenes, which are later used to understand the semantics of the images. This vision-based approach does not require installations of sensors onto labour or equipment, thus being regarded as cost-effective and highly applicable in dynamic and busy construction sites where multiple objects are presented. In addition, recent advances made in the data analysis area (e.g., deep learning) have significantly improved the accuracy of detection and tracking tasks, even for occlusions, varying illumination levels, and required computational cost, which have all been common issues with respect to construction site images (Brilakis et al. 2011).

The sensor-based tracking system has also been widely used to collect data from heavy equipment in earthmoving construction as shown in Table 2. Unlike the computer vision approach, this sensor approach requires an installation of a sensor or a tag (e.g., GPS, RFID, or mobile device) onto each piece of equipment. In that regard, a large-scale implementation of the sensor-based method can be costly, requiring not only as many sensors as there are pieces of equipment and vehicles, but also continuous maintenance or replacement of the sensors over time. Furthermore, the sensor-based approach can provide reliable data collection even when weather conditions are not favorable such as rain, snow, fog, etc. In addition to the benefit during harsh weather conditions, the sensor-based approach does not require a line of sight condition in order to provide the transportation equipment data in a large construction area (e.g., road construction), and a camera or personnel is not required to physically view construction operations.

In this study, when considering the characteristics of a short duration site construction visit for panelized residential construction, the GPS-sensor-based approach is selected to collect fleet operation data. Typical construction (not including interior finishing) time of a single-family house is approximately 1 or 2 days while performing multiple construction projects on a daily basis at multiple locations. Thus, the GPS data collection approach, which requires a single installation of a GPS sensor on a piece of equipment, does not require frequent re-installation of the sensor for other projects, and the sensors can continuously provide equipment operation data from different residential projects without being affected by adverse weather conditions.

Table 2 Different approaches for identifying activity of construction equipment

Method	Description	Data source	Reference
Computer Vision	Tracking construction project-related entities (e.g., equipment, material, and labour) by using two cameras (stereo vision)	Construction site video	Brilakis et al. 2011
	Identification of equipment idle time by performing image processing with the image colour space data.	Construction site video	Zou and Kim 2007

	The action analysis framework of the Bag-of-Video-Feature-Words was used to classify construction activities.	Construction site video	Gong et al. 2011
	Construction activities from labour and equipment were identified using the Histograms of Oriented Gradients and Colours (HOG + C).	Construction site video	Memarzadeh et al. 2013
	Spatial-temporal visual features of the heavy construction equipment are collected by using the HOG, and the SVM classifier is used to determine different types of equipment actions.	Construction site video	Golparvar-Fard et al. 2013
Mobile sensor	The data from mobile devices such as GPS, accelerometer, and gyroscope were used to classify the front loader's construction activities.	GPS, accelerometer, and gyroscope	Akhavian and Behzadan 2015
	Raw GPS data was collected to automatically analyze construction equipment operation productivity and safety.	GPS	Pradhananga et al. 2013
	The short-term GPS data were collected from the earthmoving operations for analysis.	GPS	Hildreth et al. 2005
	The web-based GPS data analysis was performed along with GIS to predict earthmoving operation costs.		Alshibani et al. 2016
	The smart device's internal measurement unit (IMU) data is used to classify the different operations of excavator.	IMU	Kim et al. 2018
Static sensor	The low-cost RFID sensors were applied to earthmoving equipment with fixed location readers to collect and analyze operation data.	RFID data	Monstaser et al. 2012

As shown in Table 1, equipment operation analysis using GPS sensors has been proposed and tested in previous studies, for earthmoving equipment in particular. For example, Hildreth et al. (2005) used position and velocity of earthmoving equipment with a geo-fence (e.g., dumping and loading zones) to find out earthmoving cycle durations. In the study, to accurately distinguish activities of the equipment, several conditions were pre-defined as follows: 1) velocity should be zero, 2) the position must be within the user-defined zone, and 3) preceding and following data points must be outside of the zone. Pradhananga and Teizer (2013) also examined potential utilization of the GPS data attached to earthmoving equipment to analyze equipment operations. In addition to operation analysis, this study further applied the GPS data to provide a collision warning between equipment with a working zone detection feature, which allowed automatic geo-fence assignment. Akhavian and Behzadan (2015) utilized smartphone device sensors such as accelerometer, gyroscope, and GPS to collect heavy equipment operations data in earthmoving works. In that study, the GPS data is used to measure the distance between a front loader and a hauler and to identify a working boundary (e.g., geo-fence) approximation. Alshibani and Moselhi (2016) collected GPS data from a hauling unit in earthmoving operations and utilized a geographic information system (GIS) to estimate hauling operation cost and productivity in a web-based environment to achieve real-time monitoring of the equipment.

These previous studies provide insight into the utilization of GPS sensors for the operation analysis of heavy earthwork equipment. However, when applied to panelized construction, such approaches can be limited in understating the status of transportation equipment (e.g., trucks) due to different operation practices in panelized construction. The practices such as delivering to a consolidation area (e.g., temporary unloading areas nearby a site), stopping at multiple locations, and picking up empty trailers can be randomly occurring during project execution depending on site conditions and project requirements. These operational conditions are different from an earthmoving operation, in which a hauling truck follows a typical cycle (e.g., load-haul-unload-return) with minimal deviation from the fixed cycle. In addition, the previous studies applying geo-fence settings to earthmoving operations have examined fixed dimensions of operating ranges (e.g., boundary of loading or unloading area) to check the status of equipment, but due to the uniqueness of the panelized construction project, a dynamic and comprehensive approach to setting up geo-fences are required to collect and analyze GPS data from the multiple construction sites.

2.5. Discrete-event simulation in offsite construction

DES in offsite construction has been studied to evaluate various construction plans or schedules prior to execution (Altaf et al. 2018). Due to the application of manufacturing processes in offsite construction, previous studies from a general manufacturing perspective have been applied to the construction process (AlDurgham and Barghash 2008). Therefore, the manufacturing aspect of construction has been explored in previous studies that have focused on optimizing the manufacturing of building components (Abu Hammad et al. 2008). In panelized construction, the multi-wall panel concept has been optimized to minimize material waste and production time using the DES approach (Altaf et al. 2018). In steel prefabrication construction, for instance, steel bridge construction processes have been simulated using DES to satisfy constraints that occur between fabrication and assembly, and the results indicate that projection duration can be reduced by 10% (Altaf et al. 2018).

The transportation operations in offsite construction are critical processes because approximately 80% of all construction activities may be directly affected by transportation operations (Browne 2015). In particular, panelized construction has a higher dependency on transportation operations due to the unique operation requirements given that a prefabricated panel needs to be delivered to designated sites within the requirement schedule while considering assembly orders. Since the panel assembly processes at the sites cannot be flexible enough to handle out-of-order panel deliveries, the transportation dispatching should be able to handle strict schedule requirements.

To generate a precisely coordinated construction schedule to construction managers and operators, DES modelling techniques have been widely applied in the construction industry (Altaf et al. 2018). In panelized construction, Altaf et el. (2018) optimized a panelized construction manufacturing facility operation schedule by using the DES model with the particle swarm optimization (PSO) method, and the results showed that the manufacturing processes were able to reduce the total scheduled duration by 10%. Lu and Olofsson (2014) integrated building information model (BIM) with a DES model to evaluate project performance. However, previous studies showed that the static DES models had limited ability to provide accurate reflection of dynamically changing construction environments (Davis and Banks 1998; Song and Eldin 2012).

To overcome the shortcoming of the static DES model, a real-time data-based DES model has been introduced. Unlike the static model, the real-time DES model utilizes live input data (e.g., location, progress, and status) from construction sites by using information technologies (e.g., a smart device) to run the model to determine an optimum schedule based on the most up-to-date information. Since the construction sites are dynamically changing due to countless factors including weather conditions, it is important to update any previously generated schedule (e.g., master schedule) to reflect current conditions. Previously, the manufacturing industry has used the real-time simulation idea to support decision-making processes (Yoon and Shen 2006). Vahdatikhaki et al. (2015) used real-time location systems (RTLSs) and ultra-wideband (UWB) method to collect operation data from earthmoving equipment, and their poses (e.g., loading or unloading) were estimated to analyze operations including potential safety risks. Recently, the concept of dynamic data-driven application system (DDDAS), which integrates simulation, measurement, and application, has been introduced to collect real-time data to perform the fine-tuning of simulation models. However, this novel idea has not yet been widely applied in practice and further research efforts would be necessary (Song and Eldin 2012).

To the author's best knowledge, no real-time DES model for dispatching transportation equipment in offsite construction has been studied, although the transportation operations have a significant impact on overall project management. In addition, previous DES models in panelized construction have mainly focused on the manufacturing processes rather than considering entire operation processes, such as manufacturing, transportation, and site assembly (Husseini et al. 2018). To improve overall project management in panelized construction, this research proposes a framework using a GPS and QR code-based real-time fleet-dispatching DES model that includes an overall system architecture design and potential implementation plan. This allows for improving fleet-dispatching efficiency as well as increasing performance of overall project management.

2.6. Equipment cost estimation in construction

In construction, equipment cost estimation methods have been studied extensively in recent decades. As an example, the traditional approach by Peurifoy

(Peurifoy et al. 2018) has been widely used in earthmoving operations. The method simply utilizes earthwork information such as a quantity of work, productivity of equipment, and a unit cost to estimate an equipment cost given earthmoving conditions and equipment specification. For instance, estimated quantity of works (e.g., volume of soil) is divided by the measured or historical productivity (e.g., volume of soil per time) and then multiplied by the unit cost (e.g., cost per hour per equipment) to determine final equipment cost. This method and other similar approaches, such as the General Contractors of America (AGC) (Popescu 1992), the Caterpillar Method (Caterpillar 2017), and the Corps of Engineers method (Hill 2009), have been proposed and used in estimating equipment costs in construction activities. Nonetheless, the comparison study by Gransberg et al. (2006) pointed out that each method had different outcomes due to different ways of calculating productivity of equipment, and these methods were mostly focused on civil construction works rather than other construction areas (e.g., building, residential houses). For the estimation of equipment productivity, a machine learning approach using historical data instead of equipment specification has recently been applied and evaluated in construction, producing reliable prediction results. Ok and Sinha (2006) used the nonlinear artificial neural network (ANN) model to predict productivities of a dozer with different specifications (e.g., engine output, bucket type, etc.). Akhavian and Behzadan (2015) utilized sensors (e.g., accelerometer, gyroscope, GPS) in a mobile device to collect front loader operation information and predict the productivity by using four different supervised learning methods (e.g., SVM).

Machine learning is an emerging technology in engineering that has been applied to a broad range of domains such as health care, manufacturing, education, finance, policing, and marketing (Jordan and Mitchell 2015). Industries involving data-intensive issues, such as logistics service providers, have been actively using this technology in order to gain better understanding of data and to improve decision-making processes. Machine learning techniques can be classified into two types: (1) supervised learning and (2) unsupervised learning. Supervised learning is applied when a user has both known output and input so that the trained model can predict outputs. On the other hand, unsupervised learning is employed when output data is unknown. Once the type of learning technique is determined based on the available data, an algorithm is selected to obtain optimum results. Broadly speaking, supervised learning uses two different algorithms—classification and regression—while unsupervised learning employs only clustering algorithms. Each type of algorithm offers various techniques that can be applied depending on the type of data and the goals to be met. For example, regression encompasses multiple methods, including linear regression, support vector machine (SVM), ensemble methods, decision trees, and neural networks (NNs), among others. Previously, the machine learning approach has been applied to forecast logistics costs in the construction industry in order to overcome the difficulties inherent in traditional forecasting methods such as activity-based costing (ABC). Various studies describe the logistics system as an open complex system whose demands are nonlinear and random (Tian and Gao 2009). Due to the nature of logistics systems, applying ABC to forecast logistics cost is time-consuming and costly. Furthermore, ABC is unable to accurately predict the demands of logistics. The same studies, it should be noted, apply two different regression methods to predict cost, SVM and NN. SVM is based on the statistical learning theory, which is adapted from the structural risk minimization principle (Weston & Watkins, 1998), and it is applied for nonlinear and multidimensional data to forecast output (Cristianini & Shawe-Taylor, 2000). NN, on the other hand, is a highly nonlinear dynamic system that has the capacity for self-learning (Kosko, 1992). The results of the machine learning application in logistics cost indicate that both regression models offer reliable results to predict the logistics cost, but the SVM presents a stronger predictive ability between the two, and, the NN reveals overfitting issues (Tian and Gao 2009).

In spite of the promising results of previous studies, the data to be used to predict transportation cost remains unexplored in the context of panelized construction projects, where equipment productivities (e.g., travel time, loaded capacity) may vary in each delivery cycle. In earthmoving operations, the equipment productivity can be assumed to be consistent because of similar loading conditions (e.g., travel distance) and materials (e.g., soil) in every cycle. On the other hand, each trailer load, loading time, and transportation time in a panelized construction project can be inconsistent due to different combinations of panels that vary in dimensions, assembly order, and level of difficulty for loading. Also, transportation demands (e.g., total duration and number of trailers) can vary between projects, which makes it difficult to assume a constant cycle time as in earthmoving operations. In this regard, further research is required to understand the types of data that must be collected in order to accurately account for the operational features associated with transportation cost.

3. Chapter: Methodology

In this section, the proposed framework for advanced transportation operation and management in the panelized offsite construction that utilize augmented reality to improve transportation accuracy during offsite facility, real-time data collection using GPS and smartphone application (e.g., web app) to efficiently collect equipment operation data, the rule-based algorithm to extract key information from the collected data, optimization of transportation planning (fleet-dispatching), and estimation of transportation cost in various projects conditions using machine learning approaches. The framework comprises four modules the outcomes of which will be utilized as inputs for the following process. Experimentation of this framework will be validated for the panelized construction process, but its application is generic and can also be applied in other offsite construction methods such a volumetric module construction.

3.1. Proposed framework

The proposed framework is illustrated in Fig. 1. Detailed data from construction project CAD drawings, contracts, and schedule documents will be used as inputs for the framework, and for the criteria, the graphical user interface (GUI) will be used to provide flexibility given the dynamically changing project environment during transportation operations in offsite construction. The project data contains project design information (e.g., dimensions, weights, materials, and identification codes) and the project information (e.g., address, type of house, total size, and customer). The project information can be acquired from the industry research partner’s estimation and project management department, while the design information can be attained from the design department after the design processes are complete. To improve data analytic efficiency, especially for a large volume of transportation operation data, the project-related data including design data will be stored in the database for this study and queried to provide the proper data to the user through the selection of a unique project identification code at the beginning of the framework application. For the database, a local structured query language (SQL) and cloud SQL database will be used to store collected data from throughout the project, including production, transportation, and site work.

For transportation quality assurance (QA), projection-based AR will be used to provide 2D drawing information to workers to visualize assembly information in order to improve the accuracy of installing construction materials. Additionally, the data collection will be accomplished using two data collection techniques, namely GPS and QR code scanning, which will be applied to collect the operation data throughout the processes. For the GPS, each truck has a GPS coordinate transmitter that will automatically update a truck's location by sending its location to the server. The QR code is similar to a barcode system in that a user can acquire data by using a scanning device. QR code technology will be used via a smartphone application to collect data throughout the transportation processes, including loading and unloading, serving as a time stamp that records the beginning and finishing time of each transportation process. Upon successful acquisition of the operation data, a discrete-event simulation (DES) model will be developed to optimize the fleet-dispatching schedule, and the transportation cost will be estimated as well to provide the overall transportation cost for various type of offsite construction projects. More details pertaining to each part of the proposed framework will be discussed in following sections.

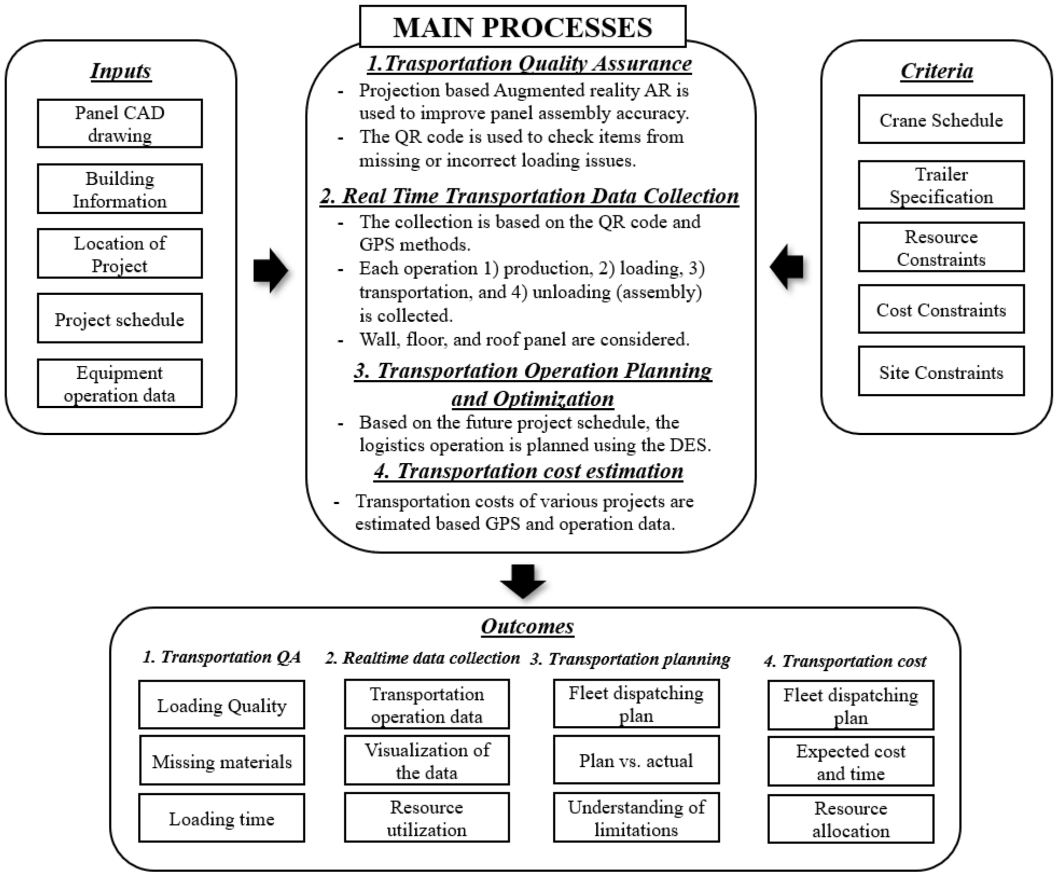

Figure 1 Overall diagram of proposed research

3.2. Transportation operation processes in the panelized offsite construction

In this research, the working definition of transportation operations used is the one presented in Fig. 2, with five steps selected to represent the overall operations. At the case company, a panelized construction manufacturer operating in Edmonton, Alberta, the loading operations (Step 1) begin once the production processes at the facility are completed. The fabricated building components (e.g., panels) are sent to a loading area where empty trailers are ready to be loaded using an overhead crane. The crane operator (loader) is given a drawing outlining the various components as well as their loading sequence and location. The loader locates the components and begins loading them onto the trailers according to the given drawing. In current practice, during the loading process, space utilization is entirely dependent on the ability of the loader. Upon completion of the loading process, the loaded trailers are driven to a yard for the final loading check (Step 2). During this checking process, smaller construction materials such as bulk materials (e.g., metal connectors) are loaded onto the trailers based on available space. However, due to the relatively disorganized loading process in current practice, these small items are often transported using a separate material handling vehicle. After the loading of the smaller components is complete, the yard workers install cargo straps on the trailers and perform the final safety check. Next, the truck drivers locate their assigned trailers at the yard and deliver each trailer to the given construction site (Step 3). Prior to their arrival at the assigned site, the drivers contact the crane operators to check on-site assembly progress. Depending on the progress, the drivers must decide whether to wait at the site to pick up the empty trailer or not. After the delivery is complete, the drivers return to the yard to make subsequent deliveries assigned by the dispatcher at the production facility. In current practice, the dispatcher manually collects information such as site progress, truck locations, and available trailers as the basis for making decisions regarding subsequent deliveries.

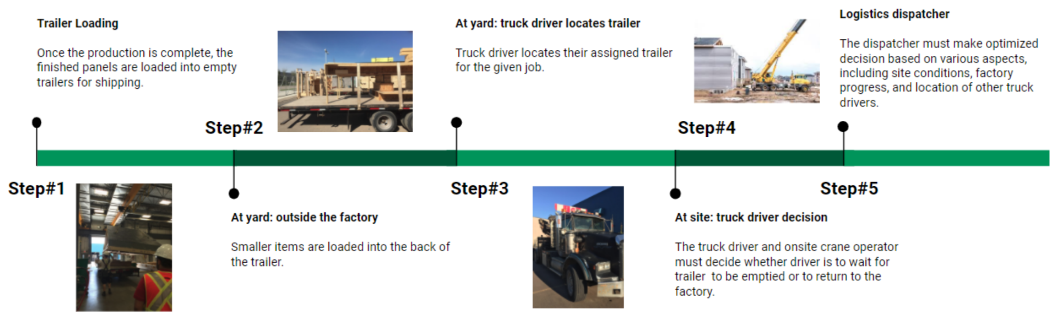

Figure 2 Overall process of logistics operations in panelized construction

3.3. Transportation operation data collection

The data collection is critical to the development and validation of the proposed framework in this study. Without reliable and robust data collection methods, the framework will not be able to reflect actual offsite construction operations and provide accurate cost estimation and fleet-dispatching schedule. In the research, two different data collection methods (QR code and GPS) will be applied for intensive data collection from both on-site and offsite processes that utilize transportation equipment (e.g., truck), with the overall data collection framework presented in Fig. 3. The data collection begins during the panel design process and continues until the final unloading process at the site. In the production and transportation processes, RFID and GPS have already been utilized to collect the data, so the proposed data collection technique will be applied to the loading, yard work, and unloading processes in order to minimize work interruptions in the plant. In addition, the limitations in data collection from previous studies that utilized a single data collection method (e.g., RFID or GPS) in offsite construction were not able to provide a complete dataset for the case company; as a result, accuracy analysis of the processes could not be performed due to missing data points. Therefore, it is important to maintain robust data collection across all processes to ensure in-depth understanding that can eventually lead to potential process improvements and cost saving.

Figure 3 Overview of the data collection structure

3.3.1. GPS data

GPS is an essential data collection method that will be used to collect fleet operation data. Each truck will be equipped with a GPS transmitter that can send location and time information to the database. Unlike the QR code, GPS is an automatic data collection method that can provide continuous data collection without user input. Additionally, a geo-fence can be applied to the system so that a dispatcher can be notified when a truck enters a geo-fenced region of interest, as illustrated in Fig. 4.

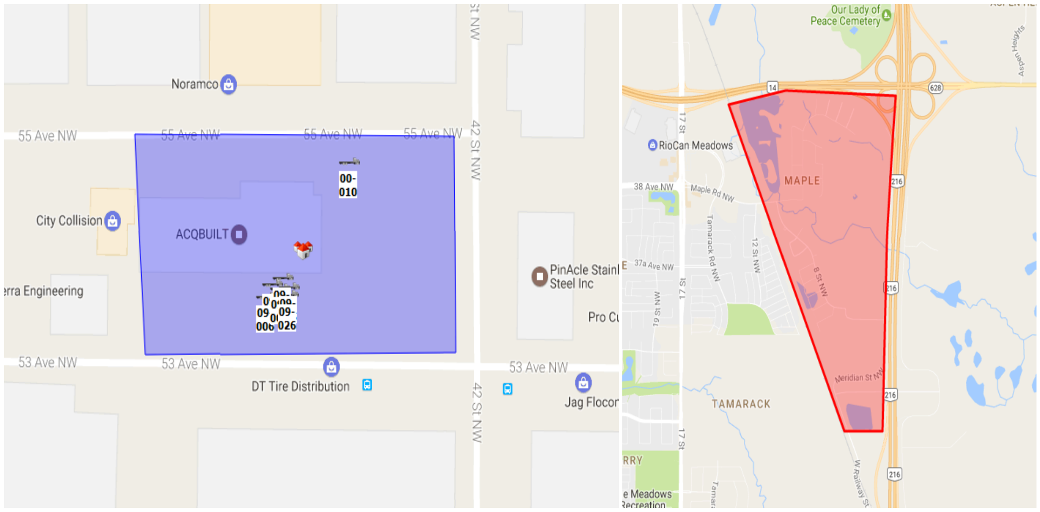

Figure 4 Example of regions of interest identified using a geo-fence

The main purpose of GPS data collection is to create input database for training machine learning models (SVR model) and input data for the DES model. Since each residential project is unique in many ways, extensive transportation demands data from various residential projects are necessary. Manual collection of fleet activities, such as the unloading duration, can be accomplished by human observation, but this would be a time and cost intensive process while also introducing subjectivity issues. To improve efficiency and accuracy of the transportation operation data, GPS data from transportation equipment has been used in previous construction equipment operation analyses. This study also uses GPS data from transportation equipment such as delivery trucks with GPS transmitters on each vehicle to track location. In this study, a commercially available Fleet Complete MGS 700 GPS tracker is used to collect fleet GPS data. The GPS tracker is hardwired to the vehicle’s ignition system so that it can automatically provide GPS data without any manual controls from drivers. Fig. 5 presents the GPS tracker and an example of the GPS data.

	SnapShotID	Asset	AssetType	TimeStamp	Speed	SpeedLimit	Distance	Direction	DirText	Lat	Lon	POI
25	3425760	Unit# 09-033	Construction	2017-04-03 05:40:00.0000000	0	90	0	0		53.48125	-113.4174	
26	3425761	09-009	Logistics	2017-04-03 05:38:00.0000000	0	50	0	0		56.68569	-111.3503	
27	3425762	09-009	Logistics	2017-04-03 05:39:00.0000000	0	50	0	0		56.6857	-111.3502	
28	3425763	09-009	Logistics	2017-04-03 05:40:00.0000000	12	50	0	146	SE	56.68567	-111.3494	
29	3425764	09-009	Logistics	2017-04-03 05:41:00.0000000	33	50	1	185	S	56.68379	-111.3487	
30	3425765	Unit# 09-040	Construction	2017-04-03 05:40:00.0000000	0	50	0	0		56.68572	-111.3499	
31	3425766	Unit# 09-040	Construction	2017-04-03 05:41:00.0000000	0	50	0	0		56.6857	-111.3499	
32	3425767	Unit# 09-040	Construction	2017-04-03 05:42:00.0000000	0	50	0	0		56.68574	-111.3499	
33	3425768	Unit# 09-036	Construction	2017-04-03 05:43:00.0000000	0	90	0	0		53.62833	-113.1716	
34	3425769	Unit# 09-033	Construction	2017-04-03 05:41:00.0000000	0	90	0	0		53.48133	-113.4175	
35	3425770	Unit# 09-033	Construction	2017-04-03 05:42:00.0000000	56	90	0.42	359	N	53.48497	-113.418	
36	3425771	Unit# 09-033	Construction	2017-04-03 05:43:00.0000000	61	90	0.59	359	N	53.49029	-113.418	
37	3425772	Unit# 09-032	Construction	2017-04-03 05:44:00.0000000	0	50	0	0		53.49155	-113.4095	A...
38	3425773	09-009	Logistics	2017-04-03 05:42:00.0000000	51	50	0	161	S	56.67693	-111.3475	
39	3425774	09-009	Logistics	2017-04-03 05:43:00.0000000	44	80	1	121	SE	56.67223	-111.342	
40	3425775	09-009	Logistics	2017-04-03 05:44:00.0000000	47	80	1	140	SE	56.66886	-111.3368	
41	3425776	Unit# 09-040	Construction	2017-04-03 05:43:00.0000000	0	50	0	0		56.68574	-111.3499	

Figure 5 Example of the GPS tracker and the raw fleet GPS data

The GPS data includes various information such as (1) a unique equipment identification code, (2) date and time, (3) speed, (4) latitude, and (5) longitude. The unique code is assigned to each truck to distinguish each GPS data point from other trucks. The date and time behave like a timestamp that is assigned when the data is transmitted to a cloud server. The speed is used to find out the vehicle's status, whether it is idle or moving. For each vehicle, the latitude and longitude are GPS coordinates that are used to compare against the geo-fence area (e.g., construction site) to calculate transportation demands. For GPS data storage purpose, the GPS trackers transmit location and other data to a cloud server for easy access and this is offered by the GPS tracker manufacture. The accuracy of the GPS location is set to the highest accuracy with 2 minutes data intervals. During the case study, one year of GPS data for the entire fleet belonging to the company participating in this research was downloaded in CSV format for transportation demands analysis.

3.3.2. QR code data

In the construction industry, manual data collection (writing by hand) has been a common mode of data collection due to its simple application (Golparvar-Fard et al. 2009). However, to analyze a large amount of data, the data in paper format needs to be converted to electronic format, such as Microsoft Excel, and the data conversion process requires significant time and manual labour to perform the conversion. Thus, to address this issue, this study utilizes the QR code data collection method.

Since the QR code was first used in the automotive industry in Japan, the method has been widely used in various industries to collect operation data by using a simple scanning tool (e.g., a hand scanner). Compared to a one-dimensional barcode, the QR code can hold approximately one hundred times more data while having less scanning error margin (Lin et al. 2014). In terms of proven track records and popularity, the traditional barcode can be a reasonable selection for data collection. However, if a company is trying to build a new data collection system, then the QR code could provide more benefits (e.g., data size, scanning accuracy, and smart device applications) than the barcode.

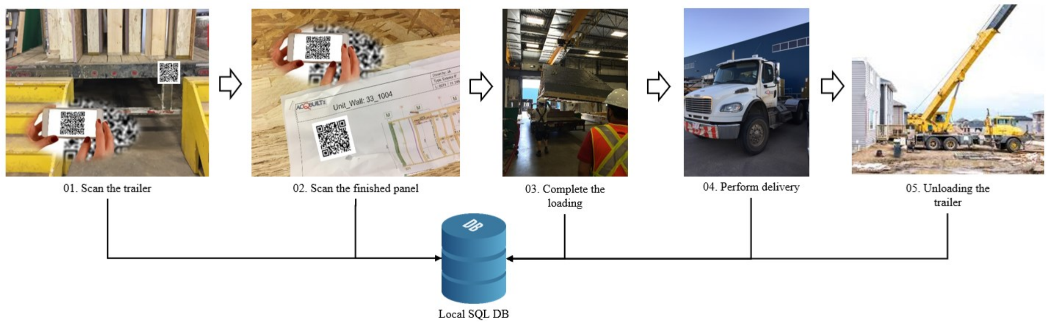

Figure 6 Proposed QR code scanning process throughout the construction project

In order to implement the QR code-based transportation operation data collection system, the system can include the following three steps, as shown in Figure 6: (1) QR code generating and printing, (2) QR code tagging, and (3) QR code scanning. For the first step, as shown in Figure 7, a user interface (UI) is connected to a local SQL server to acquire required information for generating the code. Each code consists of two unique identifiers, such as a panel ID and a project ID, and this information is loaded by using the developed interface. For printing, a user can select a specific project ID to print out the QR code. Codes are printed on self-adhesive paper (e.g., sticker) so that a worker can easily apply them.

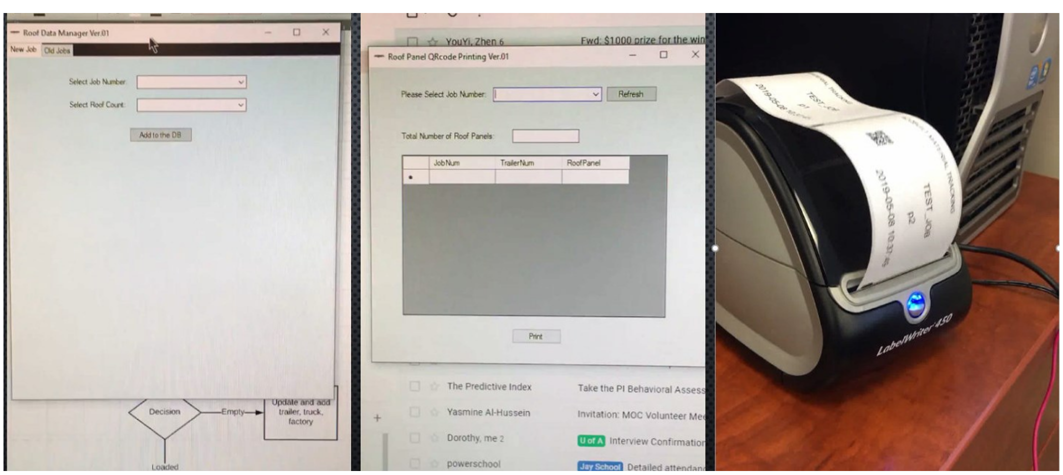

Figure 7 User interfaces and QR code printer for proposed data collection system.

For the second step, as shown in Figure 8, workers at loading areas will receive the printed QR codes to tag finished products (e.g., panels). Loaders will attach the QR code sticker to the products based on the unique identification codes for each product and project. In addition, other QR codes for trailers are prepared to minimize manual data entry time for loaders. For example, during the QR code scanning processes, workers are only required to scan QR codes to input operation data without the need for any manual data input. This approach will improve the accuracy of collected data as well as reduce data entry time required, thus improving overall data collection and operation efficiency.

Figure 8 Applied QR codes for trailers and finished panel at factory.

Furthermore, upon completion of tagging trailers and finished panels, workers (e.g., loaders and drivers) need to perform the scanning of QR codes to enter data into the database. To read a QR code, the web-based application (e.g., web app) is developed to improve the efficiency of data collection. The web-based application (web app) is different from a native application (e.g., iOS or Android app) in a smart device in that it does not require a download and an installation process. The web app can be easily accessed on any smart device by using a web browser (e.g., Google Chrome) to navigate to the web address. In other words, an iOS-based application cannot be installed and operated in another operating system such as Android; however, for the web app, the operating system limitation is not applicable. Since workers can have various types of smart devices with different operating systems, this study has decided to utilize the web app to overcome the operating system limitation. As shown in Figure 9, the web app is developed for four different logistics operations such as loading, delivering, yard managing, and craning (unloading). For the development of the web app, html5, CSS, and JavaScript (JS) are used together to create the web app.

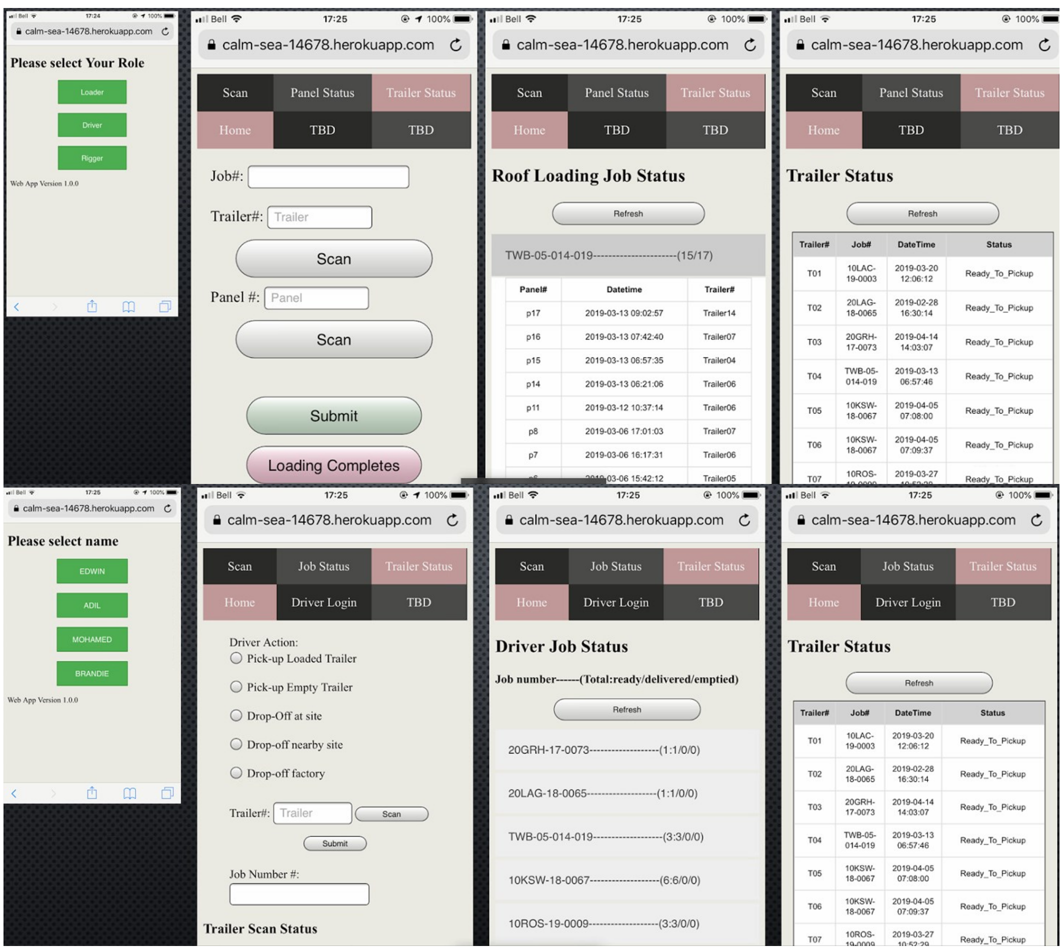

Figure 9 Developed web app interface for loaders and drivers.

For the persons responsible for loading, they are required to scan the finished panels and the assigned trailer together to provide the loaded trailer information to drivers. For example, during the loading process, the worker scans the QR codes for panels then scans the trailer QR code to complete loading operations. After loading, the yard manager brings the loaded trailer out to a yard for drivers to pick up. The yard manager only needs to scan the trailer to indicate the loaded trailer is located at the yard and it is ready to be picked up by drivers. Next, drivers will perform QR code scanning processes to provide and update trailer status through the project operations. The drivers are required to scan the trailer QR code whenever the trailer status is changed. For example, when the loaded trailer is picked up from a factory then the status of trailer is changed to transit status. More details on data type and structure will be discussed in section 3.4.

3.3.3. Project-related data collection

Along with transportation demands, the residential project data is the other important data that is included in the training database for the machine learning models. Since the models are based on the supervised learning approach, the demands are considered output and the project information is considered as input in the training database. The selected project information in this study are as follows: (1) project identification code; (2) project execution date; (3) project address; (4) project model; (5) wall, floor, and roof dimensions; (6) exterior design options; and (7) residential project type. The project ID is assigned to each project to perform queries in a relational database, and the project date and address are used to match with the GPS data during the transportation demands analysis. The rest of the project information, such as model, dimensions, design options, and building type, are collected to develop the transportation demands prediction model. An example of the project information data is presented in Fig. 10. To collect the project information, a construction project contract, a drawing, and a schedule document is used. The contract and drawing documents provide cost, address, and other detailed design-related information, and the schedule provides site assembly data.

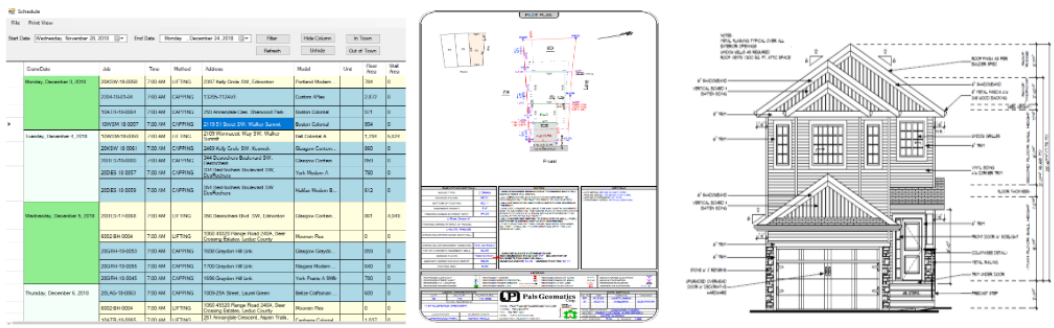

Figure 10 Examples of the project information such schedule, site plot, and building dimensions

A unit cost of transportation is used to calculate the transportation costs with a predicted transportation demand from machine learning models during the transportation cost estimation module in the proposed framework. In this study, the unit cost is calculated based on historical operation and ownership data on the fleet (Peurifoy and Ledbetter 1985). To estimate the unit cost, data is gathered by acquiring all available operation and management records for the panelized construction company, including (1) data for one year of transportation operations information (e.g., total operation hours and odometers in fleet), (2) financial expenses including fuel and maintenance costs, and (3) project information (e.g., total transported panels) For details on calculating the unit costs, the Peurifoy method can be found in Peurifoy and Ledbetter (1985). Figures 11 and 12 present the estimated ownership and operation cost calculation for the truck fleet.

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11313- 170 Street
Edmonton, Alberta T5M 3P5
Phone: (780) 413-8800
Fax: (780) 413-8808

*The undersigned hereby agrees to purchase the vehicle(s) described below pursuant to the terms and conditions hereafter outlined.
GST # 11940 1776 RT0001

VEHICLE PURCHASED

QTY.	YEAR	MAKE	MODEL	SERIAL NUMBER	TOTAL PRICE
1	2012	FREIGHTLINER	M2106	1FVHCYBS6CHBP8709	$113,600.00
X	X	X	X	X	$0.00
TIRE RECYCLING SURCHARGE					$90.00
A/C TAX					$100.00
AMVIC FEE					-$6.25
GST AND OTHER APPLICABLE TAXES					$5,689.81
TOTAL CASH DELIVERED PRICE FIRM FOR 15 DAYS					$119,486.06

119,479.50

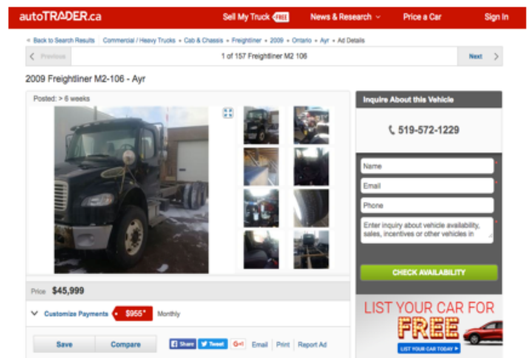
TRADE IN(S)

QTY.	YEAR	MAKE	MODEL	SERIAL NUMBER	ALLOWANCE	
X	X	X	X	X		
GST AND OTHER APPLICABLE TAXES					$0.00	
TOTAL ALLOWANCE					$0.00	
LESS PAYOUT TO :						
CUSTOMER GST #				NET ALLOWANCE	$0.00	$0.00
* UNPAID BALANCE OF CASH DELIVERED PRICE						$119,486.06

TERMS OF PAYMENT

DEPOSIT (receipt of which is hereby acknowledged by Vendor)	P/O #:	***(see condition below)	119,479.50
CASH ON DELIVERY			$119,486.06
** FINANCE CONTRACT, SUBJECT TO CREDIT APPROVAL		COMPLETED BY	$119,486.06

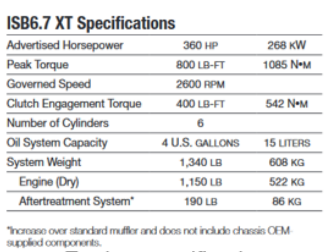
< Initial purchase of the truck >



< Resale value >

Ownership cost	31.20	CAD/hr
MARR	17%	%
Useful life	10	years
Operation hour per year	2088	hrs/yr
fuel economy	2	km/L
initial cost	119475.5	CAD
cost of tire	5000	CAD
Estimated salvage value	46000	CAD

Figure 11 Ownership cost calculation based on the historical operation data.

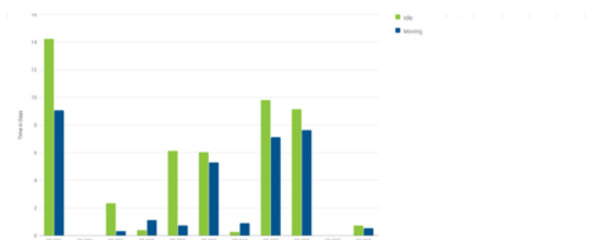


ISB6.7 XT Specifications

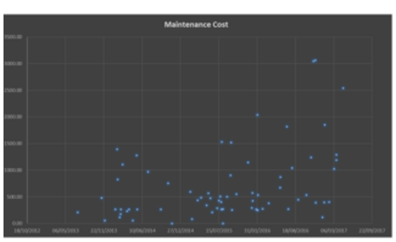
Advertised Horsepower	360 HP	268 KW
Peak Torque	800 LB-FT	1085 N•M
Governed Speed	2600 RPM	
Clutch Engagement Torque	400 LB-FT	542 N•M
Number of Cylinders	6	
Oil System Capacity	4 U.S. GALLONS	15 LITERS
System Weight	1,340 LB	608 KG
Engine (Dry)	1,150 LB	522 KG
Aftertreatment System*	190 LB	86 KG

*Increase over standard muffler and does not include chassis OEM supplied components.

< Engine specification >



< Operation factor >



< Historical maintenance cost >

Operating cost	29.17	CAD/hr
Engine factor(50% of max engine power)	0.50	
Time factor(55min/hr)	0.9	
Operation factor	0.45	
Fuel consumption per hour (diesel)	23.848083	liter/hr
Total maintenance cost(Tire, oil, grease, other fix)	2.35	CAD/hr
Repair factor	0.7	
Cost of fuel	1	CAD/Liter
fuel factor for diesel	0.04	
Crankcase Capacity	4	gal
Time between oil chnages*	1200	hrs
oil factor	0.006	lb/hp.hr
cost of lube oil	10	CAD/gal
cost of other oils and grease	0.75	CAD/hr
repairs to tires depreciation	0.14	
life of tire**	4000	hrs

Figure 12 Operation cost calculation based on the historical operation data.

3.4. Database structure and development

A clearly organized data structure in the database is an important issue in the effective management of a large volume of data. Considering that transportation operations data are constantly being generated from both GPS and QR code scanning in this study, multiple data tables in both local SQL and cloud NOSQL database are used to perform a basic CRUD operation (create, read, update, and delete). For the local and cloud databases, Microsoft SQL 2008 server and MongoDB ATLAS are applied, respectively. In Fig. 13, the entity relationship in this study is presented, and the green colour tables indicate the cloud and the rest of tables are local database. The following sections will discuss more details pertaining to the database.

The local database is a crucial tool for storing data collected by means of various techniques, allowing for the quick and efficient analysis of a large amount of data using SQL. Considering the multiple data sources in this research, the entity relationship diagram is presented in Fig. 13. The project information (pink table) is considered the primary table and is able to access other tables, the relationships between which are represented by connection lines in Fig. 13. For example, a user can access the data in the GPS table from the project schedule table based on these connections, and all connected tables are able to perform extensive data searches within the database. Each time the data collection processes are performed (e.g., GPS transmitter, QR code scanner, and results from the modules) the results will be stored in the designated table. Additionally, the equipment tables (blue table) and user tables (white table) are also included in the entity framework to acquire information.

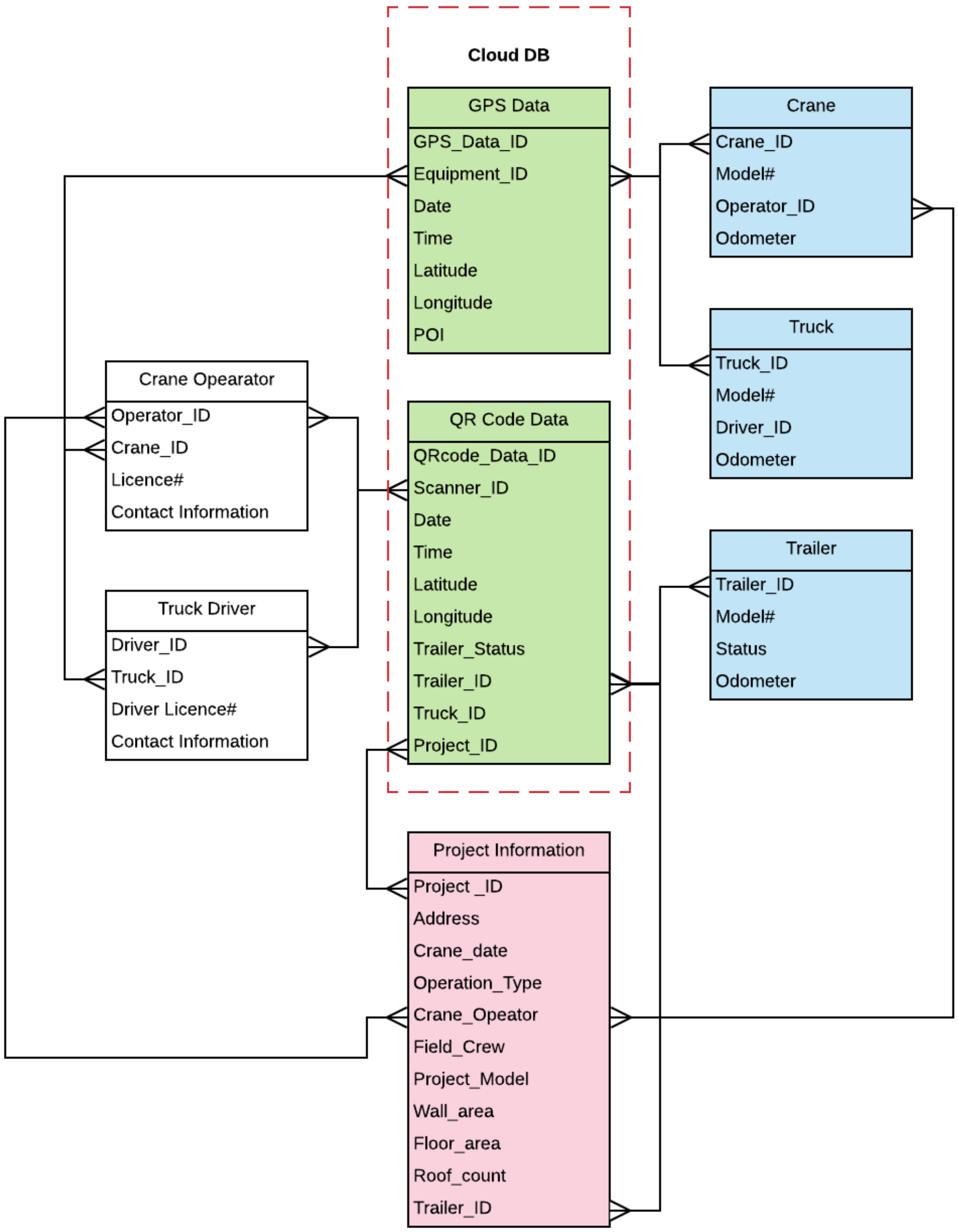


Figure 13 Overview of the entity relationship

3.5. Transportation quality assurance

3.5.1. Projection-based AR

For the implementation of spatial AR using a projector, this section presents and evaluates the projection alignment method that superimposes a 2D panel assembly drawing (e.g., a plan) onto an assembly line. To automate the alignment process, a projector and a camera are used together in a manner that the projected scene (i.e., the plan) by a projector is adjusted to the designated position marked by a user with specialized markers. In this study, a marker-based approach is adopted to set the initial position of a panel being built, as in general the position is often manually determined in practice. Fig. 14 provides the overview of the proposed framework. Specifically, potential alignment errors such as radial and perspective distortions are first eliminated using computer vision techniques. Distortion errors can commonly occur when using a digital camera and are mainly caused by the type of lens used (e.g., wide angle lens) and orientation (e.g., direction and location) of the camera to an object (Mansuriv 2017), as presented in Fig 15a and 15b. These errors are corrected through camera calibration processes in which the intrinsic and extrinsic parameters of a camera are determined for geometric transformation.

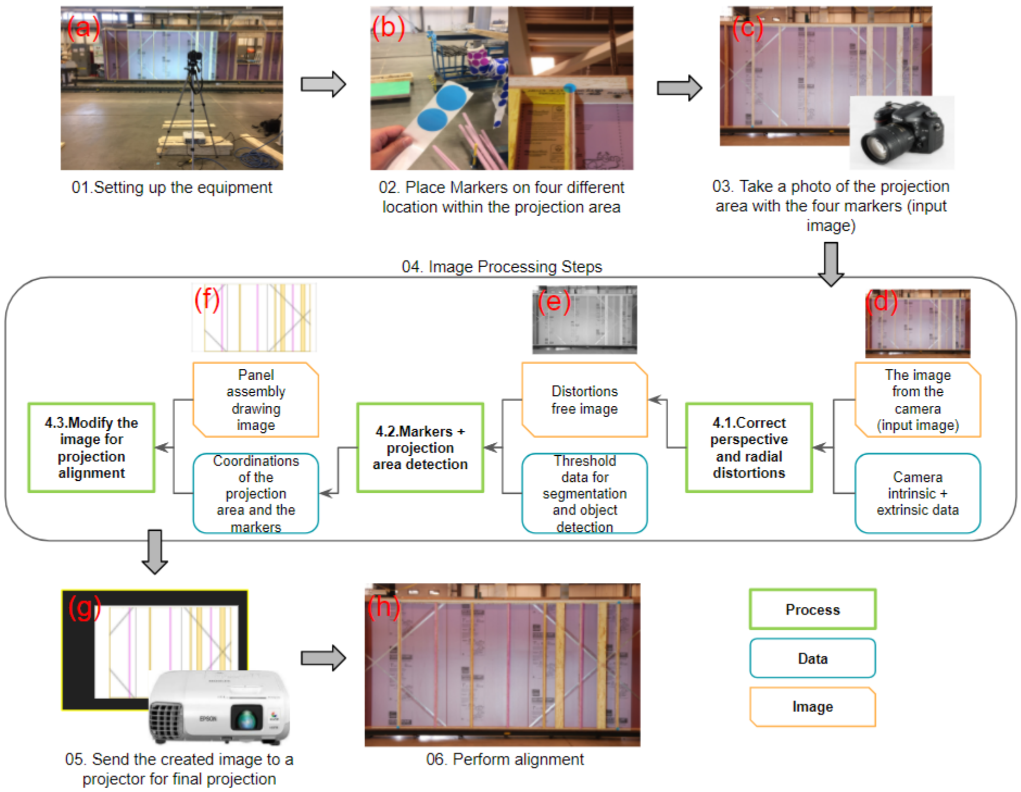


Figure 14 Overview of projection-based alignment processes: (a) setting up the experiment; (b) placing the markers on a wall panel; (c) taking a photo of the panel with the markers; (d) input image for image processing; (e) distortion-free image; (f) 2D panel drawing image; (g) alignment ready output image; (h) projection of the output image on surface of the wall panel

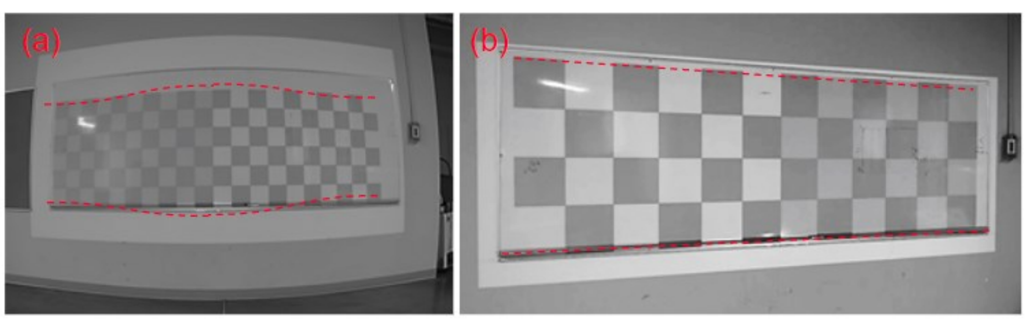


Figure 15 Examples of distortions: (a) radial distortion (e.g., barrel distortion); (b) perspective distortion

A distortion-free image resulting from the camera calibration is then used for the object detection that aims to compute coordinates of markers and a projected area (i.e., a boundary of projection). To perform the detection, image segmentation is initially performed as a pre-processing step to increase the accuracy of the detection by separating the markers and projection area from the background (Figs. 16b and 16c). In practice, this image segmentation can be performed on a shop floor or on a vertical wall assembly line prior to beginning a construction task, which makes the process computationally simple and robust. Object detection is then performed for markers and a projection area, as in Figs. 16d and 16e, respectively.

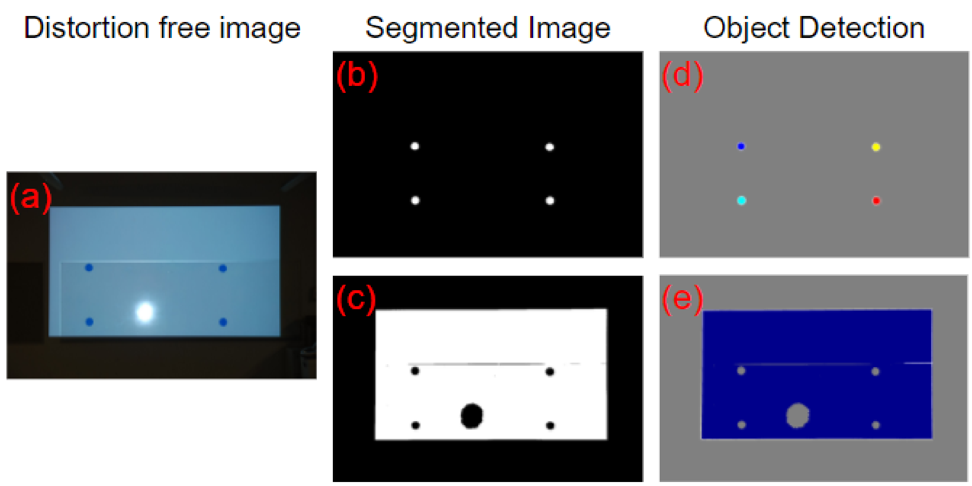


Figure 16 Examples of images in different processes: (a) distortion-free image; (b) segmentation of the markers; (c) segmentation of the projection area; (d) detection of the markers; (e) detection of the projection area

Once the successful acquisition of the coordinates is achieved, the panel assembly drawing as presented in Fig. 14f is prepared for projection by matching the four corners of a panel in the drawing with four pre-set marker positions and adjusting the image resolution of the drawing. To minimize any error in this alignment process, for example, markers can be placed at the position where vertical and horizontal studs are joined. A geometric transformation is performed to fit the panel drawing within the boundary of the markers, and the image is then translated to the correct location based on the marker coordinates. After the final image is sent to the projector, it is projected onto the surface of a wall panel to visualize the drawing (Fig 14h).

To evaluate the performance of projection alignment, alignment accuracy is measured by computing an offset distance from the center of each marker to the boundary of the projection. Since each corner point of the projection should be matched with a center point of a marker, the accuracy of projection can be estimated by measuring the distance. The accuracy is measured for various projection distances and at various levels of illumination and is compared against the tolerable level (e.g., 6.35 mm or ¼ in) of manual assembly error that the case study company has set for their production lines. This approach provides a level of potential feasibility that the proposed method could be used in actual panel assembly workplaces.

The three technical processes in Fig. 16—(1) image distortion correction, (2) markers and projection area detection, and (3) modification of the panel assembly image—are explained in detail in the following sections.

3.5.2. Distortion correction for image projection

The distortions (e.g., Fig. 17) are first corrected to improve the accuracy of image processing and provide workers with precise visual guidance through projection. It was found in the preliminary experiments that two types of distortions, such as lens distortion and perspective distortion, are significant when using a projector and a camera at a long distance. For example, Fig. 17 illustrates the images before and after the distortions are corrected. The lens distortion commonly occurs due to optical design of lenses, while the perspective distortion is mainly caused by the location and direction angle of the camera. To minimize the distortions, the focal length of the lens can be maintained at the range (e.g., 30 mm in this study) given in the lens specifications, and the camera can be placed near to the center of a target object in the scene. However, as the correction at the pixel level is difficult to achieve through manual processes, camera calibration processes are adopted in this study to minimize the impact of distortion on the image processing, particularly when using a wide-angle zoom lens. Among various methods of the camera calibration (e.g., Li et al. 2014; Sun and Cooperstock 2005), the checkboard method (Zhang 2000)—which is a widely-used method for its accuracy (Sun and Cooperstock 2005)—is applied in this experiment. This method utilizes multiple images of a checkboard to estimate the camera parameters (e.g., intrinsic and extrinsic), which are then used for the distortion correction processes (i.e., geometric transformation). For the camera calibration, multiple images of a checkboard (25 images in this study) are taken prior to the experiment.

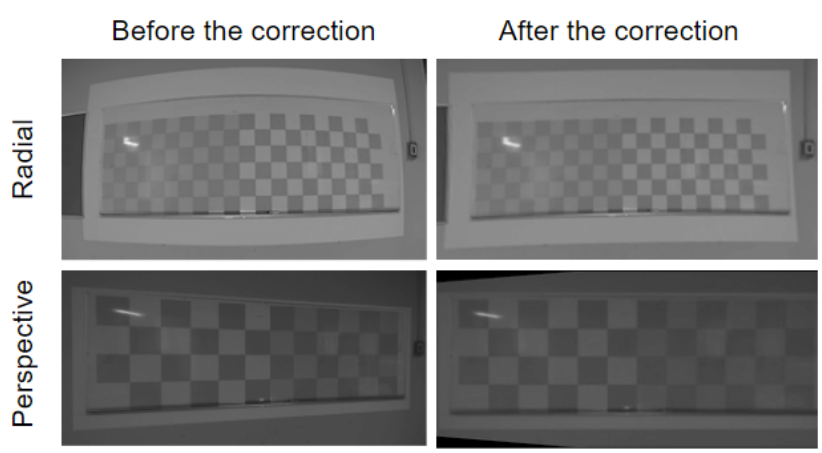


Figure 17 Examples of distortion correction

Specifically, tilting errors resulting in perspective distortion can easily be caused by the constraint on available camera positions in a field setting; for example, a focal plane of a camera can be placed facing a particular direction either slightly upward or downward rather than at the center with a right angle (90°) to the target object. To fix such a distortion, the projective transformation, which does not necessarily preserve parallelism, is adopted rather than affine transformation; Eq. (3) represents the projective transformation (Gonzalez and Woods 1992). Here, x and y represent original points in homogeneous coordinates; the x' and y' represent the scaled coordinates in projective locations; and a through h represent parameters for the projective transformation (3 × 3 matrix). The parameters a, b, d, and e control scale and rotation, c and f correct tilting, and g and h perform translation of an image during the transformation process. The equation has 8 degrees of freedom and requires four pairs of coordinates to compute the matrix.

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{3}$$

The direct linear transformation (DLT) approach is applied to estimate the matrix using the pairs (Hartley and Zisserman 2003). The four pairs of projective coordinates (x' and y') and the original coordinates (x and y) are measured by applying object detection method, which is discussed in the following section. Once the coordinates are identified, the projective transformation matrix is estimated to transform an input image (e.g., a drawing) for the projection. Additionally, a length between two diagonal points is calculated to verify the performance of the projective transformation in this process.

3.5.3. Estimation of marker positions and projection boundary

To perform a geometric transformation for projection, the coordinates of the markers and projection area are estimated using computer vision techniques. This process consists of two technical steps: (1) image segmentation to filter out a region of interest, and (2) object detection to estimate the coordinates of the region. In this study, image segmentation is applied to filter out the markers and projection area from the background, and the coordinates of the segmented objects are then detected for the image as illustrated in Fig. 18.

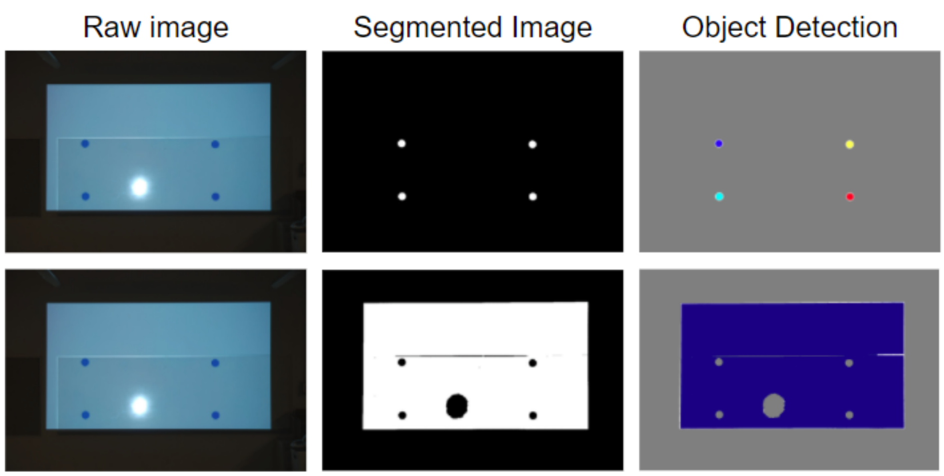


Figure 18 Examples of segmentation and object detection

The image segmentation is a technique to partition a certain area of an image by using characteristics (e.g., colour, texture, intensity) of segments in the scene (Cheng et al. 2001). The format of input images used in this study contains RGB values ranging from 0 to 255 for red, green, and blue, and the segmentation is performed based on these colour values. Taking into consideration the working environment at the panel manufacturing facility, this colour-based segmentation approach is suitable due to low colour variation in the working areas. Specifically, blue markers and white projections are used to distinguish the boundaries of the projection from the background (Fig. 19).

Figure 19 Limited colour variation on the panel assembly lines: (a) projection colour; (b) marker colour

Initially, the regions of interest (ROI), which in this study include (1) the markers, (2) the projection area, and (3) other background areas, are determined prior to the segmentation. Then, for the segmentation, each colour range is estimated by measuring similarity in Euclidean distance as defined in Eq. (4):

$$D(z,m) = [(z_R - m_R)^2 + (z_G - m_G)^2 + (z_B - m_B)^2]^{0.5} \tag{4}$$

where $D(z,m)$ denotes the Euclidean distance between an RGB vector point (z) and the mean RGB vector (m). Then, a threshold level (T), which describes a level of similarity between z and m, is used to determine the similarity. When $D(z,m)$ is smaller than T, the point (z) is converted to a white pixel and finally the points are grouped together with other similar points. Specifically, after the ROI selections, the un-selected area is first converted to black by using a binary image mask. Then the isolated ROI areas are used to calculate the mean RGB vector (m) and the covariance matrix (C) of the ROI area. Different threshold levels are examined to determine the optimal segmentation threshold value as presented in Fig. 20. The initial threshold value is estimated from the square root of diagonal of the covariance metrics (σ^2) and the largest number is selected (e.g., 25). In these experiments, several initial threshold levels, such as 25, 50, and 75, are tested for the marker, projection area, and background, respectively, providing the clearest boundary of segments. In this study, the threshold level of 75 is applied for the segmentation due to the best segmentation performance in the projection boundary segmentation.

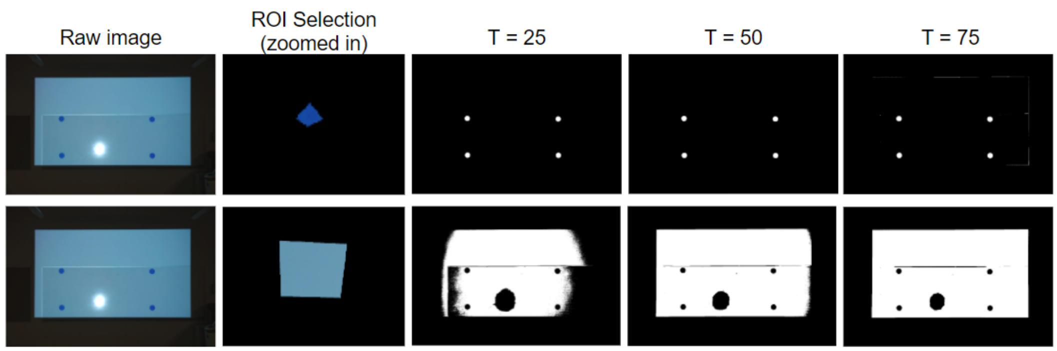


Figure 20 Segmentation of different threshold levels (T)

After the segmentation process, coordinates of the markers and the projection area are estimated using the object detection algorithm. To detect the objects from the output images (e.g., binary image) from the image segmentation, blob analysis, which is suitable to detect objects regardless of their shape (Chen et al. 2007; Kurtulmus et al. 2011), is applied. Blob analysis (Gonzalez and Woods 1992) is performed by searching every pixel in a binary image and identifying a connected region, a blob, in which all the pixels are uniform in colour. Since the binary image consists of only two colours (black and white), the blobs can easily be detected and clustered based on the colour value. In this study, objects of interest (e.g., markers and projection area) are marked in white as an outcome of image segmentation, the pixels in white are detected and grouped together as a blob. For example, when the algorithm searches every pixel in an image consecutively, each pixel is compared to other surrounding pixels to determine whether to create a new blob, add to an existing blob, or carry on to the following pixel. Here, the number of surrounding pixels to be compared is called a connectivity, the parameter for which is generally set to 4 (i.e., top, bottom, left, and right) or 8 (i.e., top, bottom, left, and right, in addition to another four diagonal pixels). This connectivity parameter affects the processing time and accuracy of the blob analysis as the number of computational operations at each pixel is determined; for instance, a higher connectivity often provides more accurate results but requires longer processing time. In the preliminary experiment, different levels of connectivity are examined (e.g., Fig. 21), and it is discovered that both levels of connectivity (i.e., 4 and 8) provide similar results in estimating the coordinates of markers and projection area due to the relatively simple shapes of the objects. The four connectivities are thus selected for reduced processing time in this study.

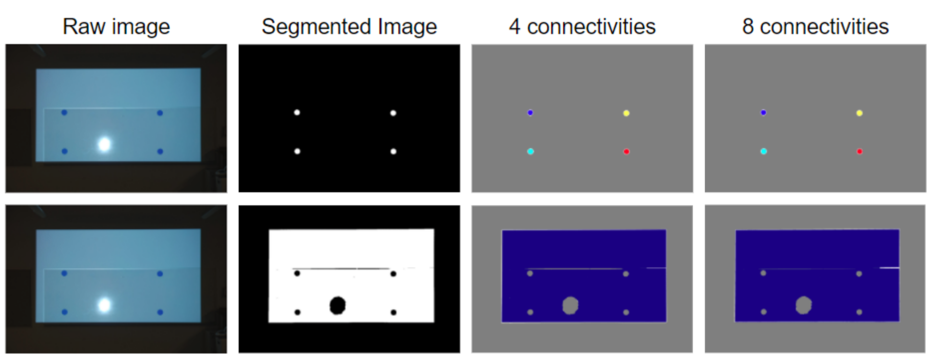


Figure 21 Levels of connectivity in blob analysis

The results of the blob analysis provide n-by-2 arrays including x- and y-coordinates of n number of pixels for each blob. For the markers, centroids of the markers are calculated to find the coordinates of center points by using Eqs. (5) and (6) where C represents a centroid coordinate, A represents an area of an object, n is the total number of points, and x and y represent the coordinates of a blob. On the other hand, the four-corner coordinate for a projection area can be calculated by finding maximum and minimum x- and y-coordinates of the blob.

$$C_x = \frac{1}{6A}\sum_{i=0}^{n-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{5}$$

$$C_y = \frac{1}{6A}\sum_{i=0}^{n-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{6}$$

3.5.4. Modification of the panel assembly image (2D drawing)

Utilizing the estimated coordinates of markers and projection area, a panel assembly drawing is re-sized and adjusted to be aligned onto the actual wall panel at a manufacturing facility. The panel assembly drawing can often contain an entire wall panel, which can be larger than the projected drawing for which the markers are placed (Fig. 22a). Therefore, a proper selection of the wall panel assembly drawing is important for accurate projection alignment. To avoid misalignment of the projection, it is recommended to place all the markers at areas where vertical and horizontal studs are jointed together, as presented in Fig. 8b, since the entire panel is divided into sub-sections as work units in current practice. In a drawing, the center of the markers can be marked (Fig. 22c) to correspond to the locations of actual markers where a user determines to build the panel. An image resolution of the selected panel drawing (Fig. 22d) is then adjusted for the projection (e.g., 1,920 × 1,080 resolution in these experiments).

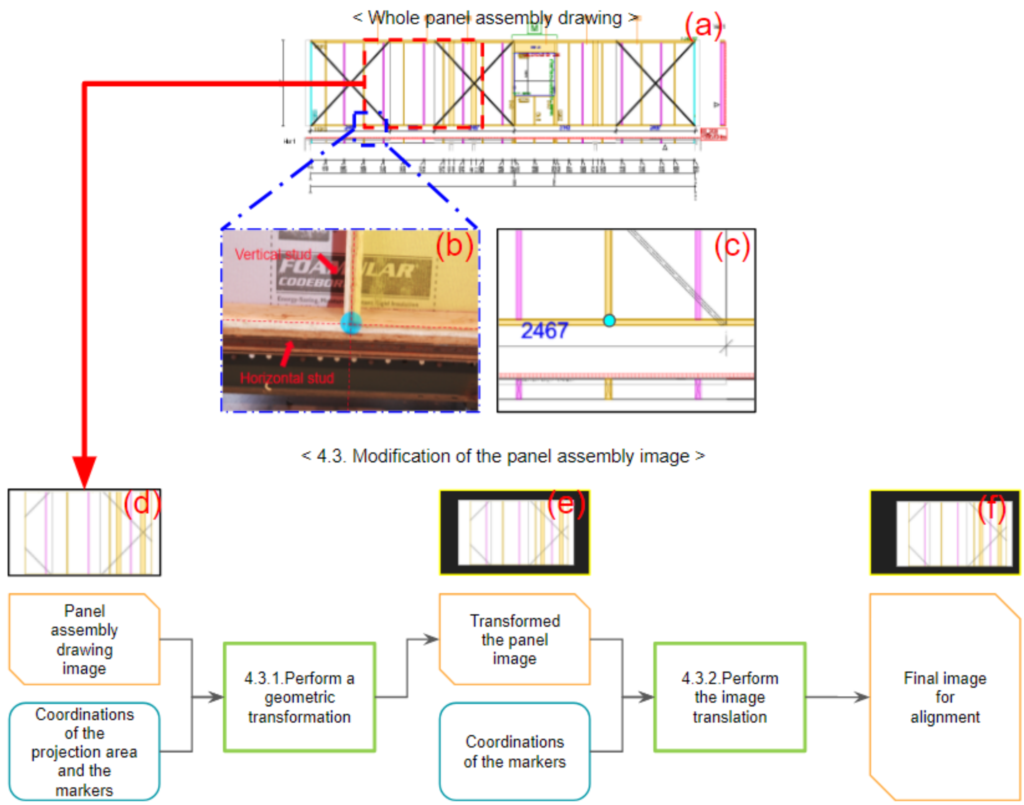


Figure 22 Overview of performing geometric transformation: (a) entire wall panel drawing; (b) locations of markers on actual panel; (c) location of marker on drawing; (d) selecting a section of panel assembly drawing; (e) transformed panel drawing image; (f) translated panel drawing image

The size of the projected image is then re-adjusted according to the coordinates of the actual markers by calculating the differences between the marker coordinates (X_m, Y_m) and the projection boundary coordinates (X_p, Y_p) as presented in Fig. 18. In particular, the resolution of the projected panel image aligns to that of the projector through the adjustment, and thus a geometric transformation (Eq. 3) can be applied to the projected panel image to be fit within the boundary of the markers (Fig. 22e). Lastly, the top left corner of marker coordinates is selected to translate the panel image onto the correct location (Fig. 22f). The completion of these processes results in an aligned panel image on which marker locations in a drawing are matched to the actual markers in the field. Once the image is sent to the projector, the image is overlaid on the surface of the wall panel to be built.

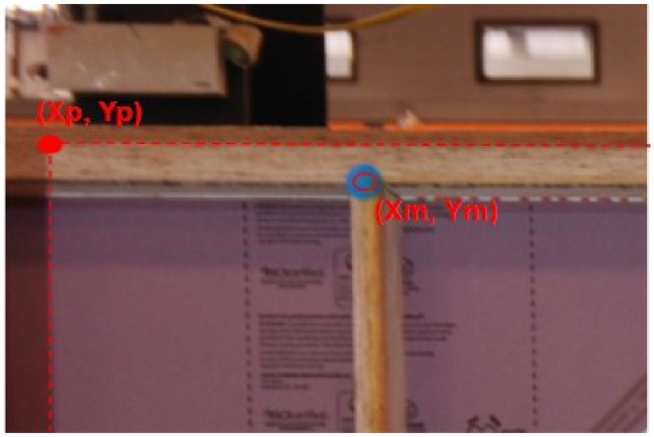


Figure 23 Marker coordinates adjustment

3.5.5. Performance evaluation

Through both laboratory and field experiments, the accuracy of the proposed projection alignment process is evaluated. The accuracy is measured by estimating an offset distance from the center of a marker to the corner of the projected area as presented in Fig. 24c. This method, which takes measurements of offset distances between a marker and the projection area boundary, has been utilized to quantify the level of accuracy in previous studies (Besharati Tabrizi and Mahvash 2015; Wen et al. 2013). In the present study, a Cartesian coordinate measurement template (Fig. 24a) is superimposed over the image, which is taken after the image projection (Fig. 24b), and an offset distance is measured from the template (Fig. 24a). In Fig. 24c, point A represents the center of a marker in a pixel coordinate, and point B represents the corner of a projection area. The coordinates of markers are acquired using the polar coordinate template to mark points A and B. After the acquisition of the offset distance in polar coordinates, the actual offset distance in mm is calculated using Eq. (7), where R represents the radius of the marker in mm and C represents the distance from the center of marker A to point B in the template with a distance range of 1 through 6 as presented in Fig. 24a. Since the radius of the marker is a constant value and can easily be measured using a ruler during the experiment, the only variable in the equation that is required to be checked in each experiment is the offset reading (point B in Fig. 24c) from the template.

$$offset\ in\ (mm) = R * C \div 6 \quad (7)$$

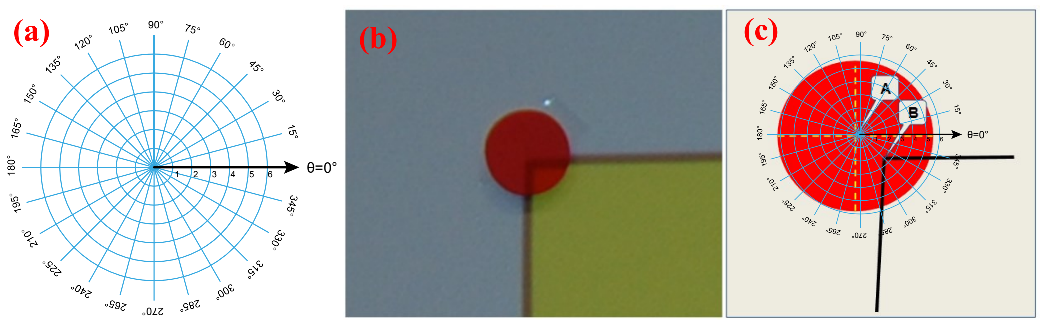


Figure 24 (a) polar coordinate template; (b) example of actual projection; (c) offset measurement using template

3.6. GPS data analysis for transportation equipment

GPS data analysis is performed in order to gain an intuitive understanding of the raw GPS data by abstracting key information (e.g., transportation demands), which is then used for building a machine learning model for the transportation demand prediction in this study. In general, GPS data is considered large scale because a single GPS data transmitter can create over 10,000 data points per month based on a 2-minute data interval, and because, in construction, multiple trucks are usually operating simultaneously. For example, in panelized construction, as shown in Fig. 25, 45,000 GPS data points (a single GPS data per row) from the transportation operations of 13 residential projects can be generated from five operating trucks. From these datasets, transportation demands for each project are extracted through the proposed methods including a structured query language (SQL) query, geo-fences, and the rule-based algorithm. These abstraction processes can allow for reducing the time and effort required to understand the GPS data, as well as for encouraging the utilization of the GPS data (Hildreth et al. 2005). In addition, through the GPS data abstraction, different outputs such as driver speeding and hard-braking situations, the frequency of potential collisions between different equipment, and ratio of idling to moving can also be collected. Therefore, accurate GPS data processing is important to generate transportation demands as well as to make it possible to apply GPS data for other purposes.

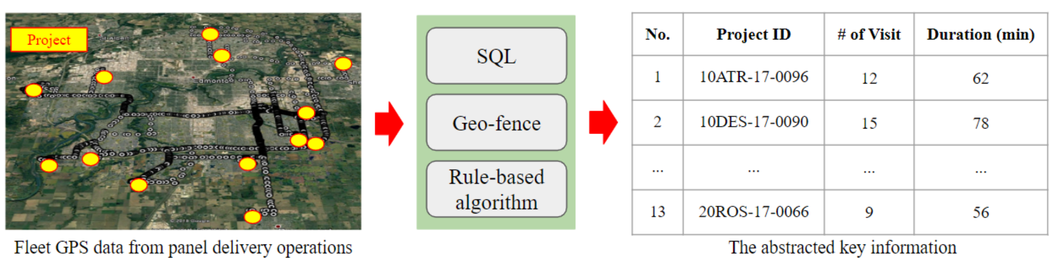
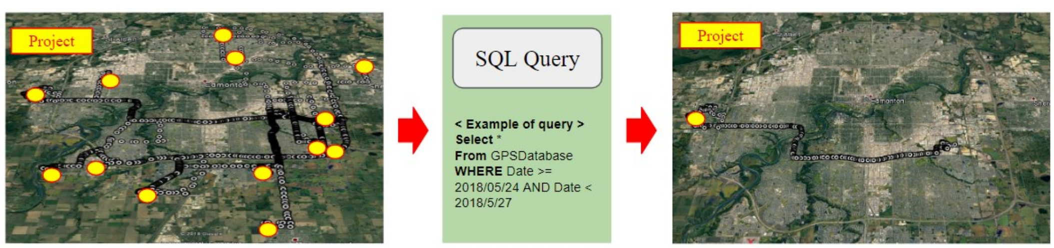


Figure 25 Example of the GPS data analysis (abstraction) processes

3.6.1. GPS data querying and the geo-fence setup

Since the collected raw GPS data contains many different projects over time in various locations, the large volume of data can negatively affect the accuracy of data processing due to multiple projects in an adjacent area. To resolve this issue, the SQL query and the geo-fence are utilized to reduce the volume of the relevant GPS data through information retrieval and to recognize GPS data points only related to a targeted project. In these processes, it is assumed that all projects have information on a starting and finishing date and a location (i.e., address) as such data can be easily acquired from project specifications and documents.

To perform the date query in the database where a historical GPS dataset is stored, the acquired project start and finish date information is applied to reduce the volume of the GPS data, as shown in Fig. 26. When applying the date query, the GPS data that satisfies the queried date range will be filtered as a result. Unlike in Fig. 26 where a single project is shown as a result, the results may contain multiple projects. In this case, another GPS date filtering condition is required to accurately determine the GPS data points for each project, and the geo-fence can be applied to improve the GPS data filtering accuracy.



Example of the entire GPS database

Filtered GPS data by date range

Figure 26 Example of the GPS data reduction by using the SQL query

The concept of geo-fence (Reclus and Drouard 2009) is adopted to check the status of transportation equipment in specific locations, such as a panel fabrication shop or construction sites. The geo-fence can be considered an imaginary fence on a map where the specific area or the area of boundary is defined by multiple GPS coordinates (e.g., latitude and longitude). The shape of the geo-fence can be varied (e.g., square, trapezoid, or diamond) based on user preference, and in this study, a circular shaped geo-fence is applied because of its advantages in determining equipment status (e.g., inside or outside of a geo-fence); namely, the circular geo-fence, because of its shape, can provide more consistent detection of equipment status compared to the other shapes. To set up the geo-fence, a center location and a radius of the geo-fence need to be determined. For the center coordinates, a construction project address can be used as the center point, and a GPS coordinate of the project address (e.g., street address) should be converted to GPS coordinates by using a geo-coding conversion process. One of the popular geo-coding service providers is the Google Maps API, which requires an http protocol in order to return the latitude and longitude of the street address. Once the center location of the geo-fence is determined, a radius of the geo-fence is also required in order to establish the boundary of the fence. As shown in Fig. 27, the virtual circular boundary (red dotted line) on the map presents the geo-fence applied area based on the user-defined radius of the fence, and in this study, a graphical user interface (GUI) is developed to get the user-defined radius and apply different radiuses (e.g., 50 m, 100 m, 150 m, 200 m, and 250 m) to find out the most accurate geo-fence setting. Once the center coordinates and the radius of the geo-fence are acquired, the status of transportation equipment can be determined by calculating a distance between the center of the geo-fence and the equipment.

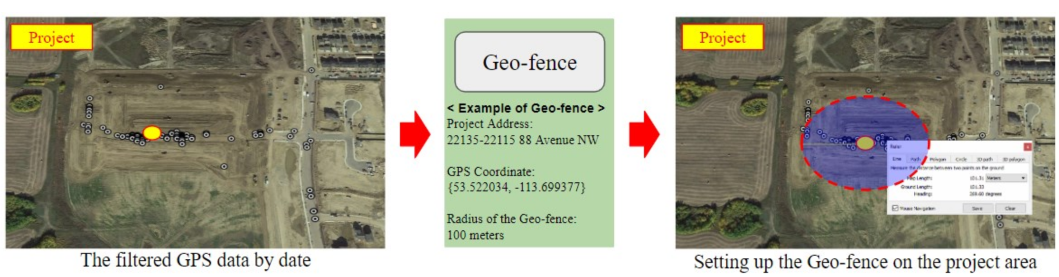


Figure 27 Example of the geo-fence set-up by using a project address and a radius

The Haversine equation shown in Eq. (7) (Sinnott 1984) is utilized to calculate the distance between two GPS points on a map as shown in Fig. 28. In this study, the two points are represented by the locations of the residential project and the transportation equipment, respectively. For example, when the user defines the geo-fence radius as 100 m, if the distance between the two GPS point is less than 100 m, then the status of the transportation equipment will be determined as inside of the geo-fence. On the other hand, if the distance is greater, then the status will be outside of the geo-fence.

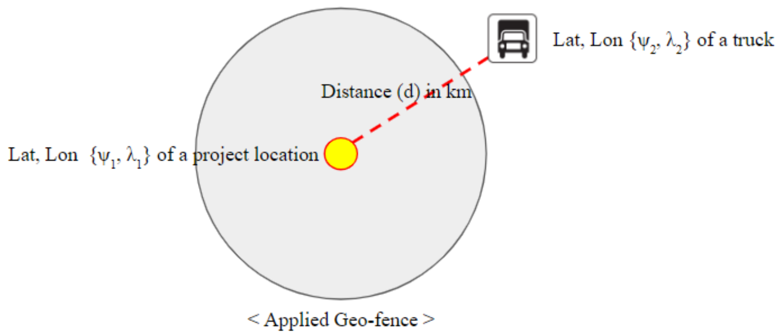


Figure 28 Haversine equation and its variables

$$d = 2r * \arcsin\left(\sqrt{sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right) \qquad \text{Eq. (7)}$$

	Description
d	Distance (km) between two GPS coordinates
r	Radius of the Earth (e.g., 6,371 km)
D	Distance between factory and site (km)
φ	Latitude
λ	Longitude

3.7. Application of machine learning in an input analysis

To develop a transportation cost prediction SVR model, the input data (training data) is prepared by combining the previously calculated transportation demands from existing projects with the detailed project specifications. The SVR is one of the supervised learning algorithms used for performing regression analysis instead of classification, as in the case of a support vector machine (SVM). Unlike the SVM, the SVR seeks to identify a hyperplane that is located as close as possible to all data points by setting up a threshold. Previously, the SVR has provided accurate prediction performance in various areas (e.g., stock price, weather forecasting, cancer diagnosis) including cost prediction (Suganyadevi and Babulal 2014), and it has shown its advantages over the popular multilayer neural network approach in the global optimum solution, robustness to outliers, and accurate and rapid prediction results in small sets of data (Pedregosa et al. 2011). The detailed project specifications are acquired from the project documents, such as drawings and contracts. As shown in Table 3, information is selected based on potential impacts on transportation costs for a total of eight different projects. For example, in the case of the building type, each building type (e.g., attached garage, detached garage, duplex), has different impacts on the transportation demands due to the differing total areas, design features, and models.

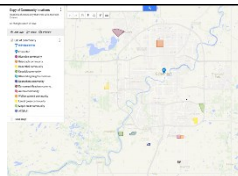
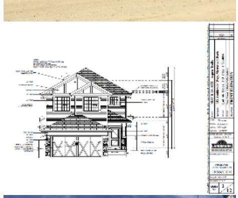
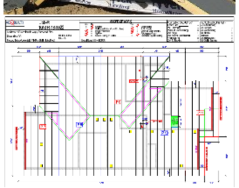
Table 3 Example of the input data for training SVR models

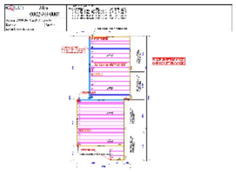
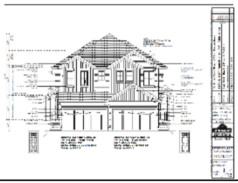
Inputs											Outputs	
Project#	Community	Wall area	Floor area	Model	Roof-Type	Roof Count	Deck	Stair Cage	Veranda	Building Type	# of Trailer	Duration in min
1	Walker Summit	1212	2705	Boston National Railroad A 9Mflr	Shop-Built	7	1	0	0	Attached garage	12	65
2	Desrochers	1230	3286	Tokyo Craftsman A OpnBe 9Mflr	Site-Built	6	0	1	0	Detached garage	15	77
3	Aspen Trail	1230	2942	Prague Craftsman B 9Mflr Stone Ens	Shop-Built	11	1	1	0	Duplex	7	48
…	…	…		…	…		…	…	…	…	…	…

The selected attributes are (1) type of community, (2) total wall area, (3) total floor area, (4) house model, (5) roof-type, (6) roof count, (5) deck, (6) stair cage, (7) veranda, and (8) building type. The community includes different residential areas where each residential project is found. Each community is unique in its location, environment (e.g., mature versus new neighbourhood), and type of house. The wall and floor area are estimated areas based on 2D CAD drawings. The model represents a different base design of house that does not include any design options, and this information can be used to determine minimum transportation demands for each project. The roof type shows the different build-type and dimension of roof. Depending on the site condition, a roof can be either pre-built or site-built to satisfy schedule constraints. The roof count is the number of sub-components that require delivery to site. The deck, stair cage, and veranda can be varied on each residential project based on the customer’s requests or designs, and the attributes represent how many deck, stair cage, and veranda are used in a project.

The building type attribute may include single detached or attached garage house, or duplex. Detailed descriptions of the selected attributes are shown in Table 4.

Table 4 Description of the selected attributes

No.	Attribute Image	Attribute Name	Data Type	Data Range	Misc.
1		Community	Categorical	17 unique	List of residential communities throughout a city
2		Wall Area	Numerical	Continuous	Total wall area in sq ft
3		Floor Area	Numerical	Continuous	Total floor area in sq ft
4		House Model	Categorical	154 unique	List of different model types
5		Roof Type	Categorical	2 unique	Two different roof types
6		Roof Count	Numerical	Discrete	Number of roof components
7		Deck Count	Numerical	Discrete	Number of deck components
8		Stair Cage Count	Numerical	Discrete	Number of stair cages

9		Veranda Count	Numerical	Discrete	Number of veranda components
10		Building Type	Categorical	3 unique	Type of building (e.g., detached and attached garage house, duplex)

After the input data acquisition from the GPS data analysis and the project documents, data pre-processing steps are required to improve the predication accuracy of SVR model. Among the selected attributes, different data types (e.g., categorical and numerical) are included, and the categorical data types, such as house models and types, should be converted to numerical types in order to train SVR models. To perform the data type conversion, one-hot-coding (Pedregosa et al. 2011) is applied to the categorical data to convert it into numerical data format. This method creates an individual data column for each data category and assigns 1 or 0 based on the original data. For example, in case of the house type, three additional data columns (e.g., detached and attached garage house, duplex) are added to the conversion. For the numerical data types, they also require the pre-processing step to normalize (e.g., Z-transformation) the numerical data into the same scale (0 to 1). Once the pre-processing is completed, the data is divided into training and test sets by a ratio of 8:2 respectively. To determine the most accurate SVR model, three different kernels, such as a linear, poly, and radial, are applied to the data set. For validation purposes, the 10-folds cross validation is adopted, which splits data into 10 equal datasets and then uses each one set as a testing dataset while the other 9 sets are used for training (Refaeilzadeh et al. 2009). In addition, the parameters (e.g., gamma and C) of each SVR model are optimized by using the grid search method (Pedregosa et al. 2009) along with cross validation as in Table 5. During the grid search, a range for each parameter should be defined and the exponential growth sequence is selected based on the recommendation from the previous grid search study (Hsu et al. 2003). Once the parameters are optimized, new project data are entered into the models to predict transportation demands while monitoring how closely the predicted demands are estimated from the actual values. To measure deviations from the actual values, the three performance evaluation measures, such as the mean absolute error (MAE), the root-mean-square error (RMSE), and the coefficient of determination (R-square), are applied to find the best models. The development of the SVR models are written in Python using the Scikit-learn library (e.g., GridSearchCV).

Table 5 Parameter ranges for the grid search processes

Kernel Type	C	Gamma (γ)
Linear	[1,10,100,1000]	N/A
Polynomial		
Radial basis function (RBF)		[0.001, 0.01, 0.1, 1, 10, 100, 1000]

3.8. Transportation cost estimation and comparison

The transportation cost estimation processes are presented in Fig. 29. The process consists of two steps: (1) new panelized construction project data is entered into the developed SVR model to predict transportation demands; and (2) the transportation unit's cost per time (hour) and distance (km) are applied to the predicted demands to estimate a transportation cost of the new project by using Eq.

(8). The equation considers both traveling and idling situations that transport trucks often face during deliveries. The distance (d) between a factory and a construction site is calculated by using Google Maps. To validate the accuracy of the estimation results, the results are compared against actual transportation costs.

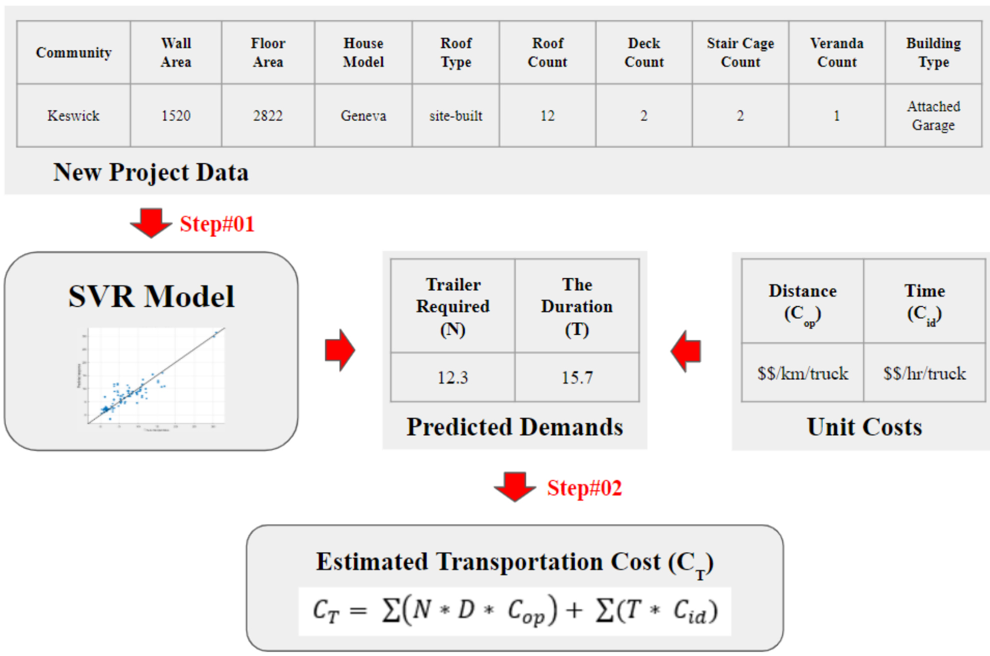


Figure 29 Example of proposed transportation cost estimation processes

$$C_T = \sum(N * D * C_{op}) + \sum(T * C_{id}) \tag{8}$$

	Description
C_T	Total transportation cost, in CAD
N	Predicted number of truck visits
D	Distance between a factory and a site, in km
C_{op}	Unit operation cost, in CAD/km
T	Predicted duration of stay, in hr
C_{id}	Unit idling cost, in CAD/hr

3.9. Development of the Fleet-dispatching schedule optimization model

Prefabricated home construction is a relatively new construction method where a prefabricated wall, floor and roof panels are built in the factory and shipped to the site for installation. As the majority of the work takes place in a factory environment, this method produces a much higher quality with less environmental impact. Compared to modular construction, the panelized system can adapt to suit different types of architectural design due to its panelized nature (two-dimensional production of wall and floors). However, panelized construction requires more coordination in terms of operational logistics, as the wall, floor, and roof panels can be in different areas of the plant at a different time and are needed on site at different times according to site assembly sequences. In modular construction, on the other hand, each module is produced and dispatched to the site in a linear manner. As shown in Figure 30, in a prefabrication facility, wall, floor, and roof panels are produced as per the production schedule and loaded into different trailers. Then, based on the site crane schedule, these trailers are dispatched from the plant accordingly. Once the site installation is complete, truck drivers go to the site and bring the empty trailers back to the plant.

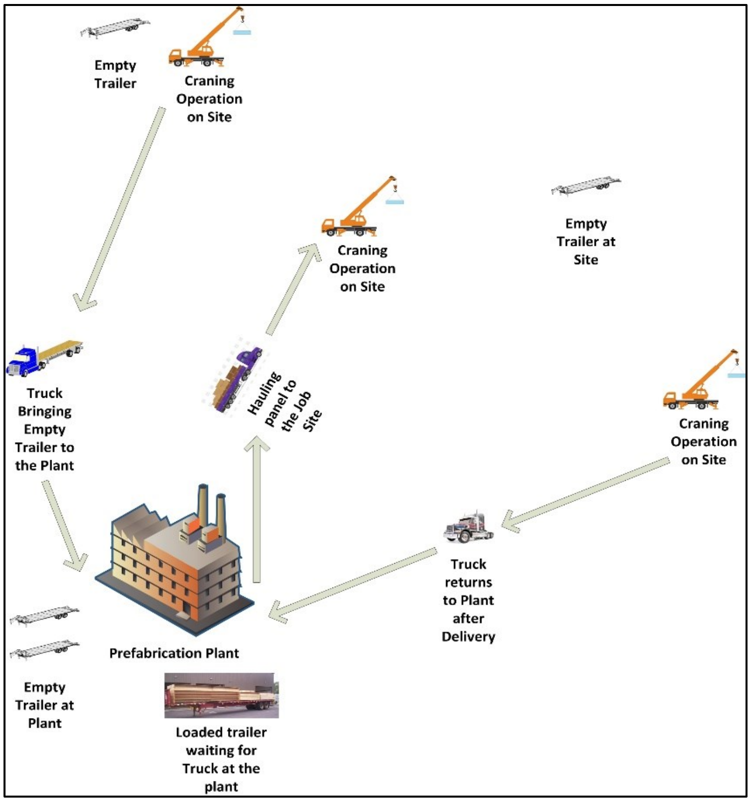


Figure 30 Logistics operation of the prefabricated home production process

Current trailer operation practices in panelized construction mainly focus on delivering panels to site to achieve high crane productivity, and due to site-focused operation approaches, the offsite panel fabrication facility needs to hold the production line until empty trailers are available. Also, to locate empty trailers at sites, current practices rely on phone calls or text messages between drivers and factory operators, which can potentially lead to inaccurate and inefficient communications between workers. The logistics operation for panelized construction is a complex system with multiple job sites, multiple truck drivers, and empty and loaded trailers in the plant and other job sites. All these different factors make it difficult to optimize a trailer dispatching schedule that is generated and updated manually.

As applications of information technologies (IT) are being increasingly used in the construction industry (FIATECH 2011), a smart device (e.g., iPhone) application based construction data have been used in a discrete-event simulation (DES) model to improve the accuracy of the master schedule (Song and Eldin 2012). Using the smart device with advanced data collection such as GPS and QR code, workers and drivers can provide accuracy operation conditions from both the factory and job sites for developing DES model as in Figure 31, and the model can provide an optimum dispatching schedule based on comparisons between all possible choices using a heuristic algorithm approach. To validate the model, the panelized residential project is selected and compared with actual operation processes with outcomes from the model.

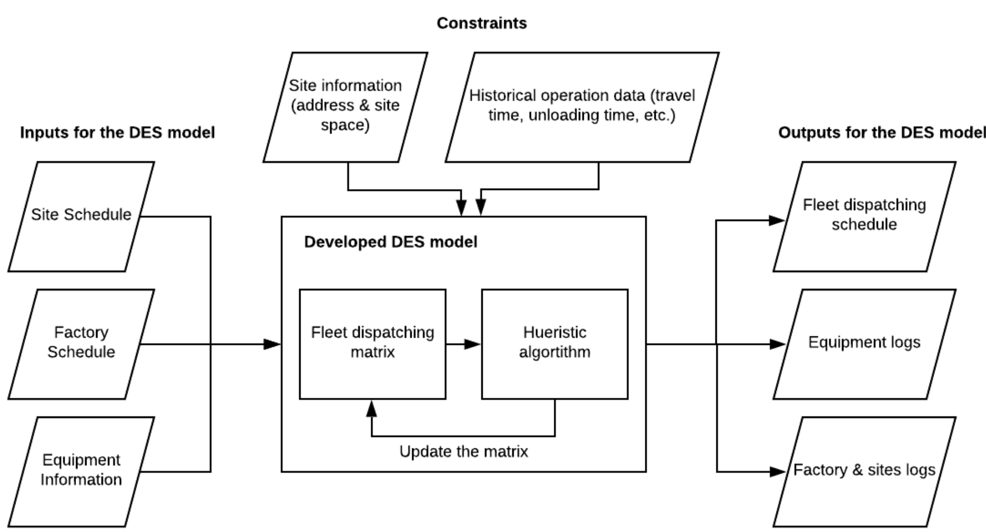


Figure 31 Overview of the proposed fleet-dispatching DES model

3.9.1. Fleet-dispatching DES model overview

The proposed fleet-dispatching DES model (Fig. 31) consists of four main modules as follows: (1) inputs for the model such as schedules, (2) the model constraints that reflect dynamically changing transportation operation environments, (3) the fleet-dispatching decision-making processes that optimize truck dispatching, and (4) the last module provides results from the developed DES model. Basically, the pre-defined factory and site schedules with equipment (e.g., truck, trailer, and mobile crane) information are entered into the model to find out an optimum fleet-dispatching schedule, while considering such given constraints as information delay, site layout, distance, travel time, unloading time, etc. During the simulation processes, a truck's availability is consistently checked in every second to assign the next optimum decision for the truck to improve overall equipment utilization, lead time, and transportation costs. The following section will discuss more details pertaining to each introduced module (1-4) above.

3.9.2. Fleet-dispatching DES input data

Three types of information are required as input for the DES model, namely site schedules, factory schedules, and equipment information. First, the site schedule data presents a required panel delivery time where a site manager usually has a tentative delivery time for both truck drivers and crane operators. The site schedule data has three columns with a unique site ID, panel ID, and delivery time. For example, as shown in Fig. 32, if the schedule data shows Site_A with panel ID of the W1_A by 8:15 am, then a truck driver needs to pick up the specific panel to perform a delivery to Site A by 8:15 am. Next, the factory schedule is similar to the site schedule, but it requires an empty trailer from project sites. Since the factory production lines need to have a consistent supply of empty trailers to maintain high productivity, the empty trailer supply is the critical part of the operation for the offsite construction facility. The factory schedule data also has three columns with a production line ID, the number of empty trailers required, and a delivery time. Lastly, the equipment information contains equipment ID, location, availability, and next available times for trucks, cranes, and trailers. For the equipment ID, each equipment has own identification code so that all activities can be tracked by equipment. The current location is where a piece of equipment is located; as the simulation is running, locations will be updated based on the assigned schedule. The availability of equipment is used to find out which equipment is available for the next upcoming delivery, and once the next delivery schedule is assigned to the available equipment then both availability and next available time are updated for next dispatching analysis. For example, as in Fig. 32, if the Truck02 is assigned a delivery to the Site A by 8:35 a.m. then the availability is changed to "No" and the next available time is assigned with the delivery time.

SITE SCHEDULES

Site ID	Panel ID	Schedule
Site_A	W1_A	8:15am
Site_B	R1_B	8:30am
…	…	…
Site_C	F3_C	8:10am

FACTORY SCHEDULES

Shop ID	Empty Trailer	Schedule
Roof	1	7:00am
Floor	1	10:30am
…	…	…
Wall	1	2:40pm

EQUIPMENT INFO

Equipment ID	Current Location	Availability	Next Available time
Truck01	Factory	Yes	TBD
Truck02	Site_A	No	8:35am
…	…	…	…
Truck05	Site_C	Yes	TBD

-The site schedule and factory schedule present loaded and empty trailers delivery time, respectively.

- The equipment info presents current equipment status.

Figure 32 Input data to the DES model

3.9.3. Fleet-dispatching DES constraints

The following constraints are considered in this DES model to simulate common obstacles that are faced in actual transportation operations of the panelized construction company. The common obstacles are (1) an information delay, (2) limited site trailer parking, and (3) serviceable area.

The information delay is a commonly occurring issue in construction projects, and its potential negative impacts are greater in panelized construction relative to traditional construction due to the fixed panel assembly order. For example, as shown in Fig. 33, the master schedule (the site and the factory schedule in this model) may not be fixed and could be changed throughout project operations due to unforeseen risks (e.g., weather conditions), which means the panel delivery schedules could be reported to truck drivers on very short notice. Since this constraint can frequently occur in practice, the DES model tries to determine the potential negative impacts due to various magnitudes of information delays.

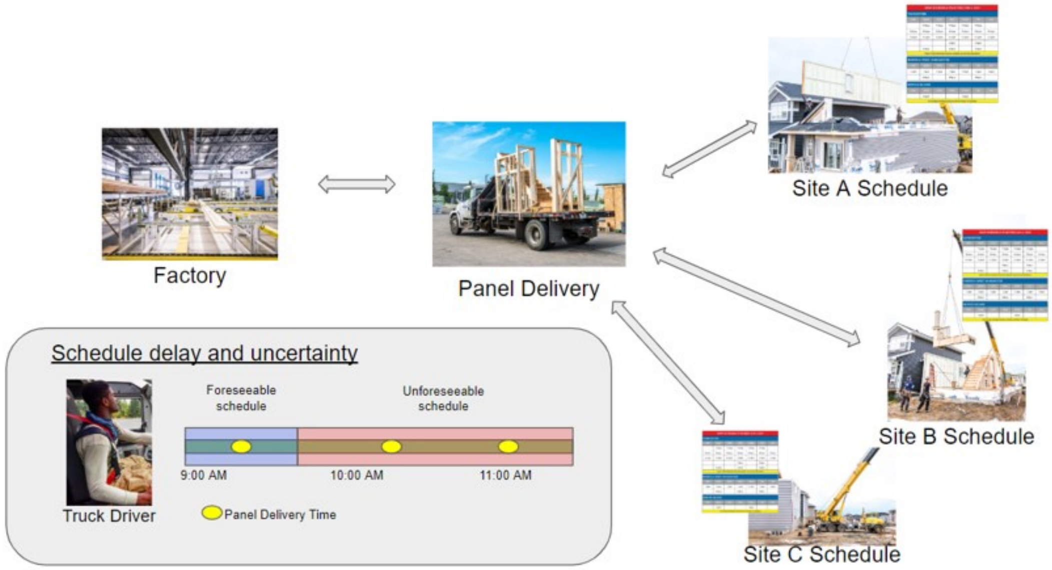


Figure 33 Information (schedule) delays in panelized construction

To evaluate the impacts from information delay in transportation operations in panelized construction, ten different time delay magnitudes are examined. From 0.5 hours up to 2.75 hours with 0.25 hour increments, each information delay is examined then its impacts are measured using the transportation key performance index to have an objective perspective on results.

The next constraint is the limited site trailer parking that allows only a limited number of trailers at construction sites due to limited available parking areas. As in Fig. 34, each job site can have a unique situation where the parking area can hold only a specific number of trailers. A certain site may hold one only trailer at a time, while other sites may hold more than one trailer, even up to 5 or 7 trailers. Sites that can hold a larger number of trailers have a buffer that provides flexibility to both truck drivers and crane operators. However, for the site with one trailer parking space, it does not have the buffer meaning trailers should be supplied and removed from the site on-time, otherwise, the site operation can be stopped and this may cause significant schedule and cost impacts to the overall project. To simulate this constraint, the DES model uses a site-specific weight factor that can provide a different factor to reflect the limited trailer parking conditions. More details pertaining to the weight factor calculation will be discussed in following section.

Due to limited space on sites, trailer parking can be limited

Project ID	Address	Model	Site Capacity
30DSM-16-27	6511-57 Avenue, Dansereau Meadows, Beaumont, AB	Dubai 9Mflr Arts & Crafts A KW	3
10GLR-18-002	16012 – 13 Ave SW, Glenridding, Edmonton, AB	Vienna Heritage A 9 Mflr	2-3
…	…	…	…
20DES-19-081	1646 Davidson Green, DesRochers, Edmonton, AB	Paris Colonial A 9Mflr	TBD

Figure 34 Limited trailer parking constraints at project job sites

The last constraint in the transportation operation in panelized construction is the serviceable area. Since transportation equipment, especially trucks, require frequent round-trips to sites, different site locations in various areas would impact the overall transportation operation performance in cases where the distance from a facility is significantly long. However, current transportation planning has been managed manually based on the logistic dispatcher's past experiences and a serviceable distance or area has not been clearly defined. As a result, long distance projects required a high estimation cost in an effort to mitigate any unforeseen potential transportation risks during job execution periods. To clarify the current vague limitations of the serviceable area, this DES model incorporates various ranges in project distances to simulate and determine potential impacts with respect to transportation key performance index. To simulate the constraint, six different serviceable areas are examined by increasing distance by 10% on each run. For example, 0% to 60% increases in the serviceable areas are simulated to determine the corresponding indexes.

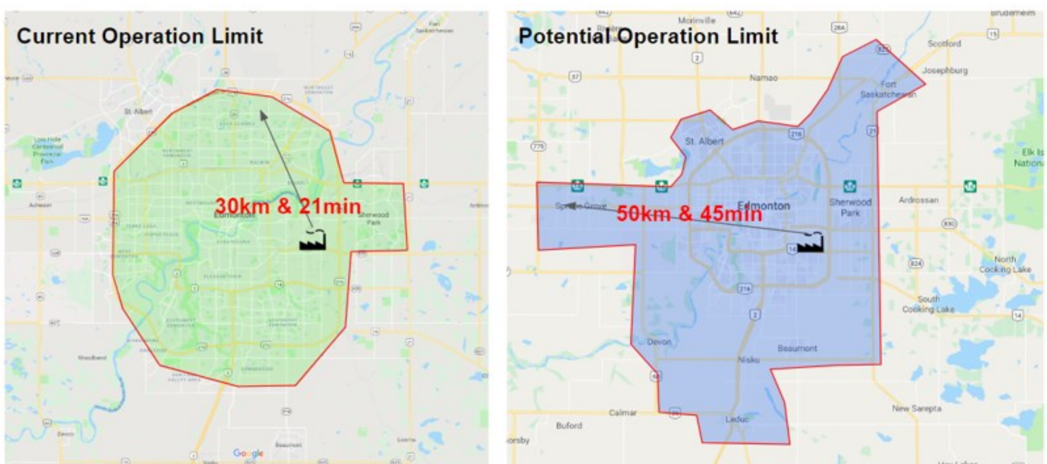


Figure 35 Serviceable area constraints in panelized construction

3.9.4. Matrix based fleet-dispatching decision-making processes

Once the input data for the DES model are entered with the constraints, two different matrices are calculated to perform heuristic optimization on the fleet-dispatching plan. As shown in Fig. 36, the DES model starts by checking for any available trucks in every one second increment to perform and assign loaded or empty trailers to the available truck. If there is an available truck at a given moment, the DES model will calculate the matrix to determine the optimum decision at that given moment, otherwise if there are no available trucks then the model increases the time until it finds available trucks. To calculate the matrix, upcoming schedules (sites and factory) with potential operation durations and distances are used to calculate transportation costs for the matrix, and site-specific weights are included in the matrix to differentiate site operation priority. Thus, by combing (1) transportation costs, (2) distances, and (3) site priority factors to calculate the matrix, the decision-making algorithm is used to determine the optimum fleet-dispatching decisions as shown in Fig. 36. Since the three different elements have different levels of importance in terms of dispatching decision-making processes, the transportation cost is set as the most important factor with 70% of total matrix (e.g., maximum matrix event point = 1.0) and the other distance and the site priority are given 20% and 10%, respectively. Considering the limitations in previous transportation simulation studies where only durations were considered for decision-making processes, this study can provide more comprehensive considerations of entire transportation operations. Therefore, using the dispatching selection matrix with the decision-making algorithm, the DES model will optimize each decision while improving on-time delivery performance.

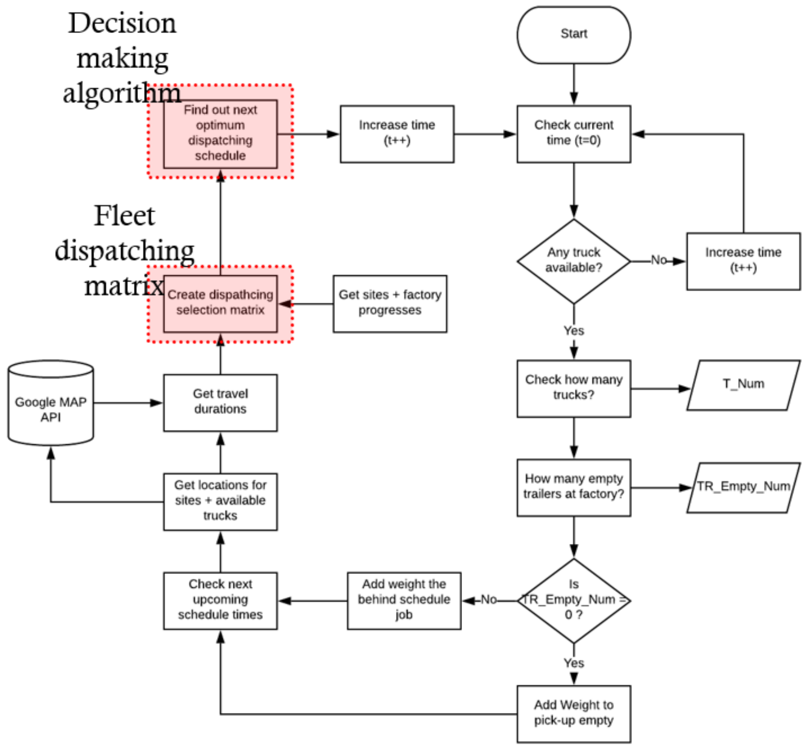


Figure 36 Detailed algorithm for fleet-dispatching DES model

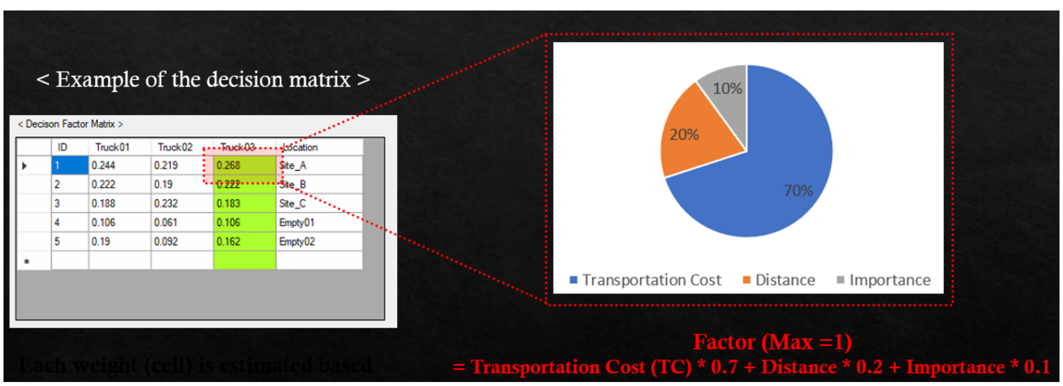


Figure 37 Fleet-dispatching decision-making matrix

Among the three factors in the matrix, the transportation costs require three element calculation processes to accurately reflect outcomes from potential dispatching decisions. The three elements presented in Fig. 37—travel time, truck unit costs, and potential waiting time—are the main contributors to the transportation cost. The cost can be calculated based on distance traveled, but considering truck idling times, the duration (cost per time) based unit cost is applied. First, the travel time presents a required duration to perform a delivery to a specific construction site, and this information can be acquired from the Google Maps API-based travel time estimation. However, the Google Maps API is currently based on passenger car travel duration rather than a commercial vehicle such as a truck; therefore, to improve the travel time estimation accuracy, the historical GPS data of trucks are analyzed to determine actual travel time to sites when they are located in newly developed areas. Next, the unit costs for mobile crane, truck, and factory production line are used with previously calculated durations to calculate the transportation cost. The calculation of the unit costs is discussed in previous sections.

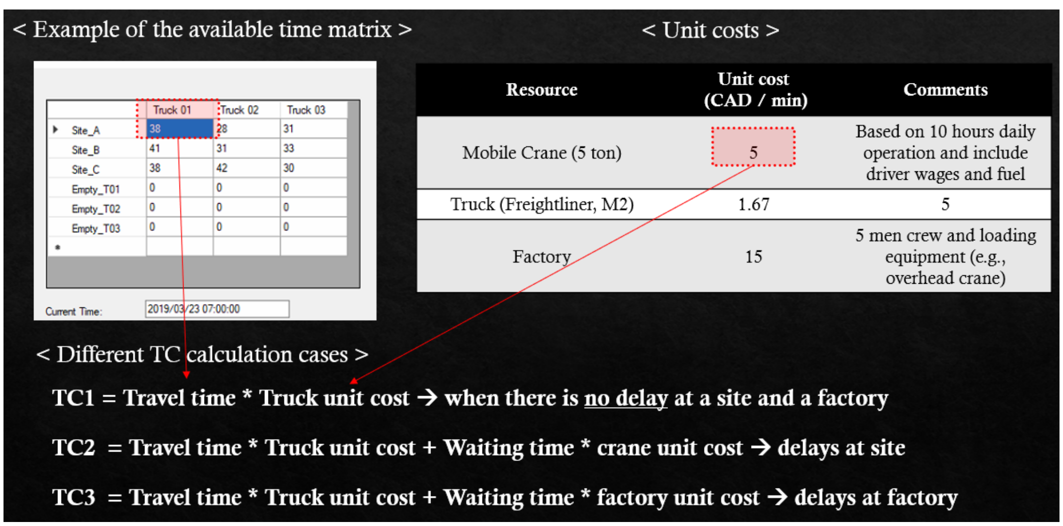


Figure 38 Transportation cost calculations for fleet-dispatching decision matrix.

Lastly, the waiting time is used to account for situations when potential delays occur due to either on-site crane operation or factory loading operations because of the late delivery of trailers. Delays are an inevitable issue in transportation operations in panelized construction, and it is important to consider the financial impacts these delays cause. To calculate the waiting time for equipment, the matrix-based available time calculation process is proposed as shown in the Fig. 38. Based on the provided schedule from the initial input, next upcoming schedules for both sites and factory can be calculated based on current time. For example, the current time is 8:00 am and the next delivery schedule at Site_A is 8:45 am, so the next event time will be in 45 minutes. By calculating time for all possible sites, factory, and trucks, the next event time matrix can be populated as shown in Fig. 38. Next, the execution time matrix needs to be calculated to determine the waiting time. The execution time matrix contains travel durations for all possible site and truck combinations as in the next event time. Based on the current location of equipment, the execution (travel) time is calculated based on the previously mentioned historical GPS data and the Google Maps API. Finally, the available time matrix can be calculated by subtracting the next event time matrix from the execution time matrix. Depending on the situation, the available time matrix could be negative or positive. Positive means that extra time will be available after completing the delivery; however, the negative number represents potential delays in delivery. For example, if the number is negative five (−5) then the time will be delayed relative to the assigned schedule. Thus, by calculating the three matrices, the waiting time can be calculated if the available time is negative. Also, if the negative number is estimated for site delivery then the crane unit cost will be applied to calculate transportation cost, and if the factory has the negative number then the factory unit cost will be used. Since the factory has more workers and equipment than site operations, the factory unit cost is highest.

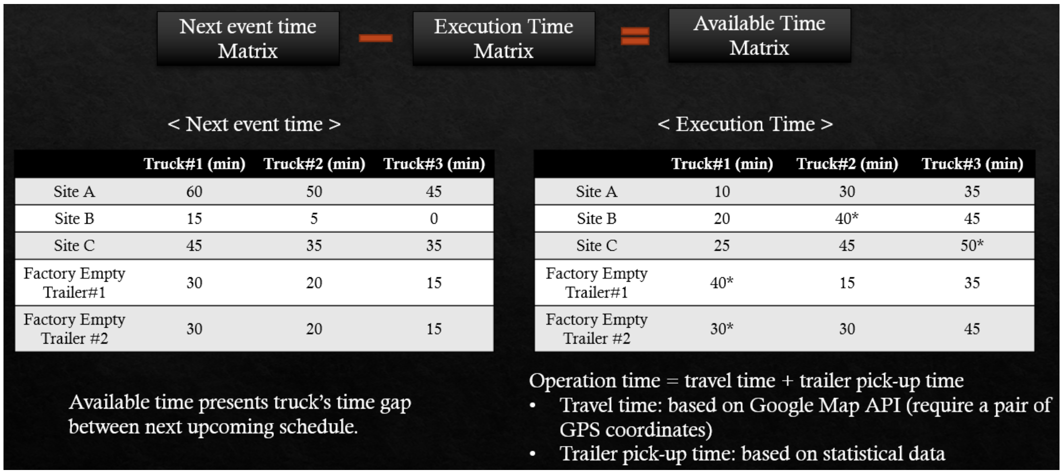


Figure 39 Available time matrix calculation process

3.9.5. Dispatching decision-making processes

As shown previously in Fig. 36, the DES model needs to determine a dispatching decision based on following a heuristic optimization approach to achieve on-time delivery, as well as improve overall transportation operation efficiency. Unlike the conventional DES model that follows given event durations, the developed DES model incorporates the heuristic greedy best-first search approach. Using the available time and the decision matrix, the DES model can make an optimum fleet-dispatching decision that considers all possible dispatching options. Since the applied heuristic approach consciously selects the event with the lowest value in the two matrices, each decision will continuously improve overall performance of the dispatching plan at the end of the simulation.

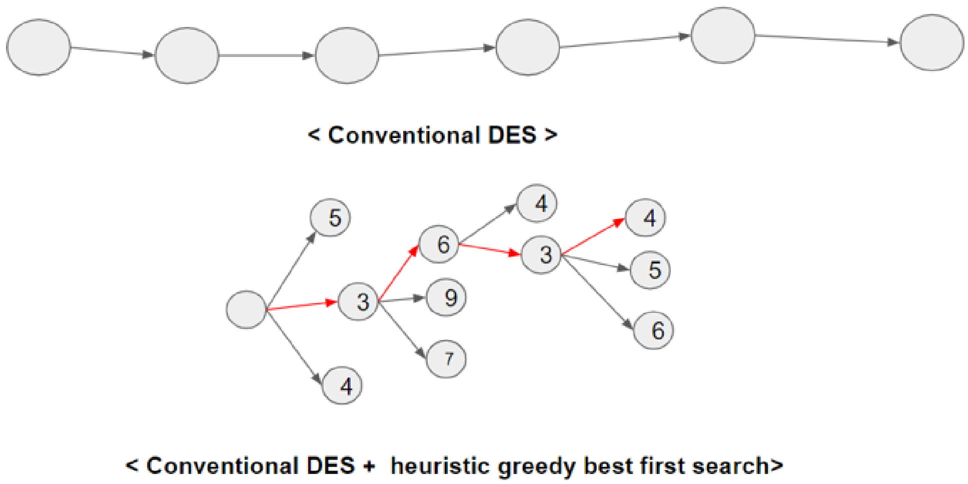


Figure 40 Comparison between conventional DES and heuristics greed best-first search integrated DES

As shown in Fig. 39, three different matrices are used to make a decision for dispatching. The left matrix is called the *available time until the next schedule* matrix that represents an available time until the next schedule on each site and factory based on the current time. For example, if the current time is 9 a.m. and the next schedule at Site A is 10 am, then $S_{A,01}$ will be 1 hour, or 60 minutes. The next matrix, called the *duration matrix*, represents expected times to perform the schedules. For example, to perform a panel delivery to Site A ($D_{A,01}$) it will calculate a potential travel time between Site A, the factory, and the current truck's location by using the Google Maps API, and it also includes estimated loading time when the truck picks up the trailer from the factory. Lastly, the final matrix, called the *difference between the times*, represents a difference between the previous two matrices. For example, for truck01 and Site A, $TD_{A,01}$ would be equal to subtracting $D_{A,01}$ from $S_{A,01}$. This difference shows the minimum time required for performing transportation operation tasks. Once the difference matrix is prepared, the next step is to determine optimum dispatching decisions, as shown in Fig. 41. If truck #1 is assumed as being the only available truck in this matrix, the truck #1 column is selected initially and the smallest number in that column is found. The negative number represents a potential delay in the schedule. In Fig. 41 the smallest number is −10 for picking up empty trailer #1. But, in the same row, truck #2 could do the same task without any delays. Thus, the picking up empty trailer #1 task would be better performed by truck #2. Then, in truck #1's column, the second smallest number is −5 for delivering a trailer to Site B. In the same row, truck #1 could better perform this task than the others, so the task is given to truck #1 in this case. Multiple trucks can be available at the same time, but in this study, it is assumed that only one truck is available at one time.

	Truck#1 (min)	Truck#2 (min)	Truck#3 (min)
Site A	40	20	10
Site B	-5	-35*	-45
Site C	20	-10	-15*
Factory Empty Trailer#1	-10*	5	-20
Factory Empty Trailer #2	0*	-10	-30

- * Truck's current location

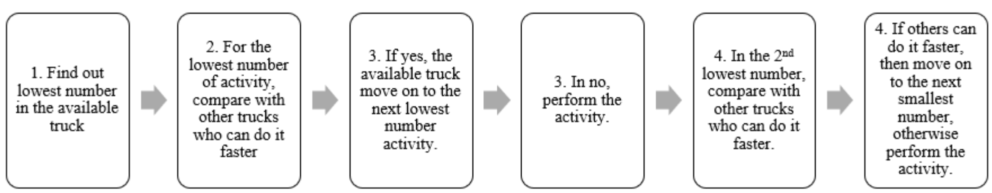


Figure 41 Fleet-dispatching selection processes (heuristic greedy best-first search)

Beside the heuristic approach for the fleet decision making, five additional rules as shown in Tables 6 and 7 are applied in this DES model to improve overall simulation operations, such as termination conditions and special situations.

Table 6 The DES model comparison excluding conditions

No.	Conditions
1	If the available time is greater than 90 min, the event is excluded for the comparison.
2	If the site is complete, then the specific site is excluded for the comparison
3	If the site has more than the allowable number of trailers, then the specific site is excluded for the comparison

Table 7 The DES model termination conditions

No.	Conditions
1	If the DES model running time exceeds the end time, then the simulation will be terminated.
2	If all project sites are completed, then the simulation will be terminated.

3.9.6. Transportation key performance indicators

Accurate performance measure in transportation operation is important to continuously improve operation efficiency (Chow et al. 1994), and this study adapts four commonly used performance measurement indicators in logistics operation and one industry (e.g., panelized construction) specific indicator (e.g., empty trailer return) is utilized to measure overall performance of the operation in panelized construction, as shown in Table 8.

On-time delivery is a measured as keeping the time window for deliveries. On-time delivery is a critical issue in the panelized and other offsite construction methods due to the high cost of mobile crane and the fixed assembly order. If a panel delivery is delayed, then the rest of the assembly processes cannot proceed until the prior assembly is complete. Thus, on-time delivery can be the single most important factor in panelized construction. The lead time presents an offset time from a schedule delivery time. This lead time provides a magnitude of the on-time delivery in that a positive time value indicates ahead of schedule, and a negative time value means a potential delay. The transportation cost is an especially important decision-making indicator for construction or transportation managers who try to reduce overall construction operation costs, but the transportation cost cannot be the single decision-making factor because the cost only reflects transportation aspects in panelized construction. Sometimes a high transportation cost can contribute to saving on overall operation costs at the end of the project. The equipment utilization is a popular indicator in the measurement of logistics performance in that it provides concise equipment operation information used to understand equipment operation efficiency. Ideally, 100 percent operation of all equipment would be desirable, but in practice, considering physical limitations, finding the maximum equipment utilization based on current resources would be beneficial for project managers. Lastly, the empty trailer return percentage is a new key performance indicator for the panelized construction operation. Due to the unique combination of two different industries, namely manufacturing and construction, transportation operations must satisfy both ends of operations (factory and sites) by supplying empty trailers for the factory and loaded trailers for the sites. Thus, for the factory side, the return percentage of empty trailers is a critical element that directly influences performance of the factory. Without the empty trailer, the factory cannot load the finished products and start a new product. Thus, this new indicator is included in this study to measure the overall transportation operation performance.

Table 8 Five transportation key performance indicators in panelized construction.

No.	Key performance indicator	Description
1	On-time delivery (%)	Assigned trailer is delivered to a designated site within the scheduled time window.
2	Average lead time (min)	A time gap between scheduled and actual delivery, Positive (+) means that an activity is performed before the scheduled time.
3	Transportation cost ($)	A cost dedicated to performing an assigned delivery
4	Equipment utilization (%)	Total operation percentage (%) of trucks, cranes, and trailers based on given working hours (e.g., 8 am – 6 pm).
5	Empty trailer return (%)	A percentage (%) of returned empty trailers back to factory (empty trailer retuned / total used trailer).

3.9.7. Fleet-dispatching DES outputs

Upon successful completion of the DES model run, each piece of equipment (truck, trailer, and crane), and the site and factory operation logs are generated to identify the optimum schedule from the model. Fig. 42 presents the structure of the logs where each activity is recorded per row with equipment ID, location, activity start and end time, duration, associated equipment ID, and previous location. For the fleet-dispatching plan, the truck logs are analyzed to identify the dispatching order.

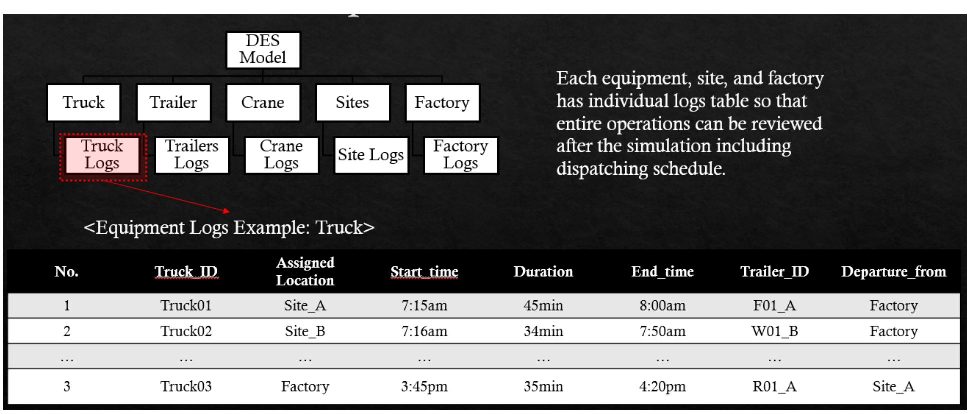


Figure 42 Outputs from the developed DES model

4. Chapter: Implementation and Case Studies

In this chapter, the implementation processes of the developed methodologies in the Chapter 3 are presented. To evaluate the developed methodologies, they are implemented in collaboration with an industrial research partner (Fig. 43) which is one of the largest and most advanced panelized residential construction company in North America. The transportation quality assurance method which utilized the projection-based AR is examined at wall panel production lines at the panel manufacturing facility, and the rest of the transportation data collections, transportation cost estimations, and fleet-dispatching schedule optimizations are applied in actual residential project to validate its performances.

Figure 43 Panelized construction facility and operations (courtesy of ACQBUILT, Inc.)

4.1. Transportation quality assurance (Projection-based AR)

The proposed framework for projection alignment is examined in both lab and field environments. In the lab experiment presented in Fig. 44a, accuracy of the projection alignment at various distances and levels of illumination is measured to determine the performance of the framework. Additionally, the field experiment presented in Fig. 44b is conducted as a proof of concept to validate the framework in a working environment as well as to determine any potential issues in practice. For performance evaluation, the results of projection accuracies and ANOVA tests are presented and analyzed in this section.

Figure 44 Experiment setup: (a) at lab; (b) at panel manufacturing facility

4.1.1. Equipment and experiment setting

This experiment utilizes four pieces of equipment as outlined in Table 9 to perform the proposed alignment. All equipment is selected considering minimal up-front costs, which may be a barrier for industry implementation (Van Krevelen and Poelman 2010). High-end equipment, such as a higher resolution projector, distortion-free lens, and faster processor, can also be considered to improve the accuracy and robustness. In the present research, the EPSON projector with 1,920 × 1,080 resolution and 3,500 lumen brightness is used. This projector is equipped with both the vertical and horizontal automatic keystone effect adjustment feature, and the feature is enabled throughout the experiment. A Nikon D80 camera with 10.2 MP sensor resolution is used to take the photograph. The level of ISO in the camera is set to 100 to minimize potential noise on the image. The Tamron zoom lens is used as an attachment to the camera, and the focal length is fixed at 30 mm to minimize image distortion according to the lens manufacturer. Lastly, a laptop with an i7 processor and 16 GB RAM is used to perform image processing.

Table 9 Summary of utilized equipment in experiment

	EPSON Powerlite 965	Nikon D80	Tamron Lens	HP Pavilion
Equipment	Home Projector	DSLR Camera	Lens	Laptop
Price	$899 CAD	$1,000 CAD	$300 CAD	$1,000 CAD
Major specifications	3,500 Lumen 1,920 × 1,080	10.2 MP	17-50 mm zoom lens	Intel core i7 RAM 16 GB

Two variables to be tested in this experiment include projection distance and level of illumination. The performance of projection AR at a distance of more than 3 m under various levels of brightness has yet to fully been examined for the various application areas (Zhou et al. 2011; Zhou et al. 2012; Besharati Tabrizi and Mahvash 2015). Additionally, the level of illumination is also a constant factor in previous studies where the experiments are performed in an indoor environment under artificial lighting sources. Therefore, in the present study, to determine any potential influences of distance and illumination levels on the projection alignment accuracy, the accuracy is measured in various conditions of distances and illuminations as presented in Table 10. In the lab experiment, four different distances with two different illumination levels are examined. For example, at a 5-m distance, projection alignment is repeated 40 times under each illumination level (e.g., low and high). The level of illumination is controlled by turning the artificial light sources on an off. In the field experiment, the projection alignment with an actual drawing is performed at a 7-m distance under a constant level of illumination; 7 m was determined to be the minimum distance to cover the height of a wall panel. The level of illumination remains constant due to the existing metal halide light bulb that is installed on the factory ceiling.

Table 10 Pre-determined inputs for alignment processes

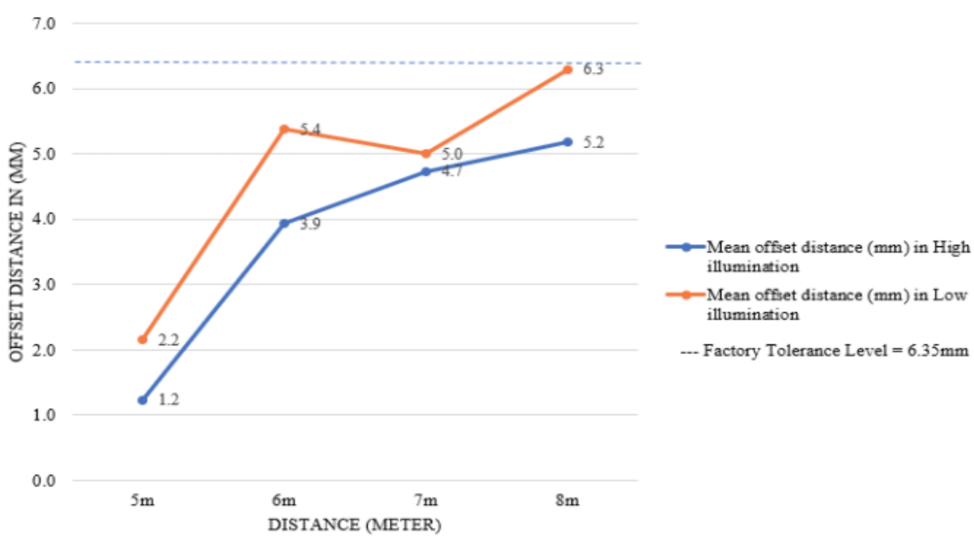
	Lab Experiment	Field Experiment
Distances	5,6,7, and 8 m	7 m
Level of illumination	With and without artificial lights	Under normal working environment
Number of repetitions	40 at each distance	8

Before each projection alignment experiment, four markers are placed within an area of projection. In the lab experiment, the markers are randomly located for each projection distance to verify projection alignment accuracy at different marker locations. In the field experiment, the markers are located at the point where a vertical and horizontal stud meet as per current practice (Fig 44b).

Aligned projection images are then collected using the digital camera. The image resolution is 3,872 × 2,592 in jpeg file type. Once the image is collected, alignment accuracy is further evaluated to record offset values.

4.1.2. Projection alignment accuracy

To assess the performance of the proposed projection alignment, the metrics outlined in Section 3.4 are used to analyze accuracy of the projection by measuring the offset distances. To understand the performance of the projection at each distance under different levels of illumination, the mean and standard deviation are calculated as presented in Fig. 45. The experiments are performed beginning with the nearest distance to the farther distance. The lowest projection offset distance is achieved at the shortest distance (at 5 m) for both low and high levels of illumination, respectively (M_{low} = 1.23, SD_{low} = 0.65; M_{high} = 2.15, SD_{high} = 2.87), and the highest offset is found at the longest distance (8 m) (M_{low} = 5.18, SD_{low} = 3.4; M_{high} = 6.3, SD_{high} = 3.84). The results also indicate that the accuracy is inversely related to the distance in general. As the distance is increased from the initial point at 5 m to the final projection of 8 m, the mean offset distances increase by 3.95 mm and 4.12 mm for high and low illumination, respectively. Overall, the mean offset distance does not exceed the factory tolerance level of 6.35 mm for all projection distances.



level of illumination		Dsitance			
		5m	6m	7m	8m
High	Mean (mm)	1.2	3.9	4.7	5.2
	SD (mm)	0.7	4.6	4.1	3.4
Low	Mean (mm)	2.2	5.4	5.0	6.3
	SD (mm)	2.9	4.1	4.9	3.8

Figure 45 Mean offset distance and standard deviation (SD) at different levels of illumination over the various distances.

Furthermore, the ANOVA test and T-test are applied to the offset distance dataset in order to understand the potential impact of the distance and illumination variables from a statistical perspective. In both tests, the level of significance (α) is set as 0.05. For the projection distance, the data set is divided into two separate groups with four different sub-groups based on the level of illumination and the distances, respectively. Considering the illumination as the independent variable, statistical significance of the projection distance is tested and the results are presented in Table 11. According to the ANOVA test, the distance is the statistically significant factor on the projection alignment accuracy since the P-values are smaller than the significance value in this test regardless of the level of illumination. Thus, it is concluded as statistically significant that a longer projection distance increases offset distances overall.

Table 11 Summary of ANOVA analysis on projection accuracy over distance change

Source of Variation	df (Between Groups)	F	F critical	P-Value (α = 0.05)
Distances in high illumination	3	9.84	2.66	5.53E-06
Distances in low illumination	3	7.83	2.66	6.64E-05

For the level of illumination, the T-test is applied to the data set to determine the statistical significance of the illumination on the projection alignment accuracy. Since the comparison is made between two groups, the T-test is used. Prior to the T-test, distribution of variances in both groups are examined using the F-test, and the results indicate that they have similar variance distributions. Considering the distance as the independent variable, the data is divided into two groups based on the level of illumination. The results are presented in Table 12; notably, the level of illumination is also a statistically significant factor on the projection alignment accuracy since the P-value is smaller than the significant factor. Consequently, these statistical results indicate that the high level of illumination reveals a smaller mean offset distance than at the low illumination level.

Table 12 Summary of F- and T-test analysis on projection accuracy under different levels of illumination

	Low illumination	High illumination
Mean	4.71	3.76
Variance	18.41	14.84
Significant value (α)	0.05	
T-Test, df	318	
T-Test, P(T ≤ t), one-tail	P(2.08 ≤ 1.65), P_Value = 0.02	

For field testing, the proposed projection alignment is conducted for a manual wall-assembly line at the case study panel manufacturing facility. The results indicate that the offset distance (M = 6.17, SD = 1.68) is greater than the lab experiment (M_{low} = 5.0, SD_{low} = 4.9) at the same distance (7 m) under low illumination. Although the lab tests offer better results for both illumination levels, performance gaps between the two environments are less than 1.3 mm, and such gaps could be acceptable in practice considering the factory tolerance level of 6.35 mm. Final overlay of the panel assembly drawing on the wall panel is presented in Fig. 46.

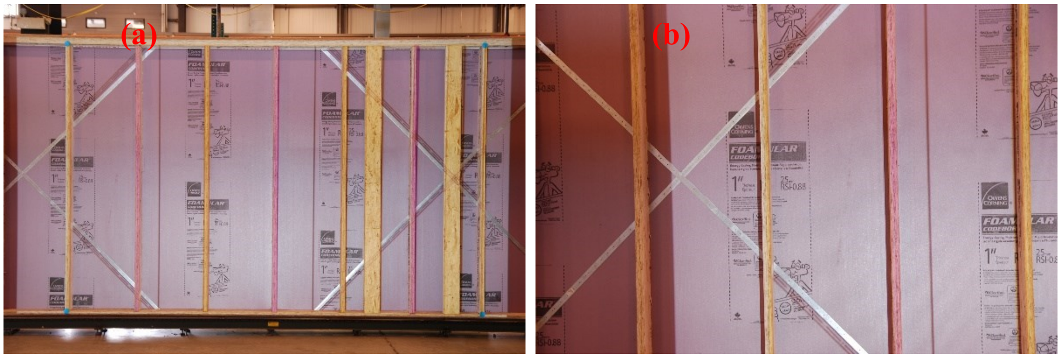


Figure 46 Projection of 2D assembly drawing on the panel: (a) zoom out view; (b) zoom in view

4.1.3. Summary

This research proposes and examines the automated projection alignment method to provide site workers with visual guidance for quality improvement in an offsite manufacturing facility. The experiment results imply that this approach can accurately provide drawing information to manual assembly workers in a large-scale manufacturing facility under limited conditions. As presented in Fig. 12, the mean offset distances are smaller than the tolerance level up to 8 m. It is statistically found that the offsets increase when the distances increase, while illumination conditions also affect performance of the proposed vision approach. The relationship between the distance and the error may be due to limited resolutions in the camera and projector. At 5 m, the diameter of a marker occupies 143 pixels, but decreases to 100 pixels when the projection distance increases to 8 m. Therefore, accuracy of marker coordinates can be reduced as a smaller number of pixels are covered by the markers during the segmentation and the blob analysis. Additionally, as the projection distance increases by moving the projector further from an object, a dimension of the projection area increases, but the total pixel number does not change. As a result, the size of each pixel increases as the projection distance increases, leading to enlargement of the line as well as reduction in sharpness of pixels. In this regard, it is possible to use equipment with a higher resolution in order to improve accuracy in long-distance projection alignment.

Projection-based AR has potential to be used in industrialized construction. The manufacturing process continues to involve a significant amount of manual work, but working environments can be easily controlled compared to outdoor environments on a jobsite. Due to the nature of manual work, quality issues can inevitably occur and should be minimized in order to successfully complete projects. Current quality control in the industry can be considered as passive: quality checks are performed after the completion of jobs. If workers are able to actively check and compare their work with a drawing as the tasks are being performed, then quality issues could be even further reduced compared to the current process. Previous studies on visualization of information in manual workplaces indicate that quality and productivity can be improved through visualizing information thereby reducing cognitive demands (Funk et al. 2015; Wang and Dunston 2006; Dunston and Wang 2005). Therefore, this proposed method can serve as a foundation for quality control study in the industrialized construction industry where the quality of prefabricated building components is critical. In addition, this proposed method offers clear benefits over other AR devices: (1) it does not require workers to hold or wear any specialized equipment while working, and (2) it is able to project information over the actual view of workers.

When the proposed method is applied in practice, the need for a longer projection distance and possible occlusions (e.g., worker's body or other moving objects) may be issues due to the limited space and task objectives in working areas. To this end, identifying appropriate installation positions for the projector can be a key to the implementation; on the other hand, the use of an advanced projector can also be considered to address such issues. For example, an ultra-short throw projector can be placed extremely near to an object, yet still providing coverage for a large projection area. Thus, different projector types should be examined to overcome issues due to the projector location. Also, the legibility issue has been identified during the experiment where the high illumination level washes out the projected drawing on the panel surface. A brighter projector will provide better legibility, but potential damage to eyes should be considered in case of direct exposure to such a high-intensity projector (Schulmeister and Daem 2016). For the limitations during the initial alignment processes, the selection of the marker colour can influence accuracy of the alignment so that the colour segmentation processes can precisely differentiate the markers from background.

4.2. Transportation demand and cost estimation

The proposed framework is implemented and assessed through a case study of a panelized residential construction company in Edmonton, Canada. The company mainly focuses on local residential construction projects, and on average 2 to 3 projects are executed per day, this rate being constrained by the availability of mobile cranes for on-site assembly operations. To deliver prefabricated panels to sites, the company operates 5 trucks with 50 flatbed trailers. For tracking purposes, each truck has an individual GPS transmitter with a location transmission to a cloud server at 2-minute intervals. For development of the reliable SVR model, GPS data from 221 residential projects was collected and analyzed for the transportation demands along with the project information, and all the residential projects were located nearby the city of Edmonton. A summary of the project data is presented in Table 13.

Table 13 Description of the residential project data

Attribute	Description
The number of panelized residential projects	221 projects
House types	Duplex:45, Detached garage: 50, Attached garage: 128
House models	27 different models
House size	Smallest: 1290 sq ft Average: 2113 sq ft Largest: 2732 sq ft
Community	11 different areas

For easier access and control of the collected fleet GPS data in the database, a simple graphical user interface (GUI) is developed as shown in Fig. 46a. Since the job name is the unique identifier in the database, the project's detailed information, such as community name, address, and others, can be accessed by performing database queries. For the radius selection, a user can choose different ranges between 50 m and 250 m from the center of the project location. In the case where the street address in a new community may not be available in the Google Maps API, manual GPS data input can be applied to provide GPS coordinates to the interface. To validate the accuracy of the calculated transportation demands, previous truck operation logs, shown in Fig. 46b, are used to compare against the calculated demands, as shown in Fig. 46c. Once the analysis of the residential projects is complete, the project information in Fig. 46d is combined with the results to create input data for training SVR models.

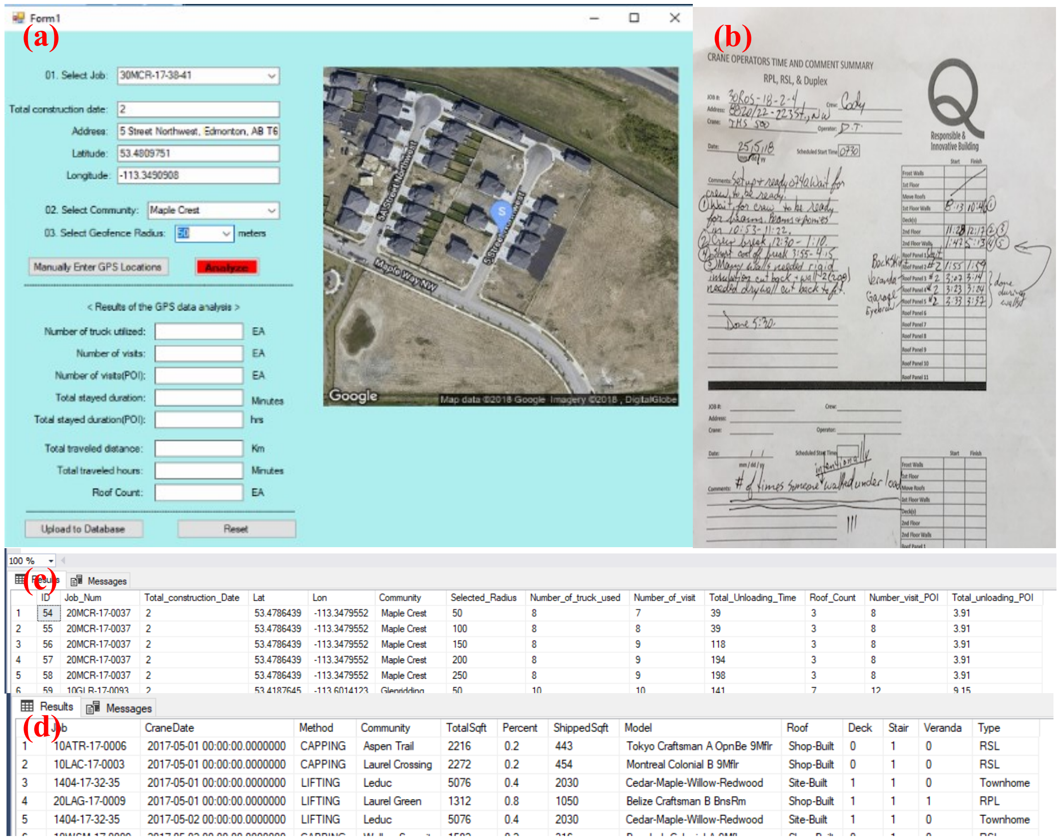


Figure 46 (a) the GUI for the GPS data access and analysis; (b) truck operation logs; (c) the results from the GPS data analysis; (d) the project-related information database

4.2.1. Transportation demands

To determine the accuracy of the proposed approach, outcomes (e.g., truck visit counts and durations) from the algorithm are compared against the actual demands from the truck operation logs that show the truck dispatching history on each residential project. In addition, different geo-fence radiuses were examined to determine the most accurate geo-fence setting. The comparison results are displayed in Fig. 47. The results showed that the smallest (50 m) geo-fence had the highest accuracy with respect to recognizing the number of visits on job sites. The average error for the 50 m geo-fence was 0.77 with 2.19 standard deviation. The largest radius, 250 m, resulted in the lowest level of accuracy with an average error of 4.29 with 3.02 standard deviation. For the unloading duration comparison shown in Fig. 10, the geo-fence with the shortest radius (50 m) had the best accuracy with the average error of −0.30 hours with 3.21 hours in standard deviation, and the largest radius again had the lowest accuracy among them with an average error of 1.84 hours and 3.34 hours in standard deviation. The main reason the reduction in accuracy with a longer radius was due to the recognition of picking up empty trailers from sites. For example, for the 250 m radius geo-fence, the visit counts falsely included activities such as picking up an empty trailer, passing through the site, and finding parking spots. These activities were identified as the main causes of the high error in the longer geo-fences radius. In addition, other potential reasons might include a situation where two projects were located close together, and this could cause a miscounting of the site visits.

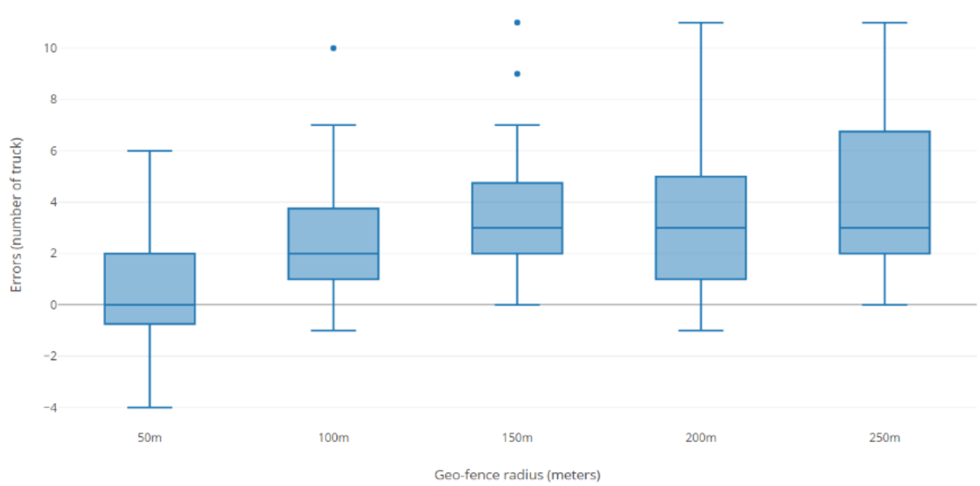


Figure 47 Truck visit accuracy comparison between different geo-fence radiuses

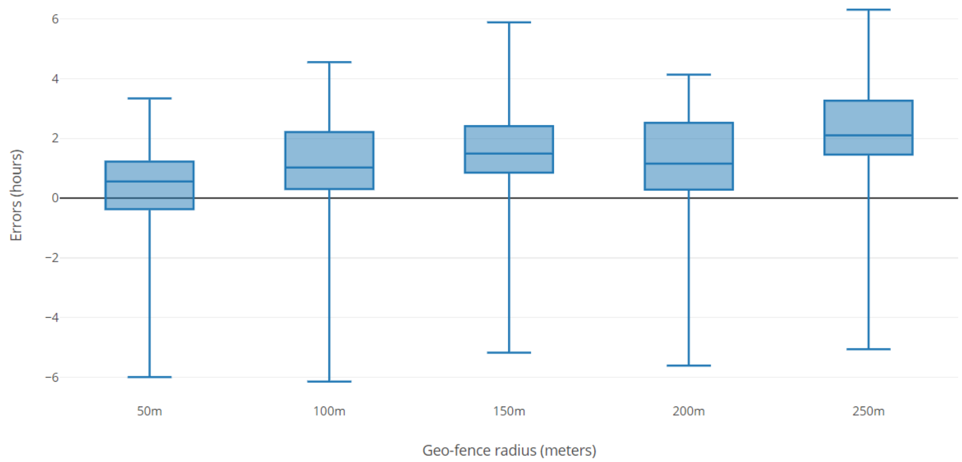


Figure 48 Unloading duration accuracy comparison between different geo-fence radiuses

Next, three different SVR kernels (linear, poly, and RBF) were examined for their ability to accurately predict transportation demands. In Fig. 48, the predicted visit counts and durations are compared against actual data. Both visit and duration predictions showed a good accuracy in lower ranges, such as 0 to 15 truck visits in the total visit plot and 0 to 5 hours in the duration plot. In the upper ranges, the prediction resulted in relatively inaccurate results (e.g., over or under-prediction) in both prediction cases. From the statistical point of view, both prediction results in Table 14 showed that the poly kernel had the best accuracy among other kernels. The total visit predictions using the poly kernel had a root-mean-square error (RMSE) of 2.86 with an R-square of 0.89. Since the difference between the RMSE and mean absolute error (MAE) is 1.18, the variances in the errors in the data are expected to be small and no significant error was identified. Moreover, for the unloading duration predictions, the poly kernel also had the best accuracy with a RMSE of 2.56 and an R-square of 0.88, and the difference between the RMSE and the MAE was 0.79. Thus, given these results, the MAE provides a better overview of the average difference between the predicted and the actual values. In addition, considering the magnitude of the MAE in both predictions, errors are not expected to cause any significant impacts on the overall transportation cost estimation.

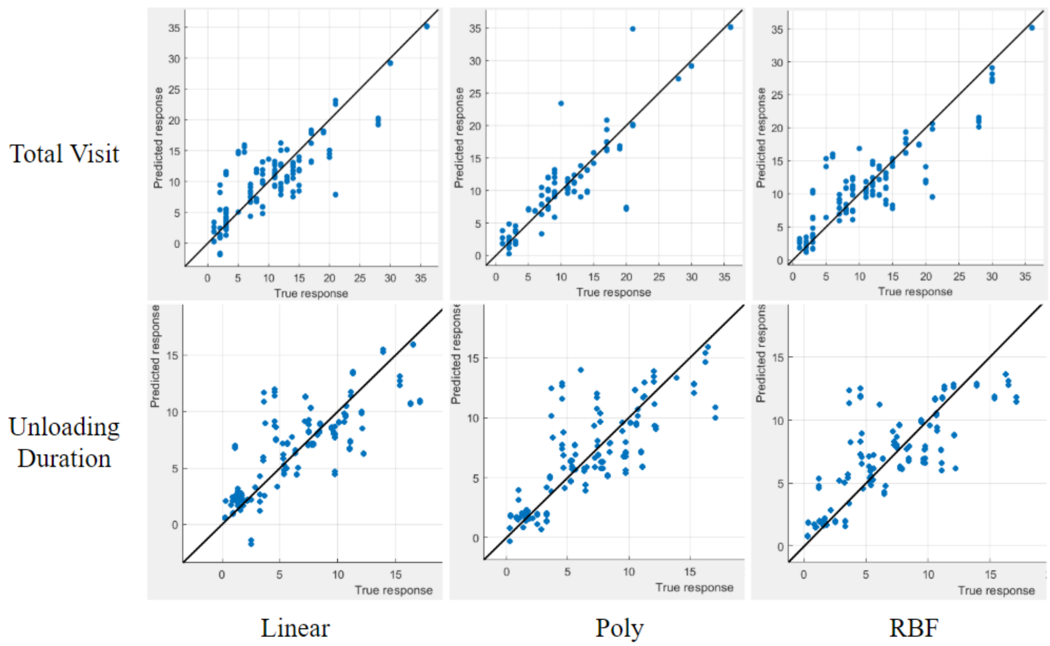


Figure 49 Predicted versus actual response plots for different kernel types

Table 14 Truck visit and duration counting conditions.

Method	Predictions	Linear Kernel	Poly Kernel	RBF Kernel
RMSE	Total Visit (Each)	3.77	2.86	3.46
	Unloading Duration (Hour)	2.71	2.56	2.84
R-Square	Total Visit (Each)	0.81	0.89	0.84
	Unloading Duration (Hour)	0.86	0.88	0.85
MAE	Total Visit (Each)	2.63	1.68	2.30
	Unloading Duration (Hour)	1.92	1.77	1.94

After the initial training, the three kernel types were optimized by using the grid search method. The ranges of parameters were given to the grid search to perform iterations to determine the most accurate model with the optimum parameters. The results of this parameter optimization are presented in Table 15. RBF was the selected as the most accurate kernel for both prediction models with accuracy of 86% and 88% for total visit and unloading duration, respectively.

Table 15 Results of optimizing parameters using grid search method

Predictions	Kernel Type	C	γ	Accuracy (%)
Total Visit (EA)	RBF	100	100	86%
Unloading Duration (hr)	RBF	1000	1000	88%

4.2.2. Transportation costs

The data for new residential projects were utilized to estimate the transportation costs and then compared with the actual transportation costs from the same actual projects. The fixed-cost-based estimation results were also compared against the actual cost to measure potential improvements in the transportation cost estimation performance of the proposed GPS-based estimation method. The comparisons were performed by calculating offset costs in percent error (%) from the actual operation data from truck logs, as shown in Fig. 50b, and the comparison results are represented visually in Fig. 50 where distances (km), house sizes (sq ft), and cost differences (%) are set as the *x*-, *y*-, and *z*-axes, respectively. To calculate cost estimation errors, differences between fixed cost and actual cost, and between GPS-based cost and actual cost, were calculated, and the results were then divided by the actual costs to determine differences as a percentage (%). The fixed-cost estimation is presented in Fig 50a, and the GPS-data-based estimation is shown in Fig 50b. In addition, the colours represent the amount of error over different distances and house sizes: the highest error percentage (e.g., over-estimation) is displayed as a yellow colour and the lowest (e.g., under-estimation) is displayed as a dark blue colour. The results show that the fixed-cost-based transportation estimation approach created over-estimations for different house sizes, and the over-estimation was especially higher for projects a short distance from the panel manufacturing factory compared to projects that were located far from the factory. However, the proposed GPS-data-based estimation method showed accurate transportation cost estimation throughout the range of distances. In different house sizes, the results were similar to the distance cases where the fixed-cost approach had produced an over-estimation in general, and the larger house projects had higher errors than smaller house projects. Overall, the fixed-cost approach had an average error (μ) of 57% with 61% standard deviation (SD), and the GPS-based estimation method showed a relatively significant improvement in errors—the method had a −14% average error (μ) with 24% standard deviation (SD), as shown in Table 16.

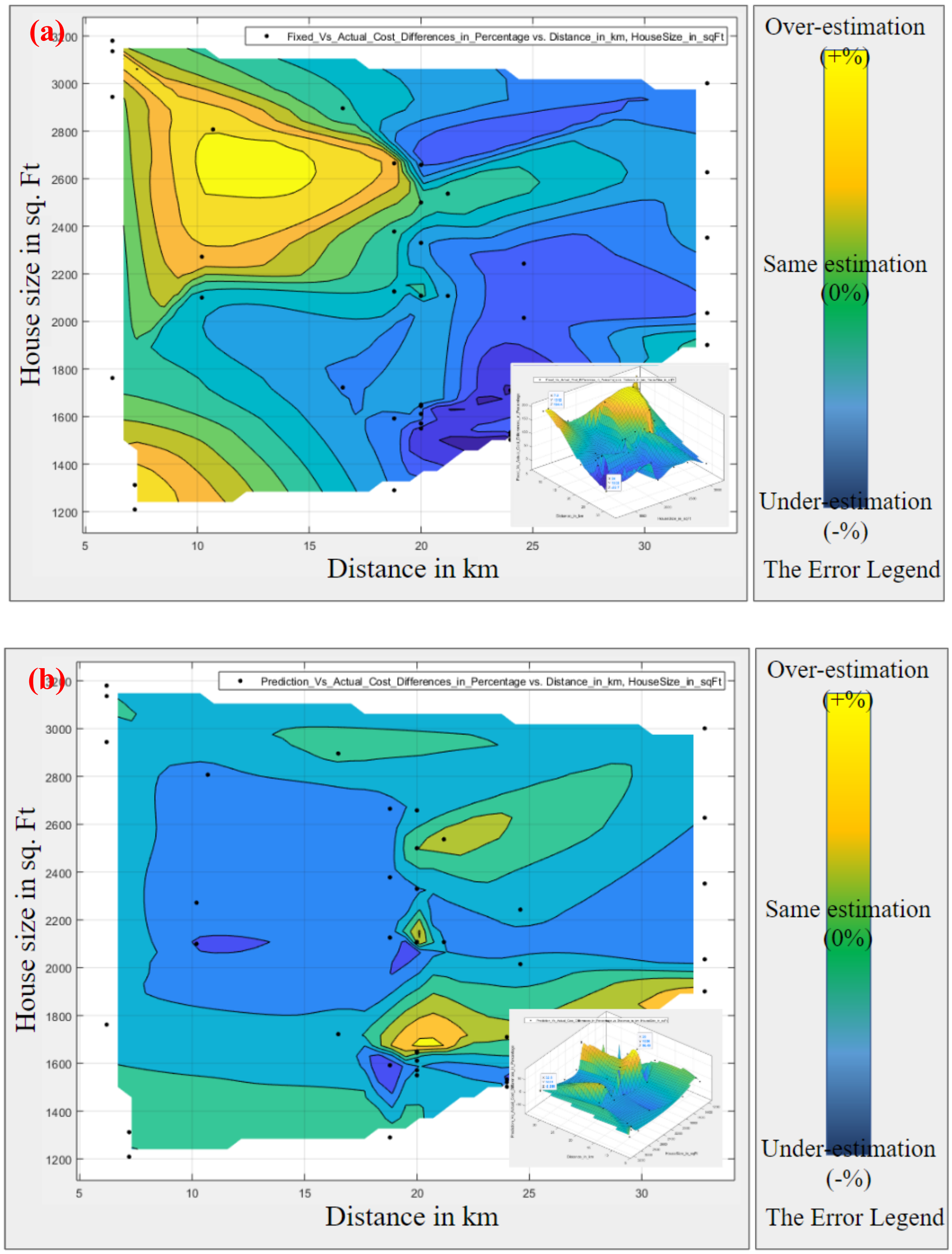


Figure 50 Transportation cost estimation comparisons: (a) Fixed cost versus actual cost estimation; (b) GPS-data-based cost versus actual cost estimation

Table 16 Comparisons between estimated transportation costs versus actual estimation costs

	Average (μ)	Standard Deviation (SD)
Fixed-cost estimation versus actual cost	57%	61%
GPS-data-based estimation versus actual cost	−14%	24%

4.2.2. Summary

The proposed GPS-data-based transportation cost estimation method is able to provide improved cost estimation over a range of different house sizes and locations of projects. The results of the case study are summarized as follows: (1) the average difference of 0.77 number of trucks and −0.3 hours of unloading duration from the fleet GPS data analysis given a 50 m geo-fence radius setting; (2) prediction accuracy of 86% and 88% in transportation demands of the visit and the duration from the SVR model, respectively; and (3) the improvement in average transportation cost estimation error of −14% (SD = 24%) over various project conditions. The 50 m geo-fence setting is similar to the range of a mobile crane's workable radius in this study, and within a distance of 50 m, the crane operator can unload the trailer without any additional entering and departure of the geo-fence. At the same time, a larger radius geo-fence, such as 250 m, can result in the potential miscounting of truck visits due to picking up empty trailers. A geo-fence setting smaller than 50 m (e.g., 25 m radius) can be considered, but considering the crane operations in practice, the smaller radius may have potential errors of skipping a visit count when a truck unloads a trailer outside the smaller radius. Next, the transportation demand prediction using the RBF kernel in SVR shows good prediction results in terms of accuracy, and the grid search technique is used to optimize parameters (e.g., C and γ) to further improve performance of the SVR model. Although the SVR and the grid search approach can provide a satisfying result using a small data set, large-scale implementation could be challenging due to the complex patterns involved in the big data. Therefore, to implement in practice, a deep-learning approach would be necessary to examine its feasibility and performance. Lastly, the GPS-data-based approach shows improved transportation accuracy over various project distances and house sizes compared to the fixed-cost method. Since the fixed-cost method applies the same transportation cost percentage for all projects based on a house size, a location has not been considered during project estimation processes. Specifically, in short distance projects within a 15 km range, the fixed-cost approach significantly overestimates costs by as much as 200%. House size is another direct influencer of transportation cost, and it does not show any distinctive error trend over various house sizes as was observed with the various distances, but overall the majority of projects are overestimated. Thus, the comparison shows large gaps between the actual cost and the estimated cost when using the fixed-cost approach in practice, and the gaps can be minimized by applying the proposed GPS-data-based transportation cost estimation method that improves both average error and standard deviation of the cost estimation. By using the proposed method, project estimation costs could have a greater competitive advantage during bidding processes while also improving transportation cost transparency issues. For example, as analyzing the GPS data along with project specification for each project, a project estimator can have a detail operation data that provides project specific transportation costs. In addition to the cost estimation benefit, the proposed method can provide potential benefits in transportation planning (i.e., delivery schedules) by more accurately predicting transportation demands for future jobs.

In addition, the utilization of GPS data can be further expanded by combining other data collection methods such as QR code, RFID, and computer vision. This study provides highly abstracted transportation operation data (e.g., loading and unloading), and more detailed data can be acquired and utilized by combining the proposed methods with other methods. For example, GPS data from trucks do not provide detailed information regarding the loads that the trucks are carrying around. By adding data from RFID or QR code, prefabricated building components (e.g., panel, module, and precast) can be tracked to provide their real-time status. The real-time tracking of the components can be used to predict progress of assembly status at site as well as manufacturing progress at the factory. Thus, the GPS data combined with other data collection methods will be worthy of further examination to provide rich and real-time information to managers who are required to control both factory and site operations while trying to achieve optimum operation conditions on entire projects.

4.3. Fleet-dispatching schedule optimization and performance

To determine the performance of the proposed framework, the roof panel delivery processes are simulated based on actual operation data from a panelized construction company in Edmonton, Canada. Initial conditions of the simulation are presented in Fig. 51 and Table 17 below. This scenario includes three different jobs (sites) around the City of Edmonton. Each site and factory have their own schedules to follow. For the sites, trailers should be delivered according to the schedule. For the factory, empty trailers should be delivered back to the factory for continuous operation. A total of three trucks are available for performing deliveries. In the beginning, all three trucks are available, and then only one truck will be available for each instance of dispatching decision making. In reality, rarely does more than one trailer become available at the same time. For empty trailers, a total of four empty trailers are available for pick-up. Two of them will be in the factory, and the other two will be outside the factory.

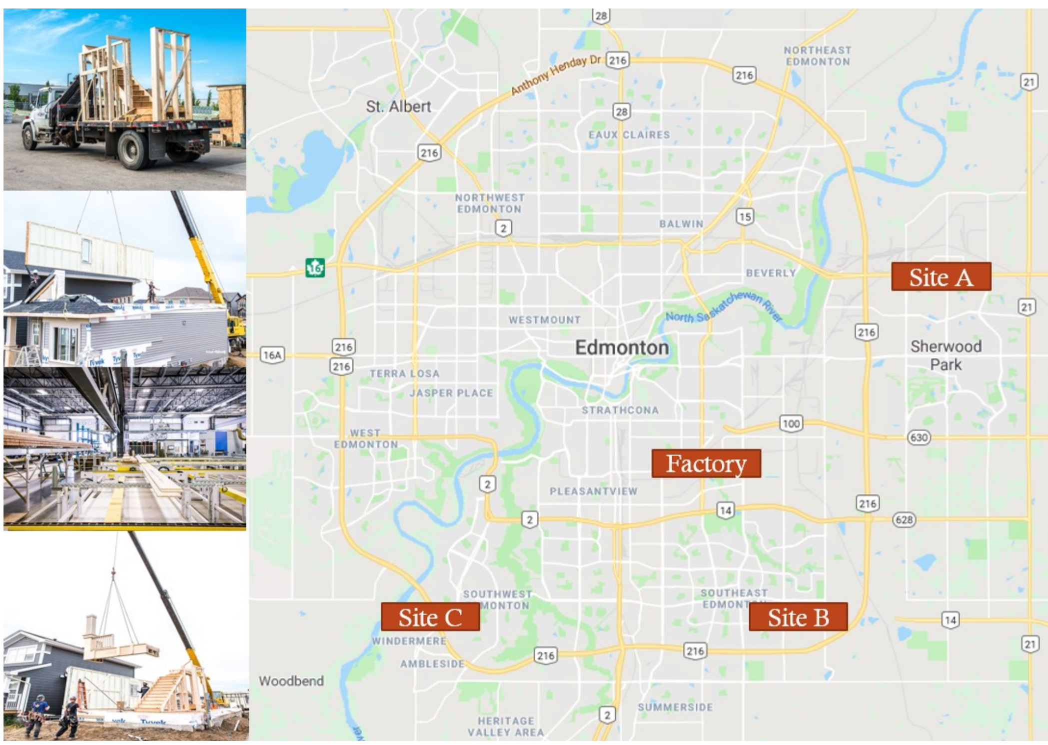
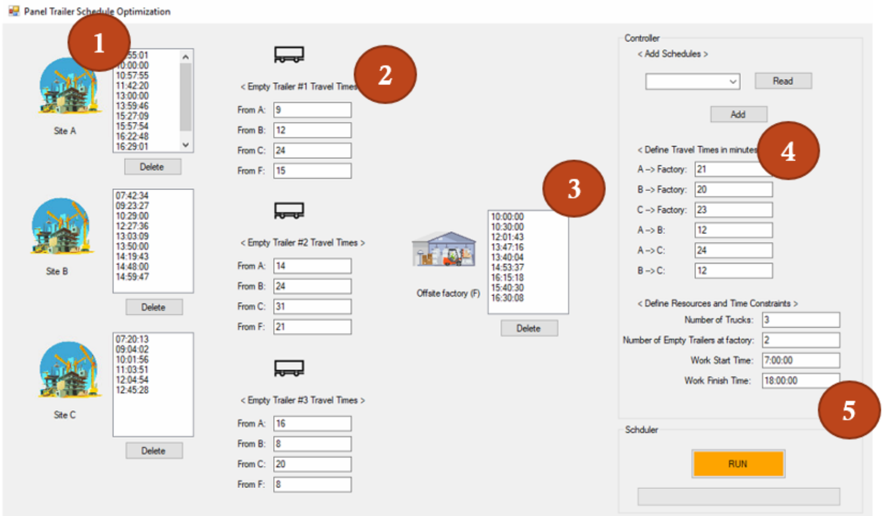


Figure 51 Initial setting for evaluating the DES model.

Table 17 Parameters for the DES model.

Parameter	Value	Description
Truck	3 each	Delivery trucks for carrying trailers
Empty trailers at sites	2 each	Did not pick up empty trailers from previous jobs
Empty trailers at factory	2 each	Available empty trailers at factory
Start time	7:00 AM	Site starts at 8 AM
End time	6:00 PM	Last delivery 4 PM to avoid working overtime
Travel time	Varies	Based on Google Maps API travel time outcomes
Unloading time (Wall, Floor, and Roof)	Wall: (50, 55, 70) Floor: (40, 50, 60) Roof: (20, 25, 30)	Triangular distributions (Min, Most likely, Max)

In addition, the user interface (UI) is also developed for improving user inputs as shown in Fig. 52. Once a user imports the factory and site schedules in CSV file format, the UI will save the schedule data into the database. After importing the schedule, a user also can change control travel times between different sites, initial empty trailer numbers, as well as working hours. In this study, three trucks, two empty trailers at the factory, and working hours of 7 am to 6 pm are used as defaults. Once the schedules and the initial settings are complete, the DES model can process the dispatching plan optimization.



1. **Site schedules**: required loaded trailer delivery times
2. **Empty trailer location from previous work**: travel time between sites
3. **Factory schedule**: required empty trailer delivery times
4. **Travel duration**: average travel time between different locations
5. **Equipment information**: Number trucks, empty trailer at factory, and work schedule.

Figure 52 Developed user interface for the DES model

4.3.1. Schedule information delay

To determine the on-time delivery percentage (%) based on different levels of schedule information delays, the equipment, site, and factory logs from the DES model area collected and analyzed based on the transportation key performance indicator. The results of the simulation are presented in Fig. 53, and the overall trend of the on-time delivery percentage showed that the percentage was improved as the information delay was reduced. At the 0.5 hours schedule notification case, only 3% of the required delivery schedules were delivered to designated sites on-time, and the average lead time was −43 minutes, which presented the average schedule delays including factory empty trailer deliveries. As the earlier schedule notifications were delivered to drivers, the on-time percentage was significantly improved as shown in Fig. 54. The results showed that if the drivers were notified of the schedules at least 2 hours ahead, then over 92% of the on-time deliveries were achieved. Along with the on-time delivery percentage, the lead time was also improved when the information was received earlier. The 1.25-hours-earlier schedule delivery changed the negative lead time to a positive lead time, which means that the magnitude of delay time was decreased. The transportation costs (Fig. 54) were decreased as information delivery time was improved, and the results showed that the best case scenario (2.75 hours) reduced transportation costs over the 34% when compared to the worst case (0.5 hours) scenario. The equipment utilizations were improved such that trucks, cranes, and trailers increased their utilization percentage up to 9%, 12%, and 15%, respectively, as shown in Fig. 56. Lastly, the empty trailer return percentage was also increased to 65% (at 2.25 hours) from 42% (0.5 hours) as shown in Fig. 57.

Information Delay

KPI List	0.5hr	0.75hr	1hr	1.25hr	1.5hr	1.75hr	2hr	2.25hr	2.5hr	2.75hr
On Time Delivery(%)	0.038462	0.230769	0.346154	0.576923	0.730769	0.846154	0.961538	0.923077	0.961538	0.961538
Avg. Lead Time(min)	-43	-24	-5	1	14	23	33	34	30	32
Tranportation Costs($)	4837.63	4795.74	4181.6	3946.7	3830.92	3572.48	3578.72	3228.15	3225.6	3149.33
Truck Utilization(%)	0.918333	0.983889	0.992222	0.997222	1	1	1	1	1	1
Crane Utilization(%)	0.622222	0.666667	0.712222	0.713333	0.728889	0.752222	0.73	0.767222	0.78	0.769444
Trailer Utilization(%)	0.700556	0.734444	0.735	0.811667	0.832778	0.841111	0.83	0.835556	0.856667	0.853333
Empty Trailer Return(%)	0.423077	0.5	0.538462	0.538462	0.538462	0.461538	0.538462	0.653846	0.653846	0.615385

Figure 53 Key performance indicator results from changing a level of the information delay.

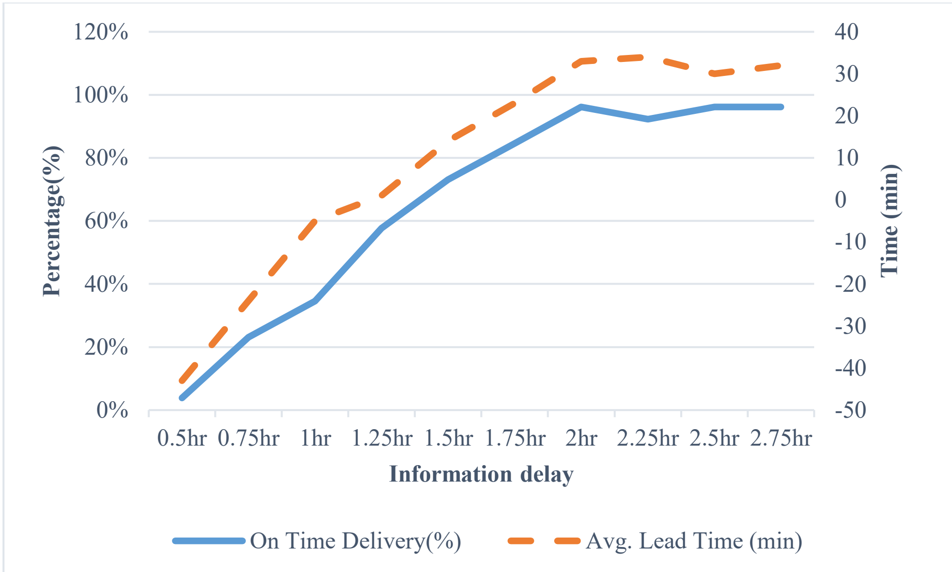


Figure 54 On-time delivery percentage versus information delays

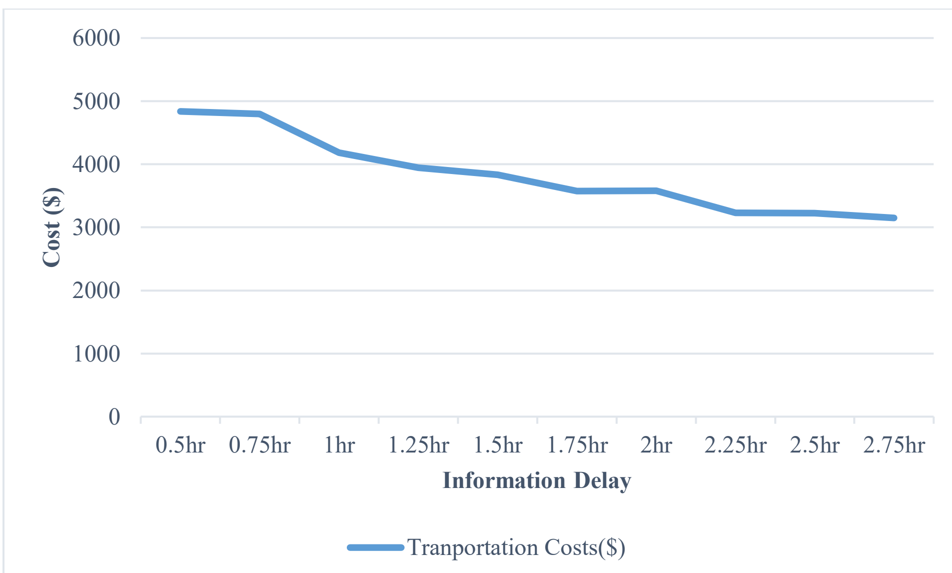


Figure 55 Transportation cost (CAD) versus information delays

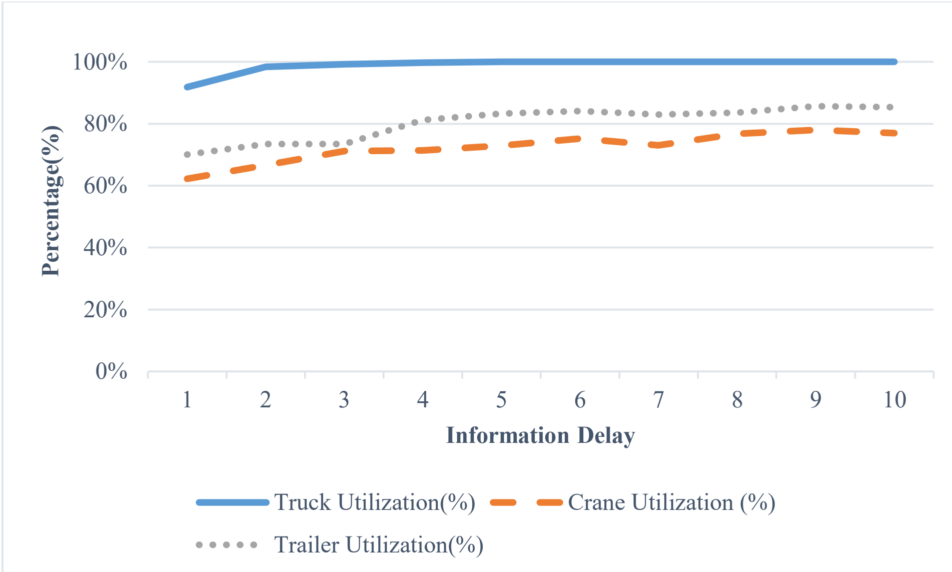


Figure 56 Equipment utilization (%) versus information delays

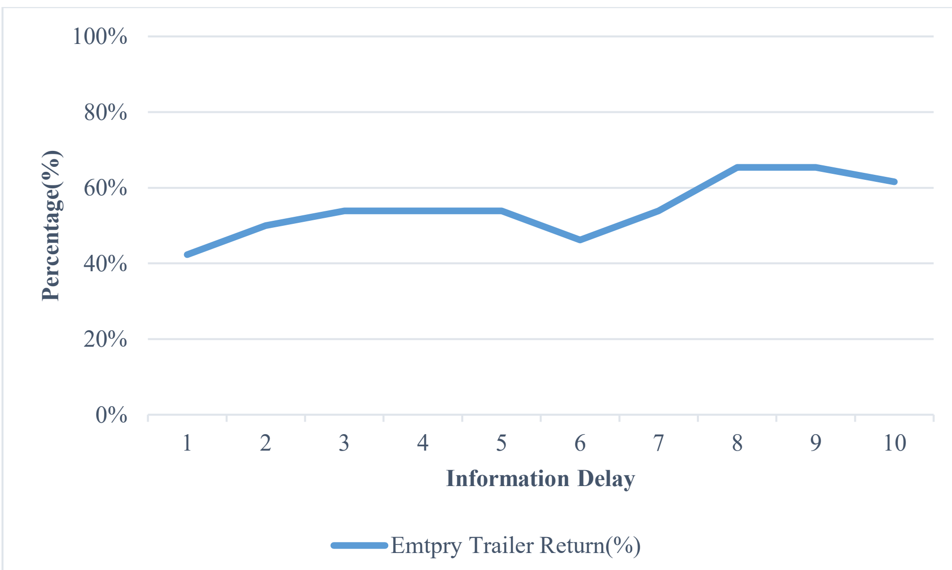


Figure 57 Empty trailer return (%) versus information delays

4.3.2. Serviceable distance variations

To determine the on-time delivery serviceable distance from the panel manufacturing facility, this study examined the key performance indicators based on seven different distance settings, as shown in Fig. 58. As expected, the on-time delivery percentage was reduced when the distance from a factory increases. At a

10% increment from 0%, the on-time percentage was reduced by approximately 38% while the lead time was still positive, which means the deliveries still arrived close to the schedule time window. Although the on-time delivery showed a significant reduction, the rest of the key performance indicators showed shallow changes relative to the on-time percentage. The transportation cost had only 6.9% increment, the equipment utilization had less than a 2% reduction overall, and the empty trailer return percentage showed an 11% reduction at the 10% distance increment. As the serviceable distance was further increased up to 30%, the lead time entered a negative range with 53% on-time delivery percentage. At the maximum 60% distance increment, the on-time delivery percentage was 34% with an average lead time of −28. In addition, the transportation cost was up by 41.4%, the crane utilization had 12% reduction, the trailer utilization had 3% reduction, and the empty trailer return percentage was reduced by 34.6%. Due to the long distance traveled, the truck utilization was maintained at a 100% utilization rate.

Distance from factory(2.75hr)

KPI List	0%	10%	20%	30%	40%	50%	60%
On Time Delivery(%)	0.961538	0.576923	0.576923	0.538462	0.307692	0.384615	0.346154
Avg. Lead Time(min)	28	5.3	1.6	-2.9	-18	-23	-28
Tranportation Costs($)	3883.36	4151.19	4432.86	4451.09	5208.16	5406.96	5491.18
Truck Utilization(%)	1	1	1	1	1	1	1
Crane Utilization(%)	0.69	0.673889	0.657778	0.665556	0.592778	0.582222	0.575556
Trailer Utilization(%)	0.853333	0.855	0.852222	0.853333	0.85	0.837778	0.826667
Empty Trailer Return(%)	0.615385	0.5	0.423077	0.423077	0.384615	0.269231	0.269231

Figure 58 Key performance indicators based on different serviceable distance settings (10% distance increments)

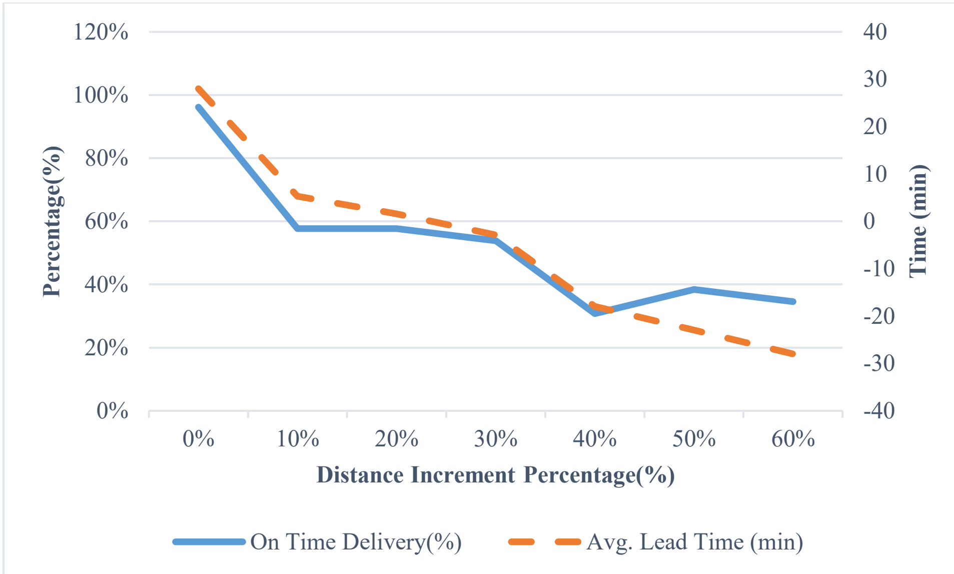


Figure 59 Serviceable distance increment percentage versus information delays

Figure 60 Transportation cost (CAD) versus serviceable distance increment percentage

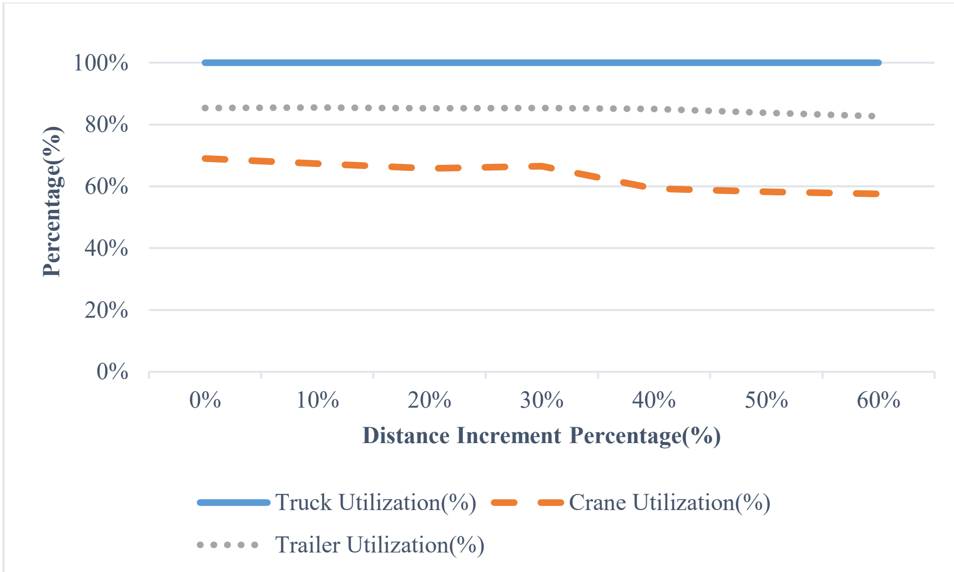


Figure 61 Equipment utilization (%) versus serviceable distance increment percentage

Figure 62 Empty trailer return (%) versus serviceable distance increment percentage

4.3.3. Visualization of the fleet-dispatching DES model

To improve the understanding of the results, two graphs were developed: (1) the trailer supply and demand, and (2) trailer count with crane status. As shown in Fig. 63, the trailer and supply graph can provide an easy visualization of trailer on-time delivery status with site progresses. The y-axis is the total delivered trailer count and the x-axis is time. In addition, the time gap between the supply and demand can show the on-time delivery status. For example, if the supply (orange dotted line) is located left side of the demand curve (blue line) then the delivery is considered ahead of schedule by the gap time; however, if the demand curve is located in front the supply curve then the delivery is delayed.

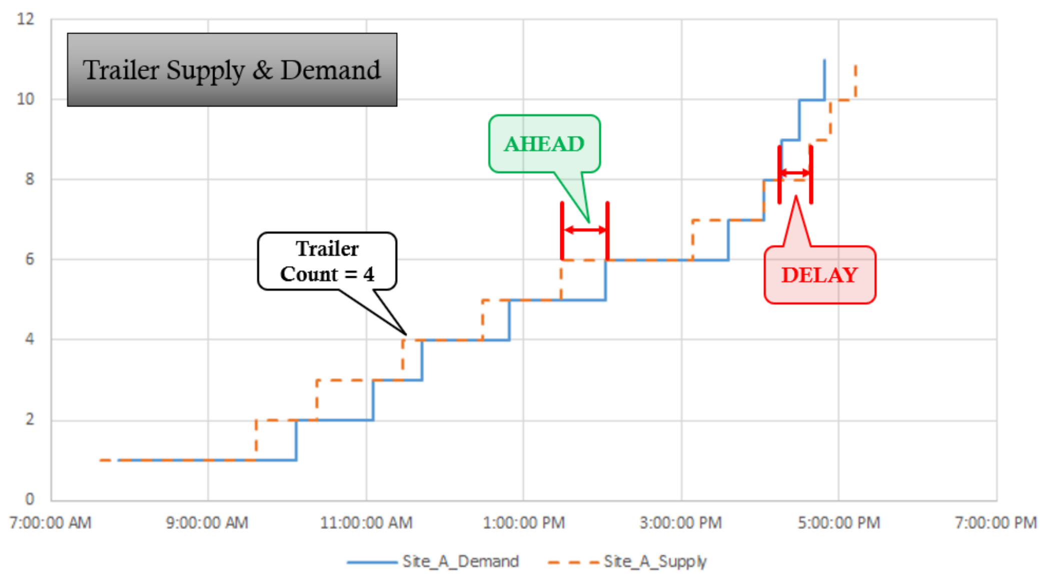


Figure 63 Trailer supply and demand at site

The graph shown in Fig. 64 shows trailer count and crane status (on/off) on site. The *x*- and *y*-axes are the same as in the previous trailer supply and demand graph. This graph allows a visualization of more detailed operation status at sites so that loaded trailer delivery, empty trailer pick-up, number of trailers at site, and crane utilization can be analyzed. For example, if the loaded trailer is delivered then the total trailer number (*y*-axis) at site is increased and the number is reduced as a driver picks up the empty trailer from the site. For crane utilization, if a crane is working or idling then the status is equal to 1 or −1, respectively.

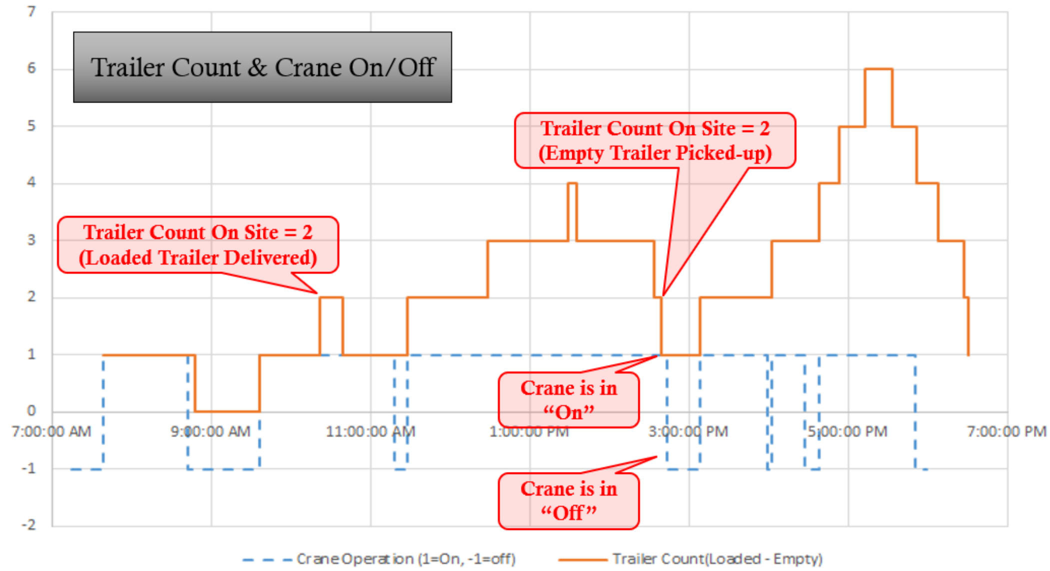


Figure 64 Trailer count and mobile crane status

4.3.3. Summary

The developed fleet-dispatching DES model is able to provide an optimized dispatching plan to achieve on-time delivery under various working conditions, such as information delays and serviceable distances. Compared to current dispatching planning, which is manual and experience-based, the DES model can improve overall performance of the transportation operations in panelized construction projects. According to the simulation results, over 96% on-time delivery could be achieved by providing delivery schedules to drivers within 2 hours. This understanding of the information delay and the transportation performance can be beneficial to project managers. Instead of planning a full schedule, which can be constantly changing due to dynamic construction environments, the manager could make a short-term plan based on current working conditions then provide the schedule information to drivers and crane operators while maintaining a high (96%) on-time delivery performance. In addition, the highest on-time delivery was limited to 96% in the DES model, but considering the average lead time of 32 minutes, the delayed delivery time (negative lead time) in the simulation result was less than −3 minutes, which could be considered as on-time deliveries in real transportation operation situations in construction.

The understanding of potential operation performances on larger serviceable area could be another benefit to the project managers during planning stage. Since the logistics dispatcher working in panelized construction has to rely on their own experience, a project that is located at new location would be difficult to plan for without past experience. Thus, this DES model can provide guidance to the dispatcher or planner in order to make a more accurate plan based on actual data. As shown in Fig. 65, 10% increments in serviceable area increased the serviceable area within the city. Although the results showed that the 10% increment (0% → 10%) reduced the on-time delivery percentage to 57% from 96%, this simulation assumed that all three projects are located on the edge of the service area boundary. So, if only one project is located at the edge of the serviceable area and the other two projects are closer to the factory, then the on-time delivery percentage would be higher than 57%. Considering the actual practice, the planner would rarely schedule multiple simultaneous projects that are located a long distance from the factory. In addition, the increased transportation cost could be recovered by applying the higher rate for long distance projects.

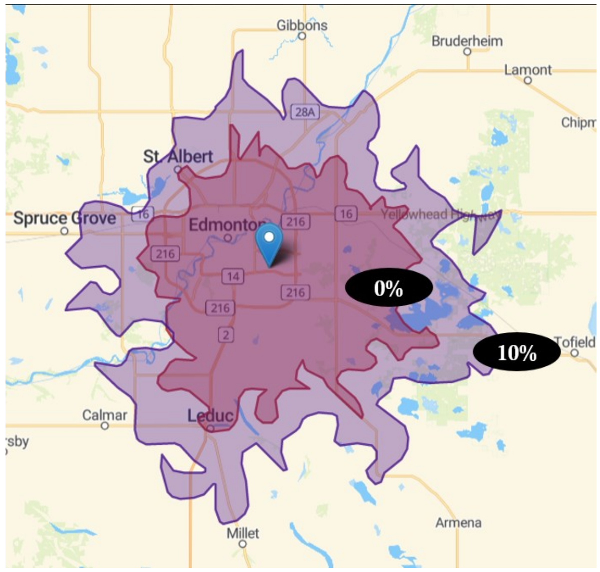


Figure 65 Serviceable area comparison between current and 10% increments from 0%

Lastly, considering the actual transportation KPI as shown in Table 18, the current practice of manual transportation planning can be easily improved by having short-term planning (for the next 2 hours) without also having an unreliable master plan (for the full day). The real-time data from QR code and GPS can be used to support the planning process by visualizing the current transportation status as shown in Figures 63 and 64.

Table 18 Comparison between actual KPI data and collected transportation operation data

KPI list	Actual projects	Information Delay (2 hours)	Serviceable area (10%)
On-time Delivery (%)	0.90	0.96	0.57
Average Lead Time (min)	58.3	33	5.3
Average Transportation Costs (CAD)	4050.2	3578.1	4151.2
Truck Utilization (%)	0.76	1	1
Crane Utilization (%)	0.68	0.76	0.69
Trailer Utilization (%)	0.75	0.83	0.85
Empty Trailer Return (%)	0.33	0.65	0.5

5. Chapter: Conclusion and Future Work

5.1. Research summary

Transportation operations in panelized offsite construction is a critical element that has significant potential impacts on both the offsite manufacturing and the on-site assembly operations. Due to its importance in panelized offsite construction operations, appropriate management and planning of transportation would be necessary to improve overall project operation, including factory manufacturing. Transportation operations have traditionally not been managed in systematic ways using advanced data collection and analysis, passive transportation quality assurance, and fleet-dispatching plan optimization. Current transportation data collection and planning processes are manual, subjective, and unreliable, which can lead to potential errors and even performance reductions in both site and factory operations. Thus, in order to achieve the systematic approaches to transportation operations in panelized offsite construction, an advanced method is necessary and this study proposes the following methods: (1) projection-based AR to improve transportation quality before loading at factory, (2) GPS-data-based transportation cost estimation using machine learning approaches, (3) web-based transportation data collection using QR code, and (4) fleet-dispatching DES model to optimize planning. In general, the transportation operations in panelized construction involved the following six steps: loading, picking up loaded trailer, performing a delivery, unloading, picking up an empty trailer, and returning to a factory. In this research, all transportation steps are involved in the data collection processes to support the proposed cost estimations and the fleet-dispatching optimization methods, and the projection-based AR is applied during the manufacturing stage.

In the projection-based AR method, the projector is used at the wall panel assembly line to visualize the 2D wall drawing to workers to reduce potential quality issues so that site operations can be performed without the need to send back defective panels to the factory, which requires unscheduled transportation operations. The web-based transportation collection is used to replace the unreliable and error prone manual data collection. The developed web application is given to all loaders, drivers, and crane operators to scan QR codes on both panels and trailers; they scan the QR code to record transportation activity data in the cloud server. The collected QR code and transportation installed GPS data are analyzed to extract key information such as transportation demands (e.g., the duration and the number of trailers required) by using the rule-based algorithm. The extracted data is used to train and develop the SVR model to predict the transportation cost for future jobs. In addition, by using the collected data from GPS and QR codes, the fleet-dispatching DES model is developed to improve on-time delivery performance given various constraints such as the schedule information delays and the serviceable area. These developed methods (except the projection-based AR) can be accessible via user interfaces on a desktop computer and any web-browser. By using the proposed methods, the transportation operations in panelized construction can be more efficient, transparent, and economical. The limitations of the research are: (1) the performance of the projection-based AR can vary in varying levels of brightness; (2) the web application-based data collection still requires manual selection of trailer status, and it can lead to errors in the data; (3) the developed SVR and DES models may not be able to perform well in an unsupervised situation when custom types of buildings and remote site locations are selected.

5.2. Research contributions

This research makes the following contributions:

a) Applied a projection-based AR method in a large-scale manufacturing facility and determines its performance in different levels of distance and brightness settings.

b) Developed a rule-based algorithm to extract key information (e.g., transportation demands) from a collection of large-scale fleet GPS data in a local server environment.

c) Determined detailed specifications of transportation data requirements to develop the SVR machine learning model, and applied this to actual panelized residential projects.

d) Developed web-based real time transportation data collection method using a web application that is simple, economical, and highly compatible on any smart device. In addition, a real-time transportation and site operations integrated visualization tool was developed to monitor overall project progress.

e) Developed the fleet-dispatching DES model for offsite construction that achieves on-time delivery for both factory and multiple construction site schedules while reducing transportation costs and number of empty trailer returns.

f) Determined the impacts on on-time delivery and transportation costs from site information delays and increasing serviceable distance in panelized construction operations.

Based on this research, the following future research topics are proposed:

a) Use an optical augmented reality device (e.g., Google Glass) to visualize 2D drawing information during the panel assembly processes and determine potential errors by using incorrect image searching.
b) Use a game engine (e.g., unity) to develop a panel loading plan simulation to figure out the optimal way to load finished panels, as well as an efficient way to unload the panel at the site.
c) Develop a QR code and RFID data connected BIM model to visualize real-time transportation operations in the web environment.
d) Develop an unsupervised machine learning model to understand fleet movement patterns to extract key information from a large-scale GPS data.
e) Convert GPS data into a heat-map image file to train a neural network model to estimate overall transportation costs and operations.
f) Use dash-cam video data in transportation equipment to analyze operation productivity by using a computer vision approach.
g) Extend application of the developed DES model to other offsite construction methods.

h) Develop an artificial intelligence (AI)-based fleet-dispatching model that is connected to multiple users in real-time to get input and provide an optimum dispatching decision in real-time.

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Ahn, S.J., Altaf, M.S., Han, S., and Al-Hussein, M. (2019). Fleet dispatching scheduling support framework using real-time construction data in the panelized construction. *Proceedings, Winter Simulation Conference*, National Harbor, USA, Dec. 8–11, pp. xxx-xxx. (accepted)

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