CONSTRUCTION EQUIPMENT TRAVEL PATH VISUALIZATION AND PRODUCTIVITY EVALUATION

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ABSTRACT

The U.S. construction industry represents approximately 4% of the U.S. gross domestic product (BEA 2015) and currently involves over 6 million workers employed by an estimated 750,000 construction firms (BLS 2015). Within this industry, productivity is a key driver for economic growth and strongly affects prosperity for the country (Vogl and Abdel-Wahab 2014). More specifically, higher construction productivity and more reliable installation (quality) translates into higher wages and increased profits (Vogl and Abdel-Wahab 2014). On many construction projects, productivity is defined or greatly impacted by equipment cycle time.

Furthermore, the U.S. construction industry continues to be one of the more dangerous work environments for employees (BLS 2015). Construction workers in the U.S. experience a disproportionate number of fatalities when compared other major industrial sectors in the U.S. (BLS 2013). Visibility has proven to be a major cause of accidents on construction sites (Hinze and Teizer 2011).

This research seeks to prove the hypothesis that visibility and location-based data can be automatically collected and analyzed for construction equipment operators to assess a construction equipment cycle. As one of the more promising recent implementations in the construction industry, sensing and design technology provide unique opportunities to capture and analyze location-based information on construction sites. These technologies can enable productivity managers to identify, assess, and decrease the overall cycle time of a specific operation. This research implements Building Information Modeling (BIM), Global Positioning

System (GPS) location identification, and laser scanning to enable automated data collection and analysis. The overall objective of the research is to automatically capture and analyze elements of a construction equipment cycle.

The outcomes of this research addresses the following key components of an equipment cycle time: 1) automated cycle time path planning, 2) location-based data capture and analysis of real-time equipment cycles, and 3) equipment path environment visualization. The research framework was tested with active construction site data, and feedback from the workforce and management was assessed and integrated into the research approach.

The research has the potential to improve productivity on construction sites and enhance construction employee safety performance. It will also assist in adding a link between productivity planning and management and existing project BIMs.

DEDICATION

This dissertation is dedicated to my parents, Chuanfu Song and Fangchao Song.

LIST OF ABBREVIATIONS AND SYMBOLS

3D	Three Dimensional
4D	Four Dimensional
AEC	Architecture, Engineering and Construction
API	Application Programming Interface
BIM	Building Information Modeling
BLS	Bureau of Labor Statistics
GA	Genetic Algorithm
ISO	International Organization for Standardization
OSHA	Occupational Safety and Health Administration
SAS	Statistical Analysis Software
UWB	Ultra-Wideband
VBA	Visual Basic for Applications
VSTA	Microsoft Visual Studio Tools for Application

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I am indebted to my parents for instilling a work ethic and strong morals within me and supporting me through this time. My parents' passion for education and impacting the lives of others was transferred to their children. None of this would be possible without the unconditional support from my family.

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CHAPTER 1 INTRODUCTION

This chapter discusses the overview and nature of the U.S. construction industry for the proposed research. A review of current construction productivity, safety statistics, and best practices, and existing assessment technologies are presented. Building Information Modeling is also introduced as a platform to assist in construction productivity and safety management. A review of BIM applications and sensing technology for construction productivity is also performed in this chapter.

1.1 Specific Problems within Construction Industry

The U.S. construction industry represents approximately 4% of the gross domestic product (BEA 2015) and currently involves over 6 million workers employed by an estimated 750,000 construction firms (BLS 2015). Construction safety and productivity are commonly used project controls for assessment and benchmarking because of their immense impact on the overall project success of a construction project. Building Information Modeling (BIM) is an intelligent 3D model-based process that equips architects, engineers, and construction professionals with the insight and tools to more efficiently plan, design, construct, and manage buildings and infrastructure (Eastman et al. 2011). It has been proposed as a means of addressing the cited problems in construction safety and productivity (Eastman et al. 2011).

1.1.1 Construction Safety

The U.S. construction industry continues to experience high rates of injuries and fatalities when compared to other U.S. industrial sectors (OSHA 2016a). In 2014, approximately one in five workplace fatalities experienced in the U.S. were in the construction industry (OSHA 2016b). The construction industry continues to rank as one of the most dangerous work environments when compared to other industrial sectors in the U.S. (BLS 2017). Several industry and research efforts have been made to improve the safety record of the construction industry (Aminbakhsh et al. 2013, Cohn and Wardlaw 2016, Ameyay et al. 2016). Although improving, construction safety performance has yet to reach zero incidents which indicates further improvement is necessary (BLS 2015).

Per OSHA regulations, construction companies are required to provide a work environment free of recognized hazards and be compliant with all the current regulations and standards for safety (OSHA 2012). Of the fatalities experienced in construction in 2014, approximately 8% (73 fatalities) were caused by struck-by incidents in which a pedestrian worker was struck by construction equipment or objects (OSHA 2016a). Furthermore, struck-by incidents represent one of the “fatal four” which are the causes of a majority of fatalities in construction (OSHA 2016a).

1.1.2 Construction Productivity

Due to the impact of productivity on the success of construction projects, a multitude of research has been performed in construction productivity. Multiple broad factors, including environmental conditions, site attributes, management strategies, and design components, have been determined to impact construction productivity (Thomas and Yiakoumis 1987).

A variety of research has been performed on construction productivity because of its inherent impact on overall project success. Construction projects in the U.S. have recorded a recent upward trend in productivity largely due to advances in technology (Allmon et al. 2000, Goodrum et al. 2004). Within the construction industry, productivity is a key driver for economic growth and strongly affects prosperity for the country (Vogl and Abdel-Wahab 2014). More specifically, higher construction productivity translates into higher wages and increased profits (Vogl and Abdel-Wahab 2014). Currently, skilled labor shortages in the U.S. are driving an urgent need to optimize equipment resources to increase productivity on U.S. construction sites (Shan et al. 2015, Caldas et al. 2014).

1.2 Building Information Modeling

BIM has gained increasing popularity in the global construction market and is perceived as a tool for visualizing and coordinating AEC (Architecture, Engineering and Construction), avoiding errors and omissions, improving productivity, and supporting scheduling, safety, cost, and quality management on construction projects. It incorporates such building component characteristics as including geometry, spatial relationships, properties, and quantities (Zuppa and Suermann, 2009). The success of BIM depends on many factors such as the size of the project, the communication of the project team, as well as other organizational external factors (Barlish and Sullivan, 2012).

BIM provides a shared digital resource for all participants in a building's lifecycle management from preliminary design through facilities management (Eastman et al. 2011). For example, BIM offers the capability to develop project cost information with more accuracy throughout the entire building lifecycle (Sabol 2008). BIM can also provide safety checking integration for dynamic safety analysis before construction starts (Zhang et al. 2013), and dynamic construction site safety management (Sulankivi et al. 2010).

BIM has been also widely used during the design phase so as to most efficiently address the concerns of the designers, constructors, and project owners. Constructors can achieve benefits from using BIM during the preparation of schedules and estimates, as well as tracking and managing changes to the project and shop drawings while managing site logistics, temporary structures, and services with particular attention to site safety (Aslani et al. 2009). One survey shows that BIM was most frequently perceived of as a tool for visualizing and coordinating AEC work, avoiding errors and omissions, and improving the productivity, schedule, safety, cost, and quality of construction projects (Zuppa et al. 2011).

With the implementation of sensing technology and BIM into construction project management, new strategies for capturing and analyzing data have become apparent. Construction project managers are integrating BIM into many aspects of a project including building life cycle, design (Penttila 2007), planning, constructability (Kymmell 2008), and operations (Akcamete et al. 2010). Sensing technology, automated through BIM, can provide additional methods for construction safety performance enhancement (Zhang et al. 2013).

1.3 Specific Research Needs

Safety and productivity are both influenced by construction equipment travel paths on a given construction site. The cycle time of construction equipment for earthwork operations has a significant direct impact on overall project productivity. The cycle time duration of scrapers or dump trucks in an earthwork excavation project can greatly impact the overall productivity. Specifically, the duration of haul vehicles, mainly scrapers or dump trucks, for a single cycle directly impacts project success with regards to productivity.

Construction productivity metrics are influenced by the traveling path of construction equipment through a construction site. One of the fundamental decision criteria for construction equipment productivity is navigating the shortest path for material transporting equipment across the construction site terrain. A common approach is to implement one or a combination of search algorithms to satisfy constraints for generating a potential equipment travel path. Furthermore, considerable opportunity exists to implement emerging and existing sensing technologies to create applications for both safety and productivity enhancement. BIM can be used as a platform for application of new technologies and methods to enhance construction safety and productivity.

The dynamic nature of construction sites often creates hazardous conditions between heavy equipment and pedestrian workers (Teizer et al. 2010a). Employees of the U.S. construction industry encounter dangerous working environments often resulting from limited visibility, hazardous proximity situations between heavy equipment and pedestrian workers and the dynamic nature of manufacturing tasks. A typical construction environment is characterized by a multitude of interactions between pedestrian workers, equipment, and materials. Visibility has been cited as a major cause of struck-by incidents on construction sites (Hinze and Teizer 2011). Statistics indicate that 659 fatalities (5% of all U.S. construction fatalities) from 1990 to 2007 are visibility related (Hinze and Teizer 2011).

CHAPTER 2 OBJECTIVES, SCOPE, AND HYPOTHESIS

In order to understand the framework, purpose, and methodology of this research, the objective, scope, and hypothesis must be defined. In the subsections to follow, each of these research components are discussed.

2.1 Objectives

The overarching objective of this research is to create a framework to collect, analyze, and visualize information of a construction equipment travel path and corresponding operation cycle. To achieve this objective, several necessary secondary objectives are listed:

- Create a framework to scientifically identify and quantify variables that have a significant impact on the cycle time of construction equipment;
- Automatically calculate and display an efficient travel path for equipment in BIM;
- Create a framework to evaluate the visibility of an equipment operator on a designated travel path.

2.2 Scope

The scope included private construction companies or government entities performing construction in the U.S. The scope also included pieces of construction equipment typically used to haul earthwork (e.g., dump trucks and scrapers). The equipment cycle time was limited to all elements required within one piece of construction equipment completing one cycle within a construction operation. Productivity measurements were limited to short-term operations.

2.3 Hypothesis

After reviewing existing research and current practices regarding equipment travel path in the construction environment, the following hypotheses were generated. These were tested using the research methodology described in the next chapters:

- Construction equipment cycle time data can be automatically collected and analyzed;
- Critical impact factors to an equipment's cycle time can be identified and quantified;
- An efficient equipment travel path can be calculated and displayed in BIM;
- Equipment operator and pedestrian worker visibility can be quantified in an equipment operation cycle.

CHAPTER 3 IMPACT VARIABLES OF DUMP TRUCK CYCLE TIME FOR HEAVY EXCAVATION CONSTRUCTION PROJECTS

The cycle time of construction equipment for earthwork operations has a significant direct impact on overall project productivity. Specifically, the duration of haul vehicles, mainly scrapers or dump trucks, for a single cycle directly impacts project success with regards to productivity. Elements that directly impact a haul vehicle's cycle time must be identified in order to accurately quantify the haul cycle time and implement strategies to decrease it. The objective of this research is to scientifically identify and quantify variables that have a significant impact on the cycle time of a dump truck used for earthmoving. Real-time location data, collected by GPS devices deployed on dump trucks in an active earthwork moving construction site, were analyzed using statistical regression. External data including environmental components and haul road conditions were also collected periodically throughout the study duration. Several statistical analyses including a linear regression analysis and a stepwise regression analysis were completed on the dump truck location data. Results indicate that a dump truck's enter idle time, exit idle time, moving speed, and driver visibility can significantly impact the dump truck cycle time. The contribution of this chapter is the identification and analysis of statistically significant correlations of identified variables with the cycle time of a dump truck. Results of this research can support construction managers in improving productivity by decreasing haul equipment cycle time.

3.1 Introduction

Within this industry, productivity is a key driver for economic growth and strongly affects prosperity for the country (Vogl and Abdel-Wahab 2014). More specifically, higher construction productivity translates into higher wages and increased profits (Vogl and Abdel-Wahab 2014). Currently, skilled labor shortages in the U.S. are driving an urgent need to optimize equipment resources to increase productivity on U.S. construction sites (Shan et al. 2015, Caldas et al. 2014).

Dump truck cycle time can be defined as the summation of time for loading, hauling, idle and dumping for a truck. (Oglesby et al. 1989). Productivity has historically been a significant standard index in construction worker measurement (Spence and Kultermann 2016). Dump truck cycle time has been identified as a key component in the assessment of construction productivity (Hinze 2007). Because of the significant impact of dump truck cycle time on the overall productivity of a construction project, it is the goal of this study to identify and analyze significant variables that influence this cycle time. To achieve this goal, location-based data of dump trucks and environmental data were collected on an active earthwork moving construction site over three months. During these three months, twelve days of actual construction production were measured. Other days in the three months were not included due to minimal productivity resulting from weather delays.

Global Positioning System (GPS) devices were deployed on dump trucks during their time on site. The dump trucks were transporting excavated clay from a desired foundation location for an academic building. GPS was selected to automatically detect and store location-based information including latitude and longitudinal coordinates, elevation, and equipment at a one Hz frequency (Song and Edlin 2012). The raw data collected from GPS and environmental observation was analyzed using statistical applications to identify the impact of each variable on the overall dump truck cycle time. A commonly-used statistical processing software was used to perform a variance regression and regression analysis on the analyzed data. Internal and external techniques were implemented to validate the data collection method as well as analysis methodology.

3.2 Literature Review

The following review explores aspects of construction equipment productivity including measurement methods and analysis. The review also specifically investigates industry methods and academic research in equipment cycle time measurement and location-based tracking of construction equipment. This section concludes with a research needs statement derived from the literature review.

3.2.1 Construction Equipment Productivity Measurement

Due to the elevated impacts of productivity on the success of construction projects, a multitude of research has been performed in construction productivity. Multiple broad factors including environmental conditions, site attributes, management strategies, and design components have been determined to impact construction productivity (Thomas and Yiakoumis 1987). Statistical models have been developed to predict construction productivity given some input factors (Han et al. 2008).

Case studies in construction productivity have indicated a recent upward trend in productivity largely due to advances in technology (Allmon et al. 2000, Goodrum et al. 2009). Specifically, technological advances in construction equipment can explain a segment of the increase in partial factor productivity (Goodrum and Haas 2002). In fact, much of the increase in labor productivity can be attributed to the advancement of construction equipment technology (Goodrum and Haas 2004). For example, one study identified a modification in the activity code structure of a piping and conduit section significantly increased the accuracy of labor productivity unit rate measurements (Dadi et al. 2014). Many changes in overall construction productivity can be explained by construction equipment modifications (Wang et al. 2014).

A strong relationship has been identified between construction equipment operating conditions and earthmoving productivity (Smith 1999). This relationship was found after modeling factors such as the number of dump trucks, excavator buckets per load, excavator bucket volume, dump truck travel time, and haul length (Smith 1999). More detailed aspects, such as the payload of a dump truck, also impact construction productivity (Schexnayder et al. 1999). A more general study realized the consequence of relationships between productivity and input parameters such as excavator bucket volume (Tsehayae and Fayek 2014). A need exists to identify and compare such input parameters in order to understand the impact on construction productivity.

3.2.2 Construction Equipment Cycle Time

One widely implemented strategy to estimate equipment productivity is a set of equations and standard values of haul vehicles and excavation equipment (Peurifoy et al. 2006). The basic production equation implemented for one excavator and multiple dump trucks is shown in Equation 1. Although this system of equations provides a simple and plausible prediction for equipment productivity, it lacks the causation relationship between initial input variables, dump truck cycle time, and overall productivity.

$$P = TL(NT)(60/TCT) \qquad \text{Equation 1}$$

P is Production in Loose Cubic Yards

TL is Truck Load in Loose Cubic Yards

NT is Number of Trucks

TCT is Truck Cycle Times in Minutes

Another theory, known as Little's Law, calculates the number of trucks for a given work of unit time (Hopp and Spearmann 2001). This equation uses a metric of work in progress divided by a single truck cycle time to determine the number of trucks required (Hopp and Spearmann 2001). Little's Law indicates a strong relationship between construction equipment cycle time and overall productivity. Based on the principles of Little's Law, a model was developed to predict the cycle time of haul equipment based on a single hydraulic excavator (Edwards and Griffiths 2000). Similarly to this model, a mining truck in an open-pit was evaluated for cycle-time measurements to understand the impact of external variables on the equipment's daily productivity (Chanda and Gardiner 2010). Although these studies are helpful in identifying the importance of measuring cycle time of construction equipment, they lack the analysis and origin of input variables. Furthermore, cycle time and throughput have been ignored in the current management system due to a lack of understanding of the correlation between input variables of construction equipment cycle time and overall productivity (Bashford et al. 2005).

3.2.3 Construction Hauling Equipment

A variety of options are available for transporting material relatively long distances on construction sites including dump trucks and scrapers. Dump trucks were chosen as the haul equipment for this research because they can be more economical and are widely implemented (HEA 2016). Other studies have identified a few variables as potentially impacting the productivity of a dump truck including payload (Schexnayder et al. 1999), available electronics (Brown et al. 2000) and travel time (Smith et al. 1995). Although these studies investigate various aspects of dump truck cycle time, a need exists to collect active site location-based data to better understand impact factors of dump truck haul cycles.

3.2.4 Location-Based Tracking of Construction Equipment

Location-based tracking technologies can quantify and store the location of different pieces of construction equipment and assist in productivity management of construction sites (Cheng et al. 2011). Selection of technological systems depends on the capabilities of that system as well as the desired data collection (Li et al. 2016). For example, knowing the location of haul vehicles and travel trajectory are essential data points for tracking and collision detection (Oloufa et al. 2003). Various technology systems exist to collect such data including GPS, Wireless Local Area Network (WLAN), Ultra-wideband (UWB) and others that have unique detection and communication strategies (Li et al. 2016). For example, GPS have been implemented for transportation management, facility delivery, urban planning, and site safety monitoring (Hampton 2004). WLAN has been deployed for point-based indoor position tracking because of its 0.1 meter accuracy (Wang et al. 2003). Furthermore, UWB has been used to improve work zone safety, job site monitoring, and outdoor resource tracking (Teizer and Sofer 2007).

GPS has been identified as the most suitable location-tracking technology for construction equipment in large open areas when very high accuracy is not of primary concern (Li et al. 2016, Hildreth et al. 2005). Construction equipment locations and trajectories were tracked using GPS to assess productivity and safety (Pradhananga and Teizer 2013). GPS was identified as a technology that can provide real-time data on vehicle position and velocity (Zito et al. 1995). GPS has the capability to provide a large amount of individual time, position, and speed data points at rapid frequencies (Zito et al. 1995, Behzadan et al. 2008, Ergen et al. 2007). Location tracking with GPS-based systems can increase productivity and decrease cost through management decisions based on analyzed tracking data (Han et al. 2006).

3.2.5 Research Needs Statement

The review of existing literature shows gaps in research for collecting and analyzing data for the cycle time of a dump truck. One research need is to investigate the implementation of location-based automated systems for assessing dump truck cycle times on construction sites. Data collected by this technology can be used to identify significant impact variables on the cycle time of haul equipment on construction sites. This technology equips construction managers to quantify several variables related to a cycle time of a construction site by creating a previously unavailable database for construction haul equipment.

3.3 Research Methodology

An active construction site of an academic research and educational building in Atlanta, GA was employed as a collection test bed for location-based dump truck cycle time data. The objective was to construct an academic research facility with laboratory and classrooms. The building is 1,891 square meters and the construction site had a surface area of 11,150 square meters 10,800 square meters (120 meters by 90 meters). Dump truck operators were required to drive 6 miles from the construction site to unload the excavated material at the fill location. Because dump truck operators requested that researchers not record their location-based information outside of the construction site, researchers were unable to provide travel information to and from the fill location.

Data was collected for a total of twelve days between November 2012 and January 2013 during the excavation phase of the construction project. The time period and specific days were times in which the excavation contractor permitted members of the research team to collect location-based data on their resources. The excavation was performed using hydraulic excavators and dump trucks. The construction site contained one entrance and one exit site with a commonly used travel path connecting both. Figure 1 presents an overview of the selected construction site.

Figure 1: Active Experimental Testbed

3.3.1 Data Collection

A GPS location system with a measured error value of plus or minus three meters was installed on dump trucks part of the excavation cycle (Pradhananga and Teizer 2013). GPS data loggers were attached to plastic mounts on each dump truck. The number of trucks on the construction site is shown in Figure 2. The dashed line in Figure 2 represents a trending average of trucks on the site through the evaluation period.

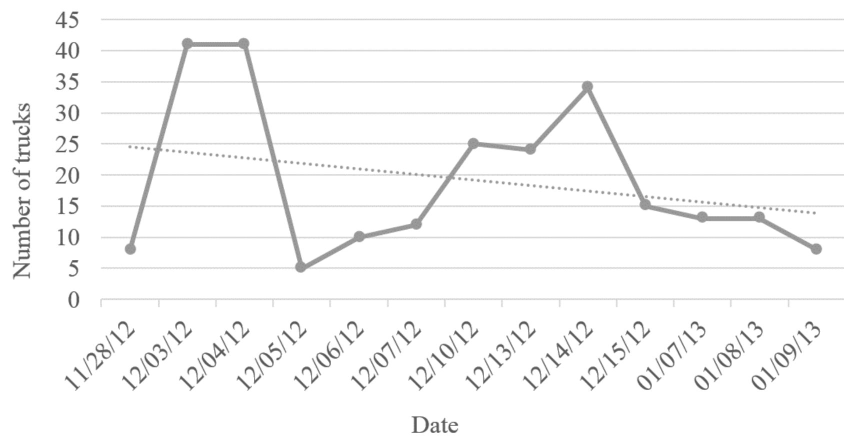


Figure 2: Daily Totals of Dump Trucks on the Construction Site

A total of fifteen GPS data loggers were attached to the dump trucks entering the construction site. One GPS device was temporarily attached to one dump truck to record and store the latitude, longitude, elevation, date, time, and estimated speed. Each dump truck had a unique GPS data logger mounted on the driver door. The commonly used truck cycle time components are defined and used for data analysis (Peurifoy et al. 2006).

Load time: Duration of time for the excavator to load earth material into a single dump truck.

Haul time: Duration of time for a single dump truck to travel from the excavation area to the fill area with a loaded payload.

Dump time: Duration of time for a single dump truck to empty the payload.

Return time: Duration of time for a single dump truck to travel from the fill area to the excavation area with an empty payload.

These cycle time components provided analysis categories for the GPS tracking data collected. Specifically, GPS data was segments into various cycle-time categories to identify which category impacted the overall excavation productivity. The flow path of dump trucks in this excavation project is shown in Figure 3.

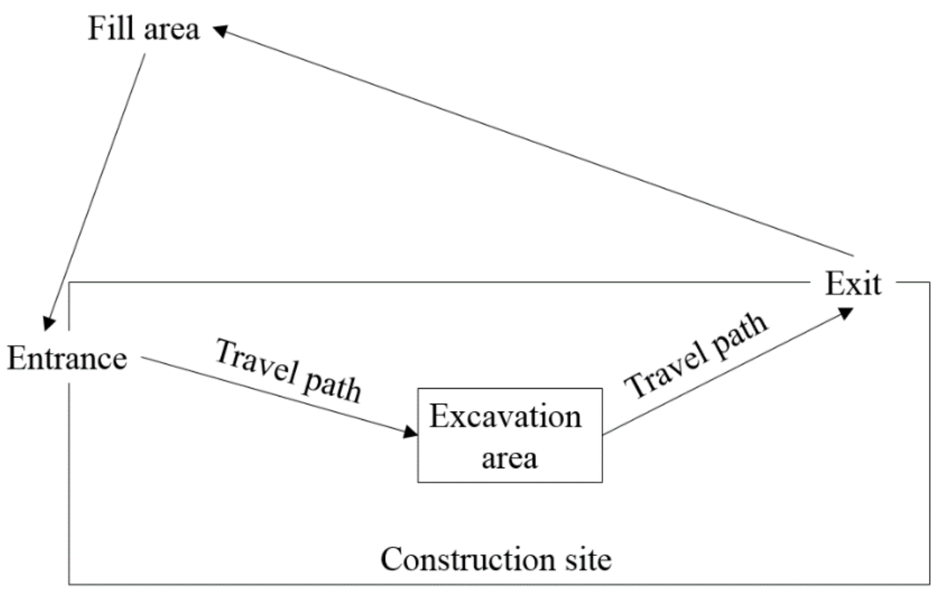


Figure 3: Cycle Time Categories for Dump Trucks

Although many exist, candidate variables were selected that were thought to potentially have an impact on a dump truck's cycle time. The selection criteria for these variables included: 1) Variables were identified in existing literature, 2) Variables were used for existing cycle time productivity calculations, 3) Ability of deployed sensing technology to automatically capture the variable, and 4) Privacy considerations of dump truck operators. For example, dump truck operators chose not to allow researchers to track their location outside of the construction site due to cited privacy issues. This consideration limited researchers from collecting probably impact variables including traffic conditions and number of individual cycles completed per day. One complete dump truck cycle is defined as the summation of the enter duration, enter idle time, load duration, exit duration, exit idle time, and haul duration.

Fifteen internal cycle time variables were identified as potentially impactful to a dump truck's cycle time. The dependent variables include: enter duration, load duration, exit duration, and haul duration. The independent cycle time variables include: enter idle time duration, enter elevation, enter elevation change, enter maximum speed, enter average speed, exit idle time duration, exit elevation, exit elevation change, exit maximum speed, and exit average speed. Idle time durations for both the entrance and exit were separated from their respective enter and exit durations in an attempt to assess their individual impact on the overall dump truck cycle time.

The following independent external variables thought to impact a dump truck's cycle time were also assessed: temperature, dew point, humidity, visibility, wind direction, wind speed, haul road material, and haul road conditions. The driving surface for the dump truck in transit was considered to be negligible because all should be smooth surfaces made of concrete or asphalt. Most construction sites do not provide smooth surface haul roads for dump trucks during excavation, so this was not included in the study. All internal variables were collected by the deployed GPS system which external variables were gathered through site visits, site pictures, and historical weather sites (TWC 2016). The external variables were collected at the end of the data analysis phase for each day of data collection in the experimental testbed. Table 1 provides the definition of each variable assessed for an individual dump truck's cycle time. Analyzed data values idle time, load duration, exit duration, and haul duration are calculated from the raw GPS data.

Table 1: Variables for Data Collection of Dump Truck Cycle Time

Variables	**Units**	**Definitions**
Enter truck duration	Second	Travel time duration from entrance to excavation area
Truck Load duration	Second	Time duration for excavator to load the truck payload
Exit truck duration	Second	Travel time duration from excavation area to the exit
Haul truck duration	Second	Travel time duration from the exit to the entrance
Enter truck idle time duration	Second	All static time during the enter duration
Truck enter elevation	Meter	Ground elevation at the entrance
Truck enter elevation change	Meter	Difference in elevation experienced when traveling from the entrance to excavation area
Enter maximum speed	Meter/ Second	Maximum speed during enter duration
Truck enter average speed	Meter/ Second	Average speed during enter duration
Truck exit idle time duration	Second	All static time during the exit duration
Exit truck elevation	Meter	Ground elevation at the exit
Truck exit elevation change	Meter	Difference in elevation experienced when traveling from the excavation area to the exit
Truck exit maximum speed	Meter/ Second	Maximum speed during exit duration
Truck exit average speed	Meter/ Second	Average speed during exit duration
Site outdoor Temperature	Degrees Celsius	Average daily temperature on the construction site
Site outdoor Dew point	Degrees Celsius	Daily dew point at the construction site
Site outdoor Humidity	Percent	Daily amount of water vapor in the environment at the site
Site outdoor Visibility	Meters	Distance at which an objective or light can be identified
Site outdoor Wind direction	Cardinal direction	Average direction of wind direction on the site
Site outdoor Wind speed	Meters/ Second	Average value of wind speed on the site
Haul road material for trucks	Soil type	Type of material used for constructing the haul road
Haul road condition for trucks	Visual observation	Daily observation of dump truck travel path

3.3.2 Data Analysis

Data collected from the GPS loggers provided the raw data points for analysis. The GPS data loggers provided the latitude, longitude, elevation (in meters), date, distance from start (in meters), distance from last (in meters), bearing, and speed (in meters per second). The internal variables were analyzed from these raw data sets through various calculations. The GPS update rate was 1 Hz and the GPS data loggers only record when movement is detected. Wintec was the company that produced the deployed GPS devices (Wintec 2016). Figure 4 provides an example of the GPS raw data set.

Elevation	Time	Dist. from Start	Dist. from Last	Bearing	Speed
272	10:03:25 AM	0.022	0.002	281	6.51
272	10:03:26 AM	0.023	0.001	270	4.26
272	10:03:27 AM	0.024	0.001	270	4.26
272	10:03:28 AM	0.026	0.002	270	6.38
272	10:03:29 AM	0.027	0.001	253	4.44
272	10:03:30 AM	0.029	0.002	270	6.38
273	10:03:31 AM	0.03	0.003	253	4.44
273	10:03:32 AM	0.031	0.003	270	4.26
273	10:03:33 AM	0.033	0.005	259	6.51
273	10:03:34 AM	0.035	0.006	259	6.51

Figure 4: Example of GPS Raw Data Set

The data collection effort resulted in approximately 250 data points across the 22 variables shown in Table 1. In order to identify the most impactful variables on a dump truck's cycle time, several regression analysis were performed on the collected data. A commonly-used statistical analysis computer program, called Statistical Analysis Software (SAS), allowed for storage, modification, simple and complex statistical analysis, and reports of data values (Salkind 2010).

The maximum outlying value for all gathered variables represented less than 2% of all data collected for that specific variable. Extreme outliers (values greater than three times the fourth spread from the quartile values) were removed from the analysis. These extreme outliers were defined as values greater than three times the fourth spread distance from each quartile value. A stepwise regression analysis was used to quantify the weighted impact of each variable on the overall dump truck cycle time. The stepwise regression is an iterative process in which the correlation of each independent variable to the dependent variable is assessed (Devore 2015). Independent variables with the highest correlation are entered into the regression equation at each iteration. The regression analysis ends when all variables are entered into the equation or the correlation between remaining independent variables and dependent variables is considered insignificant (Devore 2015). For this research, all independent variables that entered the model were deemed significant at the significance level of 0.05. No other independent variable met the significance level of 0.10 for entry into the model.

The dump truck cycle time was previously defined as the summation of the enter duration, load duration, exit duration, and haul time (Peurifoy et al. 2006). One form of internal validation performed for the collected data was performing a correlation analysis to ensure a perfect correlation existed between the overall cycle time and the summation of the enter duration, load duration, exit duration, and haul time. Furthermore, this analysis ensures that each of the cycle time components (enter duration, load duration, exit duration, and haul time) can be evaluated as dependent variables for other regression analysis to identify the impact of more detailed variables on the overall cycle time. The haul duration and enter duration were found to have the highest impact on a dump truck's overall cycle time.

A simple statistical analysis was performed on the collected data to provide insight into the following quantitative analysis. Results of this analysis are presented in Table 2. Only measured variables with quantitative values were analyzed.

Table 2: Statistical Analysis of Select Variables

Variables	Mean	Range	Standard Deviation
Enter duration	6.0 min.	69.3 min.	7.6 min.
Load duration	9.7 min.	57.5 min.	10.4 min.
Exit duration	687.5 min.	26.9 min.	133.2 min.
Haul duration	27.1 min.	992.0 min.	48.1 min.
Enter idle time duration	3.1 min.	53.0 min.	4.8 min.
Enter elevation change	1.6 m.	5.8 m.	12.4 m.
Enter maximum speed	26.2km./hr.	56.6km./hr.	16.3 km./hr.
Enter average speed	21.1km./hr.	40.7km./hr.	8.6 km./hr.
Exit idle time duration	1.4 min.	56.1 min.	3.7 min.
Exit elevation change	5.2 m.	3.9 m.	9.0 m.
Exit maximum speed	28.3km./hr.	49.2km./hr.	21.8km./hr.
Exit average speed	14.4km./hr.	23.8km./hr.	32.4km./hr.
Temperature	14.1 °C	0.6 °C	-12.9 °C
Dew point	6.5 °C	-0.6 °C	-13 °C
Humidity	1.0%	1.1%	0.2%
Visibility	15.2 km.	15.8 km.	2.6 km.
Wind speed	10.3km./hr.	24.1km./hr.	5.1 km./hr.
Construction site duration versus total cycle time	34.7%	80.1%	46.3%

In an attempt to quantify the statistical relationships between the collected data variables and the cycle time components, a processing platform was develop in a commonly-used multi-paradigm numerical computing environment, called Matrix Laboratory (MATLAB). The computing software was selected to perform detailed statistical analysis, but is not required to execute the summarized research. A regression analysis was completed between all potential combinations of the 22 evaluated variables. The platform was developed by writing code to build a linear regression model for the variables. Linear regression was selected after the regression analysis indicated a linear relationship provided the highest potential of correlation when compared to other tested functions. Of these regressions, four plots were found to show the most potential for a correlation. The four plots presented in Figure 5 identify an increasing linear relationship between each of the independent variables of the total cycle time. Regression results indicate that the haul duration has the strongest linear associated with cycle time. Figure 5 shows the graph of each fitted regression line. The lack of a correlation between the load duration and cycle time indicates that the overall cycle time is minimally impacted by the load duration.

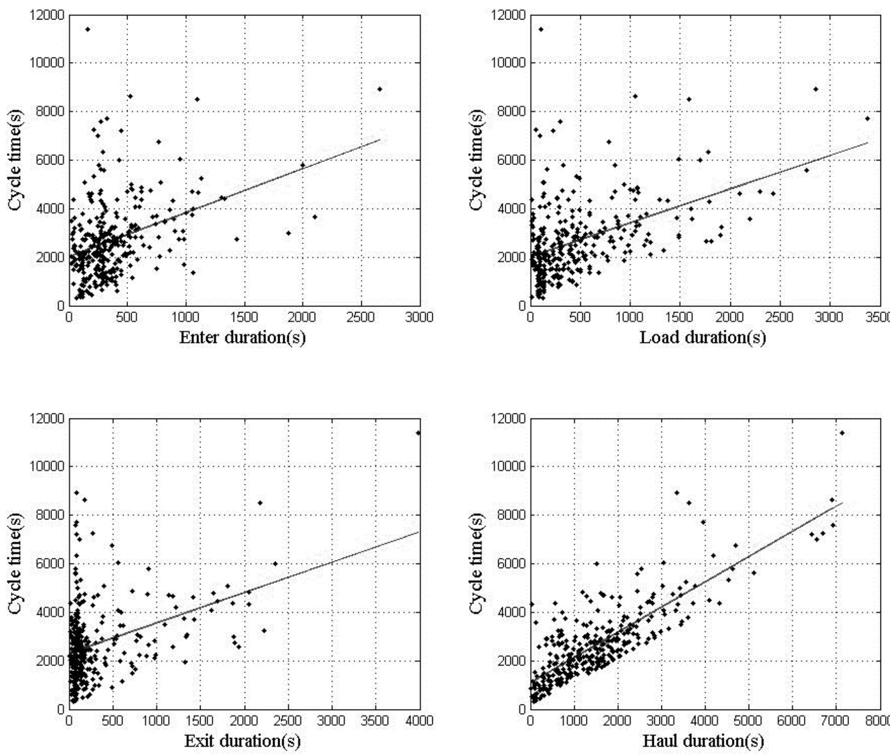


Figure 5: Linear Regression Analysis between Cycle Time Components and Overall Cycle Time

It is important to note enter and exit idle time were not included in the cycle time durations presented in Figure 5. Preliminary statistical analysis indicates no identifiable correlation existed between cycle time elements and the overall cycle time when idle time values are included. This is potentially due to the unpredictable nature of idle times. For example, many of the outlying values with extended duration times were due to equipment malfunctions of the excavator.

After verifying that the summation of individual components of the cycle time have a direct impact on the overall cycle time, the next completed step was to identify the contribution of each independent variable on the overall dump truck cycle time.

Enter Duration Variable Analysis

A stepwise regression analysis identified twelve potential impacting variables on the enter duration. Of these twelve, enter idle time (EnIT), humidity (H), and wind speed (WS) were determined the have the highest impact on the enter duration time. A suggested model for the enter duration (ED) in seconds of a single dump truck is shown in Equation 2. The model is correct on average for all fitted values as shown in Table 3.

$$ED = 17.717 + 1.0389(EnIT) + 3.7074(H) - 13.063(WS) \qquad \textit{Equation 2}$$

The R-square value was implemented to measure how well the individual variables of the enter time duration (shown in Table 3) fit the output model. Each R-square value measures the individual variable contribution to the model and how well that value fits with the overall model. These values are obtained by providing a cumulative value of best fit as the model progressed from one variable to three variables. The same regression measurement was used for variables in Equation 3.

Table 3: Output of Stepwise Regression of Enter Duration

Variable	R-square	F Value	Pr > F
Enter idle time duration	0.5663	408.74	<.0001
Humidity	0.5791	9.46	0.0023
Wind speed	0.5893	7.71	0.0058

The enter idle time was identified as having an increasing linear relationship with the overall cycle time. As expected, the overall cycle time increases as the frequency and duration of stops for a dump truck increases.

It is important to note that both Equations 2 and 3 have constant values. This represents the culmination of variables found to be insignificant in the model. For example, truck speed was deemed insignificant in the model because the travel distance on the construction site was minimal and only a marginal speed could be obtained by the truth. While speed of the truck wasn't found to significantly impact the model, a time duration was required for the truck to travel this distance requiring an initial amount of time on the cycle time.

Load Duration Variables Analysis

All of the independent variables found to be correlated with the load duration analysis were weather and environmental related. However, the R-Square and F-value indicate these variables are not reliable predictors of the load duration. Therefore, it was determined that load duration is entirely dependent on the functionality and capability of excavation equipment. Because all variables collected were individual properties of the dump truck, the data collected was incapable of explaining the load duration. However, from stepwise regression results, visibility (V) and wind direction have a P value less than 0.001 which indicates the weather conditions have an impact on the overall cycle time.

Exit Duration Variable Analysis

Two evaluated independent variables were determined to impact the exit duration of a dump truck. These variables are exit idle time duration (*ExIT*), visibility and wind speed. Similarly to the enter duration, the idle time was found to have a linear relationship with the exit duration meaning the longer duration and more frequent stops of dump trucks result in longer exit durations. The generated equation from the stepwise regression is shown in Equation 3. The R-Square value for this output is minimal indicating it may not necessarily statistically explain all of the Exit Duration (*ED*) variable in seconds. Table 4 shows the statistical assessment of output variables of the stepwise regression.

$$ED = 991.21 + 1.2208\ (ExIT) - 72.105(V) - 21.94\ (WS) \qquad \textit{Equation 3}$$

Table 4: Output of Stepwise Regression of Exit Duration

Variable	R-square	F Value	Pr > F
Exit idle time duration	0.3263	151.60	<.0001
Visibility	0.3592	15.99	<.0001
Wind speed	0.3699	5.30	0.0220

Haul Duration Variables Analysis

The stepwise regression output for the haul duration indicated that a significant correlation between the haul duration and all collected data did not exist. The output variables of the regression recorded an insufficient R-Square value to statistically explain the variation of haul duration. Of the output variables from the stepwise regression, most were environmental conditions indicating that more data is required to understand the impact on the haul duration.

3.4 Discussion of Results

Results of the data analysis indicate impactful variables to a dump truck's cycle time as well as many variables that have minimal impact. Additionally, cycle time categories that lack sufficient correlation identify areas where additional research and data collection are needed. Overall, dump truck idle time during both the entrance duration and exit duration proved to be the most influential variable on a dump truck's cycle time of the data collected. A correlation was not identified between idle time and the overall cycle time because of the large range of idle times. For example, a small entrance or exit idle time has little impact on the overall cycle time, but an extended entrance or exit idle time has a significant impact on the dump truck's overall cycle time. Larger dump truck idle times were attributed to equipment malfunctions of the excavator.

Two environmental variables cited to had an impact on the overall dump truck cycle time. The first environmental was the impact of visibility on the dump truck's load duration, and exit duration. The second environmental variable was the impact of wind direction of the dump truck's enter duration, load duration, and exit duration. Both of these variables suggest environmental factors and haul road conditions have an impact on the overall cycle time of the dump truck. Future research should investigate other variables, such as excavator productivity, to further identify impact variables to the overall construction operation.

The R-square values calculated in both Table 3 and Table 4 are both relatively low for declaration of fitness. The researchers identified several potential reasons for this including 1) a lack of additional external variables including the excavator productivity data, 2) various skill levels of dump truck operators and excavator operators, and 3) external traffic conditions impacting the hauling duration.

3.5 Conclusion

The cycle time of construction haul equipment can directly impact the overall productivity and resulting success of a construction project. The research objective was to identify and analyze the statistically significant influential variables on a single dump truck's cycle time. It is important to note that the research did not necessarily create a prediction model, but rather scientifically identified impact variables to a dump truck's cycle time. To achieve this objective, GPS technology was deployed on dump trucks in an active construction site setting for location tracking. Data collected from the GPS devices was catalogued and analyzed using linear regression models for each component of the dump truck's cycle time. Variables were categorized based on their specific impact per individual stage of the cycle. Additionally, external environmental variables were included in the regression analysis. The stepwise regression models developed for the dump truck enter and exit duration contained the most significant results. The study revealed that the following four factors have the most impact on a dump truck's enter and exit time: 1) idle time, 2) visibility, 3) wind speed, and 4) humidity. These four variables were determined to be the most impactful on the overall dump truck cycle time based on the variables assessed. Construction industry practitioners and researchers can use the primary outcomes of this study in monitoring cycle time systems to enhance and improve construction equipment productivity.

The contribution of this research is the identification and analysis of statistically significant correlations of identified variables with the cycle time of a dump truck. Limitations of this work include minimal variables available for the haul duration and load duration. Additionally, environmental factors were not considered for non-working days. For example, large amounts of rain produced an entire day of delay which was not captured in the regression. Future research could investigate the interaction of excavation equipment with haul equipment and include detailed variables regarding the haul distance.

CHAPTER 4 AUTOMATED CONSTRUCTION SITE PATH PLANNING FOR DUMP TRUCKS IN BUILDING INFORMATION MODELING

Construction productivity is commonly used in project controls because of its immense impact on the overall project success (Peurifoy et al. 2006). Productivity is influenced by construction equipment travel paths on a given construction site. Navigating a terrain and determining the shortest path on a construction site is one fundamental concern in path planning. One common approach to solving this problem is implementing one or a combination of search algorithms to satisfy constraints for generating the equipment travel path (Soltani et al. 2002). The major criterial used for our path planning process will be the shortest path between desired cycle locations and obstacle avoidance. BIM can be used as a platform for application of new technologies and methods to enhance construction productivity. The objective of this research is to design a strategy and automated tool to calculate and display an efficient equipment travel path within a BIM. The research framework is tested with active construction site data, and feedback from workforce and management will be assessed and integrated into the research approach.

4.1 Introduction

A multitude of research has been performed on construction productivity because of its inherent impact on overall project success. Construction productivity has recorded a recent upward trend largely due to advances in technology (Allmon et al. 2000, Goodrum et al. 2004).

With the implementation of sensing technology and BIM into construction project management, new strategies for capturing and analyzing data become apparent. Construction project managers are integrating BIM into many aspects of a project including building life cycle, design (Penttila 2007), planning, constructability (Kymmell 2008), and operation (Akcamete et al. 2010). The research scope is limited to short-term productivity. Short-term productivity is typically measured as a ratio value of output to input, where input is defined as physical units installed and output is cumulative work hours (Goodrum and Haas 2002).

Construction site path planning is typically performed using manual methods of experienced construction management personnel. By implementing BIM as a project communications platform, automated equipment path planning becomes possible. This enables construction managers to plan and schedule equipment cycle operations with other project stakeholders in BIM. Based on the construction site layout design concepts, path planning is a significant component of site layout design in early project phases. Safety issues, existing facilities, and overall productivity will all impact the equipment travel path. Numerous pieces of moving construction equipment pose significant risk to pedestrian workers in terms of safety and overall productivity. Equipment travel path determination during the planning phase of the project allows for elimination of potential hazards and allows for a more efficient operation cycle. Heavy construction equipment has gained considerable attention from researchers lately. The research aims to automatically calculate and display an efficient travel path for equipment in BIM.

This research is driven by several areas of national need; namely, the need to enable construction automation through advances in computer science and sensing. The National Academy of Engineering (NAE 2008) concluded that computer science and sensing research must be conducted to enable automation in construction. The National Research Council (NCR

2009) reported that advances in emerging technologies such as automation offer significant opportunities to improve the productivity, safety, and efficiency of work performance.

4.2 Literature Review

Pradhananga and Teizer (2013) found that pro-active measures can greatly advance the field of site preparation, planning, and controlling, including better organized job site layout, equipment operation and utilization, and job safety analysis. Equipment travel path planning is a significant part of site logistics including construction site layout planning (CSLP) and safety planning. This literature review aimed to find suitable travel path algorithms and explore functions in BIM that can help in designing an optimal travel path and finally improving the overall construction site productivity. The following sections review construction sit layout planning, methods of designing construction equipment travel path, and BIM application in construction.

4.2.1 Construction Site Layout Planning

Most construction sites are very complex with multiple existing facilities, materials laydown yards and motorized equipment. In different phases of a construction project, construction site layout is dynamic with multi-functions. For example, tower cranes and land cranes present significant obstacles for travel paths and their position are always changing, which may impede construction productivity. Xu and Li (2012) proposed a fuzzy random multi-objective decision making model to enhance dynamic CSLP. The development of a multi-objective site layout optimization system can help improving construction safety, construction-related security level, and user’s visibility of the generated optimal site layout plans (Khalafallah and El-Rayes 2011).

Construction site models can assist designers to analyze construction site constraints, identify potential problems, and maximize field productivity and safety (Li et al. 2008). An optimal CSLP can help project managers and planners to design a better construction site under conflicting multiple objectives, such as construction cost reduction and ease of supervision and control (Ning et al. 2011).

Equipment travel path planning is one of the significant components of construction site layout design. Alshaer et al. found that planning, controlling, and simulating heavy construction machines is feasible from a full autonomous truck loading cycle mode (Alshaer et al. 2013). The application of path planning can help to find the optimal path with shorter distance, lower risks, and higher visibility between two site locations (Soltani et al. 2002).

4.2.2 Methods of Designing Construction Equipment Travel Path

Previous work on path planning analysis in construction focused on three principal categories: 1) safety consideration, 2) earthmoving vehicles, and 3) efficient site layout design. Multiple constraints have been considered into a travel path design algorithm including shortest path, obstacle avoidances, lower risk, minimum noise pollution, minimum transport cost, and higher visibility. In order to achieve these goals, researchers have found and tested various categories of path planning methods as shown in Table 5.

Table 5: Current Travel Path Methods

Method	Description
Dijkstra's Algorithm	Mainly used for determining the shortest paths from a starting node to a goal node with graphs (Dijkstra 1959, Soltani et al. 2002)
A Star Algorithm	Uses a heuristic function h(n) to estimate the cost of the lowest cost path from a start node to a goal node plus the path cost g(n) (Hart et al. 1968, Soltani et al. 2002,)
Ultra Wideband (UWB) sensor technology for optimizing construction site operations	Post-processed trajectory information from UWB signals populate an occupancy grid use for path planning to suggest optimal paths for workers while generates optimal paths for vehicles (Cheng et al. 2011)
Floyd-Warshall Algorithm	Computes shortest path between arbitrary pairs of vehicles moving (Cheng et al. 2011)
Genetic Algorithm (GA)	A possible solution technique and includes a theoretical example of positioning temporary facilities (Mawdesley et al. 2002)
Binary tree Algorithm	Path planning with obstacle avoidance starts from source to target in the tangent visibility graph. (Rashid et al. 2013)
Ant colony Algorithm	An optimization technique based on swarm intelligence to find the shortest and collision-free route in a grid network (Brand et al. 2010)

4.2.3 Design Software Add-Ins and User Interface

Autodesk products including Revit and AutoCAD have been widely used for BIM research and implementation. Developers can choose between different programming environments: Microsoft Visual Studio or Microsoft Visual Studio Tools for Applications (VSTA). Programming using VSTA is conceptually similar to Visual Basic for Applications (VBA), where developers design in a CAD system and build projects to embed into a Revit document or to keep in a separate project file (Autodesk 2016). An application programming interface (API) allows users and developers to extend the capabilities of an existing application by writing a program or script that adds new functionality to the software. The Autodesk Revit

API allows programmers to change elements in the BIM directly or to access the data to perform specialized tasks (Autodesk 2016).

4.2.4 Research Needs Statement

The benefits of BIM have been realized in the construction industry and corresponding academic research. Results of this review indicate a need exists in construction planning and execution to create and implement a framework and tool to automatically present an efficient travel path for transporting materials on the construction site. By implementing such a framework and tool in BIM, construction site personnel can visualize an efficient travel path for equipment to support their site layout planning efforts.

4.3 Research Methodology

Travel paths of construction equipment remains a significant issue because it has a direct impact on productivity. The goal of this research is to create an automated tool and interface to design and maintain construction equipment travel paths for transporting materials. Multiple objects and areas should be considered during the planning phases of a construction site layout including existing structures, crane placement, materials and equipment laydown areas, field trailers and employee parking.

In order to create the path planning tool, a simulated construction site was designed in a commonly used BIM software package, Autodesk Revit, which was based on components of an active construction project in the southwest region of the U.S. The overall construction site dimensions are 60 meters wide by 60 meters long and is shown in Figure 6.

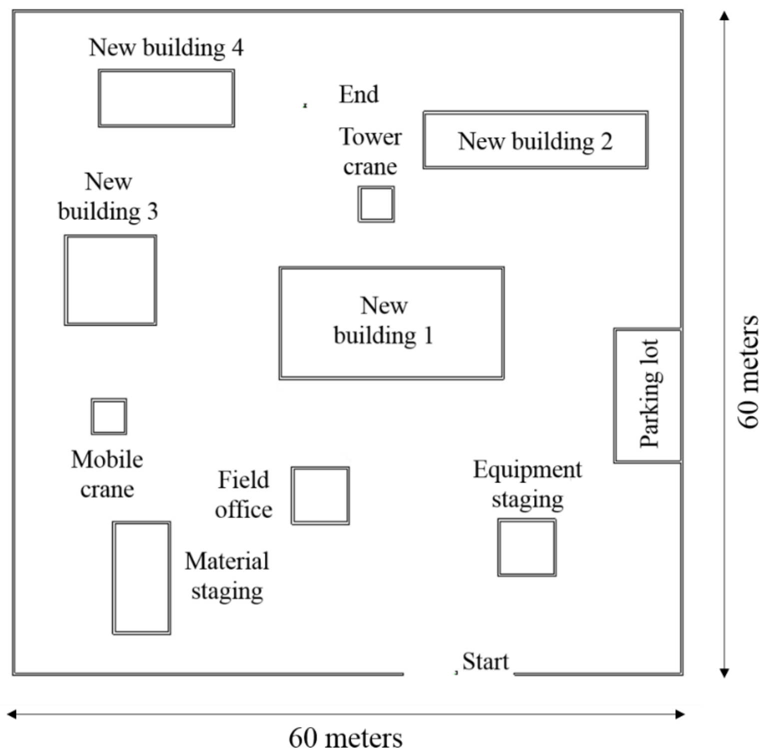


Figure 6: Simulated Construction Site Layout in Autodesk Revit

Table 6 provides the dimensions of each cited area in Figure 6.

Table 6: Surface Area of Construction Site Components

Site Component	Dimension (Length by Width)
New building 1	20 meters by 10 meters
New building 2	20 meters by 5 meters
New building 3	8 meters by 8 meters
New building 4	12 meters by 5 meters
Field office	5 meters by 5 meters
Material staging	5 meters by 10 meters
Equipment staging	5 meters by 5 meters
Parking lot	6 meters by 12 meters
Tower Crane and mobile crane	3 meters by 3 meters

4.3.1 Functionality of Automated Path Planning Tool

Constraints including shortest path and obstacle avoidance provided decision criteria during the design process of the automated path planning tool. The A Star Algorithm, using a grid based approach, provided the best functionality for the desired path planning operation and was thus selected for this application. The A Star uses a heuristic function $h(n)$ to estimate the cost of the lowest cost path from a start node to a goal node plus the path cost $g(n)$ (Hart et al. 1968). The total cost $f(n) = g(n) + h(n)$ is calculated for each successor node and the node with the smallest cost $f(n)$ is selected as a successor (Hart et al. 1968). The grid-based approach divides the construction site surface area into equal sized square grid sections (Andayesh and Sadeghpour 2014). All possible nodes are generated into each square and each node has six potential orthogonal directions. This approach is achieved by building a MATLAB code in which unoccupied nodes are marked as 2, obstacles nodes are marked as -1, the start point is marked as 1 and the end point is marked as 0. The code is established by using A Star algorithm to find the optimal path from node 1 to node 0 through all possible nodes marked as 1. Nodes that have been marked as -1 represent the obstacles and are automatically excluded from the optimal path. As a result, the optimal path will be the shortest path between the start point and the end point which avoiding obstacles throughout the travel path.

The automated path planning tool was created using the Application Programming Interface (API) capabilities of Autodesk Revit which is a commonly used BIM software package. This interface allows programmers to modify elements in an active BIM directly or to access certain datasets to perform specialized tasks. An application developer software called Microsoft Visual Studio was implemented to support the API programming environments for the automated path planning tool.

The user interface was designed through the API on a simulated construction site to create the optimized travel path. By integrating the tool to an existing BIM platform, automated generation of the travel path based on a set of construction site condition parameters became available. Add-ins that enabled the automated path planning tool are presented in Table 7.

Table 7: User Interface Functions of the Automated Path Planning Tool

Add-in Name	Description
Read Coordinates	This add-in automatically reads the coordinates of each component on the selected construction site. Based on the selected relevant point, a spreadsheet file is created including all (x,y) location-based coordinate information
Optimal Path	This add-in automatically reads the optimal path from a created spreadsheet file and plots the optimized travel path in the selected construction site model

The first functional step of the automated path planning tool is to verify that a BIM exists. One this has been established, the tool reads existing coordinates when prompted by the user interface. This allows users to select existing buildings, facilities, desired travel path start and end point, and any other objects of interest from the existing construction site in the BIM. A database spreadsheet is automatically created which includes boundary two-dimensional coordinates of all selected construction site components. Next, MATLAB is prompted to open the generated database and identify an optimal path based on the location-based coordinates. The final step utilizes the other add-in created in Autodesk Revit's open API. This function gathers automatically generated travel path coordinates from MATLAB and visualized the created path in the existing BIM. The logic of the created tool's functionality is provided in Figure 7.

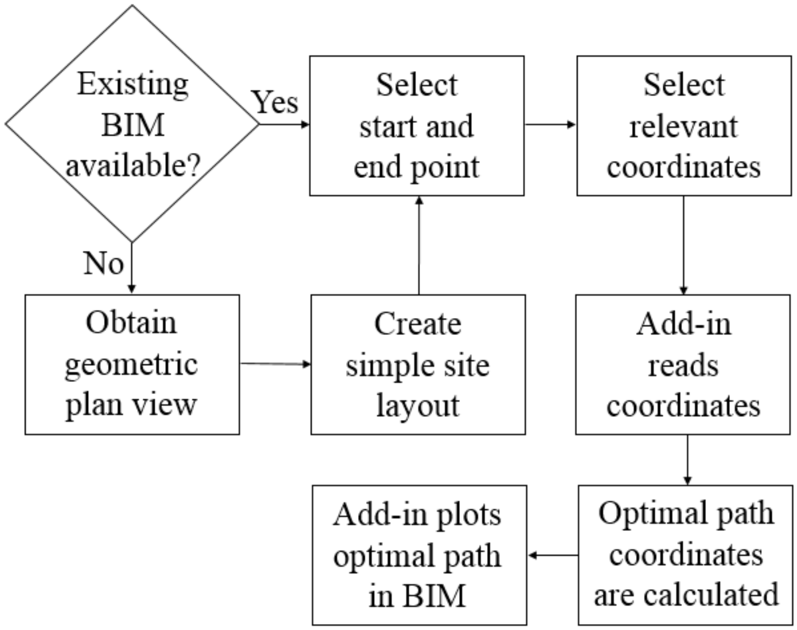


Figure 7: Flowchart of Steps for Travel Path Determination

The created automated path planning tool uses BIM software, a database organizational software, and programming enabled matrix calculation program to calculate and visualize the equipment travel path. Figure 8 shows the interface relationships and data transitions through these three software packages. The created tool was implemented on the simulated construction site shown in Figure 9.

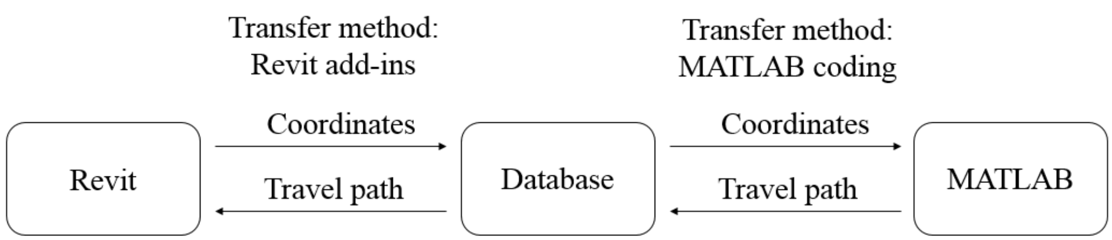


Figure 8: Interface Relationships between Software Packages for Created Tool

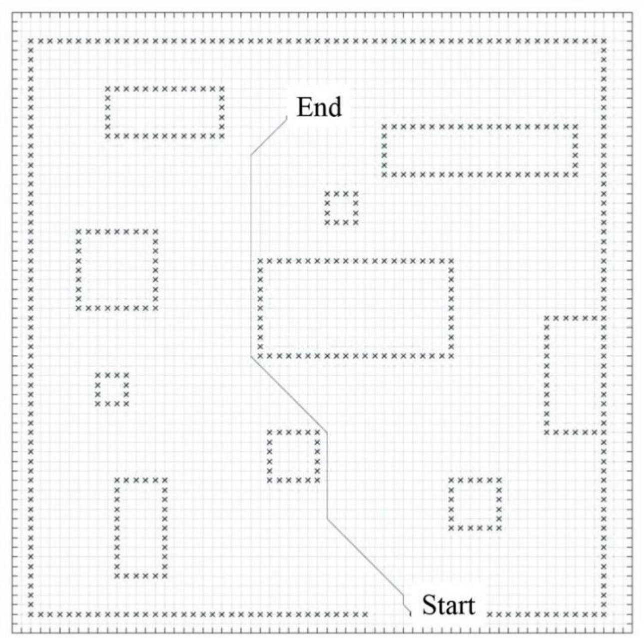


Figure 9: Travel Coordinates and Path Calculated in MATLAB

This simulated construction site contained a start point, an end point, and several obstacles. To demonstrate the capabilities of the created tool, an arbitrary start and end point were selected. Figure 9 also presents the result of a calculated path in MATLAB.

Calculated travel path coordinates from MATLAB are exported through the database to be visualized in the BIM. The final output of the automated path planning tool is a line connecting calculated coordinates in BIM. A sample output from the simulated construction site is shown in Figure 10. It is important to note that a few components changed location and size from their original properties shown in Figure 10. This is because the tool was ran on a subsequent phase of the construction project to demonstrate the dynamic nature of the tool and of construction path planning.

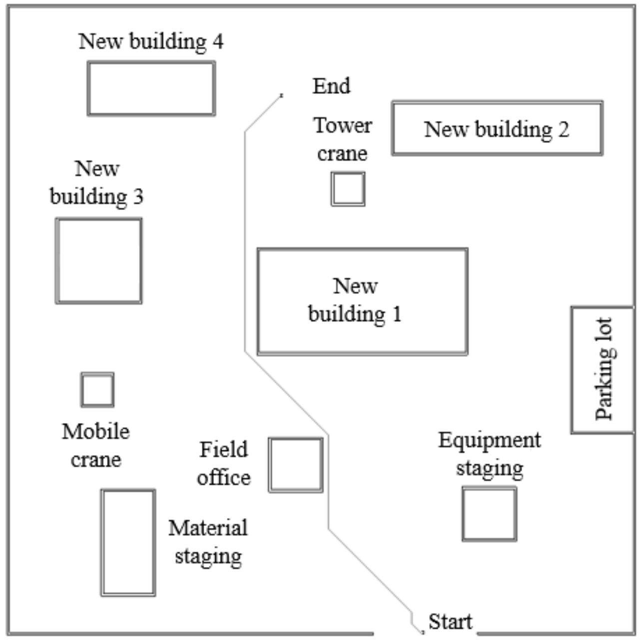


Figure 10: Finalized Travel Path Visualized in BIM

4.3.2 Results

A framework shown in Figure 11 was created to get the optimal travel path. The input is the constrains that need to be preciously determined such as buildings, equipment, hazard zone, temporary facilities for example: parking lots, material storages, workshops, and all other potential constraints that can be considered as the obstacles on the specific construction site. The next step was to confirm the size of the component and then run the created tool to get the optimal path including the path and the length of the path. This created path planning framework can be applied on any construction site during different construction phases.

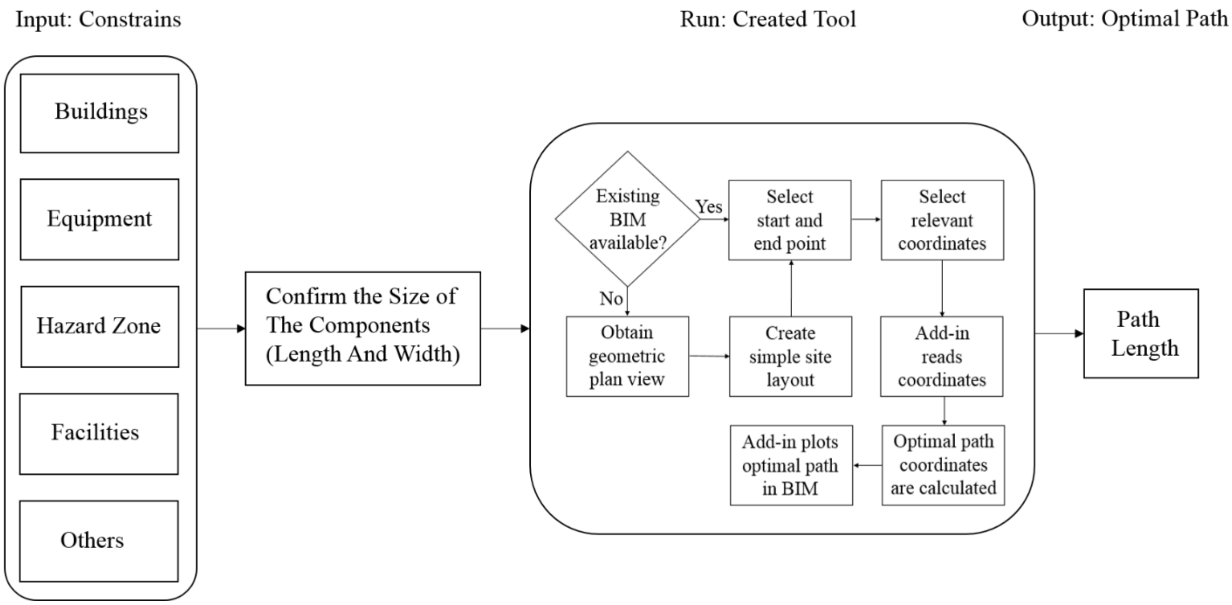


Figure 11: Created Path Planning Framework

The created construction equipment path planning framework was internally and externally validated through several specific construction site case studies and review by a construction safety manager expert review panel respectively. This section provides the analyzed results from both validation efforts and explanations for obtained results.

4.3.3 Internal Validation

Ten active construction sites were randomly selected to evaluate the abilities of the automate path planning tool in these environments. These sites were chosen from a list of over 100 active construction sites in the U.S. Aerial photos from satellite imagery were used to visualize the current construction site surface and layout. These sites were manually drawn as a simple BIM including an entrance and exit point for the material transporting equipment travel path. The distance between these two points was automatically calculated. Simple boxes were drawn in BIM to simulate the construction site aerial photographs. Lines were traced along the actual construction equipment travel path to generate data for comparison against the automatically generated travel path from the created tool. The average percentage increase or decrease of the equipment travel path was determined based on the travel path calculated by the automated path planning tool and the actual path used on the construction site. Table 8 presents a summary of the compared results and indicates an average decrease of 32% in travel path length for the calculated path.

Results from Table 8 indicate that construction site areas with larger size significantly enhance the accuracy of reliable optimal path findings. Previous research identified the construction site size has a significant impact on both accuracy and computation performance of the proposed solution (Chen et al. 2012).

Table 8: Average Decreasing Value of Length between Calculated and Actual Travel Path

Type	**Location**	**Existing Path (in meters)**	**Optimal Path (in meters)**	**Reduction Amount**
University Building	Tuscaloosa, AL	83.19	72.06	13.38%
Hospital	Birmingham, AL	166.18	110.16	33.71%
Midtown	Atlanta, GA	158.24	54.99	65.25%
Department Store	Austin, TX	160.67	116.10	27.74%
Apartment	San Antonio, TX	180.56	87.3	51.65%
Leasing Office	Houston, TX	100.40	87.86	12.49%
Grocery Store	Fort Worth, TX	626.29	323.80	48.30%
Apartment Complex	Louisville, KY	74.73	69.1	7.53%
Elementary school	Emeryville, CA	218.44	132.39	39.39%
Department Store	Cheektowaga, NY	303.11	241.96	20.17%
			Average	31.96%

4.3.4 External Validation

An expert review panel of five experienced construction engineers and management personnel was assembled. The construction project focus, company location and type of experience was varied across the expert review panel. This panel completed a demonstration of the tool and completed a survey based on their experiences with the tool. The expert review panel was asked seven questions concerning the functionality and the ease of implementation of the automated path planning tool. The research team was approved through a state university Institutional Review Board (IRB). The approval was provided for all questions asked on the survey as well as general information shared by the expert review panel. Members of the expert review panel were members of construction companies and governmental agencies experienced in conducting construction work. The group had an average experience level of 15 years with the minimum value being 11 years of experience. All members of the panel were leaders or members of their company's planning or scheduling division.

Feedback from the expert review panel was recorded and analyzed to identify the content and frequency of each statement. For each response, panel members were asked to provide a rating based on a Likert scale (Likert 1932). The questions provided ordered responses ranging from 1 to 5 with the following respective descriptions: Strongly disagree, disagree, unsure or neutral, agree, and strongly agree. Strongly disagree was assigned a rating of 1 and strongly agree was assigned a rating of 5. Table 9 provides a summary of responses from the expert review panel.

Table 9: Summary of Path Planning User Interface Expert Review Panel Responses

Proposition	**Minimum score**	**Maximum score**	**Average score**
There is a need to integrate optimization tools into existing construction project management strategies	**3**	**5**	**4.6**
It will be useful for project managers to visualize planned travel paths in BIM	**2**	**5**	**3.9**
The proposed tool would be easy to use	**3**	**5**	**3.7**
The proposed tool is implementable	**3**	**5**	**3.7**
The proposed tool would enhance productivity for equipment travel paths	**2**	**5**	**3.6**
The proposed tool would be effective in construction site planning	**2**	**5**	**3.6**
Overall, the proposed tool would be effective in improving project management	**2**	**5**	**3.3**

With a relatively high average score of 4.6 of proposition 1, members of the expert review panel believe a need exists to integrate optimization tools into existing project management strategies. Members of the panel also identified the usefulness of visualizing equipment travel paths in BIM environments. Over half of the review panel members agreed that the created tool is easy to use and is implementable into their individual company. Lastly, most panel members agreed that the created tool would be effective in improvement of project management on construction sites.

4.4 Conclusion

BIM has progressed as an integral part of construction site management currently in the industry (Eastman et al. 2011). This research created a strategy and automated tool to calculate and visualize an efficient material transport equipment travel path within a BIM. Existing algorithms were modified and implemented in an existing BIM to allow for automatic generation of an efficient travel path based on construction site input criteria. Through validation efforts, the tool was shown to be robust and applicable for various types of construction site configurations, sizes, and existing obstacles. Furthermore, the created tool proved to be desired and implementable by experienced members of the construction industry.

The created path planning framework integrated construction scheduling with interoperable BIM software capabilities and it can be applied to any phases of a construction project. It also can help construction engineers with construction scheduling simulation/modification. This framework allows users to input constraints such as buildings, temporary material storages, temporary workshops, safety concerned hazard zones, etc. and get the optimal path automatically. The authors have also validated the framework by designing software add-ins in Revit and this is easy to install and use on any computer that has a BIM software. A Star algorithm was used to get more accurate design; users can also change the accuracy by changing the grid dimensions. Automated design is efficient and save time during the design phase.

Contributions of this research include scientific evaluation data of construction equipment travel paths and a feasible method of automatically constructing an efficient travel path for construction equipment. Construction engineers and management personnel can implement the tool throughout any stage of the dynamic construction scheduling process. Future research can explore the automatic generation of new travel paths based on real-time information from tracking technology of material transport equipment on construction sites. Additionally, researchers can investigate the feasibility of automating other aspects of the design and scheduling process such as construction site layout for increased productivity and safety.

CHAPTER 5 DYNAMIC 3D BLIND SPOT MAPPING FOR EQUIPMENT OPERATIONS

Construction site characteristics tend to foster dynamic work environments with a multitude of interactions between moving equipment and pedestrian employees. Blind spot and obstructions are the most common causes of struck-by incidents between equipment and employees on construction sites. The research objective was to create a framework to identify and quantify areas not visible to construction equipment operators. A methodology including algorithms are provided to aid construction management personnel to calculate equipment operator blind spots given various situations and conditions. An indoor construction working environment was implemented to evaluate the effectiveness of the developed framework as part of the research methodology. An automated laser scanner was used to collect location-based data which was exported as a point cloud into a Building Information Model (BIM). By identifying and quantifying equipment operator blind spots in 3D, construction site personnel can automatically detect and quantify non-visible areas for construction operators along equipment travel paths.

5.1 Introduction

Visibility-related issues, specifically blind spots of equipment operators, have been known to cause injuries and fatalities on construction sites (Teizer et al. 2010). It is estimated that 5% of U.S. construction fatalities were visibility related (Teizer and Hinze 2011). Virtual environments provide an opportunity for construction management personnel to identify higher risk hazards caused by moving construction equipment (Perlman et al. 2014). Although sensing technology and other pro-active strategies have been implemented to combat this problem, injuries and fatalities still result from limited construction equipment operator visibility (Lancaster et al. 2007). A research need exists to explore more effective methods to solve the Human-Equipment interaction issue. One solution is to increase operator visibility through advanced equipment design by including nearby ground workforce equipment (Marks et al. 2013). The research is aimed to create a framework to measure and calculate blind spots for pieces of construction equipment in construction working environments.

5.2 Literature Review

Construction workers encounter multiple hazards on construction sites. The dynamic environment of construction sites often fosters hazardous interactions between construction equipment and pedestrian workers. Previous research has identified situations in which construction equipment operators experienced limited visibility, and often are unable to identify pedestrian workers around a piece of construction equipment (Marks et al. 2013). The following review discusses research concerning visibility measurement for construction equipment operators, in order to design an optimal blind spot mapping and calculation framework. The following sections discuss construction safety statistics, visibility-related incidents, and visibility research for construction site personnel.

5.2.1 Human-Equipment Interactions on Construction Sites

The U.S. construction industry experienced 937 fatalities in 2015 which accounted for 19%

of all U.S. workplace fatalities that year (BLS 2017). The total of 159 fatalities were categorized as struck-by incidents in which a piece of construction equipment or other objects struck a pedestrian worker. This value accounted for 17% of all U.S. construction fatalities in the U.S. in 2015 (BLS 2017).

Visibility has been identified as a root cause in many safety incidents between construction equipment and pedestrian employees (Teizer et al. 2010b). For example, excavator operators can experience up to 50% obstruction of their field-of-view during operation due to components of the equipment (Teizer et al. 2010b). Other research identified the design of heavy equipment as an impact factor for the level of hazard experienced by construction employees (Lingard et al. 2013 Non-visible were cited as a major issue on construction sites when specifically discussing struck-by incidents (Lingard et al. 2013).

5.2.2 Construction Operator Visibility Quantification

Other researchers have explored measuring equipment operator visibility. Static operator blind spots were automatically identified through an algorithm that analyzes point cloud data (Teizer et al. 2010a). Other researchers created a framework for quantifying and measuring the visibility of a forklift operation working in a manufacturing plant (Shen and Marks 2016). This framework includes identifying blind spots obstructed by the forklift equipment components and materials that obstruct the view of the manufacturing environment (Shen and Marks 2016).

Heat map generation is another tool that has been implemented for predictive safety planning in preventing struck-by and near miss interactions between workers-on-foot and construction equipment (Golovina et al. 2016). Various legends and colors were used to represent safety barricades, equipment paths, pedestrian worker travel paths and equipment operator blind spots.

5.2.3 Blind Spot Measurement Methods

Ray tracing is a technique for generating an image by tracing the path of light through pixels in an image plane and simulating the effects of its encounter with virtual objects (Reshetov et al. 2005). The use of a ray tracing algorithm to automatically measure the blind spot was validated on construction sites through outdoor testing (Teizer et al. 2010a).

A new approach was developed to compute blind spots through point cloud data (Ray and Teizer 2013). In order to compute the 3D blind spot of construction equipment, multiple laser scans were fused to create a comprehensive blind spot map (Ray and Teizer 2013). A blind spot measurement tool was also created based on results of laser scanning (Marks et al. 2013).

Choudhury et al. (2014) created a visibility color map, defined as a surface color map of the space, where each view point of the space is assigned a color value that denotes the visibility measure of the target from that viewpoint. Measuring the visibility of a target from different viewpoints need to consider factors such as distance, angle, and obstacles between the viewpoint and the target (Choudhury et al. 2014).

5.2.4 Research Needs Statement

Struck-by incidents resulting from limited visibility of construction equipment operators often result in injuries and fatalities. A need exist to further investigate methods for quantifying operator visibility, specifically along an equipment travel path in a construction working environment. By quantifying visibility information for construction operators, visibility-related hazards can be identified and mitigated pro-actively on construction sites.

5.3 Research Methodology

Due to the complexity and dynamic nature of typical construction sites, construction equipment operators often experience impeded visibility and may be unable to see a pedestrian worker. This research evaluates non-visible areas in an indoor construction environment and establishes a framework for measuring blind spot from different perspectives. The non-visible area is defined as blind spot for the equipment operator. The shaded area in Figure 12 represents a sample blind spot for an equipment operator that is obstructed by an object on the ground. This research identified and quantified blind spot areas for equipment operators from a specific viewpoint. The visibility was analyzed from several viewpoints along an equipment travel path. This viewpoint can be due to moving pieces of construction equipment or pedestrians. Because the non-visible area changes for different locations of the viewpoint, different situations were discussed in the following sections.

5.3.1 Laser Scanning Technology

The International Organization for Standards (ISO) has published visibility standards for work environments and equipment operators through Code 5006 and ISO Code 14401-1 (ISO, 2011). Although these standards are prescribed to manually measure visibility, laser scanning will be deployed in this research as the strategy to measure visibility within a simulated enclosed construction site environment. Benefits of using a laser scanning for measuring operator visibility include producing a registered three-dimensional spatial point cloud, automated data processing, improved accuracy in measurements, and decreased human error bias (Marks and Teizer, 2013).

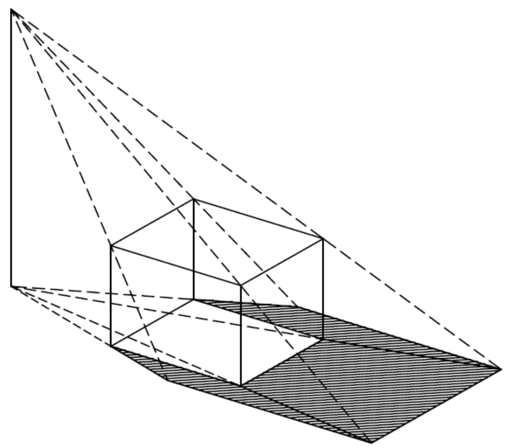


Figure 12: Conceptual Model for Analyzing Non-Visible Areas on Construction Sites

Spatial point clouds of both the equipment operator and the work environment will be generated and collected automatically with a 3D laser scanner. The commercially available 3D laser scanner will be positioned at an operator's average eye height as specified by the ISO standard code 5006 (ISO 2011). This code also specifies a 12 meter visibility radius extended from the operator's positon for the visibility assessment area (ISO 2011). The 3D laser scanner generates approximately 3 million data points in a 360 degree radius in approximately 20 minutes. Three independent locations will be selected and scanned to evaluate the visibility of the testbed environment. For these scans, the laser scanner will be positioned at 1.8 meters vertically from the ground surface to simulate an average pedestrian employee's eye height.

An indoor laser scan test of a university classroom was conducted to determine the feasibility of laser scanning an indoor environment as shown in Figure 12. After laser scanning the classroom, a 3D point cloud was registered and exported to a BIM as shown in Figure 13.

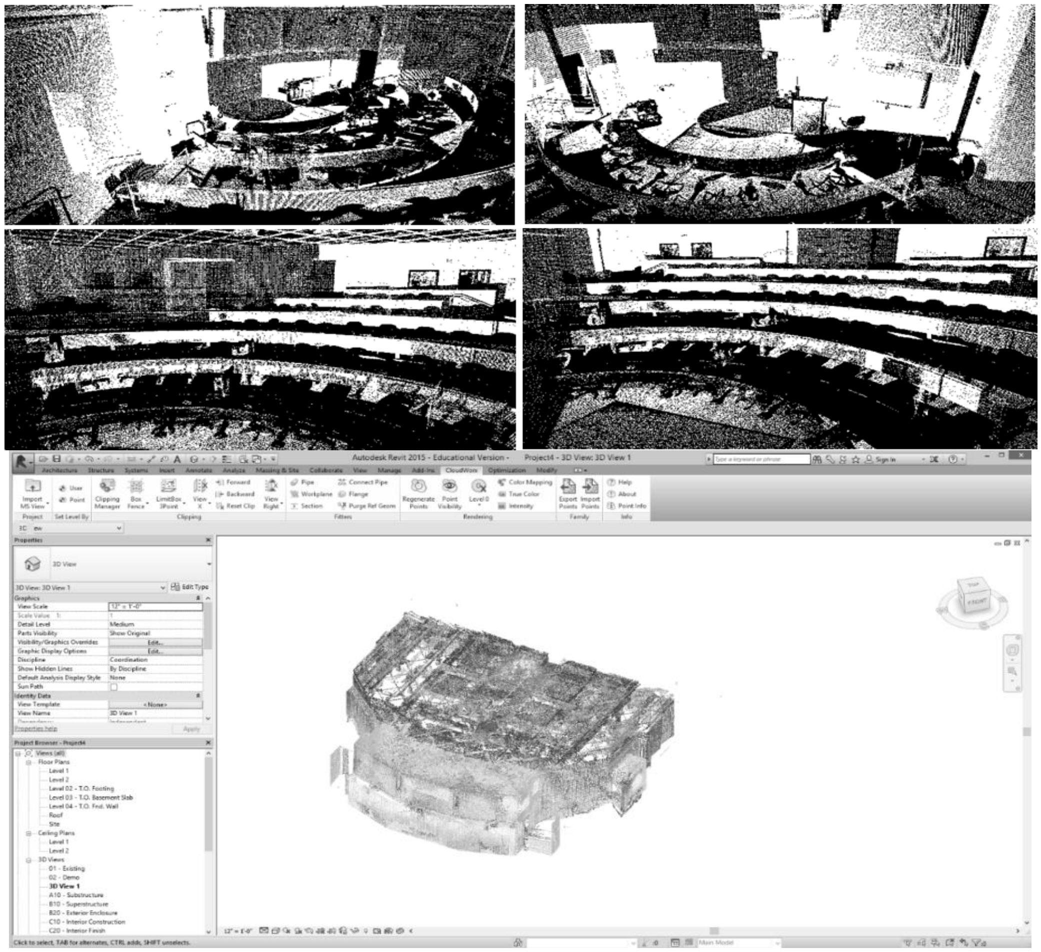


Figure 13: Cloud-based Visibility Model in BIM

5.3.2 Identification of Blind Spots

Table 10 gives the definition of variables that are used in the remainder of this paper. All variables can be found in Figure 14 and Figure 15.

Table 10: Descriptions of Variables Used to Quantify Non-Visible Area

Variable	Description
m	Viewpoint height
n	Object height
m - n	Vertical height differences between viewpoint and objects
a	Horizontal distance differences between viewpoint and objects
b	Chosen side length
α	Vertical angle between viewpoint and objects
β	Horizontal angle of chosen side
D	Non-visible area width
Y	Non-visible area length
L	The sum of horizontal distance differences and non-visible area length
R	Visual Range

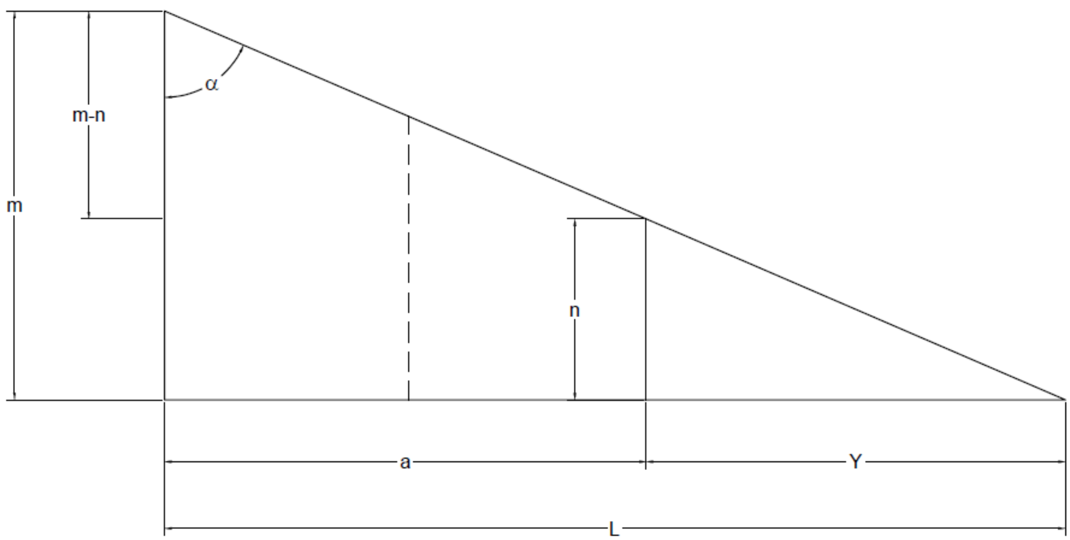


Figure 14: Side View of the Conceptual Model.

A blind spot can be determined by finding the length (Y) and the width (D) of a non-visible area. The range of α and β are defined as 0° < α < 180° and 0° < β < 180°. Assume that input viewpoint height (m) and obstacle height (n) are given. From Figure 14, It can be noticed that when α larger than 90°, Y value will be infinity without a boundary. In this way, two situations have been discussed in the following sections:

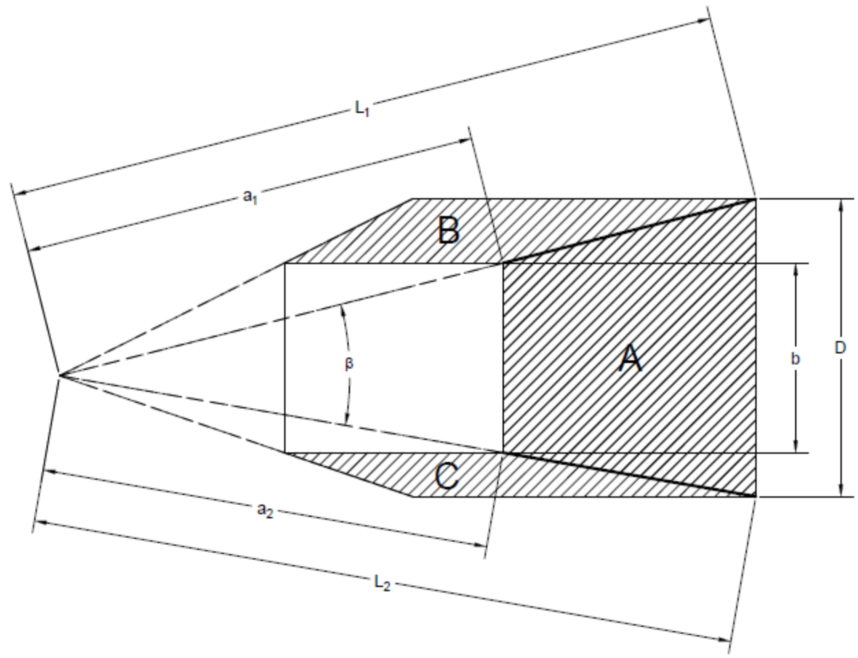


Figure 15: Top View of the Conceptual Model for Analyzing Blind Spots

Situation 1

When 0° < α < 90°, the conceptual model is an example of situation 1 (Figure 14). It can be seen from Equation 4 and Equation 5, the value of n and m are given, a value is the only variable that can affect Y value.

$$tan\,\alpha = \frac{a}{m-n} \qquad \textit{Equation 4}$$

$$Y = n\,tan\,\alpha = n\frac{a}{m-n} \qquad \textit{Equation 5}$$

From the top view of the conceptual model (Figure 15), the D value can be calculated (using the Law of Cosines) by Equation 6 and Equation 7:

$$D^2 = L_1^2 + L_2^2 - 2L_1L_2 \cos\beta \qquad \textit{Equation 6}$$

$$\begin{cases} L_1 = a_1 + Y_1 \\ L_2 = a_1 + Y_2 \\ \cos\beta = \frac{a_1^2 + a_2^2 - b^2}{2a_1a_2} \end{cases} \qquad \textit{Equation 7}$$

From Equation 5, the Y value can be calculated if the value of variable a is given. In Equation 7, β value then can be calculated if b value is also given. Variables a and b are the impact factors of the D value. Also noted that blind spot A can be determined after finding the Y and the D value. Areas of B and C can also be determined by following the same process.

Situation 2

In Figure 16, when 90° ≤ α < 180°, the shaded area will lie on both the viewpoint and work zone boundaries (or visual range R). In this situation, b value and R value become the impact factors of the blind spot.

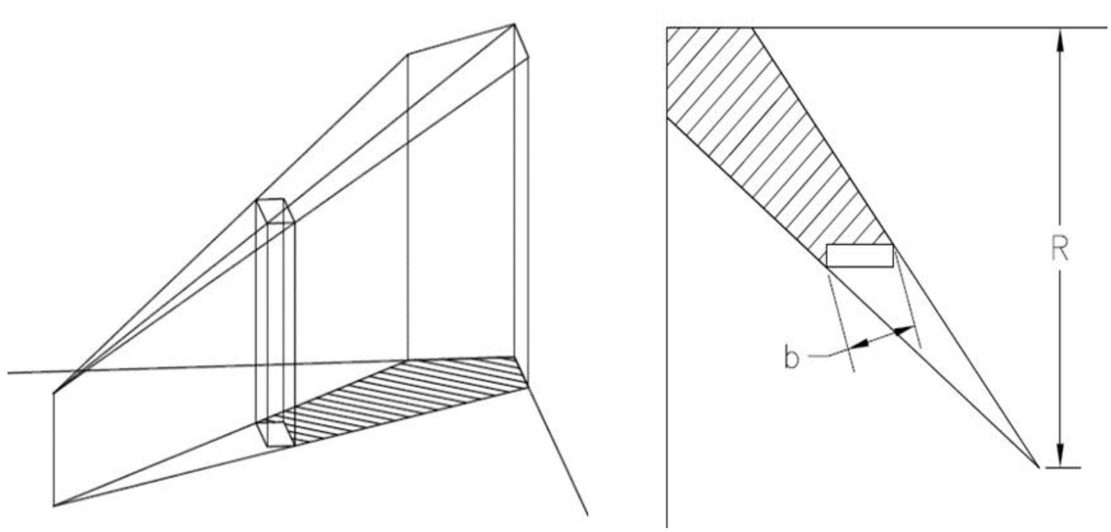


Figure 16: Model of Situation 2 When 90° ≤ α < 180°

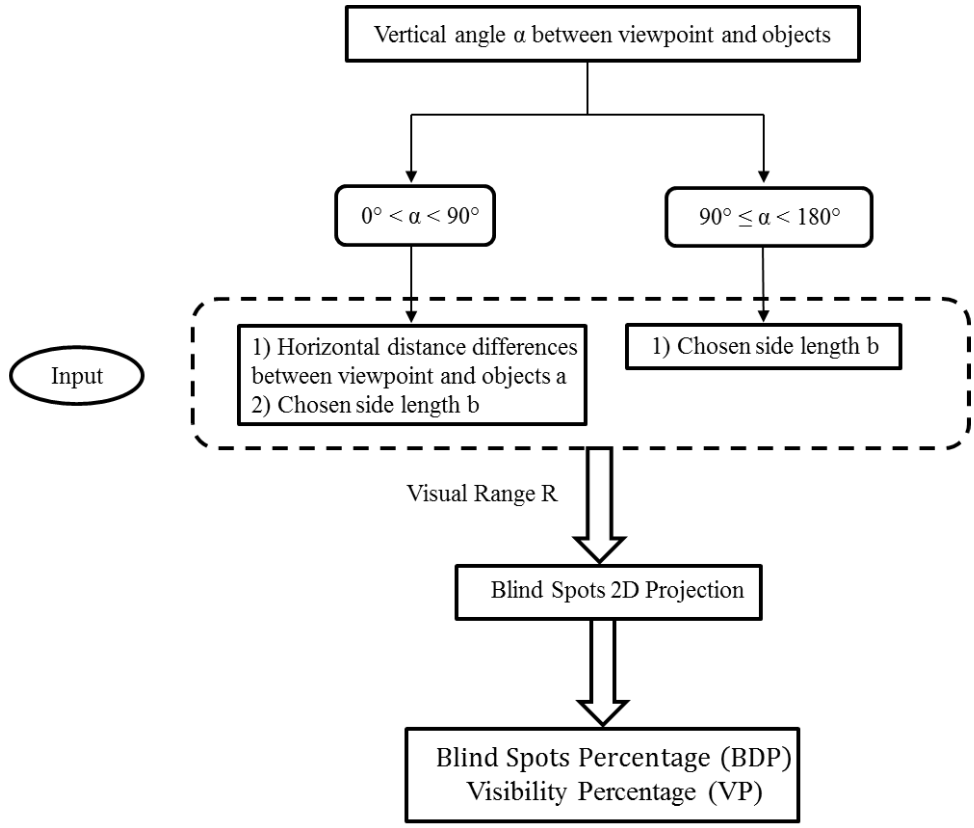


Figure 17: Blind Spot Measurement Framework

In summary, the blind spot area can be calculated by inputting the value of variables m, n, a, b, and R. The developed approach should also allow adjusting for equipment operators with different body heights or selecting different viewpoints. Combining the methodology processes, a framework is created to measure the blind spot within different situations and is shown in Figure 17.

5.3.3 Blind Spot Percentage

A construction site should decrease the percentage of blind spots to maintain a safe construction work environment. In this way, the total shared area percentage was also calculated. By following the previous calculation processes, blind spot are shown in a 2D view which is depicted in Figure 18. The area of the shaded zone can be automated calculated by using Autodesk AutoCAD internal tool (area) by selecting specific objects as shown in Figure 9. Equation 8 can be used to calculate the blind spot percentage in a certain work environment:

$$Blind\ spots\ percentage\ (BDP) = \frac{Total\ shaded\ area\ (TSA)}{Work\ zone\ area\ (WZA)} \qquad \textit{Equation 8}$$

$$Visibility\ percentage\ (VP) = 1 - BDP \qquad \textit{Equation 9}$$

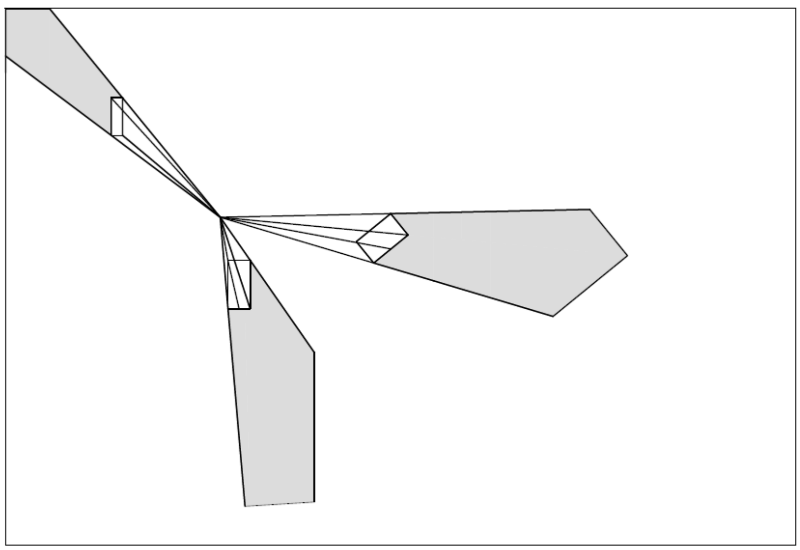


Figure 18: 2D View of Blind Spot of a Construction Site

5.3.4 Case Study

Research has verified that an automated process that measures construction progress using 3D laser scanning technology is more accurate than image processing because point clouds establish a 3D environment to represent the construction site rather than fragmentary pictures (Zhang and Arditi 2013). A 3-D laser scanner was used to generate and collect several spatial point clouds as shown in Figure 19. From a certain viewpoint, objects can obstruct visibility in the construction environment. Walk-through views have been used to define the travel path and objects in an active construction site. A simplified BIM model was created in AutoCAD to define and calculated the blind spot as shown in Figure 20.

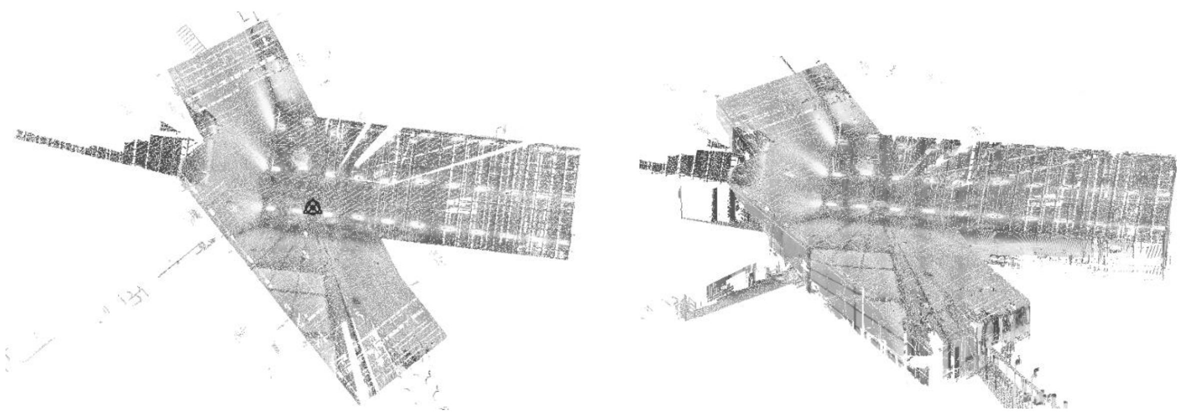


Figure 19: Sample Laser Scanning Point Cloud Data of an Indoor Construction Site

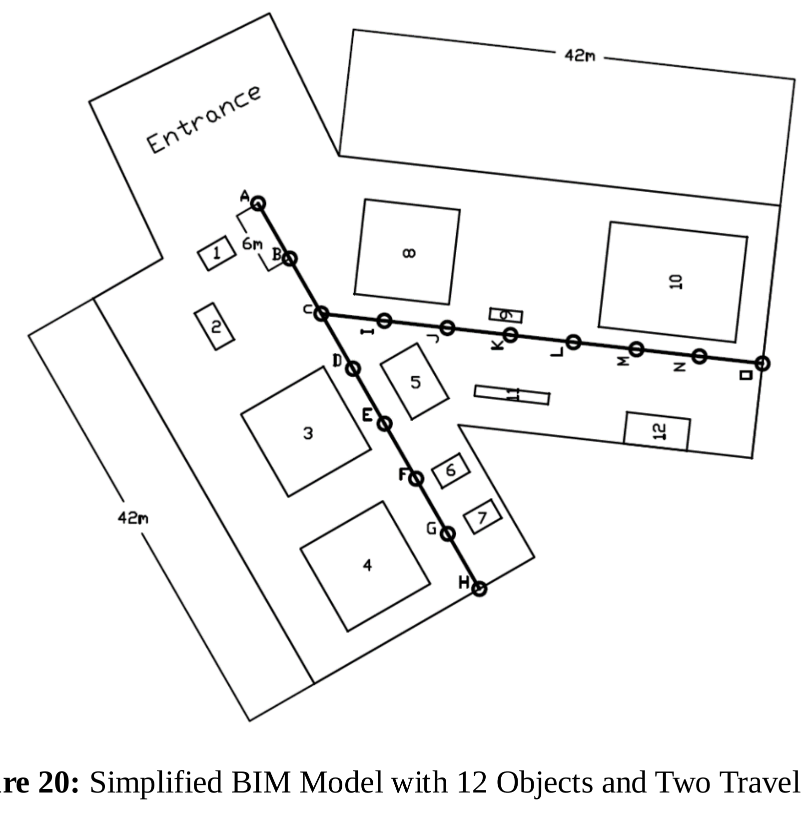


Figure 20: Simplified BIM Model with 12 Objects and Two Travel Paths.

It should be noted that each location was defined as the distance that equipment or workers move in 6 seconds. The authors assumed that the average speed of moving equipment in an indoor construction site is 1 meter per second for a safe work environment. The distance between two observation locations is 6 meters. At each selected point along the two travel paths, a 6 meter by 6 meter by 6 meter cube was projected along the ground surface to calculate the visibility percentage at the specific location. The process should also allow adjusting cube size based on different equipment moving speed, pedestrian's walking speed, construction environment, and other possible conditions. Because the 3D grid was fixed to the cube, test locations were selected every 6 seconds of travel time. For the experimental trials, two travel path and 15 locations were selected. These paths are shown on Figure 20 (Path A-B-C-D-E-F-G-H and Path C-I-J-K-L-M-N-0). The 12 elements were extracted from the point cloud data and simplified into cuboid shapes shown in Figure 21. The length of the two travel paths is 42 meters, the dimensions of the 12 elements are defined in Table 11.

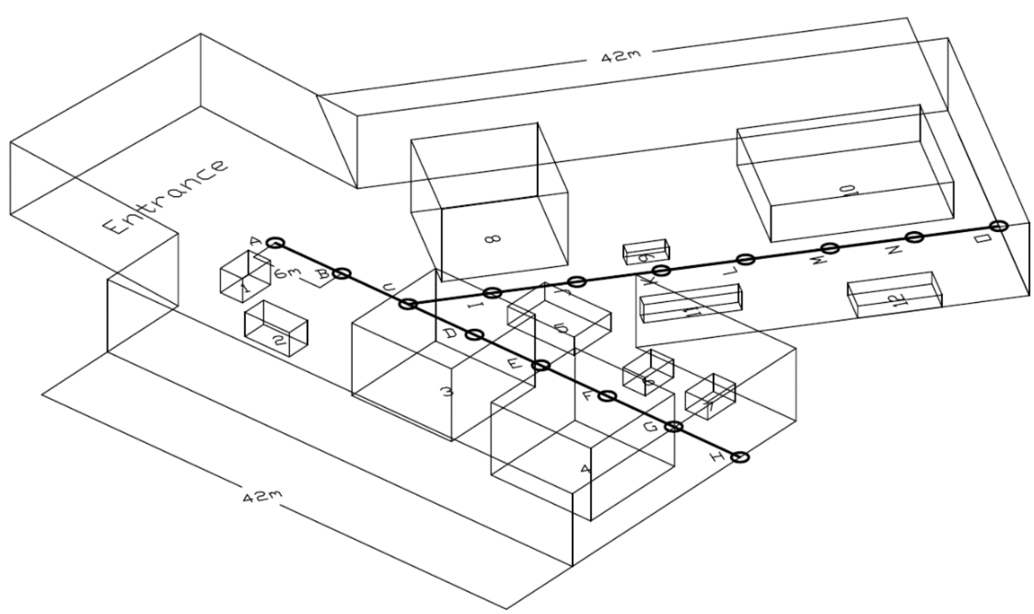


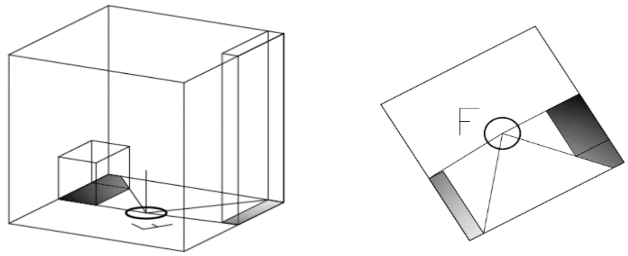
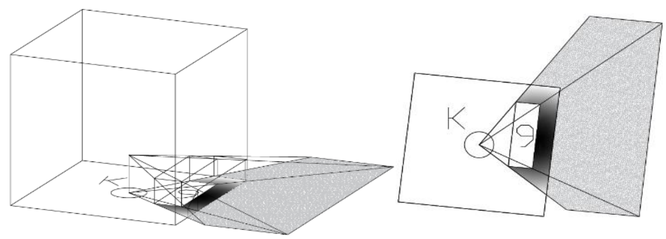
Figure 21: 3D View of Equipment Travel Paths in BIM

Table 11: Dimensions of Construction Site Components

Components	Length (m)	Width (m)	Height (m)
1	3	2	2
2	2	4	2
3	9	9	6
4	9	9	6
5	4	6	1.5
6	3	2	1.5
7	3	2	1.5
8	9	9	6
9	1	3	1
10	10	13	3
11	1	7	1.5
12	3	6	1

A 1.5 meter height viewpoint was selected to put in the center of each cube to modify a pedestrian or operator viewpoint. The methods provided in the methodology part were implemented to define the blind spot at the specific location. Results of the blind spot quantification are provided in Table 12. Table 12 includes the blind spot calculation of point F following situation 2 in the methodology section of this paper. Because the vertical angle between viewpoint and the object is larger than 90°, the chosen side length and the cube boundaries defined the blind spot in this situation. Point K is an example of situation 1 where the angle between viewpoint and the object is less than 90°. The shadowed area and grey area shows the blind spot without a boundary. Since a 6 meter cube was fixed in location K, the shadowed area represents the blind spot.

Table 12: Summary of the Visibility on the Two Travel Paths at Different Locations

Travel Path	Location	Visibility	Example of objectives fixed in 6m×6m×6m cube.
Path 1	A	100%	
	B	100%	
	C	100%	
	D	91.1%	
	E	85.0%	
	F	86.3%	
	G	85.4%	
	H	94.9%	
Path 2	C	98.4%	
	I	91.2%	
	J	91.0%	
	K	87.7%	
	L	93.3%	
	M	84.6%	
	N	84.6%	
	O	99.2%	

5.4 Conclusion

Non-visible areas for construction equipment operators can result in unsafe working conditions that can lead to injuries or fatalities. Blind spots are created when an equipment operator's line of sight is obstructed by an object either on the construction equipment or in close proximity to the equipment. This research created a framework for quantifying and measuring the visibility of an indoor construction working environment.

Pro-active safety metrics such as Personal Protective Equipment (PPE) and proximity detection devices can support the construction workers' safety with regards to struck-by incidents. Toole (2002) believes that all future construction projects will have detailed expectations on respective safety roles clearly articulated before the site work begins. The created framework can help with equipment travel path design and increase proximity detection device efficiency. By quantifying non-visible areas for construction operators, construction site managers can identify potential hazards associated with human-equipment interactions on construction sites. Future research will also want to create an automated blind spots measurement tool within BIM.

CHAPTER 6 CONCLUSIONS AND FUTURE RESEARCH

This chapter summarizes and offers concluding remarks for this research. It addresses the construction industry research needs discussed in the Introduction Chapter of this thesis. Conclusions made were derived from the literature review, research methodologies, and case studies. This chapter also concludes with a discussion on the future areas of this research for further expansion as well as the key benefits of this research.

6.1 Conclusions

The motivation for this research was to enhance construction safety and productivity for construction equipment cycle operations. The objective was to create a framework to collect, analyze, and visualize information associated with a construction equipment travel path and corresponding operation cycle. To successfully complete this objective, the research tasks were divided into three major components: 1) identify and quantify variables that significantly impact the equipment cycle time, 2) calculate and display an efficient travel path for construction equipment in BIM, and 3) quantify the visibility of an equipment travel path for both the equipment operator and pedestrian workers.

Experimental trial results indicate that location-based information from construction haul equipment can be automatically collected from location-based technologies. The cycle time duration of dump trucks in an earthwork excavation project can greatly impact the overall productivity. The research proved that it is possible to automatically collect and analyze construction equipment cycle information to identify and mitigate potential delays in a construction equipment cycle and promote safety on construction sites. Results of the data analysis indicate impactful variables to a dump truck's cycle time as well as many variables that have minimal impact.

Safety and productivity are both influenced by construction equipment travel paths on a given construction site. The research presented a scientific evaluation data of construction equipment travel paths and created a feasible method of automatically constructing an efficient travel path for construction equipment. BIM has also proven through previous research efforts to be programmable and to display results of computing algorithms. The created automated path planning tool uses BIM software, a database organizational software, and programming enabled matrix calculation program to calculate and visualize the equipment travel path.

A typical dynamic construction work environment often fosters non-visible areas which impede a person's line-of-sight. Laser scanning has been used to generate spatial point clouds of a lecture classroom at the University of Alabama. Similar spatial point clouds were used to assess the visibility of equipment operators on an active indoor construction site. This research created a framework to identify and quantify areas not visible to construction equipment operators. The percent visibility was calculated after measuring the blind spot data for both the equipment operator and construction site environment in a specific radius visibility circle at each location. By identifying and quantifying equipment operator blind spots in 3D, construction site personnel can automatically detect and quantify non-visible areas for construction operators along equipment travel paths.

6.2 Future Research

Much opportunity exists for further research in the field of automating construction site safety data collection and analysis. Gathered information and knowledge from my current research will support efforts to create and implement robust safety site layout strategies in Building Information Modeling (BIM) or other construction management interfaces. Risk factors and severity indices of safety leading indicators can also be visualized and analyzed within an existing BIM model.

The research selected the analysis aspects of an equipment travel path due to their critical impact on the overall cycle time. Only select elements of the equipment travel path and cycle operation were included. Further assessment could be completed and have been accomplished by previous research. Construction material haul vehicles were limited to dump trucks due to the researcher's availability to collect location-based data. Future research could investigate the interaction of other excavation equipment with haul equipment and include detailed variables regarding the haul distance.

Only productivity was addressed when calculating an efficient travel path for construction equipment operations. Future research in this field could also explore the automatic generation of new travel paths based on real-time information from tracking technology of material transport equipment on construction sites. Additionally, future research can investigate the feasibility of automating other aspects of the design and scheduling process such as construction site layout for increased productivity and safety.

The created automated path planning tool uses BIM software, a database organizational software and programming enabled matrix calculation program to calculate and visualize the equipment travel path. All work completed in BIM used AutoCAD and Autodesk Revit due to availability of the software at the University of Alabama. Future work can explore interoperability issues within various other BIM platforms for the proposed tool.

6.3 Key Research Contributions

The contributions of this research provide new scientific evaluation data and knowledge in the areas of construction safety and productivity associated with construction equipment travel paths. This research contributed both to the construction engineering and management body of knowledge as well as the construction industry. The following are specifically envisioned contributions of the research:

- A framework for collecting and analyzing construction equipment cycle time data with location-based sensing technology;
- A strategy and automated tool to calculate and display an efficient equipment travel path within a BIM;
- A method for quantifying visibility of equipment travel paths for equipment operators and pedestrian workers.

These contributions can potentially impact the construction industry by enhancing construction safety and productivity on construction equipment cycle operations. Research deliverables can be used for site planning, safety training, and project management education. The overall research impact is an improvement of both construction safety and productivity during construction equipment cycle operations.

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