Modeling the productivity of precast concrete operations

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2014

Ali Najafi. (2014). Modeling the productivity of precast concrete operations. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/59232>

<https://doi.org/10.32657/10356/59232>

NANYANG
TECHNOLOGICAL
UNIVERSITY

**MODELING THE PRODUCTIVITY OF PRECAST
CONCRETE OPERATIONS**

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2014

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A thesis submitted to the Nanyang Technological University in fulfillment of the
requirements for the degree of Doctor of Philosophy

2014

ACKNOWLEDGEMENTS

In the Name of God, the most compassionate, the most merciful.

I would like to express my gratitude to Prof. Robert Tiong, my supervisor, for his continuous support and guidance.

Deepest appreciation is dedicated to my wife for her encouragement, patience, and love, and to my family for their support.

I would like to thank Mr. Darren Ting and Mr. Kaung Set Zaw, two final year students who helped in some parts of data collection as well as Mr. Roshan Wahab, a PhD candidate at NTU for his support.

I should hereby thank Mr. Mojtaba Rahimi who helped in the PhP programming and development of the web based system.

Finally, I would like to thank those contractors who provided necessary data and permissions for site visits.

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SUMMARY

Precast Concrete (PC) elements are generally used to increase buildability, provide more quality, enhance site safety, reduce the impact on environment, and increase productivity. PC components are standardized and modular. They are installed in a quicker fashion and result in reduced project duration, energy usage, and emissions from on-site equipment.

Despite the extensive use of PC elements in different construction projects such as high rise residential and commercial buildings, there is no study to provide details about factors that affect productivity of PC erection (installation) process and model the productivity of the installation activities in an academic fashion. The thesis is organized to address this research gap.

To ensure data quality, primary data regarding installations of 303 PC elements (walls, columns, beams, and slabs) were directly observed. As a result, several controllable and uncontrollable factors influencing the productivity of the erection process were identified. Multiple Regression Analysis (MRA) and Artificial Neural Networks (ANN) were used as the main techniques to evaluate productivity and estimate the installation times of different PC components. The preliminary analysis showed that both techniques provide acceptable results considering complexities and uncertainties in the construction projects.

New hybrid models using Method Productivity Delay Model, MRA, and ANN, were developed for the delay analysis of the PC erection process. Based on the results, technical delay occurred during the installation of 31 percent of the vertical elements. A delay factor was calculated and used in MRA and ANN to form the final models to provide accurate predictions of the installation times of PC components.

A construction simulation model was also developed, which can provide quick and efficient estimates of the installation activities. One of the main benefits of the simulation technique is its ability to analyze the utilization of different resources. The results provide valuable information for construction site managers to plan the resources more effectively. Furthermore, simulation modeling can be used to examine several scenarios instead of costly experimentations at the construction sites.

Finally, a procedure was shown to calculate the “baseline productivity” which is useful for contractors to compare their productivity rates in different projects. Furthermore, it can be used to compare the productivity rates between different contractors, which is helpful to find the best practices as well.

A web-based user friendly system was designed and developed to help the final users such as general estimators and construction managers provide accurate estimates for productivity of erection process for different products. These estimates are extremely helpful especially for the short term planning of on-site activities in the precast projects.

The thesis contributes to the current construction management body of knowledge by providing original solutions to the problem of productivity modeling for PC construction projects. Therefore, it should be of interest to academics and industry players interested in estimating the productivity rates of PC projects. Based on the results of this research, several suggestions are provided to increase the productivity of PC installation process and directions for future research are discussed.

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ABBREVIATIONS

AMPDM: Artificial Method Productivity Delay Model

ANN: Artificial Neural Networks

BIM: Building Information Modeling

BCA: Building and Construction Authority (Singapore)

FFBP: Feed Forward Back Propagation

HDB: Housing and Development Board (Singapore)

IBS: Industrialized Building Systems

MPDM: Method Productivity Delay Model

MRA: Multiple Regression Analysis

PC: Precast Concrete

PCIT: Precast Concrete Installation Time

RMPDM: Regression Method Productivity Delay Model

CHAPTER

1

Chapter 1. **INTRODUCTION**

- Background and Problem Statement
- Research Objectives
- Research Steps
- Organization of the Research

1.1 Background, Problem Statement, and Significance of the Work

Precast concrete (PC) products are typically created by casting concrete in a mold at the precast manufacturing companies or in the temporary plants which are set up near the construction sites. Some of the main categories of PC products are agricultural products, building and site amenities, retaining walls, sanitary products, transportation and traffic related products, utility structures, water and waste water products, and marine products. PC components are produced in a controlled environment which provides the opportunity to be properly cured and monitored by plant labor. As a result, there are some advantages of PC systems over traditional cast-in-place concrete (Allen and Iano 2009) such as:

- High quality products can be produced because of close monitoring of the production process.
- Components production is performed on the ground level, therefore, more safety can be provided.
- A mold can be used many times in the precast production process (with little or no changeover at all) which ensures cost savings in terms of mold per unit of production.
- The project time can be reduced because of faster erection time.

In Singapore construction industry, PC products are extensively used in different construction projects especially in public housing projects which are managed by Housing and Development Board (HDB). HDB leads in the use of precast technology with high volume usage of PC components including external facade walls with cast-in windows, bathroom units, floor slabs, refuse chutes, columns, and staircases. With as much as **“70 percent”**¹ of HDB’s building components prefabricated, HDB has consistently achieved higher levels of construction productivity (Figure 1.1). Residents

¹ Singapore precast concrete implementation level (at the national level) by volume is currently about 8.5 percent. HDB which is the largest PC user in Singapore has the higher PC implementation than country like Hong Kong which is about 30 percent.

also benefit from better quality finishes of their flats due to better quality control of precast technology (HDB InfoWEB). Different PC components which are used in HDB building projects are shown in Figure 1.2.

Figure 1.1 Percent of precast implemented in HDB buildings (source: HDB InfoWEB)

Figure 1.2 PC components in Singapore construction industry (Source: www.bri.sg)

Additionally, the general topic of “productivity” is an area of interest in the construction industry especially in countries like Singapore and Malaysia that highly invest in prefabrication production. The Building and Construction Authority (BCA) of Singapore, has introduced S\$250-million Construction Productivity and Capability Fund (CPCF) as part of the Government’s efforts to help the construction industry improve productivity and strengthen its capability.

Furthermore, research in the United States shows that labor productivity for the total construction industry slightly declines over the past 50 years (Teicholz 2013) by minus 0.32% per year decline while the trend for all nonfarm industries is positive 3.06% per year. The net impact over the 50 year time period is very significant. The same research suggests the greater use of Off-Site fabrication and modular construction as a main source of potential positive change.

There are several factors that affect the productivity of PC projects. Problems such as inclement weather condition, lack of worker’s experience, site storage capacity restrictions, tools and equipment mechanical problems, equipment operator efficiency, poor site layout planning, and massive size of PC components are common in precast projects. These problems together with general construction challenges, greatly affect the productivity of PC erection (installation) process.

Based on the abovementioned high volume usage of PC components in the Singapore construction industry (especially in HDB construction projects) and to be in line with BCA construction productivity program, there is a need for an in depth academic research to find the factors affecting the productivity of PC installation process and provide effective productivity models to estimate the installation times of different PC elements.

The current practice is to predict the installation times of PC components based on the experience and subjective judgments of the site managers. As a result, floor cycle time

schedule² is frequently changed based on the actual data received from the construction site. This study provides more accurate estimates of the installation times of various PC elements and evaluates the utilization of the resources involved in the PC erection process. Therefore, the results of this study should be of interest to the site managers by providing necessary information to plan the activities and resources more efficiently.

1.2 Research Objectives

Based on the research problem, the main objectives of this study can be enumerated as follows:

- 1- Collect and evaluate the factors affecting PC erection process productivity.
- 2- Collect objective and subjective productivity data from different construction sites using PC technology.
- 3- Design and develop productivity models for PC installation process in order to evaluate and predict productivity rates and cycle time (The techniques to be used are Multiple Regression Analysis (MRA), Artificial Neural Networks (ANN), and construction simulation).
- 4- Analyze different delays occurred during PC installation and develop the final productivity models.
- 5- Evaluate the performance of the final productivity models and compare the results.
- 6- Determine the baseline productivity rates for PC installation.
- 7- Provide productivity charts.
- 8- Develop a user-friendly system for easy estimation of the PC installation times.

In the other words, the main objective of this research is to design and develop productivity models to predict the productivity rates of PC erection process for

² This is a schedule provided by the site supervisors to show all the activities and their duration to complete the structural works of a typical floor.

different structural products such as beams, columns, walls, and slabs considering several task and labor related factors that affect productivity. As an example, by developing such models, a user can accurately estimate the time to erect a specific type of precast product in the correct position (elevation from the ground), by considering various influencing factors.

1.3 Research Steps

This research will be accomplished by following these steps:

- 1- Literature review in order to find the factors that affect productivity of the construction projects. Literature review covers background about Industrialized Building Systems (IBS) and precast concrete production methods and products.
- 2- Required objective and subjective data will be collected by construction site visits and direct observations of the installations of PC elements. This will ensure data quality.
- 3- Preliminary productivity models are designed and developed by MRA and ANN.
- 4- Preliminary models will be validated to ensure proper functionality for the mentioned objectives.
- 5- Different delays occurred during PC installation are analyzed by Method Productivity Delay Model (MPDM). As a result, the final models to predict the installation times of PC components are developed by using the results from MPDM, MRA, and ANN.
- 6- Construction simulation technique is also used to model the productivity of the installation process and evaluate the resource utilization.
- 7- The performance of different developed models in predicting erection process cycle time and productivity will be compared to each other.
- 8- A procedure to find the baseline productivity is described so the contractors can find the best productivity rate they can achieve.

- 9- Sensitivity analysis will be performed to observe the effect of different main inputs on the models' performance.
- 10- A web based system in the user friendly graphical interface will be developed to predict productivity of precast concrete installation process.
- 11- Conclusions and recommendation for future studies.

1.4 Organization of the Research

Chapter 1, current chapter, includes a background to the research area, presentation of the research problem, main research objectives, overview of the steps to complete the research, and research organization.

Comprehensive review of the related literature is presented in chapter 2. This section contains information about Industrialized Building Systems (IBS), precast concrete production and products, productivity in the construction industry, and factors affecting productivity of different construction operations. A brief introduction to MRA and ANNs with their applications in the productivity analysis of the construction operations are described. Furthermore, concepts such as construction simulation, Method Productivity Delay Model (MPDM), and baseline productivity are also discussed. The objectives of the study can be justified based on the determined research gaps.

Research methodology is discussed in chapter 3. A typical precast erection process will be shown and the factors affecting productivity of PC installation are elaborated. Data collection and characteristics of the collected data are described. Procedures to analyze the data by MRA, ANN, and construction simulation are presented as well.

Chapter 4 includes details about data analysis. Several preliminary productivity models are developed by MRA and ANN. These models are validated to find out the performance against the actual data from the construction sites. A new hybrid model is developed based on MPDM (delay analysis), MRA, and ANN to form the final model

to predict the installation times of PC elements. This final model is also validated and based on the results, several discussions are presented.

The last chapter of this thesis (chapter 5), includes a summary of the research findings. Contributions of this study to the construction body of knowledge are listed. Based on the results of the study, suggestions for academics and industry players are provided and directions for future research are described.

- Industrialized Building Systems (IBS)
- Precast Concrete Production and Products
- Factors Affecting Productivity of the Construction Projects
- Construction Productivity Analysis by MRA, ANN, and Simulation
- Method Productivity Delay Model and Construction Baseline Productivity

This chapter summarizes the current literature relevant to the subject matter of the thesis. An introduction to Industrialized Building Systems (IBS) is provided followed by discussion on production of different PC elements such as floor slabs, interior and exterior walls, beams and columns (using different types of molds such as table molds, stacks, pre-stressing beds, and batteries). Factors affecting productivity in the construction industry are enumerated and described. Productivity analysis by Multiple Regression Analysis (MRA), Artificial Neural Networks (ANN), and construction simulation techniques are presented by providing examples of the applications of these techniques for productivity estimation of different construction operations.

2.1 Industrialized Building Systems (IBS)

IBS means to build onsite with prefabricated components like floors, walls, columns, beams, roofs, etc., which are produced in prefabrication plants and then delivered at the construction site for final installation (Badir, Kadir et al. 2002). Some of the main features of IBS can be listed as follows (Warszawski 1999):

- Most of the elements can be prefabricated offsite in a controlled environment (prefabrication plants).
- Several building works are assembled into larger prefabricated finished products in order to minimize activities on site including erection, jointing, and finishing.
- Onsite handling of materials is as mechanized as possible.
- Different processes such as design, production, and onsite installation are extremely interrelated, which requires integrated planning and coordinating from system point of view.
- Automation may be used for different processes to improve quality and speed up the project progress.

Utilizing IBS reduces manual labor onsite, facilitates faster construction processes, and increases quality of components. Some of the main types of IBS can be categorized as follows (IBS-Center-Malaysia 2011):

- Precast concrete framing, panel and box systems: Precast columns, beams, slabs, 3-D components (balconies, staircases, toilets, etc.), etc.
- Formwork systems: Tunnel forms, EPS-based forms, beams and columns molding forms, permanent steel formworks, etc.
- Steel framing systems: Steel beams and columns, portal frames, roof trusses, etc.
- Prefabricated timber framing systems: Timber frames, roof trusses, etc.
- Block work systems: Interlocking concrete masonry units (CMU), lightweight concrete blocks, etc.

In addition to the above mentioned five main groups, with technological advancement and innovation, other prefabricated materials such as gypsum, wood wool, polymer, fiber glass, glass and aluminum based IBS components have entered the market. Since this study is related to PC production, next section provides information and literature about PC manufacturing systems and different PC elements.

2.2 Precast Concrete Production Systems and Products

PC components are generally produced by inserting materials such as concrete mix and its components (including cement, aggregate, rebar cages, and other admixtures) into a mold. Some other fixtures such as mechanical/electrical conduits, window and door frames, inserts, bolts and hangers are embedded into components to form final assemblies, which are then delivered and installed at the construction sites (Warszawski 1999). Some of the general advantages of PC construction are as follows:

- Speed
 - PC manufacturing and foundation or other construction site works can be carried out simultaneously.
 - To reduce the finishing work at the constructions site, granite, tile, or brick veneers can be casted into PC panel at the time of PC manufacturing.
- Quality
 - PC components are manufactured under controlled factory conditions.
 - High quality PC elements can be produced by using state-of-art manufacturing technologies.
- Flexibility
 - Wide ranges of shapes are available for PC products.
 - Several surface textures can be achieved by surface treatments such as sandblasting and acid washes.
- Productivity
 - Productivity can be increased as a result of better working condition in the factory.
 - Repetitive processes and advanced technologies reduce the dependence on worker's skill.
- Environment
 - PC technology minimizes the site debris and dust when compared to cast-in-situ concrete works.
 - Material wastage is reduced.
 - Minimizes the noise problem.
- Economy
 - Faster construction leads to lower interest paid on construction loans, earlier occupancy, and quicker return on investment.
 - High quality will reduce the future maintenance cost of the building.
 - PC technology helps to reduce the number of workers required on-site and therefore, the total labor cost is minimized.

- Due to the high quality of PC elements, no scaffoldings are required (no plastering is required for the external walls)

Technological advancement in design and development of different types of molds has resulted in production of numerous types of precast components such as interior and exterior walls, beams and columns, staircases, service ducts, water tanks, floor slabs, hollow core slabs, double tee slabs, pipes, box culverts, u-drains, etc. Main types of PC components and different types of molds required in their production with regards to residential and commercial buildings are described in the following sub-sections (Warszawski 1999).

2.2.1 Floor Slabs

Casting of different types of floor slabs can be done by using different mold types such as table molds, stacks, prestressing beds, and batteries.

- **Table molds:** These molds are used generally for production of exterior/interior walls, partitions, and room-size slabs. Typical dimensions are 3.5-4.5 m wide and 5-10 m long (larger sizes 7-10 m are suitable for bigger exterior wall casting or to produce two walls or floors at the same time). These molds can be made from timber or steel with the typical number of uses of 20-50 for timber and 300-1000 times for steel molds.
- **Stacks:** Floor slabs might be produced on stacks, which are placed one on top of the other.
- **Prestressing beds:** Hollow core modular slabs are produced with prestressing beds with typical length of 100-200 m and width of 0.90, 1.20, or 2.40 m.
- **Batteries:** When it is required to have a smooth surface on both faces of the slab, these elements are cast in vertical molds, which are also used for interior walls.

2.2.2 Interior Walls

Bearing and nonbearing interior walls are usually cast in vertical molds to have a smooth surface on both sides of the element. Vertical molds can be categorized into battery molds (consists of 6-16 steel leaves 3.00-3.50 m high and 8-10 m long) and simple vertical molds.

2.2.3 Exterior Walls

Exterior walls typically consist of several layers, including a structural concrete layer, an insulation layer, an additional concrete layer, and the exterior finish layer. Because of this multilayer structure, a tilting table is used for casting of exterior walls, which facilitates convenient demolding of the panels.

2.2.4 Beams and Columns

Longitudinal molds with 50-120 m long and with dismantable sides are used for production of beams (including Tee beams and double Tee beams) and columns.

2.2.5 Typical Precast Production Process

Although PC products require several types of activities for their manufacturing, from general point of view, the following sequences are common in producing PC components:

- Preparing molds according to the type of precast elements.
- Placing of reinforcement and fixtures.
- Concrete pouring, compacting, leveling, and smoothing.
- Concrete curing.
- Demolding.

- Temporary storage until delivery to the construction sites for final installation.

2.2.6 Precast Concrete Off-Site Production Planning

Most of the papers in the existing PC literature are in the field of production planning and scheduling practices in the precast industry. As an example, a model was developed using genetic algorithms to meet the site demands, optimize production costs of resources, and satisfy resource constraints (Li, Tserng et al. 2010). Artificial intelligence techniques have been also used to present a framework to reduce the level of finished goods in precast fabricators' yard (Ko 2010). Flow-shop sequencing models were used for specialized method of PC production as well as planning bespoke PC production to deal with challenges such as reliability of the product delivery methods and efficient usage of molds (Chan and Hu 2001; Benjaoran, Dawood et al. 2005).

Some scholars have reported the use of Information Technology (IT) for tracking of PC elements, effective management of precast yards, and efficient supply change management by exploiting various IT tools (Ergen, Akinci et al. 2007). For instance, Radio Frequency Identification (RFID) with Global Positioning System (GPS) was used to develop an automated system with minimum labor input for more effective supply chain management as well as better information flow among different parties (Ergen, Akinci et al. 2007).

In some research papers, simulation has been used as an effective technique for PC production planning. As an example, simulation has been used for planning of PC production with two critical resources which are mold and labor (Zhai, Tiong et al. 2008). To improve the productivity and reduce the production costs, simulation was used in a study of the optimization of PC production in a workshop (Balbontín-Bravo 1998).

2.2.7 Precast Concrete On-Site Installation

There are several activities involved in the installation of PC elements. This section describes the sequence of the installation of vertical and horizontal PC components based on the BCA good industry practices guide book. Before the installation of PC elements, the following checks should be performed:

- Site accessibility for the delivery of PC components
- Crane capacity
- Delivery checklist to ensure correct type, quantity, and panel identifications

Furthermore, visual inspection should be conducted to identify any major defects. The locations and conditions of the hoisting inserts should be checked before hoisting the PC elements. To improve productivity, PC components should be properly stored according to the delivery schedule and the erection process.

Installation of vertical PC elements (walls and columns) includes the following activities:

- Setting out:
 - Set the reference and offset lines (position of the PC elements to be installed).
 - Put shim plates (level pads) to set the leveling of the elements (Figure 2.1).
 - For external PC elements, put the backer rod to waterproof the joints (Figure 2.1).

Figure 2.1 Shim plates and backer rods for the installation of vertical elements

- Lifting and installation (Figure 2.2):
 - Lift the panel to its designated location.
 - Adjust the panel to its position and secure it with diagonal props.
 - Check the alignment and verticality of the installed panel.
 - Release the hoisting cable (unrig) to begin the next cycle.

Figure 2.2 Lifting and installation of vertical elements

- Grouting work:
 - Apply non-shrink mortar to seal the gaps along the inner side of the panel (at the bottom edge).
 - Keep the panels undisturbed for at least 24 hours.

Note that the installation of horizontal PC elements (beams and slabs) is similar to the vertical components. Usually, there is no need to use the diagonal props as the elements are installed over the fixed supports. As a result, the installation of horizontal elements is faster than the vertical ones.

2.3 Productivity in the Construction Industry

Productivity rates and measurement are a crucial part in the construction management field, especially in areas such as resource allocation and management, scheduling, estimating, accounting, cost control, and payroll (Herbsman and Ellis 1990). Generally, productivity can be defined as a ratio of output to input, which can be represented by:

$$P = \frac{O}{I} \quad (2.1)$$

P: Productivity, O: Output, I: Input

In the construction industry, the input contains labor, materials, information, equipment, tools, time, and capital; output contains finished buildings, structures, or elements in a specific unit of measurement (Choy 2004).

Construction productivity can be affected by numerous factors. Some of the main factors that are common in most of the construction projects, including PC projects are discussed in the following section.

2.4 Factors Affecting Productivity of the Construction Projects

According to the existing literature (Russell 1993), factors affecting construction productivity are many and they are caused by various driving forces. This is mainly due to the complex nature of construction operations as well as extensive interaction between different project parties who directly or indirectly influence construction productivity. The major important factors that affect productivity can be categorized into the following groups:

2.4.1 Site Conditions

Site condition has been referred to as one of the most important factors, which affects construction productivity. This factor itself has several attributes such as:

- **Site cleanness:** Laborers feel safe working on a clean construction site which will in turn increase productivity. Removing debris from construction sites ensures the smoothness of materials and workers flow in the construction projects and therefore, reduces safety hazards and accidents.
- **Site layout:** Several scholars discussed that project site layout planning affects productivity and should be considered carefully to minimize the traveling time and ensure the smoothness of various construction resources flow (Hegazy and Elbeltagi 2000; Tam, Tong et al. 2002). Poor site layout planning may lead to safety hazards and power shortages.
- **Soil and subsurface conditions**

2.4.2 Environmental Conditions

A bad weather condition is one of the main factors that affects productivity by causing delays on many construction tasks (Moselhi and El-Rayes 2002). Weather itself may include some indicators such as hot and cold temperature, humidity, and

rain/wind/snow, which should be separately considered with regards to productivity modeling (Koehn and Brown 1985; Hancher and Abd-Elkhalek 1998; Thomas, Riley et al. 1999).

2.4.3 Availability of Materials and Equipment

Lack of required construction materials and equipment may prevent construction operations to be performed on time and therefore, will result in delay to the whole construction project.

2.4.4 Labor Conditions

Factors that influence labor productivity should be regarded as the most important factors affecting construction productivity. This is mainly because many construction operations are labor intensive tasks. Note that the interaction between factors should be considered as well for investigation of labor productivity (Sanders 1991). Some of these factors are:

- Appropriate crew size (overstaffing/congested areas): Crowding occurs when a contractor or subcontractor tries to finish too much work during a period which is originally planned for a smaller amount of work. Another reason for crowding is poor labor planning, which results in either exceeding or lower than the required labor force. Another factor which affects productivity in the construction projects is overstaffing. When more workers assigned to a task than are required to work efficiently, overstaffing occurs, which can be due to increased crew size or the deployment of multiple crews. Since it is not usual to frequently hire and fire required labor forces, therefore, there are sometimes during a project period that the managers or superintendents assign idle workers to perform other tasks together with preplanned required labor, which causes overstaffing and results in loss of productivity.

- Labor quality and skills
- Motivation
- Turnover rate

2.4.5 Construction Management Conditions

Conditions of the management team as well as their relationship with the crew members greatly influence construction productivity. The following factors should be considered in this category:

- Level and quality of supervision: Proper supervision ensures that workers know enough about the requirements they need to complete their daily tasks and also increases the quality of the work done.
- Communications with labors and providing adequate instructions: Communication is an important facilitator of information flow, materials, understanding, and work processes in the construction projects. Two common forms of communication for the construction projects are drawings provided by the owner or architect and instruction given by construction manager, superintendent, or foreman. Communication can be further improved by utilizing IT tools such as mobile devices and wireless networks to update construction processes more frequently and efficiently.
- Proper planning, resource scheduling and task sequencing: Project planning is among the most important critical factors for construction project success. Planning itself can be affected by the organizational environment, project environment, and the construction planning effort (Faniran, Oluwoye et al. 1994). Planning affects both project duration and cost. There is an optimal level of planning inputs, which is called the saturation planning point that minimizes the total project cost (Neale and Neale 1989). Furthermore, it can be mentioned that with suitable planning effort, the implementation time is optimized and

therefore, there is a high probability that the project objectives can be achieved (Faniran, Love et al. 1999).

- Proper coordination of different parties involved in construction projects.

2.4.6 Owner/Consultant Influence

There are many parties involved in the construction projects and they have various effects on the construction productivity. As an example, changes in drawings, specifications and contract terms are very usual and common in the construction projects. These changes happen for several reasons (Madni and Reed 2001) including design errors and omissions, unexpected field conditions, owner's requests, material or equipment substitution, extra work, and changes to the contract documents (Samad 2002). A more comprehensive list of reasons which causes changes in the construction industry is provided below:

- Acts of God causing damage to completed work or equipment.
- Incomplete bid drawings.
- Drawings lack constructability.
- Incomplete, vague, or incorrect specifications.
- Differing site or subsurface conditions.
- Schedule delays or interference with other contractors.
- Changes of federal, state, or local laws, procedures, permits, and codes.
- Shortage of construction materials and equipment.
- Labor shortages.
- Financial problems for completing the project.
- Payment schedule and incorrect invoicing.
- Weakness in contract administration.

Additionally, unusual inspections and other tests may have an adverse impact on productivity of construction projects. Insufficient and incomplete drawings, drawings

lacking constructability (according to the Construction Industry Institute (CII) which is based in Austin, Texas, United States, constructability can be defined as the optimum use of construction knowledge and experience in planning, design, procurement, and field operations to achieve the overall project objective. Constructability requires good communication between contractors and consultants or professionals in charge of design phase), and misleading material specifications are among other factors, which affect productivity.

2.4.7 Project Related Factors

Due to the wide range of construction projects (high-rise buildings; road, bridge, and highway construction projects; excavation works; tunneling projects, etc.), several factors will affect productivity in different construction projects, which are mainly related to the resources, tools, equipment, and special crew skills required for construction tasks. The project related factors can be summarized into the following categories (Sanders 1991):

- Work type: To identify design differences that may affect productivity.
- Building element: To determine different building components that requires various types of work. As an example, handling, preparing, and fixing of different PC components require different tasks.
- Construction and delivery method: To identify construction techniques chosen by the contractor. Delivery methods can also affect construction productivity. Different methods from Just-in-time (JIT) delivery to Just-in-case method (bulk deliveries of material) require different operations and storage procedures. In JIT method, double handling of materials is minimized (Thomas, Riley et al. 1999), but it may result in higher total cost considering more frequent delivery of materials.
- Design requirements: To determine unusual requirements imposed by the design team for special purposes.

2.4.8 Miscellaneous Factors

Before the initiation phase of any construction project, proper approvals should be obtained from regulatory bodies. Delay in this process leads to unexpected extension to the project duration. Other miscellaneous factors can be mentioned as safety issues, problems with utilities, theft, strikes, vandalism, shutdowns, and acts of God (earthquakes, storms, flood, etc.)

2.5 Construction Productivity Estimation by Multiple Regression Analysis

Regression analysis is generally used to find a linear relationship between a set of predictors and a dependent variable (Lin, Tserng et al. 2011). This technique has been widely used for different areas of construction management research such as cost estimation for different projects (Sonmez and Ontepeli 2009) and estimating project duration (Lin, Tserng et al. 2011). Furthermore, Multiple Regression Analysis (MRA) has been utilized in productivity estimation and modeling to develop simple but reliable prediction models of productivity measures for different construction tasks. Some of the examples are as follows:

- Productivity models for concrete pouring, formwork, and concrete finishing tasks were provided using MRA and Artificial Neural Networks (ANN) (Sonmez and Rowings 1998). Investigating and quantifying the effect of buildability factors on labor productivity of formwork has also been studied using regression techniques (Jarkas 2010).
- For productivity of earthmoving operations, several factors such as number of trucks, buckets per load and volume, the plant match factor, the truck travel time, and haul length were used to form the regression model which described over 90% of the variance of the actual productivity (Smith 1999). Combinations of simulation, MRA, and ANN were also used to predict productivity of conventional earthmoving equipment (Han, Hong et al. 2011).

- Crew size, environmental factors, and construction methods that were collected from 11 projects were used to model masonry productivity rates (Sanders and Thomas 1993).
- Seven regression models were developed to estimate pile construction productivity, cycle time, and cost, which considered both qualitative and quantitative factors such as site planning, equipment operator efficiency, job and management conditions, etc. (Zayed and Halpin 2005 a, b).

Based on the above mentioned papers, the following steps are generally used to establish valid and robust regression models for productivity estimation:

1. Literature review, interviews, and preliminary site visits to make sure that the process under study is standardized.
2. Collect the factors affecting productivity.
3. Collect the required data.
4. Find the significant factors affecting productivity through statistical tests.
5. Building the regression model based on the factors from previous steps.
6. Validate the data based upon a separate data set. These data can be obtained from additional case studies or from the primary data that has been already collected but not used during the model development. In the case the model is invalid, steps 1 to 5 should be repeated.
7. Perform sensitivity analysis for each of the input variables (optional).

2.6 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) can be defined as a massive parallel distributed processor composed of simple processing units (neurons) which are capable of storing experiential knowledge and retrieving it for future use (Haykin 1999). Therefore, ANN can be considered as an information processing technology that by learning from different experiences and generalizing from previous examples, simulate the human

brain system. In the other words, ANN resemble human brain system in two respects (Haykin 1999):

- 1- Knowledge acquisition from its environment through a learning process.
- 2- Storing the acquired knowledge is performed by interneuron connection strengths known as synaptic weights.

A simple schematic diagram of a neuron is shown in Figure 2.1.

Figure 2.3 Schematic diagram of a neuron

Figure 2.3 shows that each neuron has two distinct segments: a summing junction that sums up the received inputs from neighbors and an activation function that computes the output signal which is propagated to other neurons. The activation function can be theoretically in any form such as signum, linear or semi linear, hyperbolic tangent, and sigmoid functions.

To form a network, neurons are grouped into several layers namely input, hidden, and output layers. There are two types of network topologies that are shown in Figure 2.4 (Chennakesava 2006):

- Feed-forward networks: Data flows strictly from input to output layers, and no feedback connections are allowed.
- Recurrent networks: Feedback connections are present that allow the data flow from proceeding to preceding layers.

Figure 2.4 Different topologies of ANN

ANN should be arranged in such a way that it can provide the desired outputs for a set of inputs presented to the network. To do so, connection weights should be either set using a prior knowledge or the network should be trained by feeding training samples (training sets). Connection weights are then changed based on the “learning rule”. There are two types of learning in ANN:

- Supervised learning (associative learning): both input and output training pairs are presented to the network, and the network will learn based on the presented samples.
- Unsupervised learning (self-organization): there is no prior set of categories to be presented to the network, and the system develops its own representation of the input stimuli.

Almost all the learning rules are variants of the Hebbian learning rule which simply mentions that if two neurons are active, their interconnection must be strengthened. Based on this learning rule, “delta rule” uses the differences between actual and desired activation for modifying the connection weights.

Multi-layer feed-forward neural networks (Figure 2.4) are the most commonly used architecture in the engineering fields, including construction engineering and management. “Back-propagation learning algorithm” (Rumelhart, Hintont et al. 1986) which is a generalization of the delta rule is generally used for these types of networks. A set of training samples are presented to the network and based upon the activation functions of the hidden and output layers, the network outputs are calculated, which is then compared with the actual (desired) outputs. The error is calculated (difference between the actual and network output) and propagated back to the network, the connection weights are modified, and this procedure is repeated for several times (epochs) until the network reaches the stop criteria.

Generalization is the ability of neural networks to produce reasonable outputs for inputs not being trained before. Learning capabilities and generalization are among the differences between ANNs and conventional models. ANN are also useful where the processes to be modeled are too complex to be represented by analytical models. Based on the previous examples, neural networks can be built to make new decisions, classify new patterns, and make forecasts and predictions. The most important advantage of ANN over conventional models (mathematical and statistical models) is their ability to adjust their weights to optimize their behavior in different situations (Boussabaine 1996). Moreover, ANN may include multiple outputs simultaneously (e.g. cost and productivity are both predictable using a single network providing the required inputs) when compared to Multiple Regression Analysis (MRA) which can only estimate single output at a time.

2.6.1 ANN for Construction Productivity Analysis

Construction management problems are very complex because of the common uncertainties which are involved in any construction operations. In order to solve these problems, experience and knowledge from the experts are vital requirements. Therefore, the field of construction engineering and management has been considered as a fertile area for many expert systems and ANN applications (Moselhi, Hegazy et al. 1991).

ANN have been widely used in different areas of construction management research in the last two decades such as cost and markup estimation (Liu and Ling 2005; Cheng, Tsai et al. 2009; Pewdum, Rujirayanyong et al. 2009), contractors' prequalification (Farzad 1999; Lam, Hu et al. 2001), risk allocation and management (Jin 2011; Jin and Zhang 2011), and construction knowledge management (Kale and Karaman 2011).

Productivity rates and measurement (e.g. labor and equipment productivity rates) is a crucial task in the construction management field, especially, in areas such as resource allocation and management, scheduling, estimating, accounting, cost control, and payroll (Herbsman and Ellis 1990). It is important for contractors to have reliable estimates for different construction operations to benchmark their work against average industry levels provided by building authorities. ANN can be used as a robust tool for productivity estimation. The following is a list of areas within the context of construction management in which ANN have been used to model productivity:

- Steel drafting and fabrication processes (Song and AbouRizk 2008)
- Effects of change orders, rework, and daily workload on labor productivity (Yang, Edwards et al. 2004; David, Junli et al. 2005; Moselhi, Assem et al. 2005; Palaneeswaran, Love et al. 2008)
- Labor production rates for industrial construction activities (AbouRizk, Knowles et al. 2001)

- Concrete pouring, formwork, and finishing tasks (Portas and AbouRizk 1997; Sonmez and Rowings 1998; Ezeldin and Sharara 2006; Moselhi and Zafar 2010; Oral and Oral 2010; Dikmen and Sonmez 2011)
- Hoisting times (hook times) of tower cranes (Leung, Tam et al. 2001; Tam, Leung et al. 2002; Tam, Tong et al. 2004)
- Spool fabrication (Lu, AbouRizk et al. 2001)
- Pile construction (Zayed and Halpin 2004a; Zayed and Halpin 2005a; Zayed and Halpin 2005b)
- Pipe installation (Lu, AbouRizk et al. 2000)
- Plastering activities (Oral, Oral et al. 2012)
- Productivity estimation of construction earthmoving equipment such as excavator, push dozer, scrapers, loader, and haul trucks (C.M, Thomas K.L et al. 1993; Chao and Skibniewski 1994; Flood and Christophilos 1996; Kartam 1996; Portas and AbouRizk 1997; Shi 1999; Chao 2001; Tam, Tong et al. 2002; Yang, Edwards et al. 2004; Ok and Sinha 2006; Schabowicz and Hola 2007; Emmanuel and Steven 2010; Hola and Schabowicz 2010; Han, Hong et al. 2011)
- Concrete batch-plant-truck mixer operations and delivery systems (Zayed, Halpin et al. 2005c; Graham, Forbes et al. 2006)

Based on the above studies, Figure 2.5 shows a framework including the necessary steps to develop ANN for productivity estimations.

Figure 2.5 ANN for productivity analysis and estimations

2.7 Simulation as a Tool for Construction Productivity Analysis

Discrete event simulation is a well-established approach in the field of construction engineering and management (Martinez and Ioannou 1999). Simulation is an effective tool to be used for the planning purposes in the feasibility studies as well as during project execution. There are several simulation packages designed for the construction industry. Probably, the most famous one is CYCLONE developed by Prof. Halpin in

1970s and since then there are many advancements in CYCLONE based systems such as MICROCYCLONE (Halpin and Riggs 1992), DISCO (Huang and Halpin 1993), and STROBOSCOPE (Martínez 1996) which is capable of modeling more complex construction operations. Regardless of which simulation package to use, the steps required to design and develop simulation models are shown in Figure 2.6.

Figure 2.6 Simulation steps

There are several studies that have utilized simulation as a tool for analyzing different construction management problems. As an example, simulation has been used to assess the productivity of laying water mains (Tam 2010), modeling of public housing construction (Shi, Zeng et al. 1998), resource management of bridge deck rehabilitation (Zhang, Zayed et al. 2008), concrete batch plant operations (Zayed, Halpin et al. 2005c), and pile construction productivity assessment (Zayed and Halpin 2004b).

2.8 Method Productivity Delay Model and Analysis of the Baseline Productivity

Analysis of delay in any construction operation is useful to provide information about different types of delays occurred and how to measure, predict, and improve productivity. One of the well-established methods for delay analysis is the “Method Productivity Delay Model (MPDM)”, which is based on traditional time and motion study concepts (Adrian and Boyer 1976). It takes a sample from a specific construction cycle and analyzes the delays occurred during those cycles. Five types of delays were considered to be common in most of the construction projects: environment, equipment, labor, material, and management (Halpin and Riggs 1992). Specific types of delays can be added or deleted from this list based on the project requirements.

Measuring and documentation of different delays is a very skill-dependent task. Usually, the data collector, will continuously time the production cycles from start to finish and therefore, use of time laps recorder is required when the production cycle includes several activities like precast installation. For delay documentation, one approach is to time the actual length of the delay. However, this will quickly increase the workload of the data collector and may become too complex to measure different types of delays separately (Halpin and Riggs 1992). Therefore, installation cycles will be observed and marked as non-delay or delay production cycle. Total delay times will be then calculated as the sum of delay production cycles (those marked as delay cycles) minus the “mean” of non-delay production cycles (Adrian and Boyer 1976). Based on the analysis of different delays, required actions can be taken to improve productivity.

Another concept which is relevant to research in productivity is to define and measure baseline productivity, which is to find the best productivity rate that a company (contractor) can achieve on a particular task or project (Thomas, Riley et al. 1999). Baseline productivity is calculated based on the quantities of work for working days that no changes or rework have been reported. The following steps are required for baseline productivity calculation (Thomas and Završki 1999):

- Calculate the baseline subset (working days with highest productivity rates): at least 10 percent of the total working days which is rounded to the next odd number.
- Note the daily productivity measures for the baseline set.
- Baseline productivity equals to the median of the productivity rates in the baseline set.

2.9 Summary and Conclusions

In this chapter, relevant concepts with regards to the subject matter of the thesis were summarized. IBS, precast concrete productions systems and products, productivity in

the construction industry, factors affecting productivity of the construction projects such as site, environmental, management, and labor conditions, specific project related factors, availability of materials and equipment, and owner/consultant influences were fully described. Multiple Regression Analysis (MRA), Artificial Neural Networks (ANN) and simulation were mentioned as the most commonly used techniques to assess and model the productivity of different construction operations and several examples were listed for each of these techniques. Based on the literature review, most of the papers in the existing PC literature are in the field of off-site production planning and scheduling practices. There is no study in the productivity analysis and modeling of precast concrete projects, specifically in terms of on-site activities (precast installation process). Due to the high usage of precast elements in public and private housing construction projects in Singapore, there is a need for an in depth academic research in this field to figure out the factors affecting productivity and provide effective productivity models for contractors to be used for their planning purposes. Details about research methodology are described in the next chapter.

- Factors Affecting Precast Concrete Erection Process Productivity
- Data Collection (Questionnaire design and administration)
- Data Analysis Using MRA, ANN, and Construction Simulation

This chapter describes the research methodology through the following major steps, which are graphically shown in Figure 3.1:

- 1- Review relevant literature to describe Industrialized Building Systems (IBS) and Precast Concrete (PC) Technology as one of the main products to be used in IBS. Literature review also covers background on productivity studies and productivity modeling by Multiple Regression Analysis (MRA), Artificial Neural Networks (ANN), and simulation techniques.
- 2- Determine the factors affecting PC installation through preliminary site visits.
- 3- Prepare a data sheet for effective documentation of the required data.
- 4- Collect the primary data from contractors specialized in PC projects.
- 5- Prepare the collected data to be used as the inputs for MRA, ANN, and simulation techniques.
- 6- Develop productivity models using MRA, ANN, and simulation approaches.
- 7- Analyze delay using the combination of the developed models and Delay Method Productivity Model (MPDM)
- 8- Verify the models' performance against actual data and perform sensitivity analysis.
- 9- Analyze baseline productivity for precast contractors.
- 10- Research conclusions and discussions about future works.

Details about above mentioned steps are explained in the following sections.

3.1 Literature Review

Relevant studies have been already presented in the previous chapter to include information on IBS and PC products. Chapter 2 also covered background on productivity modeling of different construction operations by MRA, ANN, and simulation approaches. Additionally, some details about MPDM and how to calculate baseline productivity were discussed. It was concluded that, there is a need to study the

factors affecting PC projects and provide productivity models to be used by contractors or researchers in the field of construction management.

Figure 3.1 Study steps for productivity analysis of PC installation

3.2 Factors Affecting Productivity of Precast Concrete Erection Process

To collect and analyze the factors that influence productivity of PC installation, the erection process itself should be first analyzed to find the resources required as well as the sequence of the activities. Based on the preliminary site visits, different tasks involved and the resources required to finish a typical erection process are shown in Figure 3.2.

Figure 3.2 Installation of a typical PC element

In Figure 3.2 ovals and rectangles represent resources and activities, respectively. From this figure, it can be seen that a typical erection task involves different resources such as preparation, inspection, and fixing crew, tower crane (or any other type of cranes), and crane operator. Several instruments are also required to finish these tasks such as powerful drills and diagonal props (supports) to fix the vertical elements. Additionally, Figure 3.2 shows that there are four major activities in PC installation:

1. Preparation activities (preparation, inspection, and pick-up): This is performed by a signal man (rigger man) at the storage area. The component is quickly checked against physical damages (if any), and then the signal man will attach the crane hook to the lifting inserts on the element.
2. Lifting: The crane raises the component to be installed at the unloading point.
3. Fixing activities (adjustment, fix, alignment, and unrigging): The element will be adjusted and fixed at the designated location based on the drawings. Diagonal props will be used as temporary support for vertical elements.

Grouting is required for exterior vertical elements and backer rod is used to waterproof the joints. Preparation crew will check the alignment and verticality of the element, and then the crane hook will be detached from the element.

4. Crane return: As soon as the crane hook is detached from the lifting inserts, crane returns for the next cycle or other lifting purposes³.

Based on the preliminary site visits and the abovementioned activities in a PC installation cycle, 18 factors were selected to be the relevant factors that affect the productivity of PC installation. These variables are described in Table 3.1.

Data were collected from construction sites across Singapore and Malaysia and because of the tropical weather of this region, data on weather conditions such as temperature, humidity and wind speed were not collected and included in the analysis. Crane operators have also mentioned that the hoisting speed is affected only in adverse weather conditions and for safety reasons, hoisting is stopped during rain or strong wind (Leung and Tam 1999). This point was further confirmed by the research team during site visits and data collection. As a result, including weather condition variables in the analysis may not be critical. Additionally, the skill level of crane operator and site crew was not considered in this study. This is a subjective factor which could be measured by some indirect factors such as years of experience. However, based on the interviews with site staff, after one or two years of related work, crew can be considered as being trained and experienced. The primary data for this research were collected from construction sites with more than two years of experience in precast erection activities. Therefore, crew skill was eliminated from the analysis for being constant. Additionally, in most of the cases, only one signal man was in charge of preparation, inspection and pick up activities. Therefore, the number of preparation crew was not included in the analysis.

³ There are some other activities involved in the installation of PC components as described in section 2.2.7. However, activities such as setting out the reference lines and the grouting works can be performed with other tasks, and no crane is required for such activities. As a result, to be in line with the objectives of the thesis, only the main activities are analyzed in this research.

Table 3.1 Factors affecting productivity of installation of PC elements

Factor	Name	Description	Coding/Unit of Measurement	Data Source
X_1	Weight	Component weight	Ton (t)	Shop drawings
X_2	Area	Largest surface area of the component	Square meters (m ²)	Shop drawings ⁴
X_3	Length	Longest length of the element	Meter (m)	Shop drawings
X_4	Height	Component Height	Meter (m)	Shop drawings
X_5	Storage Type	The component is stored among others or being isolated	1: Isolated 2: Among Others	Observation
X_6	Storage to Crane	Distance from component to crane center at the storage area	Meter (m)	Site layout plan
X_7	Installation to Crane	Distance from the installation point to the crane center	Meter (m)	Site & Precast layout plan
X_8	Crane Angle	Angle between storage and installation	Degree	Site & Precast layout plan
X_9	Crane Type	Type of the crane used	1: Tower Crane 2: Crawler Crane	Observation
X_{10}	Installation Type	The component is installed among others or isolated	1: Isolated 2: Among others	Observation
X_{11}	Location Type	The component is exterior or Interior	1: Exterior 2: Interior	Observation
X_{12}	Rebars	Number of rebars to fix the component (for vertical elements)	Number: 1...n	Observation
X_{13}	Lifting Inserts	Number of lifting inserts of the component	Number: 1...n	Observation
X_{14}	Props	Number of diagonal props for temporary support	Number: 1...n	Observation
X_{15}	Prop Inserts	Number of holes to be drilled for props installation	Number: 1...n	Observation
X_{16}	Fix Crew Size	Crew size in charge of precast installation	Number: 1...n	Observation
X_{17}	Elevation	Elevation of the installation point	Meter (m)	Elevation plan
X_{18}	Shape	Component orientation (Vertical & Horizontal)	1: Vertical 2: Horizontal	Observation

⁴ An example of a drawing is provided in Appendix A.

It should be noted that crane productivity factors (X_1 – X_3 , X_7 – X_9 , X_{17} – X_{18}) were extracted from the relevant literature (Leung and Tam 1999; Tam, Leung et al. 2002; Tam, Tong et al. 2004). The other factors were determined through site visits and observations of precast installations.

3.3 Data Collection

To ensure data quality, required primary data for this research were collected through “direct observations” from different construction sites across Singapore and Malaysia⁵, including residential buildings and a school project (no questionnaires were administered). Based on Table 3.1, a data collection sheet (Appendix A) was designed for the documentation purposes. At the first phase of data collection, the installations of 276 PC panels (walls, columns, beams, and slabs) were observed and stopwatch was used to record the duration of different activities shown in Figure 3.2. This set of data was mainly used for the modeling purposes as will be discussed later. At the second phase of data collection, another 27 panels were studied to test the performance of the developed models. Table 3.2 shows general characteristics of PC elements studied for this research.

Table 3.2 General characteristics of PC elements

	Wall	Column	Beam	Slab
No. of cases	126	80	34	73
Length (m)	1.40 – 5.75	0.40 – 2.00	5.57 – 9.22	2.40 – 8.73
Width (m)	0.10 – 0.25	0.20 – 0.75	0.30 – 0.80	0.37 – 2.40
Height (m)	2.80 – 3.58	2.80 – 5.80	0.32 – 0.60	0.07 – 0.27
Weight (t)	0.95 – 7.31	1.00 – 3.50	2.06 – 5.66	0.80 – 3.09

⁵ A list of contractors involved in precast operations was obtained from HDB (housing and development board) and BCA (Building and Construction Authority). At the next step, eight contractors were randomly selected and several site visits were performed to ensure that the process under study is standardized. Based on their willingness to participate in the research and other conditions such as the percentage of precast being used in their project and the elevation they are currently working at, four of them were finally chosen for the primary data collection.

The range of installation height (elevation of the erection point) was between 12.65 m to 68.9 m which was considered level 3 to level 23 of residential buildings in Singapore. This will cover an acceptable range of installation points for most of the construction projects in Singapore. Note that it was deliberately arranged to collect the data above level 3 to minimize the learning effect (if any).

The first issue about data collection was to find those contractors that have precast projects on hand. The next challenge was the safety issues at the construction sites. To observe and record the timing of precast installation, the observer should have a clear view of all the activities involved. As a result, most of the time, the observer should stand near the edge of the building, so he/she can record the activities accurately. Therefore, the researcher should ensure the contractor that he is familiar with the safety requirements and practices. It should be noted that some contractors didn't allow the researcher to collect the data at their construction sites. Therefore, finding these four contractors and getting all the permissions for the data collection was a time consuming process.

3.4 Data Analysis

In this study, the collected data were prepared and analyzed by Multiple Regression Analysis (MRA), Artificial Neural Networks (ANN), and construction simulation techniques. Data preparation and model designs are described in the following sections.

3.4.1 Productivity Modeling by Multiple Regression Analysis

A linear regression model in the form of the following was developed to model the installation process productivity:

$$Y = B_0 + B_1 X_1 + B_2 X_2 + \dots + B_n X_n \quad (3.1)$$

The main dependent variable (Y) is the time (in minutes) required to finish the main installation activities. B_0 is the intercept and $B_1, B_2, \dots, B_n$ are the coefficients of the relationship. $X_1, X_2, \dots, X_n$ are the factors described in Table 3.1 and data for these factors were collected through observations and from the relevant drawings such as precast shop drawings, site storage drawings, and level layout plans (Table 3.1). Qualitative factors were coded as described in Table 3.1.

To build the model and estimate the coefficients of the regression model, the ordinary least squares (OLS) method was used by SPSS version 17. To provide better estimates and to find the significant variables, both “enter” and “stepwise” methods were considered. The difference between these two methods is that in the latter, the variables are entered for examination at each step for entry and removal analysis. However, in the former method, all the variables are entered in a single step and the predicted model will usually include all the variables (unless a variable is below the tolerance criterion – 0.0001) (Leung and Tam 1999). Selection between “enter” and “stepwise” models is based on the values of t-statistic, F-statistic, and minimization of multicollinearity. Usually stepwise method provides robust models by including most of the significant factors.

From 276 panels that were studied during the first phase of data collection, 56 cases were extracted for delay analysis. From the remaining 220 data points, 190 cases were used to build the regression models and 30 data points for preliminary data validation.

The developed models were then combined with Method Productivity Delay Model (MPDM) for the delay analysis (56 cases). Final models were validated by comparison with the actual data collected from construction sites (27 cases collected at the second phase of data collection). The final step is to perform sensitivity analysis to build a range of inputs with regards to the same output.

3.4.2 Productivity Modeling by ANN

ANN is a data oriented method, which does not consider the processes behind the collected data and therefore, deals directly with the obtained data. As mentioned in the previous chapter (literature review), this technique has been widely used in the field of construction management, including the area of productivity assessment and modeling. In this study, Feed-Forward Back-Propagation networks in which each layer consists of several processing units (neurons) were used to model the productivity. Input neurons are the factors described in Table 3.1, and the output neuron is the installation time in minutes. Note that for each qualitative factor in Table 3.1, two neurons were used with 0 and 1 values. Before the training phase, data (inputs and output) were scaled using Eq. 3. 2, which transforms the actual data to be between 0 and 1.

$$Scaled\ Value = \frac{Unscaled\ value - min.value}{max.value - min.value} \quad (3.2)$$

NeuroSolutions Version 6 was used in this research for ANN calculations. Based on the examples provided in literature review, the required steps to design and develop ANN for productivity modeling of PC installation are shown in Figure 3.3.

Similar to MRA, 56 cases were used for the delay analysis. From the remaining data points, 160 cases were used to develop ANN models, 30 cases for cross validation, and 30 cases (the same set in MRA) for preliminary data validation. Use of cross validation technique ensures that the network is not over trained. In this method, the stop criterion is chosen in such a way that as soon as the error in the cross validation set starts to increase, the training will be stopped. The same as MRA, developed models were combined with MPDM and the results of the models were compared to the actual data for the validation purposes.

3.4.3 Productivity Modeling by Construction Simulation

The simulation model was constructed by WebCYCLONE, which is based on MICROCYCLONE software and is available online for free. To develop the simulation model, the main activities involved in PC installation (preparation, lift, and fixing) were modeled. At the next step, there was a need to fit probability distribution to the activities' time. The final step was to run and validate the model by comparing the results with the actual data. The simulation model was then used to analyze the resource utilization (crane and crew).

3.4.4 Comparison of Different Techniques

To find the best model, it is necessary to compare the models developed by MRA, ANN, and simulation techniques. The differences between the results provided by these models will be discussed in the next chapter through several statistical tests.

3.4.5 Selection of the Analysis Tools (MRA, ANN, and Simulation)

In this study, MRA, ANN, and construction simulation techniques have been used to analyze the productivity of PC installation activities. This section describes the reasons why these methods have been chosen to be used in this research.

Multiple Regression Analysis (MRA) is an extremely powerful tool to figure out the relationships within the data being studied (Smith 1999). It is one of the most widely used statistical tools because it provides a simple method for establishing a functional relationship among independent and dependent variables (Dunlop and Smith 2003). This technique is a well-established method which has been widely used in different areas of construction management research. For example, MRA has been utilized in productivity estimation and modeling to develop simple but reliable prediction models of productivity measures for different construction tasks (refer to section 2.5). The

regression equation provides easy to understand relationships between the dependent and independent factors and therefore, can be used by construction practitioners in different areas of construction operations. As a result, this technique was chosen to be used in this research to establish a simple but reliable tool for the productivity analysis of PC operations.

ANN is another technique to be used in this research. ANN are simple to develop and more suitable to be used in construction management problems requiring analogy based solutions (Song and AbouRizk 2008). When compared to regression analysis, ANN have no implicit functional form and therefore, have greater freedom to fit the data (Wilmot and Mei 2005), which results in reduction of the forecasting error. Regression models are generally limited by the number of influencing factors and the linear relationship in MRA imposes a functional relationship which may not always be true. Additionally, due to the complexity of the construction research problems, the modeling process is difficult, especially when there is no clear functional relationship between input factors and project outputs. As a result, ANN is an efficient tool in this domain because (Elhag and Wang 2007):

- Assumptions that the data must follow a specific statistical distribution are not needed.
- There is no requirement of predetermining the relationships between inputs and outputs.
- ANN have very strong capability of self-learning and self-updating.

Finally, construction simulation was used as the third technique to evaluate the productivity of PC installation. Simulation is an effective tool to be used for the planning purposes in the feasibility studies as well as during project execution.

It should be noted that since this study was the first research to evaluate the productivity of PC installation activities in such details, the abovementioned three

methods, which are the most well established techniques to analyze the productivity have been chosen. This is according to the current literature that has been summarized in chapter two. This will lay the ground to form a rational basis to evaluate the productivity of PC operations at the first step, after which more advanced techniques can be used in the future studies to benchmark the results against the findings of these methods.

Additionally, the author of the thesis has tried some other techniques in the draft analysis. As an instance, Support Vector Machine was studied and applied to the data. SVM is a set of supervised learning methods capable of handling data in a high dimensional space. The main advantage of SVM to other learning techniques is that it produces a solution that is unique and globally optimal. However, this technique is more efficient in the classification problems and not for the regression type solutions (Lam et al. 2010) and therefore, was not included in the research.

3.5 Chapter Summary

This chapter described the details about research methodology. Activities involved in PC installation were discussed and factors affecting productivity of PC erection process were presented. The procedure to collect the data and characteristics of the collected data were shown. Details about how to use MRA, ANN, and simulation techniques for productivity modeling and analysis of PC installation were presented. Full details about each of the mentioned techniques with analysis of the results are provided in the next chapter.

Figure 3.3 A framework to develop ANN for productivity estimations of PC Installation

Chapter 4. DATA ANALYSIS

- Application of MRA to PC Installation Process
- Application of ANN to PC Installation Process
- Method Productivity Delay Model
- Development of the final MRA and ANN models
- Construction Simulation Model for the Productivity Analysis of PC Installation
- Analysis of Baseline Productivity

This chapter describes the applications of MRA, ANN, and simulation techniques to the PC installation process. The procedures on how to combine MRA and ANN with MPDM for the delay analysis are presented and the application of baseline productivity to the PC installation is described. Details about design, development, and validation of different models are discussed in details in the following sub-sections.

4.1 Application of Multiple Regression Analysis to PC Installation Process

In order to build regression models for PC installation, there are two alternatives:

- 1- Consider all 18 variables (Table 3.1) as the model inputs (independent variables) and total time of installation (in minutes) as the main dependent variable (model output).
- 2- Consider the main activities involved in PC installation as described in section 3.2. These activities are preparation, lift, and fixing activities⁶. As a result, three regression models can be developed for each of these activities considering relevant variables for each of the main activities. In this case, the total installation time is the sum of these three models' outputs (installation time = preparation time + lifting time + fixing time).

Our draft analysis showed that the model obtained from the first option was not valid, and the coefficients couldn't be interpreted properly. This is mainly because of the distribution of the collected data across different projects. As an example, 65 percent of the horizontal elements were collected from a project that used a crawler crane instead of tower crane for lifting purposes. Generally, installations of horizontal elements take less time than vertical elements. Therefore, if one regression model is developed for the

⁶ After the component is properly fixed, the crane can return to begin the next cycle. However, observations showed that due to other lifting purposes, the crane may not directly go to the storage area right after the installation of the previous element. Therefore, this study didn't analyze the crane return time. Based on the collected data, an average of 2 minutes can be considered for the crane return time. If a more accurate model is needed, the readers should refer to the available literature on crane productivity studies as described in the previous chapter.

whole erection process, the coefficient of the crane type will be negative, which is interpreted as erection using a crawler crane takes less time than installation using tower cranes (all other factors being constant), which is incorrect in an actual project setting. Therefore, this study has developed regression models for different activities to deal with the bias involved in the collected data and to provide valid and interpretable results as will be described in the following sub-sections.

4.1.1 Regression Model for Preparation Activities

Preparation activities are the first stage in the cycle time of precast installation. Storage type (X_5), length (X_3), area (X_2), weight (X_1), height of the component (X_4), and number of lifting inserts (X_{13}) are the relevant factors to be considered in the regression analysis of preparation activities. The results for both “enter” and “stepwise” methods are shown in Table 4.1.

Table 4.1 Regression analysis for Preparation activities

	R	R Square	Adj. R Square	Std. Error	F	Sig. ANOVA
Enter	0.670	0.449	0.431	0.582	29.016	0.000
Stepwise	0.666	0.444	0.435	0.580	48.674	0.000
Variable (Enter)	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	-0.576	0.229		-2.517	0.013	
Storage Type	1.072	0.102	0.667	10.538	0.000	1.308
Weight	-0.019	0.046	-0.034	-0.411	0.682	2.288
Length	0.080	0.020	0.274	3.915	0.000	1.603
Area	0.031	0.017	0.155	1.817	0.071	2.368
Height	0.085	0.070	0.170	1.210	0.228	6.434
Lift Inserts	0.011	0.070	0.011	0.153	0.878	1.534
Variable (Stepwise)	B	Std. Error	Beta	T	Sig.	VIF
(Constant)	-0.565	0.172		-3.293	0.001	
Storage Type	1.062	0.100	0.662	10.628	0.000	1.275
Length	0.080	0.020	0.274	3.982	0.000	1.559
Area	0.028	0.013	0.137	2.138	0.034	1.351

Table 4.1 shows that 44.9 percent (R-square of the enter method) of the variation in the preparation time can be explained by the selected factors. However, some p-values are more than 0.05, which is an indication of possible insignificant predictors. Therefore, the stepwise method was used and the results showed that 44.4 percent (with p-value from ANOVA table less than 0.05) of the variation in preparation time can be explained by storage type (X_5), length (X_3), and area (X_2). All p-values are less than 0.05 and no significant multicollinearity can be considered (all VIF values are less than 5). As a result, the final regression model for the preparation time is:

$$Y_{PR} = -0.565 + 1.062 \text{ Storage Type} + 0.08 \text{ Length} + 0.028 \text{ Area} \quad (4.1)$$

Y_{PR} is the estimated preparation time and the model implies that with one unit increase in length and area of the PC element, the preparation time will increase by 0.08 and 0.028 minutes, respectively. Additionally, when the storage type of a component changes from being isolated to be stored among others, the preparation time will increase by 1.062 minutes. Figure 4.1 confirms this point by depicting that preparation of isolated components is easier when compared to those among others.

Figure 4.1 Preparation of elements in different storage conditions

4.1.2 Regression Model for Hoisting Time (Lift)

The relevant factors to build the regression model for hoisting time are: elevation (X_{17}), area of the load (X_2), component orientation (X_{18}), crane angle (X_8), distance from installation to crane (X_7), crane type (X_9), component weight (X_{11}), distance from storage to crane (X_6), and component length (X_3). As mentioned earlier, these factors were extracted from the relevant literature and confirmed to be important through site visits. The analysis and results of the regression models for enter and stepwise methods are shown in Table 4.2.

Table 4.2 Regression analysis for hoisting time

	R	R Square	Adj. R Square	Std. Error	F	Sig. ANOVA
Enter	0.815	0.664	0.647	0.710	39.453	0.000
Stepwise	0.806	0.650	0.638	0.719	56.623	0.000
Variable (Enter)	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	-1.913	0.601		-3.182	0.002	
Orientation	-1.086	0.253	-0.443	-4.285	0.000	5.712
Storage to Crane	0.025	0.008	0.260	3.239	0.001	3.458
Installation to Crane	0.016	0.009	0.082	1.783	0.076	1.125
Crane Angle	0.010	0.001	0.514	10.138	0.000	1.376
Crane Type	1.857	0.193	0.776	9.618	0.000	3.480
Length	-0.035	0.050	-0.078	-0.706	0.481	6.517
Area	0.041	0.020	0.129	1.993	0.048	2.252
Weight	0.089	0.070	0.105	1.259	0.210	3.755
Elevation	0.037	0.005	0.516	7.287	0.000	2.685
Variable (Stepwise)	B	Std. Error	Beta	T	Sig.	VIF
(Constant)	-1.418	0.485		-2.924	0.004	
Crane Angle	0.011	0.001	0.527	10.647	0.000	1.279
Storage to Crane	0.024	0.008	0.246	3.083	0.002	3.334
Orientation	-1.155	0.128	-0.471	-9.034	0.000	1.419
Crane Type	1.856	0.186	0.775	9.992	0.000	3.146
Elevation	0.037	0.005	0.513	7.352	0.000	2.544
Weight	0.144	0.043	0.172	3.319	0.001	1.397

The analysis of the stepwise method shows that 65 percent (R Square value) of the variation in the lifting time can be explained by crane angle (X_8), distance from storage to crane (X_6), orientation of the load (X_{18}), crane type (X_9), elevation (X_{17}), and weight (X_1). Therefore, the regression model for the lifting time can be written as:

$$Y_{LR} = -1.418 + 0.011 X_8 + 0.024 X_6 - 1.155 X_{18} + 1.856 X_9 + 0.037 X_{17} + 0.144 X_1 \quad (4.2)$$

Y_{LR} is the estimated lift time and the model shows that with one unit increase in crane angle, distance from storage to crane, elevation of the installation point, and component weight, lifting time increases by 0.011, 0.024, 0.037, and 0.144 minutes, respectively. Additionally, when the crane type changes from tower crane to the crawler crane, there is an increase of 1.856 minutes in the lifting time. There is an average decrease of 1.155 minutes in the lifting time of horizontal components when compared to vertical elements.

From the significant factors of preparation and hoisting times, it can be seen that just-in-time (JIT) deliveries of PC elements will directly improve the overall productivity of the erection process. This is because the components can be picked up from the trailers (elements can be considered as isolated in the equation 4.1) and also the trailer can be positioned near the crane in such a way that the distance between the elements and crane center as well as crane angular movement are minimized. Furthermore, double handling, space constraints, and traffic congestion at the worksite can be alleviated using JIT delivery system (Pheng and Chuan 2001) which is shown in Figure 4.2.

Figure 4.2 Precast JIT delivery

4.1.3 Regression Model for Fixing Activities

In the regression model for fixing activities, the following predictors should be considered: area (X_2), weight (X_1), component height (X_4), length (X_3), location type (X_{11}), number of hooks (X_{13}), number of rebars (X_{12}), number of props (X_{14}), number of inserts for props installation (X_{15}), installation type (X_{10}), and fixing crew size (X_{16}). There might be a concern that the number of inserts for props installation (X_{15}) might be related to the number of props (X_{14}). In the other words, for each prop, at least two inserts must be available (one on the element and the other on the below slab). Our observations showed that in some construction sites (most of the public housing sites) they already indicated the inserts on the slab before concrete pouring (Figure 4.3). Therefore, no drilling will be required on the slab. This is one of the best practices, which is used in Singapore public housing projects (HDB) and increases the productivity by eliminating the drilling time. However, some construction sites do not use this technique (drilling is required). On the other side, there are readily available inserts on the components to support the props. However, sometimes, those inserts are clotted and cannot be used and therefore, workers are required to drill on the

component as well. This means that number of inserts to be used for props installation will be varied based on the project conditions.

Figure 4.3 Indicating props' inserts on the slab to increase productivity

It should be mentioned that number of props not only shows the total number of props to support the element, but also indicates the orientation of the element as well. In the other words, if the number of props equals zero, the component is a horizontal element (either beam or slab). Props must be necessarily used to support vertical components (columns and walls), which indicates that X_{14} (number of props) equals or greater than one for all the vertical elements. The results of the regression analysis for fixing activities are shown in Table 4.3⁷.

⁷ More details about the stepwise regression analysis of preparation, lift, and fixing activities are provided in Appendix B. The correlation matrices are provided as well.

Table 4.3 Regression analysis for fixing activities

	R	R Square	Adj. R Square	Std. Error	F	Sig. ANOVA
Enter	0.906	0.821	0.810	3.034	72.895	0.000
Stepwise	0.897	0.805	0.801	3.101	188.300	0.000
Variable (Enter)	B	Std. Error	Beta	T	Sig.	VIF
(Constant)	0.304	2.227		0.136	0.892	
Location Type	-2.641	0.548	-0.190	-4.821	0.000	1.516
Area	-0.142	0.104	-0.078	-1.367	0.173	3.182
Weight	2.017	0.333	0.415	6.060	0.000	4.582
Length	-0.192	0.228	-0.073	-0.843	0.400	7.337
Lifting Inserts	0.708	0.452	0.078	1.564	0.120	2.403
Joints	-0.017	0.173	-0.007	-0.098	0.922	5.000
Props	1.064	0.372	0.234	2.857	0.005	6.535
Prop Inserts	1.281	0.234	0.346	5.486	0.000	3.889
Height	0.520	0.460	0.115	1.130	0.260	10.075
Install Type	0.069	0.547	0.005	0.127	0.899	1.518
Fix Crew Size	0.795	0.416	0.080	1.914	0.057	1.699
Variable (Stepwise)	B	Std. Error	Beta	T	Sig.	VIF
(Constant)	3.534	1.033		3.419	0.001	
Weight	1.477	0.173	0.304	8.527	0.000	1.187
Location Type	-2.415	0.513	-0.174	-4.704	0.000	1.274
Prop Inserts	1.551	0.137	0.419	11.322	0.000	1.282
Props	1.780	0.166	0.391	10.733	0.000	1.242

The analysis of stepwise regression implies that 80.5 percent of variation in the fixing time can be explained by weight (X_1), location type (X_{11}), number of prop inserts (X_{15}), and number of props (X_{14}). The regression model for fixing time can be expressed as:

$$Y_{FR} = 3.534 + 1.477 X_1 - 2.415 X_{11} + 1.551 X_{15} + 1.78 X_{14} \quad (4.3)$$

Y_{FR} is the estimated fixing time (in minutes) and based on the predictors' coefficients, as the number of prop inserts, the number of props, and component weight increase by one unit, the fixing time increases by 1.551, 1.780, and 1.477 minutes, respectively.

Additionally, when the location type of a component changes from exterior to interior, the fixing time decreases by 2.415 minutes. This is mainly because, fixing of interior elements is easier due to more available space for fixing activities. Furthermore, to install some external vertical elements the workers are required to do grouting and put backer rod in order to make the joints waterproof (Figure 4.4). This will increase the fixing time respectively. Note that Table 4.3 shows that fixing crew size was not a significant factor for estimation of fixing times. This is because the crew size is usually fixed for precast activities (one rigger man at the storage area, one rigger man at the installation point with 3-4 general workers). However, in some special cases for big vertical elements (structural walls or big facades), the crew in charge of grouting activities (1-2 workers) may join to help the fixing crew.

Figure 4.4 Using backer rod to waterproof the joints of external panels

As discussed earlier, this study didn't analyze the crane return time. However, based on the collected data, an average of 2 minutes can be considered for the crane return time (If a more accurate model is needed, the readers should refer to the available literature on crane productivity studies as described in the previous chapter).

4.1.4 Assumption of the Regression Analysis

Regression technique is based on several assumptions such as existing linear relationship between predictors and the dependent variable, independency of the residuals, normal distribution of the residuals as well as equality of variance of residuals across the predictors (Devore 2011). Scatter plots and correlation matrix are used to check the linearity of the relationship between independent and dependent variables. Residual plots and normal P-P plot of regression standardized residual are used to check the assumptions regarding residuals. To show an example, the scatter plot of residuals and normal P-P plot for preparation regression model are shown in Figure 4.5 and Figure 4.6. Other plots to check the assumptions for lift and fixing activities are provided in Appendix B.

Figure 4.5 Normal P-P plot of standardized residual for preparation activities

Figure 4.6 Residual scatter plot for preparation activities

Figure 4.5 shows that there is no significant departure from linearity and based on Figure 4.6, standardized residual values are between ± 3 , which are scattered randomly. There is no non-linear or quadratic pattern, thus, the residuals can be assumed to be independent and the model looks valid. Analysis of the assumptions for the other regression models (lift and fixing) showed similar results (Appendix B).

4.1.5 Preliminary Validation of PC Installation Regression Model

The preliminary regression model to estimate the installation time (excluding crane return time) for different PC elements (non-delay cycles) is the sum of preparation, lift, and fixing activities:

$$Y_{IR} = Y_{PR} + Y_{LR} + Y_{FR} \quad (4.4)$$

Y_{IR} is the estimated installation time and Y_{PR} , Y_{LR} , and Y_{FR} are the predicted time for preparation, lift, and fixing activities that are calculated from Eq. 4.1 – 4.3. As mentioned in the previous chapter, a set of 30 cases (20 vertical elements and 10 horizontal elements) was used to verify the predictive ability of the model (these cases were selected randomly from the collected data and were not used for regression model development and therefore, exclusively used for testing purposes). Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE) were calculated by:

$$MAE = \frac{\sum_i^n |Y_{IR} - Y_A|}{n} \quad (4.5)$$

$$MAPE = (\sum_i^n 100 * \frac{|Y_{IR} - Y_A|}{Y_A}) / n \quad (4.6)$$

$$MSE = \frac{\sum_i^n (Y_{IR} - Y_A)^2}{n} \quad (4.7)$$

Y_A is the actual installation time collected from the construction sites and n is the number of cases ($n = 30$). As a result, the above mentioned errors were calculated and are shown in Table 4.4.

Table 4.4 Error estimates for the preliminary regression model of PC installation times

MAE (min.)	MAPE	MSE	Min. abs. error (min.)	Max. abs. error (min.)
2.08	14.74	8.86	0.18	9.18

Table 4.4 shows that on average, predictions from the developed regression model will be only 14.74 percent higher or lower than the actual data with an average of 2.08 (MAE) minutes error estimate (prediction accuracy of the model is 85.26 percent). This indicates that the model fits the actual data and looks valid. Figure 4.7 shows the actual and predicted data for test cases of preliminary validation of the regression model for installation times of PC elements.

Figure 4.7 Comparison of the actual and predicted installation times by MRA

Figure 4.8 illustrates the accuracy of the developed regression model through depicting the correlation between predicted and actual installation times. It can be seen that the model can effectively estimate PC installation time for test cases and since these cases have not been used in the model building, it can be concluded that the model is generalizable.

Figure 4.8 Correlation between actual and predicted installation times by MRA

Besides the graphical comparison between the actual and predicted installation times for the preliminary test cases, the Independent-Samples T Test⁸ procedure is used to compare the means for these two groups. Note that separate tests are used for horizontal and vertical elements and the results are shown in the following tables. Statistics and test results for horizontal elements are shown in Tables 4.5 and 4.6.

Table 4.5 Statistics of the actual and predicted installation times of horizontal elements for the preliminary test cases of the regression analysis

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	10	6.101	1.333	0.422
	Actual	10	6.180	1.491	0.471

Table 4.6 T-Test results for the actual and predicted installation times of horizontal elements for the preliminary test cases of the regression analysis

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
		F	Sig.	t	df	Sig.	Mean Diff.	Std. Error Diff.	Lower	Upper
Installation Time	Equal variances assumed	.091	.766	-.125	18	.902	-.079	.632	-1.408	1.25
	Equal variances not assumed			-.125	17.779	.902	-.079	.632	-1.409	1.251

⁸ The results of the normality tests are now provided in Appendix C which show no significant departure from the normality for the T-Tests used for the analysis of small sample sizes. However, it should be noted that empirical studies of the t-test have demonstrated that the assumptions of the test can be violated to an amazing degree without substantial effect on the results. In the other words, the t-test is described as a robust test with respect to the assumption of normality. This means that even deviations away from normality do not have a large influence on type I error rates (Hays 1994).

Table 4.6 shows that the p-value of the Levene's test for equality of variance is 0.766 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for equality of means is 0.902 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.125 \sqrt{\frac{10 + 10}{10 * 10}} = 0.056 \text{ (small effect size)}$$

The above mentioned results show that there is no statistically significant difference between the means of the predicted and actual installation times for the preliminary regression model (horizontal elements). The same procedure is used to test for vertical elements and the results are shown in Tables 4.7 and 4.8.

Table 4.7 Statistics of the actual and predicted installation times of vertical elements for the preliminary test cases of the regression analysis

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	20	18.226	3.9	.872
	Actual	20	18.956	5.849	1.308

Table 4.8 shows that the p-value of the Levene's test for equality of variance is 0.113 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times of vertical elements) are homogeneous.

Table 4.8 T-Test results for the actual and predicted installation times of vertical elements for the preliminary test cases of the regression analysis

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
									Lower	Upper
Installation Time	Equal variances assumed	2.632	.113	-.464	38	.645	-.730	1.572	-3.912	2.452
	Equal variances not assumed			-.464	33.108	.645	-.730	1.572	-3.928	2.468

Since the equality of variances is assumed, the p-value of the T-Test for equality of means is 0.645 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.464 \sqrt{\frac{20 + 20}{20 * 20}} = 0.147 \text{ (small effect size)}$$

The above mentioned results show that there is no statistically significant difference between the means of the predicted and actual installation times for the preliminary regression model (vertical elements).

Based on the above analysis, the preliminary regression model can predict the installation times and provide valid results. The next step is to analyze different delays occurred during PC installation.

4.2 Delay Analysis using Modification of Method Productivity Delay Model (MPDM) and Development of the Final Model for PC Installation

Measuring and documentation of different delays is a very skilled-dependent task. Usually, the data collector, will continuously time the production cycles from start to finish and therefore, use of time laps recorder is required when the production cycle includes several activities like precast installation. For delay documentation, one approach is to time the actual length of the delay. However, this will quickly increase the workload of the data collector and may become too complex to measure different types of delays separately (Halpin and Riggs 1992). Therefore, installation cycles will be observed and marked as “non-delay” or “delay” production cycles. Total delay times will be then calculated as the sum of delay production cycles (those marked as delay cycles) minus the mean of non-delay production cycles (Adrian and Boyer 1976).

Based on our observations, for PC installation, no significant delay occurred during preparation and lifting activities. However, for fixing of “vertical” elements (columns and walls), a common delay that we called “technical delay” was evident, which should be analyzed for better estimation of total installation times. This technical delay is due to the reinforcement bars (rebars) on the below slab which are needed to be fixed into the element. Usually, after the concreting activities of the slab, there will be some displacement of the rebars which hinders them to be readily fixed to the vertical PC elements. Therefore, the crew should alter the rebar spaces with specific equipment or even sometimes modify the element size with drilling (Figure 4.9).

Figure 4.9 Technical delay due to the fixing of rebars

In the original MPDM, production cycles should be more or less the same. In this study, as discussed earlier, there are several types of precast components and the installation times are different based on the component specifications and factors described in the previous sections. Therefore, there is a need to modify the original model to have more accurate delay estimates. As a result, instead of using mean cycle time of non-delay activities, the estimated fixing time will be calculated by the regression equation for fixing activities (Eq. 4.3) and this predicted time is used for delay calculation (Table 4.5). This new modification of the original model that we called “Regression Method Productivity Delay Model (RMPDM)” is more appropriate

for the studies in which production cycles are subjected to different factors (and therefore, they are not identical).

Table 4.9 Delay documentation

Cycle (1)	Actual Fixing Time (min.) (2)	Remark (3)	Predicted Fixing Time (min.) (4)	Estimated Delay (min.) (5)
1	25.48	Delay	17.01	8.47
2	15.89	Non-delay	-	-
3	12.75	Delay	6.63	6.12
4	17.08	Non-delay	-	-
5				
6				

Table 4.9 shows delay documentation for PC installation cycles. Column 4 is calculated using Eq. 4.3 and column 5 is the difference between columns 2 and 4 in minutes, which shows the estimated delay occurred for that specific installation cycle. The analysis which is needed to find the delay factor is summarized in Table 4.10 and 4.11.

Table 4.10 General information about delay and non-delay cycles

Remark	Cycles	Total Fixing Time (min.)	Mean Cycle Time (min.)
Non-delay	123	1685.85	13.71
Delay	56	1677.39	29.95
Overall	179 ^a	3363.24	18.79

a. Total vertical elements collected at the first phase of data collection

Table 4.11 Delay factor calculation using MPDM and MRA

Occurrence	Total Added Time (min.)	Probability	Relative Severity	Expected % Delay Time per Cycle	Delay Factor (DF_R)
56	849.24	0.31	0.81	0.25	1.33

Total added time is the sum of entries of column 5 in Table 4.9. Other columns in Table 4.11 are calculated as follows:

$$Probability\ of\ Occurrence = \frac{No.\ Delay\ Cycles}{Total\ No.\ of\ Cycles} \quad (4.8)$$

$$Relative\ Severity = \frac{Mean\ Added\ Cycle\ Time}{Mean\ Overall\ Cycle\ Time} = \frac{849.24/56}{18.79} \quad (4.9)$$

$$Expected\ \% Delay\ Time\ Per\ Cycle\ (E_{Tech}) = Probability * Relative\ Severity \quad (4.10)$$

$$Delay\ Factor\ for\ Fixing\ Time\ (DF) = \frac{1}{1 - E_{Tech}} \quad (4.11)$$

As mentioned earlier, the main advantage of RMPDM is to provide more accurate delay estimates. This can be shown from the information provided in Tables 4.9-4.11. As an example, if one uses mean cycle time for non-delay activities instead of predicted fixing time using the regression model, estimated delays for cycles 1 and 3 in Table 4.9 will be calculated as:

$$\text{Cycle 1: } 25.48 - 13.71 = 11.77$$

$$\text{Cycle 3: } 12.75 - 13.71 = -0.96$$

This shows that based on mean cycle time of non-delay activities, cycle 3 should be considered as a non-delay cycle because of the negative sign of the estimated delay (-0.96 min.). However, the use of the regression model resulted in 6.12 minutes to be considered as the technical delay occurred, which is more accurate based on the delay documentation. MPDM suggests using the following factor for ideal productivity (IP) to calculate the overall productivity (OP):

$$OP = IP * (1 - E_{Tech}) \quad (4.12)$$

Suppose that the ideal productivity is to fix 4 units per hour (15 min per element). Ideal productivity is usually determined based on the experience or from the analysis of non-delay cycles. Therefore, from Eq. 4.12, overall productivity is 3 (4 * (1-0.25): 20 min per element). However, our model deals with total fixing time instead of ideal and overall productivity rates. Meaning that, the regression model is used to predict the fixing time (Eq. 4.3) and then the delay factor (DF_R) defined in Eq. 4.11 is used to obtain the overall fixing time which is then added to the estimated preparation and

lifting times (Eq. 4.1 and Eq. 4.2) to form the final predicted installation time (Y_{TR}) for that specific element:

$$Y_{TR} = Y_{PR} + Y_{LR} + Y_{FR} * DF_R \quad (4.13)$$

Note that Eq. 4.13 is used as the final model to predict the installation times of the vertical elements. Since there is no delay in the installation of the horizontal components, Eq. 4.4 (the preliminary regression model) is used for these elements. Therefore the final regression models are as follows:

For horizontal elements:

$$Y_{TR} = Y_{PR} + Y_{LR} + Y_{FR} = 0.303 + 1.621 \text{ Weight} + 0.028 \text{ Area} + 0.08 \text{ Length} + 0.024 \text{ Storage to Crane} + 0.011 \text{ Crane Angle} + 1.856 \text{ Crane Type} - 2.415 \text{ Location Type} + 0.037 \text{ Elevation} \quad (4.14)$$

For vertical elements:

$$Y_{TR} = Y_{PR} + Y_{LR} + Y_{FR} * DF_R = 1.562 + 2.108 \text{ Weight} + 0.028 \text{ Area} + 0.08 \text{ Length} + 1.062 \text{ Storage Type} + 0.024 \text{ Storage to Crane} + 0.011 \text{ Crane Angle} + 1.856 \text{ Crane Type} - 3.212 \text{ Location Type} + 2.367 \text{ Number of Props} + 2.063 \text{ Number of Props Inserts} + 0.037 \text{ Elevation} \quad (4.15)$$

4.2.1 Validation and Performance of the Final Regression Model Considering Delay Analysis

As described in data collection, a new set of 27 components (both delay and non-delay cycles for vertical elements) were used to test the performance of the final model (Eq. 4.15) against the actual installation time (Fig. 4.10 and Fig. 4.11) and the error estimates are provided in Table 4.12.

Figure 4.10 Actual vs. predicted installation times of the final regression model considering delay analysis

Figure 4.11 Correlation between actual and predicted installation times for the final regression model considering delay analysis

Table 4.12 Error estimates of the final regression model considering delay analysis

MAE (min.)	MAPE	MSE	Min. abs. error (min.)	Max. abs. error (min.)
3.83	15.51	18.50	1.19	9.81

Table 4.12 shows that the estimated installation times using the final model that considers the delay factor are 15.51 percent higher or lower than the actual installation

times (predictive ability of the model is 84.49 percent) with an average error of 3.83 minutes.

Similar to the validation of the preliminary regression model, the Independent-Samples T-Test procedure is used to compare the means of predicted and actual installation times. The results are shown in Tables 4.13 and 4.14.

Table 4.13 Statistics of the actual and predicted installation times of the final regression model

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	27	26.002	5.953	1.146
	Actual	27	26	7.836	1.508

Table 4.14 T-Test results for the actual and predicted installation times of the final regression model

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
		F	Sig.	t	df	Sig.	Mean Diff.	Std. Error Diff.	Lower	Upper
Installation Time	Equal variances assumed	3.089	.085	.004	52	.997	.007	1.894	-3.794	3.807
	Equal variances not assumed			0.004	48.513	.997	.007	1.894	-3.8	3.813

Table 4.14 shows that the p-value of the Levene's test for equality of variance is 0.085 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times of vertical elements) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for

equality of means is 0.997 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.004 \sqrt{\frac{27 + 27}{27 * 27}} = 0.001 \text{ (small effect size)}$$

The above mentioned results show that there is no statistically significant difference between the means of the predicted and actual installation times for the final regression model.

Based on the above analysis and similar to the preliminary model for non-delay cycles, the final model also looks valid, which is appropriate to be used by contractors and general estimators for their planning and scheduling purposes.

4.3 Productivity Analysis of PC Installation by Artificial Neural Networks (ANN)

This section describes how ANN can be utilized in productivity analysis of PC installation process. The procedure is similar to the development of regression models discussed in the previous section in terms of developing three different neural networks for preparation, lifting, and fixing activities. This will help to provide more accurate results by keeping the network size as small as possible, which results in more efficient training. The same data used for MRA is used in this section to compare the results in order to find the most accurate analysis for prediction of PC installation times.

A set of 160 data points were randomly selected for training, 30 data points for cross validation, and 30 data points (the same set used in MRA) to test the performance of the developed ANN. Use of cross validation technique ensures that the network is not over trained. In this method, the stop criterion is chosen in such a way that as soon as the error in the cross validation set starts to increase, the training will be stopped. To deal with local minima (which is a common problem in back propagation algorithm),

each of the developed networks was redesigned for several times by using different initial random weights and trained for 10,000 epochs.

Conventional back propagation algorithm is based on the gradient descent method which directly minimizes in the direction of the steepest descent. Another alternative to be used in this research is to apply conjugate gradient approach, which is to construct a set of “n” directions that are all conjugate to each other and therefore, the minimization along one of these directions does not spoil minimization along other directions. As a result, faster convergence is achievable.

Note that at the first step, all the factors in Table 3.1 are considered as the inputs for the ANN. At the next step, the significant factors identified by MRA are considered for the analysis and the results will be compared. ANN calculations were performed by NeuroSolutions Software version 6.

4.3.1 ANN for Preparation Activities

As described in section 4.1.1, storage type (X_5), length (X_3), area (X_2), weight (X_1), height of the component (X_4), and number of lifting inserts (X_{13}) are the relevant variables to be considered as inputs for neural networks analysis. Note that storage type is a “symbol” input variable meaning that it has two values as described in Table 3.1. Therefore, one input signal is considered for each value. As a result, total number of input signals will be considered as seven.

There is no specific rule regarding the architecture of ANN (type of ANN, number of hidden layers, number of neurons in hidden layers, etc.), and it is usually determined by trial and error. Our analysis showed that a typical feed forward ANN with architecture of 7-10-5-1 (two hidden layers including 10 and 5 neurons in the hidden layers, using conjugate gradient algorithm and sigmoid function for hidden and output layers) provides more accurate results compared to other network architectures while the

selection is based on the least mean square error (MSE). Values of MSE and mean absolute error (MAE) for different network architectures are provided in Table 4.9 and the selected network architecture is highlighted. Note that other architectures with different transfer functions (e.g. Tan Hyperbolic) were also developed and trained but only most competent network architectures are shown in Table 4.15.

Table 4.15 Comparison of different ANN for preparation activities

Architecture	7-10-1	7-20-1	7-30-1	7-20-5-1	7-7-5-1	7-12-5-1	7-10-5-1
MSE	0.622	0.587	0.593	0.613	0.534	0.629	0.524
MAE	0.575	0.565	0.576	0.574	0.541	0.573	0.515

4.3.2 ANN for Lifting PC Panels (Hoisting Time)

Input variables to develop ANN for lifting PC elements are: elevation (X_{17}), area of the load (X_2), component length (X_3), component weight (X_1), component orientation (X_{18}), crane angle (X_8), distance from installation to crane (X_7), crane type (X_9), and distance from storage to crane (X_6). Therefore, there are total of 11 input signals considering that component orientation (X_{18}) and crane type (X_9) are “symbol” variables (two values for each variable).

Similar to the analysis of preparation activities, several ANN architectures were developed, and the error values are shown in Table 4.16 from which architecture of 11-14-5-1 (using conjugate gradient algorithm and sigmoid function for hidden and output layers) was chosen as the best-performing network for lifting times of PC components.

Table 4.16 Comparison of different ANN for lifting times

Architecture	11-15-1	11-13-1	11-12-1	11-13-1 ^a	11-13-5-1	11-14-5-1 ^a	11-14-5-1
MSE	0.587	0.456	0.499	0.671	0.495	0.567	0.425
MAE	0.601	0.537	0.543	0.612	0.544	0.558	0.520

a. Tanh transfer function with learning rate of 0.1 and momentum of 0.5

4.3.3 ANN for Fixing Activities

In order to develop ANN for fixing activities the following variables should be considered as the input factors: area (X_2), weight (X_1), component height (X_4), length (X_3), location type (X_{11}), number of lifting inserts (X_{13}), number of rebars (X_{12}), number of props (X_{14}), number of prop inserts (X_{15}), fixing crew size (X_{16}), and installation type (X_{10}). Since location type (X_{11}) and installation type (X_{10}) are “symbol” inputs, total of 13 input signals should be considered.

Table 4.17 shows the error estimates for different developed ANN architectures and therefore, network structure of 13-16-1 was selected for fixing activities.

Table 4.17 Comparison of different ANN for fixing activities

Architecture	13-15-1	13-16-1	13-17-1	13-16-1 ^b	13-20-7-1	13-17-6-1	13-16-1 ^a
MSE	8.105	7.528	7.863	6.975	8.421	9.045	5.222
MAE	1.990	1.816	2.008	1.896	2.006	1.908	1.444

a. Tanh transfer function with learning rate of 0.1 and momentum of 0.5

b. Tanh transfer function with learning rate of 1.0 and momentum of 0.7

4.3.4 Total Installation Times Predicted by ANN

To estimate the installation time (Y_{INN} - excluding crane return time) for different PC elements, three predicted times (outputs) from ANN for preparation, lift, and fixing activities should be summed up:

$$Y_{INN} = Y_{PNN} + Y_{LNN} + Y_{FL} \quad (4.14)$$

Thirty data points (the same set used in the regression analysis) were used for preliminary validation of the developed ANN. Mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square error (MSE) were calculated by Eq. 4-5 to Eq. 4.7 (Y_{INN} were used instead of Y_{IR} for calculation of errors) and are shown in Table 4.12.

Table 4.18 Error estimates of the developed ANN considering all the input variables

MAE (min.)	MAPE	MSE	Min. abs. error (min.)	Max. abs. error (min.)
1.79	14.00	6.43	0.11	9.25

Table 4.18 shows that on average, predictions from the developed ANN models will be only 14 percent higher or lower than the actual data and an average of 1.79 minutes error is considered (prediction accuracy of the model is 86 percent). Comparison of the results between Table 4.18 and Table 4.4 shows that the predicted installation times obtained from ANN models are slightly more accurate than the results achieved from the developed regression model (all three error estimates of ANN models are less than error estimates of MRA).

Figure 4.12 shows the actual and predicted data for test cases and the correlation between predicted and actual installation times are shown in Figure 4.13. Note that R square value (0.89) shows a very strong correlation between actual and predicted installation times, which further confirms the accuracy of the developed models.

Figure 4.12 Actual vs. predicted installation times of the developed ANN considering all the factors

Figure 4.13 Correlation between actual and predicted installation times for the developed ANN considering all the factors

To reduce the size of ANN (and therefore have a more efficient training), a good alternative is to use the significant factors identified by MRA as the inputs of the ANN (instead of considering all the variables). Therefore, the following sections describe the analysis of the developed ANN using the significant factors with the same data set used in the above mentioned analysis.

4.3.5 Using the Significant Factors as the Inputs of ANN

Table 4.19 shows network architectures, optimal models (highlighted in the table), and related errors for each of the activities involved in PC erection process. Significant factors obtained from stepwise MRA were used as the network inputs and network outputs are preparation, lifting, and fixing times (in minutes). The significant factors were identified as:

- For preparation activities: Area of the load (X_2), component length (X_3), and storage type (X_6)

- For lifting: Component weight (X_1), component orientation (X_5), distance from storage to crane (X_7), crane angular movement (X_9), crane type (X_{10}), and elevation (X_{18})
- For fixing activities: Component weight (X_1), location type (X_{12}), number of props (X_{14}), number of prop inserts (X_{16})

For nominal variables such as storage type (isolated or among others), crane type (tower crane or mobile crane), orientation (vertical or horizontal), and location type (exterior, interior) two input signals are required to represent each of the values respectively. In Table 4.19, a 4-10-4-1 architecture represents a network with four input signals, two hidden layers containing ten and four neurons, and one output⁹.

Table 4.19 Selection of best performing ANN for preparation, lifting, and fixing activities

Preparation								
Architecture	4-10-1	4-15-1	4-8-4-1	4-10-4-1	4-6-4-1	4-4-1	4-8-1	4-6-1
MSE	0.549	0.549	0.565	0.568	0.530	0.513	0.520	0.511
MAE	0.562	0.533	0.558	0.559	0.545	0.540	0.512	0.535
Lifting								
Architecture	8-15-1	8-12-1	8-10-1	8-12-6-1	8-14-5-1	8-10-5-1	8-13-1	8-12-4-1
MSE	0.607	0.683	0.556	0.767	0.656	0.668	0.611	0.531
MAE	0.614	0.598	0.567	0.636	0.593	0.627	0.614	0.565
Fixing								
Architecture	5-7-1	5-8-1	5-10-1	5-11-1	5-8-4-1	5-9-4-1	5-8-5-1	5-9-1
MSE	7.086	7.168	8.288	8.745	7.066	7.274	7.231	6.846
MAE	1.672	1.713	1.996	2.000	1.632	1.661	1.661	1.646

Based on Table 4.19, the final model to be used for total installation times includes architectures of 4-6-1, 8-12-4-1, and 5-9-1 for preparation, lifting, and fixing activities, respectively, which are graphically shown in Fig. 4.14.

⁹ Note that more than 100 network architectures were developed to find the best performing network.

4.3.6 Validation and Performance of the Preliminary ANN Models

As mentioned earlier, a set of 30 data points was used to test the predictive ability of the model. It should be noted that during data collection, in each construction project, one block was used to collect the test data and others for model development. This ensures the generalizability of the model and minimizes the need for further case studies. This is because conditions in testing blocks are different from model blocks. In the other words, in most of the projects, each block has its own storage area with separate tower crane and with different crew who are in charge of precast installation. As a result, testing blocks can be treated as separate case studies. Actual installation times versus predicted installation times using ANN and MRA are shown in Figure 4.15.

Figure 4.14 Graphical representation of the developed ANN for precast productivity analysis

Figure 4.15 Comparison between actual and predicted installation times using MRA and ANN for preliminary test cases

Fig. 4.16 shows the scatter plot that depicts the regression line and equation between actual and predicted installation times (using ANN).

Figure 4.16 Correlation between actual and predicted installation times using ANN

Finally, Table 4.20 shows comparison between developed models using ANN and MRA (considering significant factors for productivity analysis). This table shows that

all the error estimates and the error ranges are smaller in the developed ANN model when compared to MRA. Mean Absolute Percentage Error shows that on average, predicted installation times will be only 13.13 percent higher or lower than the actual installation time. In the other words, the prediction accuracy of the developed ANN model is 86.87 percent with an average of 1.82 minutes error estimate (12.5 percent reduction in the error estimate compared to MRA) between the predicted and actual installation times.

Table 4.20 Comparison of MRA and ANN for productivity estimation of PC installation

Method	MAE	MAPE	MSE	Min. abs. error	Max. abs. error
MRA	2.08	14.74	8.86	0.18	9.18
ANN	1.82	13.13	7.11	0.06	7.22

Similar to the regression analysis, the Independent Samples T-Test is used to compare the means between the actual and predicted installation times of the developed ANN models. Two tests are provided for horizontal and vertical elements and the results are provided in the following tables.

Table 4.21 Statistics of the actual and predicted installation times of the horizontal elements for the preliminary test cases of ANN models

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	10	5.921	0.967	0.305
	Actual	10	6.18	1.491	0.471

Table 4.22 shows that the p-value of the Levene's test for equality of variance is 0.214 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for equality of means is 0.65, which is more than 0.05.

Table 4.22 T-Test results for the actual and predicted installation times of the horizontal elements for the preliminary test cases of ANN models

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
									Lower	Upper
Installation Time	Equal variances assumed	1.662	.214	-.462	18	.65	-.259	.562	-1.439	.92
	Equal variances not assumed			-.462	15.411	0.651	-.259	.562	-1.453	.935

Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.462 \sqrt{\frac{10 + 10}{10 * 10}} = 0.21 \text{ (small effect size)}$$

The above mentioned results show that there is no statistically significant difference between the means of the predicted and actual installation times for the preliminary ANN models (horizontal elements). The same procedure is used to test for vertical elements and the results are shown in Tables 4.23 and 4.24.

Table 4.23 Statistics of the actual and predicted installation times of the vertical elements for the preliminary test cases of ANN models

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	20	18.594	4.471	.999
	Actual	20	18.956	5.849	1.308

Table 4.24 T-Test results for the actual and predicted installation times of the vertical elements for the preliminary test cases of ANN models

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
		F	Sig.	t	df	Sig.	Mean Diff.	Std. Error Diff.	Lower	Upper
Installation Time	Equal variances assumed	1.232	.274	-.220	38	.827	-.361	1.646	-3.694	2.971
	Equal variances not assumed			-.220	35.552	.827	-.361	1.646	-3.702	2.979

Table 4.24 shows that the p-value of the Levene's test for equality of variance is 0.274 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for equality of means is 0.827, which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.220 \sqrt{\frac{20 + 20}{20 * 20}} = 0.07 \text{ (small effect size)}$$

The above mentioned results show that there is no statistically significant difference between the means of the predicted and actual installation times for the preliminary ANN models (vertical elements).

It can be concluded that both ANN and MRA provide well accepted results considering high uncertainties involved in construction estimations. Therefore, these models can be considered as quick and simple tools to be used by estimators for site management

planning in precast projects. The next step is to analyze delay, calculate the delay factor, and provide a new hybrid model based on the MPDM and ANN to be served as the final ANN models to estimate the installation times of PC components.

4.3.7 Considering Delay to Develop Final ANN Model for Productivity Estimation of PC Installation

In the previous section, it was shown that ANN can provide more accurate models when compared to MRA for productivity analysis of PC installation. As a result, the next step is to consider delay in order to develop a comprehensive model which is more reliable in actual project settings.

The procedure is the same as the model developed by MRA. Method Productivity Delay Model (MPDM) is used as the base model. Instead of using mean cycle time for delay estimation, fixing time is predicted by ANN (Table 4.25 and Figure 4.26) and delay is calculated accordingly. In the other words, the estimated delay equals to the actual fixing time collected from the construction sites minus the predicted fixing time by ANN. This method that we call “Artificial Method Productivity Delay Model” (AMPDM) will lead to more accurate delay estimation when compared to the original MPDM. Note that as described in section 4.2, no delays were considered for preparation and lifting activities.

Table 4.25 Delay documentation using AMPDM

Cycle (1)	Actual Fixing Time (min) (2)	Remark (3)	Predicted Fixing Time by ANN (min) (4)	Estimated Delay (min) (5)
1	25.48	Delay	18.11	7.37
2	15.89	Non-delay	-	-
3	12.75	Delay	6.14	6.61
4	17.08	Non-delay	-	-
5				
6				

Table 4.25 shows delay documentation for PC installation cycles. Column 4 is calculated using the developed ANN and column 5 is the difference between columns 2 and 4 in minutes, which shows the estimated delay occurred for that specific installation cycle. The analysis which is needed to find the delay factor is summarized in the Table 4.26.

Table 4.26 Delay factor calculation using AMPDM

Occurrence	Total Added Time (min)	Probability	Relative Severity	Expected % Delay Time Per Cycle	Delay Factor (DF_{NN})
56	797.51	0.31	0.76	0.24	1.32

Total added time is the sum of entries of column 5 in Table 4.25. Other columns in Table 4.26 are calculated using Eq. 4-8 to Eq. 4-11. Note that general information about delay and non-delay cycles are provided in Table 4.10 and can be used for both MRA and ANN.

Similar to the RMPDM, the main advantage of using AMPDM is to provide more accurate delay estimates. As described earlier, if one uses mean cycle time for non-delay activities instead of predicted fixing time using ANN, estimated delays for cycles 1 and 3 in Table 4.25 will be calculated as:

$$\text{Cycle 1: } 25.48 - 13.71 = 11.77$$

$$\text{Cycle 3: } 12.75 - 13.71 = -0.96$$

This shows that based on mean cycle time of non-delay activities, cycle 3 should be considered as a non-delay cycle because of the negative sign of the estimated delay (-0.96 min.). However, the use of developed ANN model resulted in 6.61 minutes to be considered as the technical delay occurred, which is more accurate based on the delay documentation. As a result, the final model to calculate total installation time of PC elements considering the delay factor is:

$$Y_{TNN} = Y_{PNN} + Y_{LNN} + Y_{FNN} * DF_{NN} \quad (4.14)$$

In this model, Y_{TNN} is total installation time and Y_{PNN} , Y_{LNN} , and Y_{FNN} are the predicted preparation, lifting, and fixing time using the developed models in Table 4.19.

4.3.8 Validation and Performance of the Final ANN Model Considering the Delay Factor

A set of 27 components (both delay and non-delay cycles for vertical elements) were used to test the performance of the final ANN model considering delay analysis (Eq. 4.14) against the actual installation time (Fig. 4.17 and Fig. 4.18) and the error estimates are provided in Table 4.27. This is the same set used to test the performance of the final regression model.

Figure 4.17 Actual vs. predicted installation times of the final ANN model considering delay analysis

Figure 4.18 Correlation between actual and predicted installation times for the final ANN model considering delay analysis

Table 4.27 Comparison of the error estimates of the final regression and ANN models considering delay analysis

Method	MAE	MAPE	MSE	Min. abs. error	Max. abs. error
MRA	3.83	15.51	18.5	1.19	9.81
ANN	3.50	14.66	15.82	0.17	8.73

Based on Table 4.27, the estimated installation times using the final ANN model that considers the delay factor are 14.66 percent higher or lower than the actual installation times (predictive ability of the model is 85.34 percent) with an average error of 3.5 minutes. Similar to the preliminary model for non-delay cycles, the final model also looks valid, which is appropriate to be used by contractors and general estimators for their planning and scheduling purposes. The comparison of ANN and MRA shows that both models look valid for productivity analysis of PC installation. However, the model developed by ANN has slightly better performance.

The final step is to perform the Independent Samples T-Tests to check the statistics of the predicted and actual installation times of PC components provided by the final ANN models, which consider the calculated delay factor. The results of the T-Test are provided in Tables 4.28 and 4.29.

Table 4.28 Statistics of the actual and predicted installation times of the final ANN model

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	27	26.002	5.953	1.146
	Actual	27	26	7.836	1.508

Table 4.29 T-Test results for the actual and predicted installation times of the final ANN model

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
									Lower	Upper
Installation Time	Equal variances assumed	3.089	.085	.004	52	.997	.007	1.894	-3.794	3.807
	Equal variances not assumed			0.004	48.513	.997	.007	1.894	-3.8	3.813

Table 4.29 shows that the p-value of the Levene's test for equality of variance is 0.085 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times of vertical elements) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for

equality of means is 0.997 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.004 \sqrt{\frac{27 + 27}{27 * 27}} = 0.001 \text{ (small effect size)}$$

The above mentioned results show that, there is no statistically significant difference between the means of the predicted and actual installation times for the final ANN model. As a result, the developed model is an appropriate tool for the productivity estimation of the installation of PC components.

4.4 Productivity Modeling of PC Installation by Construction Simulation

Construction simulation is a technique that is mainly used to assess the productivity of repetitive operations. Hence, this technique was applied in this thesis to evaluate the productivity of PC installation, which is a highly repetitive task. In order to apply this technique for productivity assessment, the duration of each activity should be defined in a deterministic or probabilistic approach. The following steps are required to use simulation technique for productivity assessment of PC installation:

- Select an appropriate simulation program (package).
- Model PC installation process based on the selected simulation package.
- Determine the duration of PC installation activities (this may require finding the distribution of the data for each activity).
- Run the simulation model.
- Analyze and validate the simulation results.

In this study, WebCYCLONE that is based on MicroCYCLONE (Halpin and Riggs 1992), was used to model and simulate PC installation process. The basic elements of

WebCYCLONE that are necessary to model PC installation process are shown in Table 4.30.

Based on the selected simulation model, the model that is shown in Figure 4.31 has been developed to represent the installation process of PC elements. The following notes should be considered to describe the model:

Table 4.30 Basic elements of WebCYCLONE

Name	Symbol	Function
Combination (COMBI) Activity		This element is always preceded by Queue Nodes. Before it can commence, units must be available at each of the preceding Queue Nodes. If units are available, they are combined and processed through the activity. If units are available at some but not all of the preceding Queue Nodes, these units are delayed until the condition for combination is met.
Normal Activity		This is an activity similar to the COMBI. However, units arriving at this element begin processing immediately and are not delayed.
Queue Node		This element precedes all COMBI activities and provides a location at which units are delayed pending combination. Delay statistics are measured at this element
Function Node		It is inserted into the model to perform special function such as counting, consolidation, marking, and statistic collection
Accumulator		It is used to define the number of times the system cycles
Arc		Indicates the logical structure of the model and direction of entity flow

(adopted from (Halpin and Riggs 1992))

- The crane (tower or mobile) and preparation crew should be available as shown in nodes 1 and 2.
- The crew will prepare the element as shown in node 3.
- The crane lifts the element to the designated point (node 4).
- The fixing crew should be available to adjust and fix the element at the installation point. These are shown at nodes 6 and 7.
- After the element is fixed, the crane returns to begin the next cycle (node 8).
- Node 9 shows the location of the counter that is before the beginning of the next cycle.
- The following resources are available: 1 crane at node 1, preparation crew (usually one labor only) at node 2, and fixing crew (4-6 labors) at node 6.
- Node 5 is a dummy node which is required to model node 4 and 7. The reason is that in WebCYCLONE modeling, a normal element (node 4: lift) cannot be directly followed by a COMBI element (node 7: fix). Therefore, a dummy QUE node is added.

Figure 4.19 WebCYCLONE model for the installation process of PC elements

4.4.1 Simulation of the Installation of Horizontal Elements

As mentioned before, this research has not analyzed the crane return process. Furthermore, it was described that there are different activities involved in the installation of horizontal and vertical elements. Therefore, it is necessary to provide two models to simulate the installation process of different PC elements. It should be noted that the models are more or less the same. The main difference is that the duration of preparation and fixing activities for vertical elements may follow different distribution when it is compared to the installation of horizontal elements. This will be further investigated in the following sections.

The WebCYCLONE model to simulate the installation of horizontal elements is shown in Figure 4.20. The only difference to the previous model is that node 8 (crane return) is eliminated.

Figure 4.20 WebCYCLONE model for the installation process of horizontal PC elements

In order to find the distribution of different installation activities, @Risk software version 5.5 was used¹⁰. The distribution of preparation, lift, and fixing activities for horizontal elements are shown in the following figures. The differences of fixing activities between horizontal and vertical elements have been already discussed. The preparation activities for horizontal and vertical elements are more or less the same. However, our observations showed that the preparation activities of horizontal pieces are faster than the vertical elements, because they are kept isolated in the storage area. In the other words, there is more space for preparation crew to check and attach the horizontal elements to the crane hook to be lifted to the installation point. This is shown in Figure 4.21. Note that since there is no major difference between the lifting of horizontal and vertical elements, one distribution has been considered for both orientations as shown in Figure 4.24.

Figure 4.21 Preparation of the horizontal elements

Based on the results from @Risk software, the duration of preparation and fixing activities follow triangle and exponential distributions as shown in Figure 4.22 and

¹⁰ Note that @Risk software provides different distributions. Therefore, the best fitted distributions that can be used in WebCYCLONE have been selected.

Figure 4.23. Note that the characteristics of the fitted distributions are shown at the legend of these figures. The lifting times for both types of elements follow the normal distribution as shown in Figure 4.24.

Figure 4.22 Distribution of preparation time of horizontal PC elements

Figure 4.23 Distribution of fixing time of horizontal PC elements

Figure 4.24 Distribution of lifting time of both horizontal and vertical PC elements

4.4.2 Simulation of the Installation of Vertical Elements

The WebCYCLONE model to simulate the installation of horizontal elements is shown in Figure 4.25.

Figure 4.25 WebCYCLONE model for the installation process of vertical PC elements

The main difference between this model and the model developed to simulate the installation process of horizontal elements is that a probabilistic arc has been used after node 4. One of the contributions of this thesis is that it has used the results from Method Productivity Delay Model (MPDM) in the simulation process to provide more accurate results. The analysis of MPDM showed that (Table 4.26) the probability of installation of a vertical element with delay is 0.31. Therefore, this figure has been used here and two COMBI elements (node 7 and node 9) were defined to simulate fixing of vertical elements with and without delay with respective probabilities. The distributions of preparation and fixing activities for vertical elements have been calculated and are shown in Figure 4.26, Figure 4.27, and Figure 4.28.

Figure 4.26 Distribution of preparation time of vertical PC elements

Figure 4.27 Distribution of fixing time (without delay) of vertical PC elements

Figure 4.28 Distribution of fixing time (with delay) of vertical PC elements

Since the distributions of duration of different activities have been defined, the next step is to run the simulation model and evaluate the results (WebCYCLONE codes are provided in Appendix D).

Table 4.31 shows Chi-Square Statistics and p-values of the fitted distributions for different precast operations for horizontal and vertical elements (provided by @Risk software). Based on the results, p-values of the Chi-Square test for almost all the fitted distributions are more than 0.05, which shows that they look valid. The only exception is the result for the test of lifting time, which can be considered to be valid as well if the significant level of 0.01 is chosen.

Table 4.31. Chi-Square goodness of fit test

Data	Chi-Square Statistic	P-Value
Preparation time of horizontal elements	12.82	0.23
Fixing time of horizontal elements	11.25	0.26
Lifting time of horizontal and vertical elements	28.84	0.011
Preparation Time of vertical elements	14.79	0.19
Fixing time of vertical element (without delay)	18.49	0.07
Fixing time of vertical element (with delay)	10.85	0.21

4.4.3 Analysis and Performance of the Simulation Model

To evaluate the performance of the developed simulation models, the results should be compared to the actual data. A quick way to analyze the performance of the simulation model is to run the developed WebCYCLONE models (10 cycles for horizontal elements and 27 cycles for vertical elements) and then sum the total installation times obtained from the simulation results. This result will be compared to the sum of the total installation times of the actual data collected from the construction sites.

Based on the abovementioned procedure, the sum of the total installation times of the actual data equals to 763.68 minutes. The results from the simulation models show that the sum of installation times equals to 720.8 minutes. Therefore, Mean Absolute Percentage Error is 5.62 percent, which shows a very good estimation of the total installation times of PC elements.

To check the statistical characteristics and compare the means between actual and simulation data, Independent Samples T-Test is performed for both horizontal and vertical components and the results are provided in Tables 4.32 – 4.35.

Table 4.32 Statistics of the actual and predicted installation times of the horizontal elements provided by the simulation model

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	10	6.65	2.982	.943
	Actual	10	6.18	1.91	.472

Table 4.33 T-Test results for the actual and predicted installation times of the horizontal elements provided by the simulation model

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
		F	Sig.	t	df	Sig.	Mean Diff.	Std. Error Diff.	Lower	Upper
Installation Time	Equal variances assumed	1.665	.213	.446	18	.661	.47	1.054	-1.745	2.685
	Equal variances not assumed			.446	13.235	.663	.47	1.054	-1.804	2.744

Table 4.33 shows that the p-value of the Levene's test for equality of variance is 0.213 which is more than 0.05. This means that the variances are not different at $\alpha = 0.05$ and the groups (actual and predicted installation times) are homogeneous. Since the equality of variances is assumed, the p-value of the T-Test for equality of means is 0.661 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.446 \sqrt{\frac{10 + 10}{10 * 10}} = 0.199 \text{ (small effect size)}$$

The above mentioned results show that, there is no statistically significant difference between the means of the predicted and actual installation times of the construction simulation model for the horizontal elements. The same procedure is used to test the vertical elements.

Table 4.34 Statistics of the actual and predicted installation times of the vertical elements provided by the simulation model

	Group	N	Mean (min.)	Std. Deviation	Std. Error Mean
Installation Time	Predicted	27	24.23	11.88	2.286
	Actual	27	25.99	7.836	1.508

Table 4.35 T-Test results for the actual and predicted installation times of the vertical elements provided by the simulation model

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval	
		F	Sig.	t	df	Sig.	Mean Diff.	Std. Error Diff.	Lower	Upper
Installation Time	Equal variances assumed	4.327	.042	-.643	52	.523	-1.762	2.739	-7.258	3.734
	Equal variances not assumed			-.643	45.022	.523	-1.762	2.739	-7.279	3.754

Table 4.35 shows that the p-value of the Levene's test for equality of variance is 0.042 which is less than 0.05. This means that the variances are different at $\alpha = 0.05$ and the groups (actual and predicted installation times) are heterogeneous. Since the equality of

variances is not assumed, the p-value of the T-Test for equality of means is 0.523 which is more than 0.05. Furthermore, 95 percent confidence interval of the difference contains zero. The effect size is:

$$\text{Effect size} = t \sqrt{\frac{n_1 + n_2}{n_1 * n_2}} = 0.643 \sqrt{\frac{27 + 27}{27 * 27}} = 0.175 \text{ (small effect size)}$$

The above mentioned results show that, there is no statistically significant difference between the means of the predicted and actual installation times of the construction simulation model for the vertical elements.

The above mentioned analysis shows that in addition to the regression and ANN models, construction simulation can also provide valid estimates of the installation times of horizontal and vertical PC components.

One of the most useful results from the construction simulation is the analysis of the resource utilization which provides valuable information that can be directly used in more efficient resource planning. The analysis regarding resource utilization for both horizontal and vertical elements are shown in Tables 4.36 – 4.39.

Tables 4.36 and 4.38 show general characteristics of the activities involved in the installation process of PC elements. Minimum, maximum, and average duration of different activities are provided for both horizontal and vertical elements. Note that from 27 vertical elements, 19 of them were grouped under fixing without delay. This is based on the probability defined in the simulation process.

Table 4.36 General characteristics of installation activities of horizontal PC elements

PRECAST ERECTION PROCESS FOR HORIZONTAL ELEMENTS						
CYCLONE ACTIVE ELEMENTS STATISTICS INFORMATION						
Activity Type	No.	Name	Access Counts	Average Duration	Maximum Duration	Minimum Duration
COMBI	3	Preparation	10	1	2.4	0.4
NORMAL	4	Lift	10	3.7	6.1	0.7
COMBI	7	Fix	10	1.9	7.4	0.1

Table 4.37 Analysis of resource utilization for installation of horizontal elements

PRECAST ERECTION PROCESS FOR HORIZONTAL ELEMENTS						
CYCLONE PASSIVE ELEMENTS STATISTICS INFORMATION						
Type	No.	Name	Times not empty	% Idle	Total Simulation Time	Average Waiting Time
QUEUE	1	CRANE	0	0	66.5	0
QUEUE	2	PREP CREW	56	84.21	66.5	4.7
QUEUE	5	READY	0	0	66.5	0
QUEUE	6	FIX CREW	47.5	71.36	66.5	4.3

Table 4.38 General characteristics of installation activities of vertical PC elements

PRECAST ERECTION PROCESS						
CYCLONE ACTIVE ELEMENTS STATISTICS INFORMATION						
Activity Type	No.	Name	Access Counts	Average Duration	Maximum Duration	Minimum Duration
COMBI	3	PREP	27	2.3	4.1	0.3
NORMAL	4	LIFT	27	3.6	6.1	0.7
COMBI	7	FIX WITHOUT DELAY	19	12.8	26.5	3.2
COMBI	9	FIX WITH DELAY	8	31.5	44.4	5.1

Table 4.39 Analysis of resource utilization for installation of vertical elements

PRECAST ERECTION PROCESS FOR HORIZONTAL ELEMENTS						
CYCLONE PASSIVE ELEMENTS STATISTICS INFORMATION						
Type	No.	Name	Times not empty	% Idle	Total Simulation Time	Average Waiting Time
QUEUE	1	CRANE	0	0	654.3	0
QUEUE	2	PREP CREW	591.3	90.38	654.3	20.4
QUEUE	5	READY 1	0	0	654.3	0
QUEUE	6	FIX CREW	159.6	24.4	654.3	5.7
QUEUE	8	READY 2	0	0	654.3	0

The results from the analysis of resource utilization are provided in Tables 4.37 and 4.39. Based on the results, during the installation of horizontal elements, preparation crew labors are idle for 84.21 percent of the time and the percentage of idle time for fixing crew labors is 71.36 percent. These results provide valuable information for site supervisors and construction managers for efficient “labor planning.” The percentages of idle time during the installation of vertical elements are 90.38 and 24.4 percent for fixing and preparation crew, respectively. Based on these figures, several suggestions are provided in the final chapter of the thesis.

4.5 Comparison of the Performance of the Regression, ANN, and Construction Simulation Models for the Productivity Estimations of PC Installation

In the previous sections several models including, regression, ANN, and simulation models were developed for the productivity analysis and predictions of the PC installation times. Therefore, there is a need to compare the performance of these models against each other.

In section 4.3.8, the developed regression and ANN models were compared and it was shown that the results from ANN are slightly more accurate than the regression analysis. This was based on the error estimates which were calculated as the errors between the predicted and actual installation times for “each element” of the regression, ANN, and the actual data.

In the developed construction simulation models, the factors influencing the productivity of PC installation were not taken into the account. Therefore, to calculate the errors between the actual and predicted installation times of the simulation model, the previous procedure used for ANN and regression analysis cannot be used. This is because, it is not meaningful to compare the installation time of each element between the simulation and actual data. An alternative option is to calculate the sum of the installation times of the total cycles and then compare the results and calculate the error

estimates. Therefore, this option is used in this section to compare the performance of the developed models and find the best performing solution for the productivity analysis of PC installation. Note that separate analyses are provided for horizontal and vertical elements.

Table 4.40 shows the sum of the installation times of horizontal elements for different models for 10 cycles. Note that these cycles are the same set used for the preliminary validation of ANN and regression models. The error estimates are provided in the table as well.

Table 4.40 Comparison of the installation times of horizontal elements between different models

	Simulation	Regression	ANN	Actual
Sum^a	66.5	61	60.66	61.8
MAPE	7.61	1.29	1.84	

a. Sum of the installation times in minutes

Based on this table, regression analysis provides more accurate results for the productivity estimations of horizontal elements when compared to construction simulation and ANN models. To compare the means between different groups, One-Way ANOVA is used and the results are provided in the following tables.

Table 4.41 Characteristics of the installation times of horizontal elements for different models

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
					Lower Bound	Upper Bound		
Simulation	10	6.65	2.982	.943	4.52	8.78	3.90	13.70
Regression	10	6.10	1.333	.422	5.15	7.06	4.19	8.21
ANN	10	6.07	.969	.307	5.37	6.76	4.98	7.56
Actual	10	6.18	1.491	.472	5.11	7.25	4.00	8.88

Table 4.42 Test of homogeneity of variances of the installation times of horizontal elements for different models

Levene Statistic	df1	df2	Sig.
2.143	3	36	.112

General descriptive statistics of the installation times of horizontal components for different models are provided in Table 4.41. Table 4.42 shows that the P-value of Levene's test for homogeneity of variances is 0.112, which is more than 0.05. As a result, the groups are homogeneous.

Table 4.43 ANOVA table for the installation times of horizontal elements for different models

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.213	3	.738	.213	.886
Within Groups	124.483	36	3.458		
Total	126.697	39			

Based on Table 4.43, the p-value of the ANOVA test is 0.886 which is more than 0.05. This means that there is no statistically significant difference between the means of the installation times of horizontal components calculated by different models. In the other words, the results from different models have the same statistical characteristics and all can be used to provide valid results. However, Table 4.40 shows that regression analysis can provide more accurate estimates of the installation times of horizontal PC elements. The same procedure is used to test the vertical elements.

Table 4.44 shows the sum of the installation times of vertical elements for different models for 27 cycles. Note that these cycles are the same set used for the validation of the final ANN and regression models considering the calculated delay factors. The error estimates are provided in the table as well.

Table 4.44 Comparison of the installation times of vertical elements between different models

	Simulation	Regression	ANN	Actual
Sum^a	654.3	679.02	702.06	701.88
MAPE	6.78	3.26	0.03	

a. Sum of the installation times in minutes

Based on this table, ANN provides more accurate results for the productivity estimations of vertical elements followed by regression and construction simulation models. To compare the means between different groups, Statistical tests are used and the results are provided in the following tables.

Table 4.45 Characteristics of the installation times of vertical elements for different models

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
					Lower Bound	Upper Bound		
Simulation	27	24.23	11.880	2.287	19.534	28.933	8.80	49.60
Regression	27	25.15	5.249	1.01	23.072	27.225	12.36	36.30
ANN	27	26.00	5.953	1.146	23.647	28.357	12.49	37.09
Actual	27	25.99	7.836	1.508	22.896	29.096	13.80	39.52

Table 4.46 Test of homogeneity of variances of the installation times of vertical elements for different models

Levene Statistic	df1	df2	Sig.
8.219	3	104	.000

General descriptive statistics of the installation times of vertical components for different models are provided in Table 4.45. Table 4.46 shows that the P-value of Levene's test for homogeneity of variances is 0.00, which is less than 0.05. As a result, the groups are not homogeneous. Since the assumption of homogeneity is not met,

instead of ANOVA test, the Welch test of equality of means is used and the results are provided in Table 4.47.

Table 4.47 Welch test for equality of means of the installation times of vertical elements

	Statistic	df1	df2	Sig.
Welch	.237	3	56.168	.870

Table 4.47 shows that the p-value of the test of equality of means is 0.87, which is more than 0.05. Therefore, there is no statistically significant difference between the means of the installation times of vertical components.

As a summary, the statistical analysis in this section showed that MRA, ANN, and construction simulation can be all used for the productivity estimation of both horizontal and vertical PC elements. However, regression and ANN models can provide more accurate results for the analysis of horizontal and vertical elements, respectively.

4.6 Application of Baseline Productivity to PC Installation

As mentioned in section 2.8, another concept which is relevant to research in productivity and is useful to be defined in this thesis is to measure the baseline productivity, which is to find the best productivity rate that a company (contractor) can achieve on a particular task or project (Thomas, Riley et al. 1999). It was described that baseline productivity is calculated based on the quantities of work for working days that no changes or rework have been reported. The following steps are required for baseline productivity calculation (Thomas and Završki 1999):

- Calculate the baseline subset (working days with highest productivity rates): at least 10 percent of the total working days which is rounded to the next odd number.

- Note the daily productivity measures for the baseline set.
- Baseline productivity equals to the median of the productivity rates in the baseline set.

The analysis of the baseline productivity is useful for contractors to compare their productivity rates in different projects. Furthermore, it can be used to compare the productivity rates between different contractors, which is helpful to find the best practices as well.

Most of the contractors don't have the exact amount of man-hours spent on a specific job. As a result, they will estimate the productivity rates based on the general figures and site reports that may not be always valid. However, in this research, several activities involved in installation of PC components were described clearly and the exact amount of time and number of crew members with several other data were recorded. This will result in more accurate calculation of baseline productivity. Contractors can follow the research methodology explained in this thesis to estimate baseline productivity for other construction tasks.

Two construction projects using precast construction method were selected for calculation of the baseline productivity. Project A was a public housing construction including 4 blocks of 22 stories and project B was a private residential building of 4 blocks of 25 stories. The following statements will describe how to calculate baseline productivity for each project. The comparison of productivity rates will help to find why and how much a project is faster or slower at the construction phase when compared to the other projects.

The first step is to calculate the productivity rates for different working days. The productivity rate for each day is calculated by man-hour per cubic meter of PC installed on that specific day. During the data collection phase, the number of crew members and the exact amount of time required to install different PC elements were recorded.

Therefore, daily productivity rates were easily calculated based on that information. Table 4.48 shows a portion of the calculation of daily productivity rates for project A (the calculation is the same for project B).

Table 4.48 Daily productivity rates for project A

Working Day	Type of the Component	Concrete Volume (m ³)	Total Crew Size	Installation Time (hour)	man-hour	Productivity rate (man-hour/m ³)
1	plank	0.347	5	0.077	0.386	
	plank	0.347	3	0.099	0.297	
	wall	1.610	5	0.333	1.663	
	wall	1.610	6	0.427	2.562	
	wall	3.220	5	0.652	3.258	
	column	2.237	5	0.321	1.607	
	column	0.830	5	0.258	1.289	
	column	0.830	5	0.258	1.290	
	column	0.448	5	0.360	1.799	
Total		11.48			14.15	1.23
2	wall	1.624	5	0.247	1.235	
	wall	1.624	5	0.285	1.426	
	wall	1.624	5	0.300	1.501	
	wall	2.237	5	0.398	1.988	
	wall	1.955	5	0.542	2.708	
	wall	2.123	5	0.340	1.700	
	wall	1.012	5	0.286	1.432	
	column	0.664	5	0.198	0.988	
	column	0.816	5	0.168	0.842	
	column	0.700	5	0.211	1.054	
	column	0.700	5	0.187	0.935	
	column	0.700	5	0.272	1.358	
Total		15.779			17.167	1.09

Table 4.49 is the summarized format of Table 4.48, which shows the productivity rates for the baseline subset (working days with the highest productivity rates) for project A.

Table 4.49 Productivity rates for the baseline subset for project A

No.	Concrete Volume (m ³)	Man-Hour	Productivity rate (man-hour/m ³)
1	19.098	21.639	1.13
2	11.480	14.150	1.23
3	14.146	16.911	1.20
4	16.584	21.367	1.29
5	11.519	10.109	0.88
6	11.536	9.389	0.81
7	15.779	17.167	1.09

Note that since the productivity rates have been calculated in man-hour per cubic meter, the lowest rate indicates the highest productivity rate achieved. Baseline productivity is the median of the productivity rates in the baseline set which is 1.13 for project A. Baseline productivity indicates the best a contractor can perform. This is based upon the highest output possible (the median of the highest productivity rates). In the other words, this shows that without any disruptions or reworks, the contractor will be able to perform at this productivity rate. Figure 4.29 shows the graphical representation of baseline productivity for project A. In this figure, baseline productivity is shown by the red line.

Figure 4.29 Baseline productivity for project A

The same procedure is used to calculate the baseline productivity for project B which is a private housing residential building using PC construction method. The summarized calculation of productivity rates for the baseline subset is shown in Table 4.50.

Table 4.50 Productivity rates for the baseline subset for project B

No.	Concrete Volume (m ³)	Man-Hour	Productivity rate (man-hour/m ³)
1	11.814	15.897	1.35
2	8.842	12.704	1.44
3	19.214	24.694	1.29
4	10.893	14.244	1.31
5	20.247	28.401	1.40
6	14.753	16.251	1.10
7	11.074	15.779	1.12

The baseline productivity for project B is 1.31 man-hour/m³. This is shown in Figure 4.30.

Figure 4.30 Baseline productivity for project B

Project B is less productive in terms of PC installation when compared to Project A. One of the main reasons was that project A was a public housing construction and one of the requirements in these projects is that contractors should use inserts that are already available on the slab for installation of vertical elements which increases productivity. This is already discussed in section 4.1.3 and Figure 4.3. Other reasons and suggestions to improve productivity will be discussed in the next chapter.

Note that the productivity rates have been deliberately calculated in man-hour/m³ instead of man-hour per each piece of installed elements. One of the reasons was that most of the available data for productivity measures of cast-in-situ projects are provided in man-hour/m³. As a result, it is easier for researchers and estimators to compare the productivity rates between these two methods of concrete projects and provide valuable information for industry players for their future use.

4.7 Sensitivity Analysis

Productivity charts are among the most useful information that provides valuable insight to the productivity data, which can help general estimators in their prediction and planning activities. One of the contributions of this study is to provide such data by performing sensitivity analysis.

Sensitivity analysis is a procedure to find the effect of each input (significant affecting variables) on the final output (installation time). To do so, the values of each factor are varied one at a time (from its minimum to maximum value), while the other inputs are fixed at their average value.

From the regression analysis, it was found that the following factors are the most significant variables that affect the productivity of PC installation: weight, area, and length of the PC elements, storage type (isolated or among others), distance of the crane to the element at the storage area, crane type (tower or mobile crane), location

type at the installation point (exterior or interior), number of props, number of props' inserts, elevation of the installation point, and component orientation (vertical or horizontal). Among these variables, storage type, location type at the installation point, component orientation, and crane type are symbol variables; meaning that their values are either 0 or 1. Therefore, based on different arrangements of these four variables, several charts can be produced to show the effect of different input variables on the installation time. However, the most useful chart that can be developed is the one showing the effect of "weight" on the installation time. This is because, most of the time the contractors deal with "weight" or "concrete volume" of the PC components. Therefore, by providing this type of productivity charts, they can quickly check the installation time of different elements based on their weights. Note that in the shop drawing of PC elements, weight and concrete volume of the PC elements are exclusively provided in the legend of the drawing.

The productivity charts for vertical and horizontal PC components and based on different arrangement of other symbol variables are provided in the following figures. In the previous chapter, it was shown that both MRA and ANN provide accurate and valid results and their estimation of the installation times of PC components are close to each other. The productivity charts provided here are based on the sensitivity analysis of regression models. Similar procedure can be used to provide the productivity charts for the sensitivity analysis of ANN models.

Figure 4.31 The effect of weight on the installation time of vertical PC elements using tower crane

Figure 4.32 The effect of weight on the installation time of vertical PC elements using mobile crane

Figure 4.33 The effect of weight on the installation time of horizontal PC elements using tower crane

Figure 4.34 The effect of weight on the installation time of horizontal PC elements using mobile crane

Figures 4.31 and 4.32 show the productivity charts for the vertical elements calculated by the sensitivity analysis of weight as the main input variable. Based on these figures,

for both tower and mobile cranes, the installation time of those components which are among others in the storage area and should be installed as the exterior type, are longer than the other types of components.

Based on our observations, most of the horizontal elements are kept isolated in the storage area. Therefore, the productivity charts (Figures 4.33 and 4.34) are provided for isolated elements. Similar to the vertical components, the installation times of the exterior components are longer the other types.

4.8 Development of a Web Based System for Productivity Estimation of PC Installation

This section describes how a web-based user-friendly system was developed for easy calculation of PC installation productivity. This system was designed and developed using PHP programming to be installed on JOOMLA CMS (Content Management System) which is an open source package. The developed system is called PCIT (Precast Concrete Installation Time).

The main objective of PCIT was to provide an easy-access environment for final users, so they can enter the required input (significant variables that have been already identified) to get the installation times of different PC components. Therefore, a PHP program was written to perform these tasks. The simplified flowchart of such a program is shown in Figure 4.35. Note that the installation times are calculated based on the developed regression models (for horizontal and vertical elements) discussed in the previous sections to provide valid and accurate results.

Figure 4.35 Flowchart of the underlying PCIT program

Figure 4.35 shows that at the first step, the user has to input the number of components to be installed for both horizontal and vertical PC types. For each component, the required input variables should be entered at the next step. Finally, the system will calculate the installation times based on Eq. 4.14 and Eq. 4.15, sum up the results, and show the total installation times.

A PHP program was coded to perform the required objectives shown in Figure 4.35. PHP is an open source scripting language which is widely used to develop different web pages. PHP codes are executed on the server. For easy development of the website, a content management system (CMS) was needed to keep track of the content of the web site and manage it. Therefore, JOOMLA CMS which is an open source

solution was chosen. The main advantage of using CMS is that even for basic users, it can quickly help to design and develop a web site, which can be easily managed by the clients. The screen shots of the developed PCIT system are shown in Appendix E¹¹.

4.9 Chapter Summary

In this chapter the detailed analyses of precast concrete installation were provided. Productivity models based on MRA, ANN, and construction simulation were discussed. After the preliminary validation of these models, a procedure was discussed to calculate the delay factor and provide the final regression and ANN models to estimate the productivity of PC installation.

Furthermore, construction simulation was used to analyze the utilization of different resources. Comparison of the developed productivity models showed that based on several statistical tests and the calculated errors, all models provide valid results. However, the results from MRA and ANN were more accurate and the estimations of installation times of these two models were very close to each other.

At the next step, baseline productivity was calculated to show the best productivity rate a contractor can achieve. The concept is also important when the contractors want to compare their productivity with other industry players.

Productivity charts were provided based on the sensitivity analysis of “weight” as the main input factor and the installation time as the output. These charts provide valuable information to contractors interested in quick estimation of the installation times of different components.

¹¹ Note that the system is currently installed on a local server until the copy right issues are clarified by the university to be publicly available on World Wide Web.

Finally, a web-based system called PCIT was designed and developed to help the final users estimate the installation times of different PC components more efficiently.

In the next chapter, summary of the research, contributions to the construction management body of knowledge, suggestions for industry players, and directions for future research are presented.

Chapter 5. **CONCLUSIONS**

- Summary of the Findings
- Directions for the Future Research
- Suggestions to the Industry Players
- Contributions of the Research to the Construction Management Body of Knowledge

This chapter, which is the final chapter of the study, provides the concluding points such as a summary of the findings, directions for further research, recommendations for scholars and industry players, and contributions of this research to the existing body of knowledge. There are several points included in this chapter that should be of interest to both academic and practitioners.

5.1 Summary of the Findings

To summarize the research findings, the main objectives that have been mentioned in the first chapter are discussed to show that they are fulfilled. As a result, the findings are summarized under different objectives.

5.1.1 Collect the Factors Affecting PC Erection Process Productivity

From the literature and site visits, several factors affecting the productivity of PC installation process were identified. These factors and their descriptions are provided in Table 3.1. Note that these factors can be categorized to controllable and non-controllable variables. Factors such as weight, area, length, height of the component, distance from installation to crane, installation type, location type, number of reinforcement bars, number of lifting inserts, number of props, number of props' inserts, elevation of the installation point, and orientation of the component are uncontrollable factors. In the other words, these factors cannot be easily manipulated by the PC installation team. On the other hand, factors such as storage type, distance from storage to crane, crane angular movement, crane type, and fixing crew size can be managed and controlled by the installation team.

5.1.2 Collect the Required Data from Construction Sites

The required data for this study was collected through extensive site visits and direct observations. The installation cycles of 303 PC elements were observed in several

construction sites using PC technology. A data collection sheet was designed (Appendix A) to facilitate the documentation process. General characteristics of the PC components are provided in Table 3.2.

5.1.3 Develop Preliminary Productivity Models for PC Installation Process

Several productivity models were developed using different techniques to predict the installation time of horizontal and vertical PC elements. Various regression equations were developed using stepwise regression analysis for preparation, lift, and fixing activities. Validation of these preliminary models showed that regression models are able to provide valid and accurate estimates of the installation times of PC elements. Note that using stepwise regression analysis resulted in identifying the significant factors for each of the preparation, lift, and fixing activities as follows:

- For preparation activities: Storage type, length, and Area of the load
- For lifting: Crane angular movement, distance from storage to crane, orientation of the load, crane type, elevation of the installation point, and weight of the load
- For fixing activities: weight, location type, number of props, and number of props' inserts

In addition to the MRA, ANN was used to develop productivity models for PC installation process. The above mentioned significant factors were chosen as the input to the ANN and the main output was the installation time of different activities. The analysis showed that both MRA and ANN provide valid results for the prediction of the installation times of PC components.

5.1.4 Delay Analysis and Development of the Final Productivity Models

Since there were some delays during the installation of PC components, a procedure should be defined to calculate the effect of different delays. In this study, Method

Productivity Delay Model (MPDM) was used for the documentation and analysis of delays. Based on our observations, the main delay occurred during the fixation of vertical elements as we called “technical delay,” which was due to the fixing of reinforcement bars (rebars) to the PC elements. To calculate the delay factor, the developed regression and ANN models were used to estimate the fixing time of the same element without delay (this was used instead of mean installation time of non-delay cycles). This technique resulted in more accurate delay analysis. As a result, the calculated delay factors were used to form the final regression and ANN models. Two regression equations were developed for the prediction of the installation times of horizontal and vertical elements:

For horizontal elements:

$$Y_{TR} = Y_{PR} + Y_{LR} + Y_{FR} = 0.303 + 1.621 \text{ Weight} + 0.028 \text{ Area} + 0.08 \text{ Length} + 0.024 \text{ Storage to Crane} + 0.011 \text{ Crane Angle} + 1.856 \text{ Crane Type} - 2.415 \text{ Location Type} + 0.037 \text{ Elevation} \quad (4.14)$$

For vertical elements:

$$Y_{TR} = Y_{PR} + Y_{LR} + Y_{FR} * DF_R = 1.562 + 2.108 \text{ Weight} + 0.028 \text{ Area} + 0.08 \text{ Length} + 1.062 \text{ Storage Type} + 0.024 \text{ Storage to Crane} + 0.011 \text{ Crane Angle} + 1.856 \text{ Crane Type} - 3.212 \text{ Location Type} + 2.367 \text{ Number of Props} + 2.063 \text{ Number of Props Inserts} + 0.037 \text{ Elevation} \quad (4.15)$$

The final ANN models were three networks for preparation, lift, and fixing activities with architecture of 4-6-1, 8-12-14-1, and 5-9-1, respectively (Table 4.19). Using the calculated delay factor from AMPDM, the results from the model for fixing time should be multiplied by the delay factor (1.32) and then added to the preparation and lifting time to find the total installation time of PC elements.

Construction simulation was also used as the third technique for the productivity estimation of PC installation. A WebCYCLONE model was developed and the distributions of duration of different activities were estimated using @Risk software. The analysis showed that the model is able to provide valid results for quick estimation of the installation times of PC elements. One of the main advantages of using construction simulation is the ability to analyze the utilization of various resources. As an example, the results showed that, the percentages of crew idle time during the installation of vertical elements were 90.38 and 24.4 percent for preparation and fixing crew, respectively. These figures provide valuable information to the management team for more efficient labor planning.

5.1.5 Comparison of Different Productivity Models

Several statistical and general tests were used to compare the results obtained from MRA, ANN, and construction simulation. The findings showed that all these techniques provide valid and acceptable estimates for the installation time of PC elements. Simulation technique can generate quick estimates and provide resource utilization analysis. However, for more accurate predictions, MRA and ANN are recommended as they both showed similar estimates of the installation times (ANN was more accurate for the prediction of the installation times of the vertical elements and MRA was more efficient for the prediction of the installation times of horizontal components). Note that the final users may find the analysis using MRA more meaningful as they can easily understand the relationship between different variables and the final output.

5.1.6 Calculate the Baseline Productivity Rate

This study described how to calculate the baseline productivity rate which is the best productivity a contractor can achieve on a specific construction task. Since the exact amount of duration of PC installation was recorded during the data collection, a

procedure was shown to calculate the baseline productivity from the raw data. The results showed that the specific project related factors (e.g. props installation) can affect the baseline productivity rate. Several suggestions to improve the productivity rate are provided in the following sections.

5.1.7 Productivity Charts

Productivity charts provide valuable information to the contractors to estimate the required data (in our case the installation time of PC elements) based on the various factors affecting the productivity. It was discussed that “component weight” is one of the main factors influencing the productivity of PC installation. As a result, the sensitivity analysis of this factor and considering different arrangements of qualitative factors (component shape, crane type, storage type, and location type) resulted in productivity charts shown in Figures 4.31 – 4.35. These charts are generally used for quick estimation of the installation time of PC components in different situations. Note that for more accurate estimation, the developed productivity models (MRA, ANN, and construction simulation) should be used.

5.1.8 Develop a User-Friendly System for Easy Estimation of the PC Installation Times

At the final step, this research developed an online system for the calculation of the installation times of different PC components. This system which is called PCIT (Precast Concrete Installation Time) was developed as a web-based user friendly system. Final users can quickly provide the required information (input variables) and the system will provide the installation time based on the developed regression productivity models.

5.2 Suggestions to Improve the Productivity of PC Installation Process

This section provides several suggestions to the industry players to improve their productivity based on the findings of this research. The following points should be of interest to the contractors/subcontractors involved in the arrangement and erection of PC components. There are several handbooks available to the industry players which contains the best practices. Therefore, only those points that are not included in the current literature are listed in this section.

- The results of this study showed that Just in Time (JIT) arrangement of PC delivery will improve the productivity of the installation process. It has been discussed in the literature that JIT will improve the overall productivity. The regression productivity models provided in this study can more accurately quantify the effect of JIT delivery on the installation time of PC elements. The contractors can minimize the distance of the truck to the crane as well as the crane angular movement.
- It was shown that the percentages of crew idle time during the installation of vertical elements were 90.38 and 24.4 percent for preparation and fixing crew, respectively. Based on these figures, the management can take proper actions to optimize the usage of resource idle time. As an example, when the element is lifted to be fixed at the installation point, the preparation crew can perform several tasks until the crane returns for the next cycle. At first, the next element should be identified in the storage area (based on the installation schedule) and checked against any physical damages. There are several inserts on the elements for props installation. To improve the productivity, these inserts should be checked by the preparation crew to see whether they can be readily used by the fixing crew for props installation (there is a possibility that the inserts are clotted with debris). Otherwise, it is recommended that the preparation crew drill new inserts on the ground instead of passing the drilling task to the fixing crew. This will directly reduce the installation time of PC components (this

point can be confirmed by Eq. 4.15 which shows the effect of the number of props' inserts on the fixing time of vertical elements).

- It is recommended that the preparation crew check the dimensions and shape of the element before the installation process. This is to prevent further delay during the fixation of the component. Figure 5.1 shows a situation in which the fixing crew should modify the dimensions of the element to be installed correctly. Note that in this figure, the modification is performed at the installation point, meaning that the crane is still involved. Additionally, this delay will increase the idle time of the preparation crew.

Figure 5.1 Delay at the installation point due to size modification

- It was discussed that one of the main delays occurred during the installation of vertical elements was the technical delay due to the fixation of reinforcement bars (rebars) to the component. This is mainly because after the concreting works, there will be some displacement of rebars. Therefore, there is a

possibility that the rebars cannot be readily fixed to the component. It is highly recommended that whenever the concreting works are finished, the workers check the dimensions and displacements of rebars (this can be performed a day before the installation process) and modify the size if necessary.

There are some high-tech tools in the market that can be used to check the conditions of rebars after the concreting works. Using such tools will result in the automation of the checking process and therefore, increase the efficiency and productivity. Most of these tools are advanced technologies that provide accurate information (as-built conditions) to the management team. As an example, “total stations” are among those tools that deliver innovation for surveying and specialized applications. For instance, total stations can be used after concreting works to automatically collect the as-built data. Raw data and information are sent to the management office through the Wi-Fi network or via the handheld devices. The team can then find the conditions of the installed rebars (or the concrete defects if any) and take proper actions accordingly. Figure 5.2 shows a typical total station for the construction industry.

Figure 5.2 Total stations for the construction industry (source: trimble.com)

- It is suggested that the elements are properly stored and kept in the storage area. There should be enough space for the preparation crew to identify the components to be installed and perform the above mentioned checks. Heavier elements (structural walls) should be located closer to the crane.
- For the installation of horizontal elements (smaller pieces), several components can be lifted together (instead of lifting one by one) and stored near the installation point (Figure 5.3). The fixing crew can then install the components based on the schedule. This will increase the productivity by minimizing the lifting time.

Figure 5.3 Lifting of horizontal elements

- Care should be taken at the design stage of PC elements. Factors such as design complexity, size, and constructability can influence the productivity of on-site installation. It was noticed that in some construction sites, welding was also required to fix the PC elements (Figure 5.4), which resulted in further delay in the installation process.

Figure 5.4 Welding to fix the PC components

- The fixing crew should prepare the installation point as soon as the component is identified and ready to be lifted. Site preparation includes checking the location of the component, remove any debris or equipment, and remove the safety tools which are installed along the edge of the buildings. Considering these points will improve the installation productivity. Figure 5.5 shows a situation in which the component is ready to be installed, but the fixing crew are still trying to remove extra safety equipment.

Figure 5.5 Removing safety equipment

5.3 Limitations of the Research and Directions for Future Studies

There are several limitations in each research due to the defined objectives as well as uncontrollable factors that confine the scope of the study. This section discusses the directions for future research based on the limitations of this research.

- This study didn't analyze the effect of some qualitative factors such as weather condition, crew skill, management skill, crane operator efficiency, etc. Including these factors will result in more accurate productivity models for the estimation of the installation times of PC components.
- It is suggested to collect the data for other PC elements such as balconies, staircases, etc. (in this study beams, columns, walls, and slabs have been studied).
- In most of the productivity studies, increasing the sample size of the collected data will improve the accuracy of the developed models.
- In the developed ANN models, the conventional back propagation was used as the main learning algorithm. Although the model provided valid and accurate results, it is suggested to develop networks with other algorithms such as Levenberg-Marquardt or other architectures such as General Regression Neural Networks (GRNN) or Group Method of Data Handling (GMDH). Using Genetic Algorithms (GA) with ANN may also provide robust tools for productivity estimation of PC installation.
- It is suggested to use other simulation packages such as DISCO and STROBOSCOPE in future studies and compare the results.
- In this study, a web-based user friendly system which was called PCIT was developed. The main objective of this system was to facilitate the analysis of PC installation times. However, as the screen shots of the system (Appendix E) shows that the user should enter several variables manually to get the final output. This process can be automated through the integration of the developed

regression and ANN models with Building Information Modeling (BIM) packages.

With the increasing adoption of the BIM systems, there is a need to develop productivity models using ANN and regression analysis as separate modules that can be integrated with BIM system. Architects, engineers, contractors, and owners use BIM programs to plan, collaborate, and predict the performance before breaking ground on buildings. This research showed that the regression and ANN models are able to provide accurate productivity models for PC installation process. Therefore, the integration of these models with BIM systems is beneficial. Most of the input data required to be manually entered into the PCIT system are already available in the BIM model of the building. As a result, a computer program can be developed to automatically extract the required input for the PCIT system from the BIM model and perform the analysis. The output results from PCIT can be then linked back to the BIM system, which is more efficient in report generation and sharing the results with different project parties. This is graphically shown in Figure 5.6.

Figure 5.6 Integration of BIM with regression and ANN productivity models

5.4 Contributions of the Research to the Construction Management Body of Knowledge

The main objective of this research was to analyze the productivity of precast concrete installation activities. Based on the findings, the contributions of this study can be listed as follows:

- Collect and identify the factors affecting PC installation process. These factors have been categorized under different activities.
- Develop regression models based on the collected factors to predict the installation time of PC components.
- Develop ANN models based on the identified variables to estimate the installation time of PC elements.
- Identify and analyze different delays occurred during the installation process. Two “new models” were developed by hybridization of Method Productivity Delay Model (MPDM), regression analysis, and ANN. The original MPDM uses the mean of non-delay cycles to calculate the delay factor. However, in this study, regression and ANN models were used to predict the installation time of non-delay cycles. The results showed that using MPDM with regression and ANN provided more accurate delay analysis. The calculated delay factors were used to develop the final regression and ANN models for productivity analysis of PC installation process.
- Develop WebCYCLONE models to simulate the productivity of PC installation activities. Construction simulation was also used to analyze the utilization of different resources (preparation and fixing crew).
- Calculate the baseline productivity rates for PC installation process.
- Design and develop a web-based user friendly system called PCIT (Precast Concrete Installation Time) to help the final users calculate the installation times of different PC elements more easily.

- Provide several suggestions to the industry players to improve the productivity of PC installation activities.
- Provide clear directions for the future research in the field of productivity analysis of PC installation. Due to the increase in usage of BIM systems in the construction industry, a procedure was described to clarify how to integrate BIM packages with productivity models (developed by ANN and regression techniques).

5.5 Final Note

The essence of this research was to provide simple but effective productivity models, which can be readily used by the industry players for on-site daily planning of PC activities. The results showed that the developed models are able to provide valid estimates of the installation times of horizontal and vertical PC elements. The author of this research hopes that the construction managers and general estimators consider the points mentioned in this research to improve the productivity of PC erection process due to the fact that precast technology is more widely used in today construction projects. Furthermore, since “productivity” is a buzz word in the construction industry, the results of this study should be of interest to both scholars and industry players interested in the field of construction productivity estimations.

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APPENDIX A – Data Collection Sheet and Drawing

Component name:	Component location:
Preparation crew size:	Fixing crew size:
Average distance from the loading point (storage area) to the center of the crane: _____ m.	
Crane type: ☐ Tower Crane ☐ Truck Mounted Crane	
Crane capacity: _____ Ton.	

Date of data collection:	Time of data collection:
Component type: ☐ Beam ☐ Column ☐ Wall (Exterior/Interior) ☐ Slab ☐ Others: (Structural/Non-structural)	
Number of hooks:	Number of joints:
Component weight: _____ Ton.	Component size (L*W*H): _____ m.
Elevation of the installation point: _____ m.	Isolated / Among other components (Storage) No neighbors/ Among others (installation)
Average distance between the installation point and the crane: _____ m.	Angle between the loading and installation points with regards to the crane: _____ degree.

Activity	Duration (minutes)
Inspection, Preparation, and Pick up	
Lift	
Fixing	
Crane return	

Comments:

An example of a drawing to be used for the data calculation

APPENDIX B – Details about Multiple Regression Analysis and Correlation Matrices

Correlation Matrix for the Preparation Activities

		Preparation Time	Storage Type	Weight	Length	Area	Height	Lift Inserts
Preparation Time	Pearson Correlation	1	.565**	.272**	.312	.328**	.184*	.036
	Sig. (2-tailed)		.000	.000	.000	.000	.011	.620
Storage Type	Pearson Correlation	.565**	1	.187**	-.367**	.100	.529**	-.136
	Sig. (2-tailed)	.000		.010	.000	.171	.000	.062
Weight	Pearson Correlation	.272**	.187**	1	.243**	.617**	.347**	-.272**
	Sig. (2-tailed)	.000	.010		.001	.000	.000	.000
Length	Pearson Correlation	.312	-.367**	.243**	1	.432**	-.708**	.238**
	Sig. (2-tailed)	.000	.000	.001		.000	.000	.001
Area	Pearson Correlation	.328**	.100	.617**	.432**	1	-.005	.222**
	Sig. (2-tailed)	.000	.171	.000	.000		.947	.002
Height	Pearson Correlation	.184*	.529**	.347**	-.708**	-.005	1	-.502**
	Sig. (2-tailed)	.011	.000	.000	.000	.947		.000
Lift Inserts	Pearson Correlation	.036	-.136	-.272**	.238**	.222**	-.502**	1
	Sig. (2-tailed)	.620	.062	.000	.001	.002	.000	

**, Correlation is significant at the 0.01 level (2-tailed).

*, Correlation is significant at the 0.05 level (2-tailed).

Regression Tables and Plots for Preparation Activities – Stepwise Method

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Storage Type	.	Stepwise
2	Length	.	
3	Area	.	

a. Dependent Variable: Preparation Time
 Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.571 ^a	.326	.322	.63572
2	.656 ^b	.430	.424	.58606
3	.666 ^c	.444	.435	.58045

a. Predictors: (Constant), Storage Type
 b. Predictors: (Constant), Storage Type, Length
 c. Predictors: (Constant), Storage Type, Length, Area
 d. Dependent Variable: Preparation Time

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.090	1	36.090	89.300	.000 ^a
	Residual	74.766	185	.404		
	Total	110.856	186			
2	Regression	47.658	2	23.829	69.377	.000 ^b
	Residual	63.198	184	.343		
	Total	110.856	186			
3	Regression	49.198	3	16.399	48.674	.000 ^c
	Residual	61.658	183	.337		
	Total	110.856	186			

a. Predictors: (Constant), Storage Type

b. Predictors: (Constant), Storage Type, Length

c. Predictors: (Constant), Storage Type, Length, Area

d. Dependent Variable: Preparation Time

Collinearity Diagnostics^a

Model	Dimen sion	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Storage Type	Length	Area
1	1	1.943	1.000	.03	.03		
	2	.057	5.837	.97	.97		
2	1	2.649	1.000	.01	.01	.03	
	2	.314	2.905	.01	.10	.58	
	3	.037	8.423	.98	.89	.39	
3	1	3.513	1.000	.00	.01	.01	.01
	2	.319	3.318	.01	.10	.36	.01
	3	.132	5.166	.05	.01	.24	.95
	4	.037	9.808	.93	.88	.39	.03

a. Dependent Variable: Preparation Time

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.5638	2.7797	1.3719	.51430	187
Residual	-1.16700	1.69764	.00000	.57575	187
Std. Predicted Value	-1.571	2.737	.000	1.000	187
Std. Residual	-2.011	2.925	.000	.992	187

a. Dependent Variable: Preparation Time

Histogram

Scatterplot

Dependent Variable: Preparation Time

Normal P-P Plot of Regression Standardized Residual

Dependent Variable: Preparation Time

Correlation Matrix for Lifting

		Lifting Time	Orientation	Storage to Crane	Install to Crane	Crane Angle	Crane Type	Length	Area	Weight	Elevation
Lifting Time	Pearson Correlation	1	-.291**	.236**	.169*	.392**	.328**	-.151*	.095	.217**	.256
	Sig.		.000	.001	.020	.000	.000	.038	.191	.003	.000
Orientation	Pearson Correlation	-.291**	1	.050	.114	-.064	.382**	.751**	.004	-.292**	-.087
	Sig.	.000		.497	.119	.380	.000	.000	.960	.000	.235
Storage to Crane	Pearson Correlation	.236**	.050	1	.231**	-.422**	.706**	.177*	-.030	.303**	-.709**
	Sig.	.001	.497		.001	.000	.000	.015	.677	.000	.000
Install to Crane	Pearson Correlation	.169*	.114	.231**	1	-.026	.289**	.124	.037	.122	-.274**
	Sig.	.020	.119	.001		.721	.000	.087	.611	.094	.000
Crane Angle	Pearson Correlation	.392**	-.064	-.422**	-.026	1	-.213**	-.156*	.056	-.036	.216**
	Sig.	.000	.380	.000	.721		.003	.032	.439	.622	.003
Crane Type	Pearson Correlation	.328**	.382**	.706**	.289**	-.213**	1	.399**	-.080	.059	-.662**
	Sig.	.000	.000	.000	.000	.003		.000	.272	.422	.000
Length	Pearson Correlation	-.151*	.751**	.177*	.124	-.156*	.399**	1	.432**	.243**	-.209**
	Sig.	.038	.000	.015	.087	.032	.000		.000	.001	.004
Area	Pearson Correlation	.095	.004	-.030	.037	.056	-.080	.432**	1	.617**	-.050
	Sig.	.191	.960	.677	.611	.439	.272	.000		.000	.492
Weight	Pearson Correlation	.217**	-.292**	.303**	.122	-.036	.059	.243**	.617*	1	-.375**
	Sig.	.003	.000	.000	.094	.622	.422	.001	.000		.000
Elevation	Pearson Correlation	.256	-.087	-.709**	-.274**	.216**	-.662**	-.209**	-.050	-.375**	1
	Sig.	.000	.235	.000	.000	.003	.000	.004	.492	.000	

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Regression Tables and Plots for Lifting – Stepwise Method

Model Summaryⁱ

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.392 ^a	.154	.150	1.10320
2	.592 ^b	.351	.344	.96914
3	.654 ^c	.428	.418	.91235
4	.738 ^d	.545	.535	.81603
5	.736 ^e	.542	.535	.81595
6	.776 ^f	.602	.594	.76233
7	.795 ^g	.632	.622	.73576
8	.806 ^h	.650	.638	.71931

a. Predictors: (Constant), Crane Angle

b. Predictors: (Constant), Crane Angle, Storage_Crane

c. Predictors: (Constant), Crane Angle, Storage_Crane, Orientation

d. Predictors: (Constant), Crane Angle, Storage_Crane, Orientation, Crane Type

e. Predictors: (Constant), Crane Angle, Orientation, Crane_Type

f. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation

g. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation , Weight

h. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation , Weight, Storage_Crane

i. Dependent Variable: Lift Time

ANOVAⁱ

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.667	1	41.667	34.236	.000 ^a
	Residual	228.805	188	1.217		
	Total	270.471	189			
2	Regression	94.835	2	47.418	50.486	.000 ^b
	Residual	175.636	187	.939		
	Total	270.471	189			
3	Regression	115.650	3	38.550	46.313	.000 ^c
	Residual	154.822	186	.832		
	Total	270.471	189			
4	Regression	147.278	4	36.820	55.292	.000 ^d
	Residual	123.193	185	.666		
	Total	270.471	189			
5	Regression	146.637	3	48.879	73.417	.000 ^e
	Residual	123.834	186	.666		
	Total	270.471	189			
6	Regression	162.958	4	40.740	70.101	.000 ^f
	Residual	107.513	185	.581		
	Total	270.471	189			
7	Regression	170.865	5	34.173	63.127	.000 ^g
	Residual	99.606	184	.541		
	Total	270.471	189			
8	Regression	175.785	6	29.297	56.623	.000 ^h
	Residual	94.687	183	.517		
	Total	270.471	189			

a. Predictors: (Constant), Crane Angle

b. Predictors: (Constant), Crane Angle, Storage_Crane

c. Predictors: (Constant), Crane Angle, Storage_Crane, Orientation

d. Predictors: (Constant), Crane Angle, Storage_Crane, Orientation, Crane Type

e. Predictors: (Constant), Crane Angle, Orientation, Crane_Type

f. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation

g. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation , Weight

h. Predictors: (Constant), Crane Angle, Orientation, Crane_Type, Elevation , Weight, Storage_Crane

i. Dependent Variable: Lift Time

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.463	.142		17.347	.000		
	Crane Angle	.008	.001	.392	5.851	.000	1.000	1.000
2	(Constant)	.914	.241		3.799	.000		
	Crane Angle	.012	.001	.599	9.213	.000	.822	1.217
	Storage_Crane	.047	.006	.489	7.524	.000	.822	1.217
3	(Constant)	1.865	.296		6.305	.000		
	Crane Angle	.012	.001	.584	9.538	.000	.820	1.219
	Storage_Crane	.047	.006	.497	8.115	.000	.821	1.217
	Orientation	-.682	.136	-.278	-5.001	.000	.995	1.005
4	(Constant)	1.706	.266		6.423	.000		
	Crane Angle	.010	.001	.516	9.260	.000	.794	1.260
	Storage_Crane	.008	.008	.080	.981	.328	.370	2.702
	Orientation	-1.169	.141	-.477	-8.293	.000	.745	1.342
	Crane_Type	1.348	.196	.563	6.892	.000	.369	2.711
5	(Constant)	1.801	.248		7.275	.000		
	Crane_Angle	.010	.001	.493	9.713	.000	.954	1.048
	Orientation	-1.219	.132	-.497	-9.254	.000	.854	1.171
	Crane_Type	1.491	.131	.622	11.352	.000	.819	1.222
6	(Constant)	.191	.382		.501	.617		
	Crane Angle	.009	.001	.468	9.806	.000	.945	1.059
	Orientation	-1.379	.127	-.562	-10.884	.000	.805	1.242
	Crane Type	2.075	.165	.867	12.579	.000	.453	2.208
	Elevation	.025	.005	.339	5.299	.000	.524	1.907
7	(Constant)	-.876	.462		-1.895	.060		
	Crane Angle	.009	.001	.463	10.065	.000	.944	1.059
	Orientation	-1.249	.127	-.509	-9.841	.000	.747	1.338
	Crane Type	2.162	.161	.903	13.442	.000	.444	2.253
	Elevation	.032	.005	.443	6.566	.000	.439	2.278
	Weight	.167	.044	.199	3.822	.000	.738	1.356
8	(Constant)	-1.418	.485		-2.924	.004		
	Crane Angle	.011	.001	.527	10.647	.000	.782	1.279
	Storage_Crane	.024	.008	.246	3.083	.002	.300	3.334
	Orientation	-1.155	.128	-.471	-9.034	.000	.705	1.419
	Crane Type	1.856	.186	.775	9.992	.000	.318	3.146
	Elevation	.037	.005	.513	7.352	.000	.393	2.544
	Weight	.144	.043	.172	3.319	.001	.716	1.397

a. Dependent Variable: Lift Time

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.2601	6.0170	3.1496	.96441	190
Residual	-1.98048	2.35968	.00000	.70780	190
Std. Predicted Value	-1.959	2.973	.000	1.000	190
Std. Residual	-2.753	3.280	.000	.984	190

a. Dependent Variable: Lift Time

Histogram

Normal P-P Plot of Regression Standardized Residual

Scatterplot

Correlation Matrix for Fixing Activities

		Fixing Time	Location Type	Area	Weight	Length	Lifting Inserts	Joints	Props	Props Inserts	Height	Install Type	Fix Crew Size
Fixing Time	Pearson Correlation	1	-.528**	.170*	.562**	-.461**	-.425**	.684**	.612**	.695**	.781**	-.109	.244**
	Sig.		.000	.019	.000	.000	.000	.000	.000	.000	.000	.133	.001
Location Type	Pearson Correlation	-.528**	1	.050	-.173*	.327**	.440**	-.252**	-.402**	-.334**	-.435**	.032	-.154*
	Sig.	.000		.496	.017	.000	.000	.000	.000	.000	.000	.664	.034
Area	Pearson Correlation	.170*	.050	1	.617**	.432**	.222**	-.068	.008	.052	-.005	.377**	-.011
	Sig.	.019	.496		.000	.000	.002	.351	.916	.473	.947	.000	.881
Weight	Pearson Correlation	.562**	-.173*	.617**	1	.243**	-.272**	.423**	.219**	.377**	.347**	.089	-.033
	Sig.	.000	.017	.000		.001	.000	.000	.002	.000	.000	.224	.648
Length	Pearson Correlation	-.461**	.327**	.432**	.243**	1	.238**	-.588**	-.636**	-.457**	-.708**	.390**	-.392**
	Sig.	.000	.000	.000	.001		.001	.000	.000	.000	.000	.000	.000
Lifting Inserts	Pearson Correlation	-.425**	.440**	.222**	-.272**	.238**	1	-.465**	-.381**	-.419**	-.502**	.035	.088
	Sig.	.000	.000	.002	.000	.001		.000	.000	.000	.000	.633	.230
Joints	Pearson Correlation	.684**	-.252**	-.068	.423**	-.588**	-.465**	1	.553**	.696**	.802**	-.373**	.124
	Sig.	.000	.000	.351	.000	.000	.000		.000	.000	.000	.000	.090
Props	Pearson Correlation	.612**	-.402**	.008	.219**	-.636**	-.381**	.553**	1	.261**	.793**	-.167*	.557**
	Sig.	.000	.000	.916	.002	.000	.000	.000		.000	.000	.021	.000
Props Inserts	Pearson Correlation	.695**	-.334**	.052	.377**	-.457**	-.419**	.696**	.261**	1	.678**	-.137	-.084
	Sig.	.000	.000	.473	.000	.000	.000	.000	.000		.000	.059	.251
Height	Pearson Correlation	.781**	-.435**	-.005	.347**	-.708**	-.502**	.802**	.793**	.678**	1	-.228**	.274**
	Sig.	.000	.000	.947	.000	.000	.000	.000	.000	.000		.002	.000
Install Type	Pearson Correlation	-.109	.032	.377**	.089	.390**	.035	-.373**	-.167*	-.137	-.228**	1	-.118
	Sig.	.133	.664	.000	.224	.000	.633	.000	.021	.059	.002		.104
Fix Crew Size	Pearson Correlation	.244**	-.154*	-.011	-.033	-.392**	.088	.124	.557**	-.084	.274**	-.118	1
	Sig.	.001	.034	.881	.648	.000	.230	.090	.000	.251	.000	.104	

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Regression Tables and Plots for Fixing Activities – Stepwise Method

Model Summary^g

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.790 ^a	.625	.623	4.27257
2	.854 ^b	.729	.726	3.64228
3	.875 ^c	.766	.762	3.39435
4	.887 ^d	.786	.781	3.25224
5	.898 ^e	.807	.802	3.09565
6	.897 ^f	.805	.801	3.10156

a. Predictors: (Constant), Height

b. Predictors: (Constant), Height, Weight

c. Predictors: (Constant), Height, Weight, Location Type

d. Predictors: (Constant), Height, Weight, Location Type, Holes

e. Predictors: (Constant), Height, Weight, Location Type, Holes, Props

f. Predictors: (Constant), Weight, Location Type, Holes, Props

g. Dependent Variable: Fix Time

ANOVA^g

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5619.148	1	5619.148	307.817	.000 ^a
	Residual	3377.146	185	18.255		
	Total	8996.294	186			
2	Regression	6555.312	2	3277.656	247.068	.000 ^b
	Residual	2440.982	184	13.266		
	Total	8996.294	186			
3	Regression	6887.841	3	2295.947	199.273	.000 ^c
	Residual	2108.453	183	11.522		
	Total	8996.294	186			
4	Regression	7071.265	4	1767.816	167.136	.000 ^d
	Residual	1925.029	182	10.577		
	Total	8996.294	186			
5	Regression	7261.757	5	1452.351	151.554	.000 ^e
	Residual	1734.537	181	9.583		
	Total	8996.294	186			
6	Regression	7245.517	4	1811.379	188.300	.000 ^f
	Residual	1750.777	182	9.620		
	Total	8996.294	186			

a. Predictors: (Constant), Height

b. Predictors: (Constant), Height, Weight

c. Predictors: (Constant), Height, Weight, Location Type

d. Predictors: (Constant), Height, Weight, Location Type, Holes

e. Predictors: (Constant), Height, Weight, Location Type, Holes, Props

f. Predictors: (Constant), Weight, Location Type, Holes, Props

g. Dependent Variable: Fix Time

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	1.902	.516		3.688	.000		
Height	3.578	.204	.790	17.545	.000	1.000	1.000
2 (Constant)	-1.549	.602		-2.574	.011		
Height	3.036	.185	.671	16.376	.000	.879	1.138
Weight	1.672	.199	.344	8.400	.000	.879	1.138
3 (Constant)	3.675	1.123		3.274	.001		
Height	2.632	.188	.581	13.965	.000	.739	1.353
Weight	1.645	.186	.339	8.866	.000	.878	1.138
Location Type	-2.960	.551	-.213	-5.372	.000	.816	1.226
4 (Constant)	4.038	1.079		3.743	.000		
Height	2.090	.222	.462	9.396	.000	.487	2.055
Weight	1.491	.182	.307	8.205	.000	.842	1.188
Location Type	-2.855	.529	-.205	-5.402	.000	.814	1.229
Holes	.733	.176	.198	4.164	.000	.519	1.926
5 (Constant)	3.390	1.037		3.268	.001		
Height	.532	.409	.118	1.302	.195	.131	7.652
Weight	1.468	.173	.302	8.485	.000	.841	1.189
Location Type	-2.422	.512	-.174	-4.728	.000	.785	1.274
Holes	1.335	.215	.361	6.204	.000	.315	3.174
Props	1.425	.320	.313	4.458	.000	.216	4.627
6 (Constant)	3.534	1.033		3.419	.001		
Weight	1.477	.173	.304	8.527	.000	.842	1.187
Location Type	-2.415	.513	-.174	-4.704	.000	.785	1.274
Holes	1.551	.137	.419	11.322	.000	.780	1.282
Props	1.780	.166	.391	10.733	.000	.805	1.242

a. Dependent Variable: Fix Time

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.1142	21.2613	9.1302	6.23518	188
Residual	-8.27793	10.87634	.04570	3.12332	188
Std. Predicted Value	-1.477	1.948	.004	.999	188
Std. Residual	-2.669	3.507	.015	1.007	188

a. Dependent Variable: Fix Time

**Normal P-P Plot of Regression Standardized
Residual**

Dependent Variable: Fix Time

Scatterplot

Dependent Variable: Fix Time

APPENDIX C – The Results of the Normality Test (for the T-Test) for Small Sample Sizes

Statistics of the actual and predicted installation times of horizontal elements for the preliminary test cases of the regression analysis

Tests of Normality

Group		Kolmogorov-Smirnov ^a			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Installation Time	Predicted	.233	10	.131	.883	10	.140
	Actual	.104	10	.200*	.984	10	.982

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

Statistics of the actual and predicted installation times of the horizontal elements for the preliminary test cases of ANN models

Tests of Normality

Group		Kolmogorov-Smirnov ^a			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Installation Time	Predicted	.267	10	.041	.832	10	.036
	Actual	.104	10	.200*	.984	10	.982

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

Statistics of the actual and predicted installation times of the horizontal elements provided by the simulation model

Tests of Normality

Group		Kolmogorov-Smirnov ^a			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Installation Time	Predicted	.280	10	.025	.800	10	.014
	Actual	.104	10	.200*	.984	10	.982

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

APPENDIX D – WebCYCLONE Codes

For Horizontal Elements:

NAME PRECAST ERECTION PROCESS LENGTH 1000 CYCLES 10

NETWORK INPUT

1 QUE 'CRANE'

2 QUE 'PREP CREW'

3 COM 'PREP' SET 1 PRE 1 2 FOL 2 4

4 NOR 'LIFT' SET 2 FOL 5

5 QUE 'READY'

6 QUE 'FIX CREW'

7 COM 'FIX' SET 3 PRE 5 6 FOL 6 8

8 FUN COU FOL 1 QUA 1

DURATION INPUT

SET 1 TRIANGULAR 0.15 0.5 3

SET 2 NOR 3.15 1.43

SET 3 SET 3 EXP 2.37

RESOURCE INPUT

1 'CRANE' AT 1

1 'PREP CREW' AT 2

1 'FIX CREW' AT 6

For Vertical Elements:

NAME PRECAST ERECTION PROCESS LENGTH 1000 CYCLES 27

NETWORK INPUT

1 QUE 'CRANE'

2 QUE 'PREP CREW'

3 COM 'PREP' SET 1 PRE 1 2 FOL 2 4

4 NOR 'LIFT' SET 2 FOL 5 8 PROBABILITY 0.69 0.31

5 QUE 'READY 1'

6 QUE 'FIX CREW'

7 COM 'FIX WO DELAY' SET 3 PRE 5 6 FOL 6 10

8 QUE 'READY 2'

9 COM 'FIX W DELAY' SET 4 PRE 6 8 FOL 6 10

10 FUN COU FOL 1 QUA 1

DURATION INPUT

SET 1 NOR 2.03 0.7

SET 2 NOR 3.15 1.43

SET 3 TRIANGULAR 2.56 9.08 31.93

SET 4 NOR 29.95 153.02

RESOURCE INPUT

1 'CRANE' AT 1

1 'PREP CREW' AT 2

1 'FIX CREW' AT 6

APPENDIX E – Screen Shots of the PCIT System

Precast Concrete Installation Time

Welcome to PCIT (Productivity Modeling for Precast Concrete) website. We provide services to general contractors and consultants by helping them accurately estimate the cycle time required for erection of different types of precast concrete products (walls, columns, beams, slabs, etc.). To do so, multiple regression models have been designed and developed to produce precise estimates for precast erectors.

Please Fill up the following fields:

Number of Horizontal Elements:

Number of Vertical Elements:

[Next](#)

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Precast Concrete Installation Time

Weight: Ton

Longest Surface Area: Meter Squared

Longest Length: Meter

Distance From Storage to Crane: Meter

Crane Angular Movement: Degree

Crane Type:

Location Type:

Elevation of the Installation Point: Meter

Characteristics of Horizontal Elements:
Horizontal Element 1:

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Precast Concrete Installation Time

Weight: 2 Ton

Longest Surface Area: 6 Meter Squared

Longest Length: 4 Meter

Storage Type: Isolated

Distance From Storage to Crane: 25 Meter

Crane Angular Movement: 90 Degree

Crane Type: Tower Crane

Location Type: Exterior

Elevation of the Intallation Point: 55 Meter

Number of Props: 2

Number of Props' Inserts: 4

Characteristics of Vertical Elements:
Vertical Element 1:

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