AMERICAN UNIVERSITY OF BEIRUT

STUDYING THE EFFECT OF LEARNING CURVE ON LABOR PRODUCTIVITY USING AGENT-BASED MODELING

by
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A thesis
submitted in partial fulfillment of the requirements
for the degree of Master of Engineering
to the Department of Civil Engineering
of the Faculty of Engineering and Architecture
at the American University of Beirut

Beirut, Lebanon
February 2016

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ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my advisor, Professor Hiam Khoury, who offered invaluable assistance, support and guidance and provided me with useful suggestions and advices throughout my residency in this program.

I am equally thankful to Dr. Farook Hamzeh and Dr. Rita Awwad for serving on my proposal and thesis defense committees as well as for their effort in improving this work.

I remain grateful for my dear colleague, Emile Zankoul, for his assistance and advice during the simulation phase.

Last but not least, I want to express my gratitude to my dear family and friends for their understanding, endless love and moral support throughout the duration of my studies

AN ABSTRACT OF THE THESIS OF

Hanna Nizar Shehwaro for Master of Engineering
Major: Civil Engineering

Title: Studying the Effect of Learning Curve on Labor Productivity Using Agent-Based Modeling

The labor-intensive nature of construction projects requires proper management and efficient utilization of labor resources. Improvement of labor productivity can enhance project performance and thereby lead to substantial time and cost savings. Several studies focused on identifying the effect of different factors on labor productivity, whereby the learning curve factor proved of paramount importance. Previous research efforts developed models to analyze the effect of learning curve on labor productivity but failed to capture all the complexities of this mechanism and its dynamics. This paper presents an agent-based construction learning model that models a construction site as an active environment in which construction personnel or agents interact with each other and their surroundings thereby creating an adaptive environment open for learning and improvement. More specifically, the developed work illustrates many scenarios representing different learning levels and typical interactions between workers on construction sites. The components of the proposed model were created and results highlighted the potential of using the agent-based modeling paradigm to better simulate the effect of learning on labor productivity in the construction industry.

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ABBREVIATIONS

ABM	:	Agent-Based Modeling
DES	:	Discrete-Event Simulation
SD	:	System Dynamics

CHAPTER 1

INTRODUCTION

1. Background

Productivity has always been a source of attention for researchers. Productivity rates in construction specifically have been suffering from lack of standards and steadily declining over the last few decades (Shehata & El-Gohary, 2012). In construction, productivity mostly refers to labor performance (Hafez et al., 2014). Some studies focused on collecting all the factors that affect labor productivity on construction projects (Lee, 2007, Singh, 2010, Hafez et al., 2014) and in this case, overtime, overmanning, congestion, shift work, weather, and the learning curve were identified (Lee, 2007). Among these factors, the learning curve has long been proven to be of paramount importance. The learning curve theory states that, under a repetitive process, whenever the production quantity of a product doubles, the unit required for production drops by a certain percentage of the previous unit referred to as the learning rate (Jarkas, 2010). Many models have been developed to illustrate this learning curve phenomenon and show, for example, the relationship between the cycle number and the time per cycle. These models include: (1) The Straight-Line Model (Wright's Log-Linear Model) (2) The Stanford "B" Model (3) The Exponential Model (4) The De Jong's Model; and (5) The Cubic Power Model (The S-Curve Model) (Thomas et al., 1990, Hijazi et al., 1992, Naresh and Jahren, 1998, Chen et al., 2009, Taylor et al., 2009, Jarkas, 2010, Shehata and El-Gohary, 2012, Pellegrino et al., 2012, Panas and Pantouvakis 2014). On the other hand, using simulation for modeling the learning curve phenomenon has gained more and more attention over the last years. The most popular simulation techniques adopted were Discrete-Event Simulation (DES) (Hijazi et al. 1992, Lutz et al. 1994, Panas and Pantouvakis 2014) and System dynamics (SD) (Nasirzadeh and Nojedehi, 2013). However, none of the previous studies used Agent-Based Modeling (ABM) to model the effect of learning on labor productivity. ABM can be defined as a computer simulation technique allowing the examination of how system patterns develop from the behaviors of individual agents. ABM creates virtual agents that have the ability to interact with each other and their environment and accordingly make autonomous decisions (Awwad et al. 2014). ABM was used to model the effect of congestion (Watkins et al., 2009, Marzouk and Ali, 2013) and safety (Marzouk and Ali, 2013) on labor productivity but the effect of learning development was not modeled.

2. Objectives and Scope of Work

The overarching objective of this study is to analyze the effect of learning curve on labor productivity by creating an agent-based model that allows modeling different learning levels of workers on sites, observing their interaction over time, and detecting emergent construction environment behavior and learning patterns. Four specific interim objectives are identified in the proposed initiative:

- Identify construction tasks of repetitive nature and crews involved
- Develop an agent-based model to capture the complexities and dynamics of the learning curve mechanism and its effect on labor productivity, as well as pave the way for a further sophisiticated model that can allow running a variety of experiments and gaining insights into the complexity of the construction environment and tasks involving learning.

- Verify the proposed model through animation and visualization (i.e.face validation).
- Carry out a statistical analysis for a rigorous interpretation of the results.

3. Thesis structure

Besides this introductory chapter, the thesis consists of three appendices as follows:

- *Appendix A* is a review article. It is an elaborate critical review of the literature related to the learning curve effect on labor productivity
- *Appendix B* is a research article. It presents the proposed agent-based learning model in addition to a statistical analysis of the results.
- *Appendix C* is a supplementary material section. It presents a summary of the data produced from the various simulation runs, as well as a model description together with details about the statistical R code.

References

Awwad, R., Asgari, S., and Kandil, A. (2014). Developing a Virtual Laboratory for Construction Bidding Environment Using Agent-Based Modeling. J. Comput. Civ. Eng., 10.1061/(ASCE) CP.1943-5487.0000440 , 04014105.

Hafez, S., Aziz, R., Morgan, E., Abdullah, M., & Ahmed, E. (2014). Critical factors affecting construction labor productivity in Egypt. American Journal of Civil Engineering.

Jarkas, A. (2010). Critical Investigation into the Applicability of the Learning Curve Theory to Rebar Fixing Labor Productivity. Constr. Eng. Manage. 1279-1288.

Lee, S. (2007). Understanding and Quantifying the Impact of Changes on Construction Labor Productivity: Integration of Productivity Factors and Quantifying Methods. Doctoral Dissertation, University of Berkeley.

Shehata, M., & El-Gohary, K. (2012). Towards improving construction labor productivity and projects' performance. Alexandria Engineering Journal.

Singh, S. P. (2010). Factors affecting the productivity of construction operations in the United Arab Emirates.

APPENDIX A A REVIEW OF THE LEARNING CURVE EFFECT ON LABOR PRODUCTIVITY IN CONSTRUCTION

ABSTRACT

This study presents a state-of-the-art review of research studies that have focused generally on productivity in construction, and specifically on the learning curve effect on labor productivity. Although learning curve models have been reviewed and compared (Srour et al., 2015), this study takes it a step further by presenting detailed information about the general concepts of productivity in construction, proceeding into discussing the factors affecting labor productivity leading to the importance of the learning curve effect including the related research done in that regards. Then finally, the last part presents and discusses the tools and techniques used to illustrate and model the effect of learning curve on productivity in construction. As an outcome, the objective of this study is to build a comprehensive overview for researchers and practitioners in this field, as well as highlight the shortcomings of previous research and identify the gaps that need be filled in future research studies.

KEYWORDS

Construction, management, labor, productivity, learning-curve, simulation.

A.1. INTRODUCTION

The appropriate planning and control of construction sites depend heavily on the precision of estimating labor productivity of different tasks onsite in order to develop realistic schedules and control labor costs (Pellegrino el al., 2012). High-rise buildings in construction encounter many tasks that are repetitive in nature. As more projects in construction are moving towards the implementation of high-rise construction as a result of increased numbers of populations; the improvement in the rate of performance for each repetitive task has a noticeable effect on cost and time. Thus, this improvement in productivity resulting from the learning curve effect must be taken into consideration when preparing schedules and calculating costs. The objective of this study is to (1) present a comprehensive literature review for the productivity and factors affecting it, especially the learning curve effect (2) present a thorough literature review about learning curve concept itselfl, and its effect on labor productivity in construction, including the techniques that have been used to evaluate this effect (3) highlight areas that have been not adequately studied and the need for future research in these specific areas.

A.2. LITERATURE REVIEW

A.2.1 Productivity

In the construction industry, productivity refers mostly to labor productivity. This productivity can be interpreted in many different ways. Therefore, several definitions of productivity have been provided in order to avoid any misinterpretation. It is important to choose the productivity measure that can best suit the purpose (Shehata & El-Gohary, 2012). These definitions are summarized and briefly presented as follows (Shehata & El-Gohary, 2012):

Section (1): Economic models

Total factor productivity (TEP)

$$\mathrm{TEP} = \frac{\text{Total output}}{\text{Labor} + \text{Materials} + \text{Equipment} + \text{Energy} + \text{Capital}}$$

TEP factor is used in economics to calculate the ratio of output/input. This factor has no unit as both the output and the input are in dollars. The denominator could change to other variables to fit other input.

Section (2): Project-specific models

$$\text{Productivity} = \frac{\text{Output}}{\text{Labor} + \text{Equipment} + \text{Materials}}$$

This form of productivity is commonly used by designers. The unit of productivity in this form is the unit of work (e.g. square feet) per dollar.

Section (3): Activity-oriented models

$$\text{Labor productivity} = \frac{\text{Output}}{\text{Labor cost (or Work hour)}}$$

Productivity has a unit of output per dollar or output per work-hour. This form is mainly used by contractors to calculate productivity of tasks.

Also, some contractors use the same for but inverted as follows:

$$Labor\ prodctivity = \frac{\text{Labor cost or Work hour}}{\text{Output}}$$

This form of productivity is called the unit rate. Some other contractors depend on the performance factor to express productivity. This factor is calculated as follows:

$$\text{Performance factor} = \frac{\text{Estimated unit rate}}{\text{Actual unit rate}}$$

Section (4): The baseline productivity

This productivity represents the best productivity that can be achieved without disruptions. There's no accurate equation to calculate it. There are steps to estimate the baseline productivity as presented previously (Shehata & El-Gohary, 2012), but these steps have been criticized for inaccuracy.

Section (5): Cumulative productivity

$$\text{Cumulative productivity} = \frac{\text{Total work hours charged to a task}}{\text{Total quantity installed}}$$

As the name implies, this form of productivity calculate the cumulative of total work hours to the total quantity installed. This factor can give an idea of the progress of work.

Section (6): The project management index (PMI)

It is calculated as follows:

$$\text{PMI} = \frac{\text{Cumulative productivity} - \text{baseline productivity}}{\text{baseline productivity}}$$

This is a non-dimensional parameter that can be used to normalize the management influence to compare different projects performance.

The importance of labor productivity is explained by the fact that it directly affects the time and cost of construction projects. Therefore, many studies have focused on identifying major factors affecting labor productivity. Among these studies, one comprehensive reviewhas been done whereby it collected major factors of labor productivity, classified them into categories, and presented quantifying methods for measuring of impacts of change on productivity levels (Lee, 2007). From this study, seven major factors affecting productivity can be extracted. These factors are: overtime, over-manning, congestion, shift work, weather, and the learning curve. Another batch of studies has identified major factors affecting labor productivity for a specific region by collecting data from surveys. These included studies in United Arab Emirates (Singh, 2010), Egypt (Enshassi et al., 2010, Hafez et al., 2014), and Turkey (Kazaz et al., 2010). A large number of factors are identified in these studies as more detailed focus is put on the impact regarding each region. It is concluded that construction labor productivity is not under full control of project managers rather affected by workers and work environment (Kazaz et al., 2010).

It is apparent in previous studies that calculating labor productivity is a very complex process. Furthermore, there is an overlap between different factors of productivity, which make it even harder to estimate the impact of each factor separately or as a part of multiple factor calculation. Therefore, there is a clear need for further evaluation of factors affecting productivity in order to create a common technique or a generic environment that researchers can always build upon. This becomes more of a necessity given the different equations and techniques out there or that have been developed by researchers, as mentioned previously (Lee, 2007). In essence, studying the learning curve effect in construction is of importance especially given its impact on labor productivity yet it has not been evaluated thoroughly. A detailed focus on this issue is presented in the following section.

A.2.2 The learning curve

The learning curve theory states: "Whenever the production quantity of a new or changed product doubles, the unit or cumulative average cost (hours, man-hours, dollars, etc.) will decline by a certain percentage of the previous unit or cumulative average rate. This percentage is called the learning rate and identifies the learning achieved. It also establishes the slope of the learning curve". According to Lutz et al. (1994), "the lower the learning rate the greater the learning". According to Thomas et al. (1986), "A learning rate of 100% means that no learning takes place". The learning rate in construction is assumed to be between 80% and 95% (Arditi et al., 2001). Additionally, in order for learning to be effective, the flow of work should be continuous without interruptions, the type of work should be identical, and the type of activity repetitious (Thomas et al., 1986).

The concept of learning curve was first proposed by Wright (Wright T. , 1936) when he derived a mathematical linear relationship between number of units produced and productivity. Many other learning curve models have been developed. Learning curve models can be summarized as follows (Thomas et al., 1986, Arditi et al., 2001):

1. Wright's log-linear model (Straight-line model) (1936)

This is the first model representing the learning curve. The relationship between productivity and units produced is assumed to be linear on a log-log plot as the learning rate remains constant.

The mathematical model is as follows:

$$Y = A * X^n$$

Where: Y: cost, man-hours, or time. A=cost, man-hours, or time necessary to perform the first unit. X=cycle number of the unit; and n represents the slope of the logarithmic curve (the learning rate), which is calculated as:

$$n = \frac{\ln S}{\ln 2}$$

Where n is the learning rate, which is defined as the percentage reduction in the unit input, i.e., cost, man-hours, or time, as a result of doubling the number of units completed. The number 2 is explained as follows: for a learning rate of 80% each time the production rate doubles, the production rate will increase by 20%.

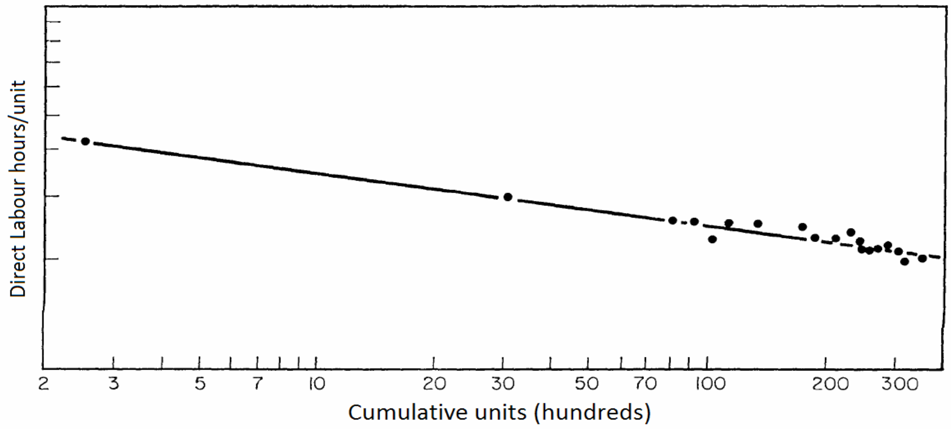


Figure A-1: Wright's Learning Curve (Kar, 2007)

This model is the most commonly used because of its simplicity although it assumes the improvements in productivity have no limit which is not realistic. Furthermore, this model assumes that the learning rate is a constant value, which many studies disagreed with and considered it as unreliable (Thomas et al., 1986).

2. Stanford B model (1961)

This model was developed by The Stanford Research institute. It incorporates additional “B” factor which represent the previous experience acquired by workers. It is apparent that this model is a modification of the straight-line model that accounts for past experience. The updated formula is as follows:

$$Y = A\,(X + B)^n$$

Where B: a factor that represents the previous experience acquired by labor

Notice that when (B=0) the formula would be the same as straight-line linear model.

3. Exponential Models

3.1 Basic exponential model (1963)

In this model that is developed by the Norwegian Building Research institute, the cost (or time) will be reduced by half after a constant number of repetitions. The formula is as follows:

$$Y = Yu + \frac{A - Yb}{2^{\frac{X}{H}}}$$

Where: Y = operational time for unit x, Yb = ultimate time per unit (minimum value that Y can reach), A = operational time for the first unit, X = unit number, H = Halving factor (constant), it is the unit number that will reduce the time or cost to the half. By obtaining one set of X, Y we can calculate it from the following equation:

$$H = \frac{X.log2}{\log(A - Yb) - \log(Y - Yb)}$$

3.2 De Jong Model (1957)

This model also modifies the straight-line model by incorporating the machine participating factor. It assumes that the ratio of worker-machine affects the learning development. The higher the participation of a machine in a task, the less compressible the duration of the task. This model's equation is as follows:

$$Y = A\left[M + \frac{1 - M}{X^n}\right]$$

Where: M is the factor of incompressibility (Constant). When M=0 the model reduce to the log-linear model, which implies a complete manual operation. If M=1, then unit cost becomes equal to C1 which suggest that there is no cost improvement possible in machine controlled operations.

4. The Cubic Power Model (The S-Curve Model) (1973)

This model was proposed by Carlson. He indicated that a further enhancement of the straight-line model can be achieved using a curve with multiple slopes. The model's formula is as follows:

$$Y = A\,[M + (1 - M) * (X - B)^{-n}]$$

This model's parameter is a combination of all parameters of other models. This model tries to incorporate both the machine-worker ratio and previous experience factor. The result is an S-Curve. Some learning curve models are illustrated in Figure A-2.

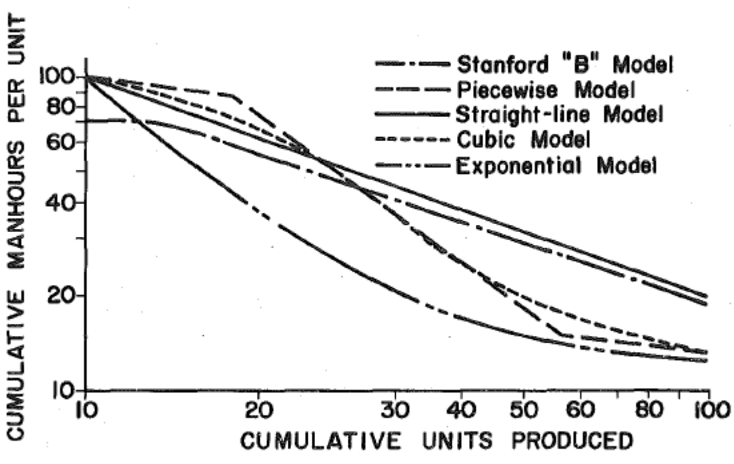


Figure A-2: Some Learning Curve Models (Thomas et al., 1986)

There are also other notable learning curve models including:

- Levy’s adaptation function
- Knecht’s upturn model
- Glover’s Learning Formula
- Pegel’s exponential function
- Multiplicative power model (Cobb-Douglas)

On the other hand, studying and analyzing the effect of the learning curve in construction, through different applications and case studies, was carried out by many researchers. In a previous study done by Jarkas (Jarkas, 2010), after the learning theory and models have been proposed, the rebar fixing operation of beams and slabs was presented. A case study of 21 residential buildings in Kuwait was done and productivity data were collected. Rebar fixing labor inputs were collected using the intermittent observation technique (collection upon the completion of an activity) as delays were calculated and deducted. A statistical analysis of data was conducted to plot the learning curve. The straight-line model was adopted because the concentration is on a task level not a project level. This study is mainly important since it had been concluded that there is no productivity improvements due to learning. A few cases showed some improvements while the others showed a reduction on productivity. This is due to many reasons especially the physical nature of fixing rebar (fatigue) that may have overshadowed the learning effect. Another notable study done by Pellegrino (Pellegrino el al., 2012) reviewed the theory of learning and its applications in construction. Data was collected from 15 multi-story concrete structures, and analysis was done to come up with the most important factors affecting learning (especially the negative impact of interruptions) by doing two multilevel regression analyses using Matlab software. As a result of the buildings being different in the crew compositions and work conditions, different learning curve for each building was plotted. Parameters affecting the learning process of the case study were suggested in order to be evaluated using the regression model. It has been concluded that the variability in productivity rates are mainly due to site management and more focus should be invested on improving the productivity of the first floor in order to reach the highest level of progress before 40% of work is completed. Learning dynamics was also studied by Taylor (Taylor et al., 2009). This paper simulated learning dynamics between multiple firms to adopt changes within the construction technologies. The main focus was on the impact of both relational instability and task interdependency, and how these two factors might influence organizational learning resulting in the affect of productivity rates. A multi-agent simulation model was developed using Python programming language. Each firm is represented as an agent with learning capabilities in the individual level and between firms. The experiment consisted of four different combinations of task interdependence and relational instability. It had been concluded that organizations adopting new technologies should reduce relational instability to achieve higher rates of productivity due to learning. Another study analyzing how learning effects the marine lock guide walls construction was addressed using SLAM simulation program. This was done by Naresh (Naresh & Jahren, 1998). Normal distribution (PERT) was implemented to account for variations in activity durations. Data was collected from experts. A sensitivity analysis was done to examine the learning effect on production, time and cost. This study concluded that learning rates should be improved to reach higher production rates. Learning effect was high in the beginning and decreased with time, so the focus was on the first period of the construction. The effect of learning on line-of-balance (LOB) scheduling was done by Arditi (Arditi et al., 2001) as famous learning models were explained briefly. LOB plots were injected with new and modified productivity rates that incorporate learning, thereby transforming them into curves instead of lines, given that the straight-line model of learning had been chosen. The learning rates are modified after the first run in order to account for factors affecting learning (number of operations, complexity, and job and management conditions), which were then divided into two categories, factual and subjective. Fuzzy set theory is used to describe subjective factors (uncertainty). An S-curve was used to modify learning rates. Fictitious project was used as a case study to illustrate the proposed method. It has been concluded that 16% decrease in total duration and 27% decrease in labor resource requirement are observed due to learning. A satisfactory industry-wide learning model that applies to all activities may not be feasible. In a study of learning curve models done by Thomas (Thomas et al., 1986), learning curve models are presented and explained. Data collected from three construction projects was plotted and Pearson's Coefficients of Determination (adjusted) were calculated to analyze the capabilities and validity of learning curve models. Least-squares curve fitting routines were applied to develop the parameter estimates that provided the best fit. This study concluded that the cubic model of learning curve has much wider application due to the complexities and variations associated with the construction activities. In project networks, learning decay effect on project performance was studied by Chen (Chen et al., 2009). This paper examines the impact of forgetting (decay) as a factor affecting learning between firms in project networks, by developing an experiment with different scenarios with varying relational instability values (degree of task interdependence). Wright curve is the basis of this study. It has been concluded that as relationship instability and task interdependence increase, the impact of forgetting diminishes. Other study by Hijazi (Hijazi et al., 1992) had investigated factors affecting learning. Variability in learning is discussed. Three cases (no learning, 95% learning rate, and learning rate as a variable with triangular distribution) were applied on a previous case study (High-rise hotel). A confidence level of 95% was constructed in the variability analysis. It was concluded that the exclusion of learning development will lead to overestimation in project duration.

Therefore, the learning curve effect was chosen to be studied for many reasons: (1) it is among the most important factors affecting labor productivity (2) it has not been adequately studied in previous research works (3) studying the effect of learning involves to a certain extent the inclusion of other factors that affect labor productivity, and (4) the need to identify a common way to estimate the effect of learning and other factors on labor productivity to reduce the divergence of available techniques. It has been stated that the modeling of the learning phenomenon results in a more competitive bidding by providing more realistic schedules and cost estimates (Lutz et al., 1994). It is also important to notice the capability of the learning curve in predicting future performance, which can help in planning and forecasting targets. It also helps in estimating the effect of a delay or an interruption in work flow. For instance, the principle of learning curve is useful to the contractor when the owner decides to delay the work of the contractor since the latter can now make a claim for compensation to regain the losses resulting from the loss of learning caused by the delay (Hinze, 2011).

Beyond highlighting the importance of the learning effect, modeling it as a variable is even more imperative. It can yield a more accurate representation of the real situation. The following section thereby presents different factors affecting the learning rate.

A.2.3 Factors affecting learning

Although many learning curve models have been developed to reflect the effect of learning on productivity, no single model incorporated all different factors affecting the learning. As a result, developing a model that can be adopted for all kinds of tasks related to different industries is not reasonable. This section highlights the most common factors that can affect the outcome of learning in construction. These factors should be taken into consideration when estimating labor productivity, estimating the cost of a delay, or estimating durations of different tasks using a learning curve model.

Some factors causing learning has been identified in construction that include: the increase in workers' familiarity, improved coordination of crews and equipment, improved job organization, better engineering support, better management and supervision, developed techniques and methods, development in material supply systems, and stabilized design leading to fewer modification and rework (Thomas et al., 1986).

In some other study, it was stated that "learning rate is greatly influenced by various factors" and provides the main factors that affect the learning rate in construction (Hijazi et al., 1992). These factors were put into four main categories: management, labor, project, and task characteristics as shown in Figure A-3.

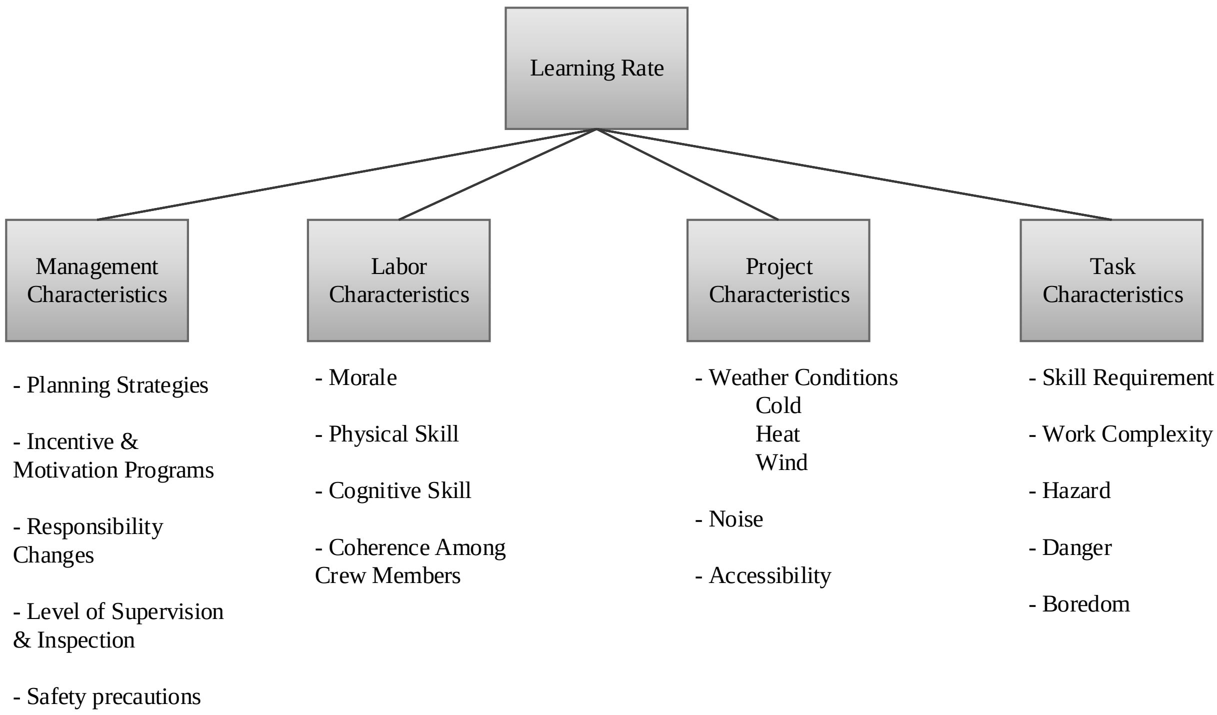


Figure A-3: Factors affecting learning rate (Hijazi et al., 1992)

Another noticeable study estimated the weight of each factor affecting the learning rate as a percentage of importance for two industries, in particular construction (Cochran, 1960, Arditi et al., 2001). These weights are shown in Table A-1.

Table A-1: Approximate weights of importance for factors of learning (Arditi et al., 2001)

Construction	**Weight of importance (%)**
Worker learning	40
Construction method	20
Managerial support	15
Quality of design	15
Others (job conditions, weather, etc.)	10
	100

In order to better represent the aforementioned factors affecting learning and include them in studies, automated tools in particular simulation tools were deemed necessary. The following section sheds the light on these tools.

A.2.4 Automating the effect of learning curve on labor productivity

Studies that used simulation to analyze the effect of learning in the construction industry have been gathered and summarized in order to get a general overview of previous research on this topic. Three main simulation techniques have been used over the past few decades. Discrete-Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM) have been adopted for illustrating any phenomenon that is affected by many factors.

Discrete-Event Simulation (DES) focuses on defining the process for simulation. Discrete-Event simulation is a top down modeling approach that is process oriented and focused on modeling the system in detail (Siebers et al., 2010). It is the most widely used technique adopted more than 40 years ago in operational research (OR) (Siebers et al., 2010).

DES has been widely and more commonly used as a simulation technique in construction with many researchers adopting DES as the modeling approach for their studies. Among these studies, two stand out as the most relevant to this topic and were found to have used DES to illustrate the effect of learning curve as a factor of labor productivity. The first study was done in 1994 by Lutz (Lutz et al., 1994). Discrete-event modeling was conducted using an improved MicroCYCLONE package that models the impact of learning based on the Boeing (Wright) learning curve. The simulation was improved to include input parameters of learning. Seven operations including 43 processes were modeled (processes that incorporate improvement). As a conclusion of this study, the use of learning-development modeling provides more realistic production forecasting, more accurate scheduling and budgeting, more competitive bidding, and improved system performance. Another study that also used DES is done by Panas (Panas & Pantouvakis, 2014). In this study, statistical analysis and Discrete-event simulation were done using an enhanced simulation platform named CaissonSim and by using Stroboscope simulation language. The results were evaluated by changing learning rates. Learning rates were plotted as a triangular distribution. Input data were collected form a case study for simulation and a statistical analysis was executed to predict future performance. The least mean-squares method was used to determine the learning rate for every activity. The point where no additional improvements occur is set prior to the simulation. It has been concluded in this study that the learning phenomenon has significant impact on productivity of caisson operations and both the simulation and statistical approaches yield satisfactory results.

System Dynamics (SD) was created by MIT Professor Jay Forrester in 1950 (Grigoryev, 2015). It illustrates the positive or negative impact of each factor on all other factors adopted for the study. “System dynamics is typically used in long-term, strategic models, and it assumes high levels of object aggregation: SD models represent people, products, events, and other discrete items by their quantities. System dynamics is a methodology to study dynamic systems. It suggests you:

- Model the system as a causally closed structure that defines its own behavior.
- Discover the system's feedback loops (circular causality) balancing or reinforcing.

• Identify stocks (accumulations) and flows that affect them." (Grigoryev, 2015)

System Dynamics (SD) have been used as a tool to model labor productivity in construction (Nasirzadeh & Nojedehi, 2013). Researchers developed a SD model that illustrates a cause and effect modeling of factors affecting labor productivity. This modeling can highlight the important factors that affect labor productivity in order to take corresponding actions to prevent loss in labor productivity. The flowchart that illustrated these factors can be shown in Figure A-4.

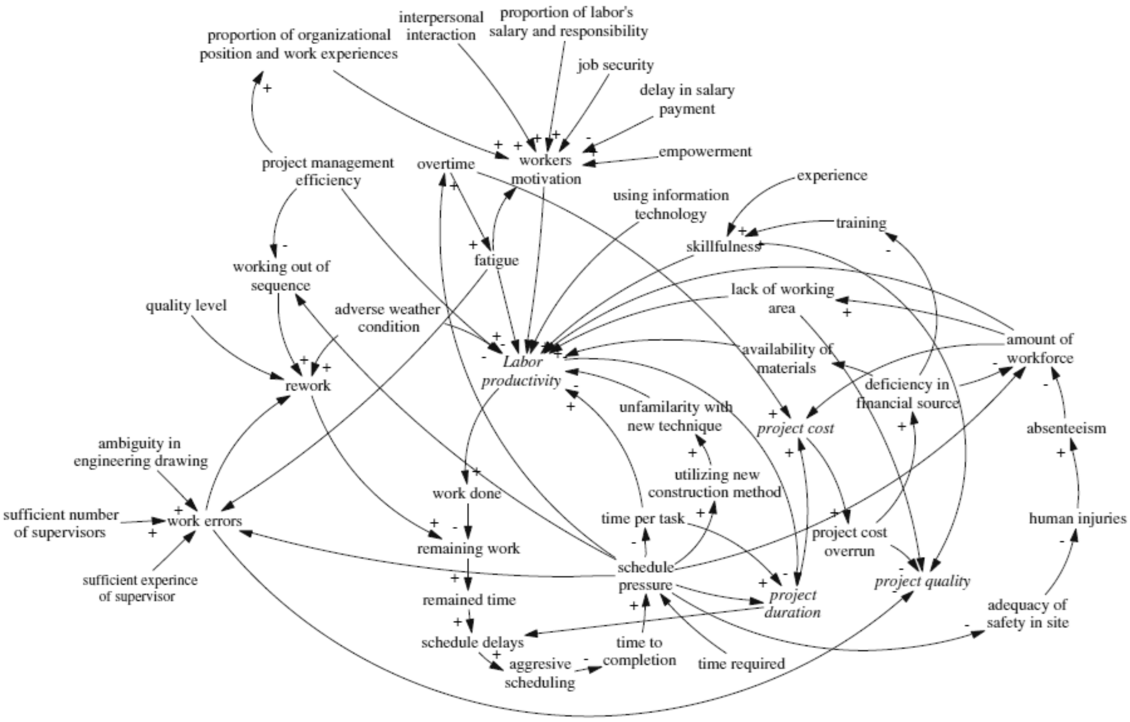


Figure A-4: Conceptual model of labor productivity using SD (Nasirzadeh & Nojedehi, 2013)

On the other hand, Agent-Based Modeling (ABM), was found in the early 90s (Grigoryev, 2015). It is not used as widely as Discrete-Event simulation (DES). ABM is an agent-oriented technique that focuses on defining agents' behaviors and relationships among different agents. This interactive environment would let the simulation emerge resulting from interaction between different agents and from interaction between agents and the environment. For instance, in a study done by Watkins (Watkins et al., 2009), an ABM model was developed to simulate congestion as a factor affecting labor productivity. This study simulated congestion that accounts for spatial locality rather than the average space for each worker. In this regards, congestion can be estimated in a simulation manner that cannot be done manually. This illustrates the importance of simulation in providing close-to-reality scenarios. Agents in this study were tasks and workers. This study concluded that ABM can depict a more realistic environment whereby congestion can be studied as an emergent property due to crew interactions. Another related study modeled the influence of congestion and other factors that affect productivity such as: space, safety and soil behavior. The agents chosen were: crane agent, rig agent and pile agent (Marzouk & Ali, 2013). This study has concluded that ABM is useful to estimate factors affecting labor productivity and to identify the ideal scenarios in which the loss in productivity is minimal.

Although ABM was used to model the effect of congestion (Watkins et al. 2009, Marzouk and Ali 2013) and safety (Marzouk and Ali 2013) on labor productivity but the effect of learning development was not modeled. As a matter of fact, it was stated in prior ABM efforts that the limitation was the exclusion of the learning curve effect (Watkins et al. 2009).

Table A-2 summarizes and synthesizes the aforementioned review.

Table A-2: Previous research studies

Author	**Title**	**Methodology**	**Main Findings**
Productivity			
(Lee, 2007)	Understanding and Quantifying the Impact of Changes on Construction Labor Productivity: Integration of Productivity Factors and Quantifying Methods	A comprehensive review of factors affecting productivity has been done as it collected major factors of labor productivity, placed them in categories, and presented the quantifying methods of these impacts of change	This comprehensive overview of all methods in calculating productivity and its factors gives a big picture that helps in capturing the limitations and advantages of available techniques. Analysis of each method is also provided.
(Singh, 2010)	Factors affecting the productivity of construction operations in the United Arab Emirates	Examining the factors affecting labor productivity in UAE is done to understand how improvement in labor productivity can be achieved.	"Results show that the induction of new players in the industry has tended to introduce waste and has had lower productivity levels attached to the product delivered." (Singh, 2010)
(Kazaz et al., 2010)	Effect of basic motivational factors on construction workforce productivity in Turkey	A questionnaire comprising 54 detailed questions under 18 subject headings, such as demographic features of firms, experience levels of respondents, or factor groups, was first prepared. In the application stage of the questionnaire, face-to-face (one-to-one) interview technique was utilized in order to ensure the validity and reliability of the survey; however, 10 firms could not be contacted and were interviewed by e-mail	Among the 4 factor groups affecting construction labor productivity, organizational factors were found as the most important group followed byeconomic factors and physical factors which came in second and third place respectively.

(Enshassi et al., 2010)	Factors affecting labour productivity in building projects in the Gaza strip	This research is based on a survey designed to gatherall necessary information in an effective way. The survey presents 45 productivity factors generated on the basis of related research work on construction productivity	The most important factors affecting productivity were identified and ranked. Several recommendations were provided (such as providing a materials' supply schedule for each project, using project scheduling techniques in each project to optimize the time span for the related activities. This alsoensured that work would flow continuously and labor force would maximize time usage. Pertaining training courses and seminars were also conducted to improve productivity in construction projects.
(Shehata & El-Gohary, 2012)	Towards improving construction labor productivity and projects' performance	Factors affecting productivity are classified into three categories: Industry, management, and labor related factors. Models of productivity were classified as follows: physical, symbolic, mental and schematic. Finally, two previous case studies were also presented. The first was concerning a building in Egypt andthe focus on a tiling system on the 2nd floor. Active and inactive work time was evaluated with subsets for each The second case study in Egypt addressed two principles of lean; benchmarking and reducing variability. It was a collection of masonry activities from 11 commercial and residential construction projects.	It was concluded that the key for productivity improvement was not to complete as many tasks as possible or to maximize workload, work output, or work hours without following the work plan. Rather, the key was to focus on maintaining a predictable work flow and thus be able to match the available workload with capacity (work hours). Hence, to improve project performance, variability in labor productivity should be reduced with regard to available workload and capacity (work hours).

(Khanh & Kim, 2014)	Determining Labor Productivity Diagram in High-Rise Building using Straight-Line Model	This study considers SLM as a tool for estimating the labor productivity of high-rise buildings. A questionnaire (in Vietnamese) was prepared to collect the appropriate data regarding the general characteristics in high-rise buildings and labor productivity rates for three main repetitive activities: formwork setting, rebar fabrication/installation, and concrete casting. A statistical analysis was applied on the data collected. The accuracy of models was assessed by Mean Absolute Percentage Error (MAPE) and R-squared index.	The hypothesis about critical floor, which labor productivity of floors above this floor is probably fixed or constant, is quite appropriate.
(Hafez et al., 2014)	Critical factors affecting construction labor productivity in Egypt	This research is based on a survey designed to gather all necessary information in an effective way. The survey presents 27 productivity factors generated on the basis of related research works on construction productivity.	In conclusion, it is believed that the outcomes of this paper can assist in achieving high labor productivity by focusing and acting upon the most important factors. Furthermore, by focusing on the significance of the evaluated factors constraining labor productivity, Egyptian construction companies could be well guided in their efforts to addressing the factors in a time, cost and quality-effective manner

Learning Curve			
(Thomas et al., 1986)	Learning curve models of construction productivity	Learning curve models are presented and explained. Data collected from three construction projects was plotted and Pearson's Coefficients of Determination (adjusted) were calculated to analyze the capabilities and validity of learning curve models. Least-squares curve fitting routines were applied to develop the parameter estimates that provided the best fit.	The cubic model has much wider application due to the complexities and variations associated with the construction activities.
(Hijazi et al., 1992)	Modeling and simulating learning development in construction	Factors affecting learning are investigated and summarized. Variability in learning is discussed. Three cases (no learning, 95% learning rate, and learning rate as a variable with triangular distribution) were applied on a previous case (High-rise hotel). A confidence level of 95% was constructed in the variability analysis.	It is suggested that a stochastic learning model be adopted due to the random factors affecting learning in construction.
(Naresh & Jahren, 1998)	Learning outcomes from construction simulation modeling	This study analyzes how learning effect of marine lock guide walls construction was addressed using SLAM simulation program. Normal distribution (PERT) was done to account for variations in activity durations. Data was collected from experts. A sensitivity analysis was done to examine the learning effect on production, time and cost.	Learning rates should be improved to reach higher production rates. Learning effect is high in the beginning and decreases with time, so the focus in on the first period of the construction.

(Arditi et al., 2001)	Effect of learning on line-of-balance scheduling	Famous learning models were explained briefly. LOB plots were injected with new and modified productivity rates that incorporate learning, which transforms them into curves instead of lines as the straight-line model of learning is chosen. The learning rates are modified after the first run in order to account for factors affecting learning (number of operations, complexity, and job and management conditions), Fictitious project was used as a case study to illustrate the proposed method.	16% decrease in total duration and 27% decrease in labor resource requirement were observed due to learning. A satisfactory industry-wide learning model that applies to all activities may not be feasible.
(Chen et al., 2009)	Simulating the effect of learning decay on adaptation performance in project networks	This paper examines the impact of forgetting (decay) as a factor affecting learning between firms in project networks, through developing an experiment with different scenarios with varying relational instability values(degree of task interdependence). Wright curve is the basis of this study.	As relationship instability and task interdependence increase, the impact of forgetting diminishes.
(Taylor et al., 2009)	Simulating learning dynamics in project networks	This paper simulates learning dynamics between multiple firms to adopt changes within the construction technologies. The main focus is on the impact of both relational instability and task interdependency, and how these two factors affect organizational learning plus productivity rates. Using a multi-agent simulation model developed using Python programming language, each firm is represented as an agent with learning capabilities at the individual level and between firms. The experiment consisted of four different combinations of task interdependence and relational instability.	Organizations adopting new technologies should reduce relational instability to achieve higher rates of productivity due to learning.

(Jarkas, 2010)	Critical investigation into the applicability of the learning curve theory to rebar fixing labor productivity	This study defines the learning theory and models, and explains the rebar fixing operation of beams and slabs. A case study of 21 residential buildings in Kuwait was done and productivity data were collected. Rebar fixing labor inputs were collected using the intermittent observation technique (collection upon the completion of an activity) as delays were calculated and deducted. A statistical analysis of data was conducted to plot the learning curve. The straight-line model was adopted because the concentration is on a task level not a project level	No productivity improvements due to learning. A few cases showed some improvements while the others showed a reduction on productivity. This is due to many reasons especially the physical nature of fixing rebars (fatigue) that may have overshadowed the learning effect.
(Pellegrino el al., 2012)	Construction of multi-story concrete structures in Italy: Patterns of productivity and learning curves	Overview of the theory of learning and its applications in construction. Data collection from 15 multi-story concrete structures and analysis to come up with the most important factors affecting learning (especially the negative impact of interruptions) by doing two multilevel regression analyses using Matlab. As a result, different learning curve for each building was plotted. Parameters affecting the learning process of the case study are suggested in order to be evaluated using the regression model.	Variability in productivity rates are mainly due to site management. More focus should be invested on improving the productivity of the first floor in order to reach the highest level of progress before 40% of work is completed.
(Tavakolan & Ashuri, 2012)	Simulation of absorptive capacity impact on the performance of project networks learning	This paper studies the capability of a firm to learn how to adapt to innovation changes in a project network. The impact of innovation has been considered based on the Wright's curve. Productivity is improved by innovation but cannot exceed the absorptive capacity. The results of 25 projects were plotted to analyze the effect of innovation and absorptive capacity.	Relational instability and the degree of task interdependence of project networks affect innovation due to technological changes.

(Srour et al., 2015)	Learning Curves in Construction: A Critical Review and New Model	Literature review on learning curve models. A new model wasproposed to accommodate both mechanization and forgetting. Evaluating learning curve models in predicting future performance by comparing 4 different case studies.	“The model used in this study demonstrates less than 1% error in predicting cumulative average unit construction times in three out of the four cases studied. Although these results are encouraging, further research is necessary to resolve multiple outstanding questions in the field.”

Automating Productivity factors Using Simulation Techniques			
System Dynamics (SD)			
(Nasirzadeh & Nojedehi, 2013)	Dynamic modeling of labor productivity in construction projects	A system dynamics qualitative model of labor productivity is constructed using governing cause and effect feedback loops. Then the inter-relationships that exist between different factors were defined by mathematical equations and a quantitative model of labor productivity was built. Sensitivity analysis is conducted to assess the impact of different factors on labor productivity. Historical data and case studies data were collected. Using multiple linear regression tool of Matlab software, the relationships that exist between labor productivity and the influencing factors were determined. The proposed SD model is employed in a housing project to validate and evaluate its performance.	The proposed SD approach offers a flexible and robust method for the simulation of labor productivity with the possibility of finding the root causes of a decrease in productivity.
(Jiang et al., 2014)	Understanding the Causation of Construction Workers' Unsafe Behaviors Based on System Dynamics Modeling	This paper presents a system dynamic model of workers' behavior effect on safety. A holistic cognitive analysis approach is developed by the authors to identify the critical factors that could result in a worker's cognitive failure. Based on factors of individual workers, environment, and management that affect safety, a preliminary model is built. In order to demonstrate that the predicted pattern by the model test is a correct reflection of the real system, a five-week survey and observation on a building construction project in Hong Kong was conducted by the authors with Interviews. A statistical analysis using Student t test.	A comparison between data statistical analysis and the model shows that the model was valid. Management conditions on supervisory level were effective on the improvement of workers' safety awareness. Where the enhancement of safety performave was considered, preventive actions were more effective than reactive ones.

Discrete-Event Simulation (DES)			
(Lutz et al., 1994)	Simulation of learning development in repetitive construction	Discrete-event modeling was conducted using an improved MicroCYCLONE package that models the impact of learning based on the Boeing (Wright) learning curve. The simulation was improved to include input parameters of learning. Seven operations including 43 processes were modeled (processes that incorporate improvement)	The use of learning-development modeling provides more realistic forecasting for production, more accurate scheduling and budgeting, more competitive bidding, and improved system performance.
(Panas & Pantouvakis, 2014)	Simulation-Based and statistical analysis of the learning effect in floating caisson construction operations	Statistical analysis and Discrete-event simulation were done using an enhanced simulation platform named CaissonSim and using Stroboscope simulation language. The results were evaluated by changing learning rates. Learning rates were plotted as a triangular distribution. Input data were collected form a case study for simulation, and a statistical analysis were executed to predict future performance. The least mean-squares method was used to determine the learning rate for every activity. The point where no additional improvements occur is set prior to the simulation.	Learning phenomenon has significant impact on productivity of caisson operations. Both the simulation and statistical approaches yielded satisfactory results.

Agent-Based Modelling (ABM)			
(Watkins et al., 2009)	Using agent-based modeling to study construction labor productivity as an emergent property of individual and crew interactions	This study simulates congestion using ABM that accounts for spatial locality rather than the average space for each worker.	ABM illustrated a more realistic simulation models which reflected real case scenarios.
(Marzouk & Ali, 2013)	Modeling safety considerations and space limitations in piling operations using agent based simulation	This paper proposes a model for estimating the productivity of bored piles, taking into consideration safety requirements and space availability. The model captures the probabilities of equipment breakdowns based on equipment historical data. The model has three agents: two types of equipment (crane and rig), and a pile agent. In the model, piling activity is divided into two processes. The first one is drilling process and second one is concreting process. Safety constraints are imposed to prevent any overlap between agents. The simulation was compared to a case study results.	The paper described a model that can be used to estimate piling productivity taking into consideration site space availability and safety requirements.

A.3. SUMMARY OF RESEARCH FINDINGS

This study presented a comprehensive literature review of the effect of learning curve on labor productivity. Productivity as a concept was been presented and factors affecting labor productivity were identified. Moreover, the importance of the learning curve as a factor affecting labor productivity was highlighted. The factors that affect the learning process were also collected and identified. In addition, methods and techniques that were used to automate the effect of learning or other factors of labor productivity had been also presented and discussed. It is shown that labor productivity has always been a major topic in previous studies, and simulating the effect of many factors on labor productivity is getting more attention over the past few decades. Among labor productivity factors, the learning curve effect is classified as a main factor affecting labor productivity and targeted by many studies, but no comprehensive demonstration of its corresponding effect was previously proposed. Thus, this factor should be further investigated. Furthermore, most studies adopted Wright's learning curve for simplicity, although other curves are more realistic and incorporate additional factors. Simulating the effect of the learning curve on labor productivity had been done using Discrete-event simulation (DES) and has not been tested using other simulation techniques such as System Dynamics (SD) and Agent-Based Modelling (ABM). Lastly, previous models of simulation lack the inclusion of the learning curve (Watkins et al., 2009).

A.4. NEED IN FUTURE RESEARCH

As presented above, many studies have focused on productivity and factors affecting it. The need for future research lies in using simulation techniques that haven't been used to illustrate the effect of these factors. DES and SD were used as techniques to illustrate the effect of learning on labor productivity unlike ABM. ABM can be promising in evaluating the effect of learning on labor productivity because it is agent-oriented and can better depict different interactions between workers on construction sites. Still, this has to be further investigated in future research. On the other hand, learning curves other than Wright's straight-line model should be adopted since they reflect more realistic scenarios. These gaps must be filled by future research to evaluate the use of different techniques in estimating the effect of different factors on labor productivity.

REFERENCES

- Arditi, D., Tokdemir, O., & Suh, K (2001). Effect of learning on line-of-balance scheduling. International Journal of Project Management, 265-277.
- Chen, J., Taylor, J., & Unsal, H. (2009). Simulating The Effect Of Learning Decay On Adaptation Performance In Project Networks. Winter Simulation Conference.
- Cochran, E. (1960). New concepts of the learning curve. Jurnal of Industrial Engineering.
- Enshassi, A., Mohamed, S., Abu Mustafa, Z., & Mayer, P. (2010). Factors affecting labour productivity in building projects in the Gaza strip. Journal of Civil Engineering and Management, 245-254.
- Grigoryev, I. (2015). Anylogic 7 in Three Days, Second edition.
- Hafez, S., Aziz, R., Morgan, E., Abdullah, M., & Ahmed, E. (2014). Critical factors affecting construction labor productivity in Egypt. American Journal of Civil Engineering.
- Hijazi, A., AbouRizk, S., & Halpin, D. (1992). Modeling And Simulating Learning Development IN Construction. Journal of Construction Engineering and Management, 118:685.
- Hinze, J. W. (2011). Chapter 11: the impact of scheduling decisions on productivity. In Construction Planning and Scheduling, 4th Edition.
- Jarkas, A. (2010). Critical Investigation into the Applicability of the Learning Curve Theory to Rebar Fixing Labor Productivity. Constr. Eng. Manage., 1279-1288.
- Jiang, Z., Fang, D., & Zhang, M. (2014). Understanding the Causation of Construction Workers' Unsafe Behaviors Based on System Dynamics Modeling. Journal of Management in Engineering.
- Kar, A. (2007). A Cost Modeling Approach Using Learning Curves to Study the Evolution of Technology. Masters Thesis, Massachusetts Institute of Technology.
- Kazaz, A., Manisali, E., & Ulubeyli, S. (2010). Effect of basic motivational factors on construction workforce productivity in Turkey. Journal of Civil Engineering and Management.
- Lee, S. (2007). Understanding and Quantifying the Impact of Changes on Construction Labor Productivity: Integration of Productivity Factors and Quantifying Methods. Doctoral Dissertation ,University of Berkeley.
- Lutz, J., Haplin, D., & Wilson, J. (1994). Simulation Of Learning Development In Repetitive Construction. Journal of Construction Engineering and Management.
- Marzouk, M., & Ali, H. (2013). Modeling safety considerations and space limitations in piling operations using agent based simulation. Expert Systems with Applications.
- NARESH, A., & JAHREN, C. (1998). Learning Outcomes From Construction Simulation Modeling. Civil. Eng. and Env. Syst., 129-144.
- Nasirzadeh, F., & Nojedehi, P. (2013). Dynamic modeling of labor productivity in construction projects. International Journal of Project Management, 903-911.
- Panas, A., & Pantouvakis, J. (2014). Simulation-Based and Statistical Analysis of the Learning Effect in Floating Caisson Construction Operations. Constr. Eng. Manage.
- Pellegrino, R., Costantino, N., Pietroforte, R., & Sancilio, S. (2012). Construction of multi-storey concrete structures in Italy: patterns of productivity and learning curves. Construction Management and Economics, 103-115.
- Shehata, M., & El-Gohary, K. (2012). Towards improving construction labor productivity and projects' performance. Alexandria Engineering Journal.
- Siebers, P., Macal, C., Garnett, J., Buxton, D., & Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! Journal of Simulation.
- SINGH, S. P. (2010). Factors affecting the productivity of construction operations in the United Arab Emirates.
- Srour, J., Kiomjian, D., & Srour, I. (2015). Learning Curves in Construction: A Critical Review and New Model. J. Constr. Eng. Manage.
- Taylor, J., Levitt, R., & Villarroel, J. (2009). Simulating Learning Dynamics in Project Networks. Journal Of Construction Engineering And Management, 1009-1015.
- Thomas, H., Mathews, C., & Ward, J. (1986). Learning Curve Models of Construction Productivity. Journal of Construction Engineering and Management.
- Watkins, M., Mukherjee, A., Onder, N., & Mattila, K. (2009). Using Agent-Based Modeling to Study Construction Labor Productivity as an Emergent Property of Individual and Crew Interactions. Journal Of Construction Engineering And Management.
- Wright, T. (1936). Factors affecting the cost of Airplanes. Journal of the Aeronautical Sciences.

APPENDIX B EVALUATING THE EFFECT OF LEARNING CURVE ON LABOR PRODUCTIVITY USING AGENT-BASED MODELING

ABSTRACT

The labor-intensive nature of construction projects requires proper management and efficient utilization of labor resources. Improvement of labor productivity can enhance project performance and thereby lead to substantial time and cost savings. Several studies focused on identifying the effect of different factors on labor productivity, whereby the learning curve factor proved of paramount importance. Previous research efforts developed models to analyze the effect of learning curve on labor productivity but failed to capture all the complexities of this mechanism and its dynamics. This paper presents an agent-based construction learning model that models a construction site as an active environment in which construction personnel or agents interact with each other and their surroundings thereby creating an adaptive environment open for learning and improvement. More specifically, the developed work illustrates many scenarios representing different learning levels and typical interactions between workers on construction sites. The components of the proposed model were created and results highlighted the potential of using the agent-based modeling paradigm to better simulate the effect of learning on labor productivity in the construction industry.

KEYWORDS

Construction, Labor Productivity, Learning Curve, Interaction, Agent-Based Modeling

B.1. INTRODUCTION AND RELATED WORK

Productivity rates in construction have been suffering from a lack of standards and declining over the last few decades (Shehata & El-Gohary, 2012). Productivity has always been of great importance for researchers and contractors due to the fact that it directly affects time and cost of construction projects. In construction, productivity mostly refers to labor performance. The evaluation effort to estimate the effect of a change in a work environment has increased the focus on analyzing factors affecting productivity (Lee, 2007, Hinze, 2011). Many studies have focused on collecting factors that affect labor productivity in construction (Lee, 2007, Singh, 2010, Hafez et al., 2014). Overtime, over-manning, congestion, shift work, weather, and the learning curve were identified as the major factors that affect the productivity of work (Lee, 2007). Many equations derived from real case studies were used to estimate the effect of each factor (Thomas et al., 1990, Gunduz, 2004, Awad et al., 2005). Some attempts have been made to combine multiple factors as the resulting effect is different when more than one factor occurs and is actually a better representation of the real construction world (Lee, 2007). Other studies have estimated the effect of these factors from surveys conducted on participants from different projects and statistical analysis (Singh, 2010, Hafez et al., 2014). Among many factors that impact construction labor productivity (Gunduz 2004, Hanna et al. 2005, Lee 2007, Singh 2010, Hinze 2011, Hafez et al. 2014), the learning curve has long been proven to be of paramount importance (Wright 1936).

The concept of learning curve was first proposed by Wright (1936). The learning curve theory states: “Whenever the production quantity of a product doubles, the unit or cumulative average cost required for production, i.e., man-hours, cost, or time, declines by a certain percentage of the previous unit or cumulative average rate. This percentage is referred to as the “learning rate,” which identifies the learning achieved in the process.” (Jarkas, 2010). This theory is applicable only if the work is repetitive, continuous (with no interruptions), and identical (Jarkas, 2010). Learning curve models show the relationship between the cycle number and the time per cycle as a mathematical equation. Many models have been developed to illustrate such a phenomenon. These models include: (1) The

Straight-Line Model (2) The Stanford “B” Model (3) The Cubic Power Model (4) The Piecewise Model; and (5) The exponential model. Most previous studies adopted the straight-line (Wright’s) model as a basis for their studies (Hijazi et al., 1992, Naresh & Jahren, 1998, Chen et al., 2009, Taylor et al., 2009, Jarkas, 2010, Shehata & El-Gohary, 2012, Pellegrino el al., 2012, Panas & Pantouvakis, 2014). The straight-line model was chosen for its simplicity and for the goal of simulation.

Although many learning curve models have been developed to reflect the effect of learning on productivity, no single model incorporated all different factors affecting the learning. As a result, developing a model that can be adopted for all kinds of tasks related to different industries is not reasonable. These factors should be taken into consideration when estimating labor productivity, estimating the cost of a delay, or estimating durations of different tasks using a learning curve model. Some factors causing learning has been identified in construction that include: the increase in workers’ familiarity, improved coordination of crews and equipment, improved job organization, better engineering support, better management and supervision, developed techniques and methods, development in material supply systems, and stabilized design leading to fewer modification and rework (Thomas et al., 1986). In some other study, it was stated that “learning rate is greatly influenced by various factors” and provides the main factors that affect the learning rate in construction (Hijazi et al., 1992). These factors were put into four main categories: management, labor, project, and task characteristics.

In order to better represent the aforementioned factors affecting learning and include them in studies, automated tools in particular simulation tools were deemed necessary. Three main simulation techniques have been used over the past few decades. Discrete-Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM) have been adopted for illustrating any phenomenon that is affected by many factors. DES has been widely and more commonly used as a simulation technique in construction with many researchers adopting DES as the modeling approach for their studies. Among these studies, two stand out as the most relevant to this topic and were found to have used DES to illustrate the effect of learning curve as a factor of labor productivity. The first study was done in 1994 by Lutz (Lutz et al., 1994). Discrete-event modeling was conducted using an improved MicroCYCLONE package that models the impact of learning based on the Boeing (Wright) learning curve. The simulation was improved to include input parameters of learning. Seven operations including 43 processes were modeled (processes that incorporate improvement). As a conclusion of this study, the use of learning-development modeling provides more realistic production forecasting, more accurate scheduling and budgeting, more competitive bidding, and improved system performance. Another study that also used DES is done by Panas (Panas & Pantouvakis, 2014). In this study, statistical analysis and Discrete-event simulation were done using an enhanced simulation platform named CaissonSim and by using Stroboscope simulation language. The results were evaluated by changing learning rates. Learning rates were plotted as a triangular distribution. Input data were collected form a case study for simulation and a statistical analysis was executed to predict future performance. The least mean-squares method was used to determine the learning rate for every activity. The point where no additional improvements occur is set prior to the simulation. It has been concluded in this study that the learning phenomenon has significant impact on productivity of caisson operations and both the simulation and statistical approaches yield satisfactory results. System Dynamics (SD) have been used as a tool to model labor productivity in construction (Nasirzadeh & Nojedehi, 2013). Researchers developed a SD model that illustrates a cause and effect modeling of factors affecting labor productivity. This modeling can highlight the important factors that affect labor productivity in order to take corresponding actions to prevent loss in labor productivity. On the other hand, Agent-Based Modeling (ABM), was found in the early 90s (Grigoryev, 2015). It is not used as widely as Discrete-Event simulation (DES).

ABM is an agent-oriented technique that focuses on defining agents' behaviors and relationships among different agents. This interactive environment would let the simulation emerge resulting from interaction between different agents and from interaction between agents and the environment. For instance, in a study done by Watkins (Watkins et al., 2009), an ABM model was developed to simulate congestion as a factor affecting labor productivity. This study simulated congestion that accounts for spatial locality rather than the average space for each worker. In this regards, congestion can be estimated in a simulation manner that cannot be done manually. This illustrates the importance of simulation in providing close-to-reality scenarios. Agents in this study were tasks and workers. This study concluded that ABM can depict a more realistic environment whereby congestion can be studied as an emergent property due to crew interactions. Another related study modeled the influence of congestion and other factors that affect productivity such as: space, safety and soil behavior. The agents chosen were: crane agent, rig agent and pile agent (Marzouk & Ali, 2013). This study has concluded that ABM is useful to estimate factors affecting labor productivity and to identify the ideal scenarios in which the loss in productivity is minimal.

Although ABM was used to model the effect of congestion (Watkins et al. 2009, Marzouk and Ali 2013) and safety (Marzouk and Ali 2013) on labor productivity but the effect of learning development was not modeled. As a matter of fact, it was stated in prior ABM efforts that the limitation was the exclusion of the learning curve effect (Watkins et al. 2009). Additionally, as a proactive complex process to simulate, learning is better be modeled by a proactive technique that can well depict its actual state. ABM defines the agents and their behaviors, and the simulation emerges from the interactions among those agents. This in turn can represent the learning phenomenon in a better way as learning is a heterogeneous process.

B.2. METHODOLOGY

The methodology adopted in this study is divided into four tasks: (1) construction process description, (2) agent-based simulation model design and development, (3) verification and face validation of the ABM model through animation, and (4) simulation data statistical analysis.

B.2.1 Construction process description

In order to best illustrate the learning curve effect, a process of repetitive nature must be selected. Typically, high-rise buildings projects incorporate many tasks of this nature whereby the floors are almost identical and learning can be witnessed. For that reason, a case study of a multi-story building was selected and only typical activities related to the structural construction, in particular erecting forms, installing steel rebars, and pouring concrete were modeled. Based on the RS Means Building Construction Cost Data book (RS Means Building Construction Cost Data, 2014), the daily outputs of the aforementioned activities together with respective crews were estimated as shown in Table B-1, in particular for a slab and a wall.

Table B-1: Productivity rates and crews

Task	Task Type	Daily Output	Crew	Nb. of Crews
Single Slab	Erect slab forms	470 S.F.[44 m^2]	1 Foreman, 4 Carpenters	4
	Install steel rebars	2.9 Ton [2.6 Ton]	4 Rodmen	3
	Place concrete	160 C.Y. [122 m^3]	1 Foreman, 5 Laborers	1
Single Wall	Install steel rebars	4 Ton [3.6]	4 Rodmen	3
	Erect Forms	280 S.F. [26 m^2]	1 Foreman, 4 Carpenters	4
	Place concrete	95 C.Y. [73 m^3]	1 Foreman, 5 Laborers	1

It is worth mentioning that the RS Means is considered as one of the best cost and productivity manuals according to professionals from the construction industry (RS Means Building Construction Cost Data, 2014). Needless to say, productivity rates vary from country to country, site to site, crew to crew. However, this does not pose a problem in this study as the objective is to evaluate the effect of learning on labor productivity rather than calculate the exact duration of the project.

B.2.2 Agent-Based model

An ABM model is typically composed of agents whose behaviors are defined by state-charts. State-charts consist of the different states an agent can take and these states are linked by transitions defining the underlying model logic. In this study, the proposed ABM model consists of five agent types, namely steel crews, formwork crews, concrete crews, slabs and walls. These agent types can be divided into two categories: the crews (active agents) and the constructed entities (inactive agents) (Figures B-1 and B-2). The crews' agents are active and interact with each other in the ABM model in order to simulate the learning phenomenon, whereas the constructed entities are inactive and their interaction within the model dictates the condition of the entity. Although in reality the type of work affects the behavior of the respective crew, it was however assumed that all crews have a similar behavior and state-charts. The same applies for constructed entities. To that end, only one of each is explained. As shown in Figure B-2, the slab agent has eight states. The first one named *Constrained* is the initial state of every slab and wall. Construction can not begin for any element if it is under the *Constraine*d state. The transition from *Constrained* to *NotConstructed* is triggered by the message "unconstrained". This message is sent in the following cases: (1) On start-up, the floor slab directly moves from *Constained* to the state *NotConstructed* since it has no predecessors; (2) Each time a slab is done, the wall to be built on top of it becomes *Unconstrained*; and (3) Each time a wall is done, the slab above it becomes *Unconstrained*. When a slab moves to the *NotConstructed* state, it sends the message "move to slab" to the formwork crew agent. As shown in Figure B-1, this message allows it to move from its initial state *Idle* to the state *WorkingSlab* and with this transition it sends a message to the slab to move from *NotConstructed* to *FormWorkErection* signaling that the formwork for the slab is currently being erected. The crew becomes idle again once the formwork erection task is complete. As such, one of the most important transitions in the model is the one that moves the crew from the working state to the idle state. In fact, this transition of type timeout represents the duration it takes to complete a certain task and varies each time the crew goes through its specific transition. In order to model the learning curve phenomenon, the timeout duration was computed in such a way it is gradually decreasing with each task repetition according to the aforementioned learning curves models. Once the specified time elapses, the crew moves back to the state *Idle* and the slab moves to the state *FormWorkDone*. The same process is then repeated for other slab related steel and concrete activities with their respective crews. The whole process is then repeated for walls. The state-charts keep interacting until the whole building is completed.

To add flexibility to the model and allow the user to try different scenarios and test different learning curve methods, the user, before running the simulation model, is prompted to select any of the five learning curve models as shown in Figure B-3. The corresponding formula then appears on the screen and the user input the needed parameters allowing him to model a specific scenario. The model then outputs the total project duration and graphs reflecting the evolution of the duration required for the completion of each task under the learning curve effect.

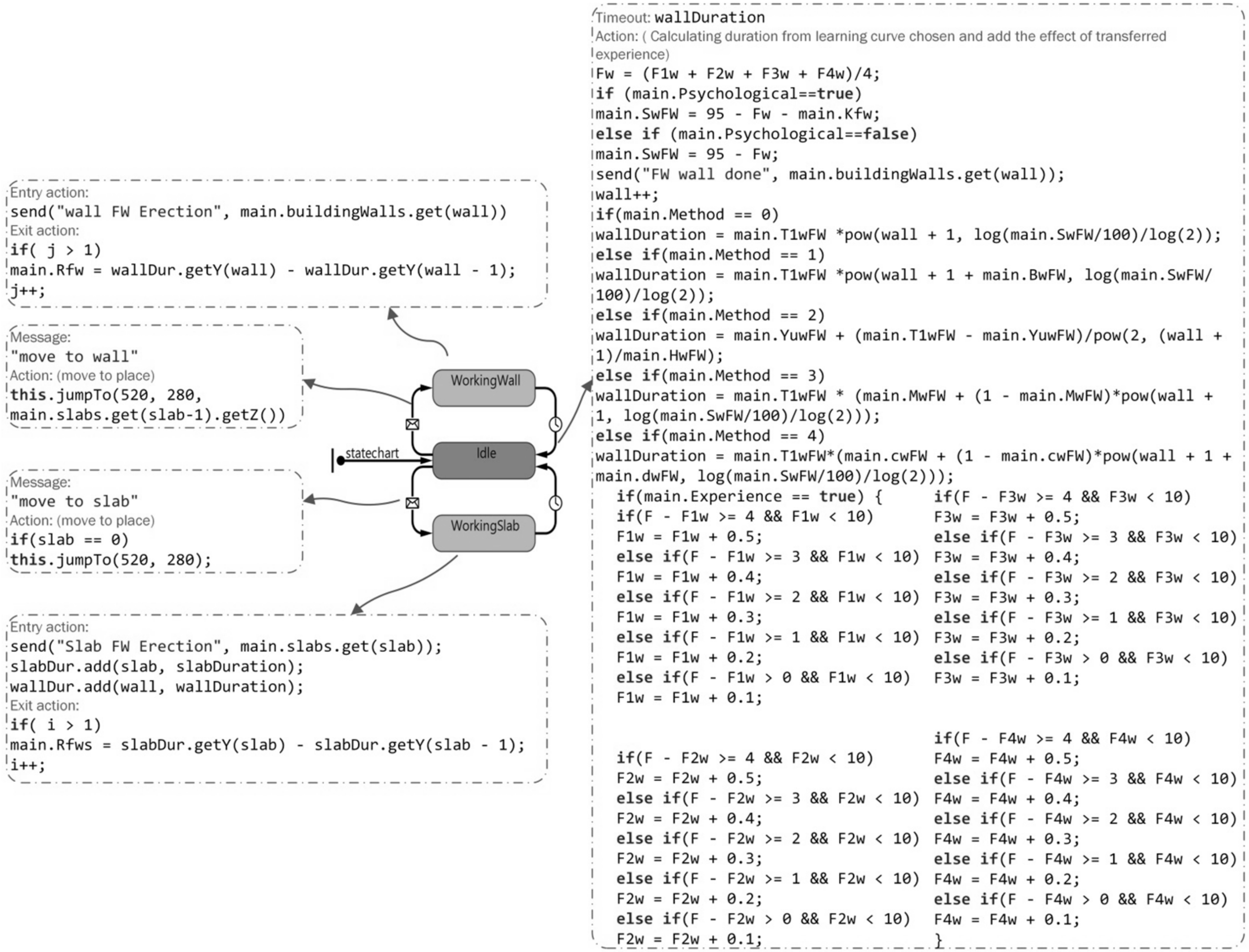


Figure B-1: Statechart of Crews Agents

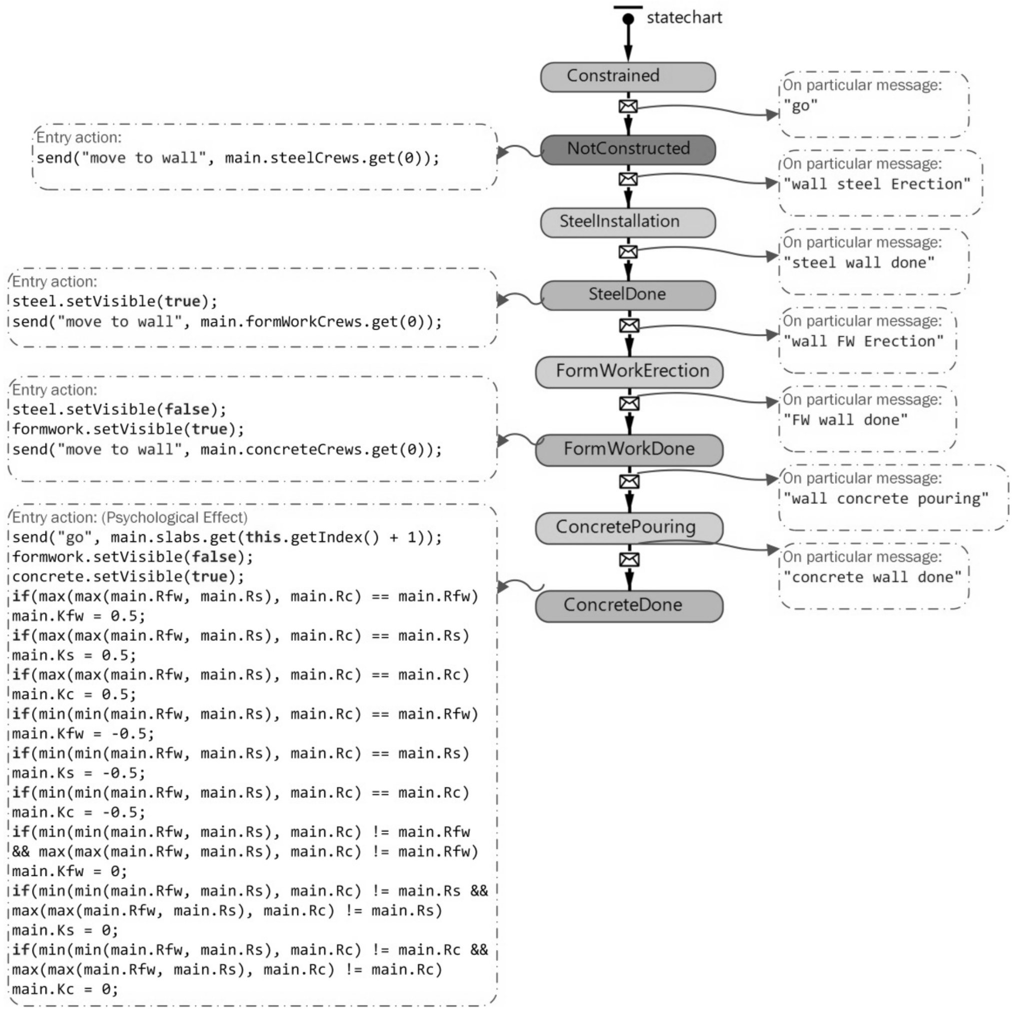


Figure B-2: Statechart of Slab/Wall agents

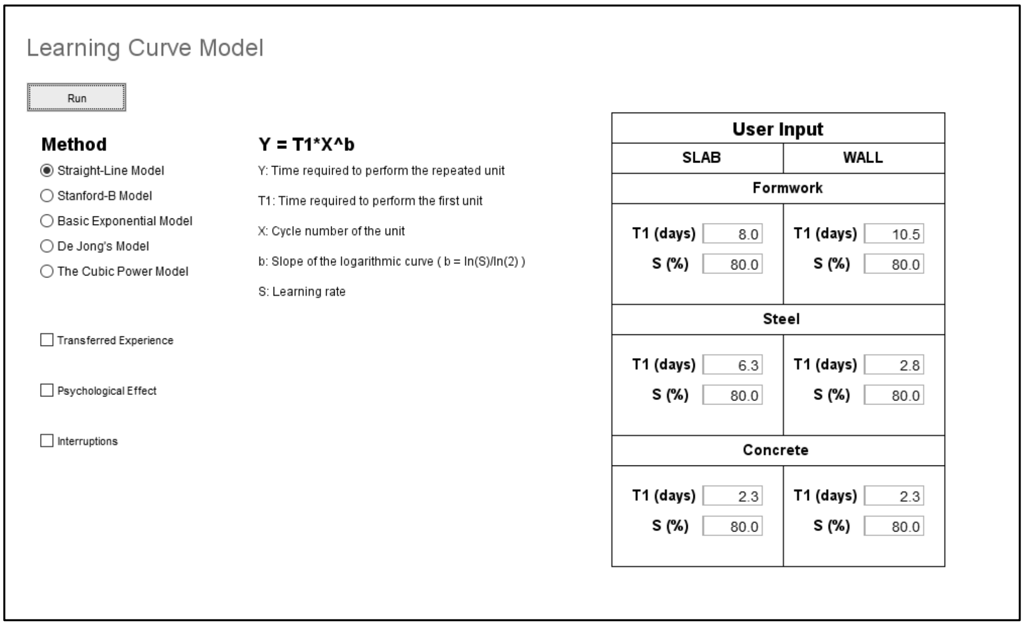


Figure B-3 : Initial simulation screen

In order to render the model more realistic and depict a better learning environment, it was decided to add other types of interactions, not only crew-structural element interaction. Since the bulk of the learning involved on a construction site results from worker's learning as shown in Table A-1 (i.e. 40%), the interactions added were thereby worker related, including interactions between different crews and within members of a crew represented in this case by crew agent's parameters. More specifically, the transferred experience and the psychological effect were chosen as factors affecting worker's learning. Additionally, work interruptions were included in the model since they affect worker's learning due to the forgetting phenomenon. All factors were modeled as follows:

1. Transferred experience effect

This factor applies to the interaction between individual crew members, as workers with high previous experience affect the ones with lower experience. Previous experience was already included in the Stanford model as B factor, but the transferred experience factor is different and represents how less experienced workers improve when learning from more experienced ones within the same crew. This is reflected in the model by assigning a parameter F for each worker within a crew, and workers with high previous knowledge increase the knowledge of unexperienced workers. The resulting average F corresponding to the average level of experience of the crew determines thereby the value of the learning rate. This rate is a variable affected by the experience and knowledge transferred within each crew. Based on the literature, the learning rate value varies between 80% and 95% in construction. The lower the learning rate, the more improvement is witnessed with each repetition. As such, the learning rate was set to (95% - Favg) in the proposed model. An experience between 0 and 10 was assigned randomly to each worker within a crew. Each worker's experience below the average experience of the crew was increased by a certain weighted percentage with every repetition. The weights of this increase in experience (i.e.reduction in learning rate) are shown in Table B-2.

Table B-2: Weight of transferred experience effect

Experience below average by	Increase in worker's experience
0→1	0.1
1→2	0.2
2→3	0.3
3→4	0.4
≥4	0.5

For comparison purposes, the initial experience of each worker in the five-member crews was assigned a value as illustrated in Table B-3. Crews with 4 workers were assigned the same experience parameter numbers excluding the worker number 3.

Table B-3: Initial experience of workers in a crew

Worker number	Experience Parameter F
1	8
2	6
3	5
4	3
5	1

The aforementioned effect is illustrated through the code snippet below (Figure B-4):

```
if(main.Experience == true) {
if(F - F1w >= 4 && F1w < 10)
F1w = F1w + 0.5;
else if(F - F1w >= 3 && F1w < 10)
F1w = F1w + 0.4;
else if(F - F1w >= 2 && F1w < 10)
F1w = F1w + 0.3;
else if(F - F1w >= 1 && F1w < 10)
F1w = F1w + 0.2;
else if(F - F1w > 0 && F1w < 10)
F1w = F1w + 0.1;

if(F - F2w >= 4 && F2w < 10)
F2w = F2w + 0.5;
else if(F - F2w >= 3 && F2w < 10)
F2w = F2w + 0.4;
else if(F - F2w >= 2 && F2w < 10)
F2w = F2w + 0.3;
else if(F - F2w >= 1 && F2w < 10)
F2w = F2w + 0.2;
else if(F - F2w > 0 && F2w < 10)
F2w = F2w + 0.1;

if(F - F3w >= 4 && F3w < 10)
F3w = F3w + 0.5;
else if(F - F3w >= 3 && F3w < 10)
F3w = F3w + 0.4;
else if(F - F3w >= 2 && F3w < 10)
F3w = F3w + 0.3;
else if(F - F3w >= 1 && F3w < 10)
F3w = F3w + 0.2;
else if(F - F3w > 0 && F3w < 10)
F3w = F3w + 0.1;

if(F - F4w >= 4 && F4w < 10)
F4w = F4w + 0.5;
else if(F - F4w >= 3 && F4w < 10)
F4w = F4w + 0.4;
else if(F - F4w >= 2 && F4w < 10)
F4w = F4w + 0.3;
else if(F - F4w >= 1 && F4w < 10)
F4w = F4w + 0.2;
else if(F - F4w > 0 && F4w < 10)
F4w = F4w + 0.1;
}
```

Figure B-4: Transferred Experience Effect

2. The psychological effect

This factor applies particularly to the interaction between different crews. The psychological effect is generally complex and can not be accurately estimated. Furthermore, this effect can be affected by on-site accidents, weather conditions, fatigue, etc. However, how a crew can be motivated or demotivated by other crews was only modeled. In this case, the crew can be either motivated by a more productive neighboring crew and as a result increases its productivity, or it can be affected negatively by a less productive crew and decreases its productivity. This was modeled as follows: with each repetition, the crew with the lowest productivity improvement feels the need to double its efforts in comparison to other crews, and therefore the crew's learning rate was decreased by 0.5% (Table B-4). Similarly, the crew with the highest productivity improvement feels comfortable regarding its performance and its learning rate was increased by 0.5% (Table B-4).

Table B-2: Psychological effect weights

Affected crew	Type of effect	Change in learning rate
The least productive	Motivation, challenge	-0.5 %
The most productive	Boredom, overconfident	+0.5 %

The aforementioned effect is illustrated through the code snippet below (Figure B-5):

```
Entry action: (Psychological Effect)
send("go", main.slabs.get(this.getIndex() + 1));
formwork.setVisible(false);
concrete.setVisible(true);
if(max(max(main.Rfw, main.Rs), main.Rc) == main.Rfw)
main.Kfw = 0.5;
if(max(max(main.Rfw, main.Rs), main.Rc) == main.Rs)
main.Ks = 0.5;
if(max(max(main.Rfw, main.Rs), main.Rc) == main.Rc)
main.Kc = 0.5;
if(min(min(main.Rfw, main.Rs), main.Rc) == main.Rfw)
main.Kfw = -0.5;
if(min(min(main.Rfw, main.Rs), main.Rc) == main.Rs)
main.Ks = -0.5;
if(min(min(main.Rfw, main.Rs), main.Rc) == main.Rc)
main.Kc = -0.5;
if(min(min(main.Rfw, main.Rs), main.Rc) != main.Rfw
&& max(max(main.Rfw, main.Rs), main.Rc) != main.Rfw)
main.Kfw = 0;
if(min(min(main.Rfw, main.Rs), main.Rc) != main.Rs &&
max(max(main.Rfw, main.Rs), main.Rc) != main.Rs)
main.Ks = 0;
if(min(min(main.Rfw, main.Rs), main.Rc) != main.Rc &&
max(max(main.Rfw, main.Rs), main.Rc) != main.Rc)
main.Kc = 0;
```

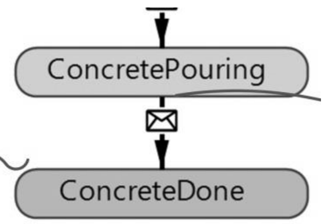


Figure B-5: Psychological Effect

3. Interruptions effect (forgetting)

The reasons for on-site interruptions include but are not limited to management decisions (or owner), unavailability of materials and tools, or weather conditions. As the work stops, losses in learning start to develop due to forgetting. This effect was modeled in Anylogic using an Event. This event is assumed to occur occasionally using a Poisson distribution. A rate of 1 interruption/hr. was chosen as interruptions randomly differ between 1 and 2 days. As a result, each time the simulation runs, it gives different values. A small duration has been assigned to interruptions to develop moderate graphs of learning curves. The effect of interruptions was set for each crew separately and was assumed as shown in Table B-5.

Table B-3: Weights of interruptions effect

Interruption time (days)	Change in learning rate
≤ 0.5	+0.5 %
0.5 → 1	+1 %
1 → 1.5	+2 %
1.5 → 2	Reset to initial value (80)

The interruption effect explained above is depicted in the following code snippet (Figure B-6):

Interruption

```
if(inState(WorkingSlab) ){
if(IntFW <= 2){
main.SFW = main.SFW + 0.5;
slabDuration = slabDuration + IntFW;
}
else if(IntFW <= 5){
main.SFW = main.SFW + 1;
slabDuration = slabDuration + IntFW;
}
else if(IntFW <= 10){
main.SFW = main.SFW + 2;
slabDuration = slabDuration + IntFW;
}
else if(IntFW > 10){
main.SFW = 80;
slabDuration = slabDuration + IntFW;
}}
else if(inState(WorkingWall)){
if(IntFW <= 2){
main.SwFW = main.SwFW + 0.5;
wallDuration = wallDuration + IntFW;
}
else if(IntFW <= 5){
main.SwFW = main.SwFW + 1;
wallDuration = wallDuration + IntFW;
}
else if(IntFW <= 10){
main.SwFW = main.SwFW + 2;
wallDuration = wallDuration + IntFW;
}
else if(IntFW > 10){
main.SwFW = 80;
wallDuration = wallDuration + IntFW;
}}

else if(inState(Idle)){
nothingChanged();
}
IntFW = roundToInt(random()*12);
```

Figure B-6: Interruptions Effect

B.2.3 Animation and Visualization

It has been long stated that a primary disadvantage in the use of simulation models is the inability of checking the credibility of the models and the authenticity of the results (Khoury et al., 2007). Visualization and animation of simulated operations can be very helpful in the verification and validation of models (Khoury et al., 2007; Sargent, 2013). In other words, displaying the model's operational behavior in 3D allows the user to verify that the code is free of errors and assure that the model is a good representation of the real world and its behavior is reasonable (i.e. face validity). As such, the simulation model presented earlier can be verified by animating the process in 3D.

B.2.4 Statistical Analysis of Data

Two sets of statistical analyses were performed on the data resulting from the simulation (Appendix C.1) using R Project for Statistical Computing (Gandrud 2013). The first set compares learning curves before and after incorporating different learning factors for the four different learning models. The objective of this analysis consists of checking whether there is significant difference in learning by incorporating different factors affecting the learning rate. This analysis was done for all learning curve models (Straight-line model, Stanford B model, De Jong's model, and the cubic model) except for the exponential one that does not include a learning rate component in its equation. More specifically, for each learning model, experiments were performed on the three different activities (i.e formwork, concrete, and steel) for both slabs and walls before and after incorporating learning factors. On the other hand, the second analysis is focused on comparing the different learning models for each activity type before and after incorporating additional factors of learning. This analysis is done to check whether there is significant difference in learning curve models that requires the use of other more complex models.

Table B-6 summarizes the two hypotheses tested in both stages of this analysis. Both stages are further explained below. Addtionally, Type 1 error of 0.05 was chosen and the respective R code is available in Appendix C.5.

Table B-4: Hypothesis Testing

Stage	Null Hypothesis	Alternative Hypothesis
1	There is no significant difference in duration with or without adding the influence of transferred experience, psychological effect, and interruptions as factors affecting learning	There is significant difference by adding the influence of transferred experience, psychological effect, and interruptions as factors affecting learning
2	There is no significant difference in duration between different learning curve models before or after incorporating factors affecting learning	There is significant difference in duration between different learning curve models before or after incorporating factors affectng learning

Stage 1

The data before and after incorporating learning curve factors were read and plotted using histograms and boxplots (check Appendix C.4.1). Then, each crew was analyzed separately for the three different tasks (formwork, concrete work, and steel work) of both slabs and walls. Shapiro tests were conducted to check if the data is normally distributed. Normality of data was not met and since the boxcox function could not transform the data into normality, Non-Parametric Tests were performed. In this case, Wilcox Signed-Ranks Test was chosen as it analyzes paired data of two samples (before and after incorporating learning factors). Data in this stage is assumed to be paired as each floor's task duration before adding the effect of learning parameters is compared to the one after adding these parameters.

Stage 2

As a first step, data was plotted as boxplots to get an idea about the changes between different learning curve models. Since the data in Stage 1 was identified as not normal, Non-Parametric tests were conducted. In this case, since more than two samples are available (4 learning curve models), Kruskal Wallis Test was chosen. After a difference in learning curve models was noted, multiple-comparison tests, in particular the Pairwise Wilcoxon Rank Sum Test was conducted to identify the model that led to the highest difference in activity's duration.

B.3. CASE STUDY: RESULTS, DISCUSSION, AND ANALYSIS

A case study of a multi-story building (50 stories) in the region of Beirut, Lebanon was adopted. The building consists mainly of a core wall, slabs and exterior walls. As mentioned earlier, only activities related to the structural construction, in particular erecting forms, installing steel rebars, and pouring concrete were modeled. The corresponding areas of formwork, volumes of concrete and steel needed were calculated and are summarized in Table B-7.

Table B-7: Materials Takeoff

Task	Area of Formwork (m^2)	Steel (ton)	Concrete (m^3)
Single Slab	982	39	196
Single Wall	778	23	117

B.3.1 Agent-Based Model Results and Discussion

Based on the case study data provided in Table B-7, the proposed ABM model was run using each of the aforementioned methods (i.e. Straight-Line, Stanford "B", De Jong, and Cubic Power) and then verified through animation (i.e face validation) to ensure an error-free process (Figure B-7).

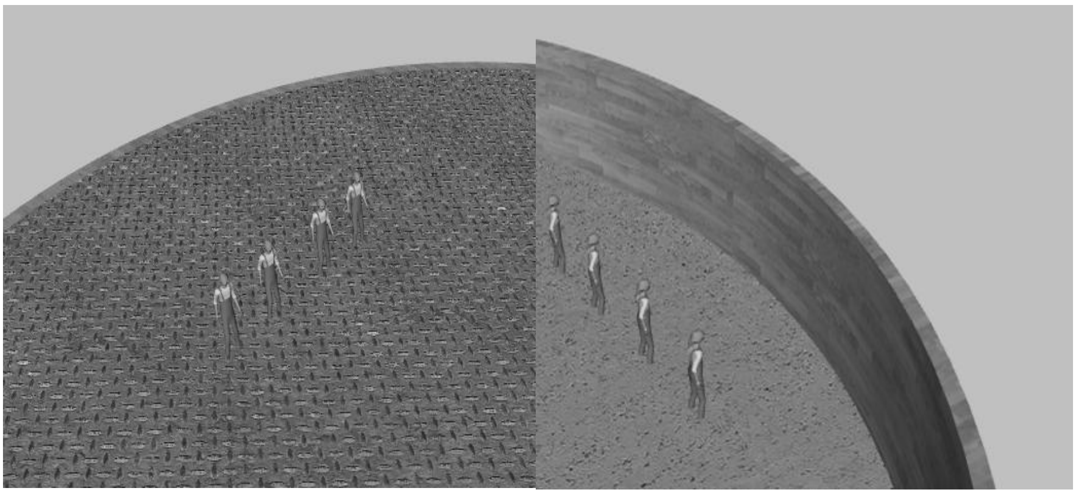


Figure B-7: Simulation of workers performing formwork and steel tasks

Figures B-8 through B-10 depict the respective learning curves (time or duration vs. floor number) for the different slabs activities under each method and with and without the inclusion of the additional interaction variables. Similarly, Figures B-11 through B-13 illustrate those for the walls activities. By comparing the graphs, it can be concluded that the application of the ABM model or the inclusion of the different interaction levels between workers leads to different results, especially in the case of work interruptions depicted as sudden jumps in the learning curves and leading to higher duration values per unit of work. In this case, the height of each jump represents the time of interruption. Some of these curves included several interruptions (e.g. Slab formwork-De Jong and Slab Formwork-Stanford), whereas others showed little or no interruption (e.g. Wall Concrete-Linear). This is due to the fact that the simulation develops different scenarios depending on the run, and with additional runs, the resulting data would change to reflect a different scenario in the interactive environment of ABM. On the other hand, the transferred experience and psychological effect factors are embedded continuously along the curve. In the case of a positive combined experience and psychological effect, productivity rates improve leading thereby to lower duration estimates as shown in Figures B-8 through B-13. Needless to say, that a negative combined experience and psychological effect leads to lower productivity rates and higher duration estimates.

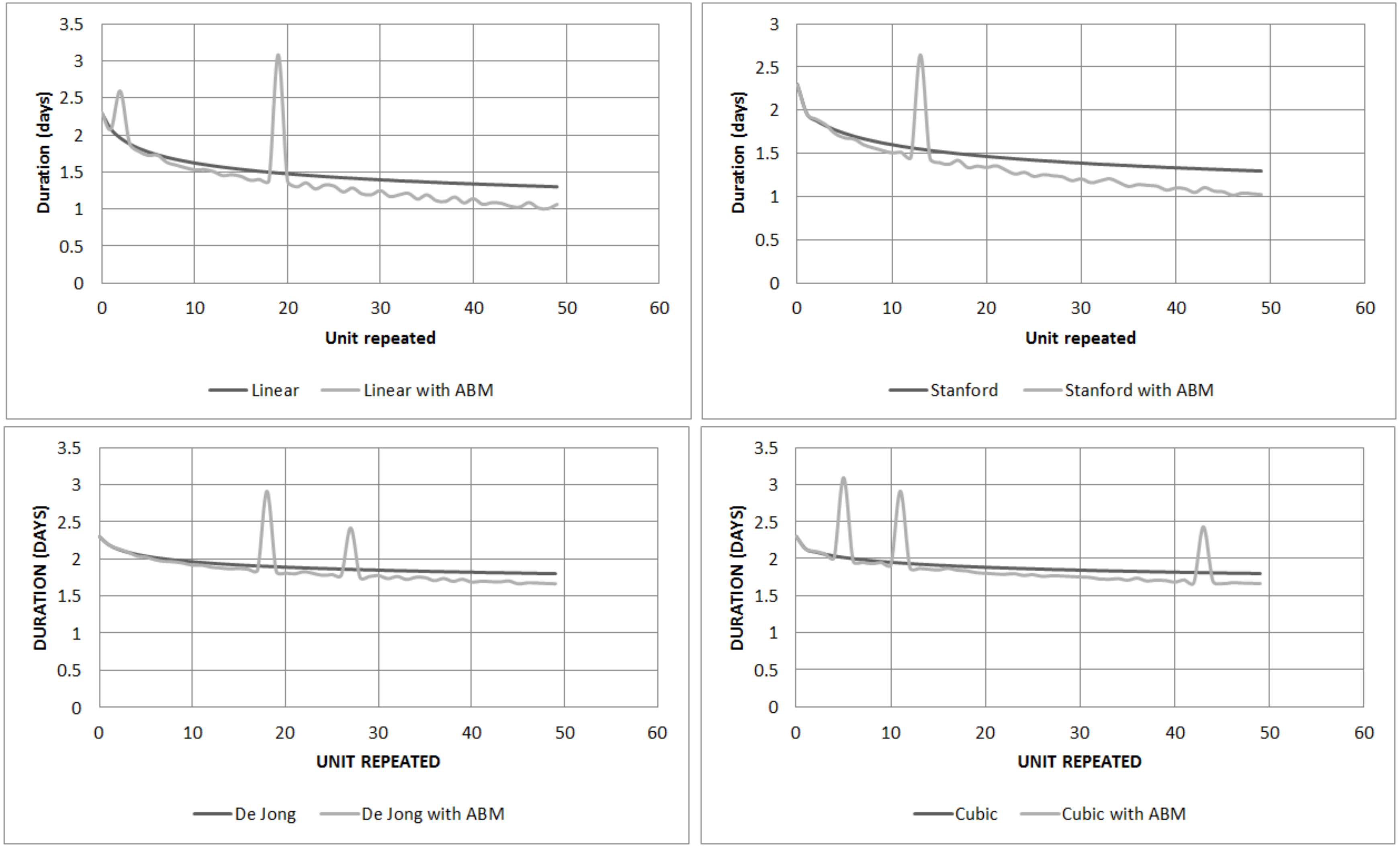


Figure B-8: Plots of Learning Curves before and after ABM for Slab Concrete work

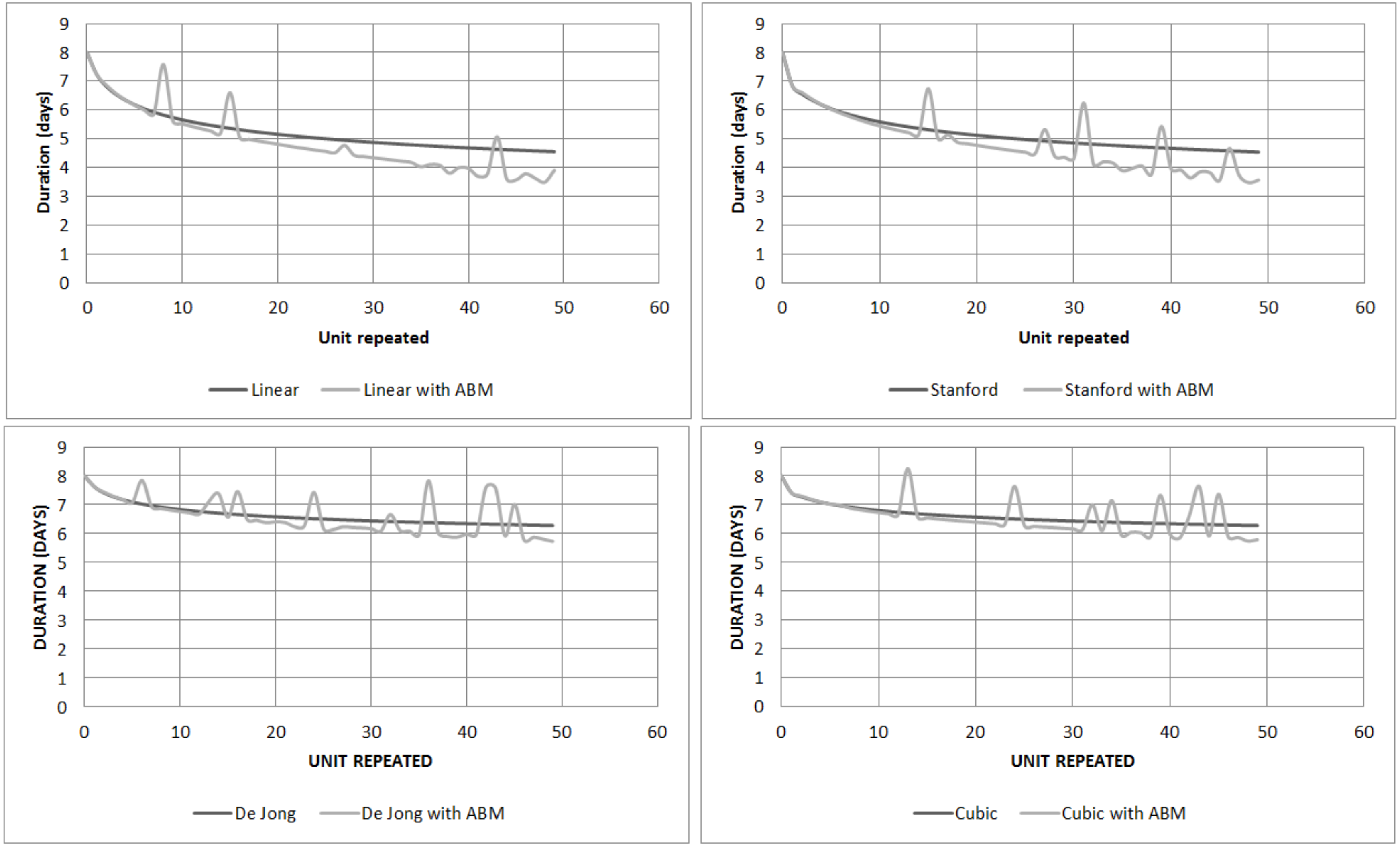


Figure B-9: Plots of Learning Curves before and after ABM for Slab Formwork

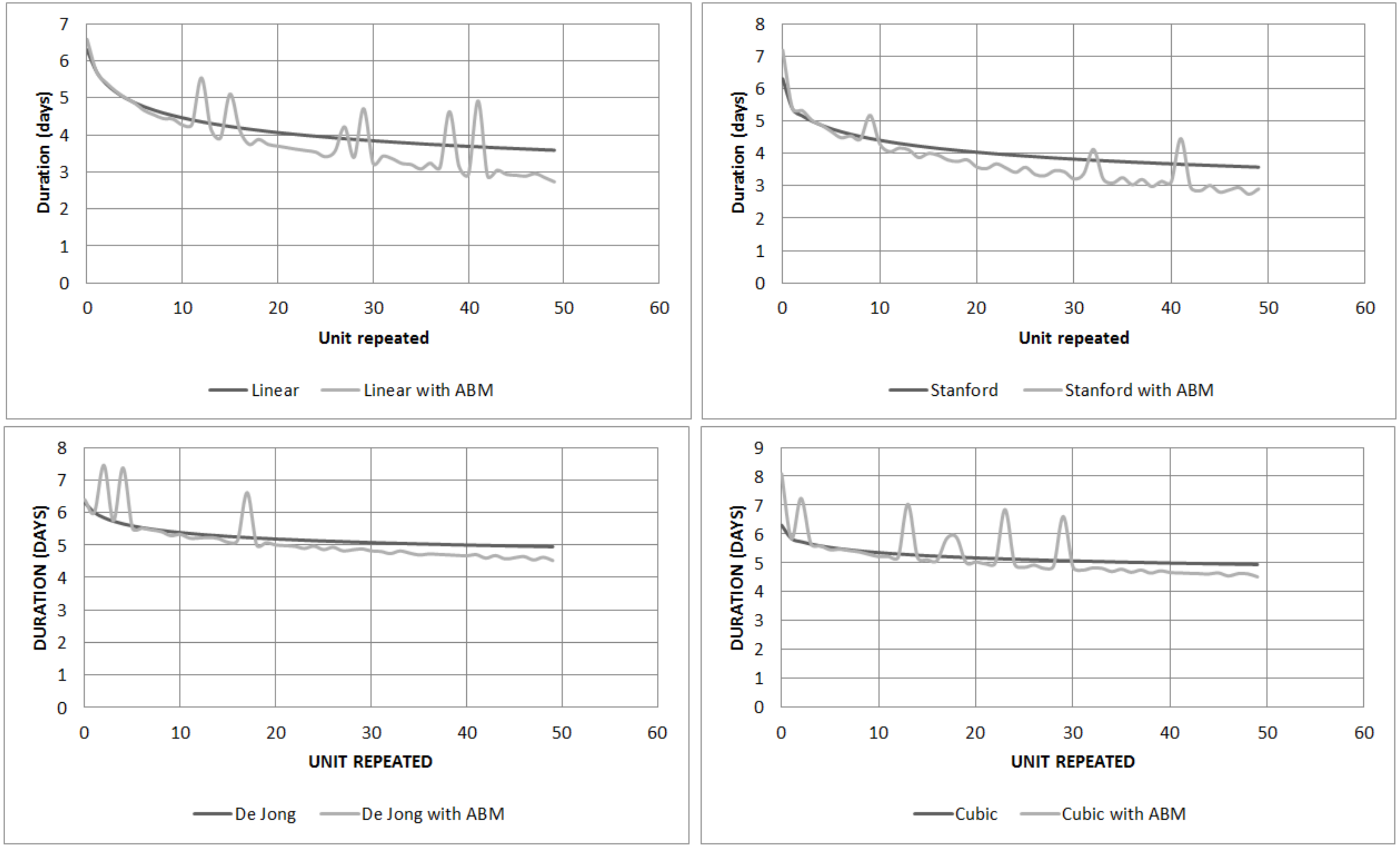


Figure B-10: Plots of Learning Curves before and after ABM for Slab Steel Work

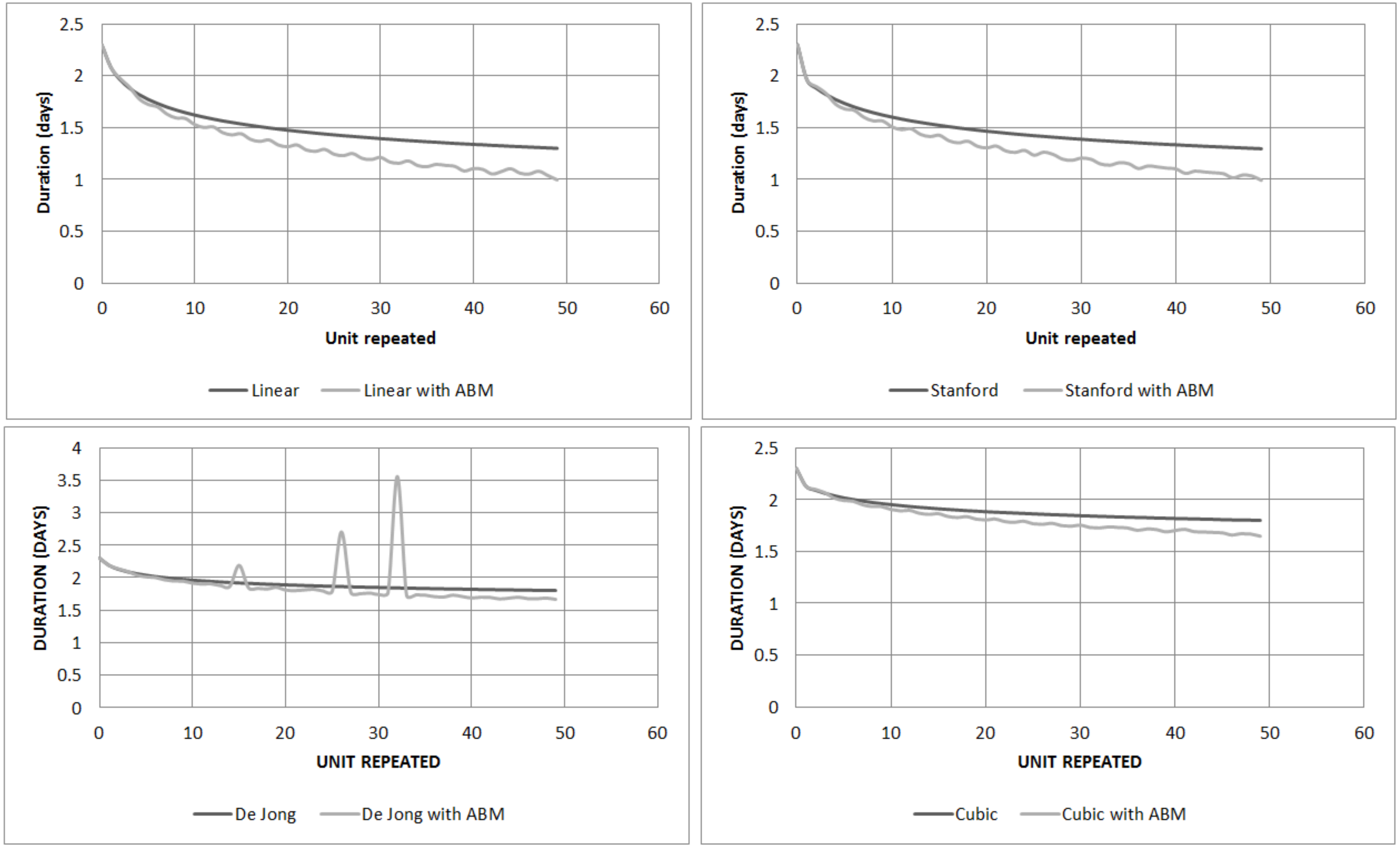


Figure B-11: Plots of Learning Curves before and after ABM for Wall Concrete Work

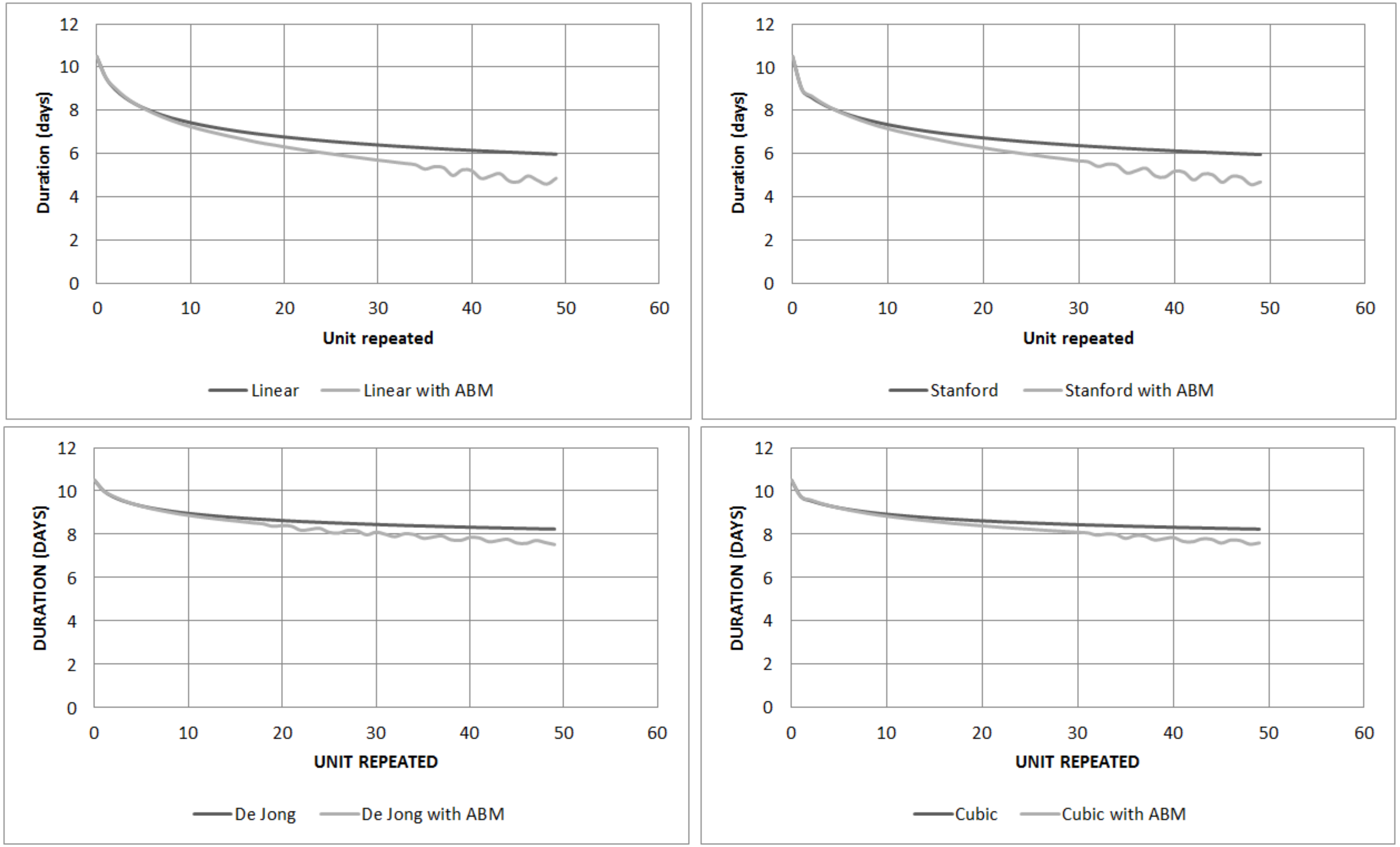


Figure B-12: Plots of Learning Curves before and after ABM for Wall Formwork

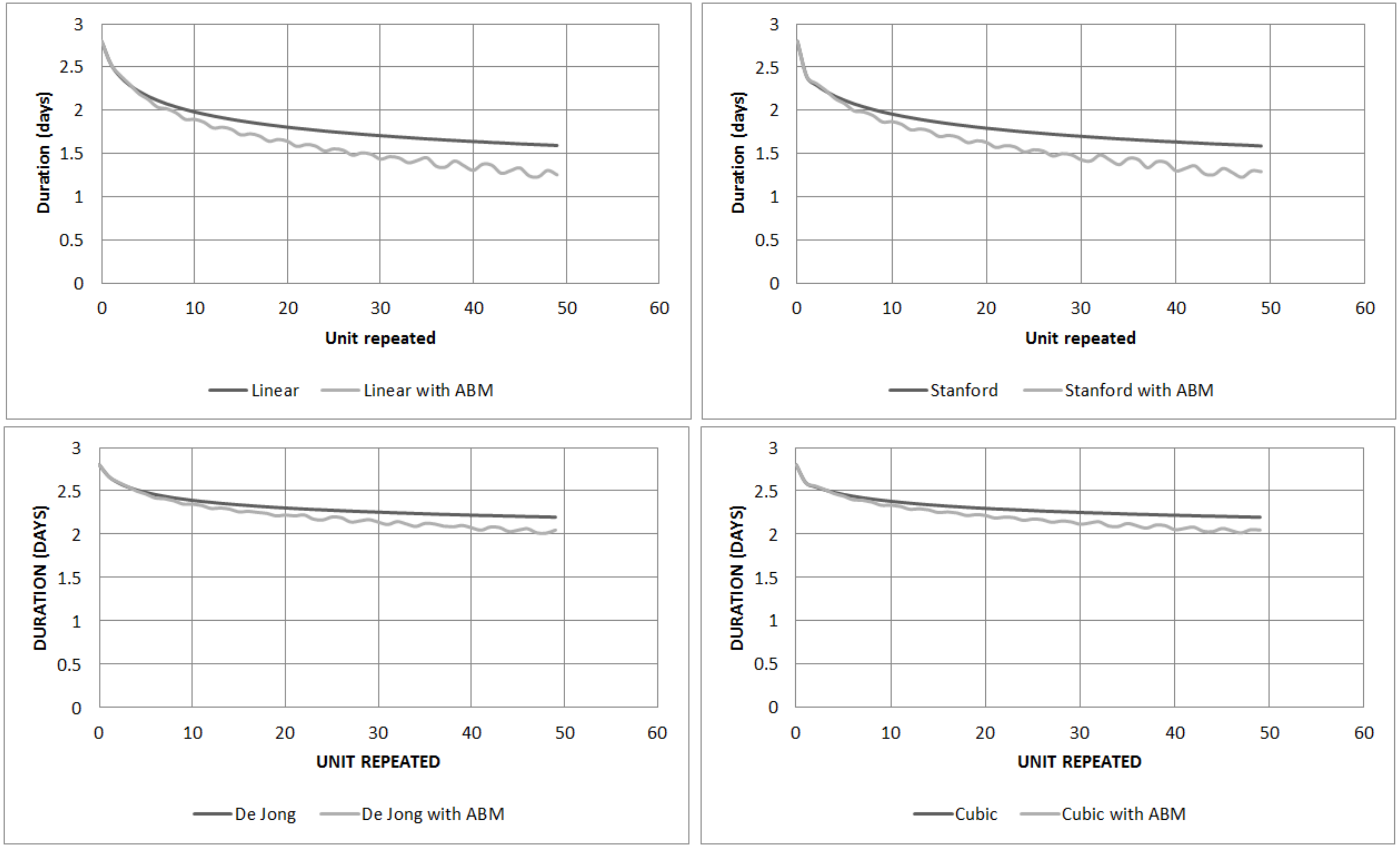
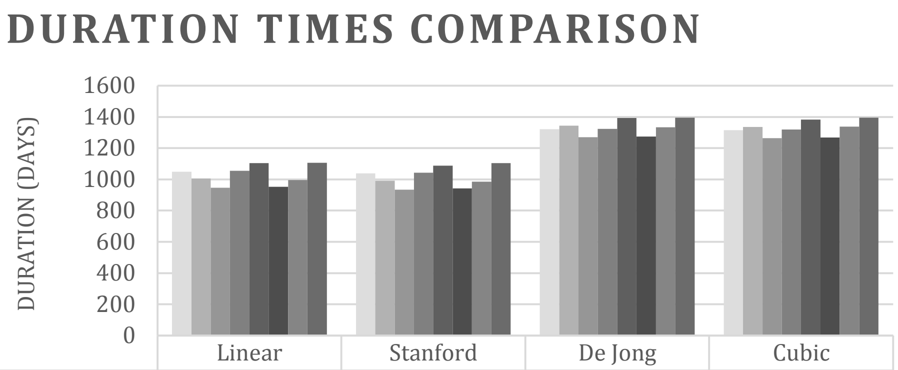


Figure B-13: Plots of Learning Curves before and after ABM for Wall Steel Work

The total project duration was then computed using each of the four models of learning and considering different scenarios created due to a various combination of the learning factors (transferred experience, psychological effect, and interruptions). A comparison of duration estimates for different scenarios is illustrated in Figure B-14.



	Linear	Stanford	De Jong	Cubic
No factors	1049	1038	1322	1316
All factors	1005	992	1343	1335
Transferred Experience	946	934	1270	1264
Psychological effect	1054	1043	1324	1319
Interruptions	1104	1088	1394	1383
Experience+Psychological	953	942	1274	1268
Experience+Interruptions	996	985	1333	1337
Psychological+Interruptions	1106	1104	1396	1395

Figure B-14: Duration Times Comparison For Different Scenarios

Based on Figure B-14, the transferred experience factor has a positive impact on productivity leading thereby to lower duration estimates. The psychological factor, being a combination of positive effect (motivation) and negative effect (boredom), has a slightly negative resulting impact on duration. The interruption factor impacts negatively duration estimates as work stops for a period of time. When combining two of these factors, the result is positive (i.e. better production rates and lower duration estimates) whenever the transferred experience factor is included. In this case, higher worker’s experience outweighs the negative effect of the other factors. However, the combined effect of psychological and interruption factors results in the highest duration estimates even higher when all three factors are incorporated. Additionally, the DeJong and Cubic models led to the highest duration values because their formula assumes that the work can be manual in one part and mechanized in the other, thereby limiting the worker’s interaction effect when compared to the first two models.

Even though the graphical analysis made earlier allowed reaching some basic conclusions, a more statistically rigorous analysis about each task separately was needed. As mentioned earlier, two sets of statistical analyses were performed on the data and results are presented in the following sections.

B.3.2 Statistical Analysis: Stage 1 Results

Plots of all learning curve models’ duration before and after incorporating the chosen learning factors show that data is right skewed and therefore can not be normalized using log transformation or The Box-Cox method. Activity duration estimates were mostly lower after incorporating all learning curve factors as illustrated in boxplots of data (Appendix C.4.1) since the resulting positive impact outweighed the negative one. On the other hand, Table B-7 summarizes the results of the non-parametric tests performed. The majority of these tests showed a significant difference before and after adding learning factors. As a matter of fact, a P-value $\ll 0.05$ for learning curve models refers to rejecting the null hypothesis and accepting the fact that learning curve models after incorporating learning factors differ from original ones. In all experiments, the null hypothesis was rejected except for the De Jong learning curve of the slab formwork task in which the null hypothesis was accepted and no significant difference was incorporated. This can be attributed to the interaction between positive and negative impacts resulting from the combination of transferred experience, psychological effect, and interruptions. To a certain extent, the negative impact has minimized the positive impact of these factors, and as a result the difference shrined.

For almost all results, it can be concluded that incorporating all three learning curve factors into the existing learning curve models contributes significantly in better evaluating the effect of learning on labor productivity. In other words, the resulting statistical difference shows that changes in productivity rates can happen within a unit because of some learning factors.This in turn can lead to over-estimating or under-estimating durations of activities that typically involve a certain degree of learning.

Table B-5: Stage 1 Parametric-Test results

Learning curve model	Task	P-Value	Hypothesis
Linear	Slab Formwork	2.322e-06	Alternative
	Slab Concrete Work	4.883e-07	Alternative
	Slab Steel work	0.0006938	Alternative
	Wall Formwork	2.967e-09	Alternative
	Wall Concrete Work	2.035e-09	Alternative
	Wall Steel Work	2.035e-09	Alternative
Stanford	Slab Formwork	1.768e-05	Alternative
	Slab Concrete Work	3.741e-08	Alternative
	Slab Steel work	9.144e-06	Alternative
	Wall Formwork	2.967e-09	Alternative
	Wall Concrete Work	2.035e-09	Alternative
	Wall Steel Work	2.035e-09	Alternative
De Jong	Slab Formwork	0.07516	Null
	Slab Concrete Work	5.148e-07	Alternative
	Slab Steel Work	5.217e-06	Alternative
	Wall Formwork	2.967e-09	Alternative
	Wall Concrete Work	5.394e-06	Alternative
	Wall Steel Work	2.034e-09	Alternative
Cubic	Slab Formwork	0.01858	Alternative
	Slab Concrete Work	5.395e-06	Alternative
	Slab Steel Work	0.004305	Alternative
	Wall Formwork	2.967e-09	Alternative
	Wall Concrete Work	2.035e-09	Alternative
	Wall Steel Work	2.034e-09	Alternative

B.3.3 Statistical Analysis: Stage 2 Results

This stage compares the four different learning curve models before and after incorporating the learning curve factors. Plots of this stage can be found in Appendix C.4.2. It was found that both the Linear and Stanford models led to similar results, which applies as well to the De Jong and Cubic models. Additionally, the Multiple Comparison Tests show that there is a significant difference in activities' duration between the first of models (i.e Linear and

Stanford) and the second set (i.e. De Jong and Cubic models). This can be mainly attributed to the similarity in the models' equations. Furthermore, the difference between the learning models is reduced after incorporating the learning factors as compared to before incorporating them. The reason why is because this integration of learning factors is a better representation of real-life construction activities and workers' interaction on sites. This difference between learning curve models can be further diminished if all learning factors are injected into the simulation. Although lower, a significant difference still resulted from the analysis. The results of this stage are summarized in Table B-8.

Table B-6: Stage 2 Non-Parametric and Multiple Comparison Tests' Results

Type	**Task**	**Difference**
Before Adding Learning Factors	Slab Formwork Slab Concrete Work Slab Steel Work Wall Formwork Wall Concrete Work Wall Steel Work	The linear model and the Stanford model are the same The De Jong model and the cubic model are the same -The De Jong model is significantly different than both the linear and Stanford models -The cubic is also significantly different than both the linear and Stanford models -Maximum difference is between the Stanford model with both the cubic and De Jong models
After Adding Learning Factors	Slab Formwork Slab Concrete Work Wall Formwork Wall Steel Work	The linear model and the Stanford model are the same The De Jong model and the cubic model are the same The De Jong model is significantly different than both the linear and Stanford models The cubic is also significantly different than both the linear and Stanford models Maximum difference is between the Stanford model with both the cubic and De Jong models The maximum difference is lower than the one before incorporating learning factors

Slab Steel Work	+ The similarity between the linear model and the Stanford model is slightly reduced to 93%
Wall Concrete Work	+ Maximum difference is between the Stanford model and the De Jong model + The similarity between the linear model and the Stanford model is slightly reduced to 82%

B.4. CONCLUSION AND FUTURE WORK

This study presented an agent-based model of learning whereby construction workers with different characteristics and attitudes work with each other over several activities, learn about each other's behavior, and act accordingly. The main advantages of this model over previous ones is that it allows the observation of the learning process dynamics, the interaction between the different agents, and the emergent learning patterns arising from multiple scenarios. Several simulation experiments or runs were conducted in this study given different learning models and learning rates and while incorporating three of the main factors affecting learning (transferred experience, psychological effect, and work interruptions). A two-stage statistical analysis was then performed and consequently, a comparative assessment was made about the different learning models and several observations were also made about the effect of each factor and their combination on learning which in turn might affect labor productivity and task durations.

While the proposed agent-based model has achieved promising results under different scenarios, it exhibits some limitations and further examination is needed to advance this line of research. One limitation of the model is that it considers that various crews exhibit the same behavior. This model is being developed further to account for different behaviors and attitudes among crews. Surveys and interviews with experts will be carried out to better define the assumptions underlying the factors affecting learning. Additionally, other important factors affecting learning must be included to develop a comprehensive agent-based model of learning. Finally, the model will be validated through real-life case studies and will be presented to professionals and experts to ensure credibility and authenticity of results.

ACKNOWLEDGEMENTS

The presented work has been supported by AUB's University Research Board (URB). The authors gratefully acknowledge URB support. Any opinions, findings, conclusions, and recommendations expressed by the authors in this paper do not necessarily reflect the views of URB.

REFERENCES

- Awad S. Hanna, P. M., Taylor, C. S., & Sullivan, K. (2005). Impact of Extended Overtime on Construction Labor Productivity. Constr. Eng. Manage.
- Chen, J., Taylor, J., & Unsal, H. (2009). Simulating The Effect Of Learning Decay On Adaptation Performance In Project Networks. Winter Simulation Conference.
- Gandrud, C. (2013). Reproducible Research with R and R Studio. CRC Press.
- Gunduz, M. (2004). A Quantitative Approach for Evaluation of Negative Impact of Overmanning of Electrical and Mechanical Projects. Building and Environment.
- Hafez, S., Aziz, R., Morgan, E., Abdullah, M., & Ahmed, E. (2014). Critical factors affecting construction labor productivity in Egypt. American Journal of Civil Engineering.
- Hijazi, A., AbouRizk, S., & Halpin, D. (1992). Modeling And Simulating Learning Development In Construction. Journal of Construction Engineering and Management, 118:685.
- Hinze, J. W. (2011). Chapter 11: the impact of scheduling decisions on productivity. In Construction Planning and Scheduling, 4th Edition.
- Jarkas, A. (2010). Critical Investigation into the Applicability of the Learning Curve Theory to Rebar Fixing Labor Productivity. Constr. Eng. Manage., 1279-1288.
- Khoury, H., Kamat, V., & Ioannou, P. (2007). Evaluation of general-purpose construction simulation and visualization tools for modeling and animating airside airport operations. Simulation,83(9), 663-679.
- Lee, S. (2007). Understanding and Quantifying the Impact of Changes on Construction Labor Productivity: Integration of Productivity Factors and Quantifying Methods. Doctoral Dissertation ,University of Berkeley.
- Lutz, J., Haplin, D., & Wilson, J. (1992). Simulation Of Learning Development In Repetitive Construction. Journal of Construction Engineering and Management.
- Marzouk, M., & Ali, H. (2013). Modeling safety considerations and space limitations in piling operations using agent based simulation. Expert Systems with Applic ations, 4848–4857.
- NARESH, A., & JAHREN, C. (1998). Learning Outcomes From Construction Simulation Modeling. Civil. Eng. and Env. Syst., 129-144.
- Nasirzadeh, F., & Nojedehi, P. (2013). Dynamic modeling of labor productivity in construction projects. International Journal of Project Management, 903-911.
- Panas, A., & Pantouvakis, J. (2014). Simulation-Based and Statistical Analysis of the Learning Effect in Floating Caisson Construction Operations. Constr. Eng. Manage.
- Pellegrino, R., Costantino, N., Pietroforte, R., & Sancilio, S. (2012). Construction of multi-storey concrete structures in Italy: patterns of productivity and learning curves. Construction Management and Economics, 30(2), 103-115.
- RS Means Building Construction Cost Data. (2014).
- Sargent, R. G. (2013). Verification and Validation of Simulation Models. Journal of Simulation, 12–24. doi:10.1057/jos.2012.20
- Shehata, M., & El-Gohary, K. (2012). Towards improving construction labor productivity and projects' performance. Alexandria Engineering Journal.
- SINGH, S. P. (2010). Factors affecting the productivity of construction operations in the United Arab Emirates.
- Taylor, J. E., Levitt, R., & Villarroel, J. A. (2009). Simulating learning dynamics in project networks. Journal of Construction Engineering and Management, 135(10), 1009-1015.
- Thomas, H. R., Maloney, W. F., Horner, R. M. W., Smith, G. R., Handa, V. K., & Sanders, S. R. (1990). Modeling construction labor productivity. Journal of Construction Engineering and Management, 116(4), 705-726.
- Watkins, M., Mukherjee, A., Onder, N., & Mattila, K. (2009). Using agent-based modeling to study construction labor productivity as an emergent property of individual and crew interactions. Journal of construction engineering and management, 135(7), 657-667.

APPENDIX C Supplementary material

C.1 SUMMARY OF DATA BEFORE INCORPORATING THE EFFECT OF LEARNING FACTORS

Table C-1: Duration times for linear learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.3	2.8
1	2.079	2.079	7.24	9.502	5.702	2.534
2	1.96	1.96	6.829	8.964	5.378	2.39
3	1.88	1.88	6.552	8.6	5.16	2.293
4	1.82	1.82	6.345	8.328	4.997	2.221
5	1.772	1.772	6.181	8.112	4.867	2.163
6	1.733	1.733	6.045	7.934	4.76	2.116
7	1.699	1.699	5.93	7.783	4.67	2.075
8	1.67	1.67	5.83	7.652	4.591	2.041
9	1.645	1.645	5.742	7.537	4.522	2.01
10	1.622	1.622	5.664	7.434	4.46	1.982
11	1.602	1.602	5.593	7.341	4.405	1.958
12	1.583	1.583	5.529	7.257	4.354	1.935
13	1.566	1.566	5.471	7.18	4.308	1.915
14	1.551	1.551	5.417	7.109	4.266	1.896
15	1.536	1.536	5.366	7.043	4.226	1.878
16	1.523	1.523	5.32	6.982	4.189	1.862
17	1.51	1.51	5.276	6.925	4.155	1.847
18	1.498	1.498	5.235	6.871	4.123	1.832
19	1.487	1.487	5.197	6.821	4.092	1.819
20	1.476	1.476	5.16	6.773	4.064	1.806
21	1.466	1.466	5.126	6.728	4.037	1.794
22	1.457	1.457	5.093	6.685	4.011	1.783
23	1.448	1.448	5.062	6.644	3.986	1.772
24	1.439	1.439	5.032	6.605	3.963	1.761
25	1.431	1.431	5.004	6.568	3.941	1.751

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.423	1.423	4.977	6.532	3.919	1.742
27	1.416	1.416	4.951	6.498	3.899	1.733
28	1.409	1.409	4.926	6.465	3.879	1.724
29	1.402	1.402	4.902	6.434	3.86	1.716
30	1.395	1.395	4.879	6.404	3.842	1.708
31	1.389	1.389	4.857	6.374	3.825	1.7
32	1.382	1.382	4.835	6.346	3.808	1.692
33	1.376	1.376	4.814	6.319	3.791	1.685
34	1.371	1.371	4.794	6.293	3.776	1.678
35	1.365	1.365	4.775	6.267	3.76	1.671
36	1.36	1.36	4.756	6.242	3.745	1.665
37	1.354	1.354	4.738	6.218	3.731	1.658
38	1.349	1.349	4.72	6.195	3.717	1.652
39	1.344	1.344	4.703	6.173	3.704	1.646
40	1.339	1.339	4.686	6.151	3.69	1.64
41	1.335	1.335	4.67	6.129	3.678	1.635
42	1.33	1.33	4.654	6.109	3.665	1.629
43	1.326	1.326	4.639	6.089	3.653	1.624
44	1.321	1.321	4.624	6.069	3.641	1.618
45	1.317	1.317	4.609	6.05	3.63	1.613
46	1.313	1.313	4.595	6.031	3.619	1.608
47	1.309	1.309	4.581	6.013	3.608	1.603
48	1.305	1.305	4.568	5.995	3.597	1.599
49	1.301	1.301	4.554	5.978	3.587	1.594

Table C-2: Duration times for Stanford learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.3	2.8
1	1.96	1.96	6.829	8.964	5.378	2.39
2	1.88	1.88	6.552	8.6	5.16	2.293
3	1.82	1.82	6.345	8.328	4.997	2.221
4	1.772	1.772	6.181	8.112	4.867	2.163
5	1.733	1.733	6.045	7.934	4.76	2.116
6	1.699	1.699	5.93	7.783	4.67	2.075
7	1.67	1.67	5.83	7.652	4.591	2.041
8	1.645	1.645	5.742	7.537	4.522	2.01
9	1.622	1.622	5.664	7.434	4.46	1.982
10	1.602	1.602	5.593	7.341	4.405	1.958
11	1.583	1.583	5.529	7.257	4.354	1.935
12	1.566	1.566	5.471	7.18	4.308	1.915
13	1.551	1.551	5.417	7.109	4.266	1.896
14	1.536	1.536	5.366	7.043	4.226	1.878
15	1.523	1.523	5.32	6.982	4.189	1.862
16	1.51	1.51	5.276	6.925	4.155	1.847
17	1.498	1.498	5.235	6.871	4.123	1.832
18	1.487	1.487	5.197	6.821	4.092	1.819
19	1.476	1.476	5.16	6.773	4.064	1.806
20	1.466	1.466	5.126	6.728	4.037	1.794
21	1.457	1.457	5.093	6.685	4.011	1.783
22	1.448	1.448	5.062	6.644	3.986	1.772
23	1.439	1.439	5.032	6.605	3.963	1.761
24	1.431	1.431	5.004	6.568	3.941	1.751
25	1.423	1.423	4.977	6.532	3.919	1.742

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.416	1.416	4.951	6.498	3.899	1.733
27	1.409	1.409	4.926	6.465	3.879	1.724
28	1.402	1.402	4.902	6.434	3.86	1.716
29	1.395	1.395	4.879	6.404	3.842	1.708
30	1.389	1.389	4.857	6.374	3.825	1.7
31	1.382	1.382	4.835	6.346	3.808	1.692
32	1.376	1.376	4.814	6.319	3.791	1.685
33	1.371	1.371	4.794	6.293	3.776	1.678
34	1.365	1.365	4.775	6.267	3.76	1.671
35	1.36	1.36	4.756	6.242	3.745	1.665
36	1.354	1.354	4.738	6.218	3.731	1.658
37	1.349	1.349	4.72	6.195	3.717	1.652
38	1.344	1.344	4.703	6.173	3.704	1.646
39	1.339	1.339	4.686	6.151	3.69	1.64
40	1.335	1.335	4.67	6.129	3.678	1.635
41	1.33	1.33	4.654	6.109	3.665	1.629
42	1.326	1.326	4.639	6.089	3.653	1.624
43	1.321	1.321	4.624	6.069	3.641	1.618
44	1.317	1.317	4.609	6.05	3.63	1.613
45	1.313	1.313	4.595	6.031	3.619	1.608
46	1.309	1.309	4.581	6.013	3.608	1.603
47	1.305	1.305	4.568	5.995	3.597	1.599
48	1.301	1.301	4.554	5.978	3.587	1.594
49	1.297	1.297	4.541	5.96	3.576	1.589

Table C-3: Duration times for De Jong learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.3	2.8
1	2.19	2.19	7.62	10.001	6.001	2.667
2	2.13	2.13	7.415	9.732	5.839	2.595
3	2.09	2.09	7.276	9.55	5.73	2.547
4	2.06	2.06	7.172	9.414	5.648	2.51
5	2.036	2.036	7.09	9.306	5.584	2.482
6	2.016	2.016	7.022	9.217	5.53	2.458
7	2	2	6.965	9.141	5.485	2.438
8	1.985	1.985	6.915	9.076	5.446	2.42
9	1.972	1.972	6.871	9.018	5.411	2.405
10	1.961	1.961	6.832	8.967	5.38	2.391
11	1.951	1.951	6.797	8.921	5.352	2.379
12	1.942	1.942	6.765	8.879	5.327	2.368
13	1.933	1.933	6.735	8.84	5.304	2.357
14	1.925	1.925	6.708	8.805	5.283	2.348
15	1.918	1.918	6.683	8.772	5.263	2.339
16	1.911	1.911	6.66	8.741	5.245	2.331
17	1.905	1.905	6.638	8.712	5.227	2.323
18	1.899	1.899	6.618	8.686	5.211	2.316
19	1.893	1.893	6.598	8.66	5.196	2.309
20	1.888	1.888	6.58	8.636	5.182	2.303
21	1.883	1.883	6.563	8.614	5.168	2.297
22	1.878	1.878	6.547	8.592	5.155	2.291
23	1.874	1.874	6.531	8.572	5.143	2.286
24	1.87	1.87	6.516	8.552	5.131	2.281
25	1.866	1.866	6.502	8.534	5.12	2.276

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.862	1.862	6.488	8.516	5.11	2.271
27	1.858	1.858	6.475	8.499	5.099	2.266
28	1.854	1.854	6.463	8.483	5.09	2.262
29	1.851	1.851	6.451	8.467	5.08	2.258
30	1.848	1.848	6.439	8.452	5.071	2.254
31	1.844	1.844	6.428	8.437	5.062	2.25
32	1.841	1.841	6.418	8.423	5.054	2.246
33	1.838	1.838	6.407	8.409	5.046	2.243
34	1.835	1.835	6.397	8.396	5.038	2.239
35	1.832	1.832	6.387	8.384	5.03	2.236
36	1.83	1.83	6.378	8.371	5.023	2.232
37	1.827	1.827	6.369	8.359	5.016	2.229
38	1.825	1.825	6.36	8.348	5.009	2.226
39	1.822	1.822	6.352	8.336	5.002	2.223
40	1.82	1.82	6.343	8.325	4.995	2.22
41	1.817	1.817	6.335	8.315	4.989	2.217
42	1.815	1.815	6.327	8.304	4.983	2.215
43	1.813	1.813	6.319	8.294	4.977	2.212
44	1.811	1.811	6.312	8.284	4.971	2.209
45	1.809	1.809	6.305	8.275	4.965	2.207
46	1.806	1.806	6.298	8.266	4.959	2.204
47	1.804	1.804	6.291	8.256	4.954	2.202
48	1.803	1.803	6.284	8.247	4.948	2.199
49	1.801	1.801	6.277	8.239	4.943	2.197

Table C-4: Duration times for Cubic learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.3	2.8
1	2.13	2.13	7.415	9.732	5.839	2.595
2	2.09	2.09	7.276	9.55	5.73	2.547
3	2.06	2.06	7.172	9.414	5.648	2.51
4	2.036	2.036	7.09	9.306	5.584	2.482
5	2.016	2.016	7.022	9.217	5.53	2.458
6	2	2	6.965	9.141	5.485	2.438
7	1.985	1.985	6.915	9.076	5.446	2.42
8	1.972	1.972	6.871	9.018	5.411	2.405
9	1.961	1.961	6.832	8.967	5.38	2.391
10	1.951	1.951	6.797	8.921	5.352	2.379
11	1.942	1.942	6.765	8.879	5.327	2.368
12	1.933	1.933	6.735	8.84	5.304	2.357
13	1.925	1.925	6.708	8.805	5.283	2.348
14	1.918	1.918	6.683	8.772	5.263	2.339
15	1.911	1.911	6.66	8.741	5.245	2.331
16	1.905	1.905	6.638	8.712	5.227	2.323
17	1.899	1.899	6.618	8.686	5.211	2.316
18	1.893	1.893	6.598	8.66	5.196	2.309
19	1.888	1.888	6.58	8.636	5.182	2.303
20	1.883	1.883	6.563	8.614	5.168	2.297
21	1.878	1.878	6.547	8.592	5.155	2.291
22	1.874	1.874	6.531	8.572	5.143	2.286
23	1.87	1.87	6.516	8.552	5.131	2.281
24	1.866	1.866	6.502	8.534	5.12	2.276
25	1.862	1.862	6.488	8.516	5.11	2.271

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.858	1.858	6.475	8.499	5.099	2.266
27	1.854	1.854	6.463	8.483	5.09	2.262
28	1.851	1.851	6.451	8.467	5.08	2.258
29	1.848	1.848	6.439	8.452	5.071	2.254
30	1.844	1.844	6.428	8.437	5.062	2.25
31	1.841	1.841	6.418	8.423	5.054	2.246
32	1.838	1.838	6.407	8.409	5.046	2.243
33	1.835	1.835	6.397	8.396	5.038	2.239
34	1.832	1.832	6.387	8.384	5.03	2.236
35	1.83	1.83	6.378	8.371	5.023	2.232
36	1.827	1.827	6.369	8.359	5.016	2.229
37	1.825	1.825	6.36	8.348	5.009	2.226
38	1.822	1.822	6.352	8.336	5.002	2.223
39	1.82	1.82	6.343	8.325	4.995	2.22
40	1.817	1.817	6.335	8.315	4.989	2.217
41	1.815	1.815	6.327	8.304	4.983	2.215
42	1.813	1.813	6.319	8.294	4.977	2.212
43	1.811	1.811	6.312	8.284	4.971	2.209
44	1.809	1.809	6.305	8.275	4.965	2.207
45	1.806	1.806	6.298	8.266	4.959	2.204
46	1.804	1.804	6.291	8.256	4.954	2.202
47	1.803	1.803	6.284	8.247	4.948	2.199
48	1.801	1.801	6.277	8.239	4.943	2.197
49	1.799	1.799	6.271	8.23	4.938	2.195

C.2 SUMMARY OF DATA AFTER INCORPORATING THE EFFECT OF LEARNING FACTORS

Table C-5: Duration times for linear learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.577	2.8
1	2.079	2.079	7.24	9.502	5.702	2.534
2	2.593	1.973	6.871	9.019	5.411	2.405
3	1.89	1.89	6.581	8.638	5.183	2.303
4	1.78	1.78	6.353	8.338	5.003	2.195
5	1.724	1.724	6.167	8.095	4.857	2.128
6	1.728	1.701	6.007	7.885	4.658	2.038
7	1.632	1.632	5.866	7.699	4.543	2.019
8	1.594	1.594	7.588	7.532	4.44	1.973
9	1.559	1.589	5.622	7.379	4.427	1.896
10	1.53	1.53	5.524	7.251	4.267	1.897
11	1.533	1.502	5.434	7.133	4.28	1.864
12	1.508	1.508	5.351	7.023	5.54	1.797
13	1.453	1.453	5.272	6.919	4.152	1.806
14	1.463	1.431	5.198	6.822	3.918	1.78
15	1.442	1.442	6.604	6.73	5.102	1.716
16	1.388	1.388	5.055	6.634	4.142	1.729
17	1.4	1.368	4.985	6.542	3.745	1.704
18	1.382	1.382	4.923	6.462	3.877	1.643
19	3.082	1.333	4.87	6.392	3.743	1.664
20	1.384	1.317	4.813	6.317	3.698	1.643
21	1.301	1.334	4.758	6.244	3.654	1.583
22	1.354	1.286	4.704	6.174	3.611	1.605
23	1.272	1.272	4.659	6.114	3.575	1.589
24	1.325	1.291	4.608	6.048	3.535	1.53
25	1.312	1.244	4.565	5.992	3.409	1.556

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.231	1.231	4.517	5.929	3.557	1.539
27	1.285	1.251	4.774	5.868	4.218	1.482
28	1.205	1.205	4.431	5.816	3.395	1.509
29	1.193	1.193	4.387	5.758	4.708	1.493
30	1.249	1.214	4.343	5.7	3.233	1.437
31	1.169	1.169	4.306	5.652	3.425	1.465
32	1.192	1.158	4.265	5.597	3.358	1.45
33	1.214	1.18	4.223	5.543	3.231	1.395
34	1.135	1.135	4.183	5.49	3.199	1.422
35	1.193	1.125	4.029	5.288	3.08	1.452
36	1.113	1.147	4.11	5.395	3.237	1.355
37	1.103	1.137	4.078	5.352	3.117	1.344
38	1.162	1.127	3.803	4.991	4.628	1.414
39	1.083	1.083	4.003	5.254	3.152	1.359
40	1.141	1.107	3.972	5.214	2.942	1.307
41	1.064	1.098	3.7	4.856	4.919	1.378
42	1.087	1.054	3.781	4.963	2.886	1.365
43	1.078	1.078	5.072	5.081	3.049	1.273
44	1.037	1.105	3.607	4.735	2.932	1.303
45	1.028	1.062	3.579	4.698	2.91	1.335
46	1.089	1.054	3.786	4.969	2.888	1.243
47	1.014	1.081	3.634	4.77	2.955	1.232
48	1.006	1.039	3.498	4.591	2.845	1.306
49	1.064	0.997	3.906	4.863	2.734	1.255

Table C-6: Duration times for Stanford learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	7.182	2.8
1	1.96	1.96	6.829	8.964	5.378	2.39
2	1.895	1.895	6.603	8.666	5.324	2.311
3	1.832	1.832	6.378	8.371	5.022	2.232
4	1.729	1.729	6.189	8.124	4.874	2.136
5	1.681	1.681	6.031	7.915	4.676	2.078
6	1.667	1.667	5.891	7.731	4.486	1.994
7	1.601	1.601	5.764	7.565	4.539	1.982
8	1.566	1.566	5.648	7.413	4.448	1.941
9	1.535	1.565	5.54	7.272	5.176	1.866
10	1.507	1.507	5.451	7.154	4.292	1.87
11	1.513	1.482	5.367	7.044	4.055	1.84
12	1.458	1.49	5.289	6.942	4.165	1.774
13	2.641	1.436	5.215	6.844	4.107	1.786
14	1.447	1.415	5.145	6.752	3.873	1.761
15	1.395	1.427	6.74	6.665	3.999	1.697
16	1.374	1.374	5.008	6.573	3.944	1.712
17	1.421	1.354	5.146	6.485	3.799	1.688
18	1.337	1.37	4.882	6.407	3.752	1.627
19	1.354	1.321	4.831	6.34	3.804	1.649
20	1.339	1.306	4.776	6.268	3.576	1.63
21	1.358	1.323	4.722	6.198	3.533	1.57
22	1.31	1.276	4.671	6.13	3.678	1.593
23	1.262	1.262	4.626	6.072	3.549	1.577
24	1.282	1.282	4.577	6.008	3.418	1.519
25	1.235	1.235	4.536	5.953	3.572	1.545

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.256	1.264	4.489	5.892	3.348	1.529
27	1.243	1.243	5.329	5.832	3.312	1.472
28	1.231	1.197	4.405	5.782	3.469	1.5
29	1.186	1.186	4.361	5.724	3.435	1.484
30	1.207	1.207	4.319	5.668	3.213	1.428
31	1.162	1.196	6.245	5.621	3.373	1.415
32	1.185	1.151	4.121	5.409	4.122	1.485
33	1.208	1.139	4.201	5.514	3.213	1.428
34	1.163	1.163	4.162	5.462	3.089	1.373
35	1.119	1.153	3.89	5.106	3.251	1.445
36	1.141	1.107	3.97	5.21	3.033	1.432
37	1.131	1.131	4.058	5.327	3.196	1.337
38	1.122	1.122	3.783	4.966	2.979	1.407
39	1.077	1.111	5.433	4.918	3.138	1.395
40	1.102	1.102	3.954	5.19	3.114	1.301
41	1.092	1.059	3.918	5.143	4.458	1.33
42	1.049	1.082	3.647	4.787	2.964	1.359
43	1.107	1.073	3.855	5.059	2.85	1.267
44	1.066	1.066	3.826	5.022	3.013	1.257
45	1.057	1.057	3.563	4.677	2.806	1.329
46	1.017	1.017	4.666	4.949	2.876	1.278
47	1.043	1.043	3.738	4.906	2.943	1.226
48	1.035	1.035	3.483	4.571	2.743	1.301
49	1.026	0.993	3.572	4.688	2.906	1.292

Table C-7: Duration times for De Jong learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	6.388	2.8
1	2.19	2.19	7.62	10.001	6.001	2.667
2	2.137	2.137	7.436	9.759	7.453	2.602
3	2.095	2.095	7.291	9.569	5.741	2.552
4	2.04	2.04	7.177	9.419	7.373	2.498
5	2.024	2.012	7.084	9.297	5.51	2.464
6	1.988	2.001	7.846	9.192	5.515	2.419
7	1.966	1.966	6.933	9.1	5.46	2.41
8	1.961	1.947	6.869	9.016	5.41	2.387
9	1.944	1.944	6.811	8.939	5.283	2.348
10	1.915	1.915	6.762	8.875	5.325	2.348
11	1.916	1.901	6.717	8.816	5.206	2.332
12	1.889	1.904	6.675	8.761	5.214	2.298
13	1.877	1.877	7.116	8.71	5.226	2.303
14	1.865	1.865	7.39	8.661	5.197	2.29
15	1.871	2.188	6.564	8.615	5.08	2.258
16	1.86	1.844	7.462	8.567	5.14	2.265
17	1.85	1.834	6.492	8.521	6.61	2.252
18	2.912	1.825	6.462	8.481	4.998	2.241
19	1.833	1.85	6.376	8.369	5.068	2.212
20	1.809	1.809	6.406	8.408	4.999	2.222
21	1.8	1.8	6.379	8.372	4.977	2.212
22	1.827	1.81	6.235	8.183	4.956	2.223
23	1.803	1.82	6.27	8.229	4.892	2.174
24	1.778	1.795	7.429	8.274	4.964	2.165
25	1.789	1.789	6.164	8.091	4.854	2.199

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.782	2.702	6.14	8.059	4.929	2.191
27	2.416	1.775	6.235	8.184	4.817	2.141
28	1.752	1.752	6.216	8.158	4.847	2.154
29	1.763	1.763	6.2	7.973	4.877	2.168
30	1.774	1.74	6.172	8.1	4.813	2.139
31	1.734	1.769	6.093	7.997	4.798	2.112
32	1.763	3.556	6.662	7.892	4.735	2.146
33	1.723	1.723	6.112	8.022	4.813	2.118
34	1.752	1.735	6.092	7.995	4.75	2.09
35	1.747	1.729	5.956	7.817	4.69	2.126
36	1.707	1.707	7.835	7.869	4.721	2.119
37	1.736	1.702	6.039	7.926	4.708	2.093
38	1.697	1.731	5.901	7.746	4.694	2.086
39	1.725	1.708	5.883	7.722	4.679	2.101
40	1.687	1.687	5.986	7.857	4.667	2.074
41	1.699	1.699	5.968	7.833	4.7	2.047
42	1.694	1.694	7.601	7.655	4.593	2.083
43	1.689	1.672	7.592	7.712	4.674	2.077
44	1.702	1.685	5.921	7.772	4.57	2.031
45	1.664	1.698	7.012	7.599	4.605	2.047
46	1.677	1.677	5.776	7.581	4.641	2.063
47	1.674	1.674	5.876	7.713	4.536	2.016
48	1.669	1.686	5.807	7.621	4.619	2.012
49	1.665	1.665	5.736	7.528	4.517	2.048

Table C-8: Duration times for Cubic learning curve model (Days)

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
0	2.3	2.3	8	10.5	8.085	2.8
1	2.13	2.13	7.415	9.732	5.839	2.595
2	2.098	2.098	7.301	9.583	7.234	2.556
3	2.066	2.066	7.189	9.435	5.661	2.516
4	2.014	2.014	7.095	9.312	5.587	2.468
5	3.094	1.991	7.015	9.208	5.452	2.439
6	1.969	1.983	6.986	9.116	5.469	2.397
7	1.95	1.95	6.882	9.033	5.42	2.391
8	1.933	1.933	6.824	8.956	5.374	2.37
9	1.948	1.932	6.77	8.886	5.29	2.333
10	1.919	1.904	6.725	8.827	5.212	2.335
11	2.911	1.891	6.684	8.772	5.22	2.32
12	1.879	1.895	6.644	8.721	5.189	2.287
13	1.868	1.868	8.257	8.672	7.03	2.293
14	1.857	1.857	6.572	8.626	5.176	2.28
15	1.847	1.864	6.539	8.582	5.104	2.249
16	1.87	1.837	6.504	8.537	5.076	2.256
17	1.844	1.827	6.47	8.492	5.838	2.244
18	1.835	1.835	6.441	8.454	5.885	2.214
19	1.811	1.811	6.415	8.42	5.006	2.225
20	1.803	1.803	6.388	8.384	5.03	2.215
21	1.795	1.812	6.361	8.349	4.963	2.185
22	1.788	1.788	6.335	8.315	4.989	2.196
23	1.798	1.781	6.313	8.286	6.847	2.189
24	1.774	1.791	7.637	8.254	4.952	2.159
25	1.784	1.767	6.268	8.226	4.842	2.173

Number of unit	Concrete Slab	Concrete Wall	Formwork Slab	Formwork Wall	Steel Slab	Steel Wall
26	1.761	1.761	6.245	8.196	4.918	2.165
27	1.771	1.771	6.222	8.166	4.806	2.136
28	1.766	1.749	6.203	8.141	4.884	2.15
29	1.76	1.743	6.181	8.112	6.604	2.142
30	1.753	1.753	6.159	8.084	4.85	2.114
31	1.748	1.731	6.141	8.061	4.742	2.128
32	1.726	1.726	6.994	7.954	4.82	2.142
33	1.72	1.737	6.101	8.007	4.804	2.093
34	1.731	1.731	7.143	7.981	4.695	2.087
35	1.709	1.726	5.945	7.803	4.776	2.123
36	1.738	1.704	6.045	7.934	4.667	2.095
37	1.699	1.716	6.029	7.913	4.748	2.069
38	1.711	1.711	5.892	7.733	4.64	2.104
39	1.705	1.689	7.327	7.786	4.719	2.097
40	1.684	1.701	5.977	7.845	4.66	2.051
41	1.713	1.713	5.841	7.666	4.646	2.065
42	1.674	1.691	6.617	7.644	4.632	2.08
43	2.429	1.687	7.637	7.78	4.621	2.033
44	1.7	1.683	5.913	7.761	4.61	2.028
45	1.662	1.679	7.365	7.588	4.646	2.065
46	1.675	1.658	5.885	7.725	4.542	2.039
47	1.671	1.671	5.869	7.703	4.622	2.013
48	1.667	1.667	5.741	7.536	4.614	2.05
49	1.663	1.647	5.786	7.594	4.511	2.046

C.3 Agent-Based Model (Anylogic 7)

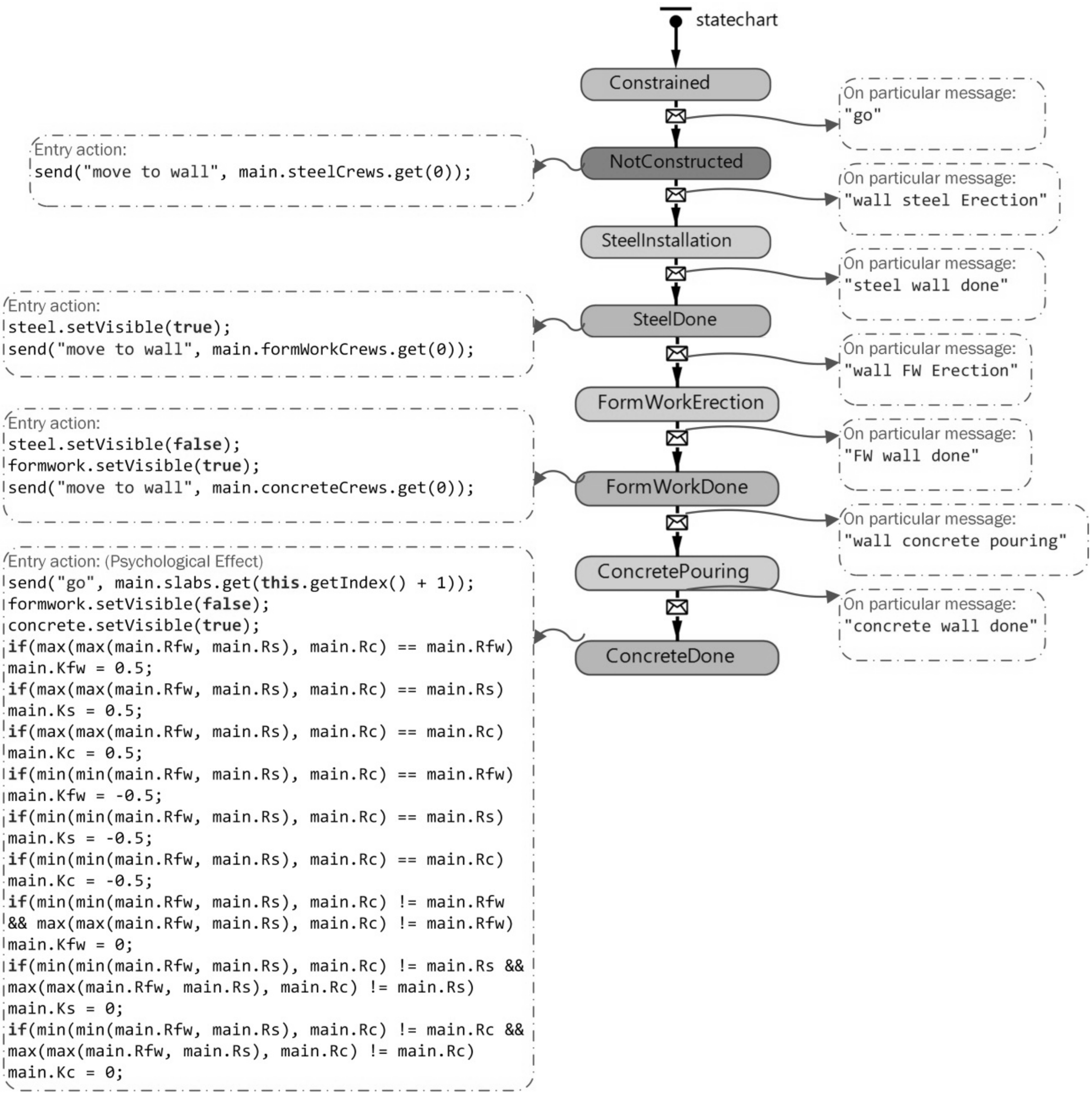


Figure C-1: Slab and Wall Agent Statechart

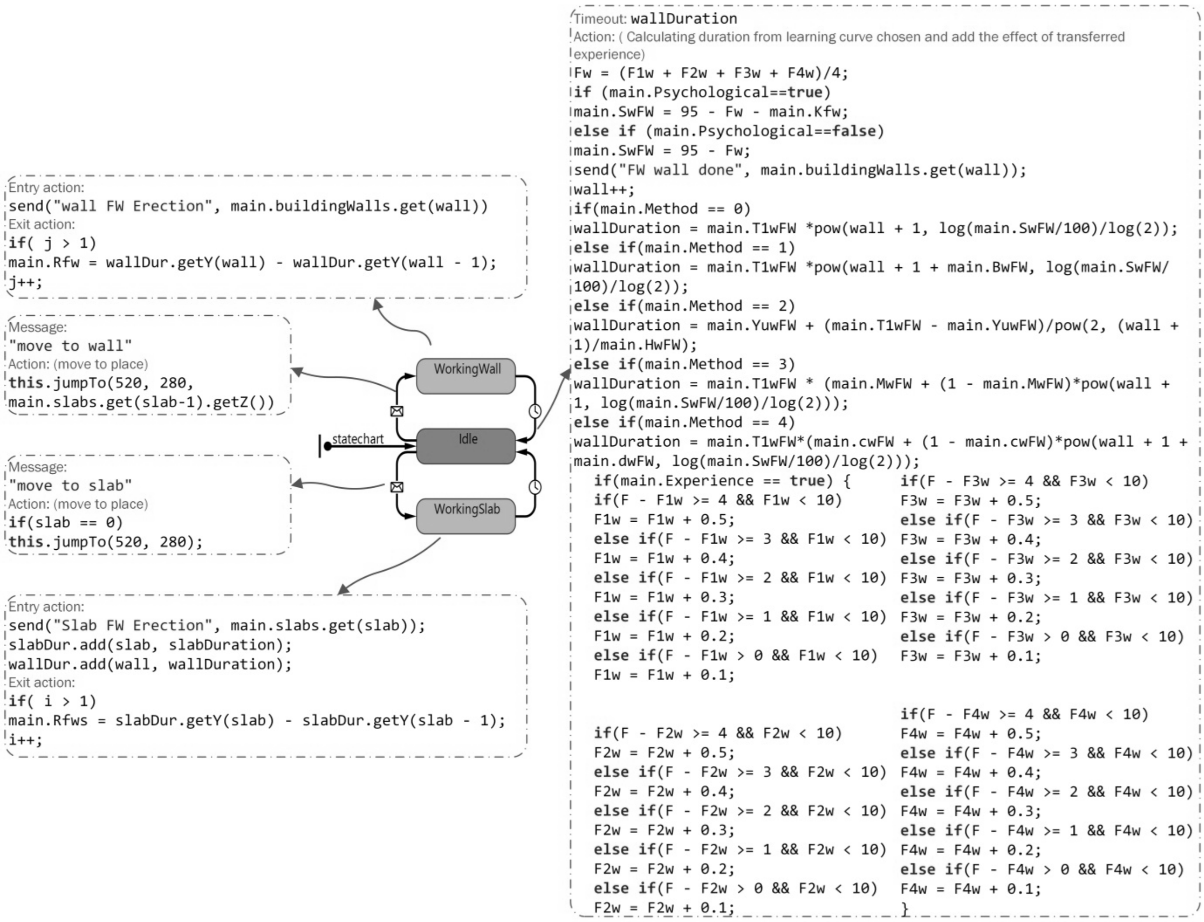


Figure C-2: Formwork, Concrete, and Steel Crews Statechart

Interruption

```
if(inState(WorkingSlab) ){
if(IntFW <= 2){
main.SFW = main.SFW + 0.5;
slabDuration = slabDuration + IntFW;
}
else if(IntFW <= 5){
main.SFW = main.SFW + 1;
slabDuration = slabDuration + IntFW;
}
else if(IntFW <= 10){
main.SFW = main.SFW + 2;
slabDuration = slabDuration + IntFW;
}
else if(IntFW > 10){
main.SFW = 80;
slabDuration = slabDuration + IntFW;
}}
else if(inState(WorkingWall)){
if(IntFW <= 2){
main.SwFW = main.SwFW + 0.5;
wallDuration = wallDuration + IntFW;
}
else if(IntFW <= 5){
main.SwFW = main.SwFW + 1;
wallDuration = wallDuration + IntFW;
}
else if(IntFW <= 10){
main.SwFW = main.SwFW + 2;
wallDuration = wallDuration + IntFW;
}
else if(IntFW > 10){
main.SwFW = 80;
wallDuration = wallDuration + IntFW;
}}

else if(inState(Idle)){
nothingChanged();
}
IntFW = roundToInt(random()*12);
```

Figure C-3: Interruption Effect on Duration and Learning Rate

C.4 R PLOTS

C.4.1 Stage 1 plots

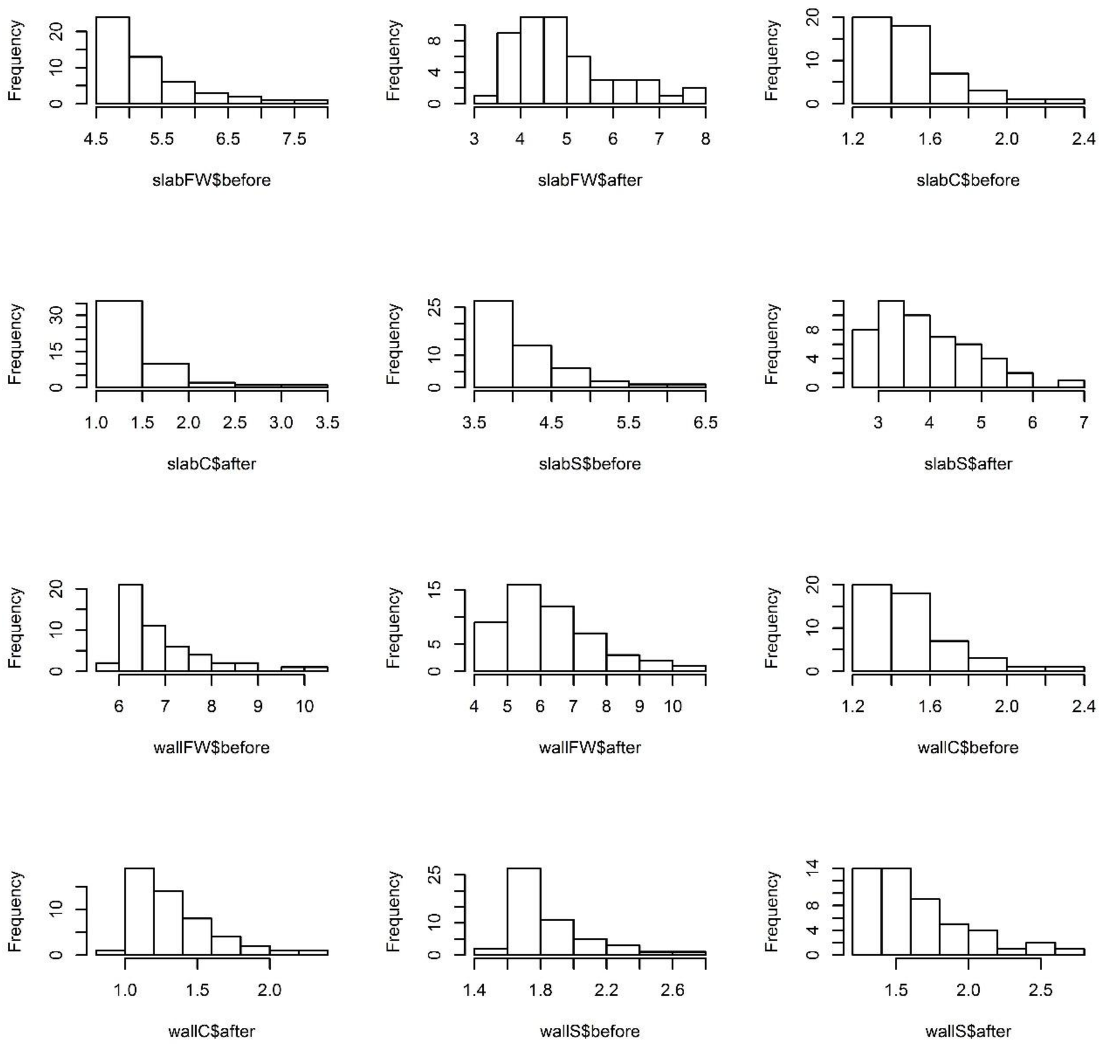


Figure C-4: Linear Model Histograms

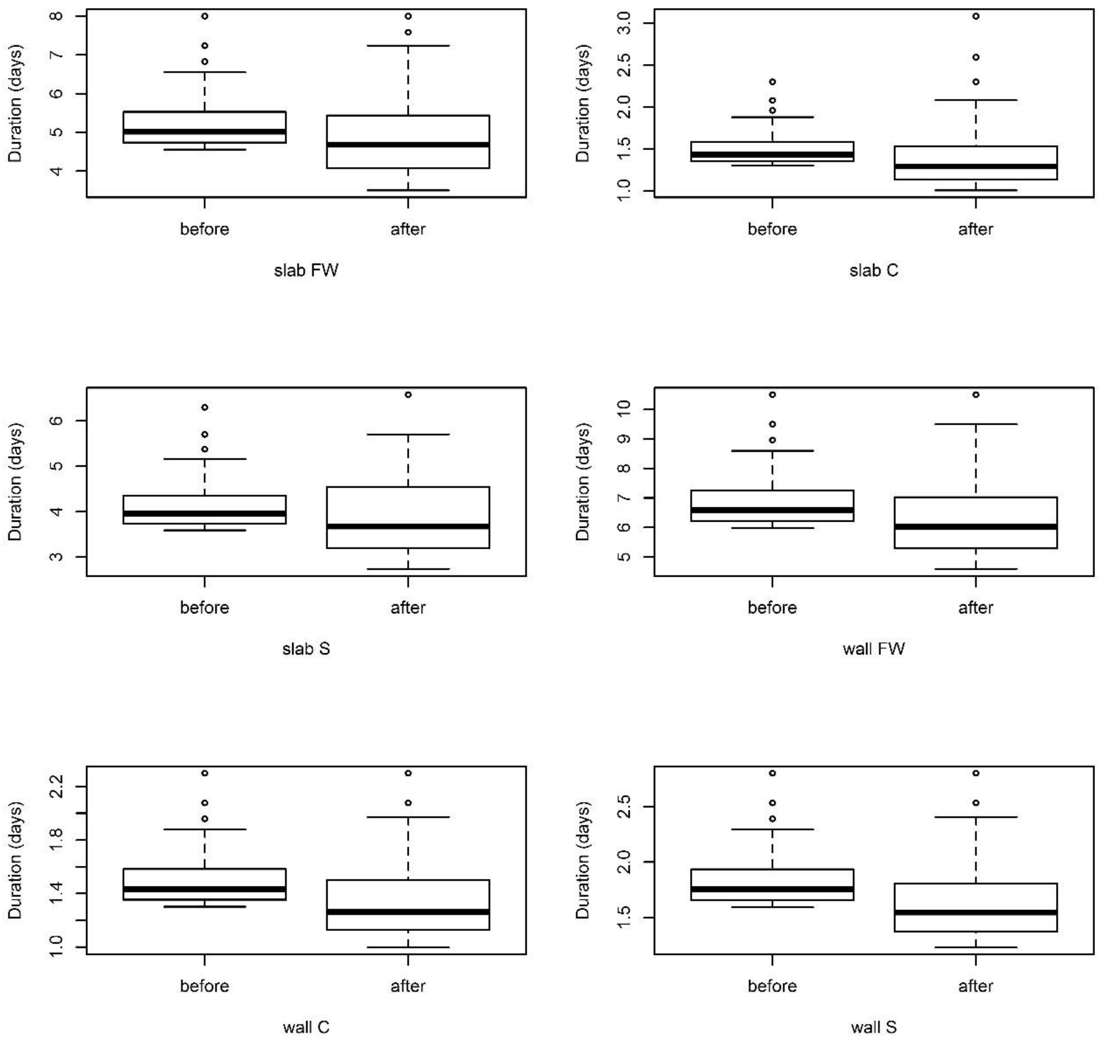


Figure C-5: Linear Model Boxplots

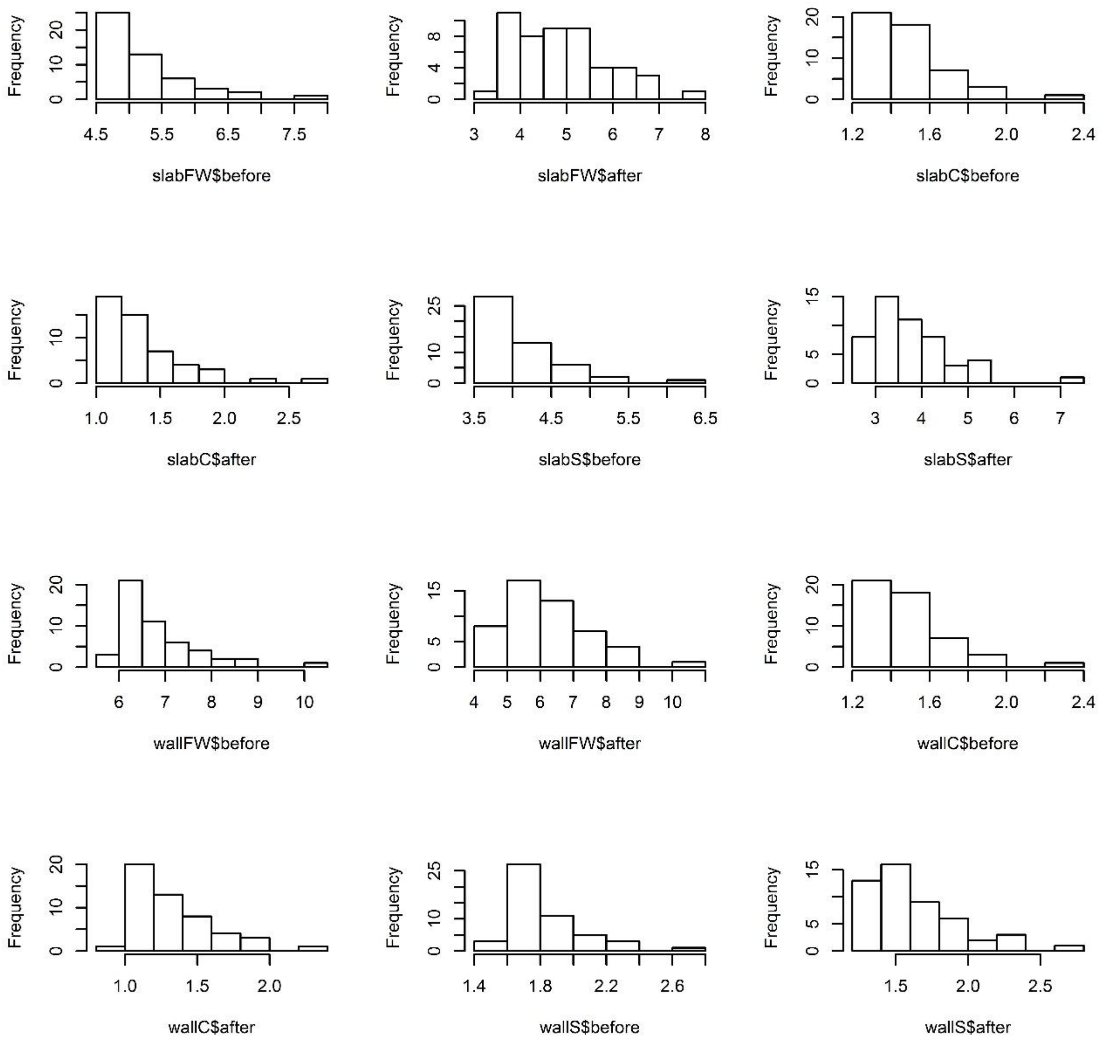


Figure C-6: Stanford Model Histograms

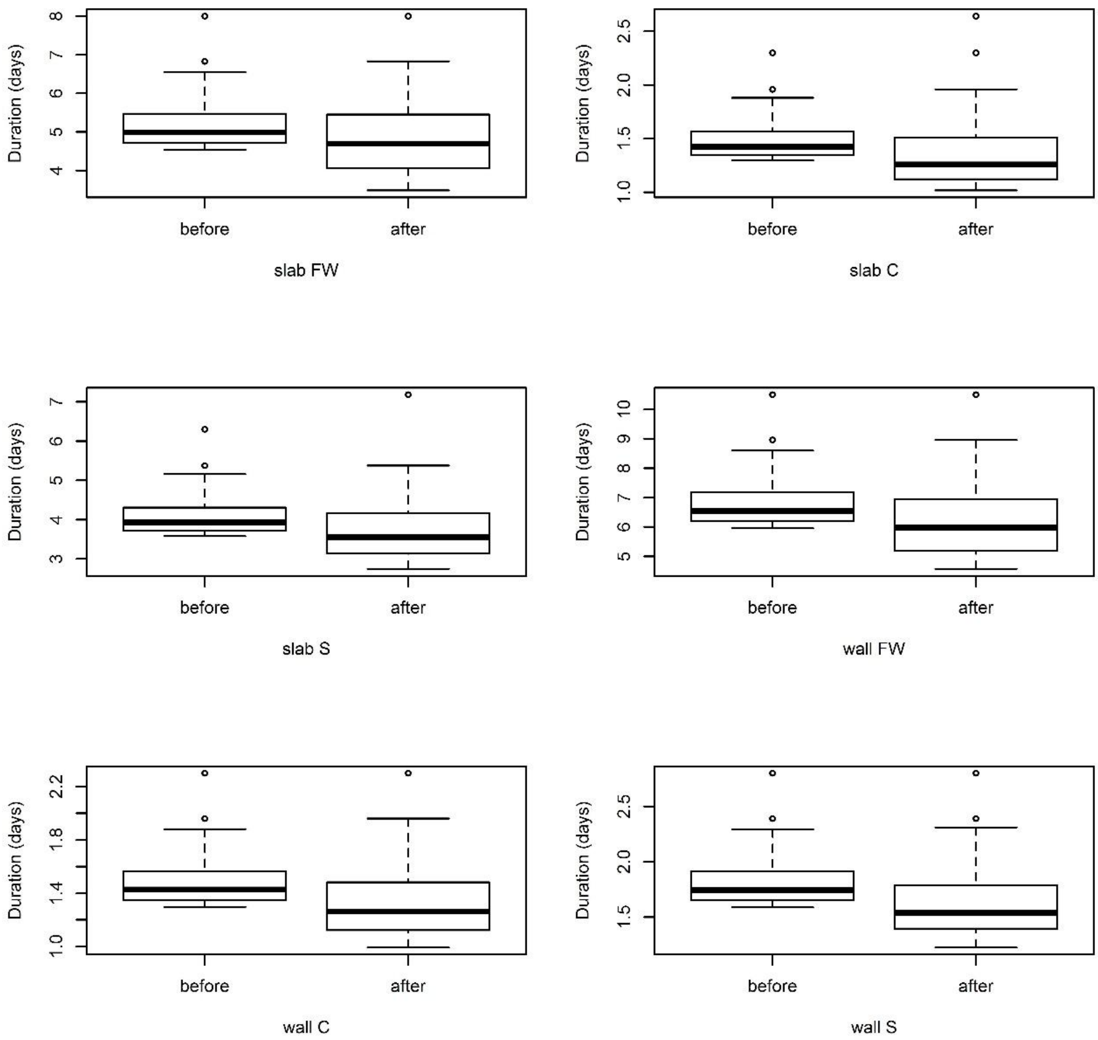


Figure C-7: Stanford Model Boxplots

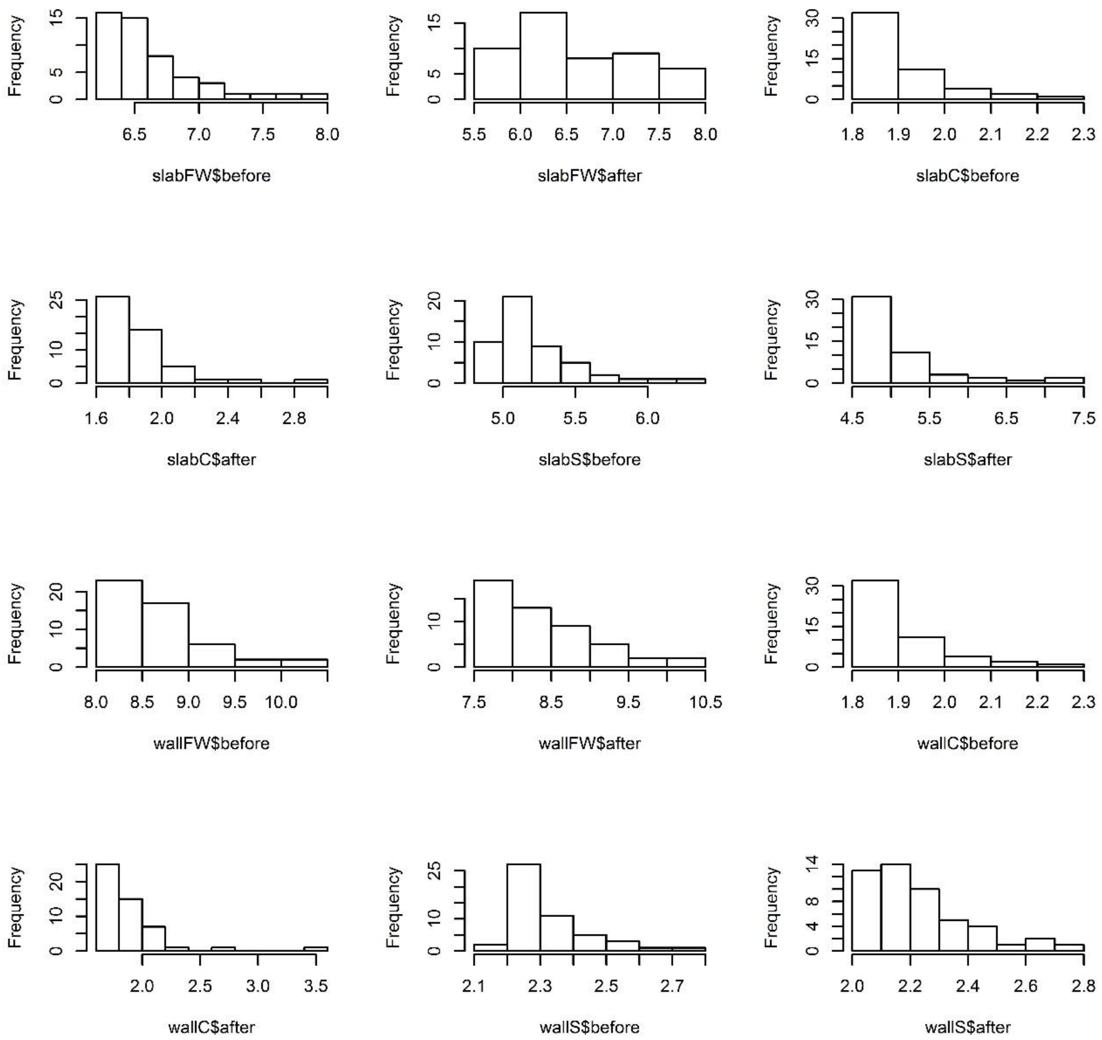


Figure C-8: De Jong Model Histograms

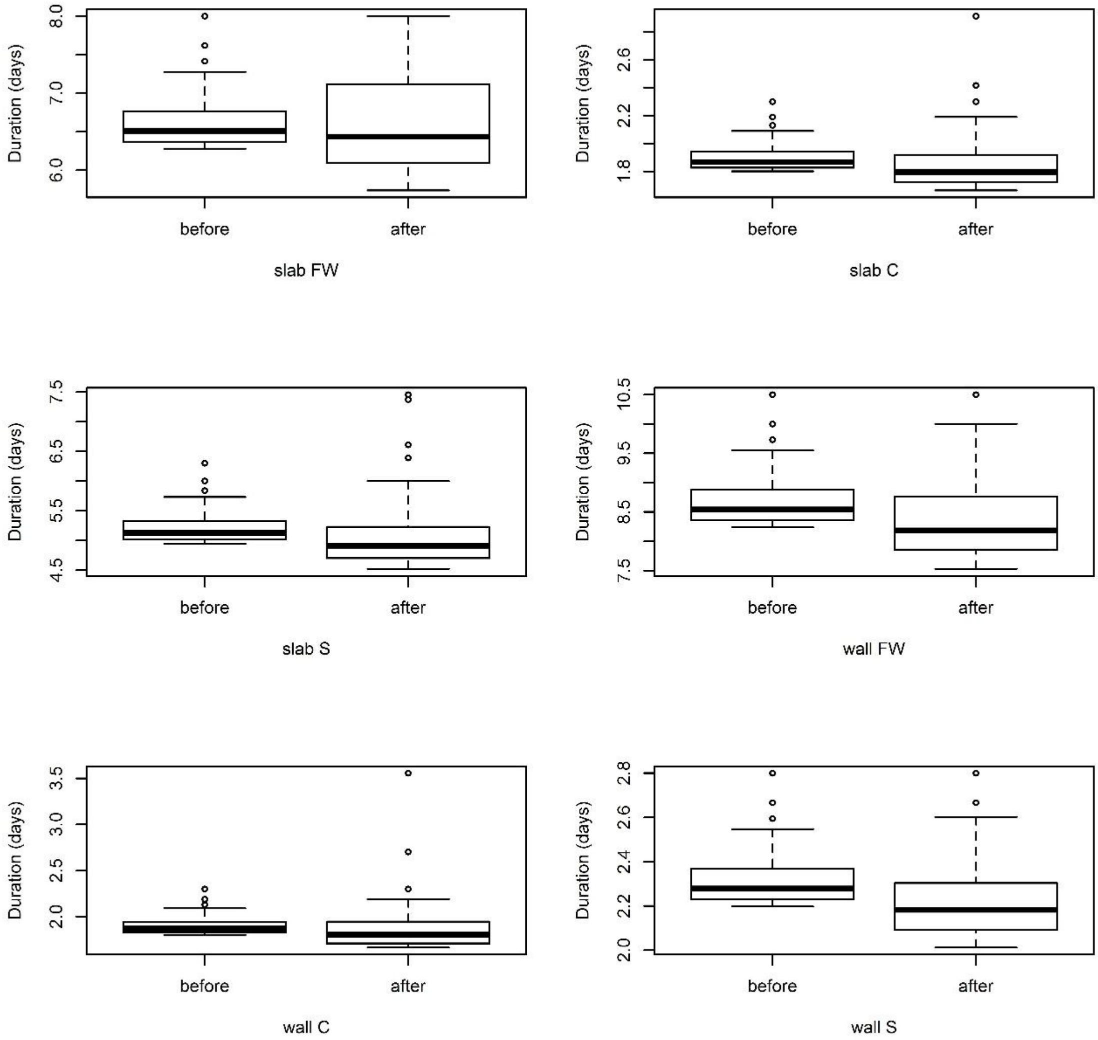


Figure C-9: De Jong Model Boxplots

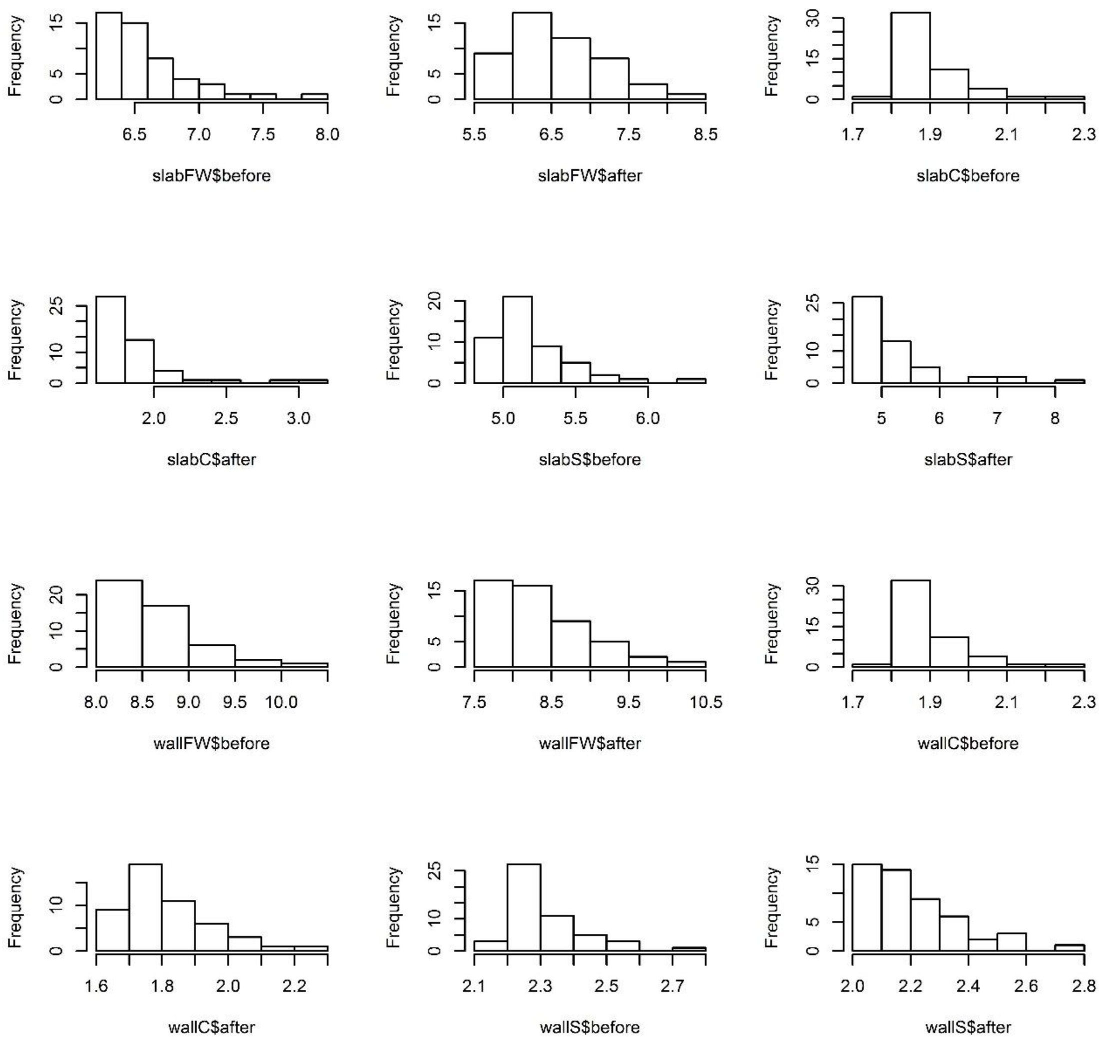


Figure C-10: Cubic Model Histograms

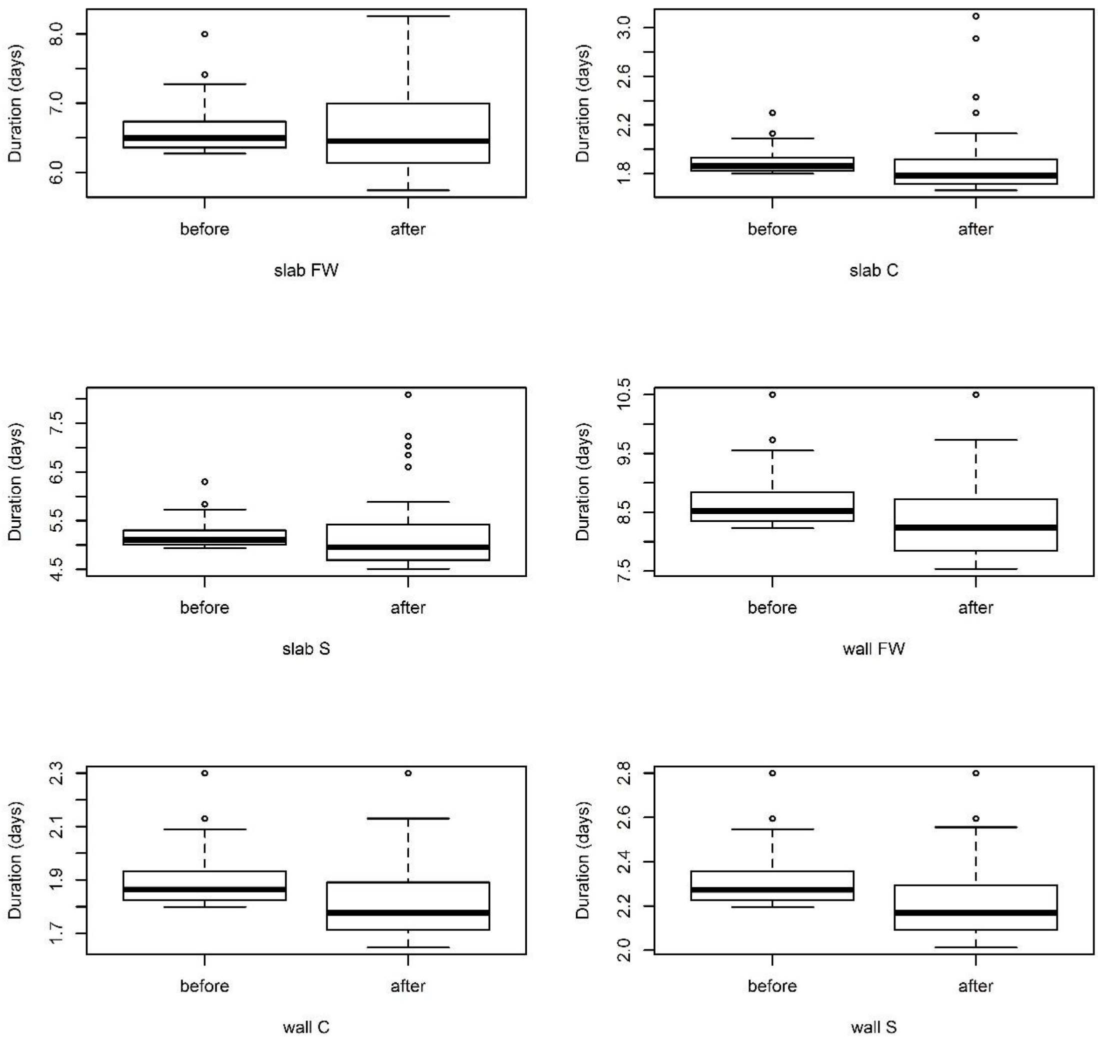


Figure C-11: Cubic Model Boxplots

C.4.2 Stage 2 plots

C.4.2.1 Plots before incorporating factors affecting learning

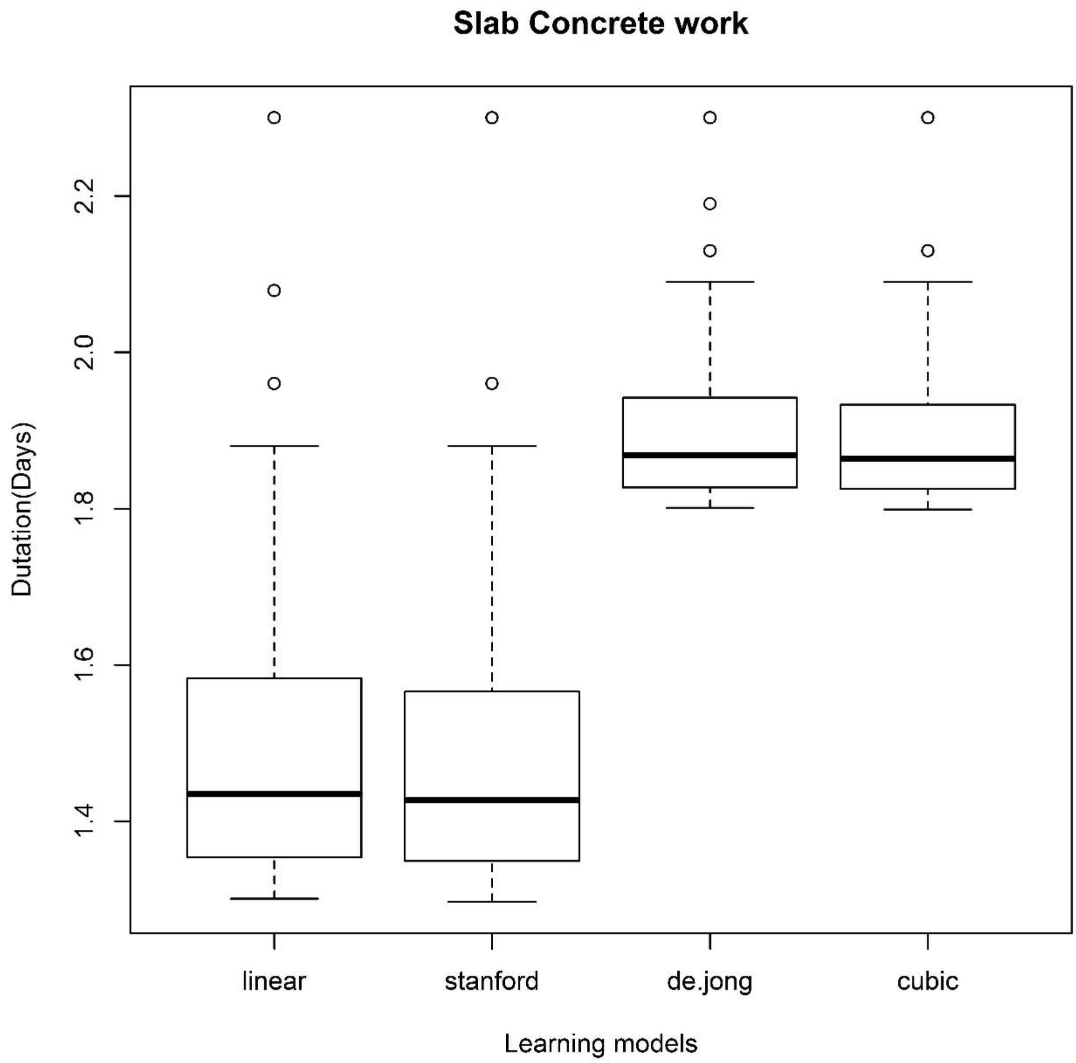


Figure C-12: Slab Concrete Work Boxplot

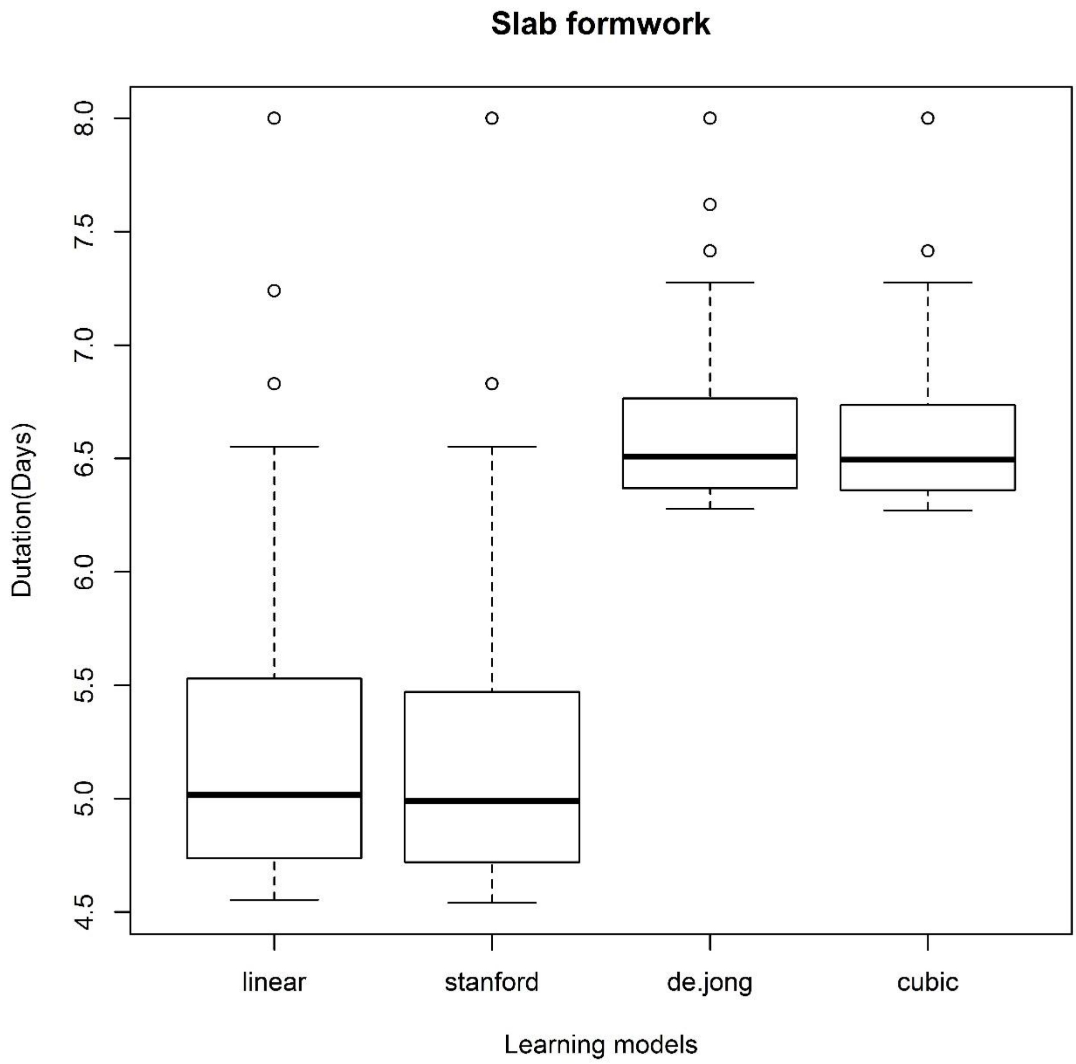


Figure C-13: Slab Formwork Boxplot

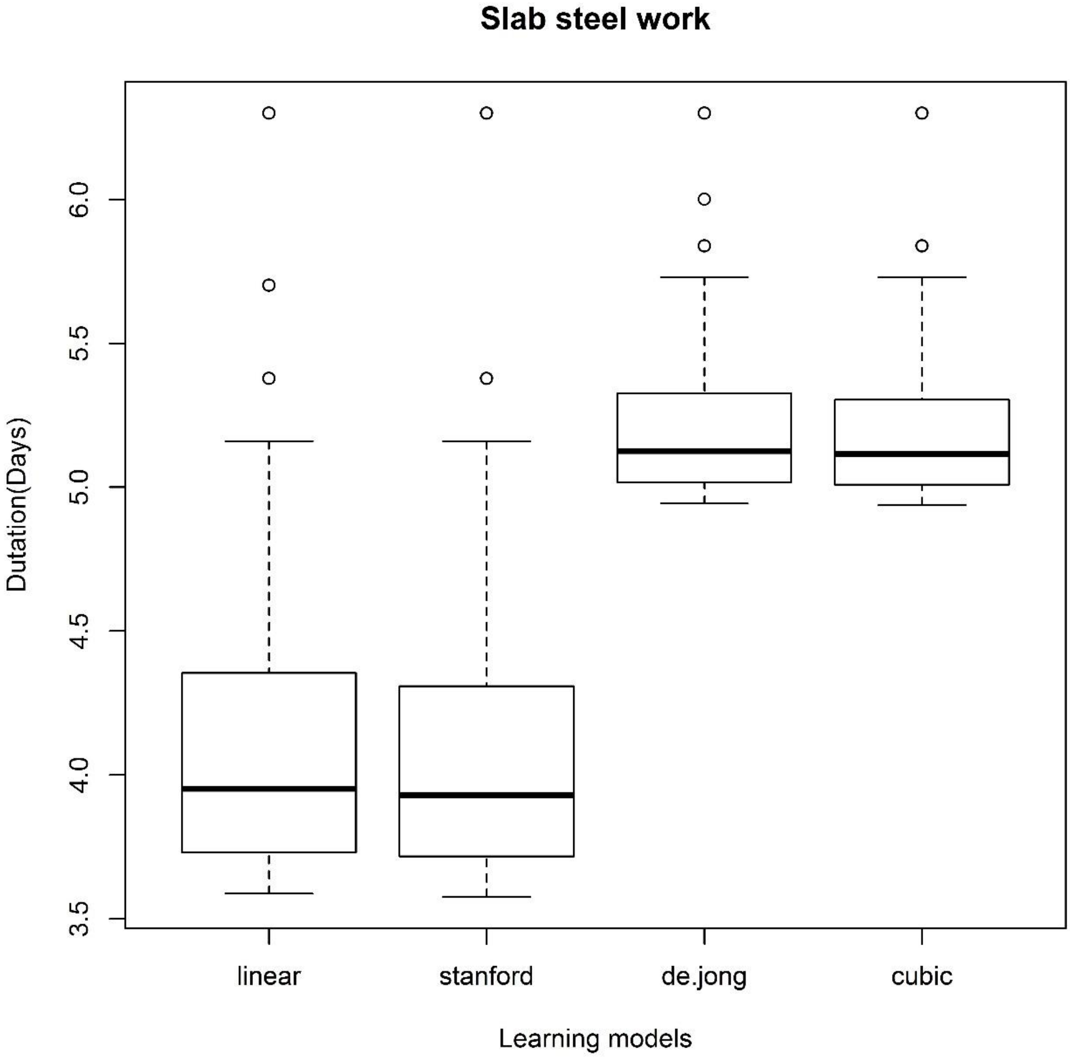


Figure C-14: Slab Steel Work Boxplot

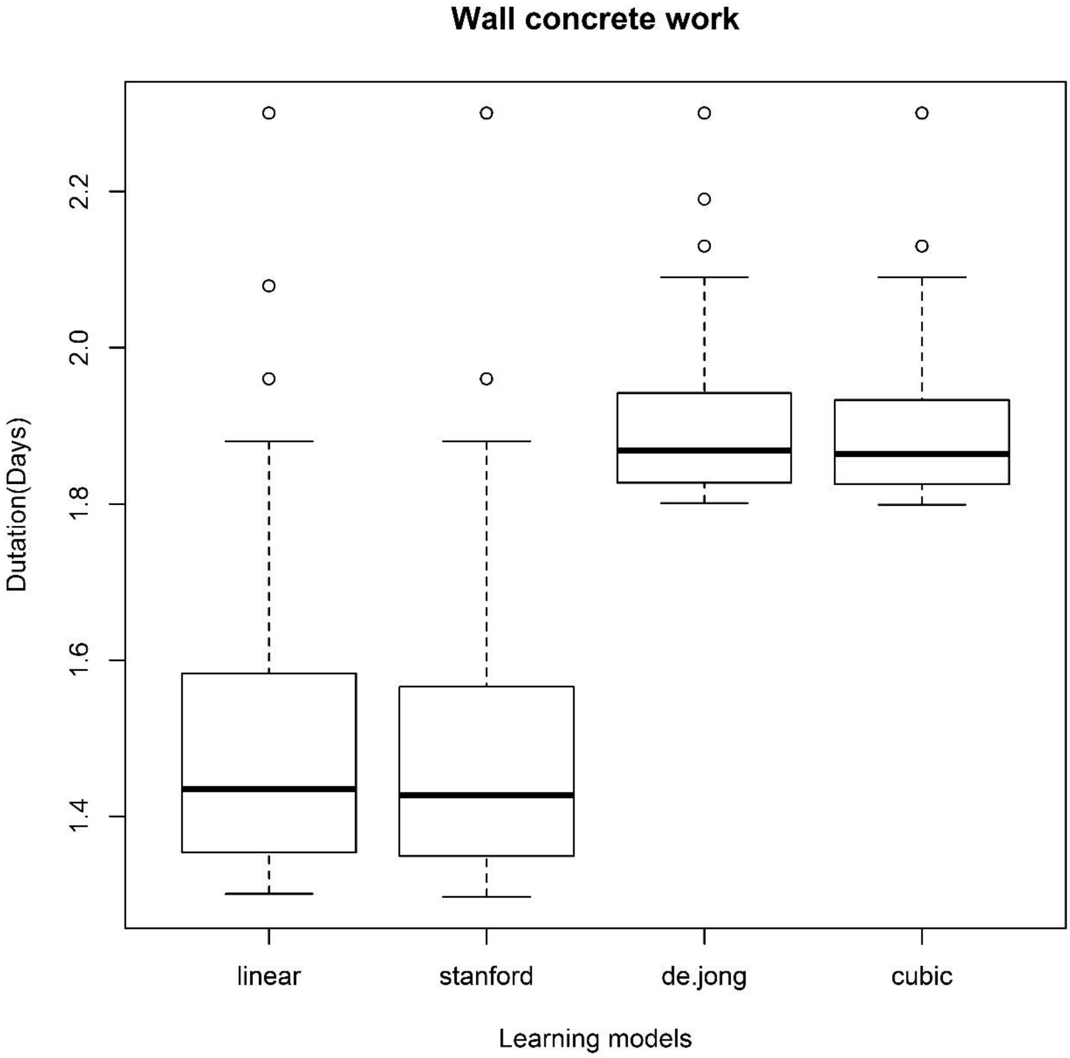


Figure C-15: Wall Concrete Work Boxplot

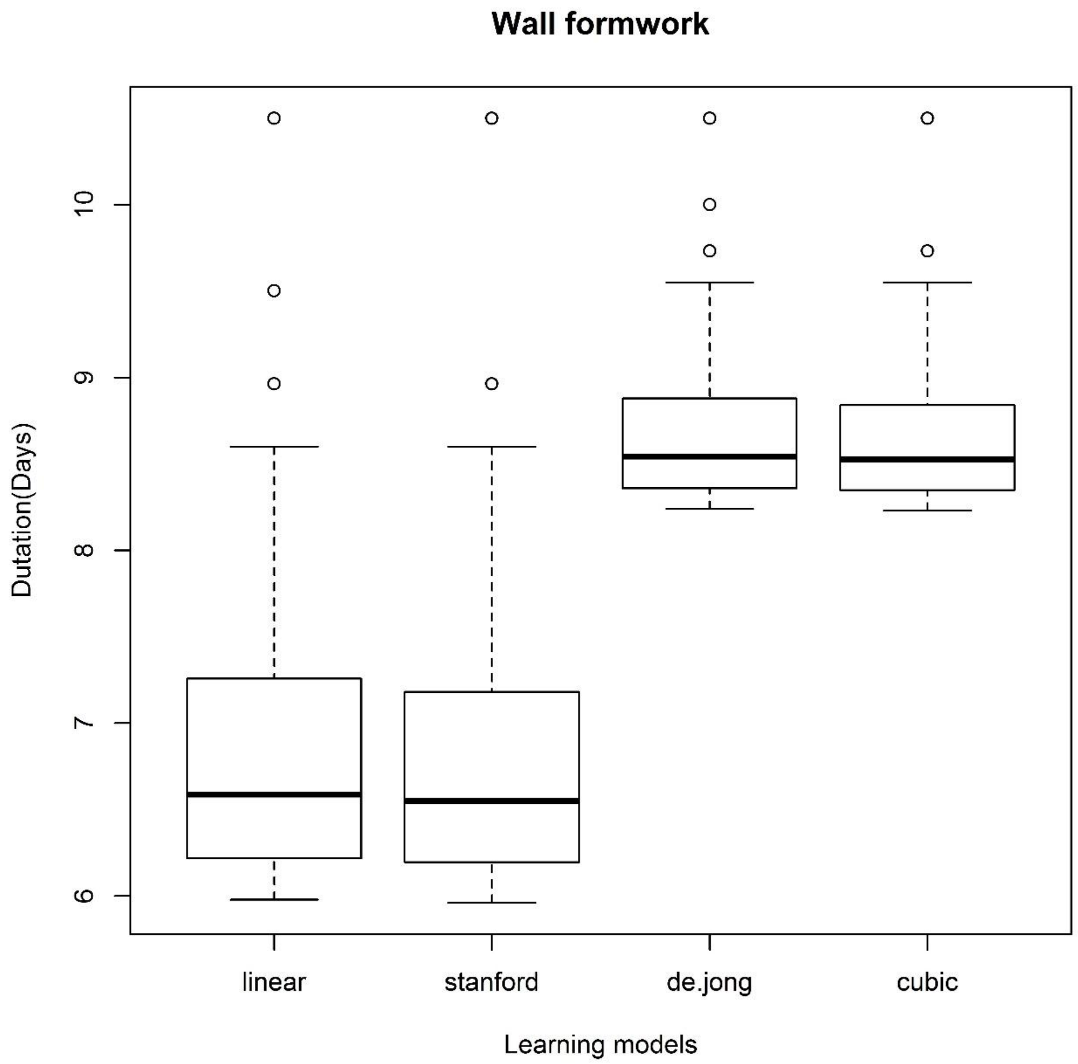


Figure C-16: Wall Formwork Boxplot

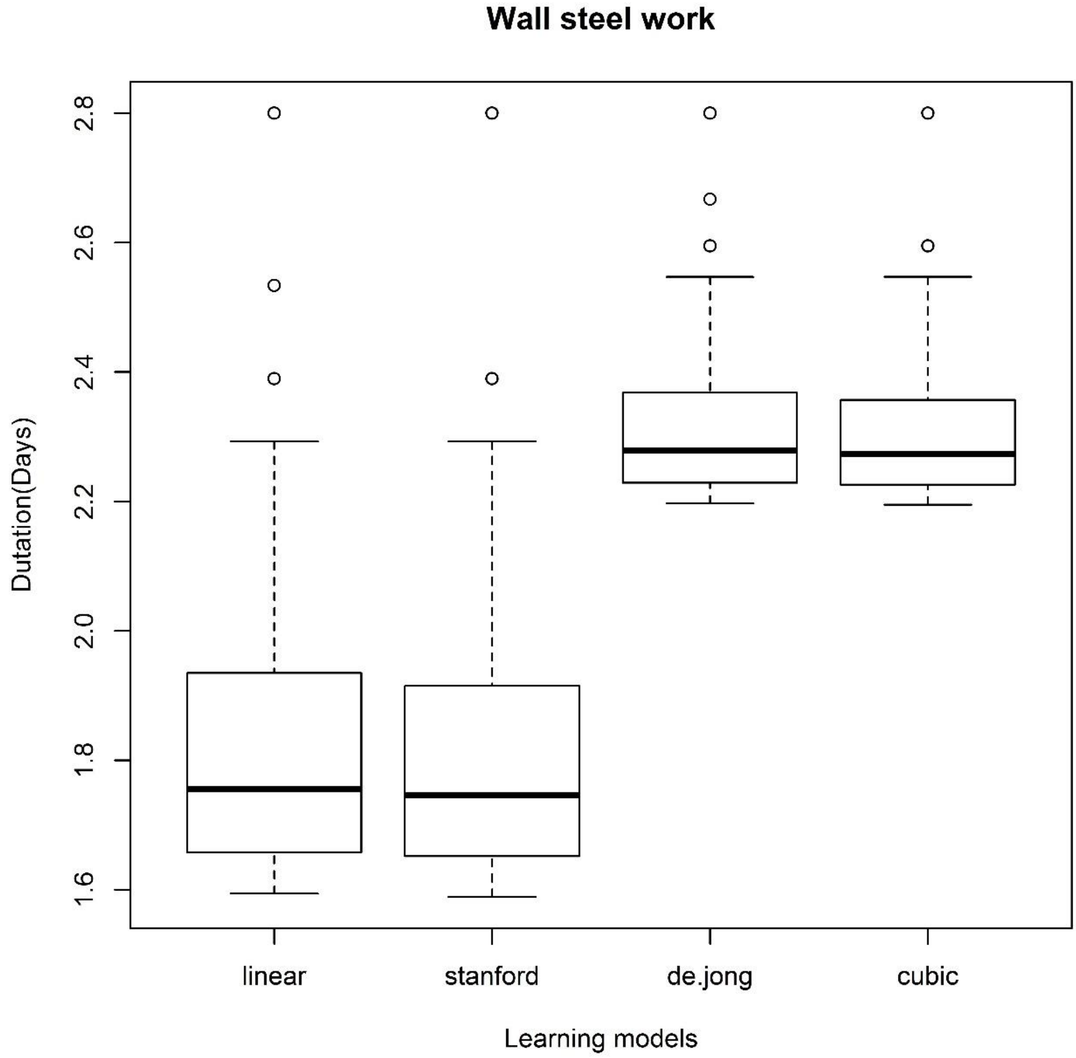


Figure C-17: Wall Steel Work Boxplot

C.4.2.2 Plots after incorporating factors affecting learning

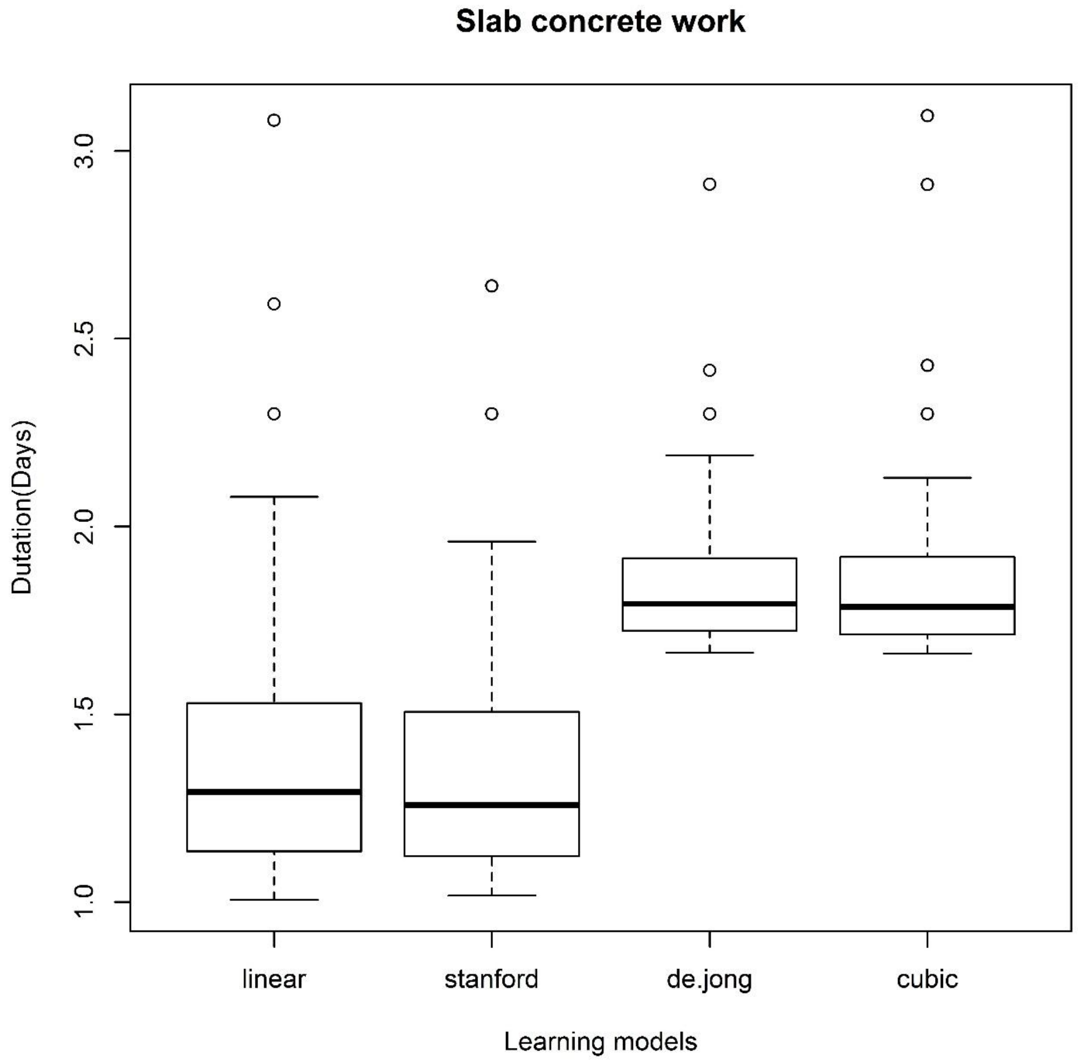


Figure C-18: Slab Concrete Work Boxplot

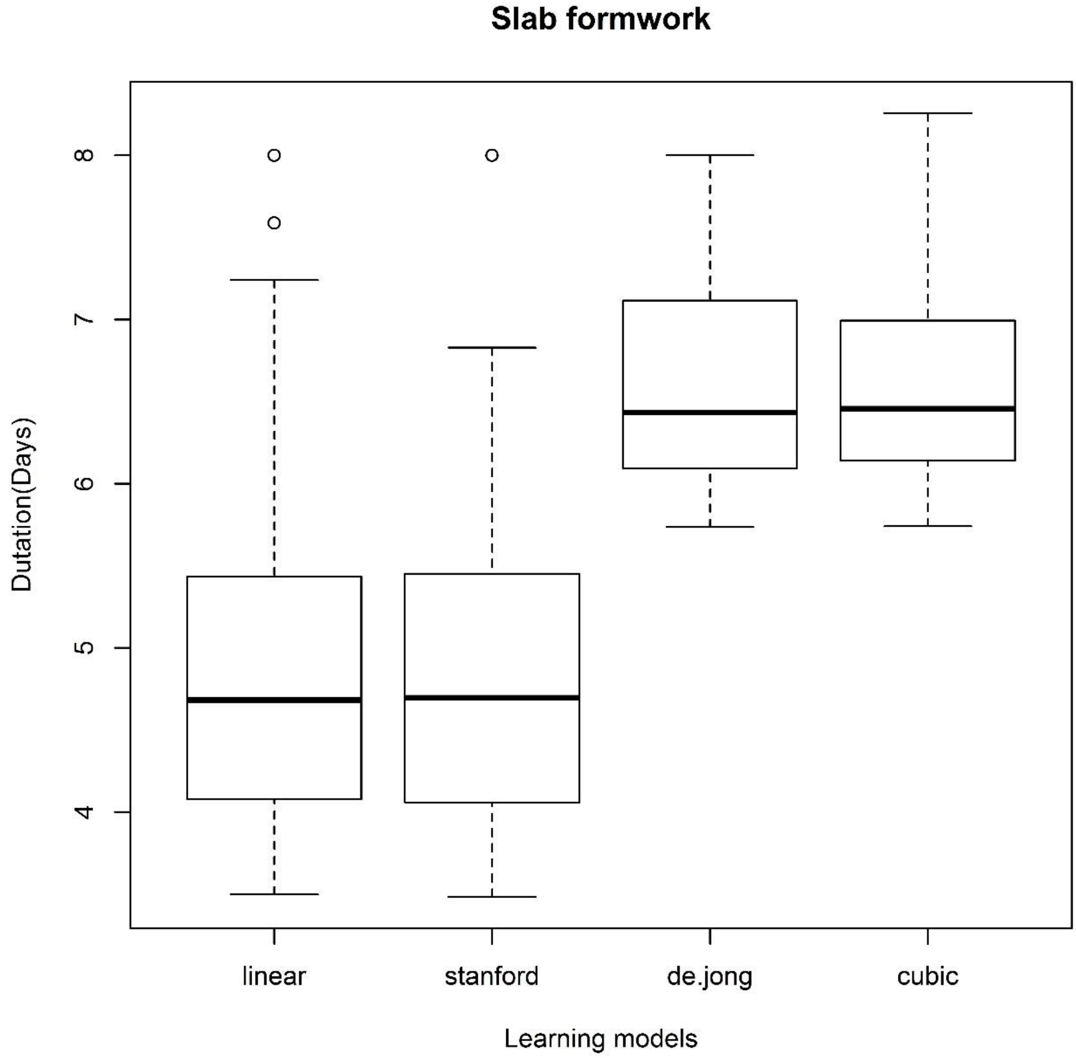


Figure C-19: Slab Formwork Boxplot

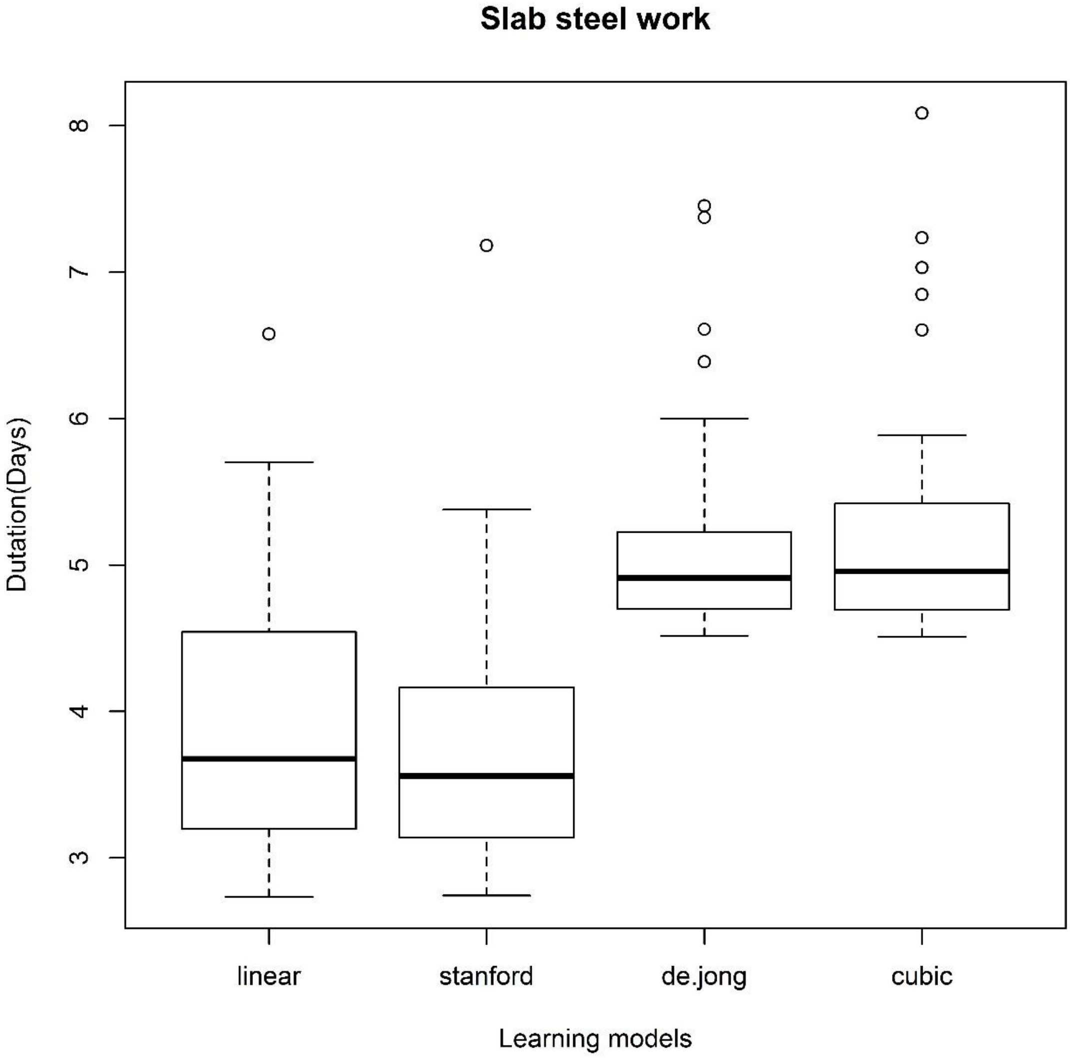


Figure C-20: Slab Steel Work Boxplot

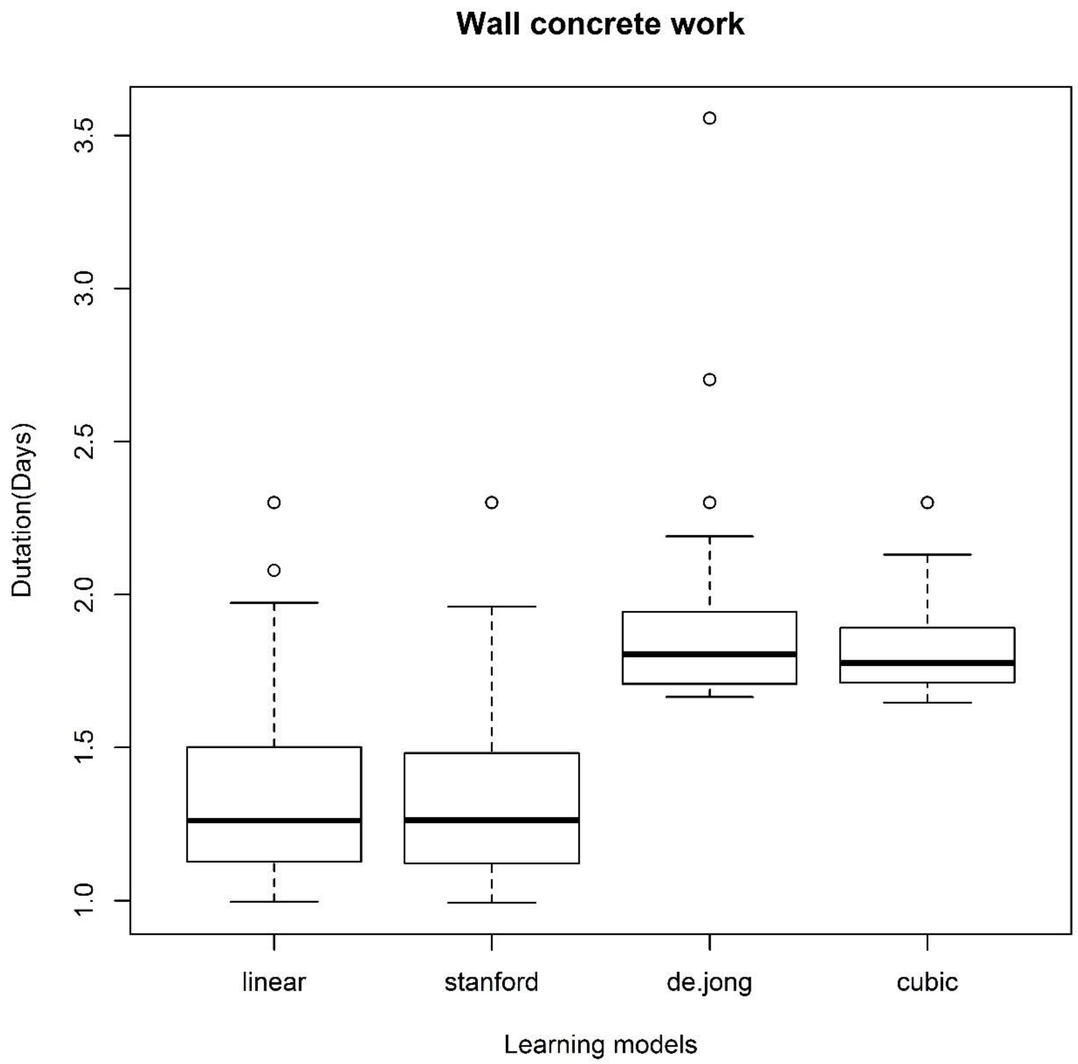


Figure C-21: Wall Concrete Work Boxplot

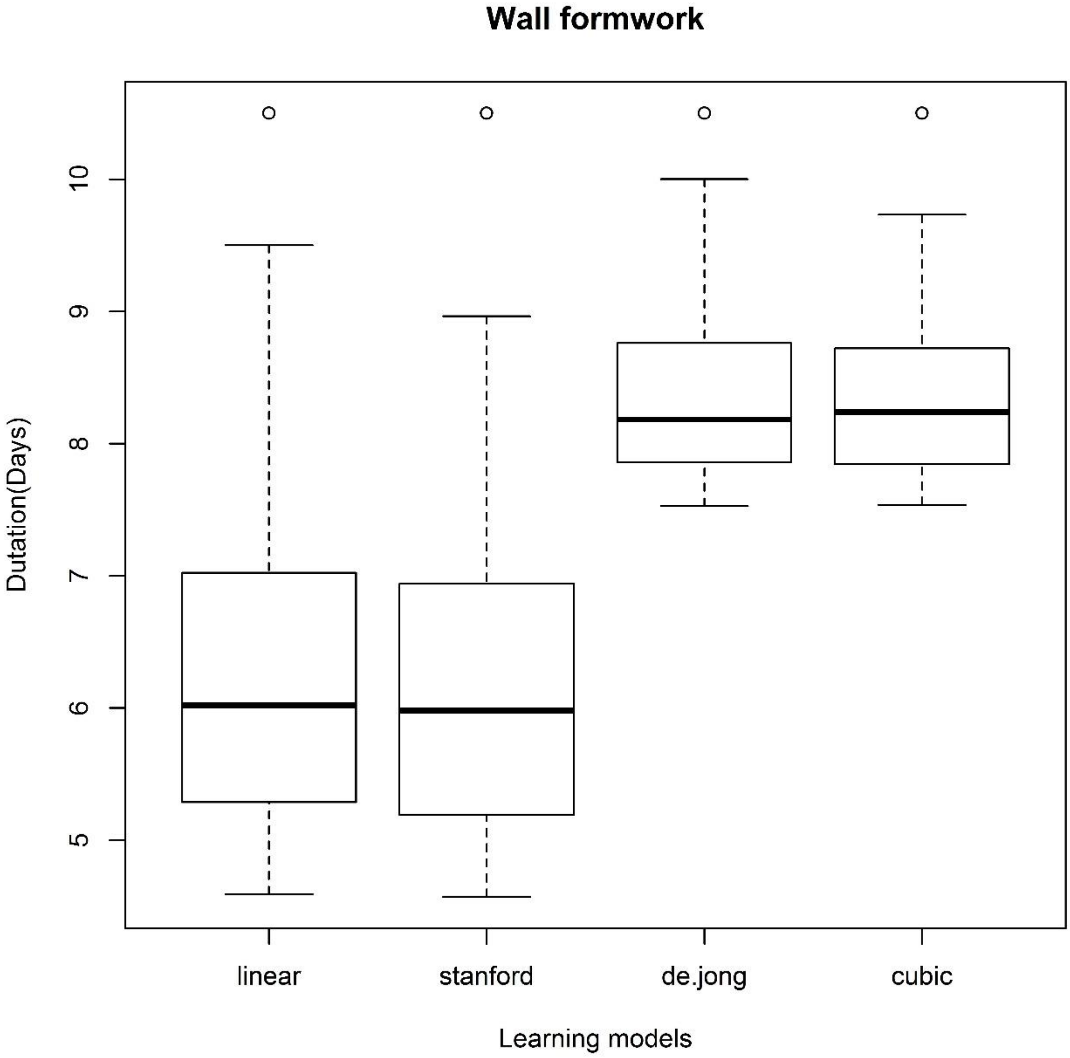


Figure C-22: Wall Formwork Boxplot

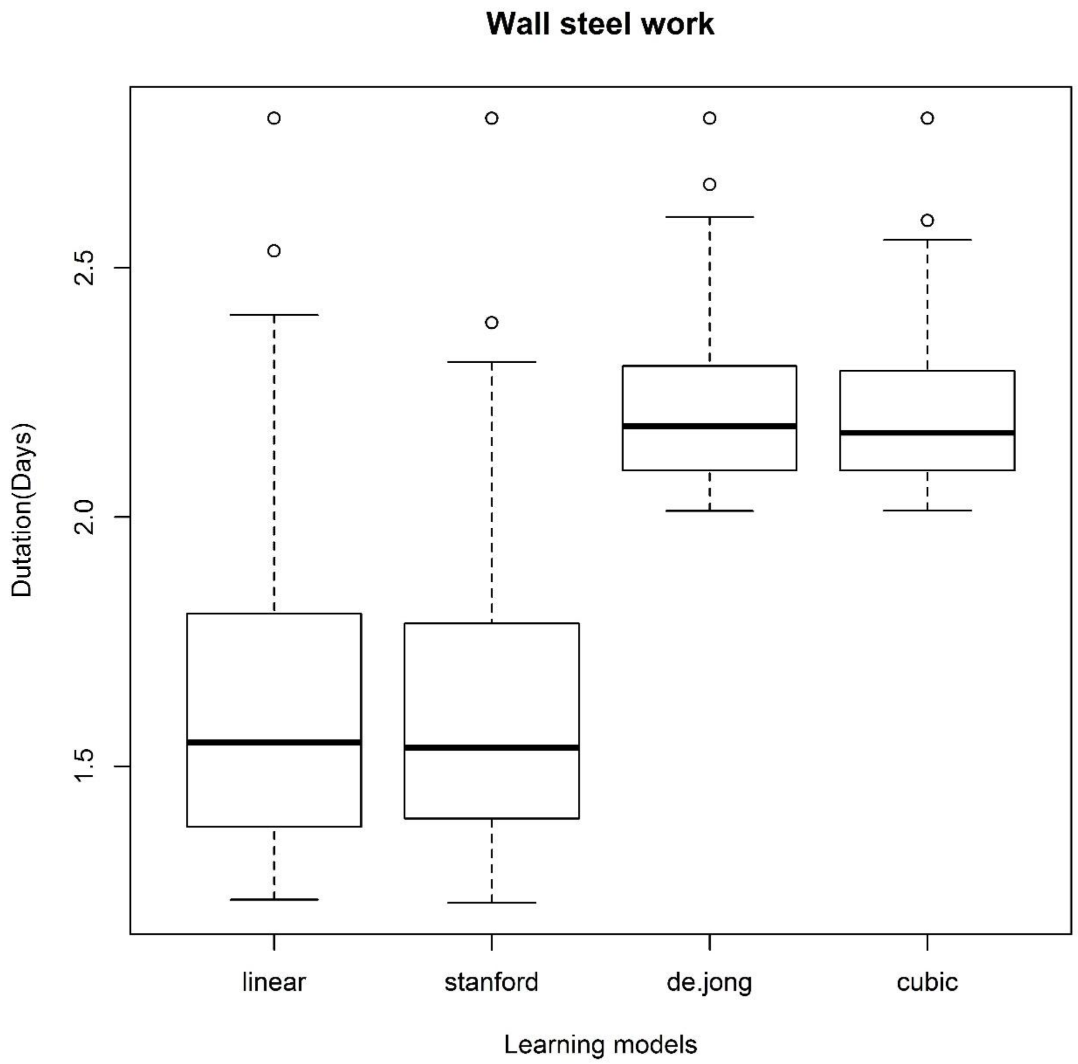


Figure C-23: Wall Steel Work Boxplot

C.5 R Code

```
getwd()
# Stage 1
# Test if incorporating factors affecting learning curve models is significant
# Straight-line Model
slabFW=read.csv("linear-slabFW.csv", header=T)
slabC=read.csv("linear-slabC.csv", header=T)
slabS=read.csv("linear-slabS.csv", header=T)
wallFW=read.csv("linear-wallFW.csv", header=T)
wallC=read.csv("linear-wallC.csv", header=T)
wallS=read.csv("linear-wallS.csv", header=T)
# Plotting the data
windows(title = "Histograms of data")
par(mfrow=c(4,3))
hist(slabFW$before,main = "")
hist(slabFW$after,main = "")
hist(slabC$before,main = "")
hist(slabC$after,main = "")
hist(slabS$before,main = "")
hist(slabS$after,main = "")
hist(wallFW$before,main = "")
hist(wallFW$after,main = "")
hist(wallC$before,main = "")
hist(wallC$after,main = "")
hist(wallS$before,main = "")
hist(wallS$after,main = "")
# The data seems not normal
windows(title = "Boxplots of data")
par(mfrow=c(3,2))
boxplot(slabFW,xlab="slab FW",ylab="Duration (days)")
boxplot(slabC,xlab="slab C",ylab="Duration (days)")
boxplot(slabS,xlab="slab S",ylab="Duration (days)")
boxplot(wallFW,xlab="wall FW",ylab="Duration (days)")
boxplot(wallC,xlab="wall C",ylab="Duration (days)")
boxplot(wallS,xlab="wall S",ylab="Duration (days)")
# Check if the data is normally distributed
shapiro.test(slabFW$before)# not normal
shapiro.test(slabC$before)# not normal
shapiro.test(slabS$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(slabFW$after)# not normal
shapiro.test(slabC$after)# not normal
shapiro.test(slabS$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
```

```
# Try log transformation
shapiro.test(log(slabFW$before)) # not normal
shapiro.test(log(slabC$before)) # not normal
shapiro.test(log(slabS$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(slabFW$after)) #  normal
shapiro.test(log(slabC$after)) # not normal
shapiro.test(log(slabS$after)) #  normal
shapiro.test(log(wallFW$after)) #  normal
shapiro.test(log(wallFW$after)) #  normal
shapiro.test(log(wallFW$after)) #  normal
# Data is not normal even with log transformation
# Try the Box-Cox Method
lm=lm(slabFW)
require(MASS)
windows()
boxcox(lm)
shapiro.test((slabFW$before)^(-2))
# Also not working
# Non-Parametric tests
# Because the analysis is for two-sample paired test, we use Wilcoxon Signed-Ranks
Test
wilcox.test(slabFW$before,slabFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabC$before,slabC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabS$before,slabS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallFW$before,wallFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallC$before,wallC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallS$before,wallS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
# Stanford Model
slabFW=read.csv("stanford-slabFW.csv", header=T)
slabC=read.csv("stanford-slabC.csv", header=T)
slabS=read.csv("stanford-slabS.csv", header=T)
wallFW=read.csv("stanford-wallFW.csv", header=T)
wallC=read.csv("stanford-wallC.csv", header=T)
wallS=read.csv("stanford-wallS.csv", header=T)
# Plotting the data
windows(title = "Histograms of data")
par(mfrow=c(4,3))
hist(slabFW$before,main = "")
hist(slabFW$after,main = "")
hist(slabC$before,main = "")
```

```
hist(slabC$after,main = "")
hist(slabS$before,main = "")
hist(slabS$after,main = "")
hist(wallFW$before,main = "")
hist(wallFW$after,main = "")
hist(wallC$before,main = "")
hist(wallC$after,main = "")
hist(wallS$before,main = "")
hist(wallS$after,main = "")
# The data seems not normal
windows(title = "Boxplots of data")
par(mfrow=c(3,2))
boxplot(slabFW,xlab="slab FW",ylab="Duration (days)")
boxplot(slabC,xlab="slab C",ylab="Duration (days)")
boxplot(slabS,xlab="slab S",ylab="Duration (days)")
boxplot(wallFW,xlab="wall FW",ylab="Duration (days)")
boxplot(wallC,xlab="wall C",ylab="Duration (days)")
boxplot(wallS,xlab="wall S",ylab="Duration (days)")
# Check if the data is normally distributed
shapiro.test(slabFW$before)# not normal
shapiro.test(slabC$before)# not normal
shapiro.test(slabS$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(slabFW$after)# not normal
shapiro.test(slabC$after)# not normal
shapiro.test(slabS$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
# Try log transformation
shapiro.test(log(slabFW$before)) # not normal
shapiro.test(log(slabC$before)) # not normal
shapiro.test(log(slabS$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(slabFW$after)) #  normal
shapiro.test(log(slabC$after)) # not normal
shapiro.test(log(slabS$after)) # not normal
shapiro.test(log(wallFW$after)) # normal
shapiro.test(log(wallFW$after)) # normal
shapiro.test(log(wallFW$after)) # normal
# Data is not normal even with log transformation
# Try The Box-Cox Method
lm=lm(slabFW)
require(MASS)
windows()
```

```
boxcox(lm)
shapiro.test((slabFW$before)^(-2))
# Also not working
# Non-Parametric tests
# Because the analysis is for two-sample paired test, we use Wilcoxon Signed-Ranks
Test
wilcox.test(slabFW$before,slabFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabC$before,slabC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabS$before,slabS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallFW$before,wallFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallC$before,wallC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallS$before,wallS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
# De Jong Model
slabFW=read.csv("de jong-slabFW.csv", header=T)
slabC=read.csv("de jong-slabC.csv", header=T)
slabS=read.csv("de jong-slabS.csv", header=T)
wallFW=read.csv("de jong-wallFW.csv", header=T)
wallC=read.csv("de jong-wallC.csv", header=T)
wallS=read.csv("de jong-wallS.csv", header=T)
# Plotting the data
windows(title = "Histograms of data")
par(mfrow=c(4,3))
hist(slabFW$before,main = "")
hist(slabFW$after,main = "")
hist(slabC$before,main = "")
hist(slabC$after,main = "")
hist(slabS$before,main = "")
hist(slabS$after,main = "")
hist(wallFW$before,main = "")
hist(wallFW$after,main = "")
hist(wallC$before,main = "")
hist(wallC$after,main = "")
hist(wallS$before,main = "")
hist(wallS$after,main = "")
# The data seems not normal
windows(title = "Boxplots of data")
par(mfrow=c(3,2))
boxplot(slabFW,xlab="slab FW",ylab="Duration (days)")
boxplot(slabC,xlab="slab C",ylab="Duration (days)")
boxplot(slabS,xlab="slab S",ylab="Duration (days)")
boxplot(wallFW,xlab="wall FW",ylab="Duration (days)")
boxplot(wallC,xlab="wall C",ylab="Duration (days)")
boxplot(wallS,xlab="wall S",ylab="Duration (days)")
```

```
# Check if the data is normally distributed
shapiro.test(slabFW$before)# not normal
shapiro.test(slabC$before)# not normal
shapiro.test(slabS$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(slabFW$after)# not normal
shapiro.test(slabC$after)# not normal
shapiro.test(slabS$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
# Try log transformation
shapiro.test(log(slabFW$before)) # not normal
shapiro.test(log(slabC$before)) # not normal
shapiro.test(log(slabS$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(slabFW$after)) # not normal
shapiro.test(log(slabC$after)) # not normal
shapiro.test(log(slabS$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
# Data is not normal even with log transformation
# Try The Box-Cox Method
lm=lm(slabFW)
require(MASS)
windows()
boxcox(lm)
shapiro.test((slabFW$before)^(-2))
# Also not working
# Non-Parametric tests
# Because the analysis is for two-sample paired test, we use Wilcoxon Signed-Ranks
Test
wilcox.test(slabFW$before,slabFW$after,paired = TRUE) # Cannot Reject the null
hypothesis. Difference is not significant
wilcox.test(slabC$before,slabC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabS$before,slabS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallFW$before,wallFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallC$before,wallC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallS$before,wallS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
```

```
# Cubic Model
slabFW=read.csv("cubic-slabFW.csv", header=T)
slabC=read.csv("cubic-slabC.csv", header=T)
slabS=read.csv("cubic-slabS.csv", header=T)
wallFW=read.csv("cubic-wallFW.csv", header=T)
wallC=read.csv("cubic-wallC.csv", header=T)
wallS=read.csv("cubic-wallS.csv", header=T)
# Plotting the data
windows(title = "Histograms of data")
par(mfrow=c(4,3))
hist(slabFW$before,main = "")
hist(slabFW$after,main = "")
hist(slabC$before,main = "")
hist(slabC$after,main = "")
hist(slabS$before,main = "")
hist(slabS$after,main = "")
hist(wallFW$before,main = "")
hist(wallFW$after,main = "")
hist(wallC$before,main = "")
hist(wallC$after,main = "")
hist(wallS$before,main = "")
hist(wallS$after,main = "")
# The data seems not normal
windows(title = "Boxplots of data")
par(mfrow=c(3,2))
boxplot(slabFW,xlab="slab FW",ylab="Duration (days)")
boxplot(slabC,xlab="slab C",ylab="Duration (days)")
boxplot(slabS,xlab="slab S",ylab="Duration (days)")
boxplot(wallFW,xlab="wall FW",ylab="Duration (days)")
boxplot(wallC,xlab="wall C",ylab="Duration (days)")
boxplot(wallS,xlab="wall S",ylab="Duration (days)")
# Check if the data is normally distributed
shapiro.test(slabFW$before)# not normal
shapiro.test(slabC$before)# not normal
shapiro.test(slabS$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(wallFW$before)# not normal
shapiro.test(slabFW$after)# not normal
shapiro.test(slabC$after)# not normal
shapiro.test(slabS$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
shapiro.test(wallFW$after)# not normal
# Try log transformation
shapiro.test(log(slabFW$before)) # not normal
shapiro.test(log(slabC$before)) # not normal
shapiro.test(log(slabS$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
```

```
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(wallFW$before)) # not normal
shapiro.test(log(slabFW$after)) # normal
shapiro.test(log(slabC$after)) # not normal
shapiro.test(log(slabS$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
shapiro.test(log(wallFW$after)) # not normal
# Data is not normal even with log transformation
# Try The Box-Cox Method
lm=lm(slabFW)
require(MASS)
windows()
boxcox(lm)
# Log transformation didn't work
shapiro.test((slabFW$before)^(-2))
# Also not working
# Non-Parametric tests
# Because the analysis is for two-sample paired test, we use Wilcoxon Signed-Ranks
Test
wilcox.test(slabFW$before,slabFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabC$before,slabC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(slabS$before,slabS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallFW$before,wallFW$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallC$before,wallC$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant
wilcox.test(wallS$before,wallS$after,paired = TRUE) # Reject the null hypothesis.
Difference is significant

# Stage 2
# Test if there is a difference between different learning models
# Before incorporating the learning factors
# Slab concrete work
slabC=read.csv("slabC-before.csv", header=T)
# Plotting the data
windows()
boxplot(slabC,main="Slab Concrete work",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabC) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabC)[,1],stack(slabC)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
```

# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong models
# Slab formwork work
slabFW=read.csv("slabFW-before.csv", header=T)
# Plotting the data
windows()
boxplot(slabFW,main="Slab formwork",ylab="Dutation(Days)",xlab="Learning models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabFW) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabFW)[,1],stack(slabFW)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong models
# Slab steel work
slabS=read.csv("slabS-before.csv", header=T)
# Plotting the data
windows()
boxplot(slabS,main="Slab steel work",ylab="Dutation(Days)",xlab="Learning models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabS) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabS)[,1],stack(slabS)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong models
# Wall concrete work
wallC=read.csv("wallC-before.csv", header=T)
# Plotting the data
windows()
boxplot(wallC,main="Wall concrete work",ylab="Dutation(Days)",xlab="Learning models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups

```
require(stats)
kruskal.test(wallC) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallC)[,1],stack(wallC)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# Wall formwork work
wallFW=read.csv("wallFW-before.csv", header=T)
# Plotting the data
windows()
boxplot(wallFW,main="Wall formwork",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(wallFW) # Reject the null hypothesis. there is a difference in learning
models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallFW)[,1],stack(wallFW)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# Wall steel work
wallS=read.csv("wallS-before.csv", header=T)
# Plotting the data
windows()
boxplot(wallS,main="Wall steel work",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(wallS) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallS)[,1],stack(wallS)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# After incorporating learning factors
# Slab concrete work
```

```
slabC=read.csv("slabC-after.csv", header=T)
# Plotting the data
windows()
boxplot(slabC,main="Slab concrete work",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabC) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabC)[,1],stack(slabC)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# The maximum diffference is lower than the one before incorporating learning factors
# Slab formwork work
slabFW=read.csv("slabFW-after.csv", header=T)
# Plotting the data
windows()
boxplot(slabFW,main="Slab formwork",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabFW) # Reject the null hypothesis. there is a difference in learning
models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabFW)[,1],stack(slabFW)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# The maximum diffference is lower than the one before incorporating learning factors
# Slab steel work
slabS=read.csv("slabS-after.csv", header=T)
# Plotting the data
windows()
boxplot(slabS,main="Slab steel work",ylab="Dutation(Days)",xlab="Learning models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(slabS) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(slabS)[,1],stack(slabS)[,2],p.adj = "holm",paired = F)
```

```
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# The maximum diffference is lower than the one before incorporating learning factors
# The similarity between the linear model and the stanford model is slightly reduced to
93%
# Wall concrete work
wallC=read.csv("wallC-after.csv", header=T)
# Plotting the data
windows()
boxplot(wallC,main="Wall concrete work",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(wallC) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallC)[,1],stack(wallC)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model and the De Jong model
# The similarity between the linear model and the stanford model is slightly reduced to
82%
# Wall formwork work
wallFW=read.csv("wallFW-after.csv", header=T)
# Plotting the data
windows()
boxplot(wallFW,main="Wall formwork",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(wallFW) # Reject the null hypothesis. there is a difference in learning
models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallFW)[,1],stack(wallFW)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# The maximum diffference is lower than the one before incorporating learning factors
# Wall steel work
```

```
wallS=read.csv("wallS-after.csv", header=T)
# Plotting the data
windows()
boxplot(wallS,main="Wall steel work",ylab="Dutation(Days)",xlab="Learning
models")
# Non-Parametric tests
# We use Kruskal Wallis Test because of multiple groups
require(stats)
kruskal.test(wallS) # Reject the null hypothesis. there is a difference in learning models
# Identify the different model (Multiple-comparison tests)
pairwise.wilcox.test(stack(wallS)[,1],stack(wallS)[,2],p.adj = "holm",paired = F)
# The linear model and the stanford model are the same
# The De Jong model and the cubic model are the same
# The De Jong model is significantly different than both the linear and stanford models
# The cubic is also significantly different than both the linear and stanford models
# Maximum difference is between the stanford model with both the cubic and De Jong
models
# The maximum diffference is lower than the one before incorporating learning factors
```