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# A Framework for Estimating Labor Productivity Frontiers

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# A FRAMEWORK FOR ESTIMATING LABOR PRODUCTIVITY FRONTIERS

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The efficiency of construction operations is typically determined by comparing actual versus historical productivity. This practice is accurate if historical data reflects optimal values. Otherwise, this comparison is a gauge of relative rather than absolute efficiency. Therefore, in order to determine absolute efficiency, one must compare actual versus optimal productivity. Optimal productivity is the highest sustainable productivity level achievable under “good management” and “typical field conditions,” while the productivity frontier is the theoretical maximum achievable under “perfect conditions.”

The productivity frontier is an abstraction useful in the estimation of optimal productivity of construction operations. This research contributes to the body of knowledge by introducing a novel framework to estimate the labor productivity frontier and applying it in a pilot study and a detailed study on the installation of lighting fixtures and the fabrication of sheet metal ducts activities.

The pilot study analyzed data on the fluorescent bulb replacement task up to the action level, collected from a school in Omaha, Nebraska to estimate the labor productivity frontier. Following two approaches–observed durations and estimated durations–the productivity frontier computed from this pilot study was found to be 22.32 stations per hour. The detailed study analyzed both action and movement levels by

collecting data from a workshop at a mechanical specialty constructor in Omaha, Nebraska. The pilot study only analyzed the sequential actions of a single worker. The detailed study analyzed the sequential and parallel actions and movements of crews of multiple workers involved in the fabrication activity. The productivity frontier for this activity computed from the detailed study, following both observed durations and estimated durations, was found to be 2.83 ducts per crew-hour.

Moreover, this research explores advanced automated frameworks using video cameras and a Kinect sensor in order to estimate the labor productivity frontier. One of the advantages of the proposed framework is that constructors, rather than being constrained by historical data, can also estimate the productivity frontier for activities they have never performed. Furthermore, scopes of this research–such as virtual environment development, recombinant synthetic workers development, and ergonomics and safety analysis–are also discussed.

To:

My parents, Dhana Prasad Mani and Shova Mani,

my wife, Lata Shrestha,

my sister, Sarika Mani and brother, Saujanya Mani,

my relatives and friends

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# CHAPTER 1

# INTRODUCTION

## 1.1 Problem Statement

The construction industry is considered one of the largest industries in the USA with the involvement of over 7.3 million workers and generating more than $1.73 trillion in annual revenue (Statistic Brain, 2015). As many construction operations are labor-intensive, the question of labor productivity becomes paramount especially as higher productivity levels typically translate into superior profitability, competitiveness, and income (Rojas & Aramvareekul, 2003). Labor productivity is becoming the prime factor because labor costs generally account for 30% to 50% of overall project costs in construction (Harmon & Cole, 2006). Unfortunately, the lack of reliable means for evaluating the efficiency of labor-intensive construction operations makes it more difficult for the construction industry to improve productivity and ensure a more effective development of the vital infrastructure that society demands, creating a problem that Drucker (1993) succinctly articulated: “if you can’t measure it, you can’t manage it.”

A project manager generally compares actual with historical productivity for equivalent operations in order to evaluate the efficiency of labor-intensive construction operations. But, this approach of examining productivity only provides a relative benchmark for efficiency. There is currently no systematic approach for measuring and estimating labor productivity (Song & AbouRizk, 2008). The operation may not be efficient even though the actual productivity equals average historical productivity because the operation’s efficiency may be well below optimal productivity. This idea further raises a concern that many factors involved in the processes of construction change overtime–productivity cannot be easily judged by the same data or information that was documented a decade or more ago (Liberda, Ruwanpura, & Jergeas, 2003).

The practice of benchmarking against historical averages will be biased and inefficient unless a standard methodology is implemented to evaluate productivity against an objective standard. This reality calls for an alternative technique to measure labor productivity. In an attempt to achieve this objective, this study introduces the terminology "*labor productivity frontier*" and develops a framework to estimate it. The labor productivity frontier is defined as the theoretical maximum productivity that could be achieved under "perfect conditions" (Son & Rojas, 2010). The perfect condition is an ideal state where all factors affecting labor productivity are at the most favorable levels, such as good weather, optimal utilization of materials and equipment, highly motivated and productive workers with flawless artisanship, no interference from other trades, no design errors, and precise understanding of the design intent, among others.

Although the labor productivity frontier is an abstraction that represents a production level not achievable in actual practice, it proves helpful in analyzing project conditions. The concept of productivity frontier can be used as an absolute benchmark because it provides a significant input value in order to estimate optimal productivity. Optimal productivity is defined as the highest sustainable productivity achievable in the field under good management and typical field conditions (Son & Rojas, 2010). By comparing actual versus optimal productivity, absolute (unbiased) efficiency can be calculated.

Several studies have been conducted regarding labor productivity, optimal productivity, and overall productivity (Rojas & Aramvareekul, 2003; Son & Rojas, 2010; Thomas & Sakarcan, 1994). However, there has been no research conducted regarding the estimation of the labor productivity frontier. This dissertation first introduces the proposed framework for estimating the labor productivity frontier, its underlying theory, and the methodology necessary for successful implementation. In turn, the estimation of the labor productivity frontier is the first significant step toward developing a process that will allow project managers to determine the efficiency of their labor-intensive operations.

## 1.2 Theoretical Framework

Figure 1.1 graphically depicts the relationships among several basic labor productivity concepts. The productivity achieved in the field is termed "*actual productivity*," whereas the level achievable under good management in sustainable manner and typical field conditions is called "*optimal productivity*." The difference between optimal and actual productivity is the operational inefficiency. Poor sequencing of activities, inadequate equipment or tools, mismatch between skills and task complexity, excessive overtime, and poor lighting conditions are examples of factors that may combine to form the operational inefficiency. Operational inefficiency can be minimized by project managers through pre-evaluation of risk factors and by exhibiting unbiased attitude while adopting explicit and systematic methods (Son & Rojas, 2010). However, there are also factors that affect productivity which are not under the control of project managers, such as high temperatures, high humidity, rainfall, and workers' poor health conditions. The collective effect of these factors constitutes the system inefficiency. If both operational and system inefficiencies are eliminated, then a theoretical maximum productivity could be achieved. The ideal theoretical maximum productivity achievable under "*perfect conditions*" is termed as "*productivity frontier*" (Son & Rojas, 2010). The productivity frontier is to be estimated once a construction activity has achieved its steady state phase (i.e. once the learning phase is over and productivity has leveled out). The point is shown in Figure 1.1 as time $T_2$.

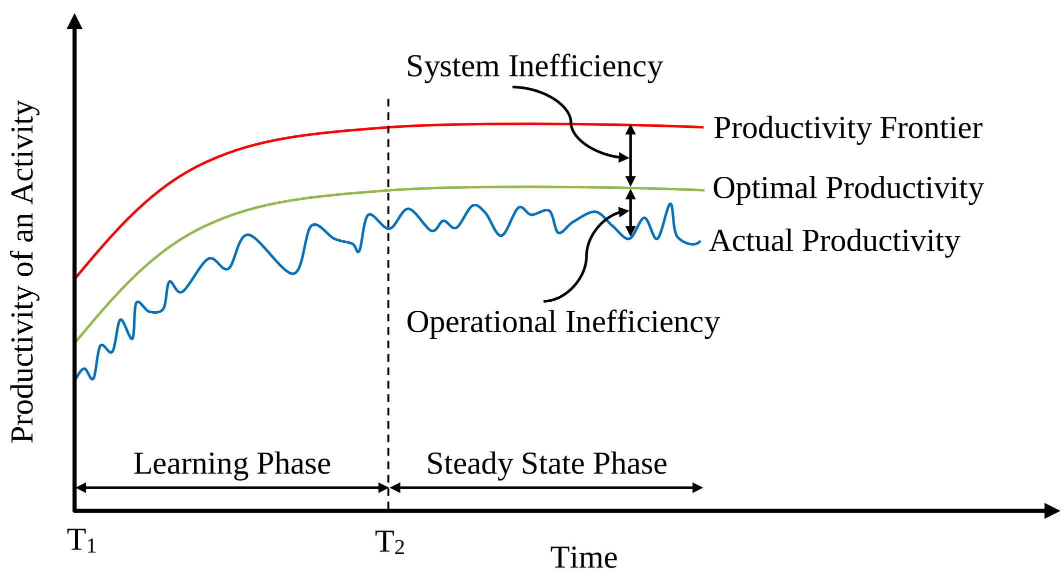


Figure 1.1 : Basic Productivity Dynamics

Out of all the variables shown in Figure 1.1, only actual productivity can be directly measured in the field. Therefore, given this limitation and the theoretical framework explained herein, the main challenges involved in the estimation of labor productivity frontier in labor-intensive construction operations include:

- Classifying the activity, tasks, actions, and movements

- Identifying the contributory and non-contributory actions
- Measuring shortest observed and estimated durations to complete an activity
- Developing the framework to estimate productivity frontier

## 1.3 Research Objectives

This study proposes the development of a dual approach for estimating the productivity frontier in labor-intensive construction operations. The first approach involves the estimation of the productivity frontier by using observed durations from a time and motion study. The movements of the workers are captured by multiple synchronized video cameras. The actions that make up a particular task are identified from the video frames and categorized into contributory and non-contributory actions. The best sequences of contributory actions are identified, based on the shortest time taken to complete a task or an activity, and used to determine the productivity as the sum of the shortest durations for each action.

Subsequently, the second approach involves the estimation of the productivity frontier by using estimated durations on the same time and motion study. The probability distributions that best represent action durations are identified, and the productivity frontier is defined as the sum of the lowest values from each of the distributions at a 95% confidence interval. The highest labor productivity value from these two approaches is taken as the best estimate of the productivity frontier.

Building upon the theory, this research specifically established the following objectives:

1. Evaluate the feasibility of the proposed framework for estimating labor productivity frontier for a specific construction activity involving a single worker performing a specific task.
2. Evaluate the feasibility of the proposed framework for estimating labor productivity frontier for entire construction activities involving crews of multiple workers performing parallel and sequential works.
3. Determine the impact of collecting data to the action level of hierarchy in the initial phase and to the lowest hierarchical level (i.e., the movement).
4. Explore automation techniques to facilitate data collection and analysis in order to estimate labor productivity frontier.
5. Explore the application of simulation and visualization techniques (for example, animation in preliminary phase) in order to evaluate the work flow process of a specific task or activity.
6. Explore the feasibility of creating recombinant synthetic workers by aggregating basic movements.

## 1.4 Significance of Research

1. If the proposed framework were found to be scalable, practical, and reliable for estimating productivity frontier in complex construction activities, then a novel and validated tool would be available to project managers to estimate optimal labor productivity as well as to evaluate the efficiency of their construction operations.

2. If the benefits of collecting movement data for the proposed framework were to outpace the costs, then the additional effort required to move beyond the action level would be justifiable.
3. If data collection and analysis of the proposed framework could be automated, then the cost of implementation would decrease significantly.
4. If a simulated and animated construction environment could be developed, then it would be helpful to project managers or other laborers to understand work flow process of a specific task or activity and also helpful to validate the working procedures.
5. If independent movements could be recombined in a simulated environment to create synthetic workers and crews, then the productivity frontier of any construction activity could be determined. One of the advantages of the proposed framework is that constructors, rather than being constrained by historical data, can also estimate the productivity frontier for activities they have never performed.

## 1.5 Research Hypothesis

1. The proposed framework for estimating labor productivity frontier is applicable to complex construction operations with crews of single or multiple workers performing both sequential and parallel processes.
2. The costs of collecting movement data for the proposed framework for estimating labor productivity frontier outpace the benefits of moving beyond the action level.

3. Data analysis and collection activities can be automated for the proposed framework for estimating the labor productivity frontier.
4. The simulated and animated work flow process of an activity and a task is applicable to validate the working procedure.

## 1.6 Dissertation Structure

This dissertation consists of eight chapters. It is a compilation of documents in a single report describing the background of the research, the significance of the research, methodology followed to conduct the research, a description about the data acquisition, pilot study, detailed study, analytical results obtained from time and motion study, as well as probability distribution analysis, formation of models and their validation, and a discussion about the limitations of the research as well as recommendations for future research. The structure of the dissertation with its components is described briefly as follows:

Chapter 1 Introduction: This chapter consists of problem statement, theoretical framework, research objectives, significance of this research, and the research hypotheses.

Chapter 2 Literature Review: This chapter covers the foundation and guidelines of research. It discusses background of labor productivity by reviewing previously published papers and books, before analyzing the labor productivity frontier, such as existing definitions of labor productivity, labor productivity benchmarking and metrics, critical analysis of various methodologies implemented to evaluate performance of construction activities, existing techniques to estimate labor productivity, and identified impediments to the achievement of high productivity levels.

Chapter 3 Research Methodology: This chapter first defines the theoretical underpinnings of the proposed framework to achieve research objectives. Then it thoroughly describes each step of the basic framework of this research, history of data collection, and statistical background. Moreover, it briefly discusses advanced framework to estimate the labor productivity frontier.

Chapter 4 Pilot Study: The preliminary study (pilot study) results appear in this chapter. The pilot study is conducted in order to determine the feasibility of proposed manual framework while estimating the labor productivity frontier considering a simple electrical bulb replacement task performed by a single worker. This chapter includes field data collection, data analysis, action identification, action classification, model development, model validation, and productivity frontier estimation following two approaches: observed duration and estimated duration. Finally, limitations of this research are also discussed in this chapter.

Chapter 5 Detailed Study: The detailed study describes extended research on labor-intensive manufacturing operations during fabrication of sheet metal duct at a workshop of the Waldinger Corporation in Omaha, Nebraska. The evaluation of the feasibility of the proposed basic framework (manual framework) for estimating labor productivity frontier is conducted for the entire manufacturing activity involving crews of multiple workers performing parallel and sequential works. The reason behind selection of this activity, working environment, video data collection, data extraction, data analysis, action and movement identification and classification, observed and estimated durations determination, labor productivity frontier estimation, comparison between performance of multiple crews on the specific task, comparison between hierarchical action and movement levels analysis, and limitations of this research are also discussed in this chapter.

Chapter 6 Conceptual Exploration of an Automated Framework: As basic framework (manual framework) to estimating labor productivity frontier is more time consuming and laborious, this chapter explains an exploration of an automated advanced framework with its scope in the construction engineering and management domain. It explains two separate frameworks: (a) using multiple video cameras and (b) using a Kinect sensor during data collection stage. Various stages involved in this automated framework–such as workers pose modeling and tracking, action identification and classification, database development, model development and validation, and productivity frontier estimation–are discussed in this chapter. Moreover, limitations of this framework and possible obstacles are also discussed in this chapter.

Chapter 7 Conclusions and Recommendations: This chapter discusses a comparison between the pilot study and the detailed study. Conclusions and limitations of the research are discussed in this section. In addition, potential research areas are also recommended in this section.

Chapter 8 Future Research: This section introduces new terminology, "*recombinant synthetic workers*," and discusses its possible applications with a brief explanation about virtual environments in construction engineering and management domain. The usability of the labor productivity frontier for estimating optimal productivity is also discussed briefly in this chapter.

# CHAPTER 2

# LITERATURE REVIEW

Productivity is generally defined as the ratio of output to input (Rojas & Aramvareekul, 2003). It is one of the most frequently discussed topics in the construction industry because of its importance to profitability. The Construction Industry Institute (2006) mentioned that productivity is one of the most frequently used performance indicators to assess the success of a construction project because it is the most crucial and flexible resource used in such assessments.

As many of the operations within the construction industry are decidedly labor-intensive, labor productivity is considered one of the best indicators of production efficiency (Maloney, 1982; Rojas & Aramvareekul, 2003). It is gaining increasing attention in construction as the industry faces multiple problems related to its workforce (Allmon, Borcherding, & Goodrum, 2000; Rojas & Aramvareekul, 2003; Teicholz, 2001). Moreover, labor productivity is a fundamental piece of information for estimating and scheduling a construction project (Song & AbouRizk, 2008) and becomes a prime factor because labor costs generally cover 30% to 50% of overall project costs in construction (Harmon & Cole, 2006).

## 2.1 Labor Productivity

Labor productivity can be defined as the ratio of output to input in the sense that output is usually measured by the production level such as number of columns poured or number of cubic yards of soil moved, while input is usually measured in units of time, such as labor hours or labor days. In the construction engineering and management domain, productivity is usually taken to mean labor productivity, which means units of work placed or produced per labor-hour. However, the inverse of labor productivity, labor-hours per unit (unit rate), is also commonly used (Halligan, Demsetz, Brown, & Pace, 1994).

In the manufacturing domain, labor productivity is defined as a measurement of economic growth of a country. It measures amount of products manufactured within an hour by labor. The U.S. Department of Labor defined labor productivity as the real output in national currency per hour worked. Bureau of Labor Statistics (BLS) measures labor productivity based on three basic measures–output, total labor hours, and total compensation (BLS, 2012). The output measures are real value added, and total labor hours refer to hours worked by all employees. The total compensation includes employer expenditure for direct pay, employer social security expenditure, and labor-related taxes and subsidies (BLS, 2012).

In the mining domain, the study of productivity in the bituminous coal mining industry became important at the macro or industry-wide level because: (a) productivity is important because of its relationship to the price of the energy resource, and (b) productivity is the key element in forecasting changes in labor demand in the industry as a whole and for specific areas to be impacted by regional shifts of production (Hannah, 1981). Labor productivity is generally defined as an average product of labor and expressed as the coal output (in tons) for physical units of labor input (in hours worked) (Hannah, 1981). It is simply measured by value added per hour worked (Topp, Soames, Parham, & Bloch, 2008).

In the agriculture domain, labor productivity is measured based on the agricultural output per labor force or worker (Lee, Craig, & Weiss, 1993; Shafi, 1984). As labor productivity indices in the agricultural sector are generally used for the description of economic performance, Dorward (2013) proposed an indicator relevant to agricultural workers for agricultural development and its wider contribution to the economics, terms as “Cereal Equivalent Productivity of Agricultural Labor (CEPAL).” It is defined as the ratio of the agricultural value added to the product of agricultural workers and cereal prices. When measuring labor productivity in the USA, the labor productivity in non-agriculture is considered higher than in agriculture, which creates a condition of “labor productivity gap” and is defined as the ratio of labor productivity in agriculture and non-agriculture (Herrendorf & Schoellman, 2011).

Several research projects were conducted regarding “production frontier” in the agricultural domain. The production frontier is considered as a bounding function and is defined as the maximum output obtained from a given set of inputs (Coelli, 1995; Kumbhakar, Ghosh, & McGuckin, 1991) in which cost function acts as an input parameter and profit function acts as an output parameter. The lower the cost function and the higher the profit function means the production frontier is higher (Coelli, 1995). The production frontier provides information regarding technologies that are used by the best performing firms and best practice technology against which the efficiency of the firm is measured (Coelli, 1995).

## 2.2 Existing Definitions of Productivity and Labor Productivity

There is no standard definition of productivity because each business defines it differently (Park, Thomas, & Tucker, 2005). However, productivity is defined in many ways because different measures of productivity serve different purposes. It is broadly defined as a terminology for the measurement of the effectiveness on employing the management skills, workers, materials, equipment, tools, and working space in order to produce a finished building, plant, structure, or other fixed facility at the lowest feasible cost (Liu & Song, 2005; Oglesby, Parker, & Howell, 1989).

Total factor productivity and partial factor productivity are two measures of construction productivity discussed by Talhouni (1990) and Rakhra (1991). Total factor productivity deals with the outputs and all inputs, whereas partial factor productivity deals with outputs and single or selected inputs. Thomas et al. (1990) defined productivity in terms of the total factor productivity, which is usually adopted by the Department of Commerce, Congress, and other governmental agencies as follows:

$$Total\ factor\ productivity\ (TFP) =$$

$$= \frac{Total\ Output}{Labor + Materials + Equipment + Energy + Capital} \ldots\ldots\ldots (2.1)$$

In an economic model, total factor productivity is measured in terms of dollars because dollars are the only measure common to both inputs and outputs (Thomas et al., 1990).

$$Total\ factor\ productivity = \frac{Dollars\ of\ output}{Dollars\ of\ input} \ldots\ldots\ldots (2.2)$$

Based on requirement, productivity is defined differently. The Federal Highway Administration defines it as (Thomas et al., 1990):

$$Productivity = \frac{Output}{Design + Inspection + Construction + Right\ of\ way} \ldots \ldots \ldots (2.3)$$

In an economic model, productivity is defined as:

$$Productivity = \frac{Lane\ miles}{Dollars} \ldots \ldots \ldots (2.4)$$

Since labor is the dominant input in the labor-intensive construction operation, construction productivity is primarily dependent on human effort and performance (Jarkas, 2010). Thus, the definition of productivity is modified in terms of labor as an input as per requirement.

In general, productivity is measured in three different levels (Chapman & Butry, 2008): task or activity level (deals with specific construction activities), project level (deals with construction of a new facility or renovation of an existing facility), and industry level (deals with total portfolio of the projects). Based on these levels of studies, three different productivity measurement models are determined, which are: (a) multifactor productivity model, (b) project-specific model, and (c) activity-oriented model (Liu & Song, 2005). According to the multifactor productivity model, productivity is defined as the ratio between total outputs and total inputs and is generally applicable to evaluate the efficiency of use of resources in the construction industry level (Liu & Song, 2005).

The project specific model defines productivity as the ratio between the outputs expressed in a physical unit and inputs expressed in labor, equipment, and materials (Thomas et al., 1990) as follows:

$$Productivity = \frac{Output}{Labor + Equipment + Materials} \ldots \ldots \ldots (2.5)$$

This approach is adopted by governmental agencies or private sectors for conceptual estimates on individual projects. The designers use historical productivity data in order to estimate and design the specific project. In an economic model, the productivity is defined as (Thomas et al., 1990):

$$Productivity = \frac{Square\ Feet}{Dollars} \ldots \ldots \ldots (2.6)$$

In an activity-oriented model, the productivity is generally expressed in units of output per labor cost (in dollar) or per work-hour (Thomas & Kramer, 1987). The productivity at the activity level is frequently referred to as labor productivity because construction activities are generally labor intensive and measure the input as labor hours or labor cost and output as installed quantities (Thomas & Mathews, 1985), as follows:

$$Labor\ Productivity = \frac{Output}{Labor\ Cost} \ldots \ldots \ldots (2.7)$$

$$Labor\ Productivity = \frac{Output}{Work\ hour} \ldots \ldots \ldots (2.8)$$

If there are various related activities, such as formwork, steel reinforcement, and concrete placement, then those are combined following the earned-value concept (Thomas et al., 1990). Some constructors use the performance factor in order to measure the productivity as follows:

$$Performance\ factor = \frac{Estimated\ Unit\ Rate}{Actual\ Unit\ Rate} \ldots \ldots \ldots (2.9)$$

In other words, labor productivity is expressed as the ratio of physical output to work-hours, in which the productivity ratio is measured as the ratio of actual work-hours to the estimated work-hours (GoodRum, Zhai, & Yasin, 2009). The actual work-hours is collected from the field, and estimated work-hours (also called earned work-hours) is calculated based on the quantity of a task and productivity performance provided by construction estimation manuals or a company's productivity databases. Performance factor is a ratio rather than absolute value, which makes it possible to compare across different projects or companies, and the impact of unique project characteristics is adjusted.

The Construction Management Research Unit at Dundee University measures labor productivity in three different approaches (Horner & Talhouni, 1998). The first approach deals with total time, also called total paid time (input). The second approach deals with available time, estimated as total time minus unavoidable delays, meal breaks, and weather. The third approach deals with the productive time, which is obtained by subtracting avoidable delays from available time.

$$Labor\ Productivity = \frac{Output}{Total\ Time} \dots\dots\dots (2.10)$$

$$Labor\ Productivity = \frac{Output}{Available\ Time} \dots\dots\dots (2.11)$$

$$Labor\ Productivity = \frac{Output}{Productivity\ Time} \dots\dots\dots (2.12)$$

In existing practice, hourly outputs are widely used to measure labor productivity in construction research (Hanna, Chang, Sullivan, & Lackney, 2008; Sonmez & Rowings, 1998; Thomas & Yiakoumis, 1987), considering a labor hour as the input unit and the physical quantity of the completed work as the output. This implies that the labor productivity consists of the number of actual work-hours required to perform the appropriate units of work. Moreover, defining the term "*hours*" as the hours actually worked, the labor productivity in the U.S. is defined by the BLS (2006), as real output per hour worked. This approach excludes vacation, holidays, and sick leave, but includes paid and unpaid overtime.

According to Eastman and Sacks (2008), this approach of measurement of labor productivity by hourly output avoids many external factors that cause cost variance when comparing with cost-based output measures. This implies that the hourly output is the most reliable approach for the measurement of productivity for construction activities (Yi & Chan, 2014). Thus, based on the simple input and output concept, labor productivity for construction operational activities is defined by:

$$Labor\ Productivity = \frac{Installed\ quantity}{Actual\ work\ hours} = \frac{Output}{Work\ hour} \ldots\ldots\ldots (2.13)$$

## 2.3 Labor Productivity as Gauging Construction Process Efficiency

On the basis of construction activity, the unit of measurement may vary while measuring productivity at the project level. For example, Yi and Chan (2014) found the average production rate for pouring columns lower than that for pouring walls because of job characteristics. The labor productivity is a measure of work process efficiency, which is defined as the ratio of the value labor produced to the value invested in labor. Thus, the American Association of Cost Engineers (AACE) (2011) defines productivity as a "relative measure of labor efficiency, either good or bad, when compared to an established base or norm" (p. 27). Moreover, this relative measure creates great difficulty in tracing it as an absolute value over time, and there is a possibility of gathering information on the movements of the established base or benchmark values (Allmon et al., 2000). In an attempt to overcome such a condition, labor productivity is redefined as a ratio of actual over expected productivity. The performance ratio is thus, defined for, "$m$" activity in project and "$i$" workday under consideration (Yi & Chan, 2014), as follows:

$$Performance\ Ratio_{im} = \frac{Actual\ productivity_{im}}{Expected\ productivity_{im}} \ldots\ldots\ldots (2.14)$$

The expected productivity is determined from the work-hours and quantities installed on days when no changes or rework, disruptions, or bad weather were reported. The performance ratio is a dimension-less measure that is determined by dividing actual productivity by baseline productivity. It defines a basis for comparing productivity data for different job types, eliminating the differences between production rate levels (Yi & Chan, 2014). The main feature of this approach is that the progress of work is based on the installed work, not the work hours consumed, and progress and performance can be determined regardless of the type of work performed.

In order to gauge construction process efficiency, benchmarking is necessary to compare observed value with the standard value (Bernold & AbouRizk, 2010). There are some process indicators to measure efficiency of construction operations.

$$Efficiency\ of\ Direct\ Labor = \frac{Direct\ hours\ budgeted}{Direct\ real\ hours} \ldots\ldots\ldots (2.15)$$

$$Or, Efficiency\ of\ Direct\ Labor = \frac{Budgeted\ cost\ direct\ hours}{Cost\ real\ direct\ hours} \ldots\ldots\ldots (2.16)$$

## 2.4 Productivity Benchmarking

Benchmarking is an important continuous improvement process that enables companies to enhance their performance by identifying, adapting, and implementing the best practice identified within a participating group of companies (CBPP, 2002; CII, 2002; Knuf, 2001; Smith, 1997). It is generally defined as a systematic and continuous measuring process comparing the output of one organization to the output of another organization anywhere in the world to acquire information that will help the organization to take action to improve its performance (Bernold & AbouRizk, 2010; Idiake & Bala, 2012; Thomas & Sudhakumar, 2013). In short, comparison and improvement are the keys behind the process of benchmarking for any topic.

According to Thomas (2012), the labor productivity benchmarking study can be conducted by using three key performance indicators–productivity variability, baseline productivity, and project waste index (PWI). Baseline productivity is generally calculated implementing Thomas's (2000) baseline productivity method. But, there are several methods to calculate baseline productivity, such as Thomas's Baseline Productivity Method (Thomas, Riley, & Sanvido, 1999), Measured Mile Analysis (Ibbs & Liu, 2005; Zink, 1986), Control Chart Method (Gulezian & Samelian, 2003), Data Envelopment Analysis (DEA) Method (Lin & Huang, 2010), and K-Means Clustering Method (Ibbs & Liu, 2005). Measured Mile Analysis gives "productivity factor" by comparing the cumulative actual work-hours with the earned work-hours. Considering baseline productivity as a norm level, a productivity control chart is developed with a center line and control limits, in which the center line value gives the arithmetic mean of the daily labor productivity and the control limits are represented by plotting with three standard deviations of the labor productivity population from the center line (Gulezian & Samelian, 2003).

Baseline productivity is considered as the best productivity when there are no or few disruptions that adversely affect labor productivity (Thomas, 2000). Thomas's baseline productivity is determined with respect to 10% of the total workdays that have the highest daily output or production, the number of days in the baseline set being not less than five (Thomas & Zavrski, 1999). Since this baseline productivity is subjective in nature, it cannot be verified that 10% of the whole daily productivity is a reasonable or well-accepted percentage to represent the best performance a contractor could achieve (Ibbs & Liu, 2005).

According to Ibbs and Liu (2005):

> Every project is different. This 10% sample is presumably 10% of the time that similar work is being performed, not 10% of the total project, which may consist of a series of quite dissimilar work categories. However, Thomas (2000) is unclear on this. This procedure selects contents of the baseline subset as n workdays that have the highest daily production or output. Daily output might be maximized by crew size. Therefore, certain days could be selected as the baseline, which are not truly indicative of the achieved productivity (p. 1251).

In order to overcome this weakness, Ibbs and Liu (2005) presented K-Means Clustering Methods for baseline productivity calculation. Meanwhile, data envelopment analysis (DEA) was introduced by Lin and Huang (2010) for deriving baseline productivity, which compared with the other four baseline productivity deriving methods–measured mile baseline, Thomas baseline, control chart baseline, and K-means clustering. This DEA method was found to be the best method in terms of objectivity, effectiveness, and consistency to find baseline productivity that represents the best performance a contractor can possibly achieve. This DEA method was capable of deriving productivity of multi-input and multi-output activities, and able to raise the scale of labor productivity from the level of single factor productivity to total factor productivity.

Variability in productivity is a determinant of performance of a construction project. Poorly performing projects exhibit higher variability in productivity when compared to projects that perform well (Thomas & Sudhakumar, 2013). The project waste index (PWI) or the project management index (PMI) is a dimensionless measure of the amount of labor waste associated with an activity/project (Thomas & Sudhakumar, 2013). If the data are not affected by the work environment and are affected primarily by the work content or design complexity, the project parameter has limited usefulness unless it can be compared to similar parameters computed from other projects or other activities on the same project, which demands the condition for PMI (Thomas, 2000). A lower value of PWI indicates better performance of the project. The value of PMI should not be a negative.

$$PMI = \frac{Cumulative\ productivity - baseline\ productivity}{baseline\ productivity} \ldots\ldots\ldots (2.17)$$

Where, cumulative productivity is defined as a ratio of combination of all the work hours charged to an activity to the total quantities installed to date. This approach predicts the final productivity rate upon completion of the activity and shows how the work is progressing as a whole (Thomas, 2000).

$$Cumulative\ Productivity = \frac{Total\ work\ hours\ charged\ to\ a\ task}{Total\ quantity\ installed} \ldots\ldots\ldots (2.18)$$

Meanwhile, the concept of measured mile is also applicable for a continuous period of time when the labor productivity is unimpacted, which compares the impacted period with the unimpacted periods if both have the same resources and are from the same project, but have different working conditions and are impacted due to the owner (Thomas, 2010).

Moreover, while considering a variety of work in a single workday by the crew, there can be problems in analyzing the performance (Thomas, 2000). For example, a concrete formwork crew works on wall formwork, column, and slab formwork simultaneously; a sheet metal crew erects several sizes of ducts plus louvers, dampers, and vents. During this condition, a weighted average approach is used to combine the quantities into an equivalent amount of one type or size unit (called the standard item).

$$Conversion\ factor_{ij} = \frac{unit\ rate\ for\ the\ item\ in\ question_{ij}}{unit\ rate\ of\ the\ standard\ item_j} \dots \dots \dots (2.19)$$

Where, $i$ is the item number and $j$ is the manual number

## 2.5 Productivity Metrics

Metrics are essential terminologies while determining productivity benchmarking. Metrics are defined as standards of measurement to provide assessment of the measurement of efficiency, performance, progress, or quality of a plan, process, or product. Cost, schedule, safety, changes, and rework are performance metrics for construction activities (Park et al., 2005). The CII benchmarking research has revealed that construction performance has been impacted by best practice use (CII, 2002). Park et al. (2005) described the construction productivity metrics for seven categories, which are concrete, structural steel, electrical, piping, instrumentation, equipment, and insulation. Moreover, labor and equipment productivity metrics are also key factors for the improvement of construction productivity. R.S. Means (2009) and the CII (2003) published task level metrics. Most task-level metrics are single factor measures and focus on labor productivity (Huang, Chapman, & Butry, 2009). Huang et al. (2009) stated that "CII fixes the output (e.g. cubic yards of concrete put in place) and measures the labor hours required to produce that output" (p. 32). If labor and equipment both come under productivity estimation, this measure is termed multifactor productivity.

There are many factors that affect construction labor productivity, such as mental fatigue, physical fatigue, stress fatigue, boredom, overtime, morale and attitude, stacking of trades, joint occupancy, beneficial occupancy, concurrent operations, absenteeism and turnover, mobilize/demobilize, errors and omissions, start/stop, reassignment of manpower, late crew build-up, crew size inefficiency, site access, logistics, security check, learning curve, ripple effect, confined space, hazardous work area, dilution of supervision, holidays, shorter daylight hours, weather and season changes, rain, shift work, working in operating area, over-manning, tool and equipment shortage, area practices, proximity of work, alternating, staggered, and rotating work schedules (Borcherding & Garner, 1981; Intergraph, 2012; Oglesby et al., 1989). The typical labor factors that affect labor productivity can be considered while developing labor productivity metrics. Thus, the labor productivity metrics are determined based on type of activity or task, output, and input functions.

There are key performance indicators (KPI) for overall labor effectiveness (OLE) that measures the utilization, performance, and quality of the workforce and its impact on productivity (Takim & Akintoye, 2002). It allows managers to make operational decisions by giving them the ability to analyze the cumulative effect of these three workforce factors on productivity output, while considering the impact of both direct and indirect labor. It supports lean and sigma methodologies and applies them to workforce processes, allowing managers to make labor-related activities more efficient, repeatable, and impactful.

However, there are not sufficient materials available to illustrate the labor productivity metrics because those metrics are identified and quantified based on project characteristics and requirements. For example, when the labor productivity is measured in terms of physical output for labor cost as an input parameter, the output per labor cost can be considered as one labor productivity metric. Similarly, if time is a major function during evaluation of labor productivity, then output per labor work-hour can be considered as another example of labor productivity metrics. Thus, number of laborers employed, labor working hours, and labor costs are the main elements of labor productivity metrics. In reality, labor and equipment generally come together during analysis of productivity of construction operations. But, there are differences in labor and equipment productivity metrics in the sense of understanding, which are discussed in the following section.

### 2.5.1 Labor and Equipment Productivity Metrics

There are various factors that significantly influence equipment productivity. Based on these, equipment productivity metrics are designated. Vorster (2014) categorized construction equipment metrics into three broad groups, which are activity metrics, input metrics, and output metrics. For simplicity, the difference between labor and equipment productivity metrics can be discussed under these broad groups.

### 2.5.1.1 Activity metrics

These metrics are designated based on involvement of the equipment in the construction activity. Deployment, utilization, and net utilization of the equipment are three different sub metrics under this activity metric (Vorster, 2014). Deployment of equipment is defined as the percentage of time the machine is actually deployed on site and required to work relative to the total ownership period. Utilization of equipment is quantified by defining it as the percentage of time the machine is actually used relative to the time it is on site and able to work. Specifically, it is necessary to estimate the net utilization of equipment, which is defined as the percentage of time the machine is actually used relative to the time it is deployed on site.

$$Deployment = \frac{Time\ a\ machine\ is\ on\ site\ and\ required\ to\ work}{The\ total\ ownership\ period} = \frac{T}{E} \ldots\ldots\ldots (2.20)$$

$$Utilization = \frac{Time\ a\ machine\ is\ actually\ used}{Time\ a\ machine\ is\ required\ and\ able\ to\ work} = \frac{W}{T-D} \ldots\ldots\ldots (2.21)$$

Labor productivity has a significant contribution in the activity or task level of work, generally in the labor-intensive construction operation. But, it is not suitable to present labor productivity metrics similar to deployment or utilization activity metrics for the equipment. However, it is possible to measure labor mobilization time to site or time utilized by labor in actual work completion.

### 2.5.1.2 Input metrics

Metrics, which are designated based on input provided to equipment, are called input metrics. These are sub classified into labor factor and repair cost. The labor factor is the ratio of repair and maintenance labor hours spent on the equipment to the hours worked by the equipment (Vorster, 2014). The repair cost is defined as the direct cost of repair parts and labor per hour worked by the equipment.

Let *RMh* be the repair and maintenance labor hours spent on the equipment, *Rpl* be the direct cost of repair parts and labor spent on the equipment in the period and *W* be the actual hours the equipment worked during the period. Then, labor factor and repair cost are quantified by using the following relations:

$$Labor\ Factor = \frac{RMh}{W} \dots \dots \dots (2.22)$$

$$Repair\ cost = \frac{Rpl}{W} \dots \dots \dots (2.23)$$

Meanwhile, the labor factor presented here for equipment input metrics is due to the involvement of labor in operating the equipment. Similarly, in labor productivity metrics, equipment factor can be considered. The labor cost may be another input metric for labor productivity metrics, which has a significant effect on labor productivity. The labor cost metric may be defined as the direct cost spent in labor for actual hours the labor worked.

#### 2.5.1.3 Output metrics

These metrics are designated based on output given by the equipment, which are sub classified into availability, down ratio, and reliability (Vorster, 2014). The availability is defined as the percentage of time the equipment is able to work relative to time on site. The down ratio is defined as the ratio of the equipment’s down duration per hour worked by the equipment. The frequency with which the equipment breaks down and disrupts production is termed as reliability. The loss in availability may be due to setup time and breakdown of equipment.

Let *T* be time the equipment is on site and required to work, *D* be the time the equipment is down and incapable of working when it is required to work, *W* be the actual hours the equipment worked during the period, and *V* be the number of times a machine breaks down and disrupts production. Then, these metrics are quantified by the following relations:

$$Availability = \frac{T - D}{T} \dots \dots \dots (2.24)$$

$$Down\,ratio = \frac{D}{W} \dots \dots \dots (2.25)$$

$$Reliability = \frac{V\ x\ 100}{W} \dots \dots \dots (2.26)$$

Similar to equipment availability, the labor availability hours metric may be defined as the ratio of actual time spent to contributory work (total time – time spent in non-contributory work) to the total time. Other equipment metrics are not suitable in the context of labor productivity metrics. However, the time spent in labor rest may be synonymous to the time the equipment is down.

The performance rate is the quantity produced during the running time versus the potential quantity given the designed speed of the equipment. A low performance rate reflects speed losses, such as idling, minor stoppages, and reduced speed operation. In the context of labor productivity metrics, the performance rate may be simply defined as the actual output achieved for labor hours input.

$$Performance\ Rate = \frac{Total\ Output}{Potential\ Output\ at\ Rated\ Speed} \dots \dots \dots (2.27)$$

## 2.6 Research Methodologies to Evaluate Performance of Construction Activities

For simplicity, the research methodologies for evaluating the performance of construction activities are primarily categorized into three broad groups: (a) qualitative, (b) quantitative, and (c) mixed-method (combined method) (Panas & Pantouvakis, 2010). Furthermore, three major fields or approaches are identified based on each study's research focus, which are archival studies (historical record) approach, empirical approach, and simulation approach (Panas & Pantouvakis, 2010).

### 2.6.1 Qualitative Research Method

Qualitative research methods focus on discovering, understanding the experiences, perspectives, and thoughts of participants that is, qualitative research explores meaning, purpose, or reality (Hiatt, 1986). It is usually conducted by allowing a detailed exploration of a topic of interest in which information is collected by a researcher through case studies, ethnographic work, and interviews.

A conceptual framework was developed utilizing the historical data and expert experience to measure productivity (Crawford & Vogl, 2006). Similar techniques were implemented to determine the factors that influence on-site performance (Park, 2006) and to formulate construction productivity related to general principles (Thomas & Horman, 2006).

The questionnaire surveys technique is implemented while performing qualitative empirical research in order to explore the role and significance of specific factors that affect productivity. For example, by surveying a variety of project actors, such as owner, consultant, and constructor, Rojas and Aramvareekul (2003) determined personal management skills and manpower issues as the two main improvements by focusing "people" to the center of focus while conducting research on labor productivity drivers and productivity within the US construction industry. Similarly, Chan and Kaka (2007) conducted a questionnaire survey combining in-depth interviews by targeting both white-collar managers and blue-collar workers in order to determine the construction productivity factors in the UK. The relative impacts of 83 productivity factors, such as behavioral issues, communication skills, project management, and safety, were determined by investigating the opinions of the craft workers following a "bottom-up" approach (Dai, Goodrum, & Maloney, 2009).

### 2.6.2 Quantitative Research Method

The quantitative research method attempts to maximize objectivity, replicability, and generalizability of findings and is typically interested in prediction (Harwell, 2011). It is frequently described as deductive in nature, in the sense that inferences from tests of statistical hypotheses lead to general inferences about characteristics of a population. It can also be sub classified based on three approaches: empirical, simulated, and historical records (Panas & Pantouvakis, 2010).

#### 2.6.2.1 Historical record approach

Historical record approach deals with the retrospective study of historical data for identifying the critical factors that affect the on-site productivity by implementing the quantitative research methodology. This approach is applicable to verify the construction management community's predilection towards the establishment of an objective conception of reality through the application of natural science methods (Panas & Pantouvakis, 2010). For example, Song and AbouRizk (2005) developed an empirical framework termed as "Quantitative Engineering Project Scope Definition (QEPSD)," in order to predict productivity quantitatively based on available historical data. Similarly, Graham and Smith (2004) collected historical productivity data regarding the concrete supply and on-site delivery. Based on this historical data, they developed a predictive model by applying Case Based Reasoning (CBR) principles.

#### 2.6.2.2 Empirical approach

In this approach, the effects of a pre-selected set of variables or factors on productivity are analyzed by developing mathematical models (Panas & Pantouvakis, 2010). Multiple regression techniques (Thomas, Riley, & Sanvido, 1999), artificial neural networks (Schabowicz & Hola, 2007), and quantitative surveys (Ng, Skitmore, Lam, & Poon, 2004) are usually implemented in order to assess empirical research for quantitative analysis. For example, Thomas et al. (1999) proposed a generic analytical framework while determining the impact of weather and materials delivery methods on labor-intensive productivity for three steel erection projects. In this study, the differences in labor productivity are quantified using the multiple regression technique because workdays often have multiple events occurring that are of interest. In general, the constant term in the regression model must be defaulted to zero for the model to be valid. It demands the conversion factors while performing comparative analyses because the data from multiple projects need to be combined or compared together, which requires that the work output be the same for all projects (Thomas et al., 1999).

#### 2.6.2.3 Simulation approach

The simulation approach is basically dependent upon knowledge of mathematics, probability, and statistics (Panas & Pantouvakis, 2010). The quantitative modeling methods, such as probabilistic analysis (Huang & Hsieh, 2005) and stochastic data modeling (Rustom & Yahia, 2007) implement the positivist epistemological aspect of a simulation's relationship (Panas & Pantouvakis, 2010).

Based on the literature, simulation models are classified into general purpose simulation platforms and special purpose simulation tools. CYCLONE, MicroCYCLONE, STROBOSCOPE, or EZStrobe (Marzouk & Moselhi, 2003; Zhang, Hammad, Zayed, Wainer, & Pang, 2007) are categorized into general purpose simulation, which are not domain specific and applicable to model any operational scenario (Martinez & Ioannou, 1999). SIMPHONY is categorized into a special purpose simulation (Mohamed & AbouRizk, 2005). The special purpose simulators are applicable to model a project even though the operator is not expert in simulation (Hajjar & AbouRizk, 2002). The developed models in both general purpose simulation and special purpose simulation studies represent an abstraction of the actual system, isolated from its general context when objectivism dominates in simulation research (Panas & Pantouvakis, 2010).

### 2.6.3 Combined Research Method

Sometimes the research objectives are both qualitative and quantitative in nature. In order to address such research objectives, a combined research method is implemented, which can bridge the difference in the properties of both qualitative and quantitative methods. This method involves historical record, empirical work, and simulation tools while formulating the mathematical models (Panas & Pantouvakis, 2010).

#### 2.6.3.1 Historical record approach

The combined method includes unobtrusive research methods, such as document analysis, historical data of existing organizations or companies, and a combination of the prior statistical regression or artificial neural networks modeling techniques. Song and AbouRizk (2008) conducted research by taking the historical database of productivity data in order to extract datasets, which were used to train an artificial neural network (ANN) and develop productivity models for steel drafting projects. In a similar fashion, Thomas and Zarvski (1999) investigated the research by analyzing the historical project databases on labor productivity measurement for masonry, concrete formwork, and structural steel activities from 42 construction projects and also performed statistical analysis to compute specific productivity metrics to identify the best and worst performing projects.

Based on historical company-specific data of construction projects, Mosehli, Assem, and El-Rayes (2005) implemented the ANN technique for modeling labor intensive operations. Chao (2001) utilized the ANN technique combining it with a simulation technique to estimate the cycle time and work zone width of excavators. An expert system (WEATHER) was created based on the climatic historical database, combining knowledge-based rules and estimating the lost productivity due to rainfall on highway construction (El-Rayes & Mosehli, 2001). These developed models were validated with the actual data obtained from different agencies, such as contractor, consultant, and public authorities.

In order to evaluate the significance of the learning curve effects on construction operations, Thomas (2009) adopted statistical analysis methods to conduct cause-effect analysis on historical cumulative productivity measurements. Doloi (2008) used a structured questionnaire to investigate the effect of planning, incentives, and job satisfaction on productivity. In an attempt to prioritize the solutions for improving productivity in construction projects, questionnaires and the analytical hierarchy process (AHP) method was implemented (Doloi, 2008). Based on the existing linear model, Hanna, Lotfallah, and Lee (2002) analyzed the effect of the quantitative, qualitative input variables, and change orders on labor productivity implemented with an integrated method based on regression analysis combined with fuzzy logic. Similar methodology was developed by Mohamed and Srinavin (2005) based on statistical regression analysis methods while determining the effect of thermal comfort and representing the influence of the external environment on productivity of labor intensive operations.

#### 2.6.3.2 Empirical approach

From the principles of a methodological point of view, there are not substantial applications of empirical approaches in the combined research method. The primary differences are found in the data elicitation techniques in which questionnaire surveys are mainly used instead of meta-data or document analysis (Panas & Pantouvakis, 2010).

In an empirical research approach, the variety of methods–such as field experiments or laboratory tests, controlled experiments, comparative evaluations, and generic productivity measurement models–are implemented in order to develop an experimental framework (Panas & Pantouvakis, 2010). Utilizing the concept of statistical analysis, Zhao, Zhu, and Lu (2009) evaluated the significance of the thermal environment on labor productivity. A benchmark for masonry labor productivity was established based on a generic statistical methodology (Enshassi, Mohamed, Mayer, & Abed, 2007), which compared actual project data to accepted industry standards. A generic measurement model was presented by Hanna, Taylor, and Sullivan (2005) by defining a statistical productivity measurement framework based on the comparison of the budgeted work hours to the actual work hours spent to reach completion. This framework was helpful to investigate the relationship between extended overtime and productivity. Not only statistical models but also simulation frameworks have been utilized in defining productivity measurement framework for construction activities. For example, Zayed and Halpin (2004) applied this approach in pile construction operations, whereas Huang et al. (2005) utilized this technique to estimate the productivity of gang formwork operations.

A continuous observation method, such as time studies (Dunlop & Smith, 2004), time-lapse visual techniques (Tam, Tong, & Tse, 2004), and image analysis (Zou & Kim, 2007), and intermittent observation methods, such as passive observation (Bernold & Lee, 2010), application of structured data elicitation protocols, deployment of specialized data elicitation instruments, are two different data collection techniques employed during research following the empirical approach. When the researcher does not actively participate in the data collection process, passive observation is implemented by declaring site personnel for time study and participation as a passive observer (Bernold &

Lee, 2010). Lee, Lee, and Ibbs (2007) implemented a similar approach to monitor and compare the production rates of freeway rehabilitation projects in California.

Various techniques are implemented during data collection and validation stages, such as a structured questionnaire survey (Proverbs, Holt, & Olomolayie, 1999) to collect and validate data; personal and phone interviews to gather additional data (AbouRizk, Knowles, & Hermann, 2001); and development of a Construction Productivity Metrics System (CPMS) in order to compare and set industry norms and benchmark construction productivity (Park et al., 2005). In an empirical approach, statistical regression (Hanna 1999a; 1999b), linear and non-linear mathematical models, probabilistic modeling, fuzzy set theory (Yang, Edwards, & Love, 2003), and the artificial neural networks techniques (Zayed & Halpin, 2001) are frequently used for processing the collected data during research conducted relating to labor productivity and efficiency.

#### 2.6.3.3 Simulation approach

The combined research approach was conducted and developed simulation models based on data collected from on-site field observation (Al-Sudairi, 2007) or time studies (Anson, Tang, & Ying, 2002). A discrete-event simulation (DES) method is employed in multiple purposes, such as studying experimental framework (Martinez, 2010) and analyzing the concrete paving operations (Hassan & Gruber, 2008) because it provides the modeling flexibility by combining with other techniques and methods to enhance modeling capabilities. In the data collection phase, this simulation modeling can be implemented for either empirical or historical record. Rustom and Yahia (2007) conducted time studies where standardized time data sheets were completed by field personnel and the data was fed into a simulation model of an embankment construction project in Gaza Beach. Several research projects were conducted to improve the capability of general purpose simulation techniques.

## 2.7 Existing Methods or Techniques to Measure Labor Productivity

There are numerous methods available to evaluate and measure construction operations performance. Selection of the appropriate method for a particular project is another challenging task. Selection criteria was established to determine the suitable method for the measurement of construction productivity (Song & AbouRizk, 2008), which are: (a) The output should be quantifiable and highly correlated with the labor hours; (b) The output measurement should be independent from factors that have influence on the productivity, such as site conditions and labor skills; and (c) the measurement procedure should be cost effective and easy to track. Based on project characteristics, different techniques of measurement are implemented. For example, some techniques require continuous observation and some require intermittent observation of a worker or a crew involved in a task.

### 2.7.1 Time and Motion Study

Time and motion study is a terminology derived from industrial engineering, which is comprised of both time study and motion study together. It was developed by Frederick W. Taylor in 1880. A time study is also called a stopwatch study in which the time required by a skilled, well-trained operator working at a normal pace doing a specific task is measured. The main objective of time studies is to set time standards in the production area and to record the incremental times of the various steps or tasks that make up an operation (Meyers, 1992; Oglesby et al., 1989).

Two observation studies are generally implemented during labor productivity measurement for the standard times of activities, which are direct observation and work study. In the first method, “the period of observation is continuous throughout the workday by a trained observer in order to record to the nearest minute the time that the workers spent on direct work, indirect work, and ineffective work” (Chui, 2010, p. 21). In the second method, the observation does not span the complete length of the workday with no continuous observation. Noor (1998) stated that the work study measurement is suitable for those operations having the definite cyclic period, and the length of the periods of observation corresponds to the work cycle of the operation monitored; thus, it can be used in order to determine the most appropriate working method and possible alternative working methods. There are several limitations of time and motion studies (Chui, 2010; Oglesby et al., 1989), which are:

- There will be deficiency or differences in identifying the starting and ending points of cycles. This limitation can be addressed by employing a single observer or several trained observers.
- Geary (1962) recommended a maximum of five workers in a crew per observer to achieve accurate observation. More than one observer or employing another method of recording would assist in collecting data in such a complex situation.
- Time and motion studies are based on information gathered by the observers and detailed notes, which precisely recorded each activity and site condition.

- Studying complex operations or recording a large amount of data in a limited time, can result in the observer's objectivity due to physical limitations or biases. In order to avoid such a natural scenario, the observer must follow the rule with no re-evaluation, hindsight, or second thoughts once the observation has been made.

This complex process can be simplified by employing video cameras and recording the performance of workers. By reviewing the video recorded data, the observer can conduct the time and motion study without missing any step.

### 2.7.2 Work Sampling Method

Work sampling is a statistical technique employed to conduct periodic observations of workers and is a key tool to establish crew size or to determine the effectiveness of a specific crew size at the workplace (Adrian, 2004). In essence, work sampling is a useful technique in determining the proportion of the direct work from indirect work and ineffective work, analyzing factors that cause indirect and ineffective work, and identifying opportunities to reduce indirect and ineffective work (Chui, 2010; Picard, 2004).

Allmon et al. (2000) defined the direct work as productive tasks or actions, such as picking up tools at the area and measurement on the area where the work is taking place, holding materials in place, inspecting for proper fit, putting on safety equipment, and all clean-up. Indirect work is defined as supervision, planning, travel with handling materials or tools, and walking empty-handed to get materials or tools (Allmon et al., 2000; Chui, 2010). Ineffective work is defined as waiting for other trade, standing, sitting, working unrelated actions, personal time, late starts, and early quits (Allmon et al., 2000).

Noor (1998) mentioned two modified work sampling techniques, which are group timing technique (GTT) and the five-minute rating technique. The group timing technique is suitable for operations with repetitive actions and short cycle time ranging from 30 seconds to three minutes (Thomas & Daily, 1983). The five-minute rating technique is employed to monitor each crew member with a minimum of five-minutes or duration in minutes equal to the size of the crew, whichever is greater. It is generally recommended to be applied between four to eight times a day and can be used to evaluate the effectiveness of a crew without depending on whether the operations are cyclic or acyclic (Noor, 1998; Sprinkle, 1972; Thomas & Daily, 1983).

### 2.7.3 Activity Sampling

While considering a typical activity of a project, work sampling can be considered as activity sampling. According to Oglesby et al. (1989), activity sampling is suitable to apply for crews or projects of any size because it depends upon the number of individual observations, which is not related to sample size. The recommended sample observation size is at least 384, which can be made by either a crew of 100 workers and four times, or a crew of 10 workers and 39 times, and confidence limit of 95%, such that there is an error plus or minus 5% (Oglesby et al., 1989). There must be an equal likelihood of the observed workers. Those observations must have no sequential relationship. They should be consistent in the work situation characteristics during observation. The sampling rating should start with the first seen person and should be conducted for each worker. Types of tasks or an activity should also be recorded during the observation period.

### 2.7.4 Delay Survey Method

Delay survey methods, such as “worker delay survey/craftsmen’s questionnaire surveys” and “foreman delay survey,” are conducted by first line supervisors of the project to identify the sources of problems from the workers’ viewpoints and monitor the workers’ performance (Noor, 1998). The total amount of time lost by each crew in each day is recorded with reasons of delay. The magnitude of problems causing delays are evaluated by the management team and multiplied by the number of workers while considering a crew of more than one worker. This method demands a high cost and is very challenging to maintain confidentiality and anonymity for the workers because of disturbance during work (Chui, 2010; Noor, 1998). It is also necessary to avoid the game of blaming each other and maintain consistency during data collection and report preparation in order to make this delay survey method effective. In addition, a combination of time study and productivity measurement techniques are employed to develop a method productivity delay model (MPDM) in which five possible types of delay, such as environment, equipment, labor, material, and management are determined (Adrian & Boyer, 1976).

### 2.7.5 Audio-visual Methods

The construction field operations are recorded using audio-visual methods like time-lapse film with one to five seconds intervals and time-lapse video with various time intervals. The recorded audio-visuals can be used to analyze the productivity improvement of construction operations, train workers, and present evidence for construction claims and contract disputes (Everett, Halkali, & Schlaff, 1998; Noor, 1998).

The data may loss due to equipment failure, technical incompetence, weak illumination, and human error (Noor, 1998). It requires high initial costs and technical competence in order to get quality pictures of the workers' movements and an entire construction process. This technique of capturing visual data is widely accepted nowadays. It can be utilized to visualize the actual status of the project (Everett et al., 1998) at distant office locations by transmitting high-resolution, full-motion live pictures or videos from construction sites through the Internet.

### 2.7.6 Secondary Data / Historical Data

Productivity data analyses are generally conducted by using historical projects' data and published productivity data as a secondary source. R.S. Means Company publishes annual construction cost and productivity data that are collected from constructors and trade organizations. Those published data consist of average productivity rates of the industry but not the performance of any particular contractor (R.S. Means, 2007). In general, R.S. Means Building Construction Cost Data is taken as the reference, which provides unit labor costs, unit equipment costs, and physical output data based on the most used, quoted, and respected unit price guide available to the construction industry for the purpose of cost estimating, budgeting, and scheduling (Chui, 2010; RS Means, 2007).

There are several sources to collect productivity data, which are contract documents, progress reports, project databases, and time studies (Song & AbouRizk, 2008). Secondary data is suitable when: (a) research scope demands a large volume of historical data; (b) there are limitations of cost, time, and accessibility for data collection; and (c) there are available reliable sources for secondary data.

### 2.7.7 Automated Methods

Measuring productivity of construction operations is a challenging task because the activity measurement manual methods are time consuming and laborious. This scenario demands an automated framework to measure productivity. With the advancement of technology, video cameras as well as the Kinect sensor are employed to acquire data of labor-intensive construction operations.

#### 2.7.7.1 Using video cameras

A Wireless Real-time Productivity Measurement system was developed to overcome limitations of the existing on-site audio-visual methods (Kim, Bai, & Huan, 2009), which includes a digital camera, a video camera, a data processor, an AC transformer, a computer, and wireless modems. This research proved statistically significant that the developed system generates the identical productivity measurements compared to the results from the stopwatch method (Kim et al., 2009). The WRITE system has specific features: (a) not disrupting the construction operations, (b) determining the real-time on-site construction productivity, and (c) sharing collected data by all parties via the Internet at any time (Kim et al., 2009). It helps to enhance the capability of the project owner, project manager, architect, or engineer to manage the project.

Peddi (2008) proposed a framework to determine the construction labor productivity in real-time by developing human poses analyzing algorithms. With the implementation of computer vision concepts and artificial intelligence, Peddi (2008) developed an automated on-site productivity measurement system, in which a sequence of construction activity images is acquired and sent to a laboratory to generate human poses associated with construction activities. The labor productivity is determined in real-time by classifying the human poses into effective, ineffective, and contributory works and compared with in coming images using the built-in neural network algorithms. As this approach is based on real-time data and does not rely on historical data, a project manager can implement the corrective actions if there is lower labor productivity.

Yang, Arif, Vela, Teizer, and Shi (2010) proposed algorithms to track multiple workers on construction sites in order to optimize construction operations. A semi-automated video interpretation method was proposed by Gong and Caldas (2011) to interpret productivity information, working processes, cycle times, and delays. This method deals with vision-based construction object recognition and tracking methods.

**2.7.7.2 Using the Kinect sensor**

Escorcia, Davila, Golparvar-Fard, and Niebles (2012) developed an automated method for vision-based recognition of construction worker’s actions for building interior construction operations using color and depth data from a Microsoft Kinect sensor. With the vision-based approach and machine learning techniques, the body poses of workers are estimated by identifying the actions and movement of workers, which assesses labor productivity, safety, and occupational health at indoor environments.

Weerasinghe (2013) developed a framework to determine location information of workers, construction workers' tool-time, site related information, construction activities, and productivity data in order to assist project managers and planners to develop effective strategies for the improvement of labor productivity.

Considering the limitation of RGB-D sensors, Starbuck, Seo, Han, and Lee (2014) proposed a stereo vision-based marker-less motion capture approach utilizing optical images and depth data obtained from stereo vision cameras in order to develop kinematic models of construction workers' tasks. This is also helpful to evaluate productivity, safety, and workplace design of labor-intensive operations.

Khosrowpour, Niebles, and Golparvar-Fard (2014) proposed a method for the activity analysis of construction workers to identify the factors affecting labor productivity using RGB-D sensors. Khosrowpour et al. (2014) developed algorithms to detect body postures in real-time. Then, a kennel density estimation model is trained to model classification scores from discriminatively trained bag-of-poses action classifiers. Most discriminative sequences of actions are labeled with a hidden Markov model (HMM) and tested for construction operations.

Blommestein (2014) proposed an automatic labor performance measurement and risk assessment framework using range imaging from the Kinect camera. This framework measures the performance of a worker by continuous sampling, employing a work sampling technique. The states (busy, static, idle, or out of frame) of workers are identified by classifying poses of a worker based on the speed of a worker's hand movement.

## 2.8 Identified Impediments to the Achievement of High Productivity Levels

After thorough investigation of the literature, it can be concluded that there are numerous methods applied in the evaluation and measurement of construction operations performance. The most commonly used techniques for measuring construction labor productivity are the activity sampling technique, foreman delay surveys technique, time study technique, motion analysis technique, and group timing technique (Shehata & El-Gohary, 2011). The work study technique and time and motion study are the systematic study of work systems for the purposes of finding and standardizing the least-cost method, determining the standard times, and assisting in training in the preferred method (Barnes, 1980). Video photography, stopwatch timing, and work sampling are the common data collection techniques used for the work study (Oglesby et al., 1989). It helps to suggest a way to improve the productivity. But, the amount of work done during short intervals may be inaccurate because no proper account is taken of the start-up (preparation) and shutdown (cleanup) components of an activity. There may be interruptions in the work, which cause further fragmentation of the work process. Moreover, the work measured during short periods is unlikely to be representative of the work as a whole. Thomas et al. (1990) stated that "productivity measurement does not involve characterizing the way in which inputs are converted to outputs, although it is clearly influenced by methods, skills, the environment, and many other factors" (p. 709). In addition, there are some limitations; for example, (a) measure outputs whose characteristics may change over time, (b) define and measure real capital strokes and inputs as well as labor inputs when the characteristics of both factors are diverse and changing, (c) change in general level of prices, (d) change in supply and demand equilibrium for a given resource, and (e) change in the quality of the output (Shehata & El-Gohary, 2011).

A questionnaire survey is a widely applicable method for collecting data. If there are gaps of information or inconsistency in data, then it leads to the misinterpretation of the results of productivity. When adopting a questionnaire survey technique, there may be some questions regarding the validity of collected data because:

- there is no way to tell how truthful a respondent is being;
- there is no way of telling how much thought a respondent has put in;
- a respondent may be forgetful or not thinking within the full context of the situation; and
- there may be an inadequacy of understanding that may vary because of changes in emotions, behavior, and feeling.

Several research projects were conducted following the ANN method because it is applicable to solve linear and nonlinear programming tasks. But, it is similar to black box and requires training to operate it. There is a greater computational burden. Sometimes, it shows proneness to over fitting. If the data do not represent or are not correlated well enough to the information sought, then it may impact the evaluation of the productivity. However, a simulation approach provides a large amount of modeling flexibility to the researcher. There may be chances of error in the evaluation of productivity because of improper handling, error in feeding training data, misinterpretation, etc. Moreover, it is essential to ensure the quality of the work in every stage of the methodology and interpretation of the results through appropriate validation techniques, which are challenging tasks as well as opportunities in the construction engineering and management domain (Lucko & Rojas, 2010).

In the qualitative approach, it is critical to establish the theoretical framework prior to presenting the research results because productivity factors can be considered multidimensional and can have a different impact or meaning depending on the subjects being investigated (Panas & Pantouvakis, 2010). There should be clarification of the experimental framework, such as the types of project, collected data, and choice of modeling technique while incorporating theoretically driven, quantitative, and empirical work in order to understand the research limitations, thus, protecting practitioners from implementing productivity estimation models that do not suit a typical project's situation. The forms or questionnaires used for the collection of productivity data should be fully explained and excerpts should be provided while following the combined research approach. The data modeling should be clear whether it is related to daily or hourly productivity data or even cumulative productivity metrics. That means the framework's structure should be clear, as well as its content be based on the inferences emerging from the investigated sample.

The research conducted based on historical data may create problems for reasons stated by Liberda et al. (2003) that many factors involved in the process of construction change over time and productivity cannot be easily judged by the same data or information that was documented a decade or month ago. In practice, efficiency of construction operations is usually determined by comparing actual versus historical productivity. However, this comparison only provides a relative (biased) measure of efficiency. For example, if actual productivity is 95% of average historical productivity, the resulting productivity rate does not necessarily mean that the operation is efficient, but only that the efficiency of the operation is in line with historical averages (Mani, Kisi, & Rojas, 2014). Indeed, the operation now and then could be significantly inefficient if it is well below optimal productivity (Kisi, Mani, & Rojas, 2014; Mani et al., 2014). Hence, the common practice is to estimate productivity based upon historical data or an individual's experience, which may lack a systematic approach. The lack of consistency in the productivity measurement system and the low quality of historical data may prevent meaningful analysis (Song & AbouRizk, 2008). This could make construction operations significantly inefficient. It is obvious that the higher the inefficiency, the lower the productivity is. This scenario generates the need for research to identify alternative techniques to measure productivity.

## 2.9 Actual versus Optimal Productivity: An Innovative Approach to Productivity Analysis

The efficiency of construction operations is generally determined by comparing actual versus historical labor productivity in existing approaches. This practice is accurate if historical data reflects optimal values. Otherwise, this comparison is a gauge of relative rather than absolute efficiency. Therefore, in order to determine absolute efficiency, one must compare actual versus optimal labor productivity.

This scenario demands an alternative technique to measure labor productivity in which an accurate estimation of optimal labor productivity would allow project managers to determine the efficiency of their labor-intensive construction operations by comparing actual versus optimal rather than actual versus historical productivity. To date, no substantive model for estimating optimal productivity has been proposed in the construction domain (Kisi et al., 2014). This research proposed a framework to estimate a labor productivity frontier, which is used as an input value to estimate the optimal productivity. The optimal productivity is necessary to calculate the efficiency of construction operations.

## 2.10 Productivity Frontier Estimation

Several studies have been conducted regarding labor productivity, optimal productivity, and overall productivity (Rojas & Aramvareekul, 2003; Son & Rojas, 2010; Thomas & Sakarcan, 1994). However, there is no research conducted regarding the estimation of a construction labor productivity frontier. In order to estimate the productivity frontier, one must be able to determine a production level that, by definition, is never achieved in the field on a sustainable basis and, therefore, not directly measurable. This research defines productivity frontier, shows how to estimate it implementing existing research methodology or techniques, and proposes innovative ideas or techniques.

### 2.10.1 Productivity Frontier Definition

The productivity frontier is a theoretical productivity or maximum ideal productivity that could be achieved under perfect conditions (Son & Rojas, 2010). The term "*perfect conditions*" explains the case of ideal productivity values, which implies an ideal state where all factors affecting labor productivity are at the most favorable levels, such as good weather, highly motivated and productive workers with flawless artisanship, optimal utilization of materials and equipment, no interference from other trades, no design errors, and precise understanding of the design intent, among others.

### 2.10.2 Research Methods to Estimate Productivity Frontier

Among three major research methods: qualitative, quantitative, and combined, this research adopts the combined research method because research objectives are both qualitative (Hiatt, 1986) and quantitative (Harwell, 2011) in nature. But, this research does not use historical data for analysis. Indeed, actual data is collected from construction sites using multiple video cameras. According to site conditions, single or multiple cameras are used to capture the movements of workers adopting either dynamic background or fixed background techniques (Bai, Huan, & Peddi, 2008; John, Ivekovic, & Trucco, 2009; Sigal, Balan, & Black, 2010).

An activity is broken down into four-level hierarchical structures, such as activity, task, action, and movement. These hierarchical structures are identified from the video data by converting it into individual images by applying the frame separation algorithm in Matlab (Cai & Aggarwal, 1996; Cai, Mitiche, & Aggarwal, 1995). After identifying actions from visual inspection (Wang, Weiming, & Tan, 2003), actions are classified into contributory and non-contributory actions (Shahidul & Shazali, 2011). There are several techniques available for data collection, such as time and motion study (Meyers, 1992; Oglesby et al., 1989), work sampling method (Adrian, 2004; Noor, 1998), activity sampling (Oglesby et al., 1989), delay survey method (Noor, 1998), and audio-visual methods (Everett et al., 1998).

As this research is mainly focused on the movement of workers, the researcher implements combined application of audio-visual methods and time and motion study. The duration for performing contributory actions for each worker is recorded analyzing time and motion study by reviewing the video data using the hierarchical structure. Techniques of simulation and visualization are employed during model development and validation phases (Loannou & Martinez, 1996). In addition, various techniques, such as literature review, expert review, and evaluation of models are employed for validation purposes (Carvalho et al., 2011). Thus, this research employs simulation and visualization approaches in the combined research method.

Labor productivity can be expressed in many ways, such as output per labor cost and output per labor hour. This research adopts output per labor hour or output per crew-hour as a metric to measure labor productivity. Moreover, the labor hour considered for labor productivity frontier is the shortest duration because minimum value of duration means the highest productivity. Ideally, the labor productivity frontier is infinity when duration is zero. Practically, this is not possible. Thus, the shortest possible duration for each movement is added to get the shortest possible duration for an action. Similarly, the shortest possible duration for each action is added to get the shortest possible duration for a task and so forth. A statistical approach is employed to validate the concept of the shortest observed duration where this duration is obtained from time and motion study as discussed in Chapter 3.

A concept of goodness-of-fit and probability distribution is implemented to determine an estimated duration. Estimated duration is determined because it is almost impossible to conduct time and motion study for all project activities from the start to the end of the project. The shortest estimated duration is obtained by estimating the threshold parameter or shifted parameter (Aristizabal, 2012) of the plotted best-fitted probability distribution curve for a given set of data. The equivalent productivity is estimated by dividing the number of units produced (output) by the estimated shortest duration. The labor productivity frontier is the theoretical maximum productivity; thus, estimated value of this frontier is obtained by choosing the highest productivity from these two approaches–observed durations and estimated durations.

Besides the manual approach, this research presents an automated framework to estimate productivity frontier, which is described in Chapter 6.

# CHAPTER 3

# METHODOLOGY

This research presents an innovative technique for labor productivity analysis by defining the labor productivity frontier and optimal labor productivity. The labor productivity frontier is an important input to estimate optimal labor productivity. In order to estimate the labor productivity frontier, one must be able to determine a production level that, by definition, is never achieved in the field on a sustainable basis and, therefore, not directly measurable. In an attempt to achieve the objectives of this research, the theoretical underpinnings of the proposed framework, conceptual analysis of the proposed basic framework with discussions, and brief illustration of the proposed advanced framework are explained in this chapter.

## 3.1 Theoretical Underpinnings

Actual labor productivity is measured based on the performance of workers at the construction site. Optimal labor productivity is the highest sustainable productivity level achievable under “good management” and “typical working conditions” while the labor productivity frontier is the theoretical maximum productivity achievable under “*perfect conditions*” (Son & Rojas, 2010). The actual productivity is typically below optimal productivity with a few instances when they can be identical. However, the difference between the optimal and actual productivity is the operational inefficiency. Poor sequencing of activities, inadequate equipment or tools, mismatch between skills, task complexity, excessive overtime, and poor lighting conditions are some factors that may combine to form the operational inefficiency. The factors that affect productivity which are not under the control of project managers, such as high humidity, high temperature, rainfall, etc., result the system inefficiency.

In general, when the estimated values are higher than the optimal productivity, productivity is optimistically forecasted. If the estimated values are lower than the optimal productivity, then productivity is conservatively forecasted (Mani et al., 2014). In reality, project managers just assume that these levels are reasonably attainable in the field based upon historical averages and personal judgment. Son and Rojas (2010) argue that both optimistic and conservative assumptions end up negatively affecting actual productivity in the field.

Although the productivity frontier is an abstraction that represents a production level not achievable in actual practice, it proves helpful in analyzing project conditions. The concept of the productivity frontier can be used to identify system inefficiency factors, as well as to estimate optimal productivity. In turn, optimal productivity is necessary to calculate the efficiency of construction operations. The advantages of the proposed frameworks are that the constructors, rather than being constrained by historical data, can also estimate the labor productivity frontier and optimal labor productivity for activities they have never performed.

The theoretical underpinnings of the proposed framework to achieve such objectives are inverse mean-variance optimization, hierarchical analysis, and probability distribution theory, as explained in the following sections.

### 3.1.1 Inverse Mean-variance Optimization

Mean-variance optimization (MVO) has been widely applied in modern portfolio theory. For a better understanding of MVO, some relevant terminologies are described below:

#### 3.1.1.1 Portfolio

Based upon an investment point of view, it is defined as a grouping of financial assets, which are held directly by investors and managed by a financial professional (Huang, 2008).

#### 3.1.1.2 Optimization

The term "*optimization*" is the selection of a best element from the alternatives available, which consists of maximizing or minimizing a real function by systematically selecting input values within an allowed set and computing the value of the function (Cai, Teo, Yang, & Zhou, 2000).

#### 3.1.1.3 Modern portfolio theory

Modern Portfolio Theory (MPT) is defined as a theory on how risk-averse investors can construct portfolios to optimize or maximize expected return based upon a given level of risk (variability) (French, 2010). MVO is a part of Markowitz's Modern Portfolio Theory (MPT), which assumes that investors will optimize their investment portfolio through diversifying their investments on a balanced risk-return basis.

#### 3.1.1.4 Mean variance optimization

It is a quantitative tool used to spread investment across different assets within a portfolio by assessing the trade-off between risk and return in order to maximize the return while minimizing any risks (Idzorek, 2006). Fabozzi, Kolm, Pachamanova, and Focardi (2002) explained that the application of a mean-variance analysis for a portfolio construction requires a significantly greater number of inputs to be estimated for the expected return of each security, variance of returns for each security, and either covariance or correction of returns between each pair of securities. According to Karl Sigman (unpublished notes on portfolio mean and variance, 2005), investing in more than one asset (diversification) may reduce a possible risk. Even if one of the assets has a disastrous (very low) payoff due to its variability, there are chances for others by sharing resources among several different assets.

Thus, the basic principle of MVO is that the variability (risk) of a portfolio of assets is reduced as the number of assets increases, assuming the assets are not perfectly correlated (well-diversified). Therefore, in a sense MVO “hides” the variability of its constituting assets by looking only at the variability of the combined portfolio. Inverse MVO, on the other hand, would make visible previously “hidden” variability when a process is broken down into its elemental components and the variability of each component is analyzed. Looking at the variability of elemental components is relevant to the proposed framework as a means to identify those occurrences when productivity is at its highest. By definition, these productivity levels are not sustainable and represent outliers in the data.

## 3.2 Hierarchical Analysis

Hierarchical analysis is used to break up construction activities into a multi-level hierarchy of subsystems–its elemental components. The difference between a traditional work breakdown structure (WBS) used in construction and the hierarchical analysis used in the proposed framework is the level of detail. For example, Tucker and Guo (1993) classified construction activities into area, activity, and task. Ahmad, Scott, and Bradley (1995) proposed five levels: project, division, activity, basic task, and elemental motion as shown in Table 3.1.

Table 3.1: Construction Operational Taxonomy

| Tucker and Guo (1993) | Everett and Slocum (1994) | Ahmad et al. (1995) | Proposed Framework |
|---|---|---|---|
| Area<br>Activity<br>Task | Project<br>Division<br>Activity<br>Task<br>Elemental Motion<br>Orthopedics<br>Cell | Project<br>Division<br>Activity<br>Basic Task<br>Elemental Motion | Activity<br>Task<br>Action<br>Movement |

Everett and Slocum (1994) classified construction field operations into seven hierarchical taxonomies, which are: project, division, activity, basic task, elemental motion, orthopedics, and cell. The project is interrelated with non-routine, unique activities, having limited time, budget, and resources allocated (Frankel, 1990). However, Everett and Slocum (1994) defined the hierarchy level into the level of cell, which is related to the study of muscle tissues and nerves, which may be suitable during the study of Ergonomics analysis but not suitable for this study. The proposed framework goes two levels deeper than Tucker and Guo (1993) and one level deeper than Ahmad et al. (1995)

since it uses four levels beginning at the activity: activity, task, action, and movement. Tucker and Guo (1993) defined a task as the lowest and simplest level, whereas the proposed framework defined a movement as the lowest level. Hence, only four hierarchy levels are defined in this proposed framework.

- An activity is defined as the collections of tasks, which represent the specific units of work with spatial limits and/or dimensions (Tucker & Guo, 1993). For example, lighting replacement and sanitary fixing.
- A task is defined as the lowest recognizable work-related characteristic. A combination of integrated tasks makes up an activity (Ahmad et al., 1995). For example, site preparation, bulb replacement, and waste management.
- An action is defined as a unitary level of task. This means it is a combination of integrated action made up of a task. For example, frame opening, bulb removal, and ballast removal.
- A movement is the lowest level of the construction operational taxonomy. A combination of an integrated movement makes up an action. For example, moving a hand to grab materials, turn right, turn left, etc.

The proposed hierarchy only includes a value added work (i.e., direct and contributory work), excluding non-contributory work. Contributory work is typically defined as the necessary work to accomplish a definite job. Non-contributory work is considered non-productive work, such as unscheduled breaks, time spent attending to personal matters, and idle time.

## 3.3 Probability Distribution Theory

The lowest possible duration for a task, action, or movement may not be observed during a particular experiment. Therefore, to uncover the lowest possible duration even if not observed, the proposed framework uses the probability distribution theory to fit the observed data at the lowest hierarchical level to a probability distribution using standard goodness-of-fit approaches to calculate the lowest value possible for each distribution. These values are then used when reassembling the elemental components into the activity to determine its overall duration. The statistical terminologies behind these approaches are described as follows:

### 3.3.1 Maximum Likelihood Estimation

It is a method to seek the probability distribution that makes the observed data most likely, which means that one must seek the value of the parameter vector that maximizes the likelihood of the function (Myung, 2003). In other words, it provides estimation for the model's parameters while applying to a data set and gives a statistical model. The maximization of the likelihood function increases the agreement of the selected model with the observed data. Once data have been collected and the likelihood function of a model given the data is determined, one is in a position to make statistical inferences about the population, that is, the probability distribution that underlies the data. Given that there are different parameter values for different probability distributions, it is useful to find the parameter value that corresponds to the desired probability distribution. The method of maximum likelihood is often the estimation method that mathematical statisticians prefer because it is usually easy to use and produces estimators with good statistical properties.

### 3.3.2 Shifted Probability Distribution

There are certain limitations in the standard distribution curves, which invite complexity or no solution while estimating the shortest possible duration using goodness of fit techniques. For example, standard exponential distribution has a range from zero to infinity. If the best-fit curve for a certain data set is an exponential distribution, then it gives the estimated shortest possible duration equivalent to zero because the lowest value for the exponential distribution is zero. This value is not realistic because no action can be accomplished in zero or negative time. In order to overcome this limitation, a concept of shifted probability distribution is adopted. Based on this concept, the exponential distribution curve is shifted by a "$\theta$" value, the threshold parameter or shifted parameter (Aristizabal, 2012). This shifted value gives the shortest possible estimated duration for the determination of the productivity frontier.

#### 3.3.2.1 Mathematical explanation

The probability distributions have their own probability distribution function (PDF) and cumulative distribution function (CDF), which characterize their properties. For example, the standard exponential distribution has a PDF as follows:

$$f(x) = \lambda e^{-\lambda x} \dots\dots\dots (3.1)$$

The PDF and CDF for this exponential distribution start at x = 0. But in general, the distribution can start at any positive value of x; the resulting distribution is called the shifted exponential distribution (Ang & Tang, 2006), having a starting value of x = $\theta$ with a PDF as follows.

$$f(x) = \lambda e^{-\lambda(x-\theta)} \quad for\ x\ >\ \theta \ldots\ldots\ldots (3.2)$$

Both "$\theta$" and "λ" are unknown and need to be estimated. The parameter "$\theta$" is also called a threshold parameter or a shifted parameter (Aristizabal, 2012). According to the SAS 9.2 documentation, the threshold parameter "$\theta$" must be less than or equal to the observed minimum value. Statistically, the value of "$\theta$" can be estimated by assuming the observed values are reasonably distributed over the exponential distribution so that the observed minimum value is approximately equal to the 100/($n$+1) percentile of the distribution, where $n$ is the number of observations.

Mathematically,

$$P(X \leq x_{min}) = \frac{1}{n+1} \ldots\ldots\ldots (3.3)$$

An alternate equation is:

$$P(X > x_{min}) = \frac{n}{n+1} \ldots\ldots\ldots (3.4)$$

The maximum likelihood estimation technique is used to estimate the parameters of the distribution (Ang & Tang, 2006).

As we know the distribution of X, we have:

$$P(X > x_{min}) = \int_{x_{min}}^{\infty} \lambda e^{-\lambda(x-\theta)}\ dx = e^{-\lambda(x_{min}-\theta)}$$

Thus, $e^{-\lambda(x_{min}-\theta)} = \frac{n}{n+1}$

Taking the log of both sides: $-\lambda\ (x_{min} - \theta) = ln\ (\frac{n}{n+1})$

$$or, \theta = x_{min} + \frac{1}{\lambda}\, ln\left(\frac{n}{n+1}\right) \ldots\ldots\ldots (3.5)$$

Now, we have $\theta$ as a function of λ, so if we can estimate λ, we can obtain an estimate for $\theta$. Using maximum likelihood estimate (MLE) to get an estimate for λ:

$$L(\lambda) = \prod_{i=1}^{n} f(x_i) = \prod_{i=1}^{n} \lambda e^{-\lambda(x_{min}-\theta)}$$

$$= \prod_{i=1}^{n} \lambda e^{-\lambda(x_i - x_{min} - \frac{1}{\lambda} ln(\frac{n}{n+1}))} = \lambda^n e^{-\lambda \sum_{i=1}^{n}(x_i - x_{min} - \frac{1}{\lambda} ln(\frac{n}{n+1}))}$$

Taking the logs, then differentiating with respect to λ and setting the equation equal to zero results in:

or, $\frac{n}{\lambda} - \sum_{i=1}^{n} x_i - n x_{min} = 0$

Thus, the MLE estimator of λ is: $\hat{\lambda} = \frac{n}{\sum_{i=1}^{n}(x_i - x_{min})}$ … … … (3.6)

Hence, the estimator of $\theta$ is: $\hat{\theta} = x_{min} + \frac{\sum_{i=1}^{n}(x_i - x_{min})}{n} ln\left(\frac{n}{n+1}\right)$ … … … (3.7)

The shifted exponential distribution has only two parameters ($\theta$ and λ) to estimate; they are comparatively easy to estimate by manual calculation. But, for other distributions, such as gamma, Weibull, lognormal, and beta distribution, it is very difficult to conduct manual computations. Therefore, "Base SAS® 9.2" is used to estimate the parameters of the best-fit probability distributions considering the shifted PDF.

But, "Base SAS® 9.2" takes the standard PDF during the estimation of parameters for the normal distribution because it has a range from negative infinity to positive infinity, and it is not possible to estimate the threshold parameter (lowest estimated value) for the shifted condition. Similarly, it does not estimate this threshold parameter for the Erlang distribution. In such a scenario, the next best-fit distribution curve is considered based on square error value and p-value for the particular test in order to estimate the threshold parameter.

### 3.3.3 Software for Probability Distribution Fitting and Analysis

It is a very time-consuming task to fit a significant number of observed data sets to theoretical distributions. Moreover, it is very difficult to fit the observed data to some of the more exotic probability distributions. Because of these reasons, "Arena Input Analyzer" (Takus & Profozich, 1997; Ungureanu, Sisak, Kristaly, & Moraru, 2005) and "Base SAS® 9.2" (Cox, Chu, Schneider, & Munoz, 2007; Schlain et al., 2010) are utilized during this research. The best-fit probability distribution for each action is plotted for the observed data from time and motion study using the "Input Analyzer" tool in Arena simulation software. This tool fits the distribution function based on the square error value. It shows the top 10 ranked distribution functions on the basis of the square error. In addition to the square error value, it also gives p-value for that particular test. The test shows that the lower the p-value when compared with the level of significance ($\alpha = 0.05$), the poorer the fit in the probability distribution is (Kelton, Sadowski, & Swets, 2010; Rockwell Automation, 2013). Based on observed data, this tool performs various tests, such as Chi-Square Test (Ungureanu et al., 2005), Kolmogorov-Smirnov Test (Massey, 1951), and Anderson-Darling Test (Stephens 1974) in order to analyze data and obtain results. For example, "gamma distribution" is plotted for a "ballast cover closure" action after conducting Chi-Square and Kolmogorov-Smirnov Test. However, the Arena software does not estimate the minimum value of the distribution (i.e. threshold parameter). It gives the best-fit probability distributions, adopting the concept of the "goodness-of-fit." This best-fit distribution is mentioned in the statement of the "Base SAS® 9.2" software tool to estimate the threshold parameter "$\theta$", scale parameter "$\sigma$," and shape parameter "$\alpha$" as shown in the following statement.

```
proc univariate data = gamma;
    histogram / gamma (theta = est sigma = est alpha = est);
run;
```

This statement fits the data in the gamma distribution and estimates the threshold parameter, the scale parameter, and the shape parameter using the concept of maximum likelihood estimation and moment method. The threshold parameter reflects the minimum value for this gamma distribution for the “ballast cover closure” action, which is lower than the minimum observed value. It provides true value for 95% of the confidence interval (0.05 significance value).

Similarly, the minimum duration to accomplish each action is estimated from the probability distribution analysis using the “Base SAS® 9.2” software. The sum of the estimated lowest durations for contributory actions gives the total shortest duration to complete a task.

## 3.4 Conceptual Analysis of Framework

Conceptually, the proposed framework can be categorized into a basic framework and an advanced framework. The basic framework follows manual steps beginning from data collection to the estimation of the labor productivity frontier through analysis of the data, whereas the advanced framework includes the generation of the new synthetic activities based upon the information gathered from the existing data. This explains that advanced framework follows partially automated methodological steps. The detail methodology of the basic framework is explained in Section 3.5 and its implementation for estimating the labor productivity frontier involving a single worker’s performance is described in Chapter 4 (Pilot Study). The basic framework is also tested for multiple workers' performances including parallel and sequential actions, as described in Chapter 5 (Detailed Study). The main objective of analyzing the framework considering different activities is to validate this framework for those labor-intensive operations ranging from simple to complex activities. The proposed explored automated framework for estimating the productivity frontier is a part of the advanced framework and is described in Chapter 6. The explorations of two different automated frameworks are discussed: (a) using multiple video cameras for collecting video data and (b) using the Kinect sensor for collecting data with skeletal views. Another part of the advanced framework is to develop "*recombinant synthetic workers*," which is discussed in Chapter 8.

### 3.4.1 Proposed Basic Framework

According to inverse MVO, as the lower one moves in a hierarchy, the more the variability will be exposed. Greater variability is sought because it allows for the identification of the lowest theoretical durations. For example, one can assume that after many observations, the lowest recorded duration for an activity in the field is X. The activity "lighting installation," if considered, would be divided into several tasks, such as site preparation, fluorescent bulb replacement, waste management, and documentation. The minimum durations to accomplish these tasks would be $X_1'$, $X_2'$, $X_3'$, and $X_4'$. Then the total duration of the activity calculated by reassembling these tasks would be X' (sum of $X_1'$, $X_2'$, $X_3'$, and $X_4'$), where $X' < X$. Analogously, if each task were broken down into its constituent actions and the minimum duration for each action measured, then the total duration for the activity calculated after reassembling actions into tasks and tasks into the activity would be X”, where X” < X’ < X.

Applying the same logic, if one goes to the movement level, then X”’ < X” < X’ < X. This reduction in durations is due to two different effects. The first one is the exposure of higher variability explained by the inverse MVO. The second effect is the fact that non-contributory tasks, actions, and movements are eliminated from the analysis as lower levels of the hierarchy are employed. For example, if one measures the duration of an activity from beginning to end, non-contributory tasks could be embedded in such a measure. However, if one calculates the duration of an activity by aggregating the durations of its constituent’s tasks, only direct and contributory work would be considered as all non-contributory tasks are eliminated because they do not form part of the value-added hierarchy. Even though X”’ would be based upon actual observations, it should not be interpreted as an actual duration associated with the actual productivity; rather, X”’ should be interpreted as a synthetic measurement of a theoretical duration associated with a theoretical productivity (Mani et al., 2014).

However, more importantly, should this theoretical productivity be considered as the optimal productivity or as the productivity frontier? This dissertation argues that the answer depends on the circumstances. This research examines the productivity frontier as the productivity under “*good management*” and in “*normal field conditions*.” Therefore, if the recorded durations occurred in a project where no management issues were present and under normal operations, then they would represent at least optimal productivity. In order for these durations to represent the productivity frontier, one would have to eliminate all system inefficiencies that could have been present during the data collection period. Even though this elimination is impossible in practice, if a concerted effort is made to minimize system inefficiencies, then the theoretical productivity calculated following these procedures would be somewhere in between the optimal productivity and the productivity frontier. Given that the probability of actually observing this level of theoretical productivity in the field is infinitesimal, this research proposes that this value should be taken as an estimate of the productivity frontier. For example, if (a) 100 observations are recorded during a construction task, (b) the task includes five actions, (c) the lowest duration recorded for each action occurs only once, and (d) the duration of each action is independent from the duration of all others, then the probability of observing the duration of the task being equal to the sum of the shortest duration of the actions would be one in 10 billion. Part of the adopted definition for optimal productivity included "on a sustainable basis," which dismisses a productivity level that happens once in 10 billion observations.

Productivity is then calculated by dividing the production rate by the observed shortest duration for the activity. However, since observed durations may not include the lowest possible duration for each action, probability distributions are fitted to the data to obtain the estimated shortest durations. Productivity is again calculated by dividing the production rate by the estimated shortest duration for the activity. This dissertation recommends taking the highest productivity from these two techniques–observed durations and estimated durations–as the value for the labor productivity frontier.

### 3.4.2 Proposed Advanced Framework

The proposed basic framework allows estimation of the productivity frontier for activities for which one has or can gather data from direct observations. However, from time to time constructors are faced with activities they have never performed. Nonetheless, estimating the productivity frontier and the optimal productivity of such activities could actually be more critical than for those for which at least historical averages are available. Furthermore, even if constructors were to work on the same activities time and again, capturing data from direct observations of all activities performed on typical projects would be a staggering undertaking. Therefore, the basic framework needs to be expanded to include the generation of new synthetic activities based upon information gathered from existing data. In order to accomplish this objective, we propose the creation of a database of activities, tasks, actions, and movements, and the implementation of a visually guided simulation system.

The visually guided simulation system would serve as the environment to generate the virtual representation of the construction activity under consideration. In such an environment, constructors would have access to a library of basic movements, actions, and tasks presented in a visual form using animations of human figures. By visually combining basic movements into actions, actions into tasks, and tasks into activities, constructors would be able to create synthetic activities and virtually perform the work at hand. The virtual environment must be robust enough to also simulate, if even at a very basic level, the surroundings, materials, and equipment used in the activity as decontextualized movements of human figures is not sufficient for building the synthetic activity.

The library of basic movements should include animations of each movement in a searchable database with parametric variables when necessary. For example, some actions, such as walking or climbing a ladder are dependent on the distance traveled. Therefore, the pace of such actions rather than their durations should be included in the database with the distance to be walked or climbed as a parameter.

## 3.5 Basic Framework (Manual Framework)

The basic framework typically consists of seven steps to estimating the labor productivity frontier, which is shown in Figure 3.1. Those steps are: field data collection, data analysis, action identification, action classification, model development, model validation, and productivity frontier estimation.

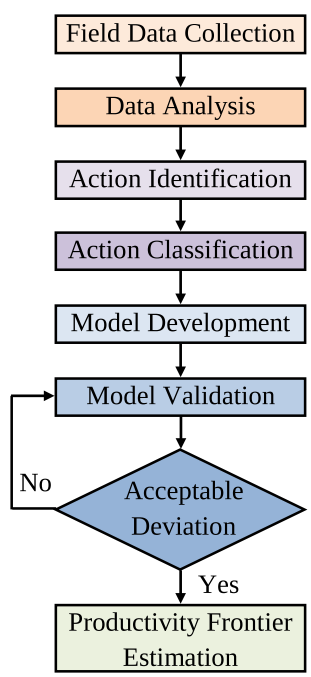


Figure 3.1: Block Diagram for Proposed Basic Framework

### 3.5.1 Field Data Collection

Construction and manufacturing sites involving labor-intensive operations are selected collaborating with local companies, such as the Commonwealth Electric Company and the Waldinger Corporation. Multiple cameras are synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004; Delamarre & Faugeras, 1999). Those cameras are set up identifying appropriate positions in such a way that movements of the concerned workers are visible from different angles. Depending upon site conditions, single or multiple cameras are employed (Bai et al., 2008; John et al., 2009; Sigal et al., 2010). Movements of workers are captured as video data, adopting either dynamic background or fixed background techniques.

A pilot study is conducted focusing on the activities performed by an electrical worker of the Commonwealth Electric Company in Omaha, which is explained in Chapter 4. Similarly, this framework is tested for a detailed study involving activities performed by crews of multiple workers consisting of parallel and sequential labor-intensive manufacturing operations. The detailed study explains "Fabrication of Sheet Metal Ducts" activity at the workshop of the Waldinger Corporation in Omaha, which is described in Chapter 5.

### 3.5.2 Data Analysis

Each activity is selected to analyze the data separately because of its homogeneity across the construction project. Each activity is broken down into the four-level hierarchy, such as activity, task, action, and movement similar to Figure 3.2. The activity, task, action, and movements are identified from the video data by converting it into individual images applying the frame separation algorithm in Matlab (Cai et al., 1995; Cai & Aggarwal, 1996).

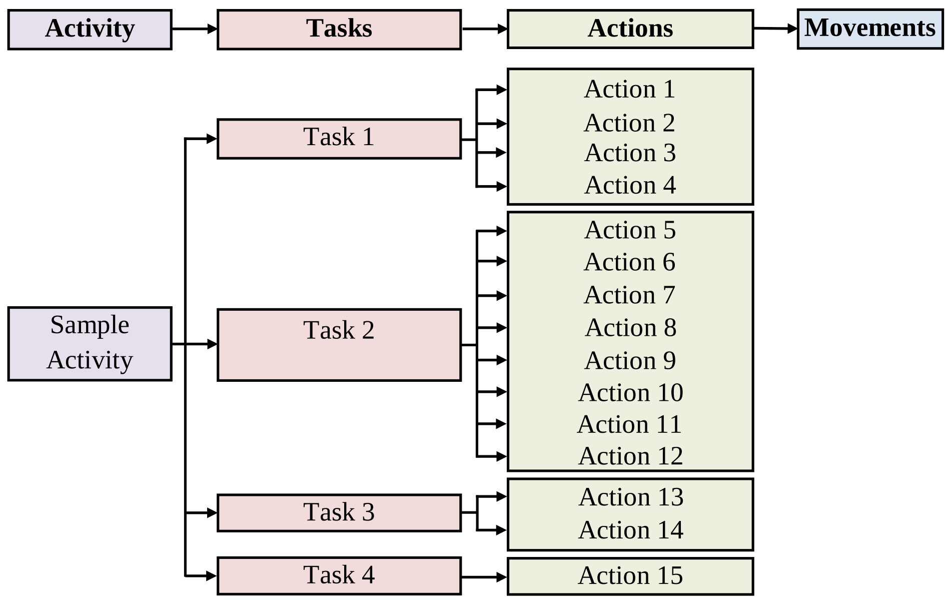


Figure 3.2: Hierarchical Breakdown of a Sample Activity

### 3.5.3 Action and Movement Identification

It is difficult to identify any action only looking at workers' movements while not arranged in sequence and without detail inspection of environment in which action performed. Vallacher and Wegner (1985) explained the action identification theory; the essence of this theory is that the identification of one's action, though highly variable in principle, is ultimately constrained by reality. Vallacher and Wegner (1987) categorized action into lower level and higher level identities explaining with examples, such as "pushing a doorbell" as the higher level action and "moving a finger" as the lower level action.

Similarly, this proposed framework categorizes the “glass frame opening” as the action and the “moving hands” while performing that action, are considered as the movement. The proposed framework only considers goal-directed physical movements (James, 1890) but it is preceded by a mental representation of such movement. Indeed, it may be a challenging job for an observer without detail knowledge, to determine whether the worker is maintaining a particular course of action over time or, instead, is doing different things (Vallacher & Wegner, 1987).

Each type of activity is analyzed separately as illustrated in Chapters 4 and 5. The action of workers’ tasks is identified manually from the image frame analysis by the visual inspection (Wang et al., 2003). It is easy to identify and record actions for an activity involving a single worker’s movement, whereas this job is complex and time consuming for an activity involving multiple workers performing parallel and sequential tasks.

### 3.5.4 Action and Movement Classification

Visual inspection technique is used to classify actions into contributory and non-contributory actions (Bai et al., 2008; Wang et al., 2003). Contributory actions for each type of activity are those necessary to accomplish the activity. Non-contributory actions include any other actions that do not directly contribute to accomplish the activity, such as unscheduled breaks, time spent attending personal matters (texting, talking), idle time, etc. A time and motion study (Finkler, Knickman, Hendrickson, Lipkin, & Thompson, 1993; Shahidul & Shazali, 2011) is conducted observing the video data and time is recorded for each contributory action based on the hierarchical structure as shown in Figure 3.2.

### 3.5.5 Model Development

Modeling and animating human figures is particularly difficult because of the complexity of the articulated human body (Calvert et al., 1993). The major difficulties are design of a realistic body model and the specification of realistic movement. One of the first attempts at computer human body modeling was made by Badler, O'Rourke, & Toltzis (1979). They presented a three-dimensional human body model designed by overlapping spheres, yielding a realistically formed and shaded body image on a raster graphics display. Sengupta and Das (1997) developed a low-cost 3D human modeling program in AutoCAD in order to support variable sizes and to provide the flexibility of a professional CAD system.

Chong (2008) stated that standard animation is "the technique of filming successive drawings or positions of models to create an illusion of the movement when the film is shown as a sequence" (p. 1). The main principles of animation (Thomas & Tufano, 2009): (a) uses the technique of producing a series of still images–each capturing incremental changes in the scene–before converting this series of images into a film sequence, (b) plays on the viewer's "persistence of vision" (Webster, 2005, 2012), and (c) requires an excellent observation of the reality to analyze movements and the sequences of movements for any particular motion to be converted into hundreds of tiny minute steps.

For a pilot study, a simplified skeleton view of a worker is used to visualize worker's movements. Even though this model does not show the level of detail of the Sengupta and Das (1997) model, it is accurate enough for the purposes of identifying and classifying actions according to the proposed basic framework.

### 3.5.6 Model Validation

It is a fact that the decision makers often do not have the training and time to check the validity of the animated models because the animation is an increasingly popular technique that can be used to verify, debug, and validate models (Loannou & Martinez, 1996). There are various techniques to validate models, such as by literature review, by expert review, and by evaluation of 3D character animations (Carvalho et al., 2011). For the pilot study, an expert team is formed to evaluate the movement of workers in the animation and to validate the process workflow.

### 3.5.7 Productivity Frontier Estimation

The productivity frontier is to be estimated once an activity has achieved its steady state phase. Time and motion studies (Oglesby et al., 1989) are generally conducted to collect and analyze the site data (Shahidul & Shazali, 2011). They are useful in determining the time required to accomplish a specific task (Oglesby et al., 1989) by a qualified and a well-trained person working at a normal pace. Information acquired through these studies includes the actual time worked by laborers, the actual volume of production, and the rates of output over the course of a shift (Finkler et al., 1993).

Two approaches are established to compute the labor productivity frontier for the activity under study, which are: (a) observed durations and (b) estimated durations. The minimum durations obtained between two approaches is selected to compute the productivity frontier.

### 3.5.7.1 Approach 1: Observed durations

Observing movements of workers, the time and motion study is conducted by thoroughly reviewing the video data and durations of the contributory actions for the specific task or activity is recorded in an Excel spreadsheet as shown in Figure 3.3.

| | Actions | | | | | | | | Total Duration |
|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H | |
| Observed Duration from Time and Motion Study | $A_1$ | $B_1$ | $C_1$ | $D_1$ | $E_1$ | $F_1$ | $G_1$ | $H_1$ | |
| | $A_2$ | $B_2$ | $C_2$ | $D_2$ | $E_2$ | $F_2$ | $G_2$ | $H_2$ | |
| | $A_3$ | $B_3$ | $C_3$ | $D_3$ | $E_3$ | $F_3$ | $G_3$ | $H_3$ | |
| | . | . | . | . | . | . | . | . | |
| | . | . | . | . | . | . | . | . | |
| | . | . | . | . | . | . | . | . | |
| | $A_N$ | $B_N$ | $C_N$ | $D_N$ | $E_N$ | $F_N$ | $G_N$ | $H_N$ | |
| Observed Shortest Duration | A′ | B′ | C′ | D′ | E′ | F′ | G′ | H′ | Say X′ |

Figure 3.3: Observed Duration from Time and Motion Study

In the pilot study, movements of a single worker are observed as explained in Chapter 4. For example: A, B, C, D, E, F, G, and H are eight sets of actions for a task. Let, $A_1$, $A_2$, ……… $A_N$, be durations to accomplish Action A. Similarly, $B_1$, $B_2$, ……… $B_N$, are durations to accomplish Action B and so on. The shortest possible observed duration for each action is identified. If frequency of this observed shortest duration for each action is k, then the probability of occurrence of this event is k/N. If all events are independent, then the probability of occurrence of the event will be:

$$Probability\ of\ occurrence\ of\ the\ event = (Number\ of\ actions)\ x\ [(Probability\ of\ occurrence\ of\ A)\ x\ (Probability\ of\ occurrence\ of\ B)\ \ldots\ldots\ldots\ x\ (Probability\ of\ occurrence\ of\ H)\ \ldots\ \ldots\ \ldots\ (3.8)$$

The shortest possible duration is estimated by adding up the shortest durations observed for each action because the task is made up of actions in a sequence. The number of quantity produced or number of output is divided by this observed shortest duration in order to compute the equivalent productivity.

Similarly, for the detailed study, movements of the multiple workers are observed and are recorded in an Excel spreadsheet as described in Chapter 5. For a complete activity, the shortest possible duration for each task is again added because the activity is made up of tasks in a sequence. For each task, the shortest possible duration for each action is added, and for each action, the shortest possible duration for each movement is added because task is made up of actions, and action is made up of movements in sequence or parallel fashion. As there are multiple workers involved to accomplish the activity, the interactions between them are precisely analyzed. Upon dividing the output produced by the observed shortest duration, the equivalent productivity can be achieved.

#### 3.5.7.2 Approach 2: Estimated durations

It is impossible to study and analyze all time data from the start to the end of the project because of various constraints, such as lack of workers to record data, limited space in video camera, lack of other tools, and the presence of all seen or unseen problems. Since observed durations may not include the shortest possible duration for a task, action, or movement, the best-fit probability distributions are proposed to obtain the estimated shortest durations. The best-fit probability distributions are plotted adopting the concept of the “Goodness of Fit” with the application of the “Input Analyzer” tool in Arena Simulation Software similar to Figure 3.4. Based on the best-fit probability distribution for each action obtained from “Arena Input Analyzer,” the threshold parameter (shortest duration value) for that distribution is estimated using the “Base SAS® 9.2.” The shortest duration of the contributory actions for this task or activity are estimated from the distribution, which are evaluated at a 95% confidence interval, and values are recorded in the Excel spreadsheet. The shortest total estimated duration is computed by adding up the shortest possible durations estimated for each action. The equivalent productivity is estimated by dividing the number of units produced (output) by the estimated shortest duration.

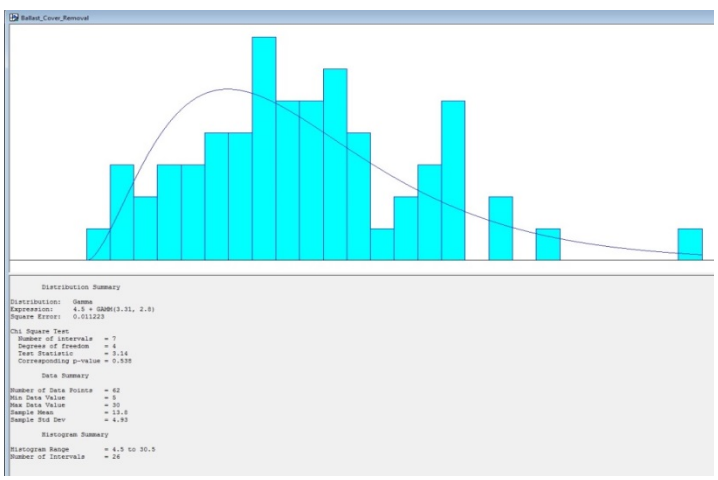


Figure 3.4: Sample Distribution Curve

During the pilot study, the lowest duration of the contributory actions for each action are estimated from the best-fit probability distribution for each action as described in Chapter 4. Similarly, during a detailed study as explained in Chapter 5, the lowest duration of the contributory movements for each action are estimated from the best-fit probability distribution for each movement. Finally, the estimated value of the labor productivity frontier is obtained by choosing the highest productivity from these two approaches–observed and estimated durations.

### 3.5.8 Discussion

Although the productivity frontier is not achievable in practice, it has significant importance while estimating optimal productivity of labor-intensive operations. Since actual productivity is compared against an objective measure rather than historical values, optimal productivity is necessary to develop an unbiased means of calculating the efficiency of construction operations.

There may be a question regarding the validity of the theoretical productivity estimated using this framework as the productivity frontier because the productivity frontier is an abstraction that cannot be measured in the actual working scenario. Thus, it seems counterintuitive while using the actual field data to estimate its value. In order to justify this issue, a deductive logic can be used (Mani et al., 2014). First, this research defines the productivity frontier as the theoretical maximum productivity under the “perfect conditions,” and optimal productivity as the productivity under “good management” and “normal field conditions.” Therefore, if the recorded durations occurred in a project without negative management issues and under normal operations, then they would represent at least optimal productivity (Mani et al., 2014). Second, one would have to eliminate all system and operational inefficiencies in order to determine the durations to estimate the productivity frontier, which could be done during the data collection period. However, this is impossible in real practice. If a concerted effort is made to minimize system inefficiencies, then the theoretical productivity calculated following these procedures would be somewhere in between the optimal productivity and the productivity frontier (Mani et al., 2014). Third, this research focuses on the instantaneous highest values of the labor productivity recorded, which is obtained from the shortest observed duration conducting the time and motion study. The probability of actually observing this level of theoretical productivity in the field is infinitesimal. For example, if (a) 100 observations are recorded during a construction task, (b) the task includes five actions, (c) the lowest duration recorded for each action occurs only once, and (d) the duration of each action is independent from the duration of all others, then the probability of observing the duration of the task being equal to the sum of the shortest durations of the actions would be one in 10 billion assuming actions are independent with each other. Fourth, part of the adopted definition for the optimal productivity included on a “sustainable basis,” which dismisses a productivity level that happens once in 10 billion observations (Mani et al., 2014). Therefore, this value can be taken as an estimate of the productivity frontier.

## 3.6 Advanced Framework

The basic framework discussed above is more time consuming and laborious in nature. This framework should be automated in order to quickly implement for the same project by collecting preliminary data and analyzing them in an automated fashion. The advanced framework involves an automated framework to estimate the labor productivity frontier as well as a study of "*recombinant synthetic workers*." With the implementation of this framework, a project manager would have access to a library of basic movements, actions, and tasks presented in a visual form using animations of a human figure. The project manager would be able to create synthetic activities and virtually perform the work at hand, which helps to analyze workflow in order to improve productivity.

The proposed automated framework explores the automated techniques to facilitate data collection and analysis. It discusses the applications of video cameras and the Kinect sensor during collection of data. The detailed steps are discussed in Chapter 6. In addition, it explores the feasibility of creating the recombinant synthetic workers by aggregating basic movements as discussed in Chapter 8.

# CHAPTER 4

# PILOT STUDY

A pilot study was conducted in order to test the proposed basic framework (manual framework) and to examine the feasibility of estimating the labor productivity frontier in labor-intensive operation. Figure 4.1 shows the different stages of the pilot study (rectangular boxes) as well as the various methods adopted to implement each stage (legends with arrows). A description of each stage is as follows.

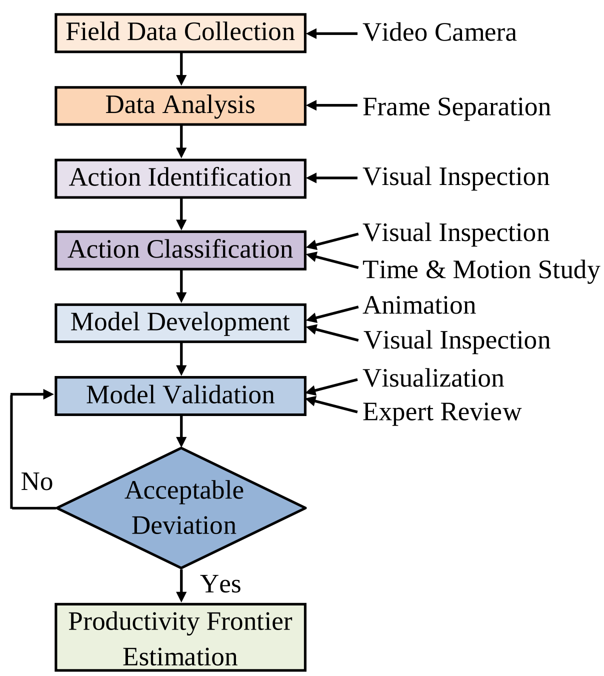


Figure 4.1: Basic Framework for Pilot Study

## 4.1 Field Data Collection

Three Canon XF100 professional camcorders were used to collect video data. These cameras were calibrated using the “Camera Calibration Toolbox” in Matlab (Bai et al., 2008). Prior to data collection, cameras were synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004; Delamarre & Faugeras, 1999). Data were captured on the replacement of electrical lighting fixtures at Omaha South High Magnet School. The scope of this electrical lighting replacement project included the replacement of old T12 with new T8 fluorescent bulbs and ballasts. Data captured included different tasks involved in the bulb replacement, such as opening a glass frame cover, removal of the old T12 fluorescent bulbs, removal of the old ballast, installation of a new ballast, installation of T8 fluorescent bulbs, and closure of the of glass frame cover.

Depending upon site conditions, single or multiple cameras were used (Bai et al., 2008; John et al., 2009; Sigal et al., 2010). One moving camera was used to capture materials and equipment delivery activities (dynamic background). Two or three fixed cameras were used to capture electrical lighting installation processes depending upon space availability at the site of installation (fixed background). For small rooms, only two fixed cameras were used whereas for the larger rooms, three cameras captured movements of workers from different angles.

Two electrical workers from the Commonwealth Electric Company, a veteran and a novice, participated in the project. However, this pilot study focused exclusively on capturing the activities performed by the veteran worker because the veteran was experienced and performed better in similar operations than the novice. Video was recorded in five different school zones: classrooms, lockers, corridor/hallway, weight room/training room, and family consumer science room. The veteran worker completed the installation of 62 Type 2 ballasts with two T8 bulbs each.

## 4.2 Data Analysis

For the purposes of this study, the four-level hierarchy of activity, task, action, and movement was implemented as shown in Figure 4.2.

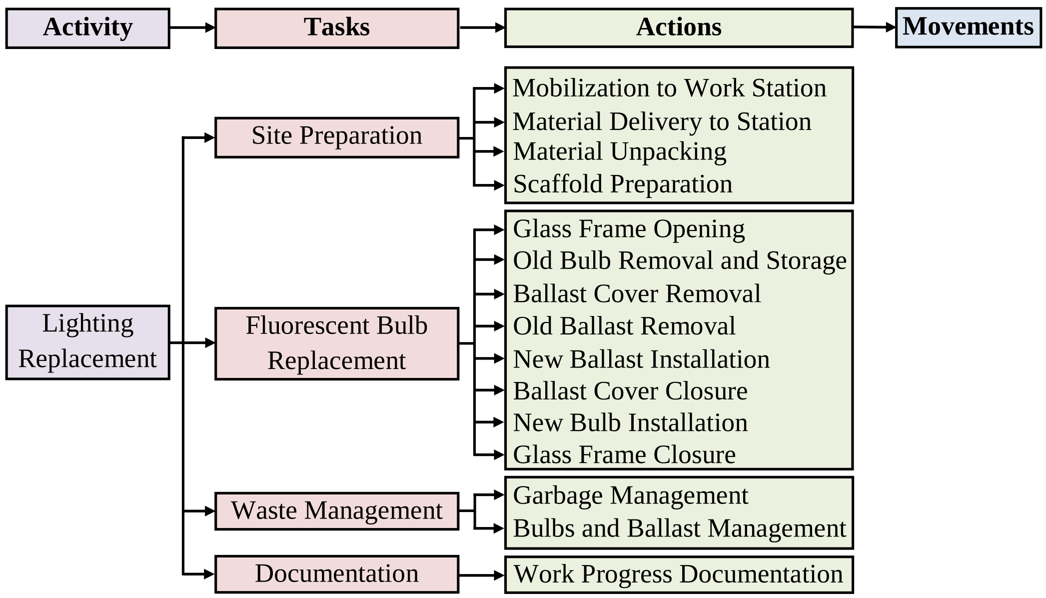


Figure 4.2: Hierarchical Breakdown of Lighting Replacement Activity

The activity “lighting replacement” was selected to analyze the data because of its homogeneity across the construction project. The reasons behind choosing the “fluorescent bulb replacement” task are: (a) availability of enough data for the pilot study, (b) involvement of repetitive actions, and (c) fixed background while capturing data, which made identification of actions and movements easier. The activity was broken down into four different tasks: site preparation, fluorescent bulb replacement, waste management, and documentation. Each task was further broken down into actions as shown in Figure 4.2. All these tasks and actions were identified from the video data by converting it into individual images by applying the frame separation algorithm in Matlab

(Cai et al., 1995; Cai & Aggarwal, 1996). Sixty-two data points for the “fluorescent bulb replacement” task were analyzed at the actions level during this study. During the pilot study, the researcher did not continue to the movement level in the hierarchy because of time and resource constraints.

## 4.3 Action Identification

During this research, the action of the worker for each task was identified and classified from the image frame analysis by visual inspection (Wang et al., 2003). Wang et al. analyzed the image sequences involving a human motion analysis for the detection, tracking, and recognition purpose and developed algorithms for automated identification. This framework is just for the pilot study; thus, action identification was done manually.

Figure 4.3 shows the eight different actions of the worker for the fluorescent bulb replacement task in four different video frames. Figure 4.3 (a), (b), (c), (d), (e), (f), (g), and (h) show the actions during glass frame opening, old bulb removal and storage, ballast cover removal, old ballast removal, new ballast installation, ballast cover closure, new bulb installation, and glass frame closure.

(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 4.3: Action Identification by Visual Inspection in Video Frames

### 4.4 Action Classification

Visual inspection (Bai et al., 2008; Wang et al., 2003) was used to classify each action of the “Lighting Replacement” activity into either contributory or non-contributory, based upon their impact to work completion. A time and `motion study (Finkler et al., 1993; Shahidul & Shazali, 2011) was conducted from the video data, and time was recorded for each contributory and non-contributory action. The contributory actions are those necessary to accomplish the different tasks as listed in Figure 4.2. Non-contributory actions include any other action not listed in Figure 4.2. Non-contributory actions are considered non-productive and include actions, such as unscheduled breaks, time spent attending personal matters (texting, or talking), and idle time. The time required for each action was recorded from the video data using the hierarchical structure as shown in Figure 4.2.

## 4.5 Model Development

Modeling and animating human figures is particularly difficult because of the complexity of the articulated human body (Calvert et al., 1993). The major difficulties are design of realistic body models and specification of realistic movement. One of the first attempts at computer human body modeling was made by Badler et al. (1979). They presented a three-dimensional human body model designed by overlapping spheres, yielding a realistically formed and shaded body image on a raster graphics display. Sengupta & Das (1997) developed a low-cost 3D human modeling program in AutoCAD in order to support variable sizes and to provide the flexibility of a professional CAD system.

For a pilot study, a simplified skeleton view of a worker is used to visualize worker’s movements. Even though this model does not show the level of detail of the Sengupta and Das model, it is accurate enough for the purposes of identifying and classifying actions according to the proposed basic framework.

(1) (2) (3) (4) (5) (6) (7) (8)

Figure 4.4: Skeleton View of Worker Performing Actions

This is just a pilot study; thus, a simplified skeleton view of a worker is enough for the purposes of identifying and classifying actions according to this proposed framework. Figure 4.4 shows an instance of the model in skeleton view developed using AutoCAD in which each frame shows a specific action as follows and frame numbers are shown in parenthesis.

1. Glass Frame Opening (7106)
2. Old Bulb Removal and Storage (7255)
3. Ballast Cover Removal (7653)
4. Old Ballast Removal (8507)
5. New Ballast Installation (9442)
6. Ballast Cover Closure (10427)
7. New Bulb Installation (10966)
8. Glass Frame Closure (11646)

In order to create a realistic representation, the surroundings of the working site were added and the process was animated using standard animation techniques (Aeluri, Bojan, Richie, & Weeks, 2004; Burtnyk & Wein, 1976; Lasseter et al., 1987) in both

FlipBook and Windows Movie Maker. These animated frames help to validate the process workflow.

## 4.6 Model Validation

It is a fact that the decision makers often do not have the training or time to check the validity of animated models, but the animation is an increasingly popular technique that can be used to verify, debug, and validate models (Loannou & Martinez, 1996). There are various techniques to validate the model, such as by literature review, by expert review, and by evaluation of 3D character animations (Carvalho et al., 2011).

An expert team was formed, which consisted of five individuals: three of them were researchers themselves, one was a veteran and another was a novice electrical worker from the Commonwealth Electric Company. The team evaluated the movement of labor in the animation, in the real video footage, as well as output of the time and motion study. In addition, the team thoroughly analyzed the animated video frames developed in Windows Movie Maker and FlipBook in order to validate the process workflow.

Developing any idea or product is a major stage, but analyzing its usability and quality is also. In order to evaluate the quality of this research, an evaluation process was conducted similar to Karat (1997). Experts' feedback was collected by developing sample questionnaires as follows.

- Is the quality of animation good enough to understand and validate the process workflow?
- Is the information provided by animation understandable?

- How useful would this animation be in the context of the labor productivity analysis?
- Are these models useful in the estimation of productivity frontier?

In order to quantify the feedback, three leveled measurement scales were developed. For example, the responses: (1) poor, (2) average, and (3) good represent the feedback of experts. Although these responses were collected only from the team of five experts, they had critically evaluated this animation product and everyone responded to it as a “good” product. The team agreed that this animation validates the process workflow and is useful in the estimation of the productivity frontier in the understandable manner.

## 4.7 Productivity Frontier Estimation

During this study, two approaches were established to compute the productivity frontier for the “Fluorescent Bulb Replacement” task, which are (a) observed durations and (b) estimated durations. For both approaches, data was collected using time and motion study. The minimum durations obtained between approaches was selected in order to compute the productivity frontier.

### 4.7.1 Approach 1: Observed Durations

Focusing on the movements of a veteran worker, the time and motion study was conducted by thoroughly reviewing the video data and the durations of the contributory actions for the “Fluorescent Bulb Replacement” task, which were recorded in an Excel spreadsheet. The shortest possible duration was estimated by adding up the shortest durations observed for each action because the task was made up of actions in a sequence. The shortest total observed duration was found to be 166 seconds. The number of units installed was divided by this observed shortest duration in order to compute the equivalent productivity. The resulting equivalent productivity was found to be 21.69 stations per hour.

### 4.7.2 Approach 2: Estimated Durations

The probability distribution for each action involved in the “Fluorescent Bulb Replacement” task was obtained with the application of the “Input Analyzer” tool in the “Arena Simulation Software.” Based on the best-fit probability distribution for each action obtained from the “Arena Input Analyzer,” the threshold parameter (lowest duration) for that distribution was estimated using “Base SAS® 9.2.” The lowest duration of the contributory actions for this task was estimated from the distributions, which were evaluated at a 95% confidence interval, and values were recorded in an Excel spreadsheet. The shortest total estimated duration was found to be 161.29 seconds, which was estimated by adding up the shortest possible durations estimated for each action as shown in Table 4.1. Its equivalent productivity was estimated by dividing the number of units installed by the estimated shortest duration, which results in 22.32 stations per hour.

The estimated value of the labor productivity frontier was obtained by choosing the highest productivity from these two approaches–observed and estimated durations. For the “Fluorescent Bulb Replacement” task, the productivity frontier was computed from this pilot study; thus, found to be 22.32 stations per hour.

Table 4.1: "Fluorescent Bulb Replacement" Action Durations in Seconds

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| Glass Frame Opening | 3 | 2.97 | Exponential |
| Old Bulb Removal and Storage | 10 | 9.99 | Weibull |
| Ballast Cover Removal | 5 | 4.15 | Weibull |
| Old Ballast Removal | 70 | 69.49 | Weibull |
| New Ballast Installation | 52 | 52 | Weibull |
| Ballast Cover Closure | 10 | 7.68 | Gamma |
| New Bulb Installation | 13 | 12.02 | Gamma |
| Glass Frame Closure | 3 | 2.99 | Weibull |
| Total Lowest Durations for Task | 166 | 161.29 | |

## 4.8 Limitations and Discussion

Although this pilot study examines data from a simple electrical activity, this methodology can be implemented in more complex operations. The shortest duration from two different approaches–one from observed and another from estimated–was considered while estimating the productivity frontier. The estimated duration was obtained by estimating the threshold parameter of each probability distribution in the "Base SAS® 9.2" software. Sometimes, it is difficult to plot best-fit probability distribution in this tool. For example, the SAS cannot plot the Erlang distribution. In this case, the second ranked distribution (from Input Analyzer in Arena) based on square error and p-value was fitted. The test shows that the lower the p-value when compared with the level of significance ($\alpha = 0.05$), the poorer the fit in the probability distribution is (Kelton et al., 2010; Rockwell Automation, 2013). However, most of the manual steps used in the pilot study would have to be automated in a more complex activity in order to determine the productivity frontier.

The pilot study provided valuable lessons. The time and motion study was found to be effective in measuring the observed shortest duration to complete the task. The probability distribution was found effective in computing the estimated shortest duration. Therefore, this pilot study demonstrates that the proposed framework for estimating the productivity frontier is adequate when applied to a simple construction operation. However, more research is required to:

- Determine the adequacy of the proposed approach when dealing with more complex construction operations. The pilot study focused on a simple operation performed by a single worker in a highly controlled environment.
- Determine the adequacy of the proposed approach when dealing with an entire activity. The pilot study focused only on the "Fluorescent Bulb Replacement" task. Data was not collected for the other three tasks that make up the "Lighting Replacement" activity.
- Determine the potential benefits of collecting more detailed information. The pilot study collected data up to the action level only.
- Explore innovative ways of automating data collection and analysis. The proposed approach, as applied in the pilot study, was labor intensive.

# CHAPTER 5

# DETAILED STUDY

The pilot study discussed in Chapter 4 estimates the labor productivity frontier using a basic framework for sequential actions performed by a single worker. It is quite simple to understand the process and estimate the labor productivity frontier because of less complexity. When multiple workers are involved in the parallel and sequential actions, it increases complexities during analysis. To examine the basic framework for such a complex scenario, a detailed study was conducted. This chapter describes an extended research on labor-intensive fabrication operations during the "Fabrication of Sheet Metal Ducts" at the workshop of the Waldinger Corporation in Omaha, Nebraska. In addition, this detailed study illustrates the analysis of this activity up to the movement level of hierarchy. A detail description of each stage is explained below.

## 5.1 Field Data Collection

A similar approach to the pilot study was implemented to collect data from the site. Depending upon site conditions, single or multiple Canon XF100 professional camcorders were used to collect video data and calibrated using the "Camera Calibration Toolbox" in Matlab (Bai et al., 2008; John et al., 2009; Sigal et al., 2010). Prior to data collection, cameras were synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004; Delamarre & Faugeras, 1999). Data were captured on the fabrication of sheet metal ducts at the Waldinger Corporation's workshop. These ducts were manufactured to install an exhaust system in a newly constructed building at the University of Nebraska Medical Center (UNMC) in Omaha, Nebraska. The scope of this fabrication of sheet metal ducts included the complete labor-intensive operations of the formation of sheet metal ducts from plain metal sheets of standard sizes. The reasons behind the selection of this activity and working environment are illustrated in the following sections.

### 5.1.1 Reason Behind Selection of This Activity

The fabrication of sheet metal duct activity is selected because of the following reasons.

- It is a controlled indoor environment, which makes it easy to collect data. It would be difficult and challenging to collect data from the outdoor environment because of unpredictable weather in Omaha. Also, there is more concern about the safety of data recording tools, such as video cameras from rainfall.
- This research is for estimating the labor productivity frontier, which can be considered as an absolute benchmark for labor productivity analysis. Since it deals with the benchmarking and efficiency of labor-intensive operations, it demands more repetitive labor-intensive operations for precise results during analysis. It is difficult to collect more repetitive construction activities in the limited time-frame. Moreover, there will be less chance of getting a large number of repetitive activities in the same construction project. Also, it is not possible to get consistent constraints and working environments throughout

the data collection period, which is a more important factor for this research to estimate precise efficiency of labor-intensive operations.

- This selected fabrication activity consists of almost a consistent working environment in terms of work approach, materials used for fabrication, and quality of output. For example, there were almost similar temperatures in the workstation, same sized plain metal sheets, same sets of equipment and tools, same sets of crews, and similar ducts fabricated throughout the data collection stage.
- Video cameras are set closer to the workstation in order to capture minor movements of workers.

### 5.1.2 Working Environment

The fabrication of sheet metal ducts activity was performed at the fabrication workshop of the Waldinger Corporation in Omaha, Nebraska. Each duct is assembled with two pieces of plain metal sheets. Each plain metal sheet has a dimension of 80.25 inches x 60 inches x 0.0336 inches. The required sizes of plain sheets are already delivered to the workshop in this ready-to-assemble condition. This activity involves eight different tasks: (a) roll bending, (b) lock forming, (c) lock setting, (d) tie rod installing, (e) flange screwing, (f) sealing, (g) packing, and (h) delivering. Eight workers were designated to complete this activity. Based on the nature of the tasks, separate crews of multiple workers were assigned. The first and second crews (Crew 1 and Crew 2) were involved in the roll bending task. The second crew was also involved in lock forming, lock setting, tie rod installing, and flange screwing tasks. The third crew (Crew 3) was involved in the sealing and packing tasks. The fourth crew (Crew 4) was involved in the delivering task. The first and second crews consist of two workers each. The third crew consists of three workers. One worker was in the fourth crew. According to crew sets, data collection and analysis was done separately for each task.

**Roll Bending Task:** The standard-sized (80.25 inches x 60 inches x 0.0336 inches) metal sheets are rolled and bended in a designated shape and size in order to form a duct. A roll bending task was performed by two separate crews. The first crew completed the roll bending task for 148 plain sheets. The second crew accomplished the roll bending task for the remaining 86 metal sheets. Figures 5.1 and 5.2 show the roll bending task performed by the first and second crews, respectively.

Figure 5.1: Roll Bending Task Performed By Crew 1

Figure 5.2: Roll Bending Task Performed By Crew 2

**Lock Forming Task:** The objective of lock forming on both edges of the roll-bended sheets is to assemble one sheet tightly over another in order to form a rigid duct. This task was started by the second crew after completing the roll bending task for all sheets. The lock forming task performed by the second crew is shown in Figure 5.3.

Figure 5.3: Lock Forming Task Performed By Crew 2

**Lock Setting Task:** The second crew started the lock setting task after all sheets were lock-formed. This is an actual stage in which two lock-formed sheets are assembled to form a duct. Figure 5.4 shows the lock setting task performed by the second crew.

Figure 5.4: Lock Setting Task Performed By Crew 2

**Tie-Rod Installing Task:** The second crew installed tie-rods at the same workstation, where the lock-setting task was performed. Just after performing a lock-setting task, the tie-rods were installed on one edge of the duct and again on the other. Each duct consists of five tie-rods, which embraces the duct at the middle such that it can bear loads. Figure 5.5 shows the working environment and the performance of the second crew for the tie-rod installation task.

Figure 5.5: Tie-Rod Installing Task Performed By Crew 2

**Flange Screwing Task:** After the lock setting and the tie-rod installing task were completed, the designated flanges were screwed at each edge of the duct by the second crew as shown in Figure 5.6. The flanges were of definite sizes and delivered to the workstation in ready-made form. The flanges were screwed on one end of the duct and again to the next end of the duct in order to protect the duct's ends from unwanted damage when delivering to or installing in the HVAC exhaust facilities. This flange is strong enough to take three times the required design loads of each duct.

Figure 5.6: Flange Screwing Task Performed By Crew 2

**Sealing Task:** The third crew was assigned a sealing task as shown in Figure 5.7. The sealing was done on a duct's edges where two sheets were joined around tie-rods installed position and around flanges of ducts in order to protect from air leakage, and prevent from weather or corrosion. However, three workers were involved in the sealing task; an individual worker was responsible for an individual duct.

Figure 5.7: Sealing Task Performed By Crew 3

**Packing Task:** After sealing, two workers from the third crew were involved in performing the packing task as shown in Figure 5.8. The main job of this task was to cover plastic (plasticking off) on both edges of the duct, where flanges were screwed in order to prevent from weather corrosion or peeling out of fresh sealer materials from joints due to rain water. The same workers were assigned to palletize and draw bending jobs in order to make the ducts ready for delivery.

Figure 5.8: Packing Task Performed By Crew 3

**Delivering Task:** The fourth crew was assigned to load the ducts contained on a cart onto the vehicle and move them out from the workstation, termed as a delivery task. The delivery task was performed only after packing ducts in a set of three or six. However, this worker was also engaged with other activities in the workshop and was not continuously involved in this task. Altogether, eight workers were employed to complete this activity.

Figure 5.9: Delivering Task Performed By Crew 4

Since the site is a fabrication workshop of the Waldinger Corporation, there was a problem of capturing movements of all workers involved in multiple simultaneous tasks because of the presence of various machines, materials, and other workers. Two or three fixed cameras were used to capture the fabrication activity of sheet metal ducts depending upon the space availability at the site of installation (fixed background). Only two fixed cameras were used to capture Tasks 1 and 2. One or two fixed cameras were used to capture Tasks 3, 4, and 5. One fixed camera was used to capture Tasks 6, 7, and 8.

## 5.2 Data Analysis

In order to achieve the purpose of this study, the four-level hierarchy of activity, task, action, and movement was implemented as shown in Figure 5.10. The "Fabrication of Sheet Metal Ducts" activity was selected to analyze the data because of its homogeneity across the project. The activity was broken down into eight different tasks: (a) roll bending, (b) lock forming, (c) lock setting, (d) tie rod installing, (e) flange screwing, (f) sealing, (g) packing, and (h) delivering. Each task was further broken down into actions and each action was broken down into movements.

Since the lock setting and the tie-rod installing tasks were repeated one after another for both sides of the duct, these tasks are analyzed together as Sides I and II as shown in Figure 5.10. All these tasks and actions were identified from the video data by converting it into individual images by applying the frame separation algorithm in Matlab (Cai et al., 1995; Cai & Aggarwal, 1996).

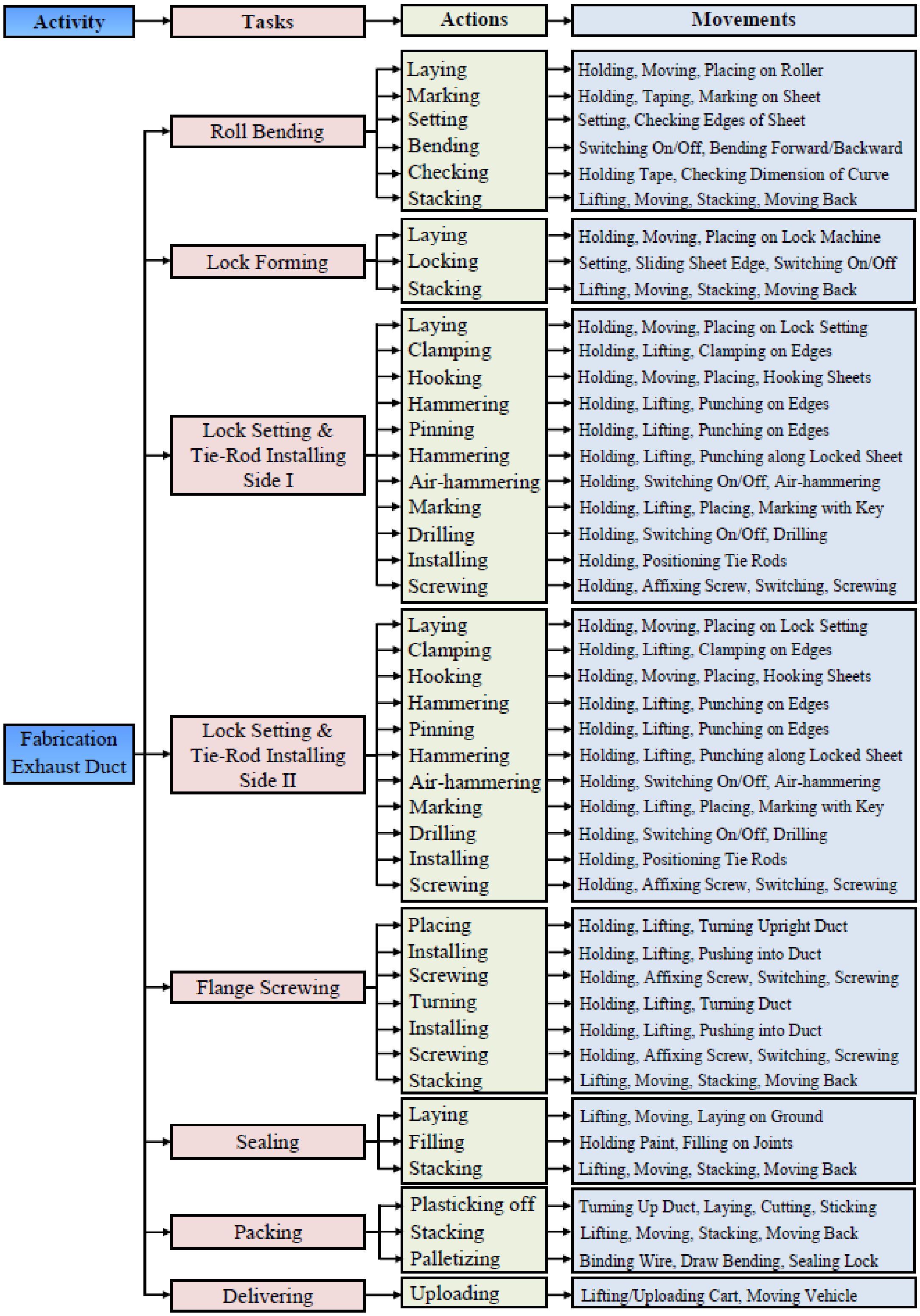


Figure 5 10: Hierarchical Breakdown of Fabrication of Sheet Metal Ducts

One hundred and seventeen data points for the “Fabrication of Sheet Metal Ducts” activity were analyzed at the action level, as well as the movement level during this detailed study. This activity consists of eight different tasks, 45 different actions, and more than 255 different movements. In the task level study, there were 936 (8 x 117 = 936) data points for analysis. In the action level study, there were 5,265 (45 x 117 = 5,265) data points for analysis. There were at least 29,835 (255 x 117 = 29,835) data points for the movement level analysis.

The roll bending and the lock forming tasks were performed on the first and second workstations, respectively. The lock setting and tie-rod installing tasks were performed on the third workstation. The flange screwing task was performed on the fourth workstation. The sealing, packing, and delivering tasks were performed on the fifth, sixth, and seventh workstations, respectively. The lock setting and tie-rod installing tasks were performed by the same crew and at the same workstation; it is combined for Sides I and II during the data extraction phase in order to minimize level of complexity. Moreover, the objective of this detailed study is to determine the feasibility of the basic framework up to the movement level in the hierarchy. The researcher analyzed data to the movement level in the hierarchy for the second task (lock forming) only because of time and resource constraints.

## 5.3 Actions and Movements Identification

During this research, the action and movement of each worker was identified and classified from the image frame analysis by the visual inspection (Wang et al., 2003). Since this is just a basic framework, actions and movements were identified manually.

Identified actions and movements for the “Fabrication of Sheet Metal Ducts” activity are described below.

### 5.3.1 Roll Bending Task

Following the hierarchical structure, this task is broken down into six different actions as shown in Table 5.1, which are: (a) laying plain sheet on roll bending table, (b) marking dimension, (c) setting plain sheet, (d) bending sheet on the roller, (e) checking dimension, and (f) stacking of roll bended sheet.

Since this task was performed by two sets of crews, they performed different sequential sets of actions as shown in Figures 5.1 and 5.2. In an attempt to lay the plain sheet on the roll bending table, workers have to approach the stacks of plain sheets in order to hold, move, and finally, place the plain sheet on the roll bending table, which are movements of the workers as shown in Table 5.1. Similarly, other movements involved in each action are listed in Table 5.1.

Table 5.1: Actions and Movements Involved in Roll Bending Task

| Task 1 | Actions | Movements |
|---|---|---|
| Roll Bending | Laying a plain sheet on the roll bending table | • Approach to the plain sheet metal stacks<br>• Hold the plain sheet metal<br>• Move the plain sheet onto the roll bending table<br>• Place the plain sheet on the roll bending table |
| | Marking dimension | • Hold a marker<br>• Hold a measuring tape<br>• Measure a dimension of radius of curvature<br>• Mark on the plain sheet by marker<br>• Keep measuring tape back to the original place |
| | Setting the plain sheet | • Move the plain sheet towards roller<br>• Check edges of the sheet along the line of roller |
| | Bending sheet on the roller | • Switch roller machine on forward direction<br>• Bend the sheet metal onto forward direction<br>• Switch roller machine off<br>• Switch roller machine on backward direction<br>• Bend the sheet metal onto backward direction<br>• Switch roller machine off |
| | Checking dimension | • Hold a measuring tape<br>• Hold edge of the roll bended sheet<br>• Measure a dimension of radius of curvature<br>• Keep measuring tape back to original place |
| | Stacking of the roll-bended sheet | • Lift the roll-bended sheet<br>• Move the sheet towards stacks<br>• Place the sheet on the stack<br>• Move back to workstation |

### 5.3.2 Lock Forming Task

This task involves three different actions, such as (a) laying the roll bended sheet on the lock machine table, (b) locking, and (c) stacking as shown in Table 5.2. Four different movements for the laying action, seven different movements for the locking action, and three different movements for the stacking action are identified as listed in Table 5.2.

Table 5.2: Actions and Movements Involved in Lock Forming Task

| Task 2 | Actions | Movements |
|---|---|---|
| Lock Forming Task | Laying the roll-bended sheet on lock machine table | • Approach to the roll-bended sheet stacks<br>• Hold the roll-bended sheet<br>• Move the roll-bended sheet onto the lock forming table<br>• Place the roll-bended sheet on the lock forming table |
| | Locking | • Set one edge of the roll-bended sheet on lock machine<br>• Slide the sheet for locking<br>• Switch another edge of the sheet<br>• Place another edge of the sheet on lock machine<br>• Set another edge of the sheet on lock machine<br>• Slide the sheet for locking<br>• Hold the sheet before moving for stacking |
| | Stacking | • Move the lock-formed sheet towards stacks<br>• Place the lock-formed sheet at stacks<br>• Move back to workstation |

### 5.3.3 Lock Setting Task

Table 5.3 shows seven different actions involved in the lock setting task, which are: (a) laying the lock-formed sheet on the lock setting table, (b) clamping edges of the lock setting setup, (c) hooking the second sheet over the first sheet on the lock setting machine, (d) hammering for lock-down on the both edges, (e) pinning for lock-down on the both edges, (f) hammering along the edge, and (g) air-hammering to set the lock. There are about 34 movements identified in order to complete this task, which are listed in Table 5.3. Four movements for the laying action, six movements for the clamping action, four movements for the hooking action, six movements for the hammering action on both edges action, six movements for the pinning action, three movements for the hammering action along the edge, and five actions for the air-hammering action are identified as shown in Table 5.3.

Table 5.3: Actions and Movements for Lock Setting Task

| Task 3 | Actions | Movements |
|---|---|---|
| Lock Setting Task | Laying the lock-formed sheet on lock setting table | • Approach to the lock-formed sheet stacks<br>• Hold the lock-formed sheet<br>• Move the lock-formed sheet onto the lock setting table<br>• Place the lock-formed sheet on the lock setting table |
| | Clamping edges of the lock setting setup | • Hold a clamp<br>• Lift and move a clamp<br>• Clamp Edge 1 on the lock setting setup<br>• Hold another clamp<br>• Lift and move the clamp<br>• Clamp Edge 2 on lock setting setup |
| | Hooking the second sheet over the first sheet on the lock setting machine | • Approach to the lock-formed sheet stacks<br>• Hold the lock-formed sheet<br>• Move the lock-formed sheet onto the lock setting table<br>• Place and hook the lock-formed sheet over first sheet |
| | Hammering for lock-down on the both edges | • Hold a hammer<br>• Lift the hammer<br>• Punch onto the sheet Edge 1<br>• Hold the hammer<br>• Lift the hammer<br>• Punch onto the sheet Edge 2 |
| | Pinning for lock-down on the both edges | • Hold a pin rod<br>• Lift the pin rod<br>• Punch onto the sheet Edge 1 by hammering<br>• Hold a pin rod<br>• Lift the pin rod<br>• Punch onto the sheet Edge 2 by hammering |
| | Hammering along the edge | • Hold a hammer<br>• Lift the hammer<br>• Punch along the locked-down sheet edges |
| | Air-hammering to set the lock | • Hold and move the air-hammer towards the lock setting setup<br>• Switch air-hammer on<br>• Air-hammering along the locked sheet<br>• Switch air-hammer off<br>• Place air-hammer back to the original place |

### 5.3.4 Tie-Rod Installing Task

According to the hierarchical structure, the tie-rod installing task was broken down into four different actions, such as (a) marking out the tie-rods locations on the sheet, (b) drilling for tie-rods installation, (c) installing the tie-rods, and (d) screwing the tie-rods as shown in Table 5.4.

Table 5.4: Actions and Movements for Tie-Rod Installing Task

| Task 4 | Actions | Movements |
|---|---|---|
| Tie-Rod Installing Task | Marking out tie-rods locations on the sheet | • Approach to marking key-sheet<br>• Hold and move the marking key-sheet<br>• Place the marking key-sheet on the lock setting sheet<br>• Hold markers<br>• Mark positions for tie-rods on the lock setting sheet<br>• Hold and move back the marking key-sheet<br>• Move back to the workstation |
| | Drilling for tie-rods installation | • Approach to drilling machine location<br>• Hold a drilling machine<br>• Switch the drilling machine on<br>• Drill the sheet metal<br>• Switch the drilling machine off<br>• Place the drilling machine on the original table<br>• Move back to the workstation |
| | Installing tie-rods | • Approach toward tie-rods storing box<br>• Hold a tie-rod<br>• Hold screws<br>• Place a tie-rod on the drilled position |
| | Screwing tie-rods | • Approach to screwing machine location<br>• Hold and move the screwing machine<br>• Attach screw on the tip of screwing machine<br>• Switch the screwing machine on<br>• Screw to fix the tie-rod<br>• Switch the screwing machine off<br>• Place the screwing machine on the original table<br>• Move back to the workstation |

Since the lock setting and tie-rod installing tasks were performed on both sides of a duct, one after another, these two tasks were analyzed together for Side I and Side II. Table 5.4 shows that there are seven movements for action 1, seven movements for action 2, four movements for action 3, and eight movements for action 4.

### 5.3.5 Flange Screwing Task

Six actions and 31 movements are identified for the flange screwing task as shown in Table 5.5. Those actions are: (a) taking the duct out from the lock setting, (b) installing a flange on one end of the duct, (c) screwing the flange on the duct, (d) installing the flange on another end of the duct, (e) screwing the flange on the duct, and (f) stacking the duct.

Table 5.5: Actions and Movements for Flange Screwing Task

| Task 5 | Actions | Movements |
|---|---|---|
| Flange Screwing Task | Taking the duct out from the lock setting | • Hold the duct<br>• Move the duct out from the lock setting setup<br>• Place the duct in the erected position to install a flange |
| | Installing a flange on one end of the duct | • Approach to the bucket containing flanges<br>• Hold a flange<br>• Lift and move the flange towards the duct<br>• Install by pushing the flange into the duct |
| | Screwing the flange on the duct | • Approach to screwing machine location<br>• Hold and move the screwing machine<br>• Attach screw on the tip of the screwing machine<br>• Switch the screwing machine on<br>• Screw the flange on the duct<br>• Switch the screwing machine off<br>• Place the screwing machine on the original table<br>• Move back to the workstation |
| | Installing the flange on another end of the duct | • Turning the duct upright<br>• Approach to a bucket containing flanges<br>• Hold a flange<br>• Lift and move the flange towards the duct<br>• Install by pushing the flange into the duct |
| | Screwing the flange on the duct | • Approach to screwing machine location<br>• Hold and move the screwing machine<br>• Attach screw on the tip of the screwing machine<br>• Switch the screwing machine on<br>• Screw the flange on the duct<br>• Switch the screwing machine off<br>• Place the screwing machine on the original table<br>• Move back to the workstation |
| | Stacking the duct | • Move by pushing the duct towards stacks<br>• Place the duct at stacks<br>• Move back to the workstation |

### 5.3.6 Sealing Task

This sealing task is the sixth task of the activity and is broken down into three actions and eight movements following the hierarchical structure as listed in Table 5.6, Three different actions are: (a) laying the duct for sealing, (b) filling sealer at joints of the duct and flanges, and (c) stacking the ducts.

Table 5.6: Actions and Movements for Sealing Task

| Task 6 | Actions | Movements |
| --- | --- | --- |
| Sealing Task | Laying the duct for sealing | • Lift and move the duct from stacks<br>• Lay the duct on the ground for sealing |
| | Filling sealer at joints of the duct and flanges | • Hold a bucket containing sealer<br>• Hold a paint brush<br>• Fill sealer on the duct joints and flanges |
| | Stacking the duct | • Move the duct towards stacks<br>• Place the duct at stacks<br>• Move back to the workstation |

### 5.3.7 Packing Task

After the sealing task is done, the duct is made ready for packing. The packing task consists of four actions and 18 movements as listed in Table 5.7. The actions are: (a) plasticking off the duct at one edge in order to prevent sealer material from weathering, (b) plasticking off the duct at another edge, (c) stacking on the cart, and (d) palletizing and draw bending to prepare for delivery.

Table 5.7: Actions and Movements for Packing Task

| Task 7 | Actions | Movements |
|---|---|---|
| Packing Task | Plasticking off the duct at one edge | • Turn the duct upright from stacks<br>• Lay the plastic covering on one end of the duct<br>• Cut edge of the plastic<br>• Affix the plastic on the duct |
| | Plasticking off the duct at another edge | • Turn the duct upright from stacks<br>• Lay the plastic covering on one end of the duct<br>• Cut edge of the plastic<br>• Affix the plastic on the duct |
| | Stacking on the cart to make ready for delivering | • Lay a cart on the ground at delivery location<br>• Lift the duct<br>• Move the duct on the cart to deliver<br>• Stack the duct on the cart<br>• Move back to the workstation |
| | Palletizing and draw bending | • Move a wire-wheeler to the cart<br>• Take out a wire and rounding about one edge<br>• Draw bending<br>• Make wires tight and lock-down<br>• Move back to the workstation |

### 5.3.8 Delivering Task

The delivering task is the last task of the activity. One worker of Crew 4 was assigned to upload the cart to the vehicle and move it out for delivery. The delivery task was performed only after packing ducts into sets of three or six. A loader (carrier equipment) was used for delivery, which is not in the scope of this research. Therefore, there is no further breakdown of this task into action and movement. However, the duration to upload the cart and leave the loader from the station was recorded.

## 5.4 Action and Movement Classification

Visual inspection (Bai et al., 2008; Wang et al., 2003) was used to classify each action and movement of the “Fabrication of Sheet Metal Ducts” activity into either contributory or non-contributory, based upon their impact upon work completion. A time and motion study (Finkler et al., 1993; Shahidul & Shazali, 2011) was conducted from the video data, and time was recorded for each contributory and non-contributory action and movement. The contributory actions and movements are those necessary jobs to accomplish the different tasks as listed in Figure 5.10. Non-contributory actions or movements include any other action or movement not listed in Figure 5.10. Non-contributory actions or movements are considered non-productive and include actions or movement, such as unscheduled breaks, time spent on attending personal matters (texting, or talking), disturbance by other workers, leaving the workstation for non-related work, and standing for a long time without doing nothing (idle time). The time required for each action was recorded from the video data using the hierarchical structure as shown in Figure 5.10.

When analyzing the movement level, it is almost impossible to record the duration of the movement by observing video data because duration of movement may be smaller than a second. Therefore, the video data was converted into individual images (30 frames per second) by applying the frame separation algorithm in Matlab (Cai et al., 1995; Cai & Aggarwal, 1996). The time and motion study was conducted by counting the number of frames to complete each movement and then converting those frames into duration in seconds scale, which were recorded into the Excel spreadsheet.

## 5.5 Productivity Frontier Estimation

During this study, two approaches were established to compute the productivity frontier for the "Fabrication of Sheet Metal Ducts" activity, which are: (a) observed durations and (b) estimated durations. For both approaches, data was extracted using the time and motion study. The shortest durations obtained between two approaches was selected in order to compute the productivity frontier.

### 5.5.1 Approach 1: Observed Durations

During the hierarchical action level analysis, the time and motion study was conducted by thoroughly reviewing the video data and the durations of the contributory actions for each task of the “Fabrication of Sheet Metal Ducts” activity, and they were recorded in the Excel spreadsheet. Since multiple workers were involved in each task, the durations for individual and combined involvement of the workers for each task were separately recorded in the Excel spreadsheet as shown in Table A-1. The shortest possible duration for individual and combined involvement of workers were separately estimated by conducting a sequence set analysis.

A sequence set analysis is defined as a process of analysis of data in different groups according to the characteristics of data set. In other words, it is an analysis process of data following the similar sequence set of actions performed by an individual worker or a crew of multiple workers for the same task. For example, an action may be accomplished by an individual worker or by the combined effort of multiple workers for the same task. According to similar sequential sets of data, a group of datasets is prepared.

The minimum duration taken to accomplish an action is determined for each sequential dataset. The shortest possible duration for a task was estimated by adding up the shortest durations observed for each action because the task was made up of actions in the specific set of sequence. Among available shortest durations for each sequential set of task, the shortest of the shortest duration is considered as the shortest observed duration for that task.

Some tasks were performed in parallel fashion by workers. For example, one worker was involved in one action, and simultaneously, another worker was involved in another action for the same activity. Therefore, there is a complexity while estimating the shortest observed duration, especially in that task involving parallel and sequential actions. In order to address such a complexity, some assumptions are developed as described below.

#### 5.5.1.1 Assumptions

Some reasonable assumptions are developed in order to make the analysis process simple and easy.

- During action level analysis, the time taken to complete each action is measured using the time and motion study in a sequential fashion, if actions are performed by an individual worker to complete a task.
- When actions are performed by two workers in a parallel fashion, the time taken to complete each action is recorded individually in the Excel spreadsheet. When they interactively perform together, the higher time taken between them is taken into account because maximum time is required to complete that task. For example, in a task consisting of four actions, Actions 1 and 4 are done by the first and second workers in a parallel fashion while Actions 2 and 3 are performed together in a sequential fashion. To start Action

2 together, either the first or second worker must wait for their coworker. That means if successive actions have to be performed together, then a worker has to wait for his coworker until he has finished his action. This is similar to critical path concept (longest duration is counted) in which without considering the longest duration for the action following through the critical path, the task would not be complete. But, it generates an issue of wait time (idle time) because wait time is considered as a non-contributory action.

- The wait time spent by a worker is evaluated before categorizing it as a contributory or non-contributory action. If the wait time is reasonably small, say 15% of the total time of the task, then it is included in the contributory action. For example, if the wait time is just 6 seconds in 60 seconds' total time for a task, then it is about 10% of the total time. It is considered a contributory time because no one can perform another action between this insignificant time-frame (6 seconds in this example).
- After completing an action, if the second worker joins with the first worker for the next action in the middle of the work, then the total time to complete that action is determined by measuring time spent by the first worker because he spent his whole time to complete that action. For example, the first worker completes Action 1 and starts Action 2 while the second worker is still working on Action 4. In the middle of Action 2, the second worker joins with the first worker to complete Action 2 after completing Action 4. Then, they together perform the remaining jobs of Action 2 and Action 3. In this case, the time taken to complete Actions 1 and 4 are measured based on the time spent

by the first and second workers, respectively. But, the time taken to complete Action 2 is measured based on the time spent by the first worker because he is involved for the entire Action 2. For Action 3, either time spent by the first worker or the second worker is considered because both durations are equal.

#### 5.5.1.2 Formulation for the sequential datasets

Since four crews of multiple workers were assigned for different tasks, it is better to analyze and estimate the shortest observed duration for each task separately.

##### *5.5.1.2.1 Task 1: Roll bending task*

Two crews performed the roll bending task ($T_1$), among which the first crew accomplished the task for 148 plain sheets and the remaining 86 plain sheets were completed by the second crew.

*Performance of the first crew:* Let, $W_2$ and $W_{12}$ represent work performed by Worker 1, Worker 2, and both workers for Task 1, respectively. The task performed by the first crew ($C_1$) involved seven different actions, which are represented by $A_1$, $A_2$, $A_3$, $A_4$, $A_5$, $A_6$, and $A_7$, respectively, as shown in Table 5.8.

Table 5.8: Sequence of Actions and Corresponding Symbol for Task 1 – Crew 1

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 1-Crew1 | Marking dimension | $T_1$-$A_1$ |
| | Laying a plain sheet on the roll bending table | $T_1$-$A_2$ |
| | Setting the plain sheet | $T_1$-$A_3$ |
| | Bending sheet on the roller | $T_1$-$A_4$ |
| | Checking dimension | $T_1$-$A_5$ |
| | Stacking of the roll-bended sheet | $T_1$-$A_6$ |
| | Stacking the plain sheets off from piles | $T_1$-$A_7$ |

Based on the sequence of actions performed, two sequential datasets are classified. The first and second datasets consist of 104 and 44 data points, respectively. Among them, 15 sample data items for each set are listed in Table A.9. Since $W_1$ performed the marking dimension action ($A_1$) for more than one sheet at once, the time taken to conduct the marking dimension action for each sheet is computed by dividing total time by number of sheets.

According to the first sequential dataset, Actions $A_1$, $A_2$, and $A_7$ were performed by $W_1$ while $W_2$ was engaged in the Action $A_6$ in the parallel fashion. The remaining Actions: $A_3$, $A_4$, and $A_5$ were performed by both workers together in the sequential fashion. Therefore, the highest duration between the time spent by $W_1$ for Actions $A_1$, $A_2$, and $A_7$ and that by $W_2$ for Action $A_6$ was taken because they performed them simultaneously. This duration was added with the shortest durations spent by both workers for remaining Actions $A_3$, $A_4$, and $A_5$ sequentially in order to determine the shortest observed duration for this task as shown in Equation 5.1. The shortest observed duration was found to be 57 seconds after computing Equation 5.1.

$$\textit{Highest of } [(T_1\text{-}A_1\text{-}\ W_1 + T_1\text{-}A_2\text{-}\ W_1 + T_1\text{-}A_7\text{-}\ W_1) \textit{ or } T_1\text{-}A_6\text{-}\ W_2] + T_1\text{-}A_3\text{-}\ W_{12} + T_1\text{-}A_4\text{-}\ W_{12} + T_1\text{-}A_5\text{-}\ W_{12} \ldots\ldots\ldots \quad (5.1)$$

For the second sequential dataset, only Actions $A_1$, $A_7$, and $A_6$ were performed simultaneously by $W_1$ and $W_2$, and remaining actions were completed together. Equation 5.2 was employed to determine the shortest observed duration for this task, and duration was found to be 62 seconds. The shortest of the shortest observed duration for Task 1 was determined by taking the minimum value between these two sequential datasets. Thus, the shortest observed duration for Crew 1 for accomplishing Task 1 was found to be 57 seconds.

$$Highest\ of\ [(T_1\text{-}A_1\text{-}\ W_1 + T_1\text{-}A_7\text{-}\ W_1)\ or\ T_1\text{-}A_6\text{-}\ W_2] + T_1\text{-}A_2\text{-}\ W_{12} + T_1\text{-}A_3\text{-}\ W_{12} + T_1\text{-}A_4\text{-}\ W_{12} + T_1\text{-}A_5\text{-}\ W_{12} \ldots\ldots\ldots (5.2)$$

*Performance of second crew:* Task 1 was also performed by the second crew for remaining 86 sheets. Among which, 15 data sample are listed in Table A.10. The roll bending task involved six different actions as shown in Table 5.9. The second crew conducted the "marking dimension" action ($A_2$) only after performing the "laying the plain sheet on the roll bending table" action ($A_1$) for each plain sheet, which is an opposite sequence of action performed by the first crew. In addition, the second crew did not perform the action "stacking plain sheet off from piles" that was performed by Crew 1.

Table 5.9: Sequence of Actions and Corresponding Symbol for Task 1 – Crew 2

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 1-Crew 2 | Laying a plain sheet on the roll bending table | $T_1$-$A_1$ |
| | Marking dimension | $T_1$-$A_2$ |
| | Setting the plain sheet | $T_1$-$A_3$ |
| | Bending sheet on the roller | $T_1$-$A_4$ |
| | Checking dimension | $T_1$-$A_5$ |
| | Stacking of the roll-bended sheet | $T_1$-$A_6$ |

According to the sequential dataset, all six actions were performed by Crew 2 in sequential order. Therefore, the shortest observed duration to accomplish Task 1 was computed by employing Equation 5.3. Thus, the shortest observed duration for Crew 2 to complete Task 2 was found to be 54 seconds. Furthermore, the minimum duration value was taken to complete Task 1 by comparing the shortest observed durations between crews 1 and 2; thus, the shortest observed duration for task 1 was found to be 54 seconds.

$$T_1\text{-}A_1\text{-}\ W_{12} + T_1\text{-}A_2\text{-}\ W_1 + T_1\text{-}A_3\text{-}\ W_{12} + T_1\text{-}A_4\text{-}\ W_{12} + T_1\text{-}A_5\text{-}\ W_{12} + T_1\text{-}A_6\text{-}\ W_{12} \ldots\ldots\ldots (5.3)$$

#### *5.5.1.2.2 Task 2: Lock forming task*

The lock forming task ($T_2$) was performed by the second crew for 234 metal sheets, which involved three different actions as shown in Table 5.10. Tables A.1 shows seven sample data representing data-extraction process employing time and motion study by observing video data for the lock forming task. Based on the sequence of actions performed by the crew, three sequential datasets were classified. The number of data points for the first, second, and third sequential datasets are 98, 15, and 121, respectively. Among them, Tables A.2, A.3, and A.4 show 15 sample data for the first, second, and third sequential dataset for lock forming task.

Table 5.10: Sequence of Actions and Corresponding Symbol for Task 2 – Crew 2

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 2-Crew 2 | Laying the roll bended sheet on the lock machine table | $T_2$-$A_1$ |
| | Locking | $T_2$-$A_2$ |
| | Stacking | $T_2$-$A_3$ |

The sequence of actions performed in the first dataset includes parallel actions $A_1$ and $A_3$ performed by Workers 1 and 2, respectively. After completing Action $A_3$, the second worker ($W_2$) joined with the first worker ($W_1$) to complete the remaining job of Actions $A_1$ and $A_2$. The minimum duration of each action was determined for this dataset. Then, Equation 5.4 was employed to determine the shortest observed duration for this task. Since the first worker was involved in Action $A_1$ from start to finish, the total time to complete Action $A_1$ was determined by measuring the time spent by that worker. The highest duration spent by both workers in Actions $A_1$ and $A_3$ were taken into account because they were performed simultaneously. This duration was added with the duration they spent together to perform Action $A_2$ in order to get the total duration for Task $T_2$. The shortest observed duration to complete this task for this dataset was found to be 44 seconds.

$$\text{Highest of } [T_2\text{-}A_1\text{- } W_1 \text{ OR } T_2\text{-}A_3\text{- } W_2] + T_2\text{-}A_2\text{- } W_{12} \ldots\ldots\ldots (5.4)$$

Similarly, the shortest observed duration for the second sequential dataset was determined based on their sequence of actions performed by employing Equation 5.5 and the value was found to be 59 seconds.

$$T_2\text{-}A_1\text{- } W_{12} + T_2\text{-}A_2\text{- } W_{12} + T_2\text{-}A_3\text{- } W_{12} \ldots\ldots\ldots (5.5)$$

The third sequential dataset represents a sequence of actions in which the second worker and the first worker performed Actions $A_1$ and $A_3$ simultaneously. After the stacking action was done, the first worker again joined Action $A_1$ and performed the remaining actions together as shown in Equation 5.6. The shortest observed duration to complete this task for this dataset was found to be 44 seconds.

$$\text{Highest of } [T_2\text{-}A_1\text{- } W_2 \text{OR } T_2\text{-}A_3\text{- } W_1] + T_2\text{-}A_2\text{- } W_{12} \ldots\ldots\ldots (5.6)$$

Furthermore, the minimum duration value was taken to complete the lock forming task (Task 2) by comparing the shortest observed durations among three sequential datasets; thus, the shortest observed duration for Task 2 was found to be 44 seconds.

#### *5.5.1.2.3 Tasks 3/4/5: Lock setting/ tie-rods installing/ flanges screwing tasks*

Tasks $T_3$, $T_4$, and $T_5$ were performed by the second crew ($C_2$) at the same time in a sequential and parallel fashion. Therefore, these tasks are analyzed together. A total of 117 ducts were fabricated, which means there were 117 data points to analyze these tasks. Among them, 15 sample data are listed in Tables A.11 and A.12. Just after performing a lock-setting task, the tie-rods were installed on one edge of the duct and again on the other. Therefore, the lock-setting task and the tie-rods installing tasks were completed in two stages for Sides I and II as shown in Table 5.11.

One sequential dataset was identified based on the sequence of actions performed by the second crew. When the second worker was engaged in Actions $T_{3I}$-$A_1$, $T_{3I}$-$A_2$, and $T_{3I}$-$A_3$, the first worker was performing Actions $T_5$-$A_3$ and $T_5$-$A_6$ in the parallel fashion. Therefore, the highest duration between them is taken into account as shown in Equation 5.7. Actions $T_{3I}$-$A_4$ and $T_{3I}$-$A_5$ were completed by both workers simultaneously. Similarly, Actions $T_{3I}$-$A_6$, $T_{3I}$-$A_7$, and $T_{3I}$-$A_8$ were completed by the second worker while the first worker was engaged on Actions $T_{4I}$-$A_1$, $T_{4I}$-$A_2$, and so on. The minimum durations taken to perform the sequential actions and the parallel actions were separately computed. The highest duration between the durations taken to complete parallel actions was computed and added with durations spent for the sequential actions as shown in Equation 5.7. Thus, the shortest observed duration to complete Tasks $T_3$, $T_4$, and $T_5$ was found to be 376 seconds.

Table 5.11: Sequence of Actions and Corresponding Symbol for Task 3/4/5 – Crew 2

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 3I-Crew 2 | Laying the lock-formed sheet on lock setting table | $T_{3I}$-$A_1$ |
| | Clamping edges of the lock setting setup | $T_{3I}$-$A_2$ |
| | Hooking the second sheet over the first sheet on the lock setting machine | $T_{3I}$-$A_3$ |
| | Holding clamps edges of the lock setting setup | $T_{3I}$-$A_4$ |
| | Hammering for lock-down on the both edges | $T_{3I}$-$A_5$ |
| | Pinning for lock-down on the both edges | $T_{3I}$-$A_6$ |
| | Hammering along the edge | $T_{3I}$-$A_7$ |
| | Air-hammering to set the lock | $T_{3I}$-$A_8$ |
| Task 4I-Crew 2 | Marking out tie-rods locations on the sheet | $T_{4I}$-$A_1$ |
| | Drilling for tie-rods installation | $T_{4I}$-$A_2$ |
| | Installing tie-rods | $T_{4I}$-$A_3$ |
| | Screwing tie-rods | $T_{4I}$-$A_4$ |
| | | |
| Task 3II-Crew 2 | Laying the lock-formed sheet on lock setting table | $T_{3II}$-$A_1$ |
| | Clamping edges of the lock setting setup | $T_{3II}$-$A_2$ |
| | Hooking the second sheet over the first sheet on the lock setting machine | $T_{3II}$-$A_3$ |
| | Holding clamps edges of the lock setting setup | $T_{3II}$-$A_4$ |
| | Hammering for lock-down on the both edges | $T_{3II}$-$A_5$ |
| | Pinning for lock-down on the both edges | $T_{3II}$-$A_6$ |
| | Hammering along the edge | $T_{3II}$-$A_7$ |
| | Air-hammering to set the lock | $T_{3II}$-$A_8$ |
| Task 4II-Crew 2 | Marking out tie-rods locations on the sheet | $T_{4II}$-$A_1$ |
| | Drilling for tie-rods installation | $T_{4II}$-$A_2$ |
| | Installing tie-rods | $T_{4II}$-$A_3$ |
| | Screwing tie-rods | $T_{4II}$-$A_4$ |
| | | |
| Task 5-Crew 2 | Taking the duct out from the lock setting | $T_5$-$A_1$ |
| | Installing a flange on one end of the duct | $T_5$-$A_2$ |
| | Screwing the flange on the duct | $T_5$-$A_3$ |
| | Installing the flange on another end of the duct | $T_5$-$A_4$ |
| | Screwing the flange on the duct | $T_5$-$A_5$ |
| | Stacking the duct | $T_5$-$A_6$ |

$$Highest\ of\ [(T_{3I}\text{-}A_1\text{-}\ W_2 + T_{3I}\text{-}A_2\text{-}\ W_2\ + T_{3I}\text{-}A_3\text{-}\ W_2)\ or\ (T_5\text{-}A_3\text{-}\ W_1 + T_5\text{-}A_6\text{-}\ W_1)] + Highest\ of\ (T_{3I}\text{-}A_4\text{-}\ W_1\ or\ T_{3I}\text{-}A_5\text{-}\ W_2) + Highest\ of\ [(T_{3I}\text{-}A_6\text{-}\ W_2 + T_{3I}\text{-}A_7\text{-}\ W_2 + T_{3I}\text{-}A_8\text{-}\ W_2)\ or\ (T_{4I}\text{-}A_1\text{-}\ W_1 + T_{4I}\text{-}A_2\text{-}\ W_1)] + T_{4I}\text{-}A_4\text{-}\ W_{12} + T_{3II}\text{-}A_1\text{-}\ W_{12} + T_{3II}\text{-}A_2\text{-}\ W_{12} + T_{3II}\text{-}A_3\text{-}\ W_{12} + Highest\ of\ (T_{3II}\text{-}A_4\text{-}\ W_1\ or\ T_{3II}\text{-}A_5\text{-}\ W_2) + Highest\ of\ [(T_{3II}\text{-}A_6\text{-}\ W_2 + T_{3II}\text{-}A_7\text{-}\ W_2 + T_{3II}\text{-}A_8\text{-}\ W_2)\ or\ (T_{4II}\text{-}A_1\text{-}\ W_1 + T_{4II}\text{-}A_2\text{-}\ W_1)] + T_{4I}\text{-}A_3\text{-}\ W_{12} + T_{4II}\text{-}A_3\text{-}\ W_{12} + T_{4II}\text{-}A_4\text{-}\ W_{12} + T_5\text{-}A_1\text{-}\ W_{12} + T_5\text{-}A_2\text{-}\ W_{12} + T_5\text{-}A_4\text{-}\ W_{12} + T_5\text{-}A_5\text{-}\ W_{12} \ldots\ldots\ldots \quad (5.7)$$

### *5.5.1.2.4 Task 6: Sealing task*

The sealing task ($T_6$) consists of three different actions, which were performed by three workers of Crew 3 as shown in Table 5.12. They individually performed this task in sequential order. Therefore, three separate sequential datasets were classified, which consisted of 44, 22, and 51 data points in the first, second, and third datasets, respectively. Among them, 15 sample data for each dataset are listed in Table A.13. The minimum duration for each action was determined for each dataset.

Table 5.12: Sequence of Actions and Corresponding Symbol for Task 6 – Crew 3

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 6-Crew 3 | Laying the duct for sealing | $T_6$-$A_1$ |
| | Filling sealer at joints of the duct and flanges | $T_6$-$A_2$ |
| | Stacking the duct | $T_6$-$A_3$ |

The shortest duration to complete the sealing task was computed for each dataset using Equations 5.8, 5.9, and 5.10. The shortest duration for the first, second, and third dataset were 601 seconds, 608 seconds, and 563 seconds for Workers $W_1$, $W_2$, and $W_3$, respectively. The minimum value among three sets was taken as the shortest observed duration to complete the sealing task ($T_6$). Thus, the shortest observed duration to complete Task $T_6$ was found to be 563 seconds.

$$T_6\text{-}A_1\text{-}\ W_1 + T_6\text{-}A_2\text{-}\ W_1 + T_6\text{-}A_3\text{-}\ W_1 \ldots\ldots\ldots (5.8)$$

$$T_6\text{-}A_1\text{-}\ W_2 + T_6\text{-}A_2\text{-}\ W_2 + T_6\text{-}A_3\text{-}\ W_2 \ldots\ldots\ldots (5.9)$$

$$T_6\text{-}A_1\text{-}\ W_3 + T_6\text{-}A_2\text{-}\ W_3 + T_6\text{-}A_3\text{-}\ W_3 \ldots\ldots\ldots (5.10)$$

##### *5.5.1.2.5 Task 7: Packing task*

The packing task consisted of four different actions as shown in Table 5.13. Two workers of Crew 3 were involved to perform this task in a sequential fashion. Based on available data, two sequential datasets were classified. The first dataset represents the performance of Workers $W_1$ and $W_2$ together; whereas the second dataset represents the Workers $W_3$ and $W_1$ together. The number of data points available for the first and second datasets were 45 and 72, respectively. Among them, 15 sample data are tabulated in Table A.14.

Table 5.13: Sequence of Actions and Corresponding Symbol for Task 7 – Crew 3

| Task-Crew | Actions Description | Symbol |
|---|---|---|
| Task 7-Crew 3 | Plasticking off the duct at one edge | $T_7$-$A_1$ |
| | Plasticking off the duct at another edge | $T_7$-$A_2$ |
| | Stacking on the cart to make ready for delivering | $T_7$-$A_3$ |
| | Palletizing and draw bending | $T_7$-$A_4$ |

The minimum duration for each action for each dataset was determined. Equations 5.11 and 5.12 were used to compute the shortest observed duration to complete the packing task for the first and second datasets, which are 348 and 341 seconds, respectively. The lowest value obtained between both equations was taken into account as the shortest observed duration to complete the packing task; thus, found to be 341 seconds.

$$T_7\text{-}A_1\text{-}\ W_{12} + T_7\text{-}A_2\text{-}\ W_{12} + T_7\text{-}A_3\text{-}\ W_{12} \ldots\ldots\ldots (5.11)$$

$$T_7\text{-}A_1\text{-}\ W_{31} + T_7\text{-}A_2\text{-}\ W_{31} + T_7\text{-}A_3\text{-}\ W_{31} \ldots\ldots\ldots (5.12)$$

#### *5.5.1.2.6 Task 8: Delivering task*

One worker of Crew 4 was involved in uploading the cart containing three or six sets of ducts and then moving out for delivery. Since there is no further breakdown of this task into actions and movements, the duration to complete this task was recorded in an Excel spreadsheet. Among 31 data points recorded in the spreadsheet, 15 sample data are listed in Table A.15. The lowest time to accomplish this task was 14 seconds, which is the shortest observed duration to complete the delivering task ($T_8$).

Therefore, the shortest observed duration for the “Fabrication of Sheet Metal Ducts” activity was estimated by adding the shortest observed duration of each task because the activity was made up of tasks in a sequence. The shortest total observed duration was found to be 1,392 seconds. The number of ducts fabricated was divided by this observed shortest duration in order to compute the equivalent productivity. The resulting equivalent productivity was found to be 2.59 ducts per crew-hour.

### 5.5.2 Approach 2: Estimated Durations

The probability distribution for each action involved in the “Fabrication of Sheet Metal Ducts” activity was obtained with the application of the “Input Analyzer” tool in the “Arena Simulation Software.” Based on the best-fit probability distribution for each action obtained from the “Arena Input Analyzer,” the threshold parameter (lowest duration) for that distribution was estimated using the “Base SAS® 9.2.” The lowest duration of the contributory actions for this task were estimated from the distribution, which were evaluated at a 95% confidence interval, and values were recorded in an Excel spreadsheet. The shortest estimated duration for each action was estimated for each task. When estimating the shortest total duration for each task, the concept of the sequence set analysis was again implemented similar to the method employed to estimate the observed shortest duration for each task.

#### 5.5.2.1 Task 1: Roll bending task

Based on the sequential analysis, the roll bending task performed by the first crew was classified into two datasets. Employing the “Arena Input Analyzer” and the “Base SAS® 9.2” software, the lowest threshold parameter for each action of each dataset was estimated based on the best-fit probability distribution. Tables 5.14 and 5.15 show the lowest estimated durations with the corresponding best-fit probability distributions for the roll bending task for the sequential datasets 1 and 2 ($C_1$-$S_1$ and $C_1$-$S_2$), respectively. The shortest estimated duration of Task 1 for the first dataset ($C_1$-$S_1$) was computed using Equation 5.1 and was found to be 53 seconds. Similarly, the lowest estimated duration for the second dataset ($C_1$-$S_2$) was found to be 61 seconds when computed using Equation

5.2. The lowest value among them was found to be 53 seconds, which is the shortest estimated duration to complete Task 1.

Table 5.14: “Roll Bending Task” Action Durations in Seconds for $C_1$-$S_1$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 5 | 4.08 | Weibull |
| $T_1$-$A_2$ | 7 | 4.49 | Lognormal |
| $T_1$-$A_3$ | 9 | 8.75 | Gamma |
| $T_1$-$A_4$ | 26 | 24.06 | Gamma |
| $T_1$-$A_5$ | 6 | 5.73 | Lognormal |
| $T_1$-$A_6$ | 15 | 14.12 | Lognormal |
| $T_1$-$A_7$ | 4 | 3.62 | Weibull |
| Total Lowest Durations for Task $T_1$ | 57 | 53 | |

Table 5.15: “Roll Bending Task” Action Durations in Seconds for $C_1$-$S_2$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 5 | 5.00 | Beta |
| $T_1$-$A_2$ | 6 | 5.73 | Lognormal |
| $T_1$-$A_3$ | 8 | 7.84 | Weibull |
| $T_1$-$A_4$ | 27 | 27 | Gamma |
| $T_1$-$A_5$ | 6 | 5.78 | Lognormal |
| $T_1$-$A_6$ | 15 | 14.60 | Exponential |
| $T_1$-$A_7$ | 5 | 2.40 | Weibull |
| Total Lowest Durations for Task $T_1$ | 62 | 61 | |

When considering the performance of Crew 2, a similar approach was employed to estimate the lowest estimated duration for each action of the third sequential dataset ($C_2$-$S_3$). The lowest observed durations and lowest estimated durations with corresponding best-fit distributions are listed in Table 5.16. Equation 5.3 was used to estimate the shortest observed duration for $T_1$-$C_2$ and was found to be 49 seconds. As the main objective of this study is to determine the possible shortest durations for each task, therefore, the shortest estimated durations obtained from Equations 5.1, 5.2, and 5.3 were compared and the lowest value was taken as the shortest estimated durations for Task 1. Thus, the shortest estimated duration for the roll bending task was found to be 49 seconds.

Table 5.16: “Roll Bending Task” Action Durations in Seconds for $C_2$-$S_3$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 4 | 2.46 | Gamma |
| $T_1$-$A_2$ | 10 | 9.71 | Beta |
| $T_1$-$A_3$ | 6 | 5.58 | Gamma |
| $T_1$-$A_4$ | 26 | 23.79 | Lognormal |
| $T_1$-$A_5$ | 1 | 0.97 | Exponential |
| $T_1$-$A_6$ | 7 | 6.45 | Lognormal |
| Total Lowest Durations for Task $T_1$ | 54 | 49 | |

**5.5.2.2 Task 2: Lock forming task**

Similar to the observed duration approach, three sequential datasets were identified based on the pattern of actions performed by the second crew. Table 5.17 shows the first dataset in which the lowest observed durations and the lowest estimated durations with the corresponding best-fit probability distributions for each action are listed. The lowest duration value for this dataset to complete the lock forming task was estimated by using Equation 5.4 and was found to be 42 seconds.

Table 5.18 shows the lowest observed durations and the lowest estimated durations with the corresponding best-fit probability distributions for each action of the second dataset ($C_2$-$S_2$). For this dataset, the lowest estimated duration to complete the lock forming task was estimated using Equation 5.5 and found to be 54 seconds.

Table 5.17: "Lock Forming Task" Action Durations in Seconds for $C_2$-$S_1$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 15 | 13.96 | Weibull |
| $T_1$-$A_2$ | 29 | 28.24 | Lognormal |
| $T_1$-$A_3$ | 9 | 7.41 | Lognormal |
| Total Lowest Durations for Task $T_2$ | 44 | 42 | |

Table 5.18: "Lock Forming Task" Action Durations in Seconds for $C_2$-$S_2$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 18 | 17.49 | Lognormal |
| $T_1$-$A_2$ | 32 | 32 | Gamma |
| $T_1$-$A_3$ | 9 | 4.5 | Weibull |
| Total Lowest Durations for Task $T_2$ | 59 | 54 | |

The lowest estimated durations of the third dataset ($C_2$-$S_3$) were estimated based on the best-fit probability distribution analysis for each action involved in the lock forming task and tabulated in Table 5.19. It shows the lowest observed as well as the lowest estimated duration for each action and the corresponding probability distribution. Equation 5.6 was employed to determine the shortest estimated duration for this task for the third dataset ($C_2$-$S_3$).

Since the objective of this research was to determine the lowest of the lowest values, the lowest estimated durations from these three datasets were compared and the smallest value was taken as the shortest estimated duration to complete the lock forming task. Therefore, from this estimation, the shortest estimated duration was found to be 42 seconds in order to complete Task 2.

Table 5.19: “Lock Forming Task” Action Durations in Seconds for $C_2$-$S_3$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_1$-$A_1$ | 15 | 14 | Weibull |
| $T_1$-$A_2$ | 29 | 27.66 | Lognormal |
| $T_1$-$A_3$ | 9 | 8.88 | Gamma |
| Total Lowest Durations for Task $T_2$ | 44 | 42 | |

#### 5.5.2.3 Tasks 3/4/5: Lock setting / tie-rods installing / flanges screwing tasks

The lock setting, tie-rods installing, and flanges screwing tasks were performed by the second crew in the sequential and the parallel fashions at the same workstation. Therefore, these tasks were analyzed together. Only one sequential dataset was formed based on the sequence of actions performed. At first, the data of each action was analyzed using the “Arena Input Analyzer” in order to determine the best-fit probability distribution. Then, the same data was employed into the “Base SAS® 9.2” in order to determine the lowest threshold value of that probability distribution, which was considered as the lowest duration to complete that action. A similar procedure was conducted for each action of each task, and the lowest estimated duration for each action was tabulated in Table 5.20. This table shows the lowest observed durations and the lowest estimated durations with the corresponding best-fit probability distributions. Equation 5.7 was used to estimate the shortest estimated duration for Tasks 3, 4, and 5 and the value was found to be 341 seconds.

Table 5.20: “Lock Setting, Tie-Rods Installing, and Flange Screwing Tasks” Action Durations in Seconds for $C_2$

| Tasks | Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|---|
| $T_{3I}$ | $T_{3I}$-$A_1$ | 11 | 10 | Gamma |
| | $T_{3I}$-$A_2$ | 11 | 10.56 | Gamma |
| | $T_{3I}$-$A_3$ | 11 | 9.91 | Weibull |
| | $T_{3I}$-$A_4$ | 11 | 9.91 | Weibull |
| | $T_{3I}$-$A_5$ | 17 | 16.09 | Weibull |
| | $T_{3I}$-$A_6$ | 7 | 5.54 | Lognormal |
| | $T_{3I}$-$A_7$ | 13 | 12.66 | Gamma |
| | $T_{3I}$-$A_8$ | 14 | 12.47 | Gamma |
| | | | | |
| $T_{4I}$ | $T_{4I}$-$A_1$ | 18 | 16.61 | Weibull |
| | $T_{4I}$-$A_2$ | 29 | 20.71 | Beta |
| | $T_{4I}$-$A_3$ | 9 | 5.67 | Gamma |
| | $T_{4I}$-$A_4$ | 28 | 27.66 | Weibull |
| | | | | |
| $T_{3II}$ | $T_{3II}$-$A_1$ | 21 | 19.56 | Lognormal |
| | $T_{3II}$-$A_2$ | 6 | 5.90 | Exponential |
| | $T_{3II}$-$A_3$ | 5 | 4.26 | Lognormal |
| | $T_{3II}$-$A_4$ | 18 | 17.83 | Weibull |
| | $T_{3II}$-$A_5$ | 18 | 17.95 | Weibull |
| | $T_{3II}$-$A_6$ | 8 | 7.95 | Exponential |
| | $T_{3II}$-$A_7$ | 12 | 10.89 | Lognormal |
| | $T_{3II}$-$A_8$ | 20 | 19.04 | Gamma |
| | | | | |
| $T_{4II}$ | $T_{4II}$-$A_1$ | 9 | 5.85 | Gamma |
| | $T_{4II}$-$A_2$ | 32 | 31 | Weibull |
| | $T_{4II}$-$A_3$ | 8 | 7.07 | Gamma |
| | $T_{4II}$-$A_4$ | 23 | 22.03 | Gamma |
| | | | | |
| $T_5$ | $T_5$-$A_1$ | 6 | 5.89 | Gamma |
| | $T_5$-$A_2$ | 9 | 8.72 | Exponential |
| | $T_5$-$A_3$ | 74 | 72.57 | Weibull |
| | $T_5$-$A_4$ | 12 | 5.85 | Gamma |
| | $T_5$-$A_5$ | 44 | 39.08 | Weibull |
| | $T_5$-$A_6$ | 8 | 7.03 | Gamma |
| | Total Lowest Durations for Tasks $T_{3/4/5}$ | 376 | 341 | |

### 5.5.2.4 Task 6: Sealing task

Since three workers of the third crew were performing each action of the sealing task individually, the duration to complete this task was evaluated based on the performance of an individual worker. Therefore, three sequential datasets were classified and analyzed separately for each action. The lowest estimated duration for each action for each dataset was determined based on the best-fit probability distribution and tabulated in Table 5.21. Using Equations 5.8, 5.9, and 5.10, the shortest duration to complete the sealing task was computed for each dataset. The shortest estimated durations for the first, second, and third datasets were 591.58 seconds, 523.25 seconds, and 547.99 seconds for Workers $W_1$, $W_2$, and $W_3$, respectively. The minimum value among these three sets was taken as the shortest estimated duration to complete the sealing task ($T_6$). Therefore, the shortest estimated duration was found to be 523 seconds.

Table 5.21: "Sealing Task" Action Durations in Seconds for $C_3$

| Tasks-Worker | Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|---|
| $T_6$-$W_1$ | $T_6$-$A_1$ | 7 | 7 | Gamma |
| | $T_6$-$A_2$ | 590 | 580.99 | Exponential |
| | $T_6$-$A_3$ | 4 | 3.59 | Gamma |
| | | | | |
| $T_6$-$W_2$ | $T_6$-$A_1$ | 9 | 8.84 | Lognormal |
| | $T_6$-$A_2$ | 591 | 506.41 | Weibull |
| | $T_6$-$A_3$ | 8 | 8 | Weibull |
| | | | | |
| $T_6$-$W_3$ | $T_6$-$A_1$ | 10 | 9.52 | Gamma |
| | $T_6$-$A_2$ | 546 | 531.76 | Weibull |
| | $T_6$-$A_3$ | 7 | 6.70 | Gamma |
| | Total Lowest Durations for Task $T_6$ | 563 | 523 | |

### 5.5.2.5 Task 7: Packing Task

Three workers of Crew 3 were involved to accomplish the packing task ($T_7$). Based on the available data, two sequential datasets were classified. The lowest estimated duration for each action for each dataset was determined based on the best-fit probability distribution and tabulated in Table 5.22. This table also shows the lowest observed durations and the best-fit probability distribution for each action. Using Equations 5.11 and 5.12, the shortest estimated duration for each dataset was computed. The lowest value obtained between both equations was taken into account as the shortest estimated duration to complete the packing task, and the value was found to be 308 seconds.

Table 5.22: "Packing Task" Action Durations in Seconds for $C_3$

| Tasks-Worker | Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|---|
| $T_7$-$W_{12}$ | $T_7$-$A_1$ | 27 | 27 | Beta |
| | $T_7$-$A_2$ | 46 | 44.53 | Exponential |
| | $T_7$-$A_3$ | 14 | 13.70 | Weibull |
| | $T_7$-$A_1$ | 261 | 230 | Weibull |
| | | | | |
| $T_7$-$W_{31}$ | $T_7$-$A_1$ | 25 | 23.65 | Gamma |
| | $T_7$-$A_2$ | 41 | 40.76 | Weibull |
| | $T_7$-$A_3$ | 14 | 13.55 | Weibull |
| | $T_7$-$A_1$ | 261 | 230 | Weibull |
| | Total Lowest Durations for Task $T_7$ | 341 | 308 | |

### 5.5.2.6 Task 8: Delivering Task

Since only one worker of Crew 4 was involved to perform the delivering task, only one dataset was identified. The shortest estimated duration to complete this task was estimated based on the best-fit probability distribution similar to previous tasks. The shortest estimated duration to accomplish the delivering task was found to be 10 seconds for its best-fit "Weibull Distribution Curve."

After obtaining the shortest estimated duration for each task, the shortest estimated duration for the "Fabrication of Sheet Metal Ducts" activity was computed by adding the shortest observed duration of each task because the activity was made up of tasks in a sequence. The shortest estimated duration for the activity was found to be 1,273 seconds. The number of ducts fabricated was divided by this observed shortest duration in order to compute the equivalent productivity. The resulting equivalent productivity was found to be 2.83 ducts per crew-hour.

The estimated value of the labor productivity frontier was obtained by choosing the highest productivity from these two approaches–observed and estimated durations. For the "Fabrication of Sheet Metal Ducts" activity, the productivity frontier computed from this detailed study was found to be 2.83 ducts per crew-hour.

## 5.6 Comparison Between Performances of Crew 1 and Crew 2

A roll bending task was performed by two crews. The first crew accomplished the roll bending task for 148 plain metal sheets while the second crew completed the remaining 86 sheets. Based on their performances and results, the following differences were identified during the analysis:

- The first crew completed 63.25% of the total work of the roll bending task (148 out of 234 sheets), whereas the second crew accomplished only 36.75% of the total work of that task (86 out of 234 sheets).

- For Crew 1, two datasets were classified based on their sequence of actions performed. But, only one dataset was identified for Crew 2 because they performed almost a similar pattern.
- There were seven actions involved in the task performed by Crew 1 as shown in Table 5.8. Whereas, only six actions were performed by Crew 2 to complete the same task as shown in Table 5.9. The “stacking plain sheets off from piles” action was not performed by Crew 2.
- Crew 1 conducted the “marking dimension” action as a first action and performed for multiple sheets at once. But, Crew 2 performed this task as a second action and for each sheet.
- Crew 1 conducted the “laying a plain sheet on the roll bending table” action only after the “marking dimension.” On the other hand, Crew 2 performed the “marking dimension” action for each sheet after laying a plain sheet on the roll bending table.
- The remaining actions–such as “setting the plain sheet,” “bending sheet on the roller,” “checking dimension,” and “stacking the roll-bended sheet,”–were performed by both crews in the sequence of Actions 3, 4, 5, and 6, respectively.
- The plain sheet was laid on the roll bending table (Action 2) either by Worker 1 or both workers of Crew 1 as shown in Equations 5.1 and 5.2, respectively. But this action was accomplished by both workers of Crew 2 as shown in Equation 5.3.

- Only Worker 2 of Crew 1 was involved to perform the “stacking of the roll-bended sheet” action, but in the case of Crew 2, both workers were involved to complete this action.
- Crew 1 performed Actions 3, 4, and 5 sequentially. But, Actions 1, 2, and 7 were performed by Worker 1 while Worker 2 was engaged in Action 6 for the first sequential dataset. But, according to the second set of data, Worker 1 completed Actions 1 and 7 when Worker 2 was performing Action 6. On the contrary, Crew 2 accomplished all actions together in a sequential order as shown in Equation 5.3.
- The lowest observed duration taken to complete Task 1 by Crew 1 was computed using Equations 5.1 and 5.2 and was found to be 57 seconds and 62 seconds, respectively. The lowest value between them, such as 57 seconds in this case was considered as the shortest observed duration to complete this task for Crew 1. Meanwhile, the lowest observed duration to accomplish Task 1 by Crew 2 was computed using Equation 5.3 and the value was found to be 54 seconds.
- Similarly, the lowest estimated durations for each action for each dataset were estimated based on the best-fit probability distribution analysis as described in the previous section. The shortest estimated durations for Task 1 were 53, 61, and 49 seconds and are tabulated in Tables 5.14, 5.15, and 5.16 for Crew 1 and Crew 2, respectively.

- The maximum theoretical productivity values were computed for the roll bending task and values were found to be 67.92 sheets per crew-hour and 73.47 sheets per crew-hour for Crew 1 and Crew 2, respectively.

## 5.7 Movement Level Analysis for the Lock Forming Task (Task 2)

One of the objectives of this research is to determine the impact of collecting data to the action level of hierarchy in the initial phase and to the lowest hierarchical level, i.e. the movement. Previous sections explained the estimation of the labor productivity frontier in the action level of hierarchy for the "Fabrication of Sheet Metal Ducts" activity. It is very challenging to study the movement level because of the lack of time and resources. Therefore, a hierarchical movement level analysis was conducted only for Task 2.

The lock forming task ($T_2$) was performed by the second crew, which involved two workers. Consistency of workers' performance is the reason behind the selection of this task for the movement level analysis because both workers were involved from the beginning of this task to the end. Three different actions were identified during the action level of the hierarchical analysis, which are: laying the roll bended sheet on the lock machine table, locking, and stacking. For the movement level of the hierarchical analysis, 14 different movements were identified by observing video data frames, which are: (a) approach to the roll-bended sheet stacks ($M_1$), (b) hold the roll-bended sheet ($M_2$), (c) move the roll-bended sheet onto the lock forming table ($M_3$), (d) place the roll-bended sheet on the lock forming table ($M_4$), (e) set one edge of the roll-bended sheet on the lock machine ($M_5$), (f) slide the sheet for locking ($M_6$), (g) switch another edge of the sheet

($M_7$), (h) place another edge of the sheet on the lock machine ($M_8$), (i) set another edge of the sheet on the lock machine ($M_9$), (j) slide the sheet for locking ($M_{10}$), (k) hold the sheet before moving for stacking ($M_{11}$), (l) move the lock-formed sheet toward stacks ($M_{12}$), (m) place the lock-formed sheet in stacks ($M_{13}$), and (n) move back to workstation ($M_{14}$) as shown in Table 5.2 and Figures B.1 to B.14.

A time and motion study was conducted to measure duration to complete each movement by observing video data and durations were recorded in the Excel spreadsheet. Table A.5 shows typical example representing data-extraction process for Action 1 of the lock forming task. Since the duration for accomplishing each movement is less than a second scale, the video data was converted into individual image frames (30 frames per second) by applying the frame separation algorithm in Matlab (Cai et al., 1995). Then, duration for accomplishing each movement was measured by counting the number of frames to complete that movement and converting it into a second scale.

Data were grouped based on the sequence set analysis of movements performed by the crew. Three different datasets were identified. The first, second, and third datasets consist of 98, 15, and 121 data points, respectively. Among them, 15 sample data for each dataset are listed in Tables A.6, A.7, and A.8.

According to the first sequential dataset, Worker 1 was involved in Movements 1, 2, and 3 while Worker 2 was engaged in Movements 12, 13, and 14. They performed these movements simultaneously. After completing Movement 14, Worker 2 again joined with Worker 1 to complete Movement 3. Then, they performed the remaining Movements 4, 5, 6, 7, 8, 9, 10, and 11 together. These movements are performed sequentially. The lowest observed duration for each movement was determined for this dataset as arranged in Table 5.23. Then, Equation 5.13 was used to compute the shortest observed duration to complete the lock forming task based on this dataset ($S_1$) and the value was found to be 38 seconds.

The best-fit probability distribution for each movement involved in the "lock forming task" was obtained with the application of the "Arena Input Analyzer." Then, the threshold parameter (the lowest duration) for that distribution was estimated using the "Base SAS® 9.2." The lowest duration of the contributory movements for this task were estimated from the distribution, which were evaluated at a 95% confidence interval and values were recorded in the Excel spreadsheet similar to Table 5.23. The shortest estimated duration was computed using Equation 5.23. Thus, the shortest estimated duration to complete this task for this dataset ($S_1$) was found to be 34.35 seconds.

$$\textit{Highest of } (T_2\text{-}M_1\text{-}\ W_1 + T_2\text{-}M_2\text{-}\ W_1 + T_2\text{-}M_3\text{-}\ W_1 \textit{ OR } T_2\text{-}M_{12}\text{-}\ W_2 + T_2\text{-}M_{13}\text{-}\ W_2 + T_2\text{-}M_{14}\text{-}\ W_2) + T_2\text{-}M_4\text{-}\ W_{12} + T_2\text{-}M_5\text{-}\ W_{12} + T_2\text{-}M_6\text{-}\ W_{12} + T_2\text{-}M_7\text{-}\ W_{12} + T_2\text{-}M_8\text{-}\ W_{12} + T_2\text{-}M_9\text{-}\ W_{12} + T_2\text{-}M_{10}\text{-}\ W_{12} + T_2\text{-}M_{11}\text{-}\ W_{12} \ldots\ldots\ldots (5.13)$$

Table 5.23: "Lock Forming Task" Movement Durations in Seconds for $C_2$-$S_1$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_2$-$M_1$ | 1.63 | 0.86 | Weibull |
| $T_2$-$M_2$ | 1.00 | 0.94 | Weibull |
| $T_2$-$M_3$ | 8.02 | 7.97 | Gamma |
| $T_2$-$M_4$ | 0.70 | 0.65 | Gamma |
| $T_2$-$M_5$ | 0.80 | 0.8 | Exponential |
| $T_2$-$M_6$ | 8.80 | 6.75 | Lognormal |
| $T_2$-$M_7$ | 3.33 | 2.91 | Gamma |
| $T_2$-$M_8$ | 0.47 | 0.32 | Gamma |
| $T_2$-$M_9$ | 0.80 | 0.79 | Exponential |
| $T_2$-$M_{10}$ | 9.97 | 9.92 | Lognormal |
| $T_2$-$M_{11}$ | 2.47 | 2.44 | Lognormal |
| $T_2$-$M_{12}$ | 3.47 | 2.98 | Weibull |
| $T_2$-$M_{13}$ | 1.40 | 1.13 | Gamma |
| $T_2$-$M_{14}$ | 0.90 | 0.79 | Gamma |
| Total Lowest Durations for Task $T_2$ | 38 | 34.35 | |

Similar procedures were implemented to determine the shortest observed duration and the shortest estimated duration for the second and third sequential datasets. Tables 5.24 and 5.25 show the lowest observed durations and the lowest estimated durations with the corresponding best-fit probability distributions for the second ($S_2$) and third ($S_3$) datasets. After getting the lowest observed durations for each movement, Equations 5.14 and 5.15 were used to compute the shortest observed duration for Task 2 for the second and third sequential datasets, respectively. Similar to this, the shortest estimated duration to complete Task 2 for the second and third datasets was computed using Equations 5.14 and 5.15, respectively.

$$T_2\text{-}M_1\text{-}\ W_{12} + T_2\text{-}M_2\text{-}\ W_1 + T_2\text{-}M_3\text{-}\ W_{12} + T_2\text{-}M_4\text{-}\ W_{12} + T_2\text{-}M_5\text{-}\ W_{12} + T_2\text{-}M_6\text{-}\ W_{12} + T_2\text{-}M_7\text{-}\ W_{12} + T_2\text{-}M_8\text{-}\ W_{12} + T_2\text{-}M_9\text{-}\ W_{12} + T_2\text{-}M_{10}\text{-}\ W_{12} + T_2\text{-}M_{11}\text{-}\ W_{12} + T_2\text{-}M_{12}\text{-}\ W_2 + T_2\text{-}M_{13}\text{-}\ W_2 + T_2\text{-}M_{14}\text{-}\ W_2 \quad \ldots\ldots\ldots (5.14)$$

Table 5.24: “Lock Forming Task” Movement Durations in Seconds for $C_2$-$S_2$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_2$-$M_1$ | 3.27 | 2.76 | Weibull |
| $T_2$-$M_2$ | 1.50 | 1.50 | Beta |
| $T_2$-$A_3$ | 8.70 | 8.13 | Weibull |
| $T_2$-$M_4$ | 0.73 | 0.71 | Weibull |
| $T_2$-$M_5$ | 0.80 | 0.80 | Weibull |
| $T_2$-$A_6$ | 10.13 | 10.02 | Lognormal |
| $T_2$-$M_7$ | 3.57 | 3.15 | Lognormal |
| $T_2$-$M_8$ | 0.80 | 0.69 | Weibull |
| $T_2$-$A_9$ | 0.80 | 0.73 | Weibull |
| $T_2$-$M_{10}$ | 10.05 | 10.02 | Exponential |
| $T_2$-$A_{11}$ | 2.63 | 2.60 | Exponential |
| $T_2$-$M_{12}$ | 3.47 | 2.90 | Gamma |
| $T_2$-$M_{13}$ | 2.13 | 1.99 | Gamma |
| $T_2$-$A_{14}$ | 1.50 | 0.96 | Weibull |
| Total Lowest Durations for Task $T_2$ | 50.08 | 46.96 | |

For the second sequential dataset, the shortest observed and the shortest estimated durations were found to be 50.08 and 46.96 seconds, respectively. Similarly, for the third sequential dataset, the shortest observed and the shortest estimated durations were found to be 39.85 and 38.09 seconds, respectively.

$$\textit{Highest of } (T_2\text{-}M_1\text{-}\ W_2 + T_2\text{-}M_2\text{-}\ W_2 + T_2\text{-}M_3\text{-}\ W_2 \textit{ OR } T_2\text{-}M_{12}\text{-}\ W_1 + T_2\text{-}M_{13}\text{-}\ W_1 + T_2\text{-}M_{14}\text{-}\ W_1) + T_2\text{-}M_3\text{-}\ W_{12} + T_2\text{-}M_4\text{-}\ W_{12} + T_2\text{-}M_5\text{-}\ W_{12} + T_2\text{-}M_6\text{-}\ W_{12} + T_2\text{-}M_7\text{-}\ W_{12} + T_2\text{-}M_8\text{-}\ W_{12} + T_2\text{-}M_9\text{-}\ W_{12} + T_2\text{-}M_{10}\text{-}\ W_{12} + T_2\text{-}M_{11}\text{-}\ W_{12} \quad \ldots\ldots\ldots (5.15)$$

Table 5.25: “Lock Forming Task” Movement Durations in Seconds for $C_2$-$S_3$

| Actions | Lowest Observed Durations | Lowest Estimated Durations | Distribution |
|---|---|---|---|
| $T_2$-$M_1$ | 2.67 | 2.28 | Weibull |
| $T_2$-$M_2$ | 1.00 | 0.98 | Weibull |
| $T_2$-$A_3$ | 8.27 | 7.77 | Lognormal |
| $T_2$-$M_4$ | 0.70 | 0.66 | Gamma |
| $T_2$-$M_5$ | 0.80 | 0.80 | Weibull |
| $T_2$-$A_6$ | 9.97 | 9.85 | Lognormal |
| $T_2$-$M_7$ | 3.33 | 3.22 | Weibull |
| $T_2$-$M_8$ | 0.47 | 0.40 | Gamma |
| $T_2$-$A_9$ | 0.80 | 0.60 | Lognormal |
| $T_2$-$M_{10}$ | 9.37 | 9.11 | Lognormal |
| $T_2$-$A_{11}$ | 2.47 | 2.42 | Lognormal |
| $T_2$-$M_{12}$ | 3.47 | 3.22 | Weibull |
| $T_2$-$M_{13}$ | 1.40 | 1.15 | Gamma |
| $T_2$-$A_{14}$ | 0.90 | 0.69 | Gamma |
| Total Lowest Durations for Task $T_2$ | 39.85 | 38.09 | |

The minimum value of durations computed among three equations is considered as the shortest observed duration. The shortest observed duration to complete the “lock forming task” was found to be 38 seconds. The number of sheets lock-formed was divided by this observed shortest duration in order to compute the equivalent productivity. The resulting equivalent productivity was found to be 94.74 sheets per crew-hour.

The lowest estimated duration for each dataset was taken as the shortest estimated duration to complete this task. The shortest estimated duration was found to be 34.35 seconds. Its equivalent productivity was estimated by dividing the number of metal sheets lock-formed by the estimated shortest duration, which results in 104.80 sheets per crew-hour.

The estimated value of the labor productivity frontier was obtained by choosing the highest productivity from these two approaches–observed and estimated durations. For the “lock forming” task, the productivity frontier computed from this study, was found to be 104.80 sheets per crew-hour.

### 5.8 Comparison Between Action and Movement Levels Analysis

The detailed study was conducted for the “Fabrication of Sheet Metal Ducts” activity in order to justify the proposed basic framework (manual framework) following dual approaches: (a) observed duration and (b) estimated duration. However, the stages of data collection and analysis are almost similar in nature. There are slight differences in the data extraction phase. During action-level analysis, a time and motion study was conducted by directly observing video data. But for movement-level analysis, it was not feasible because duration of each movement was less than a second, which is almost impossible to measure by directly visualizing the video data. Therefore, the video data were converted into individual images by applying the frame separation algorithm in Matlab (Cai & Aggarwal, 1996). Besides this, there are some other features that differentiate the action level analysis with the movement-level analysis, which is described below.

- A movement level is a lower level than the action level in the hierarchical structure. Therefore, there are more complexities present during analysis of the movement level.

- During this detailed study, the action-level analysis was performed for a whole activity, whereas the movement-level analysis was just performed for the "lock forming task."
- During action-level analysis, the time taken to extract video data was two to three times more than the actual time-length of the video clip. But for the movement-level analysis, such time was five to six times more than the actual time-length of the video clip. Such variations were due to increased complexity and methods implemented for the data extraction. It indicates that if there are more movements involved in the task, then more time is needed for the analysis and the data extraction.
- The movement-level analysis was found to be more time consuming and complex than the action-level analysis.
- The shortest observed and the estimated durations for the "lock forming task" were found to be 44 seconds and 42 seconds during the action-level analysis. But, for movement-level analysis, that durations were found to be 38 seconds and 34.35 seconds. The estimated value of the labor productivity frontier was obtained by choosing the highest productivity from these two approaches– observed and estimated durations. The productivity frontiers computed from the action level and the movement level analyses were found to be 85.71 sheets per crew-hour and 104.80 sheets per crew-hour, respectively.
- In action-level analysis, the duration required to complete an action was found to be different than the duration required to complete the similar action for the movement level of analysis in some cases. The main reason behind this

deviation was the complexity of the study in each level. For example, in the action level analysis, the duration for an action was recorded in the second scale in moving video data. On the other hand, the duration for a movement was recorded by counting the number of video frames to complete the movement because the duration was sometimes less than a second. Therefore, the movement-level analysis provides a more precise duration value than the action-level analysis.

- The result showed that the movement-level analysis is more consistent and uniform than the action-level analysis. The duration to complete contributory movements for the specific task was found lower in the movement-level analysis than the action-level analysis because of a minor level of study between workers in the same crew. Moreover, the reduction in durations is due to two different effects. The first one is the exposure of higher variability explained by the inverse mean variance optimization. The second effect is the fact that non-contributory tasks, actions, and movements are eliminated from the analysis as lower levels of the hierarchy are employed. It satisfies the concept of inverse mean variance optimization.

## 5.9 Limitations and Discussion

The shorter duration from two different approaches, one from observed and another from estimated, was considered while estimating the productivity frontier. The estimated duration was obtained by estimating the threshold parameter of each probability distribution in the “Base SAS® 9.2” software. Sometime, it is difficult to plot the best-fit probability distribution in this tool. For example, the SAS cannot plot the Erlang distribution. In such a scenario, the second best-fit distribution obtained from the "Arena Input Analyzer" was taken into account on the basis of a square error and p-value.

During goodness-of-fit test, the "Arena Input Analyzer" conducts suitable test, such as Chi-Square test and Kolmogorov-Smirnov test. In addition to the square error value, it also gives p-value for that particular test. The test shows that the lower the p-value when compared with the level of significance ($\alpha = 0.05$), the poorer the fit in the probability distribution is (Kelton et al., 2010; Rockwell Automation, 2013). During this analysis, only the best-fit curve having higher p-value is considered. Then, the threshold parameter is estimated for that probability distribution in the "Base SAS ® 9.2" software. This software not only tests the best-fit probability distribution, but also shows its parameters including the lower threshold parameter with corresponding p-value for each test.

However, most of the manual steps used in the detailed study would have to be automated in a more complex activity in order to determine the productivity frontier. The detailed study provided valuable lessons. The time and motion study was found to be effective while measuring the shortest observed duration to complete the activity. The probability distribution was found effective in computing the estimated shortest duration. Therefore, this detailed study demonstrates that the proposed framework for estimating the productivity frontier is adequate when applied to a simple construction operation. However, more research is required to address the following limitations:

- During data collection, multiple portable cameras were used but it would be better to use fixed surveillance cameras nearer to the workstation and installed in such a manner that it can capture all workers' actions and movements. It helps to minimize the necessity of the manpower in order to record on-site data. Thus, it reduces resource allocation costs. It also avoids human error while capturing video data.

- The proposed approach, as applied in the detailed study, was labor intensive and time consuming. It is necessary to explore innovative ways of automating data collection and analysis. An effective automated tool is expected to estimate the productivity frontier in an efficient manner.

# CHAPTER 6

# CONCEPTUAL EXPLORATION OF AN AUTOMATED FRAMEWORK

The methodology discussed in the pilot study (Chapter 4) for a single worker and the detailed study (Chapter 5) for multiple workers is a manual framework, which is time-consuming and laborious. If a project manager wants to quickly implement this methodology for a similar project or an identical project by collecting and analyzing preliminary data, then this methodology has to be modified in an automated fashion. But, it is a challenging task to develop a fully automated framework in the sense there has not been a perfect automated tool developed for tracking multiple workers' movements, contributory activities recognition, human poses estimation, observed duration, and estimated duration measurement for contributory actions that are defined in the manual framework. Therefore, the level of difficulty to estimate the labor productivity frontier using the automated framework is high. This chapter explains a conceptual framework to estimate the labor productivity frontier in an automated fashion.

The proposed automated framework explores the automated techniques to facilitate data collection and analysis. Based on the application of video cameras and the Kinect sensor during collection of data, two separate automated frameworks are discussed. The basic concept behind these frameworks is similar. However, these frameworks are slightly varied in field data collection, data analysis, and workers' pose modeling and tracking stages. These frameworks determine the impact of collecting data to the lowest hierarchical level–the movement. These frameworks evaluate the feasibility of the proposed framework for estimating the labor productivity frontier of the entire activity.

## 6.1 Proposed Framework Using Video Cameras

Figure 6.1 shows the different stages of the proposed research methodology (rectangular boxes), as well as the various methods adopted to implement each stage (legends with arrows) using video cameras as the equipment for the data collection.

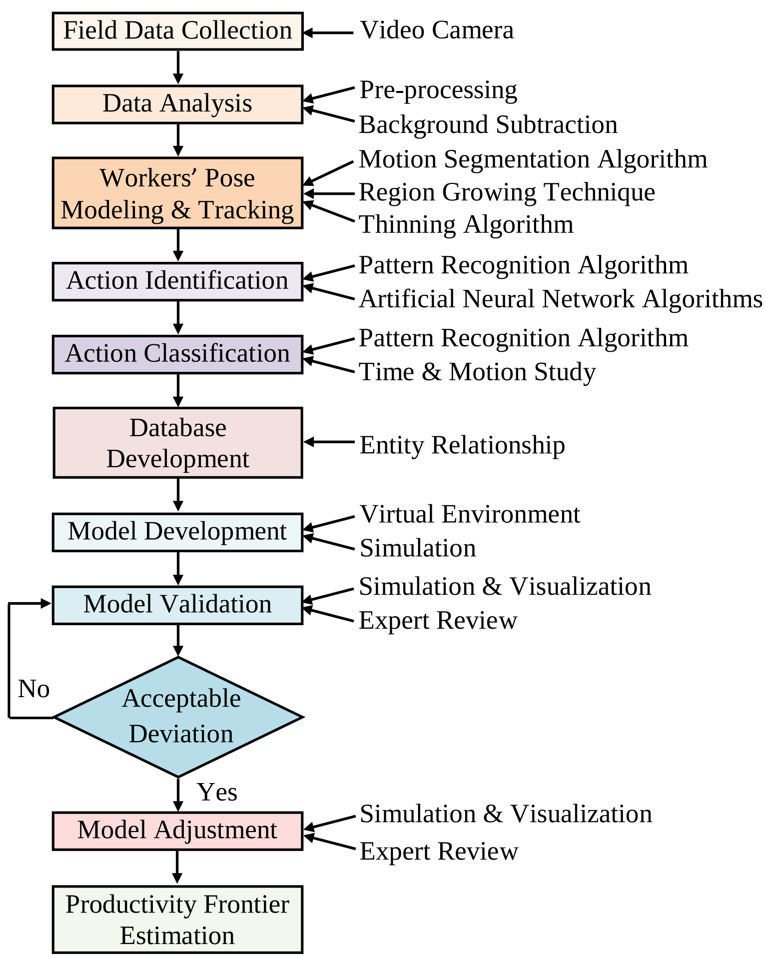


Figure 6.1: Proposed Research Methodology for an Automated Framework

### 6.1.1 Field Data Collection

Data collection is performed similar to the pilot study. Three Canon XF100 professional camcorders are used to collect video data, which are calibrated using the "Camera Calibration Toolbox" in the Matlab (Bai et al., 2008). Prior to data collection, multiple cameras are synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004; Delamarre & Faugeras, 1999). The application of multiple cameras eliminates the problems of the self-occlusion and the kinematic singularities that are usually suffered in the monocular technique (Morris & Rehg, 1998; Sundaresan & Chellappa, 2009). This also helps in minimizing errors while working with tracking tools and human pose estimation (automation techniques).

Camera setups follow the methodology described in Bai et al. (2008), John et al. (2009), and Sigal et al. (2010). Three fixed cameras are used to capture movements of workers performing a specific activity from three different angles, depending upon space availability at the site of installation (fixed background).

### 6.1.2 Data Analysis

The collected video data are pre-processed and converted into frames (Cai et al., 1995; Cai & Aggarwal, 1996) in order to conduct foreground/background subtraction and are stored in the database dynamically on the basis of the hierarchical structure of the activity. The four-level hierarchy of activity, task, action, and movement is implemented similar to the pilot study as shown in Figure 4.2.

### 6.1.3 Workers Pose Modeling and Tracking

First, a motion segmentation algorithm (Lin, Yang, Xia, & Kang, 2006) is developed to identify all moving objects in the images. Second, a filtering algorithm is used to eliminate unwanted moving objects because when applying a motion segmentation algorithm (Bai et al., 2008; Lin et al., 2006), it also captures unwanted moving objects. These unwanted objects are filtered by employing the pattern-matching of workers' uniforms, assuming that all workers have distinguishable uniforms (Peddi, 2008). For noiseless environments, a method involving pixel-to-pixel subtraction holding a fixed threshold may be suitable. But for an environment having noises, a background is computed following a moving average model similar to Peddi (2008), in which a mask-level background is subtracted from the current frame in order to extract the workers. Third, for identification purposes, an identity is assigned to each worker.

Finally, the worker's silhouettes are created by clustering the pixels around the shape of each identified worker while applying the region growing technique (Adams & Bischof, 1994), a technique in which similar pixels are grouped together to form a single region and given a distinct color. The attributes of silhouettes are computed and stored in the database dynamically.

#### 6.1.3.1 Workers' tracking approach

In an attempt to track a worker, the video frames are analyzed starting from the first frame similar to Peddi (2008). If any new worker is identified, he or she is declared "new" and is assigned an identification number. For the next subsequent frames, the search algorithm finds matching blobs of that worker, then the tracks are updated, or otherwise, the worker is declared as "lost." If the tracking finds the matching blobs for that lost worker, then it is regained. If the worker is not found for a long time limit (say lost time limit) for consecutive frames, then the worker is deleted. If the new consecutive frames are not matched with the previous matched track, then a new track is generated for it and declared as a "new," and the same process repeats.

There is a less likely chance of a blob occlusion because multiple synchronized cameras are employed. If the tracking process is obstructed and lost due to blob occlusion, then there is still a chance to regain it in the subsequent frames.

A distance based match matrix (Narayana & Haverkamp, 2007) is implemented in order to assess the matching blobs between current and previous frames. The track with the minimum distance is updated with the blob, if criterion $t \leq T$ satisfies, where $T$ represents a global distance threshold and $t$ represents a track distance. Since the speeds and directions of the movements of workers are varied on the real site, this tracking method should be modified in such a manner that the next position of a track is predicted based on its current speed and direction. Bai et al.'s (2008) approach is suitable as it uses a global value for distance threshold while considering the different motion speeds of the workers.

#### 6.1.3.2 Workers' pose extraction approach

A fast parallel algorithm similar to Zhang and Suen's (1984) is employed to extract workers' poses in the skeleton form from each image. This algorithm performs the iterative processes of deleting one from the northwest corner points and the southeast boundary points and then deleting the southeast corner points and northwest boundary points. These processes continue until a smooth skeleton is obtained, preserving the end points and the pixel connectivity.

Detailed articulated models are then developed to represent human body movements; these models initialize and track poses in an automatic manner (Sundaresan & Chellappa, 2009). The human body model consists of rigid segments, such as head, neck, arm, forearm, palm, upper trunk, lower trunk, thigh, leg, and foot. Each rigid segment has three degrees of freedom for translation and three for rotation. In addition, a thinning algorithm is employed to develop a worker’s skeleton movement tracking tool (Kannan & Ramakrishnan, 2012; Park, Palinginis, & Brilakis, 2012; Zhang & Suen, 1984). Figure 6.2 shows skeleton views with images of two different actions performed by an electrical worker: (a) moving from one workstation to another workstation and (b) glass frame opening performed by an electrical worker.


Figure 6.2: Sample Skeleton View of Actions Performed by an Electrical Worker

### 6.1.5 Action Identification and Classification

Besides manual identification and classification of workers' actions similar to the pilot study, an automated tool is developed for the analysis of the workers' poses in the silhouette models, the complete articulated models, and the skeleton models using the detailed pattern recognition algorithms and the Artificial Neural Network (ANN) algorithms developed following the methodology employed by Peddi (2008). Those poses are categorized into the contributory and non-contributory based on their impact to work completion. The contributory poses are those actions necessary to accomplish the tasks, whereas the non-contributory actions are considered non-productive and include actions, such as unscheduled breaks, time spent attending personal matters, and idle time. The objective of this process is to determine the capabilities and limitations of ANN algorithms to automatically recognize the multiple tasks that make up an activity and the multiple actions that make up a task.

During this research, a back propagation learning algorithm having a feed forward neural network is used similar to Peddi (2008) and Amin and Shekhar (1994). There are two work phases–the learning phase and execution phase–which are employed in neural networks. Training data sets are manually annotated during the learning phase in order to train networks using the back propagation learning algorithm. These trained neural networks are utilized to analyze and classify similar poses in the execution phase. Since there are variations in the shape, size, and location/orientation of workers, an image scaling phenomena is implemented to keep consistency in the sizes of these poses, such that all the poses are scaled to fixed size as described in Bai et al. (2008).

An instance algorithm for a pose classification is employed after scaled poses are obtained, which has the learning and execution phase–identifying and classifying contributory and non-contributory poses or movements (Bai et al., 2008).

There are still some challenges in the interpretation of the contributory work for different types of activities because a movement or an action in one instance may be contributory for one type of task, whereas it may be non-contributory for another type of task in another instance. Therefore, a metric should be defined in order to identify the contributory movements or actions for a specific type of activity. It is better to conduct a manual study for each type of activity, and then define suitable metrics in the form of the contributory movements or actions, before employing in the automated framework. For example, types of poses can be defined manually, such as bending, walking, or standing as contributory actions and talking with co-workers and standing idle while doing nothing as non-contributory. For simplicity, the contributory actions can be represented by positive actions and the non-contributory actions can be represented by negative actions when converting manually defined actions into actions for the automated framework.

### 6.1.6 Database Development

A digital database is developed including all kinds of data, such as video data, images of classified actions, animated action models, skeleton tracking images, human body models, necessary information in text/pdf format, and software developed during the research.

### 6.1.7 Model Development, Validation, and Adjustment

In addition to a simplified skeleton view of a worker developed using AutoCAD as shown in Figure 4. 4, the proposed framework conducted a feasibility analysis of the "*recombinant synthetic workers and crew*" as described in Chapter 8. A synthetic crew is modeled acquiring the relevant workers' poses from the digital database and by detail analyzing the interaction between workers, and workers with equipment and materials in the virtually developed environment of the sequential as well as in parallel operations. Advanced techniques of simulation and visualization are employed.

As an extension to the pilot study, the developed model is validated not only by expert reviews but also by simulation and visualization techniques in the automated fashion. The adjustment of the model is performed in order to make it more precise.

### 6.1.8 Productivity Frontier Estimation

A time and motion study is conducted to measure the observed duration for each contributory movement of the worker under observation in the video data, developing a partially automated time and motion study tool.

An algorithm is developed to link the result of partially automated time and motion study with the "Arena Simulation Software" and the "Base SAS® 9.2" software to determine the shortest estimated durations dynamically. The labor productivity frontier is then obtained by choosing the highest productivity value from the two methods–observed and estimated durations. The resulting automated observations and estimates are compared to the traditional approach to assess the feasibility of automating data collection.

## 6.2 Proposed Framework Using the Kinect Sensor

The Kinect is a useful sensor for 3D reconstruction of a scene with point clouds and for 3D skeleton extraction of human subjects combined with the motion capture solutions (Han, Shao, Xu, & Shotton, 2013). It is applicable to building 3D human models through 2D pose estimation and also the direct inference of 3D poses by integrating the depth into the pose estimation process. But there are some limitations of the Kinect sensor. For example, the Kinect sensor provides unreliable motion capture outcomes in an outdoor environment because of interaction of infra-red (IR) light and sunlight. It has limited operating ranges for motion capture ranges of 0.8 m to 4 m, depending upon tolerance of error (Han et al., 2013; Weerasinghe et al., 2012). It does not provide a precise segment length of the human body during motion (Bonnechere et al., 2012). The range of viewing angle is 43 degrees vertical by 57 degrees horizontal, and 1280 x 960 resolution at 12 frames per second or 640 x 480 resolution at 30 frames per second (Shingade & Ghotkar, 2014). It cannot track more than six people and cannot track skeleton views of more than two people. It is suitable to capture data only for indoor construction activities. Thus, a suitable construction site needs to be selected considering these limitations of the Kinect sensor.

When the Kinect camera (sensor) is employed for data collection, the previous framework using a video camera is slightly modified. Figure 6.3 shows the different stages of the proposed research methodology (rectangular boxes), as well as the various methods adopted to implement each stage (legends with arrows).

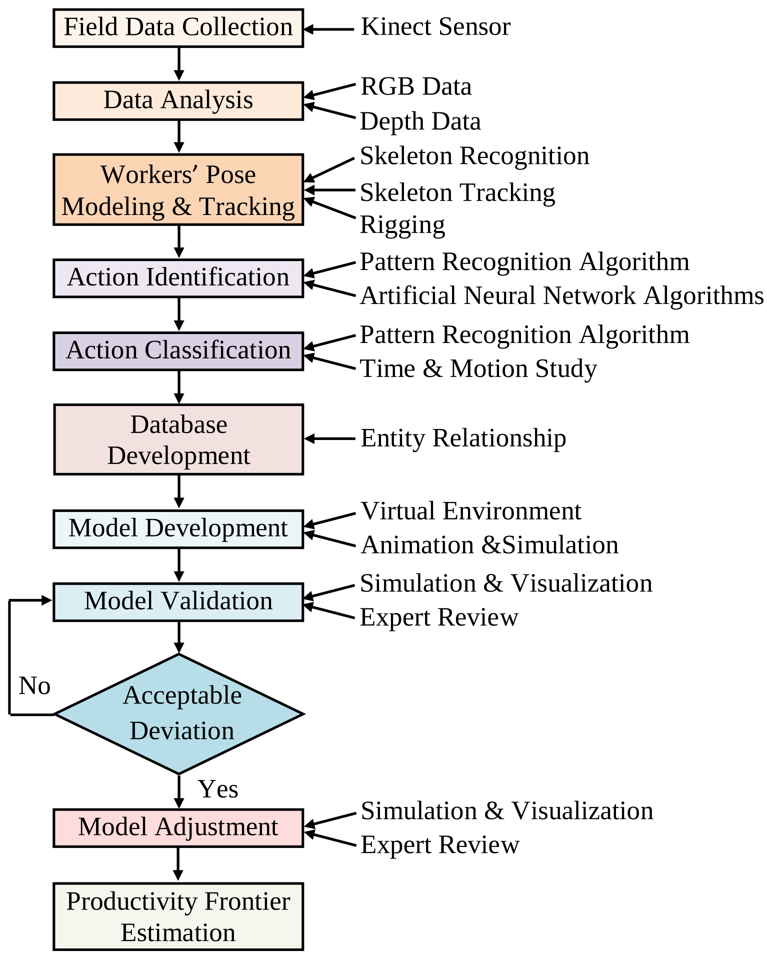


Figure 6.3: Proposed Research Methodology Using the Kinect Sensor

### 6.2.1 Field Data Collection and Data Analysis

Instead of multiple video cameras, a single Kinect camera sensor is setup at appropriate locations of the indoor construction site. With the help of depth information provided by the Kinect camera sensor, the distance between a camera and objects seen in the scene is estimated, and it tracks different parts of the 3D human body. Various information is obtained from the Kinect camera, such as depth information from the IR camera, texture information (RGB color map of the scene) from the RGB camera, and user information from binary images (including people detection) (Shingade & Ghotkar, 2014). Upon use of MS Kinect SDK, it automatically tracks the human skeleton and provides the skeleton information of people in the scene in real time. All these data are stored in the database dynamically. In addition, the four-level hierarchy of activity, task, action, and movement is implemented similar to the pilot study as shown in Figure 4.2.

### 6.2.2 Workers' Pose Modeling and Tracking

This involves various stages, such as workers' skeleton recognition, workers' skeleton tracking, 3D human model development, and skeleton and human model rigging as shown in Figure 6.4. Using MS Kinect SDK, the skeleton joint positions of people seen in the scene are obtained. After observing skeleton joints, those skeletons are extracted from input data. Such a process is called skeleton recognition. This process involves several stages, such as separating foreground from background, separating the human body out from foreground, segmenting the human body into different regions, and obtaining skeleton joints from the analysis similar to Shotton et al. (2011). The movement of each joint position is captured from each frame using MS Kinect SDK framework, also known as skeleton tracking.

Using Autodesk Maya software, the 3D human model is created, which involves different stages, such as creation of a mesh model, application of texture on the mesh, and application of clothing on the human model (Shingade & Ghotkar, 2014). Following an algorithm similar to Baran & Popovic's (2007), rigging of the 3D human model and skeleton is performed in such a way that each joint of the skeleton is placed at corresponding positions on the created human model. This process maps rigs character skeleton with the captured Kinect skeleton, and the skeleton is attached to the human model.

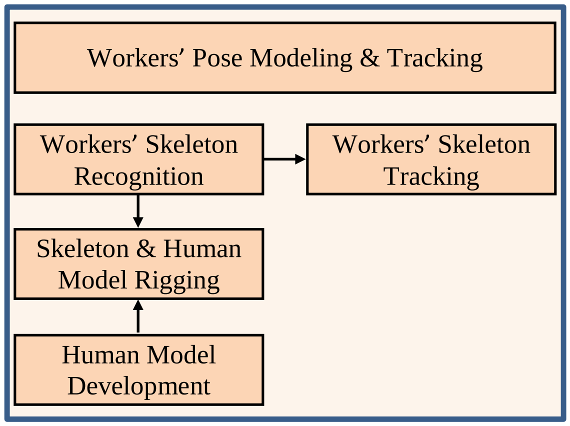


Figure 6.4: Stages Involved in Workers' Pose Modeling and Tracking

### 6.2.3 Action Identification and Classification

Besides manual identification and the classification of workers' actions similar to the pilot study and the detailed study, an automated tool is developed for the analysis of the workers' poses in the skeleton models using the detailed pattern recognition algorithms and the ANN algorithms following the methodology employed by Peddi (2008). Those poses are categorized into the contributory and non-contributory based on their impact upon work completion similar to the previous framework using video cameras. A back propagation learning algorithm, having a feed forward neural network, is used similar to Peddi (2008) and Amin and Shekhar (1994). Training data sets are manually annotated during the learning phase in order to train networks using the back propagation learning algorithm. These trained neural networks are utilized to analyze and classify similar poses in the execution phase. Since there are variations in the shape, size, location/orientation of workers, an image scaling phenomena is implemented to keep consistency in the sizes of these poses, such that all the poses are scaled to the fixed size as described in Bai et al. (2008).

An instance algorithm for a pose classification is employed after scaled poses are obtained, which has the learning and execution phase, identifying and classifying contributory and non-contributory poses or movements (Bai et al., 2008).

A time and motion study is conducted to measure the observed duration for each contributory movement of the worker under observation in the Kinect data, developing a partially automated time and motion study tool. All data are stored in the database dynamically.

### 6.2.4 Database Development

Similar to the previous framework, a digital database is developed. It includes all kinds of data, such as the Kinect data, skeleton data, human body models, images, necessary information in text/pdf format, and software developed during the research.

### 6.2.5 Model Development, Validation, and Adjustment

An animated model is developed using Unity 3D software, in which the motion data obtained from the skeleton tracking phase is applied into the rigged model (character) as shown in Figure 6.5. If the skeleton tracking phase data is not suitable to map the positions of joints because of incorrect sizes, the rotations data are extracted from the skeleton tracking phase to the rig character, adopting the concept of rotation transformation matrix similar to Shingade and Ghotkar (2014).

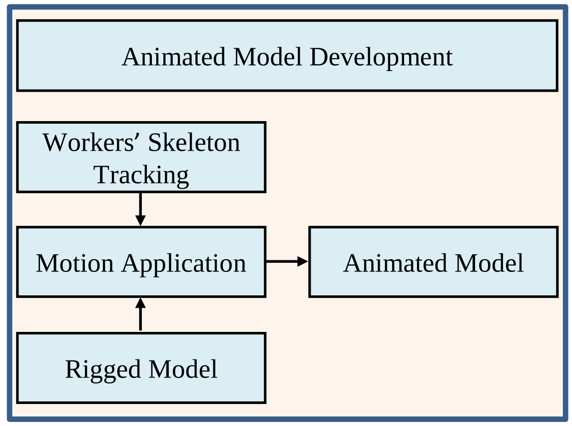


Figure 6.5: Stages Involving in Model Development

These animated models are developed only considering the contributory actions for that specific task or activity. These models can represent a synthetic crew similar to the "recombinant synthetic workers and crew" as described in Chapter 8. The synthetic crews are modeled acquiring the relevant workers' contributory poses from the digital database and by detail analyzing the interaction between workers, and workers with equipment and materials in the virtually developed environment of the activity. These models are validated not only by expert reviews but also by the simulation and visualization technique in the automated fashion. The adjustments of the models are performed in order to make them more precise.

### 6.2.6 Productivity Frontier Estimation

A time and motion study is conducted to measure the observed duration for each contributory movement of the worker under observation in the Kinect data, developing a partially automated time and motion study tool. An algorithm is developed to link the partially automated time and motion study with the "Arena Simulation Software" and the

“Base SAS® 9.2” software to determine the shortest estimated durations dynamically. The labor productivity frontier is then obtained by choosing the highest productivity value from the two methods—observed and estimated durations. The resulting automated observations and estimates are compared to the traditional approach to assess the feasibility of automating data collection.

# CHAPTER 7

# CONCLUSIONS AND RECOMMENDATIONS

This dissertation presents an innovative framework to estimate the labor productivity frontier by conducting a pilot study as well as a detailed study. The pilot study justifies the proposed basic framework by examining the data from a simple electrical activity. It focused exclusively on capturing the activities performed by a single worker for the “Lighting Replacement” activity. The detailed study also justifies the proposed basic framework for both sequential and parallel actions and movements performed by crews of multiple workers on labor-intensive fabrication operations during the “Fabrication of Sheet Metal Ducts” at the Waldinger Corporation’s workshop in Omaha, Nebraska. The comparison between the pilot study and the detailed study, conclusions and recommendations, intellectual merits, and broader impacts of this research are explained in this chapter.

## 7.1 Comparison Between a Pilot Study and a Detailed Study

At first, this dissertation introduces a framework to estimate the productivity frontier conducting a pilot study for a lighting replacement activity. Then, it extends research and justifies the framework by conducting a detailed study for the fabrication of sheet metal ducts activity. Both studies justify the proposed basic framework by illustrating dual approaches: (a) observed duration and (b) estimated duration-and confirms that this study has a significant importance for the future. Typical characteristics of both studies are described below.

**Types of Work:** The pilot study was conducted by capturing data on the replacement of electrical lighting fixtures at Omaha South High Magnet School. It is typically related to the labor-intensive regular maintenance and installation activity. The scope of this electrical lighting replacement project included the replacement of old T12 with new T8 fluorescent bulbs and ballasts. The detailed study was conducted by capturing data on the fabrication of sheet metal ducts at the workshop of the Waldinger Corporation in Omaha, Nebraska. It is related to labor-intensive manufacturing activity.

**Working Environment:** Both studies were conducted in a controlled indoor environment. But, there are some constraints that are out of control for data collectors. For example, high noise level due to the movements of students around the workstation, space congestion due to the presence of chairs and desks, high humidity, low luminance, and low temperatures are some uncontrollable constraints identified during collecting data for the pilot study. In the detailed study, similar uncontrollable constraints are identified, such as high noise due to operation of machines in the workshop, disturbances by other coworkers, high humidity, high temperature, frequent change of high and low luminance due to frequent opening and closing of doors, space congestion, and disturbances in setting up video cameras due to the presence of multiple machines and manufactured products around the workstation.

**Single Versus Multiple Workers:** However, two electrical workers from the Commonwealth Electric Company–a veteran and a novice–participated in the project. The pilot study focused exclusively on capturing the activities performed by the veteran worker because the veteran was experienced and performed better in similar operations than the novice. Thus, the pilot study only focused on the performance of a single worker. But, the detailed study was conducted by analyzing the performance of multiple workers. There were four crews (eight workers in total) involved to complete the “Fabrication of Sheet Metal Ducts” activity. Crew 1 and Crew 2 consisted of two workers each, who performed the roll bending task. Crew 2 was also involved in the lock forming, lock setting, tie-rods installing, and flange screwing tasks. Crew 3 consisted of three workers who performed the sealing and packing tasks. Crew 4, which had one worker, was involved in the delivering task.

**Number of Data for Study:** Sixty-two data points for the “Fluorescent Bulb Replacement” task were analyzed at the action level during the pilot study. During the detailed study, 117 data points for the “Fabrication of Sheet Metal Ducts” activity were analyzed at the action and the movement level of the hierarchical structure. Each activity consists of eight different tasks, 45 different actions, and more than 255 different movements. In the task-level study, there were 936 (8 x 117 = 936) data points for analysis. In the action-level study, there were 5,265 (45 x 117 = 5,265) data points for analysis. In the movement-level study, there were at least 29,835 (255 x 117 = 29,835) data points for analysis.

**Sequential and Parallel Tasks, Actions, and Movements:** During the pilot study, it was found that all actions are accomplished by a worker sequentially. No further analysis to the movement level in the hierarchy was continued in the pilot study. During the detailed study, both sequential and parallel tasks, actions, and movements were identified for the "Fabrication of Sheet Metal Ducts" activity.

**Data Analysis:** Only the fluorescent bulb replacement task was analyzed at the action level during the pilot study. During the detailed study, multiple crews were assigned multiple tasks of the "Fabrication of Sheet Metal Ducts" activity. Therefore, Task 1 and Task 2 were analyzed separately. As Tasks 3, 4, and 5 were accomplished by Crew 2 sequentially and simultaneously, these tasks were combined and analyzed. Tasks 6, 7, and 8 were analyzed separately. Because of time and resource constraints, the detailed analysis for the movement level of hierarchy was only conducted for the lock forming task. The time spent in the extraction of data during the detailed study was about 500 hours, whereas only 20 hours were spent for the extraction of data during the pilot study.

**Observed Shortest Duration Estimation:** During the pilot study, the time and motion study was conducted by thoroughly reviewing the video data and duration of the contributory actions for the "Fluorescent Bulb Replacement" task and they were recorded in the Excel spreadsheet. Since it dealt only with the movements of a veteran worker for the sequential actions of only one task, it was simple to analyze. The shortest possible duration was estimated by adding up the shortest durations observed for each action because the task was made up of actions in a sequence. But, the scenario was complicated in the detailed study. However, a similar time and motion study was conducted by reviewing video data in the detailed study. Because of the involvement of multiple workers in each task, the durations of the individual and combined involvement of the workers for each task were recorded separately in the Excel spreadsheet. A sequence set analysis was conducted in which multiple sets of data were grouped based on the similar sequence of actions performed by individual workers or crews of multiple workers for the same task. The minimum duration taken to accomplish an action was determined for each sequential dataset. Among the shortest durations available from the sequential datasets of each task, the shortest of the shortest duration were considered as the shortest observed duration for that task. Some assumptions were developed in order to address complexities as described in Section 5.5.1.1.

**Estimated Shortest Duration Estimation:** During the pilot study, the best-fit probability distribution for each action included in the “Fluorescent Bulb Replacement” task was obtained with the application of the “Arena Input Analyzer” tool in the “Arena Simulation Software.” Based on the best-fit probability distribution for each action obtained from the “Arena Input Analyzer,” the threshold parameter (lowest duration) for that distribution was estimated using the “Base SAS® 9.2.” The lowest duration of the contributory actions for this task were estimated from the distribution, which were evaluated at a 95% confidence interval. Similar approaches were implemented in the detailed study to estimate the shortest estimated duration for each action of each task. When estimating the shortest total duration for each task, the concept of the sequence set analysis was again implemented similar to the method employed to estimate the observed shortest duration for each task. In addition, the detailed study was also extended up to the movement level of the hierarchical structure for the second task, the “lock forming task.”

**Productivity Frontier Estimation:** During the pilot study, the unit of productivity was expressed in the number of stations accomplished in an hour by a worker. In the detailed study, the productivity value was expressed in the number of ducts fabricated by the crews in an hour.

**Results:** The productivity frontier computed from this pilot study for the "Fluorescent Bulb Replacement" task is 22.32 stations per hour. The pilot study was only conducted up to the action level. On the other hand, the detailed study was conducted up to the movement level. From the action level analysis of the detailed study, the productivity frontier for the "Fabrication of Sheet Metal Ducts" activity is 2.83 ducts per crew-hour. The hierarchical movement level analysis was conducted only for Task 2 because of the lack of time and resources. From the movement level analysis of the detailed study, the productivity frontier for the "lock forming task" is 104.80 sheets per crew-hour.

## 7.2 Conclusions

The existing practice of estimating the labor productivity based upon historical data or an individual's experience may lack a systematic approach. The low quality of historical data and inconsistency in the productivity measurement system may prevent meaningful analysis (Song & AbouRizk, 2008). This could make construction operations significantly inefficient. This scenario generates a space for research to identify the alternative techniques to measure labor productivity. This research presents an innovative technique by defining a theoretical maximum productivity termed as the productivity frontier.

However, the productivity frontier is not achievable in actual practice. The findings of this research shed some light on how important the concept of the productivity frontier is in order to estimate optimal productivity of labor-intensive operations. Intuitively, estimating the accurate labor productivity frontier is the first step toward allowing project managers to determine the absolute efficiency (unbiased) of their labor-intensive construction operations by comparing actual versus optimal rather than the actual versus historical productivity.

This dissertation introduces a framework to estimate the productivity frontier by conducting a pilot study for a lighting replacement activity and a detailed study for the fabrication of sheet metal ducts. Both studies justify the proposed basic framework by illustrating dual approaches: (a) observed duration and (b) estimated duration. It confirms that these studies had significant importance in the future. It also explains various theoretical backgrounds, technologies, and statistical tools pertinent to this research.

The concept of inverse mean-variance optimization was implemented to describe the importance of breaking down elements to their components because it would make visible previously “hidden” variables. Thus, four levels of the hierarchical taxonomy (activity, task, action, and movement) for construction operations were illustrated in this dissertation. The methodology of time and motion study was adopted to collect and analyze site data so that it can be used to exactly tally the number of minutes spent on each type of task and that are typically used in the analysis of body motions employed in doing work in order to find the most efficient method in terms of time and effort.

There may be a question regarding the validity of the theoretical productivity estimated using this framework as the productivity frontier because the productivity frontier is an abstraction that cannot be measured in the actual working scenario. Thus, it seems counterintuitive while using the actual field data to estimate its value. To justify this issue, a deductive logic can be used, which is described below.

- This research defines the productivity frontier as the theoretical maximum productivity under the “perfect conditions,” and optimal productivity as the level of productivity under “good management” and “typical field conditions.” If the project is executed under these conditions, then they would represent at least optimal productivity. After eliminating all system inefficiencies from this optimal productivity that could have been present during the data collection period, the productivity frontier could be achieved. However, this is impossible in real practice. If a concerted effort is made to minimize system inefficiencies, then the calculated theoretical productivity following this method would be somewhere in between optimal productivity and the productivity frontier.
- This research focuses on the instantaneous highest values of labor productivity, which is obtained from the shortest observed duration conducting the time and motion study. The probability of actually observing this level of theoretical productivity in the field is infinitesimal. For example, if (a) 100 observations are recorded during a construction task, (b) the task includes eight actions, (c) the lowest duration recorded for each action occurs only once, and (d) the duration of each action is independent from the duration

of all others, then the probability of observing the duration of the task being equal to the sum of the shortest durations of the actions would be 1 in 10 billion assuming actions are independent with each other.

- This research also presents the second approach in which the estimated shortest durations are computed from the best-fit probability distributions for the data by considering that the observed durations may not include the lowest possible duration for a task, action, or movement.

Moreover, this research defines optimal productivity as a sustainable highest productivity, which dismisses a productivity level that happens once in 10 billion observations. Therefore, this value can be taken as an estimate of the productivity frontier.

Furthermore, this research examined the research hypotheses and yielded the following outcomes:

1. The proposed research framework was found applicable and capable to estimate the labor productivity frontier in simple, as well as complex construction and manufacturing labor-intensive operations with crews of single or multiple workers performing both sequential and parallel processes.
2. It determined the value of collecting data at the lowest hierarchical level–movement–when estimating the productivity frontier. Extending the research up to the movement level provides high theoretical productivity values. For example, the duration to complete contributory movements for the lock forming task was found lower in the movement-level analysis than the action-level analysis because of a minor level of study between workers in the same

crew. Moreover, the reduction in durations is due to two different effects. The first one is the exposure of higher variability explained by the inverse mean variance optimization. The second effect is the fact that non-contributory tasks, actions, and movements are eliminated from the analysis as lower levels of the hierarchy are employed. It satisfies the concept of inverse mean variance optimization.

3. However, the movement level analysis was found to be more time consuming and complex than the action level analysis.
4. It explored the automated framework to estimate the productivity frontier using multiple video cameras and the Kinect sensors. It discussed the development of an automated action-recognition tool, partially automated time and motion study tool, and the recombinant synthetic workers. It also provided an understanding of what further research is necessary to allow this type of data collection to achieve full automation.
5. It described the possibility of implementation of simulation and visualization techniques in order to validate the working procedure. In addition, an animated model was developed in order to validate the work flow process of the “Fluorescent Bulb Replacement” task during the pilot study.

## 7.3 Recommendations

Although this research examines data from an “Electrical Lamp Replacement” activity and the “Fabrication of Sheet Metal Ducts” activity following the basic framework, it also explores the advanced framework consisting of an automated framework in order to estimate the productivity frontier. This research recommends further investigation in order to develop a complete package, including an automated action-recognition tool, automated time and motion study tool, and the recombinant synthetic workers models employing the suggested automated framework.

## 7.4 Intellectual Merits

This research enhances the body of knowledge about productivity by: (a) developing conceptual innovations and creative approaches for examining productivity, (b) replacing status quo productivity metrics by introducing a novel approach for assessing the efficiency of labor-intensive construction processes, and (c) exploring the automated framework and using primitive actions to create the recombinant synthetic workers.

## 7.5 Broader Impacts

The research of this dissertation impacts research in broader areas. These areas include: (a) improvements in profitability, competitiveness, and salaries for labor-intensive industries, (b) advancement of understanding and discovery in labor-intensive domains outside construction, and (c) enhancement of research infrastructure.

# CHAPTER 8

# FUTURE RESEARCH

The concept of the productivity frontier is a novel concept, which helps to establish a theoretical framework for developing a better benchmarking system for evaluating the efficiency of labor-intensive operations. These conceptual advancements echo the advancements found in the practice of estimating productivity frontiers by refining field activities into distilled constituent tasks, actions, and movements–novel processes developed for this research. Moreover, this research will be extended in the future by identifying typical scopes, which are discussed below.

## 8.1 Scope Identification

An accurate estimate of the labor productivity frontier is the first step toward developing a valuable concept for estimating optimal productivity of labor-intensive operations. This research provides an absolute value of the labor productivity frontier in order to estimate the upper threshold of optimal productivity by determining the physiological and systematic limits that affect the maximum productivity for labor-intensive operations. The precise estimation of optimal labor productivity would allow project managers to determine the efficiency of their labor-intensive construction operations by comparing actual versus optimal rather than actual versus historical productivity. Determining absolute value of the labor productivity frontier in order to estimate optimal labor productivity is the primary scope of this research.

In addition, various actions and movements of workers to accomplish specific activities are identified during this research. This valuable information helps to conduct further research in multiple sectors, such as (a) development of virtual environments representing labor-intensive construction and manufacturing operations, (b) recombinant synthetic workers analysis, and (c) ergonomics and safety analysis. These topics are briefly discussed in the following sections.

### 8.1.1 Virtual Environments

A virtual environment is an effective form of human-computer interaction. The virtual world technologies provide a better understanding of three-dimensional shapes and spaces through perceptual phenomena (Mine, 1995). It helps to visualize the real site scenario through its virtual prototype and also allows the creation of dynamic scenes using virtual computer generated resources, thereby providing an environment where experimentation can be done without committing real resources or endangering operational safety (Behzadan & Kamat, 2011). Considering such benefits, this research will be extended towards the development of the virtual environment related to construction and manufacturing labor-intensive operations.

The “Unity 3D” platform will be used to develop a virtual environment because it has a default software development kit (SDK). It supports multiple platforms, such as BlackBerry 10, Windows Phone 8, Windows, OS X, Linux, Android, iOS, Unity Web Player, Adobe Flash, PlayStation 3, PlayStation 4, PlayStation Vita, Xbox 360, Xbox One, Wii U, and Wii. It consists of an asset server and “Nvidia’s PhysX” physics engine (Blackman, 2011). From simulation and graphical aspects, it is comfortable and userfriendly. The 3D human body models will be created using the “Autodesk Maya” software because it involves different stages, such as a creation of a mesh model, application of texture on the mesh, and application of clothing on the human model (Shingade & Ghotkar, 2014). Various algorithms as discussed in Chapter 6, such as motion segmentation, growing technique, pattern recognition, and ANN, are also employed during this research.

A simplified virtual environment (similar to Figure 8.1) representing the specific activity will be developed to simulate conditions similar to those at one of the jobsites used to gather the source data. It will consist of basic movements of human models that could be searchable and synthesized to formulate any number of activities.

Figure 8.1: Virtual Environment a Specific Construction Activity
(Adapted from Lin, Son, & Rojas, 2011)

### 8.1.2 Recombinant Synthetic Workers

In order to estimate the productivity frontier of construction activities for different operations, managers must first have source data relevant to determine the productivity frontier, a fact that may diminish the usefulness of this proposed framework. However, it is conceivable that a construction activity could be synthetically recreated from a finite number of elemental parametric movements, termed “*primitives*.” Once a comprehensive collection of primitives is gathered over time, construction activities could be simulated to estimate an operation’s productivity frontier without the need to collect further field data. To evaluate the feasibility of this concept, the framework proposes recombining the distilled movement data gathered in this research to create synthetic workers and crews who would perform new operations in a simulated environment. If such recombinant synthetic workers are possible, the calculation of the productivity frontier for new operations would be much easier, a fact that would allow project managers to focus more time on improving their operational efficiency.

While this segment of the research foreseeably could be expanded to develop a library of basic movements that could be searchable and synthesized to formulate any number of activities, the current research seeks merely to evaluate the feasibility of such an approach. The proposed framework will create a simplified virtual environment (similar to Figure 8.1) to simulate conditions similar to those at one of the jobsites used to gather the source data. A simple construction activity that used similar movements from the reference activities will be chosen for the experiment, and field experts will be used to recombine the basic movements into actions, actions into tasks, and tasks into activities. The chosen activity will have a single worker or multiple workers performing work sequentially and simultaneously. Heuristic assessments will be used to determine the usefulness, preferability, and receptiveness of such an approach by the field experts.

Since the benefits of the proposed framework are decidedly tied to the ability of project managers to easily process the relevant data, and since the productivity frontier is a data point that is inherently unvarying (it is only possible to have one maximum productivity level), the success of this proposed objective would lay the foundation for the wide spread dissemination of this approach–successfully creating recombinant synthetic workers would facilitate the calculation of the productivity frontier for any variety of construction operations without the demands of recording new field data. Because the preliminary data that would be necessary for documenting movement durations are an inherent part of this proposal, testing the feasibility of creating such synthetic workers is a viable part of this investigation and a valuable first step for any subsequent research pursuits.

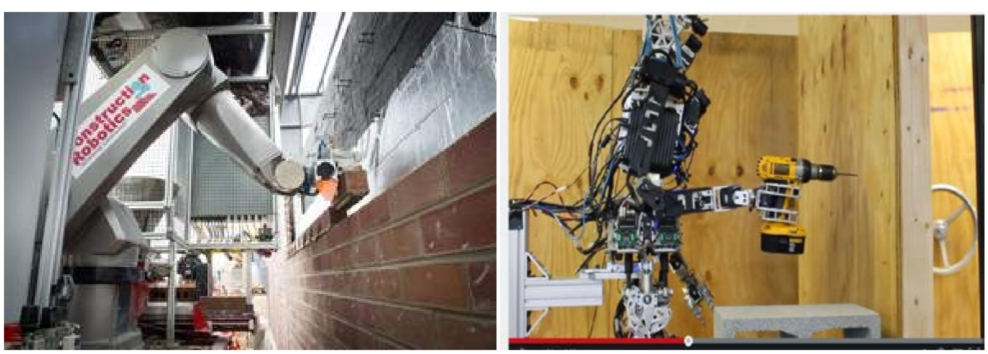

Figure 8.2: Semi-Autonomous Robots Performing Different Activities
(Adapted from DARPA Robotics Challenge, 2014; Loudon, 2013)

Moreover, the research on the “Recombinant Synthetic Workers” serves as an entrée into robotics research for the development of semi-autonomous robots (similar to Figure 8.2) to support construction field operations in hazardous environments. The first picture of Figure 8.2 shows brick laying operation performed by the semi-automated mason (SAM) robot that is developed by Victor Company (Loudon, 2013). The second picture of Figure 8.2 shows the “Tactical Hazardous Operation Robot (THOR),” which is a bipedal humanoid robot used for rescue operations (DARPA Robotics Challenge, 2014).

### 8.1.3 Ergonomics and Safety Analysis

This research will be extended on the ergonomics and occupational health and safety analysis. During movement and action level analysis, this research will perform the “Ergonomics Job Hazard Analysis.” It involves identification and classification of actions and movements, measurement and quantification of the ergonomic risk factors inherent in the elements, and identification conditions that contribute to risk factors. Finally, it determines its corrective measurements. Various platforms will be developed during the analysis in order to determine the best possible movements or poses, which are ergonomically safe and productive in the jobsite.

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# APPENDIX A
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Table A.1: Action Level Analysis: 7 Sample Data Representing Data-Extraction Process Employing Time and Motion Study by Observing Video Data for the Lock Forming Task (Durations in Seconds) (N = 234)

| SN | Worker ID | Laying Sheet on Lock Machine ($T_2$-$A_1$) | | | Locking ($T_2$-$A_2$) | | | Stacking ($T_2$-$A_3$) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | End | Duration | Start | End | Duration | Start | End | Duration |
| 1 | $W_1$ | 0:00 | 0:10 | 10 | | | | | | |
| | $W_2$ | | | | | | | 1:07 | 1:18 | 11 |
| | $W_{12}$ | 0:10 | 0:18 | 8 | 0:18 | 1:06 | 48 | | | |
| | | | | | | | | | | |
| 2 | $W_1$ | 1:07 | 1:18 | 11 | | | | | | |
| | $W_2$ | | | | | | | 2:03 | 2:16 | 13 |
| | $W_{12}$ | 1:18 | 1:24 | 6 | 1:24 | 2:03 | 39 | | | |
| | | | | | | | | | | |
| 3 | $W_1$ | 2:03 | 2:16 | 13 | | | | | | |
| | $W_2$ | | | | | | | 3:01 | 3:14 | 13 |
| | $W_{12}$ | 2:16 | 2:26 | 10 | 2:26 | 3:01 | 35 | | | |
| | | | | | | | | | | |
| 4 | $W_1$ | 3:01 | 3:14 | 13 | | | | | | |
| | $W_2$ | | | | | | | 3:53 | 4:06 | 13 |
| | $W_{12}$ | 3:15 | 3:21 | 6 | 3:21 | 3:53 | 32 | | | |
| | | | | | | | | | | |
| 5 | $W_1$ | 3:53 | 4:06 | 13 | | | | | | |
| | $W_2$ | | | | | | | | | |
| | $W_{12}$ | 4:06 | 4:13 | 7 | 4:13 | 4:45 | 32 | 4:45 | 4:56 | 11 |
| | | | | | | | | | | |
| 6 | $W_1$ | 5:03 | 5:13 | 10 | | | | | | |
| | $W_2$ | | | | | | | 0:41 | 0:51 | 10 |
| | $W_{12}$ | 0:00 | 0:09 | 9 | 0:09 | 0:41 | 32 | | | |
| | | | | | | | | | | |
| 7 | $W_1$ | 0:41 | 0:51 | 10 | | | | | | |
| | $W_2$ | | | | | | | 1:30 | 1:41 | 11 |
| | $W_{12}$ | 0:51 | 0:57 | 6 | 0:57 | 1:30 | 33 | | | |

Table A.2: Action Level Analysis: 15 Sample Data Representing the First Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 98)

| SN | $T_2$-$A_1$ | $T_2$-$A_2$ | $T_2$-$A_3$ |
|---|---|---|---|
| 1 | 18 | 48 | 11 |
| 2 | 17 | 39 | 13 |
| 3 | 23 | 35 | 13 |
| 4 | 19 | 32 | 13 |
| 5 | 20 | 32 | 11 |
| 6 | 19 | 32 | 10 |
| 7 | 16 | 33 | 11 |
| 8 | 19 | 32 | 13 |
| 9 | 24 | 31 | 11 |
| 10 | 17 | 32 | 11 |
| 11 | 18 | 31 | 10 |
| 12 | 18 | 35 | 15 |
| 13 | 22 | 33 | 11 |
| 14 | 21 | 33 | 11 |
| 15 | 18 | 32 | 13 |

Table A.3: Action Level Analysis: Sample Data Representing the Second Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 15)

| SN | $T_2$-$A_1$ | $T_2$-$A_2$ | $T_2$-$A_3$ |
|---|---|---|---|
| 1 | 21 | 33 | 14 |
| 2 | 21 | 34 | 12 |
| 3 | 19 | 34 | 13 |
| 4 | 24 | 32 | 12 |
| 5 | 22 | 32 | 15 |
| 6 | 19 | 33 | 17 |
| 7 | 20 | 32 | 15 |
| 8 | 20 | 32 | 12 |
| 9 | 19 | 34 | 13 |
| 10 | 18 | 34 | 16 |
| 11 | 20 | 40 | 9 |
| 12 | 19 | 33 | 17 |
| 13 | 26 | 32 | 14 |
| 14 | 19 | 33 | 13 |
| 15 | 20 | 33 | 14 |

Table A.4: Action Level Analysis: 15 Sample Data Representing the Third Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 121)

| SN | $T_2$-$A_1$ | $T_2$-$A_2$ | $T_2$-$A_3$ |
|---|---|---|---|
| 1 | 21 | 34 | 11 |
| 2 | 26 | 33 | 18 |
| 3 | 23 | 33 | 15 |
| 4 | 22 | 34 | 13 |
| 5 | 26 | 36 | 15 |
| 6 | 19 | 35 | 14 |
| 7 | 25 | 34 | 11 |
| 8 | 24 | 33 | 13 |
| 9 | 20 | 32 | 12 |
| 10 | 19 | 32 | 14 |
| 11 | 28 | 35 | 11 |
| 12 | 22 | 32 | 11 |
| 13 | 21 | 32 | 16 |
| 14 | 23 | 32 | 16 |
| 15 | 21 | 32 | 11 |

Table A.5: Movement Level Analysis: Sample Data Representing Data-Extraction Process Employing Time and Motion Study by Observing Video Data for Action 1 of the Lock Forming Task (Durations in Seconds) (N = 234)

| SN | Worker ID | Approach to Sheet Stacks ($T_2$-$M_1$) | | | | Hold the Sheet ($T_2$-$M_2$) | | | | Move the Sheet ($T_2$-$M_3$) | | | | Place the Sheet on the Lock Forming table ($T_2$-$M_4$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | S | E | Frame Diff | D | S | E | Frame Diff | D | S | E | Frame Diff | D | S | E | Frame Diff | D |
| 1 | $W_1$ | 1 | 50 | 49 | 1.63 | 51 | 132 | 81 | 2.70 | 133 | 275 | 142 | 4.73 | | | | |
| | $W_2$ | | | | | | | | | | | | | | | | |
| | $W_{12}$ | | | | | | | | | 276 | 514 | 238 | 7.93 | 515 | 540 | 25 | 0.83 |
| | | | | | | | | | | | | | | | | | |
| 2 | $W_1$ | 1495 | 1637 | 142 | 4.73 | 1638 | 1695 | 57 | 1.90 | 1696 | 1800 | 104 | 3.47 | | | | |
| | $W_2$ | | | | | | | | | | | | | | | | |
| | $W_{12}$ | | | | | | | | | 1801 | 1983 | 182 | 6.07 | 1984 | 2010 | 26 | 0.87 |
| | | | | | | | | | | | | | | | | | |
| 3 | $W_1$ | 3071 | 3207 | 136 | 4.53 | 3208 | 3295 | 87 | 2.90 | 3296 | 3505 | 209 | 6.97 | | | | |
| | $W_2$ | | | | | | | | | | | | | | | | |
| | $W_{12}$ | | | | | | | | | 3506 | 3740 | 234 | 7.80 | 3741 | 3768 | 27 | 0.90 |
| | | | | | | | | | | | | | | | | | |

Table A.6: Movement Level Analysis: 15 Sample Data Representing the First Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 98)

| SN | $T_2$-$M_1$ | $T_2$-$M_2$ | $T_2$-$M_3$ | $T_2$-$M_4$ | $T_2$-$M_5$ | $T_2$-$M_6$ | $T_2$-$M_7$ | $T_2$-$M_8$ | $T_2$-$M_9$ | $T_2$-$M_{10}$ | $T_2$-$M_{11}$ | $T_2$-$M_{12}$ | $T_2$-$M_{13}$ | $T_2$-$M_{14}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.63 | 2.70 | 12.67 | 0.83 | 1.13 | 12.07 | 3.87 | 0.83 | 1.13 | 10.20 | 19.00 | 5.17 | 3.13 | 1.80 |
| 2 | 4.73 | 1.90 | 9.53 | 0.87 | 1.30 | 11.47 | 3.97 | 1.03 | 1.77 | 11.63 | 6.93 | 5.37 | 2.57 | 3.47 |
| 3 | 4.53 | 2.90 | 14.77 | 0.90 | 1.37 | 11.00 | 4.97 | 1.10 | 2.00 | 10.50 | 3.93 | 6.23 | 3.07 | 3.03 |
| 4 | 5.30 | 2.30 | 10.60 | 0.83 | 1.30 | 11.13 | 3.80 | 0.47 | 0.80 | 11.13 | 3.13 | 5.47 | 5.27 | 1.50 |
| 5 | 5.47 | 1.97 | 11.60 | 1.13 | 1.13 | 10.87 | 4.57 | 0.63 | 0.80 | 10.30 | 3.13 | 5.80 | 2.13 | 2.30 |
| 6 | 4.63 | 2.97 | 10.27 | 1.27 | 1.80 | 10.47 | 3.63 | 0.63 | 1.83 | 10.43 | 2.97 | 5.33 | 2.27 | 1.67 |
| 7 | 4.63 | 1.63 | 8.80 | 0.77 | 1.23 | 11.00 | 3.83 | 0.97 | 2.20 | 10.17 | 2.70 | 4.73 | 2.17 | 3.13 |
| 8 | 5.97 | 1.63 | 10.23 | 1.00 | 1.17 | 10.40 | 3.33 | 0.97 | 1.63 | 10.43 | 3.50 | 6.30 | 2.43 | 4.07 |
| 9 | 6.47 | 5.13 | 10.87 | 1.10 | 1.57 | 9.97 | 3.93 | 0.80 | 0.80 | 10.83 | 2.63 | 5.70 | 3.87 | 1.17 |
| 10 | 5.53 | 1.40 | 8.93 | 0.97 | 2.13 | 10.63 | 3.63 | 1.10 | 1.50 | 10.30 | 2.57 | 4.93 | 1.40 | 3.97 |
| 11 | 4.93 | 1.57 | 9.60 | 1.00 | 0.80 | 10.27 | 4.27 | 0.90 | 1.63 | 10.17 | 3.10 | 4.97 | 4.47 | 1.20 |
| 12 | 4.70 | 2.73 | 9.07 | 1.13 | 0.80 | 10.43 | 4.67 | 1.63 | 4.13 | 10.97 | 2.47 | 4.83 | 7.13 | 1.80 |
| 13 | 4.83 | 3.63 | 12.47 | 0.97 | 1.13 | 11.07 | 4.23 | 1.10 | 1.30 | 10.80 | 2.97 | 5.30 | 3.63 | 1.87 |
| 14 | 4.63 | 3.13 | 10.43 | 1.97 | 1.30 | 10.63 | 3.97 | 0.80 | 1.13 | 11.13 | 3.80 | 4.63 | 3.87 | 2.07 |
| 15 | 5.30 | 1.97 | 9.93 | 0.70 | 1.07 | 11.07 | 3.97 | 0.87 | 1.47 | 10.63 | 2.50 | 5.17 | 5.90 | 1.60 |

Table A.7: Movement Level Analysis: 15 Sample Data Representing the Second Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 15)

| SN | $T_2$-$M_1$ | $T_2$-$M_2$ | $T_2$-$M_3$ | $T_2$-$M_4$ | $T_2$-$M_5$ | $T_2$-$M_6$ | $T_2$-$M_7$ | $T_2$-$M_8$ | $T_2$-$M_9$ | $T_2$-$M_{10}$ | $T_2$-$M_{11}$ | $T_2$-$M_{12}$ | $T_2$-$M_{13}$ | $T_2$-$M_{14}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4.00 | 5.00 | 10.10 | 0.80 | 0.97 | 10.37 | 4.23 | 1.13 | 2.63 | 10.13 | 3.30 | 4.67 | 2.93 | 6.13 |
| 2 | 6.97 | 1.50 | 9.97 | 1.30 | 1.63 | 11.10 | 4.33 | 1.30 | 1.80 | 10.07 | 3.20 | 5.30 | 2.13 | 3.63 |
| 3 | 6.47 | 1.80 | 8.70 | 1.23 | 0.80 | 13.13 | 4.13 | 1.13 | 1.83 | 10.10 | 2.80 | 4.63 | 3.97 | 3.63 |
| 4 | 5.53 | 5.13 | 11.37 | 1.73 | 1.03 | 10.57 | 4.17 | 0.83 | 1.37 | 10.07 | 3.30 | 4.17 | 3.30 | 4.50 |
| 5 | 5.17 | 2.03 | 13.00 | 1.23 | 0.97 | 10.13 | 4.63 | 0.97 | 1.10 | 10.67 | 2.83 | 7.60 | 3.47 | 3.63 |
| 6 | 4.30 | 2.63 | 10.63 | 1.10 | 1.13 | 10.83 | 4.77 | 1.13 | 1.67 | 10.30 | 2.73 | 4.53 | 4.30 | 7.47 |
| 7 | 5.10 | 4.30 | 9.13 | 0.93 | 0.80 | 10.80 | 3.57 | 0.87 | 1.63 | 10.63 | 2.63 | 5.80 | 3.93 | 5.00 |
| 8 | 6.03 | 2.63 | 10.33 | 0.73 | 0.80 | 10.33 | 4.60 | 0.80 | 0.97 | 10.30 | 3.47 | 4.43 | 3.10 | 3.83 |
| 9 | 6.47 | 1.80 | 8.70 | 1.23 | 0.80 | 13.13 | 4.13 | 1.13 | 1.83 | 10.10 | 2.80 | 4.63 | 3.97 | 3.63 |
| 10 | 3.63 | 1.63 | 11.43 | 0.97 | 0.80 | 11.63 | 4.47 | 1.30 | 1.63 | 10.13 | 3.97 | 3.50 | 9.63 | 2.30 |
| 11 | 3.27 | 3.83 | 11.53 | 1.13 | 1.47 | 13.20 | 6.07 | 1.47 | 1.13 | 12.80 | 3.30 | 3.47 | 2.93 | 2.37 |
| 12 | 4.30 | 2.63 | 10.63 | 1.10 | 1.13 | 10.83 | 4.77 | 1.13 | 1.67 | 10.30 | 2.73 | 4.53 | 4.30 | 7.47 |
| 13 | 5.87 | 5.80 | 12.46 | 1.09 | 1.04 | 11.34 | 4.07 | 1.02 | 1.06 | 10.05 | 2.65 | 5.07 | 3.63 | 4.53 |
| 14 | 5.30 | 2.30 | 10.60 | 0.83 | 1.30 | 11.13 | 3.80 | 1.10 | 0.80 | 11.13 | 3.13 | 5.47 | 5.27 | 1.50 |
| 15 | 4.00 | 5.00 | 10.10 | 0.80 | 0.97 | 10.37 | 4.23 | 1.13 | 2.63 | 10.13 | 3.30 | 4.67 | 2.93 | 6.13 |

Table A.8: Movement Level Analysis: 15 Sample Data Representing the Third Sequential Dataset for the Lock Forming Task (Durations in Seconds) (N = 121)

| SN | $T_2$-$M_1$ | $T_2$-$M_2$ | $T_2$-$M_3$ | $T_2$-$M_4$ | $T_2$-$M_5$ | $T_2$-$M_6$ | $T_2$-$M_7$ | $T_2$-$M_8$ | $T_2$-$M_9$ | $T_2$-$M_{10}$ | $T_2$-$M_{11}$ | $T_2$-$M_{12}$ | $T_2$-$M_{13}$ | $T_2$-$M_{14}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 6.97 | 1.50 | 9.97 | 1.30 | 1.63 | 11.10 | 4.33 | 1.30 | 1.80 | 10.07 | 3.20 | 5.30 | 2.13 | 3.63 |
| 2 | 4.97 | 9.47 | 9.80 | 1.10 | 0.97 | 10.90 | 4.53 | 0.80 | 2.63 | 9.97 | 2.63 | 5.30 | 9.97 | 1.80 |
| 3 | 6.13 | 2.63 | 12.80 | 0.97 | 1.10 | 10.43 | 3.97 | 1.00 | 1.37 | 10.10 | 4.10 | 3.47 | 2.80 | 8.47 |
| 4 | 3.47 | 7.13 | 10.07 | 1.00 | 0.80 | 10.30 | 4.10 | 0.83 | 1.63 | 10.03 | 5.63 | 4.30 | 5.47 | 3.13 |
| 5 | 7.23 | 4.97 | 10.60 | 1.63 | 0.97 | 12.17 | 5.27 | 1.13 | 0.97 | 11.90 | 2.83 | 5.33 | 7.90 | 0.90 |
| 6 | 5.13 | 2.20 | 9.67 | 1.17 | 1.83 | 10.50 | 4.57 | 1.10 | 1.97 | 10.80 | 3.63 | 4.97 | 2.80 | 5.63 |
| 7 | 4.67 | 5.03 | 14.03 | 0.80 | 1.57 | 10.60 | 4.57 | 1.00 | 1.10 | 11.70 | 3.37 | 4.63 | 1.97 | 3.97 |
| 8 | 5.47 | 1.13 | 15.57 | 0.93 | 0.83 | 11.03 | 4.07 | 0.87 | 1.07 | 10.30 | 4.63 | 4.80 | 4.13 | 3.47 |
| 9 | 4.80 | 4.13 | 9.26 | 0.92 | 1.04 | 11.34 | 4.07 | 1.02 | 1.06 | 10.05 | 3.17 | 4.63 | 4.07 | 3.37 |
| 10 | 5.60 | 2.80 | 9.43 | 0.97 | 0.83 | 10.63 | 4.77 | 0.87 | 0.90 | 10.80 | 2.80 | 4.97 | 4.47 | 4.13 |
| 11 | 4.20 | 12.60 | 10.27 | 0.87 | 0.87 | 12.20 | 4.80 | 0.83 | 2.43 | 10.00 | 2.93 | 4.83 | 3.63 | 1.80 |
| 12 | 5.13 | 3.83 | 10.67 | 0.87 | 0.83 | 10.10 | 4.83 | 1.13 | 2.13 | 10.30 | 2.77 | 3.70 | 4.87 | 1.93 |
| 13 | 3.83 | 5.50 | 10.20 | 0.80 | 0.83 | 10.60 | 4.83 | 1.10 | 1.77 | 10.10 | 2.63 | 5.47 | 3.13 | 7.13 |
| 14 | 6.80 | 4.97 | 9.60 | 0.97 | 0.83 | 10.07 | 4.27 | 1.03 | 1.30 | 10.50 | 2.77 | 4.67 | 3.77 | 6.83 |
| 15 | 5.47 | 1.97 | 11.60 | 1.13 | 1.13 | 10.87 | 4.57 | 0.47 | 0.80 | 10.30 | 3.13 | 5.80 | 2.13 | 2.30 |

Table A.9: Action Level Analysis: 15 Sample Data Representing for the Roll Bending Task Performed by the First Crew (Durations in Seconds)

| SN | First Sequential Dataset (N = 104) | | | | | | | Second Sequential Dataset (N = 44) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $T_1$-$A_1$ | $T_1$-$A_2$ | $T_1$-$A_3$ | $T_1$-$A_4$ | $T_1$-$A_5$ | $T_1$-$A_6$ | $T_1$-$A_7$ | $T_1$-$A_1$ | $T_1$-$A_2$ | $T_1$-$A_3$ | $T_1$-$A_4$ | $T_1$-$A_5$ | $T_1$-$A_6$ | $T_1$-$A_7$ |
| 1 | 6 | 13 | 11 | 29 | 8 | 18 | 5 | 12 | 18 | 20 | 29 | 21 | 18 | 27 |
| 2 | 6 | 10 | 12 | 30 | 6 | 15 | 7 | 11 | 6 | 13 | 28 | 8 | 29 | 5 |
| 3 | 6 | 10 | 9 | 30 | 21 | 18 | 16 | 10 | 31 | 9 | 12 | 30 | 7 | 19 |
| 4 | 13 | 24 | 19 | 38 | 18 | 25 | 16 | 10 | 10 | 24 | 31 | 7 | 21 | 18 |
| 5 | 11 | 13 | 11 | 29 | 7 | 23 | 15 | 9 | 10 | 13 | 29 | 7 | 21 | 21 |
| 6 | 11 | 13 | 17 | 29 | 9 | 18 | 11 | 9 | 7 | 8 | 30 | 9 | 21 | 18 |
| 7 | 11 | 13 | 17 | 29 | 7 | 20 | 12 | 11 | 10 | 14 | 29 | 7 | 22 | 12 |
| 8 | 9 | 17 | 11 | 29 | 7 | 31 | 4 | 5 | 8 | 12 | 29 | 9 | 19 | 13 |
| 9 | 9 | 11 | 12 | 29 | 10 | 27 | 25 | 10 | 8 | 9 | 28 | 7 | 21 | 15 |
| 10 | 9 | 15 | 12 | 30 | 7 | 17 | 10 | 9 | 7 | 8 | 29 | 6 | 21 | 20 |
| 11 | 11 | 12 | 12 | 28 | 8 | 20 | 9 | 5 | 8 | 16 | 30 | 11 | 22 | 13 |
| 12 | 5 | 13 | 10 | 30 | 7 | 21 | 6 | 6 | 9 | 16 | 30 | 7 | 20 | 13 |
| 13 | 14 | 36 | 30 | 32 | 20 | 37 | 10 | 6 | 20 | 24 | 30 | 6 | 21 | 27 |
| 14 | 5 | 13 | 12 | 29 | 10 | 43 | 13 | 12 | 11 | 13 | 30 | 9 | 19 | 18 |
| 15 | 5 | 11 | 39 | 35 | 19 | 26 | 32 | 12 | 8 | 19 | 38 | 7 | 25 | 15 |

Table A.10: Action Level Analysis: 15 Sample Data Representing for the Roll Bending Task Performed by the Second Crew (Durations in Seconds) (N = 86)

| SN | $T_1$-$A_1$ | $T_1$-$A_2$ | $T_1$-$A_3$ | $T_1$-$A_4$ | $T_1$-$A_5$ | $T_1$-$A_6$ |
|---|---|---|---|---|---|---|
| 1 | 4 | 16 | 13 | 29 | 13 | 15 |
| 2 | 7 | 14 | 9 | 29 | 11 | 8 |
| 3 | 5 | 21 | 14 | 27 | 3 | 9 |
| 4 | 6 | 14 | 9 | 28 | 2 | 7 |
| 5 | 6 | 22 | 6 | 27 | 1 | 8 |
| 6 | 6 | 25 | 9 | 28 | 2 | 8 |
| 7 | 6 | 15 | 7 | 27 | 3 | 9 |
| 8 | 7 | 18 | 10 | 26 | 2 | 9 |
| 9 | 9 | 18 | 8 | 29 | 2 | 9 |
| 10 | 8 | 20 | 6 | 28 | 1 | 9 |
| 11 | 7 | 19 | 10 | 27 | 2 | 11 |
| 12 | 7 | 21 | 8 | 28 | 2 | 9 |
| 13 | 9 | 19 | 8 | 29 | 3 | 9 |
| 14 | 6 | 15 | 9 | 28 | 1 | 12 |
| 15 | 6 | 17 | 19 | 28 | 5 | 19 |

Table A.11: Action Level Analysis: 15 Sample Data Representing for the Lock Setting & Tie-rods Installing Tasks Performed by the Second Crew (Durations in Seconds) (N = 117)

| SN | Task 3I | | | | | | | | Task 4I | | | | Task 3II | | | | | | | | Task 4II | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ | $A_6$ | $A_7$ | $A_8$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ | $A_6$ | $A_7$ | $A_8$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
| 1 | 20 | 74 | 30 | 18 | 17 | 11 | 33 | 28 | 24 | 47 | 10 | 38 | 31 | 13 | 9 | 20 | 20 | 12 | 32 | 28 | 21 | 61 | 8 | 127 |
| 2 | 58 | 43 | 44 | 22 | 22 | 19 | 35 | 35 | 36 | 59 | 19 | 44 | 30 | 164 | 11 | 27 | 27 | 12 | 31 | 29 | 20 | 61 | 18 | 69 |
| 3 | 19 | 19 | 22 | 33 | 33 | 14 | 23 | 28 | 28 | 65 | 35 | 51 | 38 | 16 | 7 | 27 | 27 | 16 | 19 | 30 | 32 | 60 | 9 | 140 |
| 4 | 22 | 19 | 26 | 34 | 34 | 11 | 35 | 29 | 32 | 77 | 15 | 35 | 31 | 37 | 11 | 41 | 41 | 11 | 23 | 41 | 28 | 86 | 12 | 58 |
| 5 | 24 | 24 | 31 | 40 | 40 | 16 | 41 | 38 | 31 | 74 | 27 | 82 | 60 | 17 | 5 | 38 | 24 | 11 | 15 | 46 | 22 | 76 | 9 | 38 |
| 6 | 30 | 42 | 27 | 47 | 17 | 10 | 26 | 28 | 23 | 66 | 10 | 44 | 42 | 20 | 9 | 48 | 48 | 15 | 26 | 26 | 34 | 94 | 40 | 55 |
| 7 | 25 | 51 | 20 | 35 | 25 | 10 | 40 | 49 | 27 | 100 | 9 | 68 | 38 | 27 | 9 | 32 | 32 | 8 | 35 | 28 | 12 | 96 | 31 | 42 |
| 8 | 28 | 33 | 11 | 26 | 26 | 8 | 24 | 59 | 23 | 64 | 19 | 76 | 30 | 10 | 10 | 40 | 40 | 11 | 22 | 32 | 27 | 70 | 14 | 51 |
| 9 | 26 | 27 | 34 | 27 | 27 | 11 | 22 | 33 | 30 | 69 | 18 | 68 | 24 | 33 | 9 | 27 | 27 | 18 | 23 | 37 | 36 | 53 | 18 | 45 |
| 10 | 21 | 51 | 20 | 48 | 36 | 11 | 28 | 28 | 30 | 57 | 45 | 84 | 37 | 18 | 10 | 32 | 32 | 18 | 24 | 25 | 33 | 72 | 21 | 82 |
| 11 | 18 | 20 | 58 | 37 | 37 | 13 | 21 | 35 | 32 | 71 | 37 | 56 | 25 | 16 | 9 | 27 | 27 | 11 | 23 | 35 | 38 | 59 | 16 | 91 |
| 12 | 19 | 47 | 30 | 40 | 40 | 13 | 28 | 36 | 44 | 74 | 22 | 52 | 36 | 21 | 12 | 25 | 25 | 18 | 28 | 33 | 30 | 83 | 20 | 44 |
| 13 | 15 | 40 | 31 | 33 | 27 | 8 | 20 | 24 | 34 | 73 | 62 | 55 | 43 | 13 | 14 | 23 | 23 | 10 | 21 | 26 | 28 | 59 | 29 | 65 |
| 14 | 66 | 23 | 33 | 21 | 21 | 11 | 18 | 33 | 33 | 61 | 42 | 54 | 34 | 6 | 10 | 26 | 26 | 22 | 26 | 44 | 45 | 71 | 28 | 47 |
| 15 | 18 | 23 | 35 | 29 | 29 | 15 | 26 | 24 | 31 | 55 | 38 | 48 | 28 | 9 | 10 | 26 | 26 | 15 | 25 | 35 | 35 | 54 | 25 | 53 |

Table A.12: Action Level Analysis: 15 Sample Data Representing for the Flanges Screwing Task Performed by the Second Crew (Durations in Seconds) (N = 117)

| SN | $T_5$-$A_1$ | $T_5$-$A_2$ | $T_5$-$A_3$ | $T_5$-$A_4$ | $T_5$-$A_5$ | $T_5$-$A_6$ |
|---|---|---|---|---|---|---|
| 1 | 9 | 22 | 135 | 12 | 141 | 24 |
| 2 | 7 | 22 | 145 | 43 | 128 | 8 |
| 3 | 54 | 15 | 144 | 44 | 147 | 21 |
| 4 | 11 | 18 | 136 | 41 | 178 | 20 |
| 5 | 18 | 24 | 123 | 48 | 169 | 20 |
| 6 | 10 | 19 | 122 | 38 | 150 | 28 |
| 7 | 10 | 20 | 110 | 41 | 124 | 37 |
| 8 | 7 | 16 | 111 | 46 | 178 | 11 |
| 9 | 7 | 14 | 127 | 39 | 153 | 30 |
| 10 | 9 | 22 | 201 | 46 | 133 | 15 |
| 11 | 8 | 19 | 122 | 57 | 137 | 21 |
| 12 | 10 | 27 | 145 | 53 | 163 | 17 |
| 13 | 8 | 25 | 141 | 58 | 171 | 15 |
| 14 | 8 | 24 | 127 | 78 | 178 | 13 |
| 15 | 17 | 19 | 125 | 52 | 120 | 10 |

Table A.13: Action Level Analysis: 15 Sample Data Representing for the Sealing Task Performed by the Third Crew (Durations in Seconds) (N = 117)

| SN | Worker 1 | | | Worker 2 | | | Worker 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_1$ | $A_2$ | $A_3$ | $A_1$ | $A_2$ | $A_3$ |
| 1 | 22 | 977 | 10 | 12 | 1655 | 11 | 12 | 2094 | 7 |
| 2 | 11 | 671 | 4 | 10 | 1923 | 8 | 12 | 1114 | 10 |
| 3 | 11 | 874 | 8 | 9 | 1488 | 10 | 14 | 2066 | 11 |
| 4 | 12 | 788 | 5 | 13 | 1286 | 11 | 14 | 1381 | 8 |
| 5 | 12 | 681 | 6 | 10 | 1109 | 9 | 36 | 1159 | 45 |
| 6 | 11 | 1268 | 25 | 13 | 960 | 10 | 37 | 1375 | 12 |
| 7 | 33 | 868 | 15 | 10 | 1077 | 11 | 33 | 1272 | 23 |
| 8 | 15 | 1556 | 11 | 10 | 1848 | 8 | 55 | 1162 | 78 |
| 9 | 20 | 1371 | 9 | 10 | 728 | 12 | 50 | 712 | 22 |
| 10 | 8 | 1661 | 16 | 12 | 1128 | 14 | 39 | 612 | 21 |
| 11 | 15 | 1880 | 15 | 10 | 750 | 37 | 34 | 729 | 34 |
| 12 | 10 | 2243 | 7 | 29 | 1276 | 20 | 19 | 1043 | 25 |
| 13 | 9 | 1620 | 11 | 46 | 1014 | 15 | 21 | 740 | 20 |
| 14 | 13 | 1386 | 9 | 19 | 1043 | 24 | 136 | 920 | 22 |
| 15 | 10 | 1340 | 22 | 24 | 1032 | 18 | 21 | 803 | 17 |

Table A.14: Action Level Analysis: 15 Sample Data Representing for the Packing Task Performed by the Third Crew (Durations in Seconds) (N = 117)

| SN | Workers 1 & 2 ($W_{12}$) | | | Workers 3 & 1 ($W_{31}$) | | | Workers 1, 2, & 3 ($W_{123}$) |
|---|---|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
| 1 | 27 | 66 | 18 | 125 | 104 | 21 | 328 |
| 2 | 47 | 69 | 19 | 25 | 105 | 53 | 437 |
| 3 | 42 | 55 | 26 | 103 | 70 | 19 | 434 |
| 4 | 36 | 53 | 26 | 43 | 46 | 37 | 434 |
| 5 | 54 | 46 | 31 | 45 | 46 | 54 | 515 |
| 6 | 51 | 49 | 17 | 175 | 297 | 55 | 418 |
| 7 | 85 | 109 | 17 | 216 | 301 | 62 | 502 |
| 8 | 133 | 110 | 14 | 239 | 74 | 34 | 464 |
| 9 | 156 | 108 | 37 | 190 | 58 | 27 | 428 |
| 10 | 122 | 109 | 38 | 180 | 280 | 31 | 441 |
| 11 | 80 | 153 | 50 | 111 | 92 | 39 | 469 |
| 12 | 90 | 147 | 39 | 149 | 94 | 22 | 354 |
| 13 | 42 | 137 | 26 | 36 | 96 | 24 | 421 |
| 14 | 68 | 188 | 25 | 146 | 245 | 64 | 455 |
| 15 | 88 | 130 | 32 | 140 | 84 | 30 | 403 |

Table A.15: Action Level Analysis: 15 Sample Data Representing for the Delivering Task Performed by the fourth Crew (Durations in Seconds) (N = 31)

| SN | $T_8$ |
|---|---|
| 1 | 42 |
| 2 | 35 |
| 3 | 29 |
| 4 | 20 |
| 5 | 40 |
| 6 | 35 |
| 7 | 30 |
| 8 | 22 |
| 9 | 35 |
| 10 | 25 |
| 11 | 43 |
| 12 | 41 |
| 13 | 29 |
| 14 | 28 |
| 15 | 14 |

# APPENDIX B

# ADDITIONAL LIST OF FIGURES

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Figure B.1: Approach to the Roll-Bended Sheet Stacks ($M_1$)

Figure B.2: Hold the Roll-Bended Sheet ($M_2$)

Figure B.3: Move the Roll-Bended Sheet to the Lock Forming Table ($M_3$)

Figure B.4: Place the Roll-Bended Sheet on the Lock Forming Table ($M_4$)

Figure B.5: Set One Edge of the Roll-Bended Sheet on Lock Machine ($M_5$)

Figure B.6: Slide the Sheet for Locking ($M_6$)

Figure B.7: Switch Another Edge of the Sheet ($M_7$)

Figure B.8: Place Another Edge of the Sheet on Lock Machine ($M_8$)

Figure B.9: Set Another Edge of the Sheet on Lock Machine ($M_9$)

Figure B.10: Slide the Sheet for Locking ($M_{10}$)

Figure B.11: Hold the Sheet Before Moving for Stacking ($M_{11}$)

Figure B.12: Move the Lock-Formed Sheet Towards Stacks ($M_{12}$)


Figure B.13: Place the Lock Formed Sheet at Stacks ($M_{13}$)

Figure B.14: Move Back to Workstation ($M_{14}$)