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A Case Study on Estimating Labor Productivity Frontier

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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, one must compare actual versus optimal productivity in order to determine absolute efficiency. The labor productivity frontier is the theoretical maximum production level per unit of time that can be achieved in the field under perfect conditions. This level of productivity is an abstraction that is useful in the estimation of optimal productivity for labor-intensive operations. This research contributes to the body of knowledge by introducing a dual approach framework to estimate the labor productivity frontier and applying it in a case study on the fabrication of sheet metal ducts. Following these two approaches–observed durations and estimated durations–the productivity frontier for this activity was found to be 2.83 ducts per crew-hour. This paper reviews relevant literature, presents the details of the proposed dual approach, introduces results from the case study, and evaluates the feasibility of this methodology for estimating the labor productivity frontier.

Key Words: Labor productivity, Time and motion study, Labor productivity frontier, Optimal productivity, Probability distribution

Introduction

The construction industry is 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 (Statistics 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). 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. However, this approach of examining productivity only provides a relative benchmark of efficiency. There is currently no systematic approach for measuring and estimating labor productivity (Song & AbouRizk, 2008). Indeed, an operation may not be efficient even though actual productivity equals average historical productivity because the operation’s efficiency may be well below optimal levels. This idea further raises a concern that many factors involved in the processes of construction change over time –productivity cannot be easily judged by the same data or information that was documented a decade or more ago (Liberda, Ruwanpura, & Jergeas, 2003). This reality calls for an alternative technique to measure labor productivity.

In an attempt to achieve this objective, this paper uses the terminology “labor productivity frontier” and presents 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, 2011). The “perfect conditions” 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 error, 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 the productivity frontier can be used as an absolute benchmark because it provides a significant input value necessary to estimate optimal productivity. Optimal productivity is defined as the productivity level achievable on a sustainable basis under good management and typical field conditions (Son & Rojas, 2011).

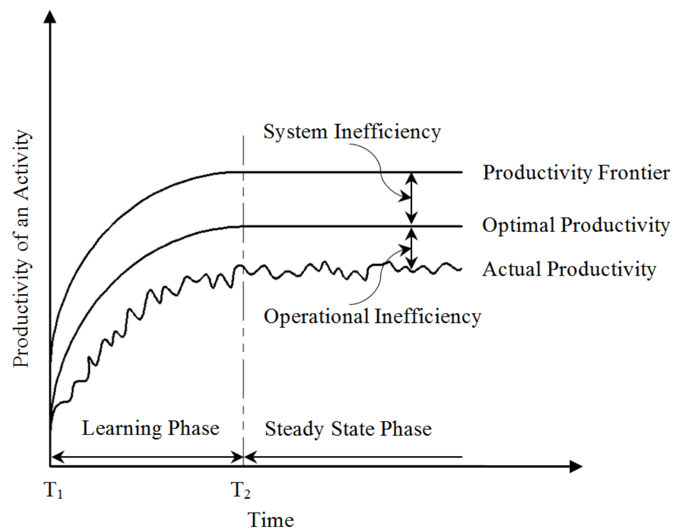

Figure 1: Basic productivity dynamics (modified from Son & Rojas, 2011)

The relationships among productivity frontier, optimal productivity, and actual productivity are illustrated in Figure 1. A 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). This point is shown in Figure 1 as time T_2. The productivity frontier diverges from optimal labor productivity levels due to system inefficiency –those factors outside the project manager's purview that affect productivity, including environmental conditions (high humidity, cold, or hot temperatures), breaks, workers' health, absenteeism driven by health or family issues, interference from other trades, and design errors, among others. Actual productivity generally manifests as suboptimal 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 make up the operational inefficiency. Operational inefficiency can be minimized by project managers through pre-evaluation of risk factors and by exhibiting unbiased attitudes while adopting explicit and systematic methods (Son & Rojas, 2011).

Kisi, Mani, and Rojas (2014) explains a top-down approach and a bottom-up approach to estimate optimal productivity. The top-down approach yields the upper level estimation of optimal productivity by deducting system inefficiency losses from the labor productivity frontier. The bottom-up approach yields the lower level estimation of optimal productivity by adding actual productivity with operational inefficiency losses. Kisi et al. (2014) presents a detailed description on how the productivity frontier is used to estimate optimal productivity. Such a process is outside the scope of this paper.

Given these definitions, one can state that productivity is optimistically forecasted when the estimated values are higher than the optimal productivity and is conservatively forecasted when the estimated values are lower than the optimal productivity. Of course, managers do not purposely forecast at these levels. They simply assume that these levels are reasonably attainable in the field based upon historical averages and personal judgment. Son and Rojas (2011) assert that both optimistic and conservative assumptions end up negatively affecting actual productivity in the field.

This paper reports on a case study performed to evaluate the feasibility of a dual approach for estimating the productivity frontier for a “Fabrication of Sheet Metal Ducts” activity. This study focuses on the estimation of the productivity frontier which is required as input to estimate optimal labor productivity.

Theoretical Framework

Construction activities can be broken down following a hierarchical structure. Tucker and Guo (1993) classified construction activities into area, activity, and task. Ahmad, Scott, and Bradley (1995) classified them into five levels: project, division, activity, basic task, and elemental motion. For the purposes of this case study, and depending upon the complexity of a project, activities are broken down into tasks, tasks into actions, and actions into movements.

There are numerous methods available to measure construction labor-intensive operations, such as work sampling method (Orth, Welty, & Jenkins, 2006), activity sampling, and time studies (Oglesby, Parker, & Howell, 1989). Time studies also called time and motion studies were developed by Frederick W. Taylor in 1880. They are used to measure the time required by a skilled, well-trained operator working at a normal pace doing a specific task. 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, Knickman, & Hendrickson, 1993). These studies are helpful in documenting and improving inefficient methods and eliminating or reducing avoidable delays in the workplace. 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). Time and motion studies are also used to exactly tally the time spent on each type of task and are typically used in the analysis of body motions employed while doing a job in order to find the most efficient method in terms of time and effort.

The time and motion study was performed at the action level because, as the lower one moves in a hierarchy, the more variability may be seen among duration values. Greater variability is preferable 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. If that activity were divided into several tasks and the minimum duration for each task measured, then the total duration of the activity calculated by reassembling its tasks would be X’, 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 effect results from the fact that higher hierarchical levels “hide” the variability of its constituent parts since one only “sees” the variability of the aggregated whole. By breaking down a process into its elemental components, one makes visible previously “hidden” variability. 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 tasks, only direct and contributory work would be considered as all non-contributory tasks would be eliminated because they do not form part of the value-added hierarchy. Even though X”’ would be based on 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. Detailed information about theoretical framework is discussed in previously published paper (Mani, 2015; Mani, Kisi, & Rojas, 2014).

Once durations are determined, productivity may be calculated by dividing the production rate by the observed shortest durations for the activity. However, since observed durations may not include the lowest possible duration for a task, action, or movement, probability distributions are fitted to the data to obtain estimated shortest durations. Productivity is again calculated by dividing the production rate by the estimated shortest durations for the task. The highest productivity from these two techniques—observed durations and estimated durations—are taken as the value for the labor productivity frontier.

The estimated shortest duration from the best fitted probability distribution is computed using "Base SAS® 9.2" software. This software defines the lowest value as the lowest threshold parameter and also called "shifted parameter" (Aristizabal, 2012) for the shifted probability distribution (Ang & Tang, 2004). The maximum likelihood estimation is used to estimate the parameters of the distribution (Ang & Tang, 2004).

Case Study

A case study was conducted to evaluate the proposed framework in order to determine the feasibility of estimating labor productivity frontier in construction. This case study analyzed data captured during the "Fabrication of Sheet Metal Ducts" activity at the workshop of the Waldinger Corporation in Omaha, Nebraska. The steps involved in this framework are described below.

Field Data Collection

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, Huan, & Peddi, 2008; Sigal, Balan, & Black, 2010). Prior to data collection, cameras were synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004). Data were captured on the fabrication of sheet metal ducts at the Waldinger Corporation's workshop. These ducts were manufactured to install for an exhaust system in a newly constructed building at the University of Nebraska Medical Center (UNMC) in Omaha, Nebraska. The scope of this activity included the complete labor-intensive operations of the formation of sheet metal ducts from plain metal sheets of standard sizes. The "Fabrication of Sheet Metal Ducts" activity is selected because:

- It consists of a large number of repetitive labor-intensive operations
- It is a controlled indoor environment and video cameras are able to sit closer to the workstation in order to capture minor movements of workers.
- It consists of a homogeneous and consistent working environment in terms of work approach, materials used for fabrication, and quality of output.

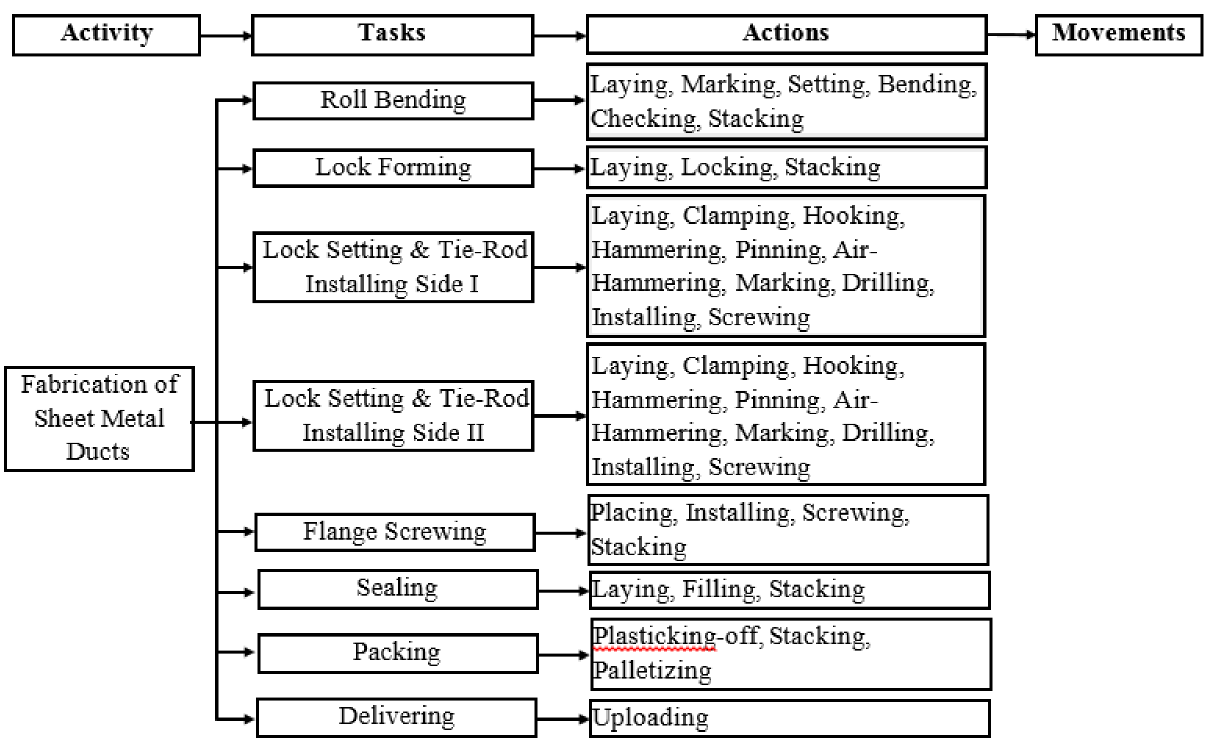

Figure 2: Hierarchical breakdown of fabrication of sheet metal ducts

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 2. 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. 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 consists of two workers each. The third crew consists of three workers. The fourth crew contained one worker. 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 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 & Aggarwal, 1996).

One hundred and seventeen data points for the "Fabrication of Sheet Metal Ducts" activity were analyzed at the action level. This activity consists of eight different tasks and 45 different actions. 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.

Actions Identification and Classification

Visual inspection (Bai et al., 2008) was used to identify and classify each action and movement of the activity into either contributory or non-contributory, based upon their impact on work completion. The contributory actions and movements are those which are necessary to accomplish the different tasks as shown in Figure 2. 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 anything" (idle time).

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.

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 activity. 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. 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. 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 was 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 a specific sequence. Among available shortest durations for each sequential set of tasks, the shortest of the shortest duration is considered as the shortest observed duration for that task.

The shortest observed duration for the 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 as shown in Table 1. 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.

Approach 2: Estimated Durations

The probability distribution for each action involved in the 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 (shortest duration) for that distribution was estimated using "Base SAS® 9.2." The shortest duration of the contributory actions for this task were estimated from the distribution, which were evaluated at a 95% confidence level, and values were recorded in the 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.

After obtaining the shortest estimated duration for each task, the shortest estimated duration for the activity was computed by adding the shortest estimated duration of each task. The shortest estimated duration for the activity was found to be 1,273 seconds as shown in Table 1. The number of ducts fabricated was divided by this 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 higher productivity from these two approaches –observed and estimated durations. For the "Fabrication of Sheet Metal Ducts" activity, the productivity frontier computed was found to be 2.83 ducts per crew-hour.

Table 1

Shortest observed and estimated durations for the fabrication of sheet metal ducts activity (durations are in seconds)

Tasks	**Crews (Number of Workers)**	**Number of Sequential Datasets**	**Shortest Observed Durations**	**Shortest Estimated Durations**
Roll Bending	Crews 1 & 2 (2 workers in each crew)	3	54	49
Lock Forming	Crew 2 (2 workers)	3	44	42
Lock Setting/Tie-rods Installing/ Flanges Screwing	Crew 2 (2 workers)	1	376	341
Sealing	Crew 3 (3 workers)	3	563	523
Packing	Crew 3 (3 workers)	2	341	308
Delivering	Crew 4 (1 worker)	1	14	10
Total Durations (in seconds)			1392	1273

Limitations and Discussion

The shortest duration from two different approaches, one observed and another estimated was considered while estimating the productivity frontier. The estimated duration was obtained by estimating the lowest threshold parameter of each probability distribution in the "Base SAS® 9.2" software. Sometimes, it is difficult to plot best fitted 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, Sadowski, & Swets, 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

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the best-fit probability distribution, but also shows its parameters including the lower threshold parameter with corresponding p-value for each test.

The required number of sample size is 385 for 95% confidence level and 5% confidence interval. For this research, the number of data points are 936 in the task level study and 5,265 data points in the action level analysis. These data points are more than enough to achieve statistically significant result.

The validity of taking the theoretical productivity estimated using this framework as the productivity frontier may be questioned given that field data is used for the analysis. In essence, the productivity frontier is an abstraction that cannot be measured in the field. Therefore, using actual field data to estimate its value may seem counterintuitive. However, deductive logic can be used to justify this choice. First, this research defines 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. Second, 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. Third, given that this methodology focuses on the instantaneous highest values of labor productivity recorded, the probability of actually observing this level of theoretical productivity in the field is infinitesimal. Therefore, this value can be taken as an estimate of the productivity frontier.

Conclusion

The findings of this research shed some light on the applicability of this research framework for a complex project involving multiple workers and consisting of parallel and sequential actions. This paper illustrates a dual approach for the estimation of the productivity frontier by conducting a case study for the "Fabrication of Sheet Metal Ducts" activity. The productivity frontier for this activity was found to be 2.83 ducts per crew-hour. This productivity frontier value is used to estimate optimal productivity. 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 actual versus historical productivity. Furthermore, research efforts are currently underway to develop efficient automated tools to apply the framework proposed in this paper.

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