Labor Productivity Frontier: A Case Study of Two Crews

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The practice of comparing actual versus historical productivity only manifests relative efficiency rather than absolute efficiency. To achieve absolute efficiency, project managers must compare actual versus optimal productivity. This research coins a novel concept, productivity frontier—the theoretical maximum level of productivity that could be achieved under perfect conditions. The productivity frontier is a construct that acts as a benchmark to estimate optimal productivity. This paper reviews the relevant literatures, implements the proposed dual approach—observed durations and statistically estimated durations—to estimate the labor productivity frontier by comparing performances of two crew members for a roll bending task, and presents the comparative results of both crews from the study. The theoretical highest labor productivity for this task were 67.92 sheets per crew-hour and 73.47 sheets per crew-hour for the first and second crews, respectively. Thus, the labor productivity frontier for this task was 73.47 sheets per crew-hour. In addition to the contribution towards the body of knowledge, this research presents a decision-making framework for project managers that will help to improve the productivity level of labor-intensive operations by avoiding or minimizing the impact due to operational inefficiency factors.

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

Introduction

In the construction engineering and management domain, labor productivity can be defined as the ratio of output to input (Rojas & Aramvareekul, 2003), where output means units of work placed (production level) and input means units of time taken to accomplish that work. In general, hourly outputs are widely used to measure labor productivity (Hanna, Chang, Sullivan, & Lackney, 2008; Thomas & Yiakoumis, 1987). 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). In the manufacturing domain, the U.S. Department of Labor defined labor productivity as the real output in national currency per hour worked and it is measured based on output, total labor hours, and total compensation (BLS, 2012). In the mining domain, labor productivity is defined as an average value added product per hour worked (Hannah, 1981).

In the agriculture domain, labor productivity is measured based on the agricultural output per labor force (Lee, Craig, & Weiss, 1993).

Labor productivity is one of the most frequently discussed topics in the construction industry because of its importance to profitability (Mani, 2015). It becomes a prime factor because labor costs generally cover 30% to 50% of overall project costs in construction (Harmon and Cole, 2006). Therefore, labor productivity is considered one of the best indicators of production efficiency (Rojas & Aramvareekul, 2003). In order to gauge construction process efficiency, benchmarking is necessary to compare observed value with the standard value (Bernold & AbouRizk, 2010). In current practice, a project manager generally compares actual with historical productivity for equivalent operations in order to evaluate the efficiency of labor-intensive construction operations (Mani 2015; Mani, Kisi, Rojas, & Foster, 2016). This approach of examining productivity only provides a relative benchmark of efficiency. In addition, 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). 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, Haas, Borcherding, & Goodrum, 2000). 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 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 (Mani, 2015; Mani, Kisi, & Rojas, 2014).

To achieve this objective, this research proposes a framework to estimate the "labor productivity frontier," which acts as a benchmark input value to estimate optimal productivity. 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. Optimal productivity is defined as the productivity level achievable on a sustainable basis under good management and typical field conditions (Son & Rojas, 2011). Mani et al. (2016) presents the relationships among productivity frontier, optimal productivity, actual productivity, system inefficiency, and operational inefficiency as shown in Figure 1. System inefficiencies are loss in productivity due to 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. 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.

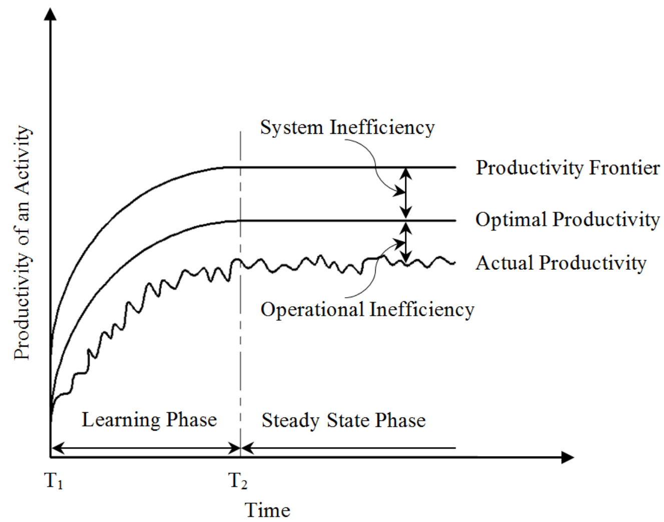

Figure 1: Basic productivity dynamics (modified from Son & Rojas, 2011)

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.

This case study compares performances of two crews and evaluates the feasibility of a dual approach for estimating the productivity frontier for a “Roll Bending” task.

Theoretical Background

This is an extension research of Son and Rojas (2011), who identified different level of productivity. Mani et al. (2014) and Kisi et al. (2014) presented frameworks to estimate the productivity frontier and optimal productivity, respectively for the “Fluorescent Bulb Replacement” task involving a single worker performing sequential actions. This paper presents a framework to estimate the productivity frontier for a complex task involving multiple workers consisting of sequential and parallel actions. In order to estimate the productivity frontier, this research adapts various methods as the theoretical underpinnings of the proposed framework, such as hierarchical analysis, time-and-motion study, and probability distribution analysis. These concepts combine to yield a robust calculation of the productivity frontier, which are briefly described below.

Hierarchical analysis: Researchers broke down an activity into four level hierarchy of subsystems, such as activity into tasks, tasks into actions, and actions into movements (Mani et al., 2016). This study goes two levels deeper than Tucker and Guo (1993) classification (area, activity, and task). Ahmad, Scott, and Bradley (1995) classified them into five levels: project, division, activity, basic task, and elemental motion.

Time-and-motion study: This study used time-and-motion study to measure observed durations required by workers to perform the “Roll Bending” task. The main objective of time-and-motion study 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). 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 (Mani et al., 2016). Greater variability is preferable because it allows for the identification of the lowest theoretical durations. Mani et al. (2016) presented a detailed information about this concept with relevant examples.

Probability distribution analysis: 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 statistically estimated shortest durations. The estimated shortest duration from the best fitted probability distribution is computed using “Base SAS® 9.2” software. This software defines the shortest 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

This case study compares the “Roll Bending” task performed by two crews and evaluates the proposed framework in order to estimate the labor productivity frontier. The “Roll Bending” is a task of the “Fabrication of Sheet Metal Ducts” activity. The previously published paper in ASC (Mani et al., 2016) described how to estimate the labor productivity frontier for this entire activity. This case study only focuses on the performances of two sets of crews, who were involved in the “Roll Bending” task. The steps involved in this study are described below.

Field Data Collection

Multiple Canon XF100 professional camcorders captured video data on the “Roll Bending” task of the “Fabrication of Sheet Metal Ducts” activity at the workshop of the Waldinger Corporation in Omaha, Nebraska. Prior to data collection, those cameras were calibrated using the “Camera Calibration Toolbox” in Matlab (Bai, Huan, & Peddi, 2008; Sigal, Balan, & Black, 2010) and synchronized based upon a mode, frames per second, and initial time (Caillette & Howard, 2004). 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 study included labor-intensive operations of the formation of roll bended sheet from a plain metal sheet of a standard-sized (80.25 inches x 60 inches x 0.0336 inches). Two crews, each consisting of two workers rolled and bended a metal sheet in a designated shape and size. The first crew (team of old workers) completed the roll bending task for 148 plain sheets. Then, they were absent in the next day and the project supervisor assigned the second crew to complete the remaining task. The second crew (team of young workers) accomplished the roll bending task for the remaining 86 metal sheets. Both crew members were skilled at their work. Figures 2 (a) and (b) show the "Roll Bending" task performed by the first and second crews, respectively. This task is selected for the study because:

- It consists of a large number of repetitive labor-intensive operations. Also, two different crews involved to complete the same task with their own sequences of actions.
- 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. However, there were few disturbing factors, such as disturbances by other workers in the workshop, tight working space, and noise generated from heavy manufacturing equipment.
- It consists of a homogeneous and consistent working environment in terms of work approach, materials used for fabrication, and quality of output (Mani et al., 2016).

Figure 2: Roll bending task performed by (a) crew 1 and (b) crew 2

Data Analysis

The "Fabrication of Sheet Metal Ducts" activity was broken down into the four-level hierarchy, such as activity, task, action, and movement. This activity consisted of eight different tasks: (i) roll bending, (ii) lock forming, (iii) lock setting, (iv) tie-rod installing, (v) flange screwing, (vi) sealing, (vii) packing, and (viii) delivering (Mani et al., 2016). This study mainly focuses on the "Roll Bending" task. The first crew (Crew 1) accomplished this task in seven stages, whereas the second crew (Crew 2) completed it in six different stages as shown in Table 1. All these tasks, actions, and movements were identified from the video data by converting it into individual images by applying the frame separation algorithm in Matlab (Cai & Aggarwal, 1996).

At the action level study, data points for the analysis were 888 (148 x 7 = 1036) and 516 (86 x 6 = 516) from the performances of the first crew and the second crew, respectively. Therefore, the total data points for the analysis were 1552 in the action level study.

Table 1
Actions involved in "Roll Bending" task

Task	Actions Performed by Crew 1	Actions Performed by Crew 2
Roll Bending	Marking dimension (A_1)	Laying a plain sheet on the roll bending table (A_1)
	Laying a plain sheet on the roll bending table (A_2)	Marking dimension (A_2)
	Setting the plain sheet (A_3)	Setting the plain sheet (A_3)
	Bending sheet on the roller (A_4)	Bending sheet on the roller (A_4)
	Checking dimension (A_5)	Checking dimension (A_5)
	Stacking of the roll-bended sheet (A_6)	Stacking of the roll-bended sheet (A_6)
	Stacking the plain sheets off from piles (A_7)	

Actions Identification and Classification

Actions were identified by visual inspection (Bai et al., 2008; Wang et al., 2003) and classified into either contributory or non-contributory based upon their impact on work completion. The contributory actions are those which are necessary to accomplish this task. Non-contributory actions are considered non-productive and include actions, 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). All contributory actions performed by the first and second crews for "Roll Bending" task are listed in Table 1.

Productivity Frontier Estimation

During this study, two approaches—observed durations and statistically estimated durations—were established to compute the productivity frontier for the "Roll Bending" task.

Approach 1: Observed Durations

The time and motion study was conducted by reviewing the video data and recorded the durations of the contributory actions for the "Roll Bending" task. Since multiple workers were involved in this task, the durations for individual and combined involvement of the workers for each action 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 a process of analyzing the data in different groups according to the characteristics of data set (Mani et al., 2016). A group of datasets was prepared according to similar sequential sets of data. The minimum duration taken to accomplish an action is determined for each sequential dataset. The shortest possible duration for this task was estimated by adding up the shortest durations observed for each action based on sequence of actions performed by an individual worker or by the crew because the task was made up of actions in a specific 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. The shortest observed duration to complete the "Roll Bending" task for the first crew was 57 seconds and that for the second crew was 54 seconds as shown in Table 2. The number of sheets roll bended was divided by this observed shortest duration in order to compute the equivalent productivity. The resulting equivalent productivity were 63.16 sheets per crew-hour and 66.67 sheets per crew-hour for the first crew and the second crew, respectively.

Approach 2: Estimated Durations

The probability distribution for each action involved in the 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 (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 this task, the concept of the sequence set analysis was again implemented similar to the method employed to estimate the observed shortest duration for the task. The shortest estimated duration to complete this task for the first crew was 53 seconds and that for the second crew was 49 seconds as shown in Table 2.

Results

When comparing results obtained from the research, this study identified several differences in the performances of two crews: (i) 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). (ii) There were two datasets classified based on the sequence of actions performed by the first crew. But only one dataset was identified for the second crew because they performed this task in a similar pattern. (iii) The first crew performed this task in seven stages and second crew accomplished it in six stages as shown in Table 1. The "stacking plain sheets off from piles" action was not performed by the second crew. (iv) The first crew conducted the "marking dimension" action as a first action and performed for multiple sheets at once. But the second crew performed it as a second action and conducted for each sheet. (v) The first crew conducted the "laying a plain sheet on the roll bending table" action only after the "marking dimension." On the other hand, the second crew performed the "marking dimension" action for each sheet after the "laying a plain sheet on the roll bending table." (vi) The plain sheet was laid on the roll bending table (i.e., second action) either by first or second worker of the first crew. But both workers of the second crew accomplished this action together. (vii) Only one worker of the first crew involved in the "stacking of the roll-bended sheet" action, but both workers of the second crew involved to complete this action. (viii) The shortest observed duration taken by the first crew to complete the "Roll Bending" task was 57 seconds and that for the second crew was 54 seconds. The shortest estimated duration by the first crew to complete this task was 53 seconds and that for the second crew was 49 seconds. Therefore, the shortest durations to calculate productivity for the first crew was 53 seconds and that for the second crew was 49 seconds, respectively. (ix) From two approaches—observed durations and statistically estimated durations, the productivity computed for the "Roll Bending" task were 67.92 sheets per crew-hour and 73.47 sheets per crew-hour for the first and second crews, respectively. The highest productivity between them gives the labor productivity frontier for the "Roll Bending" task, which was 73.47 sheets per crew-hour.

Table 2
Shortest observed and estimated durations of actions performed by the first and second crews for the "Roll Bending" task (durations are in seconds)

For First Crew (Crew 1)				For Second Crew (Crew 2)			
Actions	**SOD**	**SED**	**Distribution Curve**	**Actions**	**SOD**	**SED**	**Distribution Curve**
A_1	5	4.1	Weibull	A_1	4	2.5	Gamma
A_2	7	4.5	Lognormal	A_2	10	9.7	Beta
A_3	9	8.8	Gamma	A_3	6	5.6	Gamma
A_4	26	24.1	Gamma	A_4	26	23.8	Lognormal
A_5	6	5.7	Lognormal	A_5	1	1	Exponential
A_6	15	14.1	Lognormal	A_6	7	6.5	Lognormal
A_7	4	3.6	Weibull	-	-	-	-
Total Lowest Durations	*57*	*53*			*54*	*49*	

(Note: SOD = Shortest observed duration; SED = Shortest Estimated Durations)

Limitations and Discussion

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

To achieve statistically significant result from analysis, the required minimum number of sample size is 384 for 95% confidence level and 5% desired margin of error (Gouett, Haas, Goodrum, & Caldas, 2011). For this research, there are 1,552 data points in the action level analysis. These data points are more than enough to achieve statistically significant result. Mani et al. (2016) presented a detailed information about the limitations of this framework.

Conclusion

This research presents a novel approach of analyzing productivity in the project level and discusses the research framework for a complex project involving multiple workers and consisting of parallel and sequential actions. This paper reports the results of a case study for the "Roll Bending" task by comparing performances of two crews. The maximum productivity that could be achieved by the first crew was 67.92 sheets per crew-hour and that for the second crew was 73.47 sheets per crew-hour. For the "Roll Bending" task, the theoretical highest productivity between them is 73.47 sheets per crew-hour, which is the productivity frontier for this task. This labor productivity frontier acts as a benchmark to estimate optimal productivity. Estimating the accurate labor productivity frontier is the first step toward allowing project managers to determine the absolute efficiency of their labor-intensive construction operations by comparing actual versus optimal rather than actual versus historical productivity. Moreover, this research framework helps project manager to improve the level of productivity by avoiding or minimizing the impact due to operational inefficiency factors.

Acknowledgement

The authors acknowledge the assistance of the Waldinger Corporation and express their special gratitude to the manager, site supervisor, and workers for providing access to their manufacturing workshop. Without their support, this case study would not have been possible.

References

Ahmad, A. N. B., Scott, J. N., & Bradley, D. A. (1995). Task decomposition in support of automation and robotics in construction. *Automation and Robotics in Construction*, IMBiGS, 407-414.

Allmon, E., Haas, C. T., Borcherding, J. D., & Goodrum, P. M. (2000). US construction labor productivity trends, 1970-1998. *Journal of Construction Engineering and Management*, 126(2), 97-104.

American Association of Cost Engineers (AACE) (2011). *AACE international certified cost technician primer: Supporting skills and knowledge of a cost engineer* (1st ed.). Morgantown, WV: Michael Pritchett, AACE International, Inc.

Ang, A. H-S., & Tang, W. H. (2004). *Probability concepts in engineering*. Planning, 4(1), 1-3.

Aristizabal, R. J. (2012). *Estimating the parameters of the three-parameter lognormal distribution*. Florida International University.

Bai, Y., Huan, J., & Peddi, A. (2008). Development of human poses for the determination of on-site construction productivity in real-time. *The National Science Foundation, Division of Civil, Mechanical, and Manufacturing Innovation,* Award Number: 0741374.

Bernold, L. E., & AbouRizk, S. M. (2010). *Managing performance in construction*. New Jersey: John Wiley & Sons, Inc.

Bureau of Labor Statistics (BLS) (2012). *International comparisons of manufacturing productivity and unit labor cost trends* (News Release). USA: U.S. Department of Labor.

Cai, Q., & Aggarwal, J. K. (1996). Tracking human motion using multiple cameras. *Proc. 13th International Conference on Pattern Recognition*, IEEE, Vienna, 3, 68-72.

Caillette, F., & Howard, T. (2004). Real-time markerless human body tracking with multi-view 3D voxel reconstruction. *Proc. BMVC*, Rio de Janeiro, 597-606.

Eastman, C. M., & Sacks, R. (2008). Relative productivity in the AEC industries in the United States for on-site and off-site activities. *Journal of Construction Engineering and Management*, ASCE, 134(7), 517-526.

Gouett, M. C., Haas, C. T., Goodrum, P. M., & Caldas, C. H. (2011). Activity analysis for direct-work rate improvement in construction. *Journal of Construction Engineering and Management*, ASCE, 137(12), 1117-1124.

Hanna, A., Chang, C., Sullivan, K., & Lackney, J. (2008). Impact of shift work on labor productivity for labor intensive contractor. *Journal of Construction Engineering and Management*, ASCE, 134(3), 197-204.

Harmon, K. M., & Cole, B. (2006). Loss of productivity studies-Current uses and misuses. *Construction Briefings*, 8(1), 1-19.

Kelton, W. D., Sadowski, R. P., & Swets, N. B. (2010). *Simulation with Arena* (5th Ed.) New Delhi, India: McGraw
Hill Education (India) Private Limited.

Kisi, K. P., Mani, N., & Rojas, E. M. (2014). Estimating optimal labor productivity: A two-prong strategy. *Proceeding to Construction Research Congress*, ASCE, Georgia, 757-766.

Lee, A., Craig, T., & Weiss, T. (1993). Agricultural productivity growth during the decade of the civil war. *The Journal of Economic History*, Economic History Association, Cambridge University, 53(3), 527-548.

Liberda, M., Ruwanpura, J. Y., & Jergeas, G. (2003). Construction productivity improvement: A study of human, managerial and external factors. *Proceeding to Construction Research Congress*, ASCE, Hawaii, 1-8.

Mani, N. (2015). *A framework for estimating labor productivity frontiers*. Ph.D. Dissertation, Lincoln, USA: University of Nebraska-Lincoln.

Mani, N., Kisi, K. P., & Rojas, E. M. (2014). Estimating labor productivity frontier: A pilot study. *Proceeding to Construction Research Congress*, ASCE, Georgia, 807-816.

Mani, N., Kisi, K. P., Rojas, E. M., & Foster, E. T. (2016). A case study on estimating labor productivity frontier. *Proceeding to 52nd ASC Annual International Conference*, Provo, Utah.

Meyers, F. E. (1992). *Motion and time study*. New Jersey: Prentice Hall, Englewood Cliffs.

Oglesby, C. H., Parker, H. W., & Howell, G. A. (1989). *Productivity improvement in construction*. New York: McGraw-Hill.

Rockwell Automation (2013). *Arena simulation software* (Release 14). Wexford, PA: Rockwell Automation.

Rojas, E. M., & Aramvareekul, P. (2003). Is construction labor productivity really declining? *Journal of Construction Engineering and Management*, ASCE, 129(1), 41-46.

Sigal, L., Balan, A. O., & Black, M. J. (2010). HumanEva: synchronized video and motion capture dataset and baseline algorithm for evaluation of articulated human motion. *International Journal of Computer Vision*, 87(1), 4-27.

Son, J. W., & Rojas, E. M. (2011). Impact of optimism bias regarding organizational dynamics on project planning and control. *Journal of Construction Engineering and Management*, ASCE, 137(2), 147-157.

Thomas, H. R., & Yiakoumis, I. (1987). Factor model of construction productivity. *Journal of Construction Engineering and Management*, ASCE, 113(4), 623-639.

Tucker, R. L., & Guo, S. J. (1993). Automated needs determination using analytical hierarchical process (AHP) approach. *Automation and Robotics in Construction X*, Elsevier, Houston, 39-46.

Yi, W., & Chan, A. P. C. (2014). Critical review of labor productivity research in construction Journals. *Journal of Management in Engineering*, ASCE, 30(2), 214-225.

Wang, L., Weiming, H., & Tan, T. (2003). Recent developments in human motion analysis. *National Laboratory of Pattern Recognition, Institute of Automation*, China, 36(3), 585-601.