Estimating Optimal Labor Productivity: A Two-Prong Strategy

Krishna P. KISI¹, Nirajan MANI², and Eddy M. ROJAS³

¹ Ph.D. Student, The Durham School of Architectural Engineering and Construction, University of Nebraska-Lincoln, 1110 S. 67th St., Omaha, NE 68182; email: kkisi@unomaha.edu
² Ph.D. Student, The Durham School of Architectural Engineering and Construction, University of Nebraska-Lincoln, 1110 S. 67th St., Omaha, NE 68182; email: nirajan.mani@huskers.unl.edu
³ Director and Professor, The Durham School of Architectural Engineering and Construction, University of Nebraska-Lincoln, 1110 S. 67th St., Omaha, NE 68182; email: er@unl.edu

ABSTRACT

In an attempt to evaluate the efficiency of labor-intensive construction operations, project managers compare actual with historical productivity for equivalent operations. However, this approach towards examining productivity only provides a relative benchmark for efficiency and may lead to the characterization of operations as authentically efficient when in reality such operations may be only comparably efficient.

Optimal labor productivity—the highest sustainable productivity achievable in the field under good management and typical field conditions—can provide an absolute benchmark for gauging performance. This optimal productivity level is lower than the productivity frontier—the theoretical maximum achieved under perfect conditions—because of system inefficiencies, which emerge due to factors outside the control/influence of project managers. Conversely, optimal labor productivity tends to be higher than actual labor productivity—the productivity achieved in the field—because of operational inefficiencies, which are the result of suboptimal managerial strategies. Estimating the magnitude of these system and operational inefficiencies will help project managers determine optimal labor productivity.

This paper develops a two-prong strategy for estimating optimal labor productivity. The first prong represents a top-down approach that estimates optimal productivity by introducing system inefficiencies into the productivity frontier. A Qualitative Factor Model is used to determine the impact of system inefficiencies. This top-down approach yields the upper level estimation of optimal labor productivity. The second prong is a bottom-up approach that determines optimal labor productivity by removing non-contributory work from actual productivity in a discrete event simulation. This bottom-up approach generates the lower level estimation of optimal labor productivity. An average of the upper and lower limits reveals the best estimate for optimal labor productivity.

In conjunction with a relevant literature study and a discussion of the two-prong approach’s methodology, this paper ultimately analyzes data from a pilot study, presents results, and evaluates the feasibility of this two-prong strategy for estimating optimal labor productivity in construction operations.
INTRODUCTION

Productivity is generally defined as the ratio of output to input. Yi and Chan (2013) concluded that hourly output is the most reliable measurement of productivity for construction activities. For labor-intensive operations, the focus of analysis is labor productivity, which measures the input as labor hours and the output as installed quantities (Dozzi and AbouRizk 1993). Traditionally, such labor productivity has been benchmarked against historical averages. However, this practice only provides a relative measure of efficiency since no objective yardstick exists. Optimal labor productivity, defined as the level of sustainable productivity that may be achieved in the field under good management and typical field conditions (Son and Rojas 2010), can provide such a yardstick. In order to estimate optimal labor productivity, though, it is necessary to identify and estimate inefficiencies usually present in construction operations that impact labor productivity values. These inefficiencies are categorized into system and operational inefficiencies.

System inefficiencies are outside the control or influence of project managers. They may include high temperatures, high humidity, poor workers’ health, and interferences from other trades. On the other hand, operational inefficiencies are under the control of project managers. Examples of such inefficiencies include poor scheduling, inadequate resource planning, inappropriate construction methods, and poor quality control.

Accurate estimation of optimal productivity would allow project managers to determine the efficiency of their labor-intensive construction operations by comparing actual vs. optimal rather than actual vs. historical productivity. However, to date, no substantive models for estimating optimal productivity have been proposed in the construction domain. This study therefore enhances the body of knowledge in construction engineering and management by introducing a two-prong strategy for estimating optimal labor productivity in labor-intensive construction operations. Ultimately, this research reports on a pilot study performed to evaluate the feasibility of using this two-prong approach within a simple electrical installation.

LITERATURE REVIEW

A multitude of factors impact labor productivity (Thomas and Yiakoumis 1987, Borcherding and Alarcon 1991, Alinaitwe et al. 2007, Rivas et al. 2011). Rojas and Aramvareekul (2003) suggest that management systems and strategies have the greatest influence on labor productivity, followed by manpower, industry environment, and external conditions. Alternatively, Dai et al. (2009) identify the most significant factors based on workers’ perception of productivity performance. They determine that the significant factors affecting craft workers’ daily productivity include materials, tools, and the equipment managed at the jobsite.

In response to the assorted variables that affect productivity, some researchers develop models to measure and forecast labor productivity. These models take advantage of a variety of techniques, including simulation, artificial intelligence, expert systems, factor models, and statistical and regression approaches. Srinavin and Mohamed (2003) develop a model using regression analysis for qualitative evaluation of the impact of different factors on construction labor productivity. However, since a regression equation is limited to certain variables, this analysis does not allow for the
subjective evaluation of qualitative factors. In response to this limitation, expert systems are widely used to quantify this kind of subjective evaluation. Yi and Chan (2013) perform a critical review of labor productivity research published in construction journals and claim that expert systems are superior to statistical models because of their flexibility in adapting to different project contexts.

Other researchers model construction data using probability approaches. Smith (1998) uses discrete event simulation to model construction operations utilizing the probability distribution of each event involved in a construction activity. Hamm et al. (2011) presents an optimization framework to determine efficient construction schedules by linking discrete-event simulation with optimization concepts. Zhang (2013) presents an alternative discrete event simulation method for estimating construction emissions by addressing uncertainties and randomness as well as complex interactions.

In practice, productivity analysis utilizes historical data. However, Liberda et al. (2003) state that many factors involved in the process of construction have changed over time and productivity cannot be easily judged by the same data or information that was documented a decade or more ago. Additionally, Song and AbouRizk (2008) state, “the current practice of labor productivity estimation relies primarily on either published productivity data or an individual’s experience. There is a lack of a systematic approach to measuring and estimating labor productivity.” This assessment implies that there are no benchmarks or standards to validate historical data as appropriate for either estimating or evaluating productivity.

**RESEARCH METHODOLOGY**

Figure 1 depicts different productivity levels once the steady state condition is reached for a construction operation. As illustrated in the figure, optimal productivity (OP) lies between the productivity frontier (PF) and actual productivity (AP). The PF is the theoretical maximum productivity under perfect conditions. The AP is the productivity achieved in the field.
The difference between OP and PF is the system inefficiencies ($\Delta_{si}$), while the difference between OP and AP is the operational inefficiencies ($\Delta_{oi}$). Since inefficiencies cannot be measured, they must be estimated. The estimate of the system inefficiencies is represented by $\Delta'_{si}$, while $\Delta'_{oi}$ represents the estimate of the operational inefficiencies. The upper limit of optimal productivity (OPUL) is the result of introducing the estimated system inefficiencies, $\Delta'_{si}$, to the PF, while the lower limit of optimal productivity (OPLL) is the result of taking away the estimated operational inefficiencies, $\Delta'_{oi}$, from the AP.

This study proposes a two-prong strategy for estimating optimal labor productivity by assessing system and operational inefficiencies. The first prong of the strategy includes a top-down process that estimates optimal labor productivity after taking into account system inefficiencies ($\Delta_{si}$). This process includes identifying factors that affect productivity and are outside the control of project managers, and applying a qualitative factor model to estimate the loss due to system inefficiencies ($\Delta'_{si}$). By introducing the estimated losses ($\Delta'_{si}$) to the productivity frontier, the upper level estimation of optimal productivity (OPUL) is determined.

The qualitative factor model uses a severity score technique following a probabilistic approach. Based on this qualitative factor model, the system inefficiency estimate is calculated as follows:

$$\Delta'_{si} = \Delta'_{PF-OP_{UL}} + \sum_{z=1}^{n} \left[ \sum_{i=1}^{n} \left( \frac{S_i P_i^z}{T S_i} \right) \right] W_z \quad (1)$$

Where:

- $\Delta'_{si}$ = estimate of productivity loss due to system inefficiencies
- $\Delta'_{PF-OP_{UL}}$ = estimate of difference between the productivity frontier and the lower limit of optimal productivity
- $n$ = number of parameters
- $z$ = work zone
- $i$ = system inefficiency factors in each zone $z$
- $S_i$ = severity score of individual factor $i$
- $P_i$ = probability of individual factor $i$
- $T S_i$ = total severity score (sum of severity scores of all factors)
- $W_z$ = relative weights of each zone

Qualitative definitions of severity for each of the factors are determined by a severity ranking score: score “0” = no impact; score “1” = very low impact; score “2” = low impact; score “3” = medium impact; score “4” = high impact; score “5” = very high impact. Probabilities are used to establish the likelihood of factors being present during the work; for example, a severity score of 4 with a 0.5 probability means that the factor has a probability of occurrence of 50 percent, and when it occurs, it has a high impact on labor productivity.

The final two inputs for Equation 1 are the value of the productivity frontier (PF) and the lower limit of optimal productivity (OPLL). To determine the productivity frontier, this model uses a time and motion study performed by Mani et
al. (2014), which uses the same dataset. The lower limit of optimal productivity assesses the effects of operational inefficiencies and is explained below.

To strengthen estimates for optimal productivity, the second prong of this approach includes a bottom-up process that examines the loss to optimal labor productivity caused by operational inefficiencies ($\Delta_{\beta i}$). This process includes collecting field data on actual productivity, analyzing the data, and developing a discrete event simulation model to separate direct, indirect, and non-contributory actions to thereby estimate the loss due to operational inefficiencies ($\Delta'_{\beta i}$). Oglesby et al. (1989) discussed activity sampling to carry out this type of analysis, which involves making and analyzing the results of field observations to determine what individual workers are doing at specific time instances. By eliminating non-contributory actions $\Delta'_{\beta i}$ from the model, the lower limit of optimal productivity ($OPLL$) determines productivity levels unhampered by operational inefficiencies.

The process for validating the lower limit of optimal productivity necessitates running a discrete event simulation. In order to build the simulation model, an activity is broken down into tasks, with each task breaking into measurable actions; the duration of each action is then modeled with probability distribution curves. The sequence of workflow is also modeled to simulate the construction operation. Ultimately, the simulation’s output is compared with the actual field results to establish validity. After validation, the simulation is run again, but this time eliminating non-contributory actions from the task, decreasing its original duration. The productivity value resulting from this modified simulation is the estimation of the lower limit of optimal productivity.

In summary, the upper and lower limits of optimal productivity are calculated as follows:

\[
OP_{UL} = PF - \Delta'_{\alpha i} \tag{2}
\]
\[
OP_{LL} = AP + \Delta'_{\alpha i} \tag{3}
\]

Where:

$\Delta'_{\alpha i}$ = estimate of productivity loss due to system inefficiencies $\Delta_{\alpha i}$

$\Delta'_{\beta i}$ = estimate of productivity loss due to operational inefficiencies $\Delta_{\beta i}$

It is now important to examine how these procedures are implemented in an actual case study.

PILOT STUDY

The primary purpose of the pilot study was to evaluate the feasibility of the proposed methodology for estimating optimal labor productivity. Commonwealth Electric Company conducted an electrical lighting fixture installation project at Omaha South High Magnet School. This project involved repetitive processes during the replacement of lighting fixtures inside the school building. Data were recorded from three different zones: classrooms, locker room, and corridors/hallways. This project included multiple tasks, such as removal of the existing mainframe for the lighting fixtures, removal of the old T-12 fluorescent bulbs, removal of the ballast,
installation of new Type-2 ballasts, installation of T-8 fluorescent bulbs, and closure of the main outer cover.

**Data collection**

A hierarchical structure was defined to break down activities into tasks and actions. The activity “Replacement of Electrical Lighting Fixtures” was selected for analysis given its homogeneity across the construction project and was broken down into four tasks: (1) Site Preparation, (2) Fluorescent Bulb Replacement, (3) Waste Management, and (4) Documentation. The task “Fluorescent Bulb Replacement” was broken down further into eight actions: (1) Glass Frame Opening, (2) Old Bulb Removal and Storage, (3) Ballast Cover Removal, (4) Old Ballast Removal, (5) New Ballast Installation, (6) Ballast Cover Closure, (7) New Bulb Installation, and (8) Glass Frame Closure. Data were collected at two levels: activity and action. Factors contributing to system inefficiencies were collected at the “Replacement of Electrical Lighting Fixtures” activity level since system inefficiencies tend to affect all tasks and actions within an activity equally. Factors contributing to operational inefficiencies were analyzed at the action level for the “Fluorescent Bulb Replacement” task since actions produced enough data for a preliminary analysis without creating an unnecessary burden for data processing. Table 1 shows the nature of the data collected.

<table>
<thead>
<tr>
<th>Level</th>
<th>Inefficiencies Analysis</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
<td>System Qualitative Factor Model Severity Scores and Probabilities</td>
<td>Estimation of System Inefficiencies</td>
<td></td>
</tr>
<tr>
<td>Action</td>
<td>Operational Discrete Event Simulation Events</td>
<td>Estimation of Operational Inefficiencies</td>
<td></td>
</tr>
</tbody>
</table>

The data were collected in video files, which document all of the tasks, actions, and movements necessary to replace the old lighting fixtures with new ones.

As stated in Table 1, a Qualitative Factor Model was used to estimate actual system inefficiencies. This model identifies the factors that influence productivity and assigns severity scores and probabilities of each factor’s occurrence. Thanks to a comprehensive literature review process, a list of productivity-influencing factors at the system level could be generated for the installation. Next, five experts provided severity scores and probabilities of occurrence for each factor. These scores and probabilities were inputs for the Qualitative Factor Model to determine system inefficiency estimates.

As discussed in the methodology section, a discrete event simulation yielded operational inefficiency estimates. Using a detailed video analysis, events and their stochastic durations were identified and defined.
Results

Qualitative factor model

Table 2 shows the system inefficiency factors present in the pilot study (those with probability of occurrence different than zero), their severity scores, and their probabilities. The product of severity and probability is used in the Qualitative Factor Model as described in Equation 1 above.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Factors</th>
<th>Severity Score ((S_i))</th>
<th>Probability of Occurrence ((P_i))</th>
<th>Product ((S_iP_i))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classroom</td>
<td>High humidity</td>
<td>2</td>
<td>0.4</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>Low temperature</td>
<td>2</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>Low luminance</td>
<td>2</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>High noise level</td>
<td>2</td>
<td>0.6</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Space congestion</td>
<td>4</td>
<td>0.8</td>
<td>3.2</td>
</tr>
<tr>
<td>Lockers</td>
<td>High humidity</td>
<td>3</td>
<td>0.4</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Low temperature</td>
<td>2</td>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Low luminance</td>
<td>2</td>
<td>0.4</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>High noise level</td>
<td>4</td>
<td>0.3</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Restricted access zone</td>
<td>2</td>
<td>0.6</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Space congestion</td>
<td>3</td>
<td>0.6</td>
<td>1.8</td>
</tr>
<tr>
<td>Corridor/Hallway</td>
<td>High humidity</td>
<td>1</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>Low temperature</td>
<td>2</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>High luminance</td>
<td>2</td>
<td>0.3</td>
<td>0.6</td>
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<td></td>
<td>High noise level</td>
<td>4</td>
<td>0.4</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>Space congestion</td>
<td>1</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Mani et al. (2014) estimated the productivity frontier for the “Fluorescent Bulb Replacement” task at 20.23 stations per hour. When substituting all the required parameters in Equation 1, the estimate of productivity loss due to system inefficiencies \((\Delta_{st})\) is 2.15 stations per hour, which, when subtracted from the productivity frontier, gives 18.08 stations per hour as an estimate of the upper limit of optimal productivity \((OP_{UL})\).

Discrete event simulation

An activity sampling approach called “productivity ratings” discussed in Oglesby et al. (1989) is used to find operational inefficiencies where activities are reported as effective, contributory, and not-useful work. However, for the purposes of this paper it was not necessary to differentiate between effective and contributory work and both types of work where combined under contributory. Therefore, the
actions observed in the field were categorized into: (1) contributory (effective or
direct and contributory or indirect work), and (2) non-contributory. Contributory
included those actions that are necessary to accomplish the task or work involved in
the actual process of putting together a unit being constructed (Oglesby et al.
1989)—for example, basic actions and movements required to replace bulbs. Non-
contributory actions include those that are non-productive in nature, such as
unscheduled breaks, late starts and early quits, idle time, and engagement of workers
in personal discussions (Oglesby et al. 1989, Heizer and Render 1996).

Contributory and non-contributory actions were modeled into a discrete event
simulation model to represent process workflow. The simulation was run under two
scenarios: actual (including non-contributory actions) and synthetic (excluding non-
contributory actions). The actual scenario was used for model validation while the
synthetic scenario was used for estimating the lower limit of the optimal labor
productivity.

The field data were compared to the simulation results from the actual
scenario. Recorded field data show that laborers completed 30 stations at an average
of 4.68 minutes per station or 12.80 stations per hour. The simulation results from the
actual scenario show a completion rate of 12.62 stations per hour. These results
represent less than 1.5% deviation from recorded field values. The simulation results
for the synthetic scenario show a completion rate of 13.76 stations per hour. This is a
9% improvement over the results from the actual scenario.

The mean values from the actual and the synthetic models were compared to
determine if they were statistically different. Using Arena’s output analyzer and a
95% confidence interval, a paired-T means comparison test of the null hypothesis that
both means were equal concluded that the means were different.

The productivity from this synthetic scenario is taken as an estimate of the
lower limit of optimal productivity (OPLL) rather than as the optimal productivity
itself because even when non-contributory actions are excluded, a simulation model
that relies on field data cannot eliminate all operational inefficiencies embedded in a
construction operation.

Optimal labor productivity

The average of the upper and lower limits of optimal productivity results in an
optimal productivity (OP) of 15.92 stations per hour. Compared to actual average
productivity, which is 12.80 stations per hour, the estimate of optimal productivity
may seem high. However, recorded field data shows that at one point during the
installation, a station was completed in 3.52 minutes, which is equivalent to 17.04
stations per hour if such productivity were sustained. This duration demonstrates that
the estimate of 15.92 stations per hour is achievable. In summary, during the pilot
study, the “Fluorescent Bulb Replacement” tasks achieved 80.4% efficiency (actual
recorded productivity as a percentage of estimated optimal productivity).

CONCLUSION

Accurate estimation of optimal productivity allows project managers to
determine the absolute (unbiased) efficiency of their labor-intensive construction
operations by comparing actual vs. optimal rather than actual vs. historical
productivity. In practice, efficiency of construction operations is usually determined by comparing actual vs. historical productivity. However, this comparison only provides a relative (biased) measure of efficiency. For example, actual productivity equal to 95% of average historical productivity does not necessarily mean that the operation is efficient but only that the efficiency of the operation is in line with historical averages. Indeed, the operation now and then could be significantly inefficient if it is well below optimal productivity.

This study contributes to the body of knowledge in construction engineering and management by introducing a two-prong strategy for estimating optimal labor productivity in labor-intensive construction operations and reporting on a pilot study performed to evaluate its feasibility using a simple electrical installation. The proposed two-prong strategy for estimating optimal labor productivity was successfully applied in this pilot study. The Qualitative Factor Model was found to be effective in modeling system inefficiencies, an abstract concept difficult to measure in the field. The discrete event simulation was also found effective at modeling operational inefficiencies. Therefore, this pilot study demonstrates that the proposed methodology for estimating optimal labor productivity is adequate when applied to a simple electrical operation. However, more research is required to determine the adequacy of the proposed approach when dealing with more complex construction operations, such as those involving crews of multiple workers performing parallel and sequential work. Future research will focus on determining the applicability, usefulness, and reliability of this methodology across a variety of construction tasks in both small and large projects.

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