

On the Use of Learning Curves for the Estimation of Construction Productivity

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Abstract

To account for the skill of construction crew, an ad-hoc coefficient is used as a multiplier of productivity estimations in most available methodologies today. However, little has been published on the determination of this coefficient and, moreover, on the way it is affected by repetition at the same working conditions. As such, research has been undertaken to associate the crew skill coefficient to the learning curve of a specific repetitive activity. Field measurements have been used as the basis to develop statistically sound datasets for subsequent use in simulation-based analysis. Field and simulation results have been compared in order to determine the most appropriate crew skill coefficient. The main conclusions are that the crew skill coefficient is better represented by an exponential learning curve, and that the accuracy of construction productivity estimation based on learning curves as opposed to empirical ad-hoc coefficients can be improved by 10- 15%.

Keywords

Crew skill coefficient, Learning curve, Productivity, Simulation

1. Introduction

Crew skill has a significant effect on construction productivity (Liu and Wang, 2012). Enhanced crew skill has been proven to improve craft time utilization and reduces labour waste (Gong *et al.*, 2011). The integration of the crew skill in the productivity estimation process is realized in the form of an ad-hoc coefficient (multiplier) in most available methodologies today. The values for the coefficients are derived empirically, mostly in the form of deterministic and constant values of questionable applicability (AbouRizk *et al.*, 2001). However, the construction industry is both labour-intensive and highly stochastic and the use of low reliability data may create difficulties in obtaining accurate benchmarks for productivity comparisons (Hwang and Soh, 2013). The intense variability in short-term productivity is often attributed to the involvement of the human factor, which is essentially represented by the skill level of the deployed crews in a construction project (Thomas and Horman, 2006). As the project evolves, the crew skills evolve as well, thus initiating a learning process that leads to a continuous improvement of construction productivity (Hwang, 2010). The latter, is specifically evident in repetitive projects that comprise complex construction operations (Thomas, 2009). Despite its importance, little has been published on the determination of the crew skill effect and, moreover, on the way it is affected by repetition at the same working conditions. As such, the purpose of this research is to associate the crew skill coefficient to the learning curve of a specific repetitive activity. The research objectives relate to the evaluation of the dynamic evolution of the learning phenomenon for individual activities and estimate their effect on construction productivity at the project level.

This paper first provides background information on pertinent research regarding the importance of crew skill in construction productivity studies, followed by a concise description of the learning curves theory. Then, the research methodology is going to be delineated and, subsequently, the model set-up process, including the definition of the workflow and the learning parameters assignment will be presented in a step-wise fashion. The models' analysis and sensitivity will be described along with the estimation of the crew skill coefficient and, finally, the main emerging inferences will conclude the study.

2. Crew skill and learning curves

Crew skill is one of the most important labour productivity drivers (Rojas and Aramvareekul, 2003). Construction productivity research is differentiated on the parameters that are associated with crew skill, as well as the analytical tools that are used for its investigation. For example, typical crew-related parameters examined in pertinent literature are crew composition and number (Florez and Castro-Lacouture, 2014), continuity of labor flow (Thomas *et al.*, 2004), the net crew utilization time (Gong *et al.*, 2011), the degree of multi-skilling within a specific crew or groups of crews (Liu and Wang, 2012) and the skill of the operators for equipment-intensive operations (Bernold, 2007). In terms of the deployed analytical tools, the crew skill effect has been examined through statistical regression models (O'Connor and Huh, 2006) and by the use of artificial neural network models (Oral *et al.*, 2012). More advanced tools, such as simulation, have been used, but crew skill has only been examined indirectly, merely as a system parameter and not as an explicit productivity variable (Huang *et al.*, 2004).

The amount of time, cost or number of work-hours required for the execution of a series of activities is graphically expressed by the use of learning curves (Everett and Farghal 1994). The straight line (or Boeing/Wright) model has been the preferred mathematical model for learning curve studies (Hinze and Olbina 2009). Its name is derived from the fact that it yields a straight line when plotted on a log-log scale (Hijazi *et al.*, 1992). Hinze and Olbina (2009) argue that using alternative models does not change much for the accuracy of the analysis and therefore the straight-line model has been adopted for this study as well. The mathematical expression of the straight line model is provided as follows (Hijazi *et al.*, 1992):

$$Y_x = A \times X^n \quad (1)$$

$$n = \ln L / \ln 2 \quad (2)$$

where Y_x = the cumulative average time expressed in work-hours (whs) to complete the construction of X units, A = the time required to construct the first unit; X = total number of units for which Y_x is calculated; n = the slope of the logarithmic scale; and L = learning rate expressed as a percentage value.

3. Research Methodology

The research methodology is depicted in Figure 1 below. First, the model is set up. This study makes use of the prototype simulation platform *CaissonSim*® (Panas and Pantouvakis, 2014; Pantouvakis and Panas, 2013). Although the reader is referred to Pantouvakis and Panas (2013) for more information about the particulars of the simulation platform, it should be noted that *CaissonSim*® contains standard simulation models which describe the caisson fabrication process. In general, floating caissons are prefabricated concrete box-like elements with rectangular cells that are suited for marine and harbor projects and are usually cast on floating dry docks. As such, each one of the seven models in *CaissonSim*® represents a different method statement and activity sequence for their construction. Then, the data collection process initiates which comprises direct observation of construction activities combined with experts input (e.g. interview with project manager) to improve the robustness of the created data sets. The possible distribution functions can be selected along with their parameters based on summary statistics (e.g. quantile summaries, box plots) (Martinez, 2010). The goodness of fit for the selected distribution is being evaluated by the creation of specific graphs (e.g. Q-Q or P-P plots) combined with statistical checks (e.g. Chi-square, Kolmogorov-Smirnov, Anderson-Darling) (AbouRizk and Halpin, 1990; Maio *et al.*, 2000). An iterative process is being initiated until the proper distribution has been defined. Following the successful statistical checks, the estimator should assign learning parameters to each model activity “T”. By learning parameters the following is meant: (a) the learning rate of the activity (ActTLR belongs to [0,1]) and (b) the number of caissons (ActTCaissonLimit) beyond

which the trend of improvement has converged to zero, which represents the standard production point or learning development threshold. It should be noted that the standard production point has been defined in terms of the number of units after which no learning occurs and not as a standard duration value. This decision has been reached after consultation with project experts who believed that when no previous knowledge of the activity is present, determining the number of expected cycles to reach the productivity threshold gives a more realistic view than defining some random activity duration input. Upon the specification of the learning parameters for all activities, simulation runs can be executed, by determining, inter alia, the number of independent replications and the level of confidence. The results are compared to the actual data and the extent to which the abstract model corresponds to the actual situation on-site is evaluated, i.e. model validation. If the validation results are not satisfactory, new data must be provided to the model, so as to improve its accuracy.

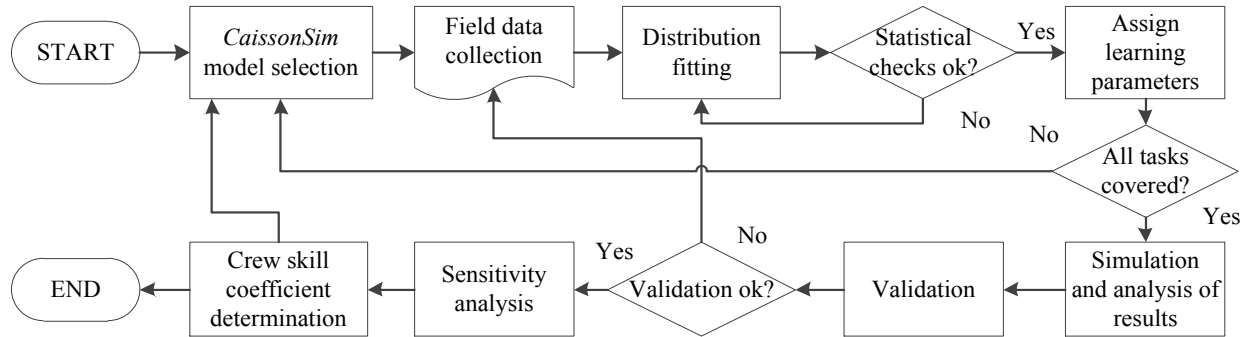


Figure 1: Research Framework

Sensitivity analysis is performed to optimize the model’s performance under variation of the critical model parameters. Sometimes, the decision making process requires the examination of alternative scenarios (e.g. different construction methods and techniques). In this case, alterations in the model set-up must be induced, so as to represent the variations in the operational setting. Then, the crew skill coefficient is determined as follows: From a productivity-oriented stance, it can be argued that the crew skill in repetitive activities is effectively represented by the learning rate of the crew that is deployed in that activity. The learning rate expresses the improvement that is gradually induced in the crew’s performance, which is subsequently transformed into a dynamic increase of the achieved productivity. In that sense, there is a positive correlation of the crew skill and the learning rate: the more learning-efficient the crew, the more skilled it becomes. Therefore, the ratio of the theoretical productivity to the actual on-site productivity, if all other system parameters are held constant, represents the overall crew skill coefficient on the project-level:

$$Q_{eff} = Q_{th} \times f_{crew} \quad (3)$$

where: $Q_{eff/th}$ = effective/theoretical productivity for a given activity; f_{crew} = crew skill coefficient (multiplier) for the adjustment of theoretical to effective productivity.

A detailed description of the methodological framework’s implementation in a real construction project is presented in the following sections.

4. Framework implementation

Step 1 – Definition of workflow and CaissonSim® model selection: Due to the standardized shape of the caissons and the repetitive nature of the works, since caissons are always constructed in batches, the concreting process is most commonly executed with the use of the slipforming construction technique. Slipform is a sliding-form construction method, which is used to construct vertical concrete structures (Zayed et al. 2008). Generally, the concreting and slipforming process comprises three sub-phases (see Fig. 2): (i) slipform assembling phase, (ii) slipforming phase (including an initial concreting phase) and (iii) slipform dismantling phase. Although Pantouvakis and Panas (2013) identified nineteen activities for the construction of a caisson, this study focuses only on the aforementioned activities, because a fundamental prerequisite for the learning phenomenon to develop is for productivity improvements to be able to occur as a result from repeating “sufficiently complex” activities (Thomas, 2009). As such, in the case of caissons construction operations, only these activities were found to inherently possess such characteristics, since the observed productivity of the other activities did not fluctuate significantly during the construction phase. From the simulation models library, the standard model that corresponds to the project under study was “Model 5.3.1” whose description is the following: *Construction of caissons on a floating dock in a single phase, meaning that the caissons are removed from the dock when the entire production cycle has been completed. Deployment of the same concrete crew and rebar installation crew for both the foundation slab and caisson core construction.*

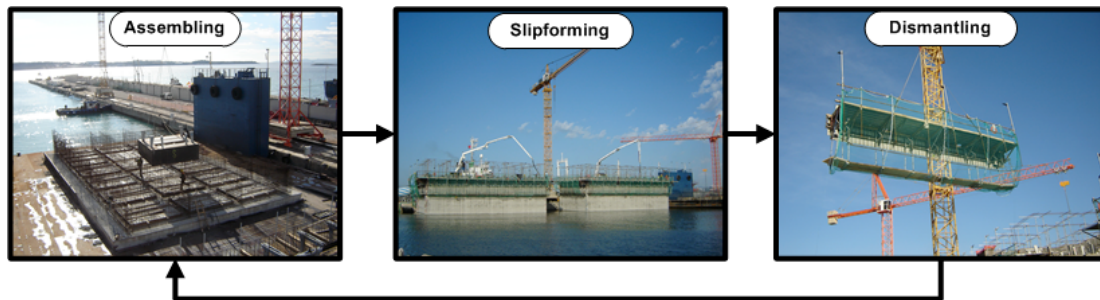


Figure 2: Floating caisson production cycle

Step 2 – Field data collection and distribution fitting: Productivity field data expressed in workhours/activity’s output (e.g. whs/m²) have been collected for all caisson fabrication activities. The recorded durations for each activity were fitted to a pre-defined probability distribution (Beta, Erlang, Exponential, Gamma, Normal, Triangular and Uniform) based on the analysis of field data representing the first four of the twenty-four caissons that have to be constructed in total. The BestFit distribution fitting add-on of the @RISK (Palisade, 2013) software package has been used for the distribution fitting process.

Step 3 – Assignment of learning parameters: The studied project comprised the construction of 24 caissons. The learning parameters have been determined for the estimation of both the theoretical and the effective productivity. The theoretical productivity is a benchmark against which the efficiency of the construction process would be evaluated. The learning rate for the derivation of the theoretical productivity was determined from the detailed historical database of the project contractor, whereas the respective learning rates for the effective productivity were calculated from actual field measurements. More specifically, the least mean square method has been used to determine the learning rate for every activity, namely the assembling (92%), the initial concreting (78%), slipforming activity (100%) and dismantling (87%). Subsequently, in an attempt to provide a more accurate representation of reality, a triangular distribution in the region of ±5% was defined for the previous learning rates. For example, the learning rate for the assembling activity is defined as triangular (0,87; 0,92; 0,97) (see Table 1 below). The standard production point for the simulation analysis was set at the 19th caisson, since it has been

found that at this point (namely at $19/24 \approx 80\%$ completion of the total project scope) the learning phenomenon fades out and no additional improvement is expected.

Table 1: Learning parameters for theoretical and effective productivity estimation

Activities	Learning rate		Learning threshold
	Theoretical productivity (historical data)	Effective productivity (actual on-site data)	
Assembling	Triangular[0,74;0,78;0,82]	Triangular[0,87;0,92;0,97]	19 th caisson
Initial concreting	Triangular[0,85;0,89;0,93]	Triangular[0,74;0,78;0,82]	19 th caisson
Slipforming	Triangular[0,83;0,87;0,91]	Triangular[0,95;1,00;1,00]	19 th caisson
Dismantling	Triangular[0,91;0,96;1,00]	Triangular[0,83;0,87;0,91]	19 th caisson

Step 4 – Simulation, analysis of results and validation: Each simulation experiment consisted of thirty independent replications at a 90% confidence level. Two models were created: the first model is based on the theoretical learning rate (left column of Table 1), whereas the second model is based on the actual on-site learning rates (right column of Table 1). Both models have the same activity durations, which were specified according to the fitting procedure described in Step 2. The results of the simulation experiment are depicted in Figure 3. It can be seen that the simulation of the actual on-site data yielded an average cumulative productivity of 6.822 whs/caisson, whereas the historical data case produced an average cumulative productivity of 4.976 whs/caisson. This is translated into a productivity difference of 37,09%, which is very significant for projects of this magnitude.

Step 5 – Sensitivity analysis: In an attempt to investigate the cause of the productivity variation between the two models (i.e. historical and actual on-site), the learning rate of the Slipforming activity was modified. This decision was based on the suggestion of Panas and Pantouvakis (2013), who found that the learning rate of the slipform activity is the critical productivity parameter in slipforming construction operations. Thus, the improved slipform learning rate was derived as the average value of the triangular distribution parameters between the historical and the actual case. In that sense, the new learning rate was defined as Triangular[0,89;0,94;0,96], where $0,89 = (0,83+0,95)/2$. The simulation experiment was repeated with all other parameters constant and the results are depicted on Figure 3, where the average cumulative productivity is estimated at 5.886 whs/caisson. It is evident that a marginal improvement (i.e. reduction) of the learning rate in the region of 6% leads to an average improvement of average cumulative productivity at about 13%.

Step 6 – Crew skill coefficient determination: The crew skill coefficient (f_{crew}) is estimated by applying Equation 3 to all datapoints for each caisson whose productivity is predicted, i.e. caissons 5 to 24. The theoretical productivity values (Q_{th}) are derived from the simulation-based analysis of the historical data, whereas the effective productivity (Q_{eff}) is estimated from the respective productivity values of the actual data simulation. The trendline of the estimated crew skill coefficient is plotted on Figure 4.

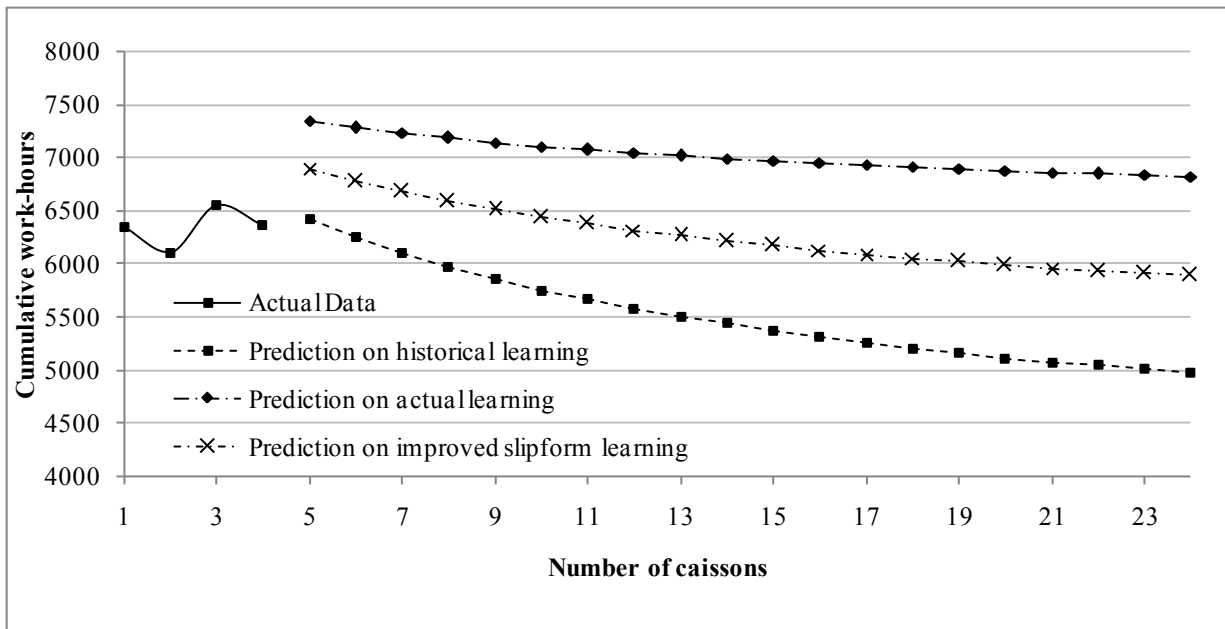


Figure 3: Simulation-based analysis of caisson fabrication productivity

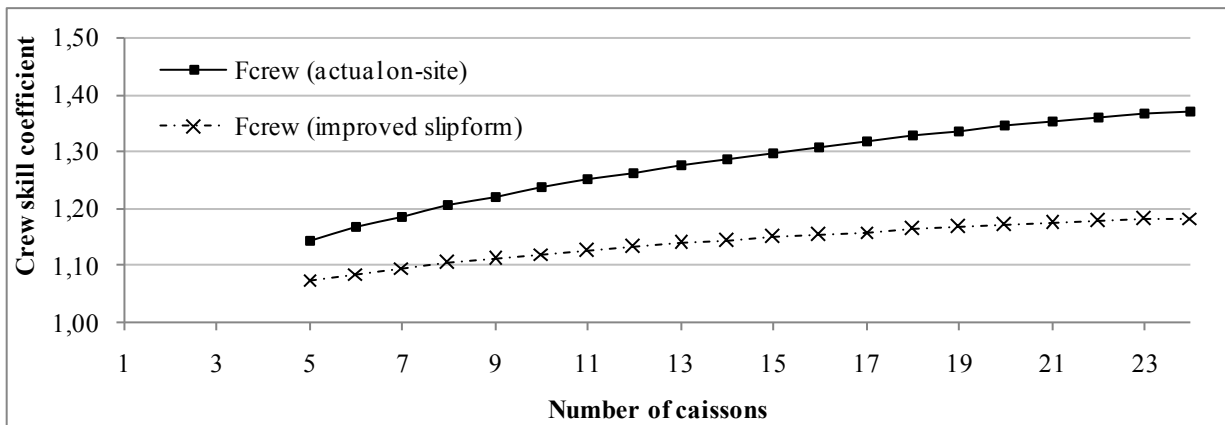


Figure 4: Diagrammatic depiction of the crew skill coefficient (f_{crew}) trendline

5. Discussion and conclusions

The results of the analysis show that there is a significant divergence of the predicted productivity values derived from the actual on-site measurement and the historical record of the project contractor. The sensitivity of the system to the slipform's learning rate denotes that an improvement is needed for the execution of the slipforming operations. Besides, the fact that the slipform activity had a learning rate of 100% based on the least square method, meant that the learning phenomenon in this critical activity did not evolve during the construction of the first four caissons. According to interviews with key project actors this was attributed to the concrete's chemical composition, which did not allow for fast curing and, consequently, fact sliding rates. This highlights the importance of the technical factors in construction productivity analysis, apart from the deployment of equipment or labour crews. The sensitivity analysis demonstrated that a small improvement of the learning rate, results in major gains in construction

productivity and accelerates the project's progress. The crew skill coefficient's graph illustrates the dynamic variation of its values. It should be noted that $f_{crew} > 1$ for all remaining caissons with an increasing pace. This practically means that even though the learning phenomenon will develop eventually, the deployed crew will never be able to reach the efficiency levels represented by the contractor's historical data.

On any case, this research has demonstrated the direct relationship of the crew skill coefficient and the learning curves. The use of the validated prototype simulation platform *CaissonSim*® has contributed in combining the merits of simulation-based analysis and learning curves for the investigation of a project's progress from a productivity perspective. Although the reviewed project is in an initial state, the analysis has substantiated the delay in the learning phenomenon development, which resulted in a sub-optimum project performance. The presented methodology represents a practical tool for evaluating the project status, which could be further elaborated into a fully developed ranking system (e.g. targeted at projects and/or activities) for more efficient project control. As more data are fed into the simulation models, the more accurate predictions are going to be made, which will help project executives in reaching informed decisions.

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