Technical Note

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Learning Curves in Construction: A Critical Review and New Model

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Abstract: This paper brings forth from the literature a series of learning curve models and evaluates them through the lens of the construction industry. The review suggests that there is still no consensus on which model provides the best fit and predictability for construction data. As such, this paper puts forth a new model that is suitable for the modern construction industry as it accommodates for both mechanization and forgetting. The proposed model is similar to the Wright model (an exponential model of learning), but, through recursion, places more emphasis on recent data. The proposed model shows an error of less than 1% when predicting the cumulative average completion times in three out of four cases examined. **DOI: 10.1061/(ASCE)CO.1943-7862.0001096.**

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Introduction

Practice makes perfect is a proverb that exists in almost every culture and language. From experience, the time and effort required to perform any task decreases as the number of repetitions increases (Lam et al. 2001). This decrease is caused by a phenomenon called the learning effect, which is represented mathematically by the learning curve. The learning curve concept originated in the airplane manufacturing industry and was first formalized by T. P. Wright in 1936 (Wright 1936). Subsequently, applications of the learning effect spread throughout other sectors within the realm of manufacturing (Argote and Epple 1990): the automotive industry (Baloff 1971), the chemical industry (Lieberman 1984), photovoltaic production (Nemet 2006), and semiconductors (Cook 1991; Gruber 1992, 1994, 1996, 1998; Chung 2001). As witnessed in these fields, understanding the dynamics of the learning effect through the use of the learning curve supports planning. The construction industry is no different and also stands to gain significantly when applying the learning curve (Rosenbaum et al. 2012).

The first reference to learning in the construction industry is in the 1965 Economic Commission for Europe report, *Effect of Repetition on Building Operations and Processes on Site* (Nations 1965). From the time of this initial report, the learning effect was applied to various site activities, such as prestressed concrete piles (Hinze and Olbina 2009), formwork (Jarkas and Horner 2011), rebars (Jarkas 2010), and caisson construction (Panas and Pantouvakis 2014). The learning effect also applies to the various stages of construction projects: design (Hamade et al. 2009), bidding (Wong et al. 2007), planning (Zhang et al. 2014), and even claim management (Lam et al. 2001; Hinze and Olbina 2009).

Despite the importance and the relevance of the learning effect in the construction industry, the literature addressing this matter is still limited (Thomas 2009; Malyusz and Pem 2014). There is no consensus regarding a model that provides good fit to historical data and, simultaneously, has acceptable predictive capabilities. A model with good fit is a model that can match historical data, whereas a model with good predictive capability is one that can use historical data to predict future data. The predictive capabilities of a model are particularly important in the construction industry as proper planning and resource allocation requires the prediction of future costs and durations. A contractor will not benefit from a model that perfectly matches the rebar fixing times in past projects but predicts negative completion times when extrapolated to future data.

Learning in Construction

As in any other industry, learning in the construction industry is not instantaneous and happens gradually. Generally, the learning process is divided into two stages: the operational learning stage and the routine acquiring stage (Nations 1965; Thomas et al. 1986; Gottlieb and Haugbølle 2010). It is during the first stage that the worker acquires the basic skills and becomes familiar with the task. For example, during this stage, workers tasked with the installation of drainage pipes learn the functionality of the excavating machines and become familiar with the soil in which they are working. During the second stage, the performance of the workers is boosted as shortcuts are discovered. It is during this second stage that the workers know how the equipment will react to the various soil types and can start organizing the workplace in a manner that permits optimal performance. However, Stage one and Stage two are overlapping because the workers can start optimizing their performance while they are becoming familiar with the equipment.

When measuring learning as a reduction in time to complete a task or cycle, the curve will be steepest following the startup point, the time to complete the first cycle. Following the startup point, the curve will begin to level beyond the standard production point, or the point in which the minimum time or maximum reduction in time to complete the task is achieved (Hinze and Olbina 2009).

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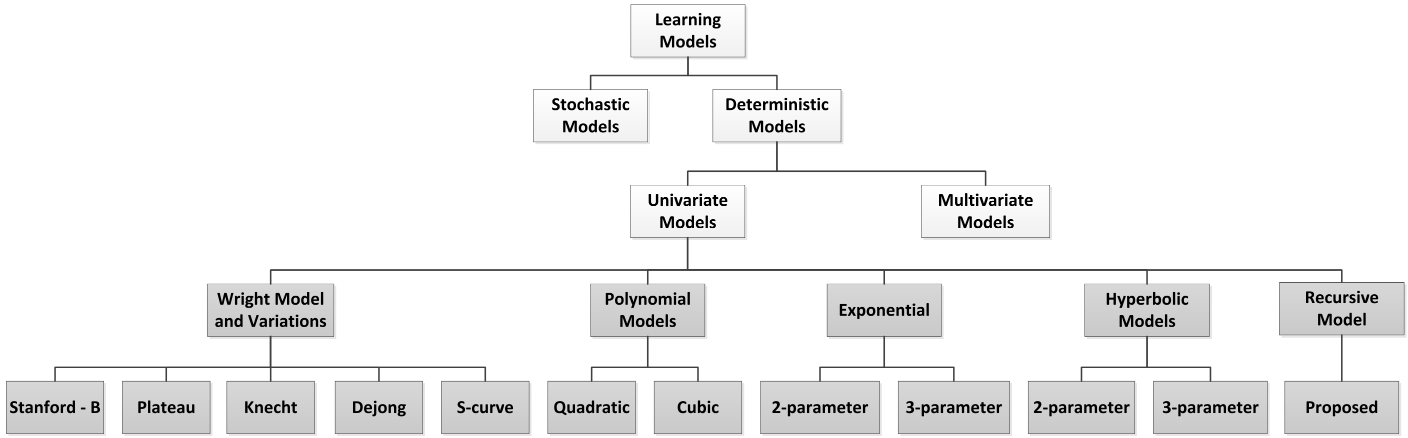

Fig. 1. Learning models

The major decrease in the cost or time, when compared to the initial cost or time, happens at the routine acquiring stage. After this stage no further improvement is witnessed and the performance reaches its steady state.

Learning Models

Given this two-point understanding of the learning process, multiple learning curve models have entered the literature. Fig. 1 highlights the main classes of learning models and shows how they differ in their mathematical form; the shaded boxes are the models reviewed in this paper. This selection highlights models of practical use within the field of construction. The model classes not included in this selection are the multivariate and stochastic models. While useful, these models require significant data and expertise for calibration—as such, they are not practical in the field of construction.

The oldest learning curve model is the Wright Model, $y = Ax^{-n}$ (Anzanello and Fogliatto 2011). In this model, y is the cumulative average, cost per unit; A is the cost of the first unit; x is the repetition or repetition cycle number; and n, a value between zero and one, is the slope of the logarithmic curve (Thomas et al. 1986). The learning rate, L, can be derived from the slope of the logarithmic form by using $L = 2^{-n}$. This learning rate information is of particular interest to a construction manager because it can be used to benchmark performance. Learning rates for various trades, which can be used as a starting point or benchmark, are listed in Hijazi et al. (1992) and Gottlieb and Haugbølle (2010). The Wright Model remains the most widely used learning curve model because of its simplicity (Baloff 1971; Globerson and Gold 1997), and its ability to provide acceptable precision and a simple mathematical structure (Vits and Gelders 2002).

Despite its popularity, one shortcoming of the Wright Model in construction is that it ignores the workers' previous experience. The Stanford-B Model, $y = A(x + B)^{-n}$, developed by the U.S. Department of Defense, uses B to represent the number of experience units and shift the curve downward (Badiru 1992; Nembhard and Osothsilp 2002). If $B = 0$, then this model reduces to the basic Wright Model (Badiru 1992; Gottlieb and Haugbølle 2010).

However, both of these models assume a continuous decrease in the cost, which is not realistic because there is a minimum nonzero time required to complete every task. The Plateau Model, originally introduced by Baloff (1971), $y = C + Ax^{-n}$ solves this problem through the use of C, representing the steady state performance of the worker; all other terms are as introduced previously (Li and Rajagopalan 1997; Anzanello and Fogliatto 2011). Knecht (1974) also recognized that learning does not continue ad infinitum and proposed a model with a changing learning rate, $y = Ax^{-n+1}/1 - n)$, in which the value of n, as before, falls in the interval (0,1).

While the plateau and Knecht (1974) models accommodate for a limit on learning, construction workers also are limited by the technology in use onsite. For example, the learning curve for manual excavation using a shovel is limited by the maximum labor performance, whereas excavation done by a mechanical excavator limits the operator's learning by the specifications and capabilities of the excavator. Therefore, when the operation is less mechanized and highly manual the time or cost is more prone to decrease with learning (Kara and Kayis 2005). The DeJong Model, $y = A[M + (1 - M)x^{-n}]$, developed in 1957 includes an incompressibility factor M that ranges from 0 to 1 (Hijazi et al. 1992). Thus, if the process is completely mechanized $M = 1$, no improvement will arise with more repetitions (Badiru 1992).

The S-curve model $y = A[M + (1 - M)(x + B)^{n}]$, developed following World War Two, combines both mechanization and experience (Badiru 1992). In this model, M is the incompressibility or mechanization factor and B represents the acceptable units of previous experience. Zhang et al. (2014) developed a similar variation of the S-Curve Model that accommodates for the effects of experience, steady state labor productivity, and mechanization. This model, termed the Improved Learning Curve Model, is represented by $y = AM + C_0 + [A(1 - M) - C_0](x + B)^{-n}$, in which C_0 is the standard time needed to complete the product under optimal conditions with perfect labor; all other terms are as before.

Most planners and estimation engineers assume flat learning rates and calculate costs. Of course, learning is rarely so steady. As such, the Polynomial Models—quadratic and cubic—may exhibit better fit. Both the Quadratic Model, $y = A + \beta_0 x + \beta_1 x^2$, in which A is the cost of the first unit, β_0 is the initial slope, and β_1 is the quadratic factor (Everett and Farghal 1994), and the Cubic Model, $y = A + \beta_0 x + \beta_1 x^2 + \beta_2 x^3$, in which β_2 is the cubic factor, require one to assume or calculate the coefficients. Unlike the learning rate and the cost of the first unit, these parameters have no direct practical meaning and thus may be difficult to estimate or justify. Moreover, these models do not have any limiting parameters allowing for negative estimates of the costs. Therefore, they are unsuitable for using past data to extrapolate and predict future performance as is necessary when preparing bids in construction.

The exponential model was recommended by the Norwegian Building Research Institute as a means to improve predictive capabilities of the model (Nations 1965). The most basic Exponential

Model is that proposed by Knecht (1974), $y = Ax^{-n}e^{cx}$, in which c is a constant. Just as the Wright model has variations, so too does the exponential model. The Three-Parameter Exponential Model, $y = \{k[1 - e^{-(x+p)r}]\}^{-1}$, includes k as a maximum performance parameter expressed as the number of units per operation time, p as the previous experience parameter expressed in units of time, and r as the learning rate given in units of time; x in this model is the number of units of operation time. By taking the inverse on the right hand side, y becomes the cumulative average time to complete a unit after the passage of x units of time. The Two-Parameter Exponential Model is identical to the three-parameter model save for the exclusion of the term p. The value of the exponential models is their ability to estimate and forecast data over long production runs in which the bound on learning is encountered. The limitation of the exponential models is that they are best applied to simple tasks such as fixing steel, manual excavation, cable pulling, installing wiring devices, and backfilling (Mazur and Hastie 1978).

A final set of models, the hyperbolic models, was originally designed to capture the effect of learning within compound measures of performance (Wong et al. 2007). These models have since been adopted to capture the number of units that can be produced within x units of time (Anzanello and Fogliatto 2011). In this paper, the models are manipulated further by taking the inverse to represent the cumulative average time required to produce a unit after x units of time have already been invested. The Two-Parameter Hyperbolic Model, $y = \{k[x/x + r)]\}^{-1}$, and the Three-Parameter Hyperbolic Model, $y = \{k[(x + p)x + p + r)]\}^{-1}$, allow for the inclusion of a maximum performance parameter k, a measure of previous experience p, and the learning rate r. The hyperbolic model can be used for novel and complex tasks (Anzanello and Fogliatto 2011). Moreover, by adjusting the learning rate appropriately, one can estimate costs after long breaks or model the performance of the workers during crash periods when they are fatigued (Uzumeri and Nembhard 1998).

All of the models presented in this paper assume that learning is measured as a cumulative average time to complete a task after a given number of repetitions or amount of time (as in the exponential and hyperbolic models), and that a decrease in that cumulative average time depends on only one variable, the number of repetitions. However, task time reduction within the construction industry likely depends on multiple site-related factors. Unlike manufacturing, the layout in the location in which a specific task is performed easily can vary from cycle to cycle despite the repetitive nature of the task itself.

Proposed Model

One strategy to capture site-specific information in the model is through the use of recursion. The need for a recursive model was noted by Adler and Clark (1991) who recognized that experience or repetition alone was not enough to fully explain gains and losses in productivity among workers. By including a term relating the time required for the last or previous item to that of the current or next item, the intrinsic changes in the learning process can be captured.

Given these considerations, a recursive model is proposed, represented by $y_n = y_{n-1}2^{-(r_{n-1}+\varepsilon)} + b_0 y_{n-1}H^{-a} + M$, in which y_n is the cumulative average cost or time required to produce the nth unit, y_{n-1} is the cumulative average cost of the previous unit or the last unit before an interruption (if applicable), r_{n-1} is the learning rate associated with the $n - 1$th item, ε is an additive factor that updates the learning rate between repetitions and prevents the productivity from reaching infinity, b_0 is a binary parameter that allows for the exclusion (0) or inclusion (1) of the experience

Table 1. Parameters for Models Derived from Optimization over the First Half of Each Respective Dataset

Model	Case 1, parameters	Case 2, parameters	Case 3, parameters	Case 4, parameters
Wright, $y = Ax^{-n}$	$A = 10.95$, $n = 0.17$	$A = 26.74$, $n = 0.39$	$A = 100.31$, $n = 0.14$	$A = 221.91$, $n = 0.0074$
Quadratic, $y = A + \beta_0 x + \beta_1 x^2$	$A = 10.71$, $\beta_0 = -0.48$, $\beta_1 = 0.01$	$A = 29.25$, $\beta_0 = -4.35$, $\beta_1 = 0.26$	$A = 113.67$, $\beta_0 = -14.46$, $\beta_1 = 1.62$	$A = 221.90$, $\beta_0 = -0.52$, $\beta_1 = 0.01$
Exponential, $y = Ax^{-n}\exp^{cx}$	$A = 10.99$, $n = 0.17$, $c = 0.001$	$A = 26.63$, $n = 0.43$, $c = 0.013$	$A = 99.10$, $n = 0.18$, $c = 0.016$	$A = 221.91$, $n = 0.01$, $c = 0.00$
2-parameter hyperbolic, $y = [k(x/x + r)]^{-1}$	$k = 0.15$, $r = 7.89$	$k = 0.16$, $r = 88.81$	$k = 0.01$, $r = 33.84$	$k = 0.005$, $r = 3.66$
Proposed, $y_n = y_{n-1}2^{-(r_{n-1}+\varepsilon)} + b_0(y_{n-1}H)^{-a} + M$	$y_0 = 10.97$, $r_0 = 1.55$, $\varepsilon = 0.15$, $b_0 = 0$, $M = 6.40$	$y_0 = 27.00$, $r_0 = 1.05$, $\varepsilon = 0.12$, $b_0 = 0$, $M = 8.74$	$y_0 = 100.63$, $r_0 = 0.83$, $\varepsilon = 0.00$, $b_0 = 0$, $M = 34.25$	$y_0 = 221.43$, $r_0 = 0.12$, $\varepsilon = 0.00$, $b_0 = 0$, $M = 16.94$

Table 2. Summary of Fit and Predictability of the Models across the Four Cases

Case, measure	Wright	Quadratic	Exponential	2-parameter hyperbolic	Proposed
Case 1, fit R^2	0.998	0.954	0.998	0.898	0.999
Case 2, fit R^2	0.998	0.957	0.9995	0.999	0.997
Case 3, fit R^2	0.821	0.821	0.831	0.725	0.863
Case 4, fit R^2	0.578	0.651	0.578	0.323	0.652
Case 1, predictability, MAPE (%)	4.56	58.44	2.98	7.53	0.57
Case 2, predictability, MAPE (%)	9.59	146.4	2.80	4.47	0.55
Case 3, predictability, MAPE (%)	2.23	36.54	2.08	3.48	2.99
Case 4, predictability, MAPE (%)	0.54	0.41	0.54	0.94	0.51
Case 1, paired t-Test, p-value, $n = 40$	0.00	0.00	0.00	0.00	0.87
Case 2, paired t-Test, p-value, $n = 19$	0.00	0.01	0.00	0.00	0.88
Case 3, paired t-Test, p-value, $n = 10$	0.14	0.06	0.31	0.13	0.15
Case 4, paired t-Test, p-value, $n = 26$	0.12	0.13	0.12	0.00	0.97

gained prior to an interruption, H is the length of the interruption, a is a forgetting factor, and M captures the steady state performance, likely influenced by mechanization.

Fit versus Predictability

The majority of the existing literature focuses on analyzing the goodness of fit of models rather than their ability to predict future performance (Farghal and Everett 1997). The most widely accepted metric for the goodness of fit is Pearson's coefficient of determination, R^2 (Thomas et al. 1986). However, when using the learning curve in planning activities, it is equally important to analyze a model's capability to predict future performance. The works of Everett and Farghal (1997) and Farghal and Everett (1997) are among the major contributors in this domain. The method suggested by these works requires splitting the existing set of data exactly in the middle and then applying the fitted equation to predict the future values in the second set of data. The predictability of the model is then evaluated as an absolute percentage difference between the predicted and actual costs.

To study the capabilities of the models presented in this paper, in terms of both fit and predictive capability, benchmark data from four different projects cited in the literature were used. The first project requires estimating the effect of learning in the construction of each floor in a 40-floor building in China (Zhang et al. 2014). The second project models learning across 19 cycles associated with the construction of tunnel formwork (Farghal and Everett 1997). The third project studies learning across the cementing of 10 floors within a comparatively smaller housing project in Poland (Nations 1965). The fourth project examines learning across 26 cycles associated with installing formwork for floors in an office building (Jarkas and Horner 2011). These projects were selected given their representative nature in terms of size, type, and era of construction, with older projects representing cases with potentially less automation.

In reality, the model parameters could be obtained either by an optimization process that minimizes the least sum of squares or by using expert opinion. In this paper, the relevant parameters for all models were derived via an optimization process over the first half of the data. The specific models resulting from the optimization of the parameters are shown in Table 1. Only one representative model was studied from each of the categories: (1) the Wright model was selected from the Wright model and variations, (2) the quadratic model was selected from the polynomial models, (3) the basic Exponential Model from the exponential models, (4) the Two-Parameter Hyperbolic Model from the hyperbolic models, and (5) the proposed model as the only recursive model. The models excluded, include those requiring the estimation of experience, mechanization, or performance bounds as reasonable estimates for these terms, were unknowable from the data provided in the case studies.

The results of both fitting the models to the first half of the data and using the fitted models to predict the second half of the data are summarized in Table 2. The fit is stated as the R^2, for which a value closer to 1 represents a better fit; the predictability was measured using the mean absolute percent error (MAPE), for which a value closer to 0% indicates a better result. Table 2 also provides the p-value for a paired t-test between the model-predicted cumulative average times per unit and the actual observed cumulative average times. In these tests, the null hypothesis is that the difference between the predicted and actual data is zero; a p-value greater than 0.05 supports this null hypothesis.

The results in Table 2 indicate that the proposed model exhibits a level of fit comparable to all other models. This is to be expected as the parameters were set with the goal of optimizing the fit across the first half of the data in all cases and for all models. The ability of the proposed model to predict the values in the second half of the data is superior in the first two cases, moderately worse in the third case, and comparable in the fourth case. Overall, however, when performing a paired t-test between the actual and the predicted values, the proposed model is superior in three of the four cases (Cases 1, 2, and 4). Case 3 presents an interesting finding as all models confirm the null hypothesis of no difference between the observed and predicted values. Furthermore, the significance of the results in Case 3 indicates that the Exponential Model is superior to the others. Not only does this confirm the findings in the article from which this case originates, but it also highlights the models' capabilities on small projects. Case 3 had only 10 data points, five used for fitting and five used for prediction. The real value of the proposed model is in application to large projects in which the learning rate is likely to exhibit changes over time as in Case 1 with 40 floors.

Conclusion

Over the last four decades, the learning curve concept has gained popularity in the construction industry. One reason behind this increased popularity lays in an industry trend toward cost control as a reaction to the steady increase in labor and construction material costs. Contractors are developing schedules, checking progress, and gathering data about site productivity on a regular basis. These data can be used to develop models describing cost reductions over time because of learning.

Various mathematical models have been developed for modeling learning in different industries. This paper presents a summary of the learning models from a mathematical and practical point-of-view within the construction industry. This review led to the proposal of a new model that accommodates both mechanization and forgetting. The proposed model is similar to the Wright model, but through recursion places more emphasis on the time consumed by the previous unit rather than the time used to construct the first unit. The model used in this study demonstrates less than 1% error in predicting cumulative average unit construction times in three out of the four cases studied.

Although these results are encouraging, further research is necessary to resolve multiple outstanding questions in the field. The issue of data representation should be handled with care when applying any learning model. Throughout this paper, the models focused on the use of a cumulative average for the xth unit or after x units of time. Using the cumulative average has the effect of smoothing the data, which eases the process of finding a mathematical function to fit the data. However, this smoothing process may make the predicted values less useable for the purpose of controlling activities on site. The proposed model, with its recursive structure may be better at supporting unit data as opposed to cumulative data relative to the other models. Further research is needed to verify this assumption.

Quality assurance and quality control are also possible future directions and the following question is to be answered: Does an improvement in quality occur alongside the observed reduction in time associated with learning? Moreover, multiskilling and job assignments also could be considered because managers must decide whether they should allow their workers to learn numerous trades or maintain their dedication to a single task.

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