Comparative Analysis of Learning Curve Models on Construction Productivity of Diaphragm Wall and Pile

SaravanaPrabhu G1* and Vidjeapriya R1.
Division of Structural Engineering, Department of Civil Engineering, College of Engineering Guindy, Anna University Chennai, India

* Corresponding Author: gsaravanaprabhu360@gmail.com

Abstract. In the analysis of construction operations, Learning Curves (LC) are considered one of the most important factors that determines the on-site variation in the productivity, which is usually considered in the construction projects during the estimation and planning stage. This research attempts to assess the suitability of LC models for the analysis of the learning phenomenon using productivity data for fairly complicated construction operations concerning the Diaphragm Wall and Pile Construction process from large-scale construction projects. In this study, the role of different LC models (i.e., Wright or Straight Line, Quadratic, Cubic, Knecht or Combined Exponential Log-linear, Stanford B) is investigated by the comparison of their outcomes through the utilization of cumulative productivity data of the activities involved in the Diaphragm Wall and Pile Construction process. The two main research objectives are (i) the investigation of the model which is the best fit for the historical productivity data of the completed construction activities (ii) an endeavour is formed to work out which model predicts the future performance better. The best suited LC model is predicted based on the least deviation from the yielded results of each model with respect to the actual construction data. Analysis of the cumulative average productivity data predicted that the Knecht or Combined Exponential Log-linear Model best fits both the complete Diaphragm Wall and Pile Construction Process in both the cases of fitting Historical data and in predicting future performance.

Key words: Learning Curve, Learning Curve Models, Productivity, Diaphragm Wall, Pile.

1. Introduction
In construction project management, for the construction activities to evaluate and boost the productivity is a significant challenge. There are many factors based on the managerial perspective of the individuals working on the project are taken into account while evaluating productivity of construction activities (Panas and Pantouvakis, 2010; Shan et al., 2011; Ralli et al., 2020)[1], [2], [3]. The repetitive nature of the activities involved especially in the construction projects is considered as one of the fundamental factors that tend to affect productivity of the construction activities. Therefore, due to the repetitive nature of construction activities it has been noticed that when executing construction activities (e.g. construction of high-rise building) in a repetitive manner each succeeding cycle of execution of activities may be improved because of the learning nature developed with the resources deployed in the project (Thomas et al., 1986; Panas and Pantouvakis, 2014; Pellegrino and Costantino, 2018; Srour et al., 2018). [4], [5], [6], [7]. For the repetitive tasks due to the increase in the experience of the crews deployed in the project the productivity is improved (Pellegrino et al., 2012; Ralli et al., 2020) [8], [3].
As the repetitions of execution of the construction activities increase, the required time (man-hours) for the execution of repetitive construction activities is decreased. This decrease in the man-hours due to repetition may be of the following reasons (i) the increase in the familiarity of the crew with respect to the nature of the works, (ii) the increase in the familiarity of the crew with respect to the working environment and site conditions (iii) the improvement in the coordination of the mechanical equipment (e.g. crane operation) and the crews involved in the repetitive activities, (iv) the betterment in the project management discipline with respect to the project, (v) the implementation of more efficient construction methods and techniques according to the project, (vi) The improvement in the logistics team by implementing more effective and efficient logistics management methods in the progressing projects (vii) the scope of the project is narrowed as the project progresses, thus reducing the need for more corrective actions. (Thomas et al., 1986; Ralli et al., 2020) [4], [3]. The learning phenomenon, also known as the learning curve effect, describes how the human aspect, mainly the skill and experience of the deployed personnel, affects construction productivity.

Learning curve theory studies, on the other hand, have been criticised for a number of flaws, including oversimplification of the construction process and use of a one-dimensional study approach which uses single learning curve model to predict and compare with the actual field data (Jarkas, 2016; Jarkas & Horner, 2011; Ralli et al., 2020) [9], [10], [3]. More specifically, the Wright or straight-line model is used in the majority of learning curve studies in construction, restricting the scope of the reported results and sometimes neglecting the effect of other learning parameters on the researched construction process. In order to analyze a quite complex construction process linked to the accomplishment of a large-scale construction project, this research will undertake a comparative analysis of five (5) established and widely recognized learning curve models. The overall objective of this study is to find the learning curve model which fits the best to the historical productivity and predicts the best to the future performance among the available learning curve models using cumulative average data for the Diaphragm Wall and Pile Construction. To the best of the authors knowledge this forms the first study to look into the application of learning theory concepts and comparison of LC models to Diaphragm Wall and Insitu Pile Construction Works from a productivity standpoint.

2. Literature Review
2.1. Learning Curve Theory
First Learning Curve Theory emerged from the aircraft manufacturing industry. In 1936 T.P. Wright was the first person who realized this concept and implemented (Jarkas, 2016) [9]. He made this as a model called the Wright Model (Srour et al., 2018) [7].

The learning curve theory indicates that the required time taken (man hours) for producing one unit (e.g. a floor of a high-rise building) is reducing successively with some percentage of time taken for the production of previous unit (Jarkas and Horner, 2011) [10]. That percentage rate at which time gets reduced is called "learning rate". This learning rate acts a variable for the learning phenomenon (Thomas et al., 1986). Suppose if the learning rate is lesser for an activity then it implies that the presence of more learning effect in that activity. Activities with the learning rate of 100% implies that there is no learning at all (Jarkas, 2016) [9].

Learning Curve Theory is applied in different construction activities by different researchers are (i) Megaprojects construction by Everett and Farghal in 1997 [11] (ii) RC Buildings Construction by Couto and Teixeira in 2005 [12] and Pellegrino et al in 2012 [8]. (iii) Offsite Precast Pile Fabrication by Hinze and Olbina in 2009 [13](iv) rebar steel and formwork installation by Jarkas in 2010 [14] and by Jarkas and Horner in 2011[10] (v) cell-shaped concrete caissons construction by Panas and Pantouvakis in 2014 [5](vi) gas pipelines construction by Ammar and Samy in 2015 [15](vii) Caisson Fabrication Process by Panagiota Ralli et al in 2020[3]

2.2. Data Representation
The data representation for the study of theory of learning curves has to be represented by the following techniques: (i) unit data, (ii) cumulative average data, (iii) moving average (iv) exponentially weighted
average data (Everett and Farghal, 1997 [11]; Malyusz and Pem, 2013 [16]; Ammar and Samy, 2015 [15]; Ralli et al., 2020 [3]).

The Unit data representation technique involves the time taken or the cost required per unit production or per activity execution. This data is nothing but the actual data of a repetitive construction activity (Everett and Farghal, 1997 [11]; Ammar and Samy, 2015 [15]). The Cumulative average data representation technique involves the average time taken or the cost needed for the execution or production of corresponding number of cycles or units (Everett and Farghal, 1997 [11]). This cumulative average data is nothing but the fraction of the total time taken for execution of required number of units to the corresponding number of units (Hinze and Olbina, 2009 [13]; Panas and Pantouvakis, 2014 [5]). The moving average representation technique uses the recent data with the timeframe based on the researcher’s preference for the analysis (Everett and Farghal, 1997 [17], Malyusz and Pem, 2013 [16]). The exponentially weighted average technique uses the most recent data integrated with the previous average and gives a result (Everett and Farghal, 1997 [11]).

The most used data representation technique especially in construction industry is the cumulative average technique particularly in the prediction analysis of LC Models. This detailed data representation can be referred to Everett and Farghal (1997) [17] and Malyusz and Pem (2013) [16].

2.3. Learning Curve Models
By the use different mathematical models, the learning curve phenomenon can be easily understood. The variation in onsite productivity with increase in the repetitive execution of number of units can be interpreted with the help of the mathematical learning curve models. By using these learning curve models during the execution of repetitive construction activities, the improvement in productivity can be observed by measuring the performance and also by predicting the performance (Jarkas 2016) [9].

From the understanding of the learning phenomenon, multiple learning curve models have been researched in the literature. The different mathematical learning curve models from literature are presented in this paper as a summary below.

2.3.1. Wright Model. Wright Model or Straight-Line Model or Log Linear Model is the oldest learning curve model. This model was developed by TP Wright in 1936 and its motive was the identification of factors affecting the cost in the aircraft manufacturing sector (Hijazi et al., 1992) [18]. The mathematical representation of the Wright model is

\[ y = A x^n \] (1)

where, \( y \) -is the cumulative average time (or cost) per unit required to produce \( x \) units, \( x \) -represents the number of the unit in production (repetition or repetition cycle number), \( A \) -time or cost required for the production of first unit, \( n \) -is a value between zero ‘0’ and one ‘1’ which represents the slope of the logarithmic curve (Thomas et al. 1986) [4]. The mathematical representation of the Learning Rate is \( L = 2^{-n} \) and \( L \) -represents the learning rate which will be derived from slope of the learning curve’s logarithmic form. Information about the learning rate depends on the interest of a particular construction manager. Based on the learning rate the performance benchmarking is done. Because of the simplicity in the model proposed by T P Wright, this LC model remains the most used model in the research (Baloff 1971 [19]; Globerson and Gold 1997 [20]). Besides this simple mathematical model is able to provide results with acceptable precision (Vits and Gelders 2002 [21]).

2.3.2. Stanford B Model. The popular Wright learning curve Model in construction has a limitation that the worker’s previous experience in their field is ignored. The US Department of defense developed the new learning curve model called the Stanford B Model by including the constant ‘B’ in the Wright model which includes the worker’s previous experience. The mathematical representation of the Stanford B model is represented by

\[ y = A (x + B)^n \] (2)
B represents the experience of number of units produced by workers. This parameter B shifts the learning curve downwards (Badiru 1992 [22]). In case if B = 0, then this Stanford B model reduces to the basic Wright Model (Badiru 1992).[22]

2.3.3. Plateau Model. The above models by Wright and Stanford B assumes that a continuous decrease in the time or cost will be achieved when activity is done in a repetitive manner. But in reality there is a minimum nonzero time or cost required to complete any kind of activity or production. This problem is solved by the model introduced by Baloff called the Plateau model. The mathematical representation of the Plateau model introduced by Baloff is given by

\[ y = C + A x^n \]  

C is the constant which represents the steady state performance of the worker (Baloff 1971) [19]

2.3.4. Dejong Model. All the above learning curve models lacks the use of parameter which gives an impact on the learning process because of mechanization. The process or activity which involves more of mechanization leads to less amount of learning or the learning period will be less. The process or activity which involves more of manual work leads to more amount of learning. DeJong proposed the model with an incompressible parameter in his model. The mathematical representation of DeJong Model is given by

\[ y = A \left[ M + (1-M) x^n \right] \]

where y, A, x, n are same as the Wright model, M is the incompressibility factor M that ranges from 0 to 1 (Hijazi et al. 1992) [18]. In the above model in case of complete mechanization the parameter M becomes 1 which stops the learning at all.

2.3.5. S-Curve Model. The mathematical representation of S-Curve Model is given by

\[ y = A \left[ M + (1-M) (x+B)^n \right] \]

where, y, A, x, n are same as the Wright Model, M is the incompressible parameter, B is the previous experience of the worker. This S-Curve Model developed combines both the previous experience gained and the amount of mechanization involved in the activity or process.

2.3.6. Quadratic Model. The mathematical representation of the Quadratic learning curve model is given by

\[ y = A + b_0 x + b_1 x^2 \]

where, A is the cost or time for the first unit, x is the repetition cycle, b0 represents the initial slope, b1 represents the quadratic factor (Everett and Farghal 1994) [23]

2.3.7. Cubic Model. The mathematical representation of the Quadratic LC model is given by

\[ y = A + b_0 x + b_1 x^2 + b_2 x^3 \]

where b2 represents the cubic factor which requires to be assumed or the coefficients to be calculated.

Unlike the parameter learning rate and the parameter for the cost of first unit used in the linear models, these parameters in the polynomial models have no direct practical meaning and therefore this will be difficult to calculate or justify. Besides this there is no limiting parameters for these models when this model may tend to predict a negative value.

2.3.8. Knecht Model. To improve the prediction capabilities of the model Norwegian Building Research Institute recommended the exponential learning curve model (Nations 1965). So, Knecht proposed a learning curve model called the Combined Exponential Log Linear Model. This model is a combination of Wright Model with exponential functions. The mathematical representation of this basic exponential model is given by

\[ y = A x^n e^{cx} \]

where y, A, x, n are same as the wright model and c is the constant that has to be found out by optimization or can be assumed.
2.3.9. **Two Parameter Exponential Model.** The mathematical representation of the two parameter exponential model is given by

\[ y = k \left[ 1 - e^{-\frac{x}{r}} \right] \]  

(9)

where \( y \) describes the worker’s performance in terms of number of items produced after \( x \) units of operation time, \( x \) represents the operation time, \( r \) represents the learning rate, also given in time units and \( k \) represents the maximum worker’s performance when the learning process is concluded, given in number of items produced per operation time (\( k \geq 0 \)).

2.3.10. **Three Parameter Exponential Model.** The mathematical representation of the three parameter exponential model is given by

\[ y = k \left[ 1 - e^{-\frac{(x+p)}{r}} \right] \]

(10)

where \( y, k, r, x \) are the parameters which are same as the two parameter model, \( p \) is the parameter which represents the worker’s prior experience evaluated in time units (\( p \geq 0 \));

2.3.11. **Two Parameter Hyperbolic Model.** The mathematical representation of the two parameter exponential model is given by

\[ y = k \left( \frac{x}{x+r} \right) \]

(11)

where \( y \) is the number of units produced after \( x \) units of time, \( x \) is time period and \( r \) is the learning rate.

2.3.12. **Three Parameter Hyperbolic Model.** The mathematical representation of the three parameter exponential model is given by

\[ y = k \left( \frac{(x + p)}{(x+p+r)} \right) \]

(12)

where \( y, x, r \) are same as the three parameter exponential model and \( p \) is the parameter representing the previous experience. The hyperbolic learning curve model can also be used for unique and complex tasks (Anzanello and Fogliatto 2011 [24]; Srour et al., 2016 [25]).

Besides these models in previous researches there are many variation of the above models using log to any parameter is also analysed (Ammar and Samy 2015 [15]).

### 3. Methodology

#### 3.1. Case Study Selection

Diaphragm Wall and Pile Construction Works from different large scale construction projects in India has been selected for the present study as testbed. The scope of the present study investigates to the construction of forty eight (48) Diaphragm Wall and also to the construction of thirty six (36) Piles.

The research case study selected is justified with number of reasons which includes: (a) Both Diaphragm Wall and Pile Construction is considered as an iterative and also complex construction activity, hence this satisfies the pre-requisition of the learning phenomenon to be developed; (b) besides availability of the sufficient number of data from activity output which is expressed in manhours (workhours)/activity to yield strong and reliable learning curves.

#### 3.2. Selected Activities

Diaphragm Wall Construction of dimension (2.5m x 0.9m) starts once the guide wall is constructed. The first activity is the Excavation of the soil inside the guide wall by Hydraulic Grab mounted in a crane upto a depth of 25meters which is the depth of Diaphragm Wall. Simultaneously the Bentonite is circulated in the pit during excavation which gives the lateral stability for the soil. The second activity is the Lowering of Stopends inside the pit on both ends. In this D Wall Construction Study for one end, two stopends are lowered one by one and connected by welding. The third activity is the lowering of Cage inside the pit. Here in the case of Cage Lowering, Rebar Cages are made into two half segments and lowered one by one with the upper half hanging from the crane gets welded with the lowered bottom half which is hanging in the pit with the help of supporting rods. Once the welding done Cage is lowered. The fourth activity is the Tremie Pipe Lowering and in this Tremie pipes of height 2m and 300mm dia
is lowered one by one connected by welding. The final activity is the concreting of D Wall with quantity of nearly 150 cum per wall which is done with the help of the pump and through the tremie pipe and tremie is uplifted simultaneously with concreting. The study on these activities is concentrated because: (a) these activities are critical activities and (b) these activities are of repetitive nature (c) these activities are highly complex in nature which needs highly specialized crews (d) these activities also satisfies that there would be a presence of learning phenomenon. In this study the onsite productivity data of all these activities mentioned above for D Wall is collected and analysed with respect to the learning perspective.

Pile Construction starts with initial marking following the initial boring upto certain depth depend upon the soil conditions of site. Then casing (1.21m dia) is installed in that boring which acts as a lateral support and guide for the further excavation. Once the installation of casing is done, then further boring upto a depth of 9m is done with the help of the auger attached with the hydraulic rig mounted with crane. This boring is simultaneously followed with the polymer stabilization. Then rebar cage with sufficient cover is lowered into the pit followed by tremie (150 mm dia) lowering. Then concreting (13cum/pile) of pile is done. In this study the onsite data for total pile construction is collected and analysed with respect to learning perspective, but not for its individual activities.

3.3. Learning Curve Models Investigation

In this study, five different learning curve (LC) models are examined. This assessment of the learning curve model is to find the best model that fits the historical productivity data of the completed construction activities and to find the best model for predicting the future productivity values of those activities. The evaluation of suitability of each learning curve model is based on the deviation of the prediction results of each learning curve model from the actual data collected from the construction site for those activities. Most of the learning curves drawn for the construction activities is plotted with the cumulative average time data rather than the unit data because of its easy convenience. (Thomas 2009 [26]). So, this research is based on the assessment of the LC model for the cumulative average data. In the case of long-term planning of projects, cumulative average time data plays a major role than the unit data (Everett and Farghal, 1997 [17]); Besides Cumulative average data gives curve smoothness and it is preferred to avoid scattered data (Ammar and Samy, 2015 [15]).

3.3.1. Stage A: Assessment of best fit model with historical productivity data. Based on the suggestions of Thomas et al. (1986) [4], this research approach is formulated. Besides most of the researches on Learning Curve Theory adopted the same approach as Thomas et al. (1986) [4] (Everett and Farghal, 1994 [23]; Wong et al., 2007 [27]; Ammar and Samy, 2015 [15]; Srour et al., 2016 [25]; Ralli et al., 2020 [3]). In this present research three types of data are used: (a) data from the field, (b) empirical data and (c) the data that are calculated or estimated by the mathematical relationships of the learning curve models.

To find out the optimum learning curve model and to determine its optimum parameters and to fit the curve, MS Excel solver function (version 2010) in conjunction with the least squares curve fitting analysis method (LSCFA) has been used. The analysis of best fit model with historical productivity data has been done under the following steps: (i) Optimization of Learning Curve Models with respect to the actual data with the Solver Addon in MS Excel. (ii) Then R^2 value is found out for each learning Curve Models using MS Excel by least square curve fitting Analysis. (iii) Finally Ranking of LC Models by giving high priority for LC Model with highest R^2 Value and low priority for LC Model with lowest R^2 Value.

Pearson’s coefficient of determination (R^2) is the most preferred metric and is quite often used as a tool for doing regression analysis especially for depicting the quantitative critical parameters in learning curve LC models for each LC model’s adjustment evaluation to historical productivity data. R^2 values fluctuate in the range from 0 to 1.00 whereas the R^2 values closer to 1.00 indicates the better correlation of the fitted data to the selected model.
3.3.2. Stage B: Assessment of best prediction model for future performance. The research methodology is based on the concept created by Everett and Farghal (1994) [23]. Everett and Farghal (1994)[23] had developed and proposed a methodology to assess the possibility and capability of estimating or predicting the expected productivity of the scheduled activities.

According to this research approach, the collected productivity data of the construction activities of n (n=48 for Diaphragm Wall and n=36 for Pile Construction) number of repetitions from the construction projects are divided in half as (m=n/2). The first half of the collected data (m=n/2) of the activities become the "historical data", while the second half of the collected data (m=n/2) of the activities be regarded as the future dataset for evaluation.

The analysis of best prediction model for future performance has been done under the following steps: (i) The least square curve fitting analysis method is applied for the first half of the collected data (m=n/2) of the activities in order to determine the optimum fitting curve, as well as the main model parameters. This involves Optimization of Learning Curve Models with respect to the first half of actual data with the Solver Addon in MS Excel. (ii) Pearson’s coefficient of determination (R$^2$ for 1st m repetitions) is calculated for the first half collected dataset of the activities and the estimated best-fitting learning curves are extended for predictions of the next half repetitions of the activities. However, since Pearson’s coefficient of determination (R$^2$) yields results that are acceptable only within the range of the data which were used to plot the respective learning diagrams (Everett and Farghal, 1994) [23], another metric was used for the evaluation of future performance. More specifically, the statistical metric Ef ("average percentage error") that was proposed by Everett and Farghal (1994) [23] specifically for learning curve models was used, with its mathematical expression being as illustrated in

$$E_f = \frac{100}{k} \sum_{i=1}^{k} \left| \frac{y_{m+i} - y'_{m+i}}{y_{m+i}} \right|$$

where: m = the number of Diaphragm Wall and Pile data to be fitted and here m = 24 (1-24) for the D Wall and m=18 (1-18) for the Pile; k = the number of Diaphragm Wall and Pile to be predicted here k = 24 (25-48) for the D Wall and k=18 (19-36) for the Pile; $y'_{m+i}$ = the value found on the extension of the optimized learning curve models; $y_{m+i}$ = the actual measured values of the construction activities; $E_f$ = is the statistical parameter called the average percentage error (APE), and its value ranges from 0% which shows a presence of perfect correlation between the extended optimized learning curve and the actual data to large positive values which indicates no correlation between the extended optimized curve and the actual data.

$E_f$ is the statistic metric which defines the average difference in percentage between the actual data from field and the predicted data by the models. The same method used in the historical best fit analysis is used for the evaluation of parameters but here (i) the optimization of the models with the actual data is done for the first half of the data i.e for first twenty-four (24) activities of D Wall and for first Eighteen (18) activities of Pile Construction then (ii) the Average Percentage Error $E_f$ is calculated for the remaining half the predicted data i.e for first 25 - 48 cycles of D Wall and for 19-36 cycles of Pile Construction.

4. Results and Discussion

4.1. Stage A: Assessment of Best Fit Model with Cumulative average Historical Productivity data

At first it is clarified that the LC models included in the evaluation process for best fit with respect to historical productivity data are (i) Wright, (ii) Quadratic, (iii) Cubic, (iv) Knecht, (v) Stanford B. Table summarizes the performance of each LC model with respect to cumulative data for the total Diaphragm Wall Construction as well as the activities involved in the D Wall Construction process and also for the Total Pile Construction Process. From the results of the Table 1 it is clearly indicated that for the Diaphragm Wall Construction the Cubic Model fits the best with respect to the cumulative average data for (a) Excavation by hydraulic grab for D Wall, (b) Stopend Lowering, (c) Tremie Lowering whereas the Knecht Model fits the best with respect to the cumulative average data for (a) the total Diaphragm
Wall Construction, (b) Cage Lowering (c) the Total pile construction. Both the Knecht Model and Cubic Model performed better for best fit.

Table 1 Correlation of LC Models for Completed Activities with Cumulative Average Data

| Activity          | Pearson’s coefficient of Determination ($R^2$) for LC Models |
|-------------------|-------------------------------------------------------------|
|                   | Wright          | Quadratic        | Cubic           | Knecht         | Stanford B     |
|                   | $R^2_{(1-n)}$  | Rank             | $R^2_{(1-n)}$  | Rank           | $R^2_{(1-n)}$  | Rank           |
| Total D-Wall      | 0.9415         | 5                | 0.9739         | 4              | 0.9925         | 2              | 0.9975         | 1              | 0.9899         | 3              |
| Excavation        | 0.9541         | 4                | 0.9832         | 2              | 0.9845         | 1              | 0.9818         | 3              | 0.9418         | 5              |
| Stopend Installation | 0.8092       | 5                | 0.9978         | 1              | 0.9934         | 3              | 0.9970         | 2              | 0.9547         | 4              |
| Cage Lowering     | 0.9717         | 4                | 0.9296         | 5              | 0.9763         | 3              | 0.9936         | 1              | 0.9924         | 2              |
| Tremie Lowering   | 0.9310         | 5                | 0.9789         | 4              | 0.9963         | 1              | 0.9960         | 2              | 0.9826         | 3              |
| Concreting        | 0.9781         | 4                | 0.9323         | 5              | 0.9827         | 3              | 0.9917         | 2              | 0.9953         | 1              |
| Pile Construction | 0.9306         | 5                | 0.9897         | 3              | 0.9940         | 2              | 0.9989         | 1              | 0.9875         | 4              |

Figure 1 illustrates the comparison of the developed learning curves (Optimized LC Models) for the total Diaphragm Wall construction process and similarly. It would be noted that equivalent learning curves (Optimized LC Models) for each activity of the Diaphragm Wall Construction also have been drafted, but those are not included in this paper for brevity reasons.

The following paragraphs which briefs the results of analysis of best fit with historical data for D Wall Construction, its individual activities and Pile Construction are as follows:

Total Diaphragm Wall Construction: Entire Diaphragm Wall Construction involves learning by the improvement in crane operation, coordination between different crews, adopting with crews, adopting with environmental conditions and site. From the analysis done for the total D wall Construction and from the results shown in Table 1, it has been observed that the Knecht model is found to be the best historical fit for the D Wall Construction done with $R^2_{(1-48)}$ value of 0.9976 following that the Cubic Model occupied the second position with $R^2_{(1-48)}$ value of 0.9925. Stanford-B Model occupied the third position with $R^2_{(1-48)}$ value of 0.9899. Quadratic Model occupied the fourth position with the $R^2_{(1-48)}$
value of 0.9739. The Basic Wright Model commonly used for learning curve research occupied the last position with $R^2 \text{(1-48)}$ value of 0.94.

Excavation by Hydraulic Grab: The Cubic model has performed the best while fitting the cumulative average data amongst all the LC models. Excavation by Hydraulic Grab is a complex activity, which was executed by highly specialized crews. Here the learning effect is observed in the operation of crane and hydraulic rigs, improvement in the methodology in excavation, improvement in the removal of muck, and also due to the improvement in the circulation of Bentonite which gives support to the soil. From the analysis done for the Excavation by Hydraulic Grab and from the results shown in Table 1, it has been observed that the Cubic Model is found to be the best historical fit for the Excavation activity done by both teams with $R^2 \text{(1-48)}$ value of 0.9845 following that the Quadratic Model occupied the second position with $R^2 \text{(1-48)}$ value of 0.9832 the Knecht Model occupied the second position with R2 value of 0.9813. The Basic Wright Model occupied the last position with $R^2 \text{(1-48)}$ value of 0.95. Therefore the Cubic model is found to simulate better for the effect of previous experience, as well as productivity (Thomas et al.,1986) [4].

Stopend Lowering: Here. The learning is mainly due to the improvement in the crane operation and frame positioning. From the analysis done for the Stop-end Lowering and from the results shown in Table 1, it has been observed that the Cubic Model is found to be the best historical fit for the Stopend Lowering with $R^2 \text{(1-48)}$ value of 0.9978 and Cubic model is found to be the best historical fit for the Stopend Lowering done with $R^2 \text{(1-48)}$ value of 0.9959 following that the Knecht Model occupied the third position. The Basic Wright Model occupied the last position with $R^2 \text{(1-48)}$ value of 0.81.

Cage Lowering: For Cage lowering the learning effect is observed in the operation of crane, lifting of cages, due to the change in the methodology of lifting cages, due to the improvement in productivity of welding team, also due to the improvement in the coordination between different teams. From the analysis done for the Cage Lowering and from the results shown in Table 1, it has been observed that the Knecht model is found to be the best historical fit for the Cage lowering activity done by both teams with $R^2 \text{(1-48)}$ value of 0.9936 following that the Stanford B Model occupied the second position with $R^2 \text{(1-48)}$ value of 0.9924. The Quadratic Model occupied the last position with $R^2 \text{(1-48)}$ value of 0.929.

Tremie Lowering and Flushing: For Tremie lowering and flushing the learning effect is observed in the operation of crane, improvement in the productivity of welding team and in their coordination. From the analysis done for the total Tremie Lowering & Flushing and from the results shown in Table-1, it has been observed that the Cubic model is found to be the best historical fit for the Tremie Lowering done with $R^2 \text{(1-48)}$ value of 0.9963 following that the Knecht Model occupied the second position with $R^2 \text{(1-48)}$ value of 0.9960 which is nearly same as the Cubic Model’s $R^2 \text{(1-48)}$ Value. The Basic Wright Model occupied the last position with $R^2 \text{(1-48)}$ value of 0.93.

Concreting: For Concreting works the learning effect is observed in the increase in the pouring rate of pump, improvement in the batching plant production rate, due to improvement in the transportation planning of concrete from batching plant to the site and also due to the improvement in the rate of tremie upliftment. From the analysis done for Concreting and from the results shown in Table 1, it has been observed that the Stanford B model is found to be the best historical fit for the Concreting Activity done with $R^2 \text{(1-48)}$ value of 0.9953 following that the Knecht Model occupied the second position with $R^2 \text{(1-48)}$ value of 0.9917. The Quadratic Model occupied the last position with $R^2 \text{(1-48)}$ value of 0.93 and 0.94.
Figure 2 illustrates the developed LC’s for the total Pile Construction Process.

Pile Construction: From the analysis done for the total Pile Construction and from the results shown in Table 1, it has been observed that the Knecht model is found to be the best historical fit for the Pile Construction with $R^2$ value of 0.9989 following that the Cubic Model occupied the second position with $R^2$ value of 0.9940. The Quadratic Model occupied the third position with $R^2$ value of 0.9897. The Stanford B Model occupied the fourth position with $R^2$ value of 0.9875. The Basic Wright Model occupied the last position with $R^2$ value of 0.9306.

As a summary from these results while analysing for the best fitting model it has been understood that in both the cases of Diaphragm Wall Construction and Pile Construction the Knecht Model and the Cubic Model performed best compared to all other models studied here. Quadratic Model performed better than the most used Basic Wright Model. When there was an previous experience with the crew then Stanford B Model is performing better as the polynomial models. When compared to the other models in all the cases the Wright Model performed poor in the best fit analysis.

Since most of the Construction Industry goes with the Wright Model, Learning Rate Analysis is also included in this study and the learning rates find out for different activities are given in Table 2. The learning rate was observed to be in the range of (83 – 89 %) for activities of D Wall and 85.15% for Total Diaphragm Wall Construction and 89.06% for Pile Construction.

| Activity                          | LR%  |
|-----------------------------------|------|
| Total Diaphragm Wall Construction | 85.45|
| Excavation By Hydraulic Grab      | 88.81|
| Stopend Lowering                  | 89.07|
| Cage Lowering                     | 83.86|
| Tremie Lowering and Flushing      | 83.22|
| Concreting                        | 85.36|
| Pile Construction                 | 89.06|
4.2. Stage B: Assessment of best prediction model for future performance using Cumulative Average Data

Table 3 presents the Pearson ($R^2_{1,m}$) $m=24$ for D Wall and $m=18$ for Pile values and the statistical metrics APE or $E_f(25-48)$ for D Wall and APE or $E_f(19-36)$ for Pile and the rank R of each model for the Diaphragm Wall, its individual activities and Pile Construction.

**Table 3** Results of LC Models for Future Performance Prediction with Cumulative Average Data

| Activity       | Wright     | Quadratic | Cubic     | Knecht    | Stanford B |
|----------------|------------|-----------|-----------|-----------|------------|
|                | $R^2_{1,m}$| $E_f$     | R         | $R^2_{1,m}$| $E_f$     | R         | $R^2_{1,m}$| $E_f$     | R         |
| Total D-Wall   | 0.9627     | 14.85     | 3         | 0.9879    | 66.24      | 4         | 0.9989    | 101.6     | 5         | 0.9942     | 3.22      | 1         | 0.9899    | 4.77      | 3         |
| Excavation     | 0.6576     | 24.5      | 4         | 0.9250    | 16.01      | 3         | 0.9491    | 136.3     | 5         | 0.9565     | 10.62     | 1         | 0.7650    | 12.61     | 2         |
| Stopend        | 0.7988     | 21.29     | 4         | 0.9942    | 11.20      | 3         | 0.9948    | 116.5     | 5         | 0.9957     | 5.04      | 1         | 0.950     | 10.86     | 2         |
| Cage Lowering  | 0.9812     | 9.85      | 3         | 0.9296    | 121.8      | 4         | 0.9763    | 233.4     | 5         | 0.9936     | 1.23      | 1         | 0.9924    | 5.17      | 2         |
| Tremie         | 0.8697     | 23.13     | 2         | 0.9926    | 67.05      | 4         | 0.9922    | 95.45     | 5         | 0.9975     | 9.02      | 2         | 0.9994    | 2.16      | 1         |
| Concreting     | 0.9743     | 8.11      | 3         | 0.9323    | 97.41      | 4         | 0.9987    | 140.8     | 5         | 0.9917     | 5.80      | 2         | 0.9953    | 1.60      | 1         |
| Pile           | 0.9673     | 11.8      | 3         | 0.9816    | 22.5       | 4         | 0.9940    | 76.3      | 5         | 0.9986     | 0.74      | 1         | 0.9932    | 5.4       | 2         |

**Figure 3** Comparison of LC Models for Best Prediction – D Wall Construction

Figure 3 indicates the comparison of LC models fitted for the first half of the values of Diaphragm Wall and extended for the remaining half of the D Wall datasets. Total Diaphragm Wall Construction: From the analysis done for the entire D Wall Construction and from the results shown in Table 3, it has been observed that the Knecht Model is found to be the best predicting model for the D Wall Construction done with APE ($E_f$) value of 3.22% following that the Stanford B Model occupied the second position with APE ($E_f$) value of 4.77%. Wright Model predicted with APE ($E_f$) value of 17%. The cubic model is the worst predictor with APE ($E_f$) value of 101% and
also the cubic model has no control in negative prediction. Quadratic Model also predicted with APE (E_f) of 66%.

Excavation by Hydraulic Grab: For the Excavation by Hydraulic Grab, it has been observed that the Knecht Model is found to be the best predicting model for the Excavation activity done by both teams with APE (E_f) value of 10.62% following that the Stanford B Model occupied the second position with APE (E_f) value of 12.61%. Wright Model predicted with APE (E_f) value of 25%. The cubic model is the worst predictor with APE (E_f) value of 136.3% with negative prediction values.

Stopend Lowering: For Stopend Lowering, it has been observed that the Knecht Model is found to be the best predicting model with APE (E_f) value of 5.04% following that the Stanford B Model occupied the second position with APE (E_f) value of 10.86% and 9.96% for Team A and for Team B. Wright Model predicted with APE (E_f) value of 21.29% and 23.41%. The Quadratic Model occupied the 4th position. The cubic model is the worst predictor with APE (E_f) value of 116.5% and also the cubic model has no control in negative prediction

Cage Lowering: For Cage Lowering, it has been observed that the Knecht Model is found to be the best predicting model for the activity done with APE (E_f) value of 1.23% following that the Stanford B Model occupied the second position with APE (E_f) value of 5.17%. Wright Model predicted with APE (E_f) value of 9.85%. The Quadratic Model and the cubic model are the worst predictors with APE (E_f) value of greater than 100% and also the cubic model has no control in negative prediction.

Tremie Lowering: For Tremie Lowering and flushing, it has been observed that the Stanford B Model is found to be the best predicting model for the activity done by both teams with APE (E_f) value of 1.55% following that the Knecht Model occupied the second position with APE (E_f) value of 9.02%. Wright Model predicted with APE (E_f) value of 7.17%. The Quadratic Model and the Cubic Model predicted with a APE (E_f) value of greater than 50%.

Concreting: For Concreting Works, it has been observed that the Stanford B Model is found to be the best predicting model for the activity done with APE (E_f) value of 1.60% following that the Stanford B Model occupied the second position with APE (E_f) value of 5.8%. Wright Model predicted with APE (E_f) value of 5.69%. The Quadratic Model predicted with the APE (E_f) value of greater than 90% and the Cubic Model predicted with the APE (E_f) value of greater than 130%. Both the polynomial Models are bad predictors. The Knecht, Stanford B and Wright Model are considered to be the best predictors.

**Figure 4** Comparison of LC Models for Best Prediction – D Wall Construction

Figure 4 indicates the comparison of LC models fitted for the first half of the values of Pile Construction and extended for the remaining half of the Pile Construction datasets.
Pile Construction: From the analysis done for the entire Pile Construction and from the results shown in Table 3, it has been observed that the Knecht Model is found to be the best predicting model with APE value of 0.74% following that the Stanford B Model occupied the second position with APE value of 5.4%. Wright Model predicted with APE value of 11.8%. The cubic model is the worst predictor with APE value of 76.3% and also the cubic model has no control in negative prediction. Quadratic Model also predicted with APE of 22.5%. The polynomial Models are poor predictors of future performance when compared to straight line models.

5. Conclusions
The conducted study found that the learning impact was strong in the analysed projects of both Diaphragm Wall and Pile Construction, resulting in substantial increase in productivity and efficiency in both the cases of construction of fifty (50) Diaphragm Wall and thirty-six (36) Piles.

More precisely, it has been observed that the initial time taken for the Diaphragm Wall Construction was 88hrs and 15mins and the average time taken for 48 cycles was 37hrs and 6mins which show a percentage decrease in average time taken with respect to initial time taken was 51.15%. Similarly for Pile Construction, the initial time taken was 9hrs and the average time taken for 36 cycles was 4hrs and 59mins (approx. 5 hrs) which show a percentage decrease in average time taken with respect to initial time taken was 44.66%. This further signifies that the decrease in time taken was achieved due to the repetition in the Diaphragm Wall and Pile Construction.

In the case of the total Diaphragm Wall construction process, all five learning curve (LC) models were examined for cumulative historical productivity data and yielded coefficient of correlation $R^2 > 0.90$, indicating a close connection to actual cumulative average data. In terms of convergence to historical results, the Knecht model (Knecht 1974) [28] has proven to be the best performer with $R^2$ value of 0.9975 followed by the Cubic Model with $R^2$ value of 0.9925. Similarly for the Pile Construction also, in terms of convergence to historical results the Knecht model (Knecht 1974) has proven to be the best performer with $R^2$ value of 0.9989 following the Cubic Model with $R^2$ value of 0.9940.

The learning Rate by Straight line Model of D Wall and Pile Construction was approximately 85% and 89%.

In the case of prediction analysis of future performance with Cumulative Average data for the total D Wall construction the Knecht Model (Knecht 1974) [28] gave the best predictions with the Average Percentage Error of 3.22% followed by the Stanford B Model with APE value of 4.77% and Straight-Line Model with APE value of 14%. Our results support previous studies (e.g., Everett and Farghal,1994) [23] by demonstrating that linear models are better at forecasting future efficiency. Here in this study the Knecht Model which is a Combined Exponential Log Linear Model performed well as the Straight-Line Model and Stanford B Model a modified version of Straight line Model. Similarly for the Pile Construction in the case of prediction analysis the Knecht Model (Knecht 1974)[28] gave the best predictions with the Average Percentage Error of 0.74% followed by the Stanford B Model with APE value of 5.4% and Straight-Line Model with APE value of 11.8%. In both the D Wall and Pile Construction Process both the polynomial models Quadratic and Cubic are observed to be performed worser with higher APE value in the case of analysis of future performance prediction and also observed that the Cubic Model predicted the negative values with no control on the model.
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