International Journal of Civil and Structural Engineering– IJCSE
Volume 2 : Issue 2 [ISSN : 2372-3971]
Publication Date: 19 October, 2015

Investigation of Learning Curve Effect on Gas Pipeline Construction in Egypt

[Mohammad A. Ammar and Mohammad Samy]

Abstract- Learning development effect plays an important role in planning and scheduling of repetitive projects. Several mathematical models, or learning curves, have been proposed to investigate improvement in productivity as a function of the number of units produced. Deciding the best-fit learning curve model for the activity under consideration is a management challenge. In this paper, the best-fit learning curve model for describing past performance of gas pipeline construction in Egypt is presented. Data were collected from real-life projects that are constructed in different types of land and having different size, length, pipe diameter and under various weather conditions. Only welding activity is considered in the present work because it is a labour-intensive activity. Cumulative average data is used to represent collected data, which gives a smooth curve as well as avoids scattered data. The commercial Statistical Package for Social Science (SPSS) is used to calculate Pearson's coefficient of determination as a descriptive measure of the association of dependent and independent variables. The cubic curve models are found to be the best fitting curves for describing welding activities in gas pipeline construction activities in Egypt.

Keywords- Repetitive Projects, Gas Pipeline Construction, Learning Development Effect, Learning Curve Models, Cumulative Average Data.

I. Introduction

Repetitive activities are those repeatedly performed from unit to other similar units. Projects comprising mostly repetitive activities are commonly classified as repetitive ones. Learning development effect is usually neglected in repetitive construction analysis and, therefore, time and cost estimates usually exceed actual values.

It is widely recognized that labor productivity improves when an operation is repeated several times. That is, the time and effort expended to complete repetitive activities decease as the number of repetitions increases due to learning [1]. This phenomenon is usually referred to as learning curve effect, or learning curve theory. Several reasons for this phenomenon are addressed [2].

Mohammad A. Ammar

Professor, Structural Engineering Department, Faculty of Engineering, Tanta University, EGYPT

Presently: Dean of the Faculty of Engineering, Madina Institute of Science and Technology, Accra, Ghana.

Mohammad Samy

M.Sc. Student, Structural Engineering Department, Faculty of Engineering, Tanta University, EGYPT

Learning curve models were employed to predict contractors' performance change [2,3,4,5]. Everett and Farghal [3] found that the straight-line model provides best correlation between actual and predicted performance for the tested models and activities. However, the cubic model that best correlates to historical data showed poor prediction of future performance. Adler and Clark [6] studied the effect of engineering changes and workforce training on learning curves and concluded that these effects vary substantially across processes.

Wideman [7] applied learning curve theory to identical floor construction of 25-story concrete building. The straight-line learning curve model is found useful in many practical applications and project management observation. Norfleet [8] used learning curve theory to track productivity during the construction process and to calculate damages incurred to support disruption claims. The conclusion was that the application of the learning curve should be used more in the construction industry, especially when cost data are available. Couto and Teixeira [5] successfully predicted the future performance of repetitive construction activities and incorporated the straight-line model in new planning methodologies for repetitive construction.

Hinze and Olbina [9] showed that pile fabrication crew improves its learning throughout the pile fabrication effort, but this improvement was quite small. The learning curve theory was found applicable well to large number of repeated items, and that the predictions made with learning curves are reasonably accurate. Jarkas [10] investigated the influence of learning effect on the rebar fixing trade, concluding that improvements continued for large number of units.

It is widely accepted that production rates of repetitive activities will improve with acquired experience and practice. Pipeline projects are good examples of repetitive projects that affected extremely by learning curve effect. The primary objective of this paper is to provide the best-fit learning curve model for gas pipeline construction in Egypt.

II. Learning Curve Theory

Learning curve theory states that whenever the quantity of a product doubles, the unit or cumulative average cost-hour, man-hour, dollars, etc. will decline by a certain percentage. This percentage is called the learning rate which identifies the learning achieved, and establishes also the slope of the learning curve. The lower the learning rate, the greater the learning. A learning rate of 100% means that no learning takes place [2]. The main categories of factors that influence the learning rate are summarized by Hijazi et al. [11] as: Task characteristics, Management on job site characteristics, Labor characteristics, and Project characteristics

Learning curve theory is a powerful tool for predicting, guiding, and encouraging increase in productivity. In large-scale repetitive projects, improvement occurs smoothly and continuously. The phenomenon has specific applications in cost analysis, cost estimating, or profitability studies [12]. Although the improvement of labor productivity due to repetition has been widely recognized, there have been only few attempts to account for its effect in the design or production of construction projects [13]. Several mathematical models have been developed to describe the variation in productivity as a function of the number of units produced.

A. *Learning Curve Models*

Learning curves are set of equations that describe the patterns of ongoing improvement found in stable processes. As a set of equations, learning curves describe specific patterns of improvement that can be used to predict future productivity [14].

Thomas et al. [2] proposed five basic mathematical models for describing learning curve effect. These models are: (1) Straight-line model; (2) Stanford "B" model; (3) Cubic power model; (4) Piecewise (or stepwise) model; and (5) Exponential model. These models are shown graphically in Fig.1.

Out of the five models, the straight-line model and the Stanford B model are based upon the assumption that the learning rate is a constant value (except for previous experience adjustments in the Stanford "B" model). However, many researchers have shown that the learning rate is not constant throughout the progress of an activity [11,15,16].

B. *Data Representation in Learning Curve Theory*

The analyst has to choose from several methods of representing data, usually trading-off between response and stability of forecasting information. Traditionally, learning curve data has been represented using either unit data or cumulative-average data. There are two other techniques: moving average and exponentially weighted average.

Unit data shows actual performance of a repetitive activity exactly as it happened, when it happened. This is the raw data in its simplest form. Unfortunately, for many construction activities, there may be a great deal of noise or scatter in the data. When the learning curve is plotted using unit data, trends may not be readily apparent to the construction manager trying to forecast future performance [17].

Cumulative average data is the average data (time or cost) to complete all cycles up to and including the given cycle versus the cycle number. It helps smoothing-out some of the noisy in the data by averaging many cycles together. Long-term trends become much more obvious, while short-term trends, however, may be hidden. As more and more cycles are incorporated into the data set, the most recent cycles are discounted and contribute relatively little to the overall cu-mulative average. The predictive capabilities are obviously enhanced using the cumulative average data [18].

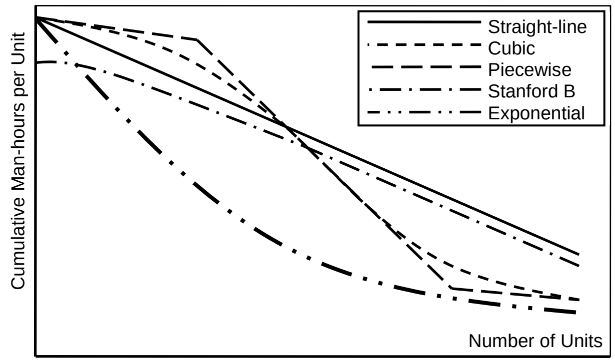


Figure 1. *Common Learning Curve Models* [2]

In this paper, cumulative average data technique will be used because of: (1) Simplicity of application, (2) No constrains or assumptions like exponential weighted average or moving average and (3) It helps smoothing-out some of the noisy in the data.

III. Gas Pipeline Construction

Pipeline projects represent a considerable portion of the construction industry. Examples are water, wastewater, gas, oil, etc. The construction of a gas pipeline involves many operations most of which are repetitive in nature. Pipeline construction activities usually follow standard industry practice, which include right-of-way, trenching (excavation), stringing, welding, coating of joints, non-destructive testing, lowering-in (laying), sand padding, and backfilling.

The right-of-way is a narrow strip of land that contains the pipeline and where all onsite construction activities occur. It is surveyed, cleared of brush and trees, and leveled to give workers and equipment access to build, inspect, and maintain the pipeline.

Lengths of pipe are moved from stockpile sites to the right-of-way. They are lined-up along the right-of-way, ready for welding. Welding is used to join lengths of pipe. This activity is repeated number of times until multiple pipe sections are joined to form a pipeline. A rigorous quality assurance and quality control programs are followed to ensure strength and quality of welding.

A trench must be dug to allow soil to bury the pipe. Once the pipe is welded, bent, and coated, it can be lowered into the previously dug trenches. Once lowered into the ground, the trench is filled-in carefully, to ensure that the pipe and its coating do not incur damage. The last step in pipeline construction is the hydrostatic testing.

Welding is a labor-intensive repetitive activity in which learning phenomenon can best represent repetitive activities. Therefore, it will be used to investigate learning effect in gas pipeline construction in Egypt.

IV. Data Collection and Analysis

In order to investigate learning curve effect in gas pipeline construction in Egypt, data are collected form real-life projects. Data collection for studied activities, data analysis, and used statistical tools are discussed in the following sections.

A. Data Collection

Data were collected from real-life gas pipeline projects in Egypt. Studied projects are constructed in different types of land (desert and agriculture). These projects have different size, length, and pipe diameter, and have been constructed under various weathering conditions. The contractor is classified as a large scale multidisciplinary international company operating in eight countries. Since inception in Egypt in 1975, the company has maintained a steady pace building world class experience across various sectors including pipeline construction [19].

B. Studied Activities

Data were collected from daily and weekly reports that usually contain information regarding daily quantities for each activity. These activities include surveying, right of way, stringing, welding, wrapping, excavation and backfilling. Arditi et al. [13] advised that operations which have a high degree of labor content are expected to have much steeper learning slopes than operations that are machine paced. Therefore, focus will be made on welding activity in the present study because it depends mainly on human resources. In addition, welding activity represents a major operation in gas pipeline construction projects. Data collected and analyzed for WASCO project will be presented in the following sections.

Data of daily reports for welding activities are used as raw data for further analysis. Sample of data collected were rearranged in tabular form as shown in Table 1. Column 1 is the number of working day, column 2 shows daily welding production in meter while column 3 shows cumulative welding production from work start to date.

C. Data Analysis

The collected data can be presented in several forms such as man-hour/cycle, dollars/cycle, minutes/cycle, and so on. In the present analysis, man-hour/cycle will be used. The collected data given in Table 1 is not suitable for learning curve modeling. Instead, the project is divided into sections of equal length (1000m). The man-hour consumed in performing each section is then calculated from data collected. Each section will be referred to as cycle. Sample of the collected data in the modified form are given in Table 2. For welding crews used in WASCO project, 100 man-hour per day is used to convert data given in the daily reports.

D. Statistical Tools

In order to specify the best descriptive model for learning curve effect for gas pipeline projects, the commercial Statistical Package for Social Science (SPSS 14) is used, because of its wide acceptance. Pearson's coefficient of determination (R^2) was usually used as a descriptive measure of the association of dependent and independent variables. R^2 ranges from zero to one, where zero denotes no correlation and one denotes perfect correlation.

TABLE 1. DATA COLLECTED FOR WASCO PROJECT

Day No. (1)	Daily Prod. (m) (2)	Cum. Prod. (m) (3)	(Date) (4)
1	250	250	April 28, 2006
2	250	500	April 29, 2006
3	475	975	April 30, 2006
4	475	1,450	May 1, 2006
5	445	1,895	May 2, 2006
:	:	:	:
41	268	24,501	June 21, 2006
42	408	24,909	June 22, 2006
43	344	25,253	June 24, 2006
44	198	25,451	June 25, 2006

TABLE 2. Modified Data for WASCO Project

Cycle No. (X)	Cum. Man-Hour	Cum. Average Man-Hour per Cycle (Y)
1	305	305
2	522	261
3	683	228
4	804	201
5	973	195
6	1,123	187
:	:	:
23	3,666	159
24	3,917	163
25	4,226	169

V. Modeling Learning Effect

In the present study, 12 mathematical models were evaluated. These models are given in Table 3. Three models (linear, cubic and exponential) were previously tested. Thomas et al. [2] tested also another two models. The first one is the Stanford B model which is identical to the straight-line model except for the first few cycles. The second is the piecewise model, which requires assumptions about the values of certain parameters (the ultimate or steady-state time/cycle). Therefore, Stanford B and piecewise models were not included in the present study. The general form of the 12 mathematical models, used in the present study, are given in Table 3.

The selected mathematical models are tested using data collected from real-life projects. Case-study projects have varied pipe diameter (4”~32”), pipe length (2.4~126 km), project duration (10~205 days), and budget ($150,000 ~ $30,200,000). For space limitation, analysis and results of only WASCO project are presented.

TABLE 3. TESTED Mathematical MODELS

No.	Group	Type	Form
1	X- Y	Linear	Y = a + b(X)
2		Quadratic	Y = a + b(X) + c(X)^2
3		Cubic	Y = a + b(X) + c(X)^2 + d(X)^3
4		Exponential	Y = a (e^{bX})
5	X- Log Y	Linear	Log Y = a + b(X)
6		Quadratic	Log Y = a + b(X) + c(X)^2
7		Cubic	Log Y = a + b(X) + c(X)^2 + d(X)^3
8		Exponential	Log Y = a (e^{bX})
9	Log X- Log Y	Linear	Log y = a + b(Log X)
10		Quadratic	Log Y = a + b(Log X) +c(Log X)^2
11		Cubic	Log Y = a + b(Log X) + c(Log X)^2 + d(Log X)^3
12		Exponential	Log Y = a (e$^{b(\text{Log x})}$)

Note: X = independent variable (Cycle No.), Y = dependent variable (CMH), and a, b, c and d = models' parameters.

WASCO is a gas pipeline project owned by Wastany petroleum company with 25.5Km long. The pipeline diameter is 12 inch which handles about 120 Million Standard Cubic Feet per Day (MSCFD) of gas at 600 PSI pressure. This project was designed and implemented by Petrojet under the supervision of Wastany petroleum company over a period of 58 days with a budget of $4,640,000.

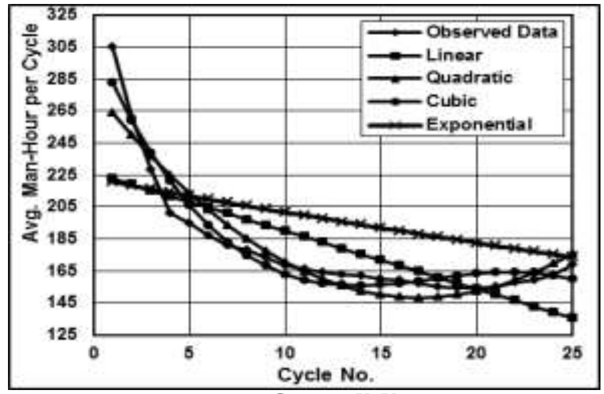
Coefficient of correlation as well as parameters of the tested learning models are calculated and are given in Table 4. Graphical representation of the three groups of the tested learning models are shown in Fig. 2. It is apparent that models number 11, 10, 7, 3, 6, and 12 have values of R^2 exceed 0.90, which indicate high degree of correlation.

TABLE 4. Correlation Coefficient and Parameters for Tested Learning Models[a]

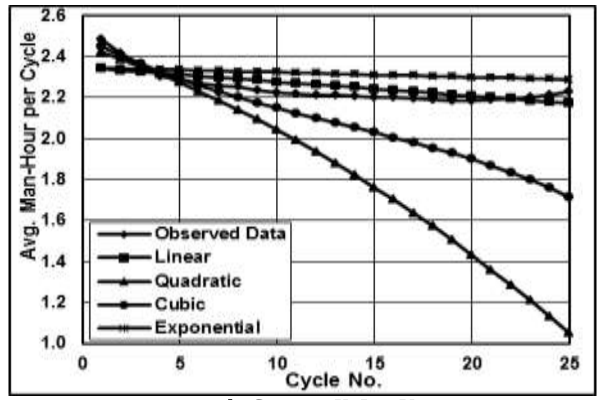
Model No.	R^2	a	b	c	d	Rank
1	0.539	226.2	-3.628	NA[b]	NA	12
2	0.875	278.3	-15.21	0.445	NA	8
3	0.940	308.9	-28.09	1.66	-0.031	4
4	0.598	222.9	-0.01	NA	NA	10
5	0.598	2.348	-0.007	NA	NA	11
6	0.927	2.453	-0.031	-0.001	NA	5
7	0.961	2.499	-0.05	0.002	-0.00005	3
8	0.609	2.347	-0.001	NA	NA	9
9	0.906	2.443	-0.196	NA	NA	7
10	0.974	2.503	-0.401	0.128	NA	2
11	0.987	2.485	-0.198	-0.219	0.156	1
12	0.911	2.44	-0.08	NA	NA	6

Note: a. *WASCO Project*, b. NA: *Not Applicable*

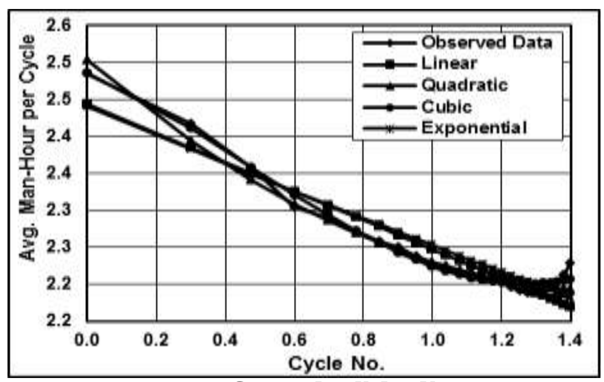
The cubic models, in general, have the highest degree of correlation. The graphical representation of the three cubic model only are shown in Fig. 3. The cubic learning curve model with logX-logY configuration has the absolute top R^2 value (0.987).



a. Category X, Y



b. Category X, Log Y



c. Category Log X, Log Y

Figure 2. *Learning Curve Models for WASCO Project*

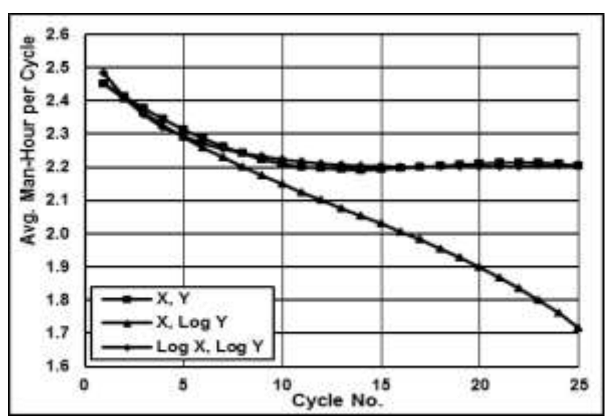


Figure 3. *Cubic Learning Curve Models for WASCO Project*

VI. Conclusions

In order to investigate the best descriptive learning curve model for gas pipeline construction in Egypt, 12 learning curve models were evaluated using data collected form real-life projects. Cumulative average data is used to represent collected data giving smooth curve as well as avoiding scattered data. Only welding activity is considered in the present work because it is a labor-intensive activity. Using SPSS, coefficient of determination (R^2) is explored in order to evaluate different models. The results show that cubic models are generally the best-fit curves which have largest values of R^2 and followed by quadratic models. The cubic learning curve model with log X log Y configuration has the absolute top R^2 value. The learning curve effect phenomenon can be extended to consider other types of construction projects such as road construction.

References

[1] D. Arditi, O. Tokdemir, and K. Suh, "Challenges in Line-of-Balance Scheduling," Journal of Construction Engineering and Management, Vol. 128, No. 6, pp. 545-556, 2002.

[2] H. Thomas, C. Mathews, and G. Ward, "Learning Curve Models of Construction Productivity," Journal of Construction Engineering and Management, ASCE, Vol. 112, No. 2, pp. 245-258, 1986.

[3] J. Everett, and S. Farghal "Learning Curve Predictors for Construction Field Operation," Journal of Construction Engineering and Management, ASCE, Vol. 120, No. 3, pp. 603-616, 1994.

[4] S. Farghal, and J. Everett, "Learning Curves Accuracy in Predicting Future Performance," Journal of Construction Engineering and Management, ASCE, Vol. 123, No. 1, pp. 41-45, 1997.

[5] J. Couto, and J. Teixeira, "Using Linear Model for Learning Curve Effect on High Rise Floor Construction," Journal of Construction Management and Economics, Vol. 23, pp. 355-364, 2005.

[6] P. Adler, and K. Clark "Behind the Learning Curve: A Sketch of the Learning Process," Management Science, Vol. 37, No. 3, pp. 267-281, 1991.

[7] R. Wideman, "Applying Resource Loading, Production and Learning Curves to Construction: A Pragmatic Approach.," Canadian Journal of Civil Engineering, Vol. 21, No. 6, pp. 939–953, 1994.

[8] D. Norfleet, "Loss of Learning in Disruption Claims," International Transactions No. CDR 10, the Association for the Advancement of Cost Engineering, Washington, D.C., 2004.

[9] J. Hinze, and S. Olbina "Empirical Analysis of the Learning Curve Principle in Prestressed Concrete Piles," Journal of Construction Engineering and Management, ASCE, Vol. 135, No. 5, pp. 425-431. 2009.

[10] A. Jarkas, "Critical Investigation into the Applicability of the Learning Curve Theory to Rebar Fixing Labor Productivity," Journal of Construction Engineering and Management, ASCE, Vol. 136, No. 12, pp. 1279-1288, 2010.

[11] A. Hijazi, S. AbouRizk, and D. Halpin, "Modeling and Simulating Learning Development in Construction," Journal of Construction Engineering and Management, ASCE, Vol. 118, No. 4, pp. 685-700, 1992.

[12] K. Humphreys, "Jellens Cost and Optimization Engineering," McGraw-Hill, Inc., New York, 1998.

[13] D. Arditi, O. Tokdemir, and K. Suh, "Effect of Learning on Line of Balance Scheduling," International Journal of Project Management, Vol. 19, pp. 265-277, 2001.

[14] L. Raccoon, "A Learning Curve Primer for Software Engineers," ACM SIGSOFT Software Engineering Notes, Vol. 21, No. 1, pp. 77-86, 1996.

[15] J. Carlson, "Cubic Learning Curves: Precision Tool for Labor Estimating," Manufacturing Engineering and Management, Vol. 67, No. 11, pp. 22-25, 1973.

[16] J. Tarnanidis, J. Papathanasiou, and P. Filakis, "Learning Curves as a Tool of Enterprises Development," Advanced Modeling and Optimization, Vol. 8, No. 2, pp. 209-216, 2006.

[17] J. Everett, and S. Farghal, "Data Representation for Predicting Performance with Learning Curves," Journal of Construction Engineering and Management, ASCE, Vol. 123, No. 1, pp. 46-52, 1997.

[18] H. Thomas, "Construction Learning Curves," Practice Periodical on Structural Design and Construction, Vol. 14, No. 1, pp. 14-20, 2009.

[19] Petrojet (2010), "http://www.petrojet.com.eg," Accessed on January 13, 2011.

About Author (s):

Dr. Ammar is now the Dean of Faculty of Engineering, Madina Institute of science and Technology (MIST), Accra, Ghana. He was a Visiting Scholar, Building, Civil, and Environmental Engineering Department, Faculty of Engineering and Computer Science (ENSC), Concordia University, Montreal, Quebec, Canada, H3G 1M8 (2008).

Dr. Ammar research interest covers a wide range of research topics, including (but not limited to): Management of Infrastructure Projects, Fuzzy Scheduling of Construction Projects, Planning and Scheduling of Linear/Repetitive Projects, Delay Analysis and Legal Aspects in Construction, Analysis of Earthmoving Systems, Bidding and Bid-Evaluation, etc.

Current activities includes: (1) Member, Technical Committee of Egyptian Code of Construction Project and Management, Housing and Building national Research Center (HBRC), Egypt, (2) Reviewer and Arbitrator, Egyptian Universities Promotion Committees (EUPC), Committee No. 50 (Structural Engineering and Construction), Ministry of High Education, Egypt. (3) Peer reviewer for more than ten international reputable journals.