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NEW PRODUCT PRODUCTION COSTS AND LEARNING THEORY*

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ABSTRACT

One of the most uncertain elements in budget planning is estimating production costs of items that have heretofore only been produced in prototype configurations and quantities. This paper examines the use of learning theory to predict production costs of products that are in transition from development to commercial application. The traditional learning concept is examined as well as modifications to account for the transition and the long-term cost trends.

INTRODUCTION

Evidence gathered over the last forty years demonstrates that the resources required to complete a unit of production will show a constant percentage decrease (learning) each time the production quantity is doubled. The extent and rate of the reduction are direct factors of production planning, design stability, the design itself, and management attitudes.

Learning curves are applicable to many aspects of production planning and control. They can be used predict unit cost, calculate selling price, compute quantity discounts, determine make/buy decisions, and make budget forecasts. Learning will influence schedules, efficiencies, labor standards, training programs, and wage incentive schemes. Learning theory is a powerful tool; however, it must be applied with a thorough understanding of the statistics, design, and manufacturing processes involved.

This paper will examine the use of learning theory to predict production costs of products in transition from development to commercial application. The first step will be to explore the basics of learning theory, then adapt theory to production of new products, and conclude with a look at some example rates.

LEARNING BASICS

In 1936 Wright [7] published the first article that defined learning curves. Since that time numerous articles have been published describing alternative mathematical representations for learning. However, the basic assumptions and properties of learning theory have remained fairly consistent over the past forty-plus years.

Learning Properties

The basic assumption of learning theory is that people, as well as organizations, learn according to a predictable pattern. This assumption is backed up by an abundance of experimental data and is statistically derived from actual data, mainly in the aircraft industry. The assumption holds for individual workers, products, groups of workers, and for complex systems with many components or subassemblies. The learning process has two basic properties: (1) direct labor decreases with experience, and (2) there is a limit to the learning process. After a certain period relatively little further improvement takes place.

In addition to the above properties the customer(s) has a large influence on learning. Learning theory has its roots in the World War II aircraft industry, and a large portion of learning research has been done on Government procurements. These two factors tend to limit direct application of past learning experience to industries which have the following characteristics:

1. The industry is monopolistic - there is only one customer.

2. Price and to a great extent return on investment are determined more by customer practices than by the market or producer efficiency.

3. Price competition is a factor but not as dominant as in the case of consumer goods.

4. Limited sources tend to weaken price competition.

5. Schedule is preeminent over cost.

6. The first phase is a "cost-plus-fixed-fee" arrangement, which tends to negate incentive to minimize cost.

7. Most capital assets are owned or paid for by the customer directly or indirectly through accelerated amortization or progress payments.

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By comparison, industries which do not conform to the above characteristics will tend to experience accelerated learning; however, basic learning theory will still apply in most instances.

Learning Equations

In almost all cases a plot of unit cost as a function of cumulative quantity produced will approximate a negative power curve. A negative power curve will plot as a straight line on log-log paper as shown in Figure 1.

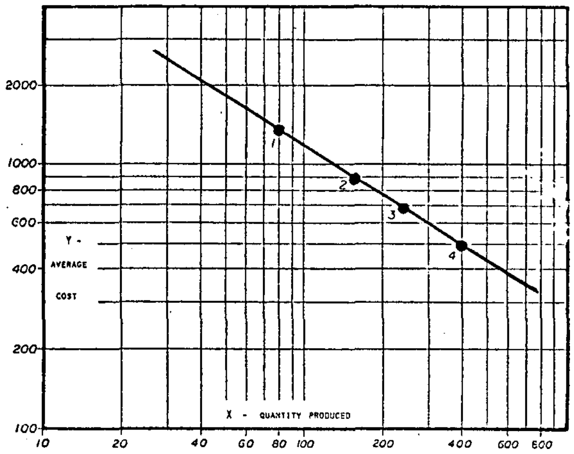

Figure 1: Learning Curve

Recall that the equation of a straight line is:

$Y = N X + K$

where:

Y = dependent variable

X = independent variable

N = slope

K = the Y axis intercept

For a log-log plot:

$^*\log Y = N \log X + \log K$

or: $^*\ln Y = N \ln X + \ln K$

*NOTE: Any logarithm base may be used as long as it is used consistently throughout the computations.

Such that:

$Y = K X^N$

Selecting points 1 (X_1, Y_1) and

2 (X_2, Y_2) on Figure 1:

$Y_1 = K X_1^N$

$Y_2 = K X_2^N$

or:

$K = Y_1/X_1^N = Y_2/X_2^N$

Solving for N:

$(X_2/X_1)^N = Y_2/Y_1$

or:

$N \ln (X_2/X_1) = \ln (Y_2/Y_1)$ and:

$N = \ln (Y_2/Y_1)/\ln (X_2/X_1)$

Productivity Measurement

The value of N is the standard measure of productivity, as developed by Wright [7], based on the concept that as quantities double, the rate of learning remains constant. For example, a 90% learning rate indicates that the average unit hours to produce the first two units are 90% of the time required to produce the first unit. Further, the average unit hours required for a total of 10,000 units (again with 90% learning) are 90% of the average unit hours used to produce the first 5,000 units. Therefore, with the points shown on Figure 1:

$X_2/X_1 = 2$

and: Y_2/Y_1 = rate of learning (L)

resulting in a value for N of:

$N = \ln (L)/\ln (2)$

again: $y = K X^N$

where:

Y = average unit cost of X units

X = cumulative units produced

when $X = 1$

$Y = K$ = cost of the first unit

L = learning rate

NOTE: The learning rate is generally less than one, which results in a value of N that is negative.

Other Learning Concepts

Doubling of quantities has been the traditional way of expressing learning, but any multiplier could be selected with the same end result.

For example:

Consider points 1, 2, 3, and 4 on the learning curve depicted in Figure 1. Form the following ratios and compute the appropriate value for N:

1. $X_2/X_1 = 2$

   $Y_2/Y_1 = 0.648$ = 64.8% learning rate

   $N = \ln (0.648)/\ln (2.000) = -0.626$

2. $X_3/X_1 = 3$

   $Y_3/Y_1 = 0.503$ = 50.3% learning rate

   $N = \ln (0.503)/\ln (3.000) = -0.626$

3. $X_4/X_1 = 5$

$$Y_4/Y_1 = 0.365 = 36.5\% \text{ learning rate}$$

$$N = \ln(0.365)/\ln(5.000) = -0.626$$

The measure of productivity (N) has remained constant even though the numerical value of the learning rate has changed.

As further illustration, consider the four points of Figure 1 and compute the cost at each point with each of the above three learning concepts. The results of these computations are shown in Table 1. Again, the end results are identical regardless of the learning concept used.

Table 1: Learning Concept Comparison

		Average Cost through Point			
Learning Concept	L(%)	1	2	3	4
Quantity Double	64.8	1370	887	688	500
Quantity Triple	50.3	1370	887	688	500
Quantity Quintuple	36.5	1370	887	688	500

NEW PRODUCT LEARNING

The learning experienced during the development of new products will be influenced by the stability of design, prototype experience, and the myriad problems associated with production startup. This analysis will assume that the product will make a typical transition from development to production. "Typical" includes a nominal number of false starts, design changes, quality control problems, et cetera.

The new product analysis was based on Cochran's [2] "S" learning curve or "three-stage" new product learning.

New Product Patterns

The S-curve (cost as a function of quantity and stage of production) is applicable to products in transition from development to commercial application because almost all products will follow a pattern of slow learning in early production, faster learning after the initial production problems have been corrected, and finally slower learning when the process has reached maturity. Several factors explain this pattern:

1. Early production stages will be a time of partial experimentation. Various approaches will be tried with very little improvement; also, last minute changes in design and materials will occur during this period.

2. Corrections to tooling, production methods, and producibility design changes will permit a rapid reduction in cost after the early stage experimentations.

3. After the middle period (2 above), production should settle down to a more routine activity, with the rate of learning slowing appreciably.

S-Curve Modifications

Cochran's S-curve was modified to account for the fact that production rate and cost will approach linearity at some point. The first step in the modification was to determine the number of units produced before learning approaches 100%. Both Cochran [1] and Young [8] addressed this problem. These two papers made it possible to develop the following relationship:

$$C_T = (5 + C_I)^5$$

where C_T = total units produced to approach linearity

C_I = initial unit production time in minutes <60 minutes

The next step was to force learning to approach 100% as production approached C_T. This was accomplished by making N a function of X and C_T as well as learning, such that:

$$N' = \frac{\ln[L \exp(BX)]}{\ln(2)} \quad \text{when } X < C_T$$

$$N' = 0 \text{ when } X > C_T$$

$$\text{where: } B = \frac{\ln(1/L)}{C_T}$$

N' = revised slope

L exp (BX) = revised learning rate

The modified N is then applied to the standard negative power curve incrementally using the value of preceding unit as the new cost of the first unit (K) for the next increment of production.

As an example, Table 2 shows typical revised learning rates for three base learning rates at three cumulative production points with three different initial cycle times.

Table 2: Revised Learning Example

(L) Learning Rate	(C_I) Initial Time	(C_T) Total Units	Revised Learning Rate		
			5×10^5 Units	5×10^7 Units	5×10^8 Units
95%	10 min.	760,000	98.2%	100%	100%
90%	30 min.	52,000,000	90.1%	99.6%	100%
85%	60 min.	1,200,000,000	85.0%	85.6%	91.0%

Typical Learning Rates

The basic question in any learning analysis is: What is a realistic learning rate? The "correct" rate is highly dependent upon the manufacturing process in question. The greater the ratio of manual to mechanical operations, the faster the rate of learning.

The learning rate for a completely automatic process is 100%, semi-automatic part fabrication is near 95%, and subassembly rate 87%. For major subassemblies, overall learning will be about 80%, and final assemblies may approach 70%. An examination of a number of studies [1, 2, 3, 5, and 6], which addressed learning rate and the ratio of manual/mechanical operation involved, resulted in the following rule-of-thumb:

Fabrication: Learning = (0.25)(% automated) + 75%
Assembly: Learning = (0.27)(% automated) + 73%

The above requires that for the best results each step in the manufacturing and assembly process must be examined, the learning rate determined, and the results related to the whole. The overall curve for the entire manufacturing process is typically in the 85-95% range [5].

Extensive analyses of published reports [1, 2, 3, and 4] and the author's experience in product development has generated learning rate envelopes which should cover the extremes that can be expected during development of new product production. The resulting envelope, shown as Table 3, bounds 95% of the labor and material variations that can be expected in the production development of such items as aircraft, jet engines, heavy equipment, et cetera.

Table 3: New Product Learning Rates

Production Stage	Labor Learning Rate O	Labor Learning Rate P	Material Learning Rate O	Material Learning Rate P
Early	95%	100%	97%	100%
Middle	80%	90%	95%	98%
Final	90%	95%	97%	100%

Code: O = Optimistic Rate
P = Pessimistic Rate

EXAMPLE PROBLEM

The following assumptions will now be applied to a typical example of heavy equipment, three-stage, new production:

1. The first unit labor cost will be $1,000.
2. The first unit material cost will be $1,000.
3. 50 Units will constitute early stage production.
4. 500 Units will constitute middle stage production.
5. Over 10,000 units will be produced.

Figure 2 graphically shows the envelopes resulting from the example assumptions and Table 3 learning rates.

The cost shown on the ordinate (Y) axis of Figure 2 is the average unit cost over a cumulative production of X units.

If the unit cost is of interest, it may be found by considering the total cost difference between the last unit and the next to the last unit produced:

Total cost of i units = $(X_i)\ (Y_i)$

where X_i is the total produced through i

Y_i is the average unit cost of X_i units

therefore:

Total cost through i = $(X_i)(K)(X^N_i) = (K)\ (X_i^{N+1})$

total cost through i-1 units =

$$(X_{i-1})\ (K)\ (X_{i-1}^{N})$$

$$= (K)\ (X_{i-1}^{N+1})$$

The cost of the last unit is therefore:

$$= K\ (X_i^{N+1} - X_{i-1}^{N+1})$$

The above is parallel to the cumulative average curve at large values of X (>25). The following relationship may be used to approximate the cost of the ith unit [3]:

$$Y_i = K\ (1+N)\ X_i$$

where Y_i = cost of the last production unit.

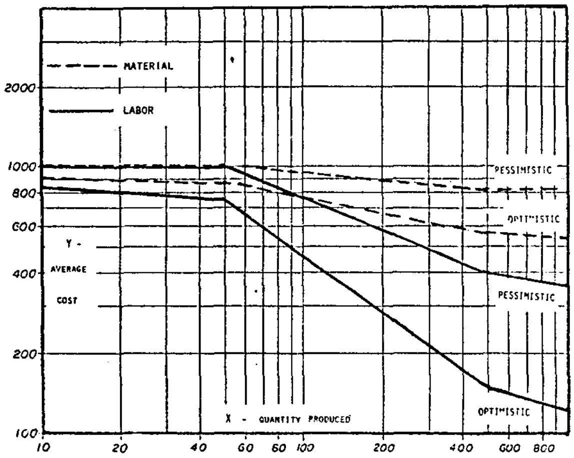

Figure 2: Labor/Material Learning Envelope

The Figure 2 and Table 3 S-curve learning ranges may be consolidated into standard, mean value learning rates. The resulting composite learning rates, which are representative for mechanical manufacturing, are shown as Figure 3 and Table 4.

Table 4: Composite Rates of Learning

Cumulative Units Produced	Labor Learning	Material Learning	Composite Learning
Less than 50	97.7%	99.1%	98.4%
50 - 500	86.8%	96.6%	90.8%
Greater than 500	94.1%	99.1%	94.6%
Composite of Rate for Total Production	92.0%	98.2%	93.1%

The above values show very close correlation with experience in high volume turbo machinery production over a period of several years [4].

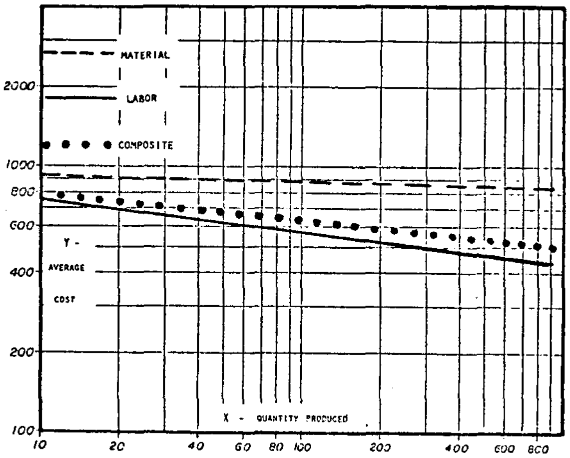

Figure 3: Composite Learning

SUMMARY

The factors influencing learning theory and its application are complex and interrelated; however, the past four decades have demonstrated the viability of its use as a production estimating tool. Research on this subject has been fragmentary with few attempts at logically constructed experiments. The investigations which have been accomplished have been limited to highly specialized industries, mainly in the Government sector. Caution should, therefore, be exercised in the use of data which may have been obtained under conditions which have forced predetermined results.

The learning rates defined in this paper as "typical", "nominal", or "representative" should be useful for first order and/or total product estimates. Component parts and items in varying stages of manufacturing will require individual examination on an item-by-item and stage-by-stage basis.

In spite of various difficulties and unsolved problems, a number of positive conclusions may be drawn:

1. Learning does exist for long periods of production.

2. Learning theory is applicable to a variety of products.

3. There are differences in learning patterns for different industries.

4. Learning envelopes can be derived which will account for a majority of like production items.

5. Learning can be predicted with the accuracies required for budget forecasting.

6. Caution must be used in the application of learning theory with the knowledge that its very application may influence the results.

7. Implicit in any learning analysis is the assumption that the product will make the normal transition from development to production. "Normal" includes a nominal amount of false starts, design changes, workmanship problems, etc. However, learning does not just happen - it is made to happen. A program left to devise its own methods and standards will show little or no improvement throughout the entire project, but a project with definite controls on methods, work measurement, manufacturing process and management that is willing to acknowledge, learn from, and have timely response to errors and problems can show definite learning.

REFERENCES

1. Cochran, E. B.; "Learning: New Dimension in Labor Standards"; *Industrial Engineering*, Vol. 4, pp 38-47; January 1969.

2. Cochran, E. B.; "New Concepts of the Learning Curve"; *The Journal of Industrial Engineering*, Vol. II, pp 317-327; July-August 1960.

3. Conway, R. W., and Schultz, Jr., Andrew; "The Manufacturing Progress Function"; *Learning Curves Theory and Application*, Publication No. 6, pp 7-22; American Institute of Industrial Engineers, Inc., Norcross, Georgia; 1977.

4. Derbes, D. W.; AiResearch Manufacturing Company of California, Torrance, California; *Letter to Dale Myers*, U. S. Department of Energy; February 15, 1978.

5. Maynard, E. I., Schappel, H. N., and Thue, H. W.; "Introduction, Theory, and Application", *Proceedings of the 5th Annual Industrial Engineering Institute*, pp 27-37; University of California; 1953.

6. Turban, E.; "Learning Curves"; *Facilities and Plant Engineering Handbook*; McGraw-Hill Book Company, New York; 1973.

7. Wright, T. P.; "Factors Affecting the Cost of Airplanes"; *Journal of the Aeronautical Sciences*, 3, pp 122-128; February 1936.

8. Young, S. L.; "Misapplications of the Learning Curve Concept"; *The Journal of Industrial Engineering*, Vol. 17, pp 410-415; August 1966.

BIOGRAPHY

Vance K. Wilkinson (Van) is a project manager in the Gas Centrifuge Enrichment Program with Union Carbide's Nuclear Division at Oak Ridge, Tennessee. Prior to his Union Carbide affiliation, Mr. Wilkinson spent over ten years in the military weapons development field. Preceding his development assignment, he spent a decade in USAF First Line Operational Units, including over 100 Vietnam combat missions.

Mr. Wilkinson is presently pursuing a Systems (Industrial) Engineering doctorate at the University of Tennessee. He holds an M.E. in Industrial Engineering, an M.S. in Systems Engineering, and a B.S. in Aeronautical Engineering.

Mr. Wilkinson is a distinguished graduate of the Air Force Institute of Technology and was elected to Tau Beta Pi. He holds the Distinguished Flying Cross, the Meritorious Service Medal, five Air medals, the Air Force Commendation medal, and the Vietnamese Cross of Gallantry with Palm.

Van is a Registered Professional Engineer in the states of Ohio, Tennessee, and Texas. He is a senior member of AIIE and a member of ASME, NSPE, and TSPE.