A Cost Modeling Approach Using Learning Curves to Study the Evolution of Technology

by

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Submitted to the Department of Materials Science and Engineering
in Partial Fulfillment of the Requirement for the Degree of

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Abstract

The present work looks into the concept of learning curves to decipher the underlying mechanism in cost evolution. The concept is not new and has been used since last seven decades to understand cost walk down in various industries. The seminal works defined learning in a narrower sense to encompass reduction in man hours as a result of learning. The work done later expanded this concept to include suppliers, long term contracts, management and some other economic and technological factors. But the basic mechanism in all these study was to look at manufacturing cost in an aggregate sense and use the past data to predict the cost walk down in future.

In the present work the focus has shifted from looking at cost in an aggregate manner and understanding it more at a manufacturing level using process based cost modeling. This would give a new perspective to the age old problem of cost evolution. Besides it would also give the line engineers and managers a better insight into the levers which eventually lead to cost reduction at manufacturing level. This is achieved by using learning curves to define the manufacturing parameters based on previous observations.

The work further looks at cost evolution for new and non-existent technology for which historic data does not exist. This is achieved by building a taxonomic classification of industry based on certain parameters which can be easily guessed.

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1. Introduction

1.1 Study of cost evolution with time

In the 20th century, industries of every form have had to deal with a number of externalities which drove a nearly continuous change in technology. There have been significant changes in policies and consumer demand over the last three decades that have resulted in advances in material and manufacturing process. The policies pertaining to the environment have become more stringent and consumer demand has shifted to more personalized products. In response to these changes, industries were forced to adopt newer and more effective technology, or else they feared the chances of being left behind. In this context, firm decision-makers repeatedly face critical questions of what technologies to select and when to apply them. Similarly there might be issues with making production strategy decision, for example, will it be more effective to produce a part in house or to outsource its production. Making a decision based on present time cost data will lead to misleading results, similarly making a decision on some speculated future ball park number might be wrong. For savvy decision-makers a key element of answering these questions depends upon their understanding or projection of how new technologies would evolve and develop over time. The focus of this thesis is to present an analytical framework that allows decision makers to better incorporate information about technology evolution into their technology decisions.

For an outside observer, it is pretty simple to point out that whenever a new product or a new technology is launched its initial cost of manufacturing is usually quite high, but with the passage of time the cost of production goes down. The driving force behind this observation has been the focus of a various researchers over the past seven decades. This began with a study by Wright (Conway and Schultz 1959) who observed a simple phenomenon: the man hours involved in airframe manufacturing decreased as the cumulative number of frames increased. Wright concluded that the decrease in man hours and its resulting decrease in cost were due to experience gained by the workers as more parts were produced. This led Wright to propound the now-famous learning curve concept in which a process improves by some percent as the volume of production is doubled. Inspired by this work, researchers began to apply the knowledge of learning curves to a variety of different industries in an attempt to decipher their learning trends and predict their future costs.

The evolution of cost for different industries has been shown to be very different from each other and varies with product, technology, and capital investment. Grubber (1992) studied this phenomenon for various semiconductor memory chips. According to his observations, the cost curves for EPROMs are mainly determined by the cumulative output, confirming the learning curve hypothesis. However, for DRAMs, economies of scale were more important than learning. Baloff (1967) made similar observations in steel startups. Even though the processes involved in steel production are very similar across companies, they exhibit significantly different learning parameters. Baloff also compared the learning parameters for 17 different startup firms and demonstrated how the learning pattern varied with industry. These differences present a new challenge for decision makers looking to estimate learning patterns and cost trends for different types of industries.

One of the major motivating factors for the study of learning curves has been to understand the cost evolution trends of the past and try to use them to guide decisions about the future. The use of learning curve may provide a mean for better estimate in this direction.

Researchers in the past have used the concept of a learning curve as a tool for formulating future strategies (Amit 1986). Much of the work has focused on relating the reduction in average cost to the cumulative output of the process (Alchian 1963; Baloff 1971; Stobaugh and Townsend 1975). This work has largely relied on the use of regression analysis of historical price data without addressing the mechanisms by which costs decrease and the specific driving forces behind cost reduction. There are some cases where it would be interesting to know where costs were going even if one can't influence it, although admittedly, it is obviously better to know how to influence it as well. But there's another point. Predicting future costs for new products or processes through the use of historical data is only justifiable if the cost drivers for these products are structurally similar to those of the existing product. Consequently, understanding the mechanisms by which costs evolve is a necessary part of this type of analysis.

This thesis will look at the problem of cost evolution by breaking down the manufacturing process and studying both the major underlying cost drivers and the mechanisms by which learning within these drives cost change. In particular, this thesis will address how learning influences process variables such as cycle time, down time, reject rate and material cost and in turn, how these variables interact to yield cost reductions. This approach provides not only an understanding of how cost is expected to evolve with time but also understanding of the manner by which this occurs.. This will not only help industry with future cost estimates, but will give guidelines as to how to best achieve these cost reductions in the most timely fashion.

1.2 Previous Work

The learning curve theory is based on the observation that the cost of an item depends on cumulative volume produced which is a function of the production rate and the time frame over which production has or will occur. This theory is usually attributed to J. P. Wright, who introduced a mathematical model (1.1) describing a learning curve in an article published in The Journal of Aeronautical Science titled "Factors Affecting the Cost of Airplane." (Wright 1936) Wright showed that the cumulative average direct labor input for an aircraft manufactured on a production line decreased in a predictable pattern. The decrease was related to the increased proficiency (i.e., learning) of the manufacturing laborers on the line as they performed the various repetitive tasks. The model described the learning as an exponential function which is as follows.

$$h_v = aV^{-b} \tag{1.1}$$

$V =$ production count
$h_v =$ labor hour required for the V^{th} unit
$a =$ labor hour required for the first unit, hence $a = h_1$
$b =$ exponent of learning

The rate of progress is given by the complement of reduction that occurs with doubling of production volume. In the learning literature, a learning curve is referred to as an '80% learning curve' if the cost reduces by 20% every time the cumulative volume is doubled.

That is;

$$\frac{h_{2v}}{h_v} = \frac{a(2V)^{-b}}{aV^{-b}} = 0.8 \tag{1.2}$$

$$\frac{h_{2v}}{h_v} = 2^{-b} = 0.8 \quad \Rightarrow b = 0.322 \tag{1.3}$$

For an 80% learning curve the value of b will be 0.322

Arrow (1962), cited a Swedish iron plant (Hordal iron works) which had witnessed a 2% productivity increase in output per man hour even though there had been no new capital investment in past 15 years. He attributed the increase in productivity to the experience gained 'learning by doing' by the plant workers. The 'learning by doing' aspect of the learning curves was further expanded by Bahk etal (Bahk and Gort 1993), who tried to decompose it into organizational, capital and manual task learning.

The learning curve proposed by Wright had cumulative volume as the only factor responsible for a reduction in labor hours. Conway and Schultz (1959) pointed out that the method of manufacturing is also influenced by the rate of production and the estimated duration of production at this rate which gives the cumulative volume. Similarly Carrington (1989) pointed out that total cost is a function of cumulative output as well as the firms rate of output. Carrington also pointed out that marginal cost must be rising in general for the firm to be a part of competitive industry but most econometric studies of cost functions (1.1) fail to substantiate this implication.

Boston Consulting Group (Henderson 1972) added a new dimension to the concept of learning curves in late 1960s when it demonstrated that learning curves not only encompass labor cost but also administrative, capital and marketing costs. These analyses have included studies of refrigerators in Britain, polystyrene molding in USA, production of integrated circuits, direct cost of long distance telephone calls in the United States, and motorcycle production in Japan and Britain. This led to further recognition of the wide applicability of learning curves.

Hartley (1965; Hartley 1969) applied the concept of learning in the aircraft industry. Similarly, Baloff showed how the concept could be applied to labor intensive industries like automobile assemblies, apparel manufacturing and production of large musical instruments (Baloff 1971). Dudley (1972) soon followed and showed that a similar trend existed in the metal products industry. Zimmerman (1982) and Tan et al. (Tan and Elias 2000) showed that learning curves could even be used in the construction industry. Lieberman (1984) and Sinclair et al (Sinclair, Klepper et al. 2000) showed how the learning concept could be extended to chemical manufacturing plants. Other studies in this direction have been made by Preston et al. (Preston and Keachie 1964) for radar equipments, Grubber (1992), Chung (2001), Grochowski et al (Grochowski, Hoyt et al. 1996), Dick (1991) and Hatch (Hatch and Mowery 1998) for semiconductors, Sultan (1974) for steam turbine generators, Jarmin (1994) for the rayon industry, Argote et al. (Argote and Epple 1990) for manufacturing, and Tsuchiya (2002) to predict the cost of fuel cells.

Stobaugh et al. (Stobaugh and Townsend 1975) studied the price change for eighty-two petrochemical products over a time period of one, three, five and seven years as a function of number of competitors, product standardization, experience and static scale economies. They concluded that by the time a petrochemical has three or more competitors, experience has a much larger effect on price than the other three factors.

Liebermann (1984) also observed similar trends after he analyzed the three year price change for thirty-seven chemical products. He examined several other candidate explanatory variables of learning such as time, cumulated industry output, cumulative industry capacity, annual rate of industry output, average scale of plant, rate of new plant investment, rate of new market entry and level of capacity utilization. After analyzing all of the parameters he concluded that the cumulative industry output is the single best proxy for learning.

In most real-world cases, experience curves reflect the convolved effects of learning, technological advances, and economies of scale. Generally, it is difficult to distinguish between the contributions of economies of scale and learning because both tend to occur simultaneously. Learning generally results in better utilization of resources which leads to higher and more efficient production. Efficient production means higher potential volumes which if realized result in economies of scale. Few studies have tried to decouple the effects of learning and economies of scale. In one study, Hollander (1965) analyzed the sources of efficiency increase at a DuPont rayon plant and concluded that only 10-15% of the efficiency gains were due to scale effects, whereas the rest were accounted for by technology and learning. Hollander found that a large part of the cost reduction from technology improvement could be attributed to a series of minor technical changes. This could be justified to some extent as learning by observation because generally, over time, engineers in a production facility “learn” to tweak the machinery in a way to give maximum production efficiency. Sinclair (Sinclair, Klepper et al. 2000) also looked at cost reduction in specialty chemical divisions and observed that technology triggered cost reductions were largely the result of small technological changes in production and manufacturing based on R&D and related activities.

Significant work has also gone into using learning curves to develop firm operational strategies. Spence (1981) developed a model of competitive interaction and industry evolution in the presence of a learning curve. He concluded that, under certain conditions, if a firm can lower its future costs by increasing current production, then the firm should produce parts even if this is not the short term profit maximizing strategy. By doing so, the firm achieves higher profits in the long run by moving further down the learning curve faster than its competitors. The learning curve also creates entry barriers and protection from competition by conferring cost advantages on early entrants and those who achieve large market shares (Spence 1981; Porter 1984; Lieberman 1989). Spence's analysis also showed that the largest barriers to entry occur when there are moderate rates of learning rather than when there is either very slow or very fast learning.

The form of the learning curve has been debated by many researchers and practitioners. However, Wright's learning curve is, by far, the most widely used and accepted (Henderson 1972; Lloyd 1979; Day and Montgomery 1983; Lieberman 1987). The method that is commonly used by most of researchers is to look at the industry data and try to find a relationship between various parameters. This regression analysis of the industry data gives a relationship between various parameters which can be extrapolated to predict future cost trends. All these analyses result in different patterns for a set of industries without indicating how to influence the trend.

1.3 Learning Curves and Concept

A variety of functional forms have been used for learning curves. The choice of a functional form depends on the way costs decline over time. Some suggest that doubling the cumulative volume results in decrease of cost while others argue that this decline in cost cannot be sustained forever and should reach some saturation.

The most common form of experience curve is given by

$$C_n = C_o n^{-\lambda} \quad \text{(Wright's Learning Curve)} \qquad (1.4)$$

This can be written as $\ln C_n = \ln C_o - \lambda \ln \text{n}$ (1.5)

This equation implies a constant decline in unit cost each time n units are produced (Figure 1)

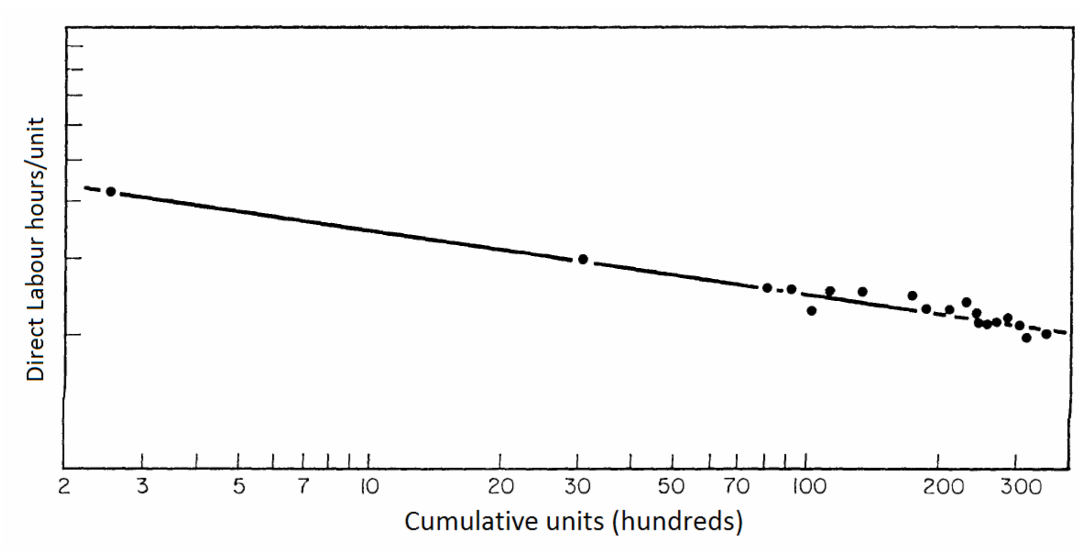

Figure 1: Wright's learning curve

Wright's model describes the learning of a new product 'start-up phase'. It is based on the idea that the decreases in labor hours can be sustained forever. However, in practice, the decrease cannot continue indefinitely and eventually saturation would be expected to take place. As a result of this saturation production reaches a kind of steady state where the direct labor hours remain constant.

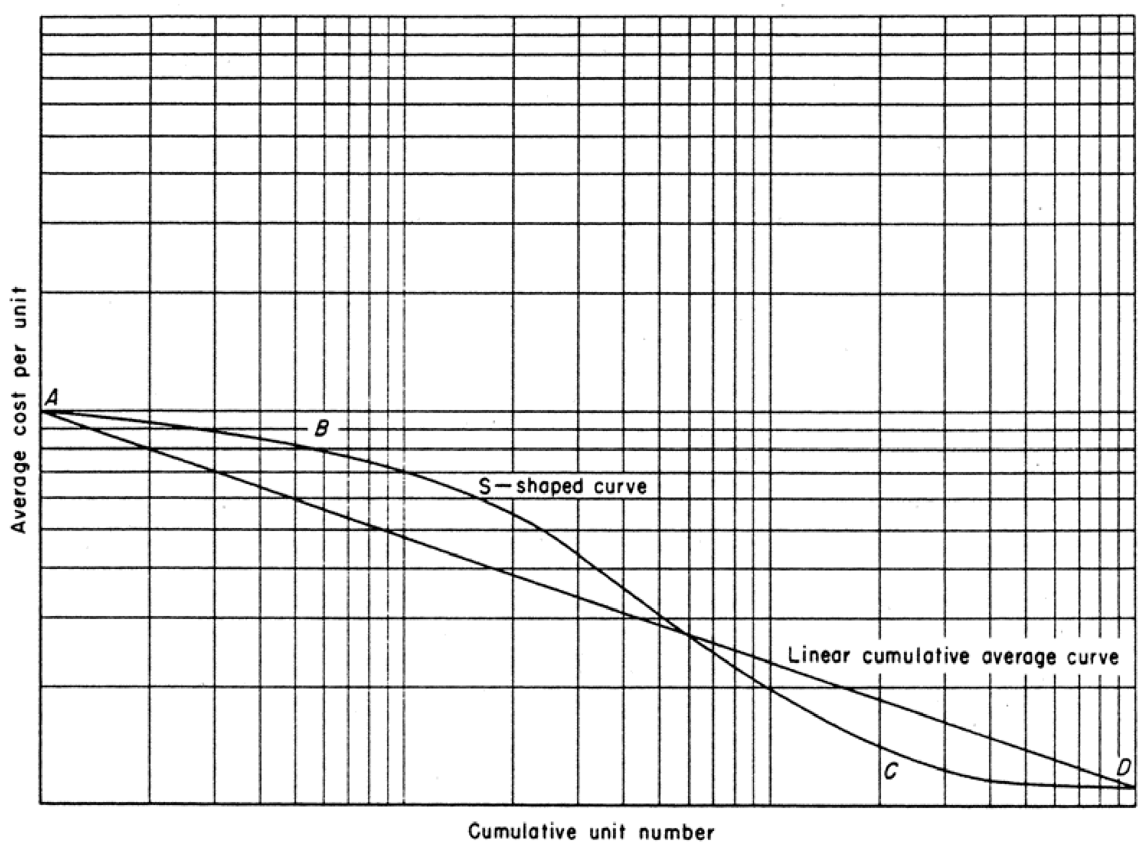

Figure 2: Cumulative average S-shaped learning curve proposed by Carr (1946)

Carr (1946) argued that shape of the learning curve should be S in nature rather than a straight line. He explains the concavity in this curve (Figure 2) by first assuming that each worker in all the production crews hired for a particular job produces along an 80 percent curve. However, the crews are not all hired at the beginning of the program but are hired one at a time during the acceleration period. Hence the crew works at different points of their individual linear cumulative average progress curves at the same point of time. This would lead to concavity in the learning curve. While Carr does not explicitly state the saturation effect in his approach, his proposed learning curve incorporates the essence of saturation at the later stages of production.

Baloff studied this plateauing phenomenon (Figure 3) and found it to be extensively present in machine intensive manufacturing. He studied twenty eight separate cases of new product and new process startups that occurred in four different industries and observed plateauing in twenty of the cases. In a subsequent study, while analyzing data for musical instrument manufacturing and automobile assembly firms (both of which were labor intensive in nature), Baloff (1971) found that some sets of firms within these industries reached steady state in the long run. However, the time to reach the steady state was higher for labor intensive industries. Yelle (1979) postulated that the reason for this observation could be smaller progress ratio for machine intensive learning or management's unwillingness to invest more.

Another likely reason the saturation effect is often not included in the learning curve is that the life cycle of the product might be short, and thus the production may never reach the steady state during the time of observation. Past analyses have often focused on product rather than manufacturing processes used in the industry. Long term study of manufacturing process data would be more likely to show the saturation effect.

However, Wright's approach can be easily modified to include the saturation effect as shown in Figure 3.

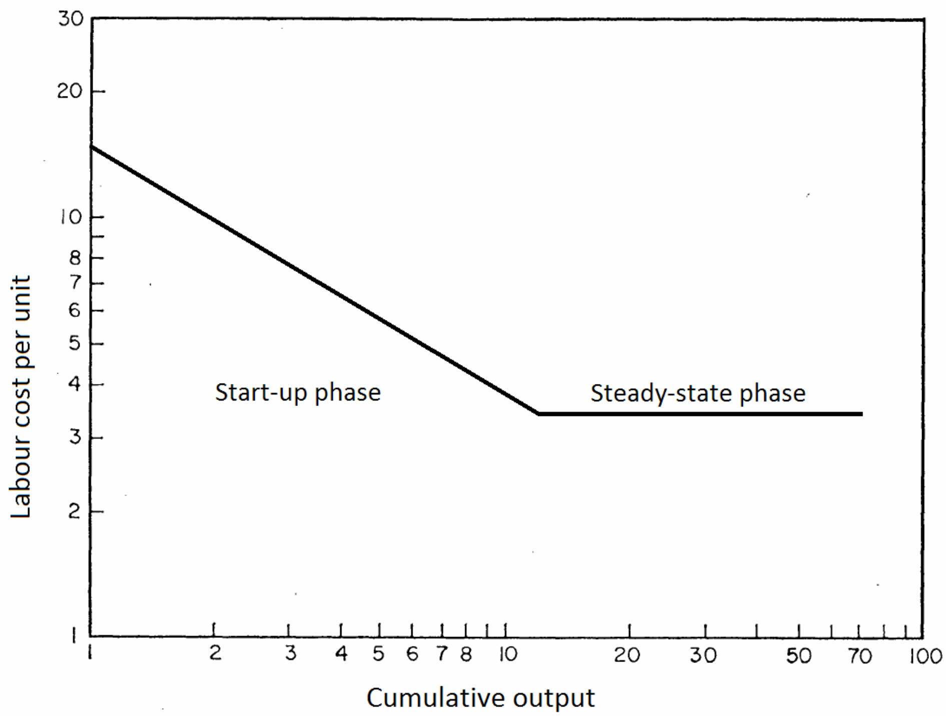

Figure 3: Learning curve with steady state phase (saturation) (Baloff 1971)

Other notable learning models include

1. The Stanford-B model

This model derives its name from Stanford Research Institute, where an early study commissioned by US defense department led to this model. This model was found to be more representative of World War II data compared to log linear learning curves. The model is represented as:

$$Y_x = C_1(x+B)^b \qquad (1.6)$$

Y_x : direct cost of producing x$^{\text{th}}$ unit
C_1 : direct cost of first unit
B : constant (1<B<10), equivalent unots of previous experience at start of a process

It is noted that when B=0, then this model reduces to the log normal model

2. DeJong's learning formula

This model uses a power functions which incorporates parameters for the proportion of manual activity in a task. DeJong's formula introduces an incompressible factor, M, into the log linear model to account for the man-machine ratio. The model can be expressed as follows:

$$MC_x = C_1\left[M + (1-M)x^{-b}\right] \tag{1.7}$$

$MC_x =$ Marginal cost for producing x$^{\text{th}}$ unit
$M =$ Incompressibility factor (constant)

When M=0 the model reduce to the log-linear model, which implies a complete manual operation. If M=1, then unit cost becomes equal to C_1 which suggest that there is no cost improvement possible in machine controlled operations.

3. Levy's adaptation function

Levy recognized that the log linear model could not account for the leveling off of production rate and the factors that might influence learning. In light of this observation he proposed the following model:

$$MC_x = \left[\frac{1}{\beta} - \left(\frac{1}{\beta} - \frac{x^b}{C_1}\right)k^{-kx}\right]^{-1} \tag{1.8}$$

β : production unit for the first unit
k : constant used to flatten the learning curve for large values of x

The flattening constant k causes the curve to reach a plateau instead of continuing to decrease or turning in the upwards direction.

4. Knecht's upturn model

Knecht observed the divergence of actual cost from those predicted by the learning curve theory at higher production volumes. He modified the basic functional form of the learning curve to avoid zero limit unit costs at large volumes. He altered the expression for curve to allow an upturn in the learning curve at larger values of cumulative production volume. The form suggested by him is as follows:

$$C_x = C_1 x^b e^{cx} \tag{1.9}$$

$c =$ constant

5. Glover's Learning Formula

This model is based on a bottom up approach which uses individual worker learning results as the basis for plant wide learning curve standards. The functional form of the model is expressed as:

$$\sum_{i=1}^{n} y_i + a = C_1 \left[\sum_{i=1}^{n} x_i \right]^m \tag{1.10}$$

y_i : elapsed time of cumulative quantity
x_i : cumulative quantity or elapsed time
a : commencement factor
n : index of curve (usually 1+b)
m : model parameter

6. Pegel's exponential function

Pagels learning curve has an exponential functional form and it is represented as:

$$MC_x = \alpha\, a^{x-1} + \beta \tag{1.11}$$

α, β, a : parameters based on emperical data analysis

7. Multipicative power model (Cobb-Douglas)

The multiplicative model can be used to represent various factors which might influence the cost of production. The independent variables can vary from to include both tangible and intangible parameters which might affect future costs.

$$C = k\, x_1^{b_1} x_2^{b_2} x_3^{b_3} \ldots x_n^{b_n} . \varepsilon \qquad (1.12)$$

C : estimated cost
k : model constant
x_i : i$^{\text{th}}$ independent variable
b_i : exponent of i$^{\text{th}}$ variable
ε : error term

These formulas have differed in their functional forms and can be seen below (Figure 4).

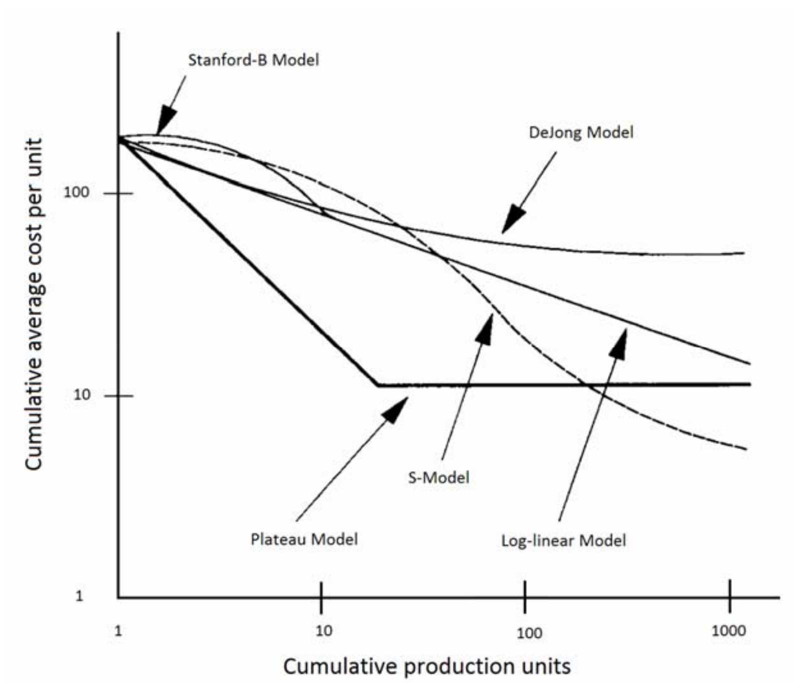

Figure 4: Comparison of learning curve models (Badiru 1992)

1.4 Application of learning to industry

Learning curves have been extensively used in industry in various forms and with different perspectives. It has undergone a wide transformation in its understanding and application since it was first coined by Wright in 1936. Initially, researchers had used learning curves as a tool to predict how the labor hours for manufacturing would evolve over time. With time, the scale of measurement changed from labor per hour to labor cost per unit and finally to cost per unit produced.

On similar lines the various factors used to justify the learning trends also increased and became more comprehensive in nature. Wright believed that learning happened due to repetition of task alone, but later researchers have included many other factors to justify the learning curves.

Some of the learning processes can be listed as follows (Badiru 1992; Malerba 1992; Goldberg and Touw 2003)

1. Learning by doing: This form of learning is internal to a company and depends upon the production activity.

2. Learning by using: This form of learning is also internal to a company and is related to the use of resources, machinery and other inputs

3. Learning from advances in science and technology

    a. Basic Science

    b. Applied Science

c. Engineering

This form of learning can be internal or external to a company and depends upon development or adoption of new technology.

4. Learning from inter-industry spill over: Acquiring technical knowledge developed by the competitor.

5. Learning by interacting: This form of learning is external to a company and depends upon the level of interaction with upstream or downstream sources of knowledge within or outside the firm. The outside knowledge can come from the suppliers or with knowledge sharing with other firms in the industry.

6. Learning by searching – Internal to a firm and related to activities aimed at generating new knowledge base (like R&D).

Similarly, other researchers have also tried to incorporate the effect of management decisions, industry structure, competition, etc. into the learning curve. This has undoubtedly shown the power of learning curves and their importance to the industry, but has made their application very cumbersome and often quite difficult. In the literature learning has been shown to be pervasive. However, as the next section will detail, there are limits to how learning curves can be used to guide technology selection decisions.

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2. Current approach and proposed methodology

2.1 Shortcomings of the current approaches

Until recently, most of the research done in this field has taken a top down approach to understanding cost reductions over time. Researchers have taken an aggregate outlook towards this problem. The general approach has been to regress data of cost per unit against cumulative volume (Tsuchiya 2002) and to understand the patterns followed by different industries and products. Figure 5 shows the work done by Tsuchiya et al. In this work, the cost of fuel cells has been calculated over time for nine different scenarios depending upon the power density of fuel cell (L, M and H for Low, Medium and High) and cost reduction speed for material(A, B and C for fast, medium and slow) used to make the fuel cell. It has been assumed that cost would be reduced by some fixed percentage for different scenarios, based on some speculations. Using different assumed rates of learning, the cost of fuel cells has been calculated over a period of time.

This study is based on an underlying assumption that the cost reductions observed for existing technologies can be applied to future products/technologies, such as fuel cells. Such an assumption must be made with great caution and only with deep understanding in the related field of technology. Otherwise such a speculation might make the learning curve look like self fulfilling prophecies.

Secondly, it can be difficult to explain cost reduction for a technology based on just a single variable, i.e. cumulative production by applying some pre determined learning rate to it.

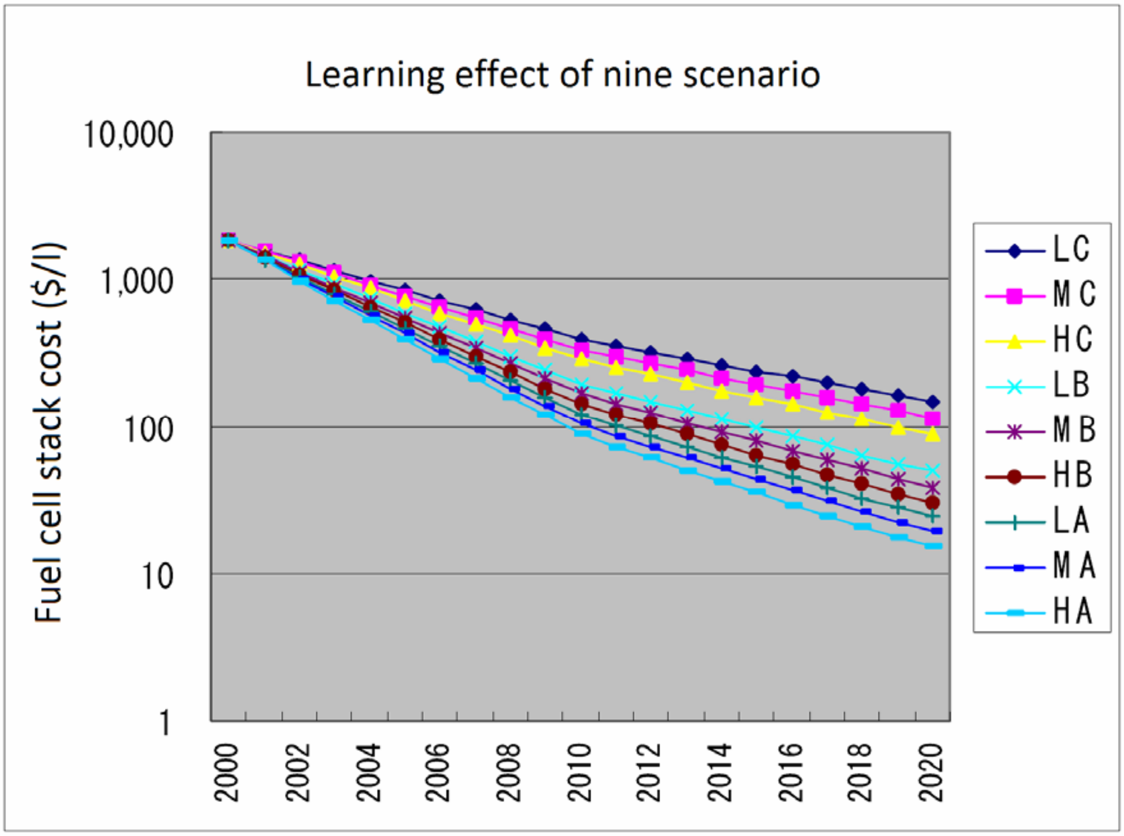

Figure 5: Effect of learning rate on cost evolution of fuel cells (Tsuchiya 2002)[i]

Finally, this approach also neglected the effect of changes in technology which gave an impression that this technique is technology blind.

While learning curves are valuable for estimating future costs, an additional significant contribution should be to help managers and engineers make decisions. The decision should be based on a technical understanding of the learning effects on production, not just the resulting cost reductions.

The current method of analysis, based on regression just tells the managers to produce some quantity of parts before their cost can be expected to go down to a certain level. It

[i] In the figure, H, M and L stand for high, medium and low power density. A, B and C represent scenario of fast, medium and slow cost reduction for the cost of material used.

does not probe deeper to understand the reasons that actually caused the cost of production to go down. If the managers and engineers could be given a perspective about the factors actually affecting the cost of production, and their contribution in bringing down the cost, they would be in a better position to decide future strategies for production.

For example, suppose a regression analysis of a data set gives a result that a product follows an 80% learning curve (Wright 1936). This result provides a variety of information. First and foremost, it indicates that the cost of production goes down by 20% each time the production volume is doubled. Second, it indicates the cumulative production volume needed to achieve a given cost target. However, an engineering perspective about the production improvements that will lead to these cost reductions is missing. There is no way to know if the same cost reductions could be achieved through specific technical advances instead of increased production. A method that decomposes the cost analysis into smaller parts would allow the engineer to pinpoint the factors that influence cost and thus provide other means to achieve cost savings besides increased production.

2.2 Proposed methodology: A process based cost modeling approach

To analyze the affect of learning curves on production it is essential to break down a production process into its constituent sub-processes and understand how learning applies to each of these sub processes. It is much simpler to understand the learning process at a sub-process level compared to aggregate level. Furthermore, it gives engineers and managers insight into the causation factors. The break down of a specific production process and its analysis is achieved by using a technique developed at MIT's Materials Systems Laboratory entitled Process Based Cost Modeling.

Process Based Cost Modeling (PBCM) (also know as Technical Cost Modeling) is a powerful analytical tool that integrates elemental costs derived from technical and operational drivers to estimate the total cost of production (Kirchain and Field 2001). PBCMs allow one to predict manufacturing costs for new designs, using well characterized processes, by relying on engineering fundamentals of the manufacturing process rather than historic data.

A specific manufacturing process can be looked at with respect to some factors such as reject rate, down time, cycle time, equipment cost, tool cost, and material cost; and the concept of learning curve can be individually be applied to each of these factors. These factors can then be passed into the PBCM to get the cost per part being produced. (2.1)

$$\$ = f(\text{cycletime, downtime, reject, labor, energy, equipment, tools...}) \qquad (2.1)$$

This decomposition of cost into these tangible factors allows for insight into causation talked about earlier. However to use the process variables like (cycle time, down time and reject) one still needs to make separate predictions. In this case uncertainty of forecasting still exists, but it is focused around tangible technology and operational aspects. This gives the engineers a scope to apply their subject matter expertise to build confidence around the predictions made.

3. Structured cost modeling approach

3.1 Process based cost modeling

Process based cost modeling (PBCM) is a method for analyzing the cost of manufacturing technologies by capturing the key engineering and process characteristics which relate to the total production cost of a component. PBCM is an improvement over the previous cost estimation techniques which relied on rules of thumb, past experience and accounting practices.

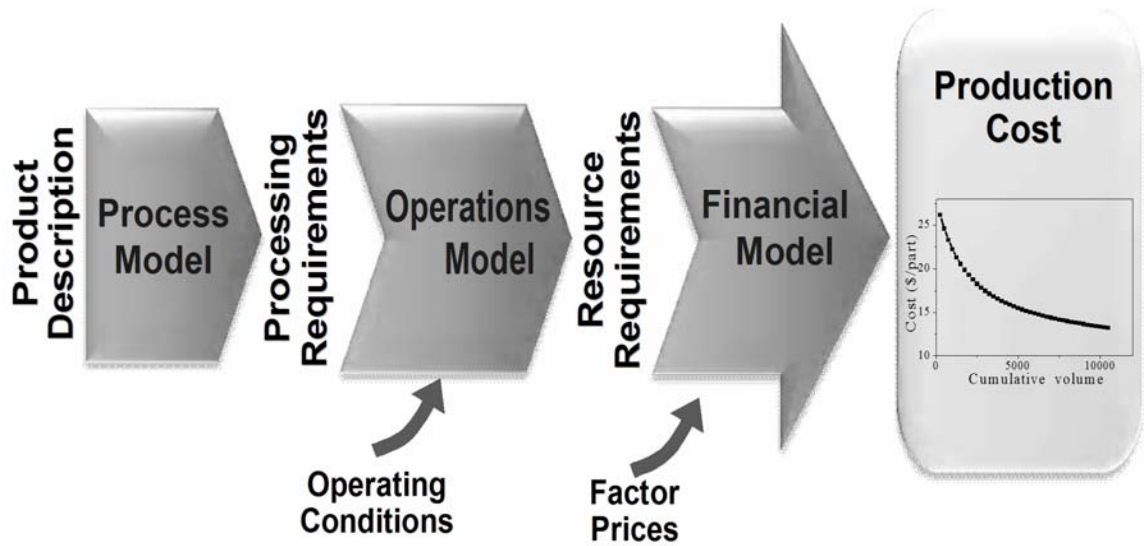

Figure 6: Illustration of Process Based Cost Modeling

For practical purposes, the PBCM can be broken down into three sub-models as shown above (Figure 6). The first one describes the processes needed to produce the part. The next model considers the operations of the manufacturing facility. The final model applies financial considerations to the operation.

3.1.1 Process Model

The process model is built on strong pillars of science and technology. It uses the principles of engineering and science to calculate the processing parameters (Figure 6). The process model requires inputs for the size, shape and material of the final product. Depending upon the technology and material inputs, the process model calculates the total cycle time for the process. The model also gives output for the equipment capacity (for example, size and tonnage in case of press) and tools which might be required to carry out the process. Since the process model is governed by the engineering principles, it also addresses the constraints on cycle time and reject. For example, for a deformation process there is a limit on maximum strain rate at which a defect free part can be produced. The cycle time for such a process cannot be lower than that calculated by this maximum strain rate. Similarly for semiconductor industry there is a minimum number of reject that will be produced depending upon the thermodynamics of the processing technique. In no situation the reject rate can be lower than this value. The processing requirements augmented with the operating conditions including the shifts schedule, working hours, desired annual production volume, etc., are passed into the operations model.

3.1.2 Operating Model

The next part of the PBCM is the operating model, which determines the time required to meet a given target production volume (required operating time). Once the time is calculated, number of parallel lines can be determined based on the total time available (uptime) in a year and therefore the scale of the production facility. This information is then used to calculate the total amount of equipment, labor and other resources needed to achieve the desired product output.

a. Annual Available Operating Time and Uptime

The calculation of annual available operating time involves the integration of several available metrics. The line utilization for a day can be divided primarily into available and unavailable time. The available time includes the time when the plant is manufacturing and also the idle time when the plant is staffed and running but is not producing due to a lack in of demand. The unavailable time includes unplanned breakdown, worker breaks, maintenance time and the time when the facility is not operating (Figure 7).

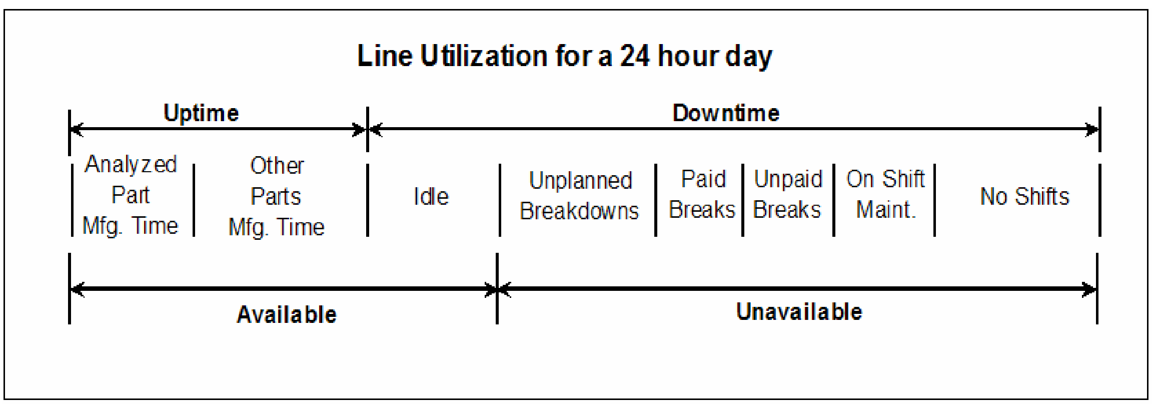

Figure 7: Available operation time based on a 24 hour day clock (Fuchs 2006)

The available line time can be calculated as:

$$AT = DPY.(24 - NS - UB - PB - UD) \qquad (3.1)$$

AT : Available line time
DPY : Days per year
NS : No Shift
UB : Unplanned breakdown
PB : Paid break
UD : Unpaid break

Finally, the uptime for the line can be calculated as the time when the line is running and actually producing the desired parts.

$$UT = AT - Idle$$

b. Annual Required Operating Time

Annual required operating time is the total time required to produce the target number of parts and is defined as the product of cycle time and number of parts required annually (3.2). Since target volume of production for a given year is known, equation (3.3) can be used to determine the actual number of parts which is required to be produced based on the reject rate.

$$t = \sum_i CT_i * n_i \tag{3.2}$$

$$n_i = \frac{n_{i-1}}{1 - reject_{i-1}} \tag{3.3}$$

CT_i = Cycle time for process i

n_i = number of parts at the ith sub process

$reject_i$ = reject rate in fraction for the ith sub process

n_0 = Target Volume

Annual available operating time tells us the amount of time a single line would be running in a year. This can be used to calculate the number of lines that would be required to attain the target production volume. The number of lines can be calculated by dividing the annual required operating time by the uptime (3.4)

$$nl = \left| \frac{t}{UT} \right| \tag{3.4}$$

$nl =$ Number of parallel lines

Annual paid time equation (3.5) is used to calculate the time for which the labors are paid. It is defined separately from annual available time to account for paid breaks and unplanned downtime for which labors are paid.

$$APT = (24 - NS - UB).nl \tag{3.5}$$

3.1.3 Financial Model

The final part of the PBCM is the finance model which works in conjugation with rest of the model to eventually calculate the unit cost of the product. The role of the financial model is to apply unit prices to the levels of resources consumed as determined by the operations model and to correctly allocate the costs over time and across products. The cost element can be broken down into material, labor, energy, building, equipment, tool and overhead cost. Each of these cost are calculated separately using the information from the previous models to give the total cost (Fuchs 2006)

$$C_{total} = C_{material} + C_{labor} + C_{energy} + C_{building} + C_{equipment} + C_{tools} + C_{overhead} \tag{3.6}$$

The cost of material, labor and energy are considered to be variable costs and therefore can be directly applied to the cost of the product. However, some allowance is needed to account for the variable costs associated with downtime, rejected parts, etc. The financial model is also used to sum the individual cost elements to determine a fully accounted unit cost of production(3.6).

Material cost is the product of number of parts produced, weight of the product and the price per unit mass of the product. The scrap which is produced is sold as at scrap rate and is credited from the material cost

$$C_{material} = n_i.W.P - (n_i - n_0).W.P_{scrap} \tag{3.7}$$

n_i : Total number of parts produced to meet the demand
$n_i - n_o$: Number of scrap
W : Weight of product
P : Price of material per unit mass
P_{scrap} : Price of scrap per unit mass

Labor cost can be specified in three separate classifications – technician, skilled and unskilled labor. The annual cost can be calculated as the product of annual paid time, wage rate and fraction of line for which the production was carried out.

$$C_{labor} = \sum_j APT_j.P_j.\frac{t}{AT} \tag{3.8}$$

j : technician, skilled, unskilled labor
APT_j : Annual paid time
P_j : Wage rate
$\frac{t}{AT}$: Fraction of line

Energy cost can be calculated in many different ways. Generally the energy cost can be calculated based on specified energy consumption rate for each machine. The energy cost is given as a product of annual required line time and the energy consumption rate for the equipment (3.9) .

But some time the energy consumption can be tackled in a more comprehensive manner by using energy balance. This is generally used for process involving heating and the energy cost might be calculated on the basis of the thermal content supplied to the material and the thermal losses involved in maintaining the temperature for some fixed amount of time (3.10).

$$C_{energy} = \sum_i t.E_i \tag{3.9}$$

E_i : Energy consumption rate for equipment i

$$C_{energy} = \text{Energy absorbed by material} + \text{Rate of heat loss.Time} \tag{3.10}$$

Building, tool and equipment are considered to be capital investment. The capital investment is treated as fixed cost that must be spread over years of production. The financial model amortizes these investments over their useful lives to determine a series of equal annual payments equivalent to the initial investment. Time value of money is also factored into this calculation to ensure that the full costs of these investments are taken into account in the unit cost or production.

The opportunity cost of associated with capital investment is calculated using standard capital recovery factor (de Neufville 1990).

$$CRF_j = \frac{r(1+r)^n}{(1+r)^n - 1} \quad (3.11)$$

CRF_j : Capital recovery factor
j : Building, Equipment, Tool
r : Interest rate
n : Number of years

The annual amortized cost for building, equipment and tool is the investment times the capital recovery factor equation(3.12). This is the amount of money which needs to be paid annually for using the resources.

$$AC_j = CRF_j . EI_j \quad (3.12)$$

AC_j : Annual cost for j
CRF_j : Capital recovery factor for j
EI_j : Capital investment made in j

The production cost obtained from process based cost model can be analyzed in different ways. Fixed costs versus variable costs can be examined, or these costs can be further broken down into the contribution to cost attributed to capital, labor, material, energy etc. Costs can also be explored by process step and each of the previous cost elements can be examined by process step as well. This type of model also provides a means to run sensitivity analysis with respect to various parameters which gives a more complete picture about how different parameters might affect the final price.

Such a detailed level of sensitivity analysis based on process variables is possible because the models are constructed to derive cost from the process level, and therefore do not use statistical methods to derive cost from the part description (Although statistical models are sometimes used within the process model to derive process conditions from part descriptions). This makes this method a powerful tool to study the effect of various operational parameters on the cost of the part produced. The cost can be analyzed in different ways to understand how each of the parameters interacts with each other and the final cost. It can also be used to identify the primary drivers which affect the manufacturing cost.

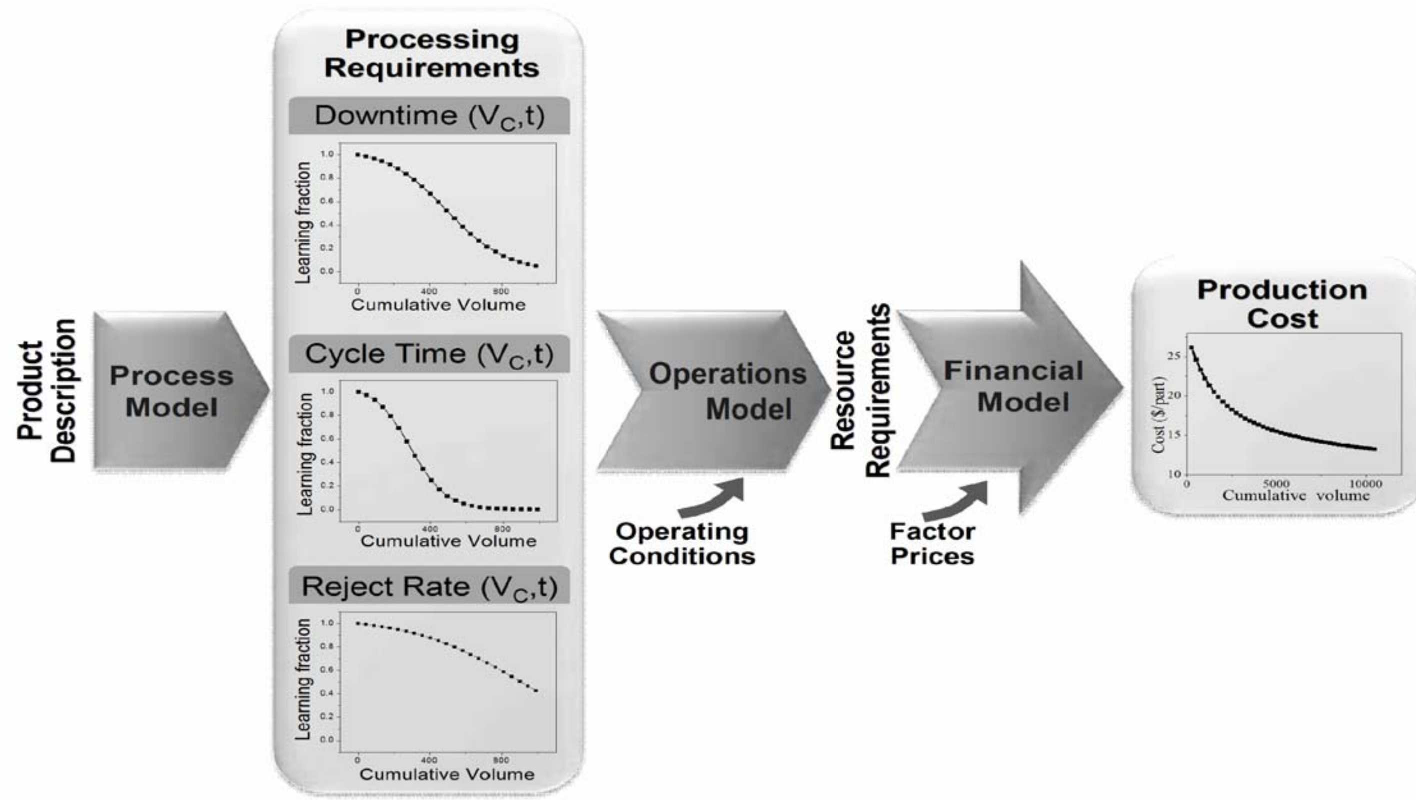

Figure 8: Modified PBCM to calculate cost walk down with time

3.2 Dynamic/Time Dependent Cost Model

In the previous section the power and usefulness of PBCM was demonstrated. However, these models provide cost estimates only at a fixed point in time. In this section, a method for expanding the use of PBCMs to address the question of cost evolution with time will be presented.

As discussed in the previous section, the process model portion of a PBCM is used to determine production parameters based on inputs related to final product. There are many process parameters which are included in a typical PBCM and each has their own impact in determining the final cost. Some of the common process parameters are shown in Figure 8, but this is not an exhaustive list and there might be others.

In a typical, static process based cost model, best case values for these variables are determined, often based on theoretical minimums. In practical situations, the values of these process parameters are often higher than those predicted by the model. This is due in part to an inability to ever achieve theoretical limits, but also reflects the fact that in some cases learning with respect to these variables is not complete, and therefore these variables have not yet reached their long term steady state values. Representing the values of the process parameters as a function of time or cumulative volume provides a good way to investigate the cost improvements possible over time. Compared to the top down approach of learning where total cost is treated as a function of time or cumulative volume, this method provides insight into the mechanisms that lead to cost reduction. Process engineers and technical specialists may be able to provide reasonable estimates for improvements in production parameters thus leading to a better perspective on how to further improve the cost.

3.2.1 Using learning curves for process variables

As suggested in the previous section, the process variables can be expressed as a function of cumulative volume or time in the dynamic PBCM.

Process variables are likely to have several different phases of learning and therefore a learning curve approach which comprehends these concepts must be employed. These learning phases can generally be categorized as an initial transient phase, followed by a learning phase and finally a saturation phase.

The initial transient takes place just after the implementation of a new process. During this phase the improvements in the process parameters are slow. Initial transients are observed because just after implementation of a new process, it takes some time before line workers and engineers begin to understand the practical intricacies and details.

The second phase is the learning phase, which is characterized by major improvements in the process parameters. The improvements in this phase can be attributed to (Carrington 1989):

a. Job familiarization by the workmen, which results from repetition of manufacturing operations.

b. General improvements in tool coordination, shop organization, and engineering liaison

c. Development of more efficient sub assemblies, part-supply systems and tools.

After spending some time understanding the practical intricacies of the line, the line engineers are in a better position to apply their knowledge to improve the overall line performance.

The final phase is the saturation phase where improvements in the process parameters plateau. The saturation effect illustrates the fact that some of the parameters cannot be improved indefinitely and are constrained by laws of nature. Cycle time provides an excellent illustration of this concept. The cycle time will initially be high but may come down with time due to learning at an operational level. However, cycle time cannot go below a theoretical minimum value. This theoretical minimum could be related to physical limits based on scientific principles involved in the manufacturing process. For example, limits to how quickly cooling can be accomplished will be based on principles of heat transfer. While there are often opportunities to reduce cooling times, eventually the laws of physics regarding heat transfer will limit any further reduction. Similarly, for processes involving chemical reactions, theoretical limits for reaction kinetics will result in a minimum possible cycle time. Once this minimum is achieved we can assume that the learning process is fully completed and there is no scope for further improvements with regard to this variable.

3.2.1.1 Selection of process variables

There are a number of process variable which can be represented as function to time or volume to showcase the effect of learning which can be used to determine the cost evolution. But the choice is based on the impact the variable is bound to make in the final outcome. While there are many process parameters included in a typical PBCM, three variables in particular often have a strong impact on cost and are likely to improve with time as the process matures: cycle time, downtime and reject rate.

3.2.1.2 Trade off between S curves and log linear learning curves

The log linear learning curves (1.5) are based on the concept that learning takes place indefinitely over time and can be represented by a logarithmic function.

The positive aspect of using this curve is that only two parameters (initial value of process parameter and learning rate) need to be specified to obtain the learning curve. The major drawback of this type of curve is that it cannot account for the initial transient or the saturation phases appropriately. The log linear curve does attain some kind of saturation effect but since the saturation value cannot be specified, it generally occurs at values much lower than the theoretical limit (Figure 9).

The learning rate of log linear curves does not explicitly state whether the observed learning is fast or slow. It is very much dependent on the production volume of the product. For example, a learning rate of 95% might be a fast rate for a semiconductor company producing millions of chips annually, but it might be a slow learning rate for a turbine manufacturing company producing just thousands of units annually.

Even with these shortcomings, log linear curves have found widespread acceptance in the learning literature. The plausible reasons these issues are seldom raised in the learning literature could be that the life cycle of the product under observation is so short that the saturation level is never reached.

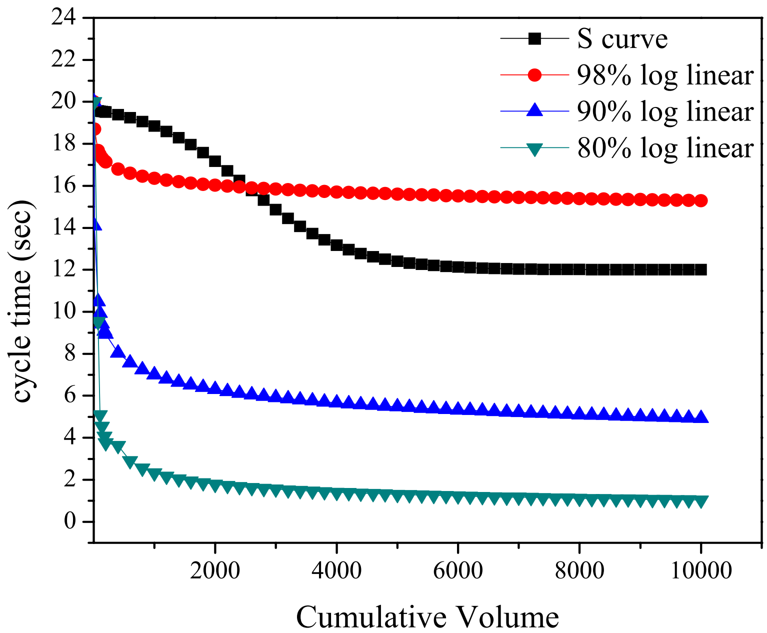

Figure 9: The comparison in learning trends shown by s curves and log linear curves

The initial transient is generally not observed because the transient phase generally occurs in the R&D stages and the initial period of production, which is often not included in data collection. Data collection is generally started once the product is fully under production.

To overcome these problems, S shaped learning curves have been proposed. These curves provide more power and flexibility to capture the observations made with regard to the initial transient and saturation phases. The figure above (Figure 9) shows an S shaped learning curve. It can be seen from the shape of the curve that it can be used to represent the initial transient as well as the saturation effect, in a very effective manner. Compared to log linear curve it has a shortcoming in terms of number of parameters required to specify the curve. For S curves four parameters are required to be specified to completely define the learning curve, as compared to log linear which requires just two. The tradeoff between the accuracy of curve representation and easy of collection data often determine the choice of the learning curves. It is left to the discretion of the user to make a decision between the two curves.

For the current study S curves were chosen over log linear curves to represent the learning behavior.

3.2.1.3 Benefits of using non dimension learning variables

Traditionally the S-curves (Carr 1946; Yelle 1979) were specified as process variable versus cumulative volume. The process variables learn and improve over a period of time. The improvement in the process variables can be expressed by using a non dimensional learning variable (y*) (3.13) which could be mapped to different process variables.

$$y^* = \frac{PV - PV_{\min}}{PV_{\max} - PV_{\min}} \qquad (3.13)$$

PV = process variable

The non dimensional learning variable (y*) varies between 0 and 1, (Figure 10) where 1 corresponds to its maximum value and 0 can correspond to its minimum value. The normalization increases the ease of application of learning curves to different process parameters.

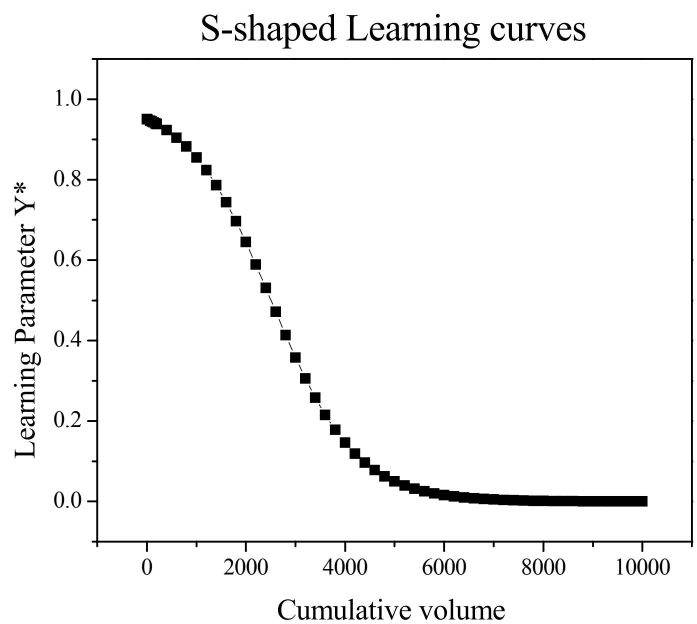

Figure 10: Learning curve in terms of dimensionless learning parameter y*

The learning curve can further be normalized with respect to the cumulative volume axis (Figure 11). The normalization of the curve with respect to volume makes it a powerful tool to compare learning across industry with varying annual production.

For example, if we compare the manufacturing of an airplane industry with that of an automobile industry, then the volume produced annually would be quite different. For the airplane industry it might be somewhere in thousands whereas for auto manufacturer it would be somewhere in millions. Normalizing volume makes it simpler to compare both these industry and puts them on same page. This answers the problem faced using log linear learning curve where 95% learning could have a different implication for both these industries

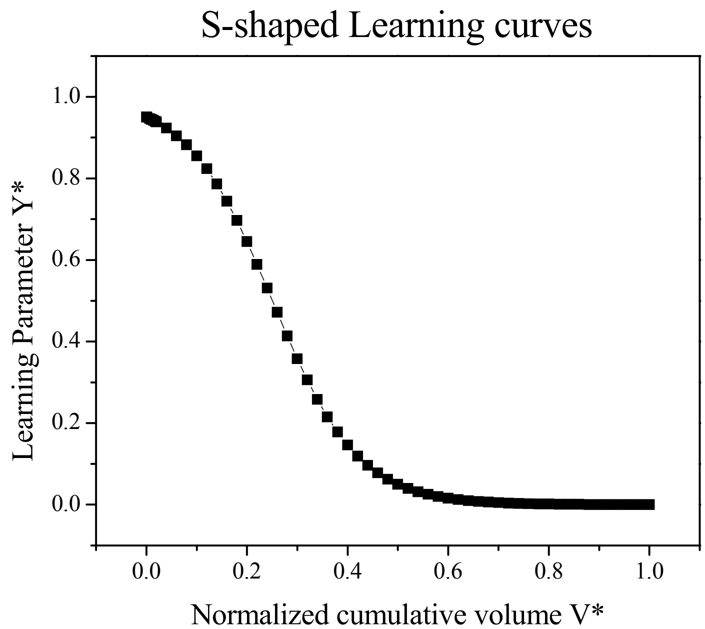

Figure 11: Normalized learning curve (normalized with respect to learning parameter and cumulative volume)

The normalization of the cumulative volume axis is brought about by diving it by 'equivalent volume'. The term equivalent volume needs to be defined and used consistently across the model to avoid errors. Equivalent volume can be defined in many ways, but for this study it has been defined as the number of parts which could be produced by the equipment if it was operated for 24 hours a day for 365 days, throughout its life time.

$$V_{eq} = \left(\frac{60}{cycle\ time\ (\min)} \right) .24\ hour.365 days.Equipment\ Life\ (Years) \quad (3.14)$$

$$Normalized\ cumulative\ volume\ (V^{*}) = \frac{Cumulative\ Volume\ (V)}{Equivalent\ Volume\ (V_{eq})} \qquad (3.15)$$

The volume produced by the equipment is dependent on cycle time, which varies with time and learning. To overcome this problem, the cycle time used in the calculation is the theoretical minimum cycle time CT_{min} which can be attained for the process.

3.2.2 Example of application

In this section examples will be presented to explain the use of S-curves in representing the set of data for different process variables.

3.2.2.1 Defining a normalized S curve

Normalized S curves are a powerful way of representing learning data for different process parameters and comparing it across industries with different production volumes.

The normalized S curve can be defined as follows:

$$y^* = \frac{1}{1+\exp(\alpha V^* + \beta)} \tag{3.16}$$

α, β = constant
V^* = Normalized cumulative volume
y^* = learning fraction,

The parameters α and β, defines the shape of the learning curve. In particular, α conveys the rate of learning, while β represents any initial transient phases if present during learning. A high value for α is associated with fast learning and means that a low value of volume fraction V^* would be required to attain a certain fraction of learning (y^*). Similarly, a low value of α suggests slow learning, and a higher value of V^* will be required to attain the same value of y^*.

β causes the graph to shift along the V^* axis, and hence represents the initial transient in learning. If the transient phase is very long then it would be reflected by a higher value of β and vice versa. Based on the value of α and β a process can be defined to be slow, medium or fast.

3.2.2.2 Derivation of alpha α and beta β for the S curves

Alpha and beta are the parameters which are necessary to define the S curves. To determine alpha and beta (2 unknowns), at least two points are required to be defined on the S curve. For the current study the two points that have been used are 5% learning and 95% learning points. The cumulative volume fraction can be chosen with respect to these points which would determine the value of alpha and beta respectively.

For example, a fast learning process can be defined as one where 95% learning is completed within half equipment life and 5% of learning is completed within 0.01 equipment life (Figure 12)

This leads to the following values:

$\alpha = 11.801$ and $\beta = -2.956$ (3.17)

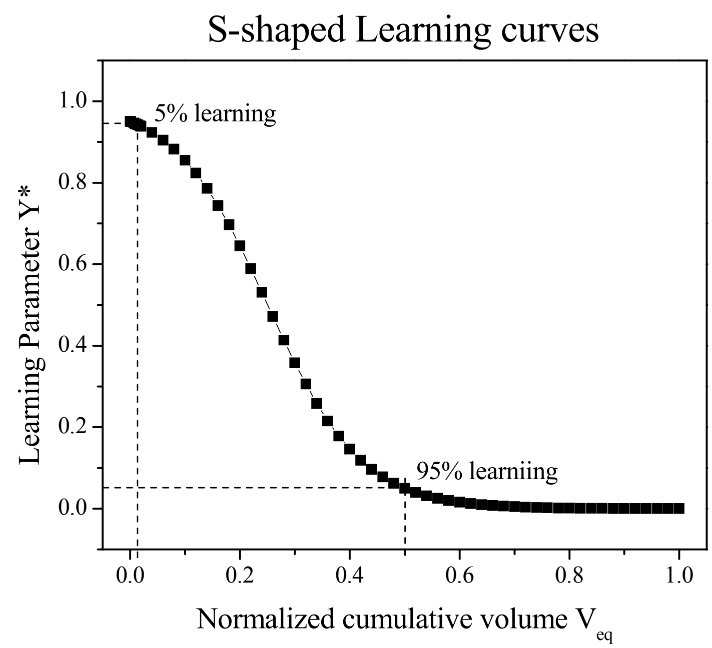

Figure 12: Derivation of alpha and beta for fast learning s-curve

Similarly, a slow learning process can be defined as one where 95% learning is completed within one full equipment life and 5% of learning is completed within 0.01 equipment life.

This leads to the following values:

$\alpha = 5.948$ and $\beta = -3.004$ (3.18)

The value of alpha and beta can also be calculated by regressing given set of data and will be demonstrated in later chapters (chapter 4.1.2.1)

3.2.2.3 Illustration of using normalized S curve to determine learning parameters (cycle time) versus cumulative volume

It is assumed that the cycle time starts at some value of CT_{max} and evolves with time to attain a final value of CT_{min}. CT represents the cycle time for any intermediate time of interest. The fraction of learning at any instance of time for the cycle time can be defined by y* as shown in equation (3.19).

$$y^* = \frac{CT - CT_{\min}}{CT_{\max} - CT_{\min}} \qquad (3.19)$$

$$CT = CT_{\min} + y^*(CT_{\max} - CT_{\min}) \qquad (3.20)$$

The value of y* defined by equation (3.19) is analogous to y* shown in equation (3.16) The full cycle time learning curve equation can be found by plugging the value of y* from the S-shaped learning curve equation (3.16) into equation (3.20) to obtain

$$CT = CT_{\min} + \left[\frac{1}{1+\exp(\alpha V^* + \beta)}\right] * (CT_{\max} - CT_{\min}) \qquad (3.21)$$

Thus the cycle time can be calculated as a function of the normalized cumulative volume and will lie between the maximum and theoretical minimum value. It should be noted here that it is not necessary for every process variable to reach its saturation point. This would be governed by the value of alpha and beta in the above equation.

A similar analysis can be done in terms of cumulative volume instead of normalized cumulative volume.

$$V^* = \frac{V}{V_{eq}} \qquad \text{From equation (3.15)}$$

$$CT = CT_{\min} + \left[\frac{1}{1+\exp\left(\alpha \dfrac{V}{V_{eq}} + \beta \right)} \right] * (CT_{\max} - CT_{\min}) \qquad (3.22)$$

By defining $\alpha' = \dfrac{\alpha}{V_{eq}}$ then,

$$CT = CT_{\min} + \left[\frac{1}{1+\exp\left(\alpha' V + \beta \right)} \right] * (CT_{\max} - CT_{\min}) \qquad (3.23)$$

In equation (3.23) the learning in cycle time has been expressed as a function of cumulative volume rather than normalized cumulative volume.

Numerical Illustration

For a process the cycle time and equivalent volume has been defined as following:

$CT_{max} = 20$

$CT_{min} = 12$

$V_{eq} = 500{,}000$

Both fast and slow learning rates can be applied to understand how the cycle time will reduce with volume as learning is achieved (Figure 13).

$$CT = 12 + \left[\frac{1}{1+\exp\left(\dfrac{\alpha}{500000} V + \beta \right)} \right] * (20 - 12) \text{ [ii]}$$

α = 11.801 and β = -2.956 for fast learning from (3.17)

[ii] V represents cumulative volume and not normalized cumulative volume

$\alpha = 5.948$ and $\beta = -3.004$ for slow learning from (3.18)

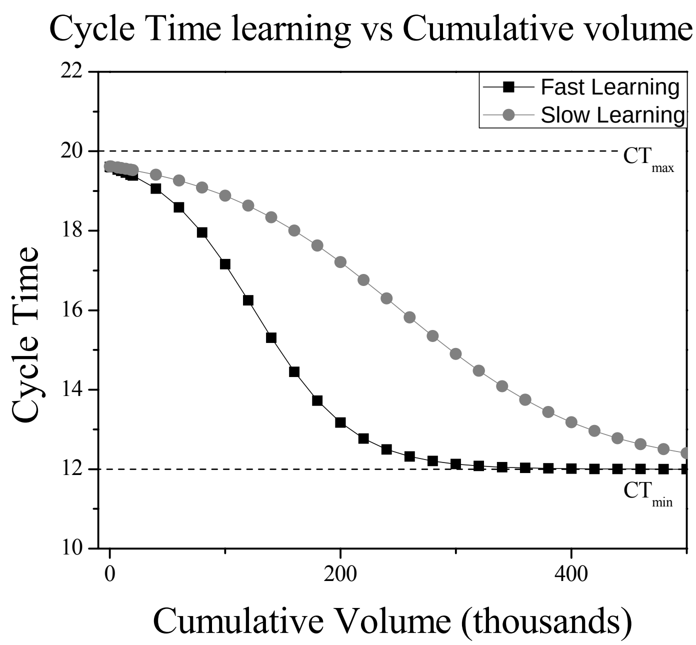

Figure 13 : Evolution of cycle time with volume for fast and slow learning rates

The evolution of process parameters demonstrated in this chapter using the S learning curves would be used as inputs to the process based cost model (chapter 4) and taxonomic classification model (chapter 5) to calculate the production cost as a function of volume.

4. Case of Tube hydroforming

In the previous chapter it was shown how PBCM along with the S-curves could prove to be a powerful method to predict cost evolution for a product. It also touched upon the fact that using S-curves to define process parameters gives a more causal insight into cost reduction. In this chapter a case study involving the process of tubular hydroforming will be used to illustrate the idea.

Tube hydroforming came as a natural choice for looking at cost evolution because it is a relatively new process which was developed in last couple of decades. The data collected for hydroforming should be able to represent the learning associated with the process since its inception. The data for tube hydroforming was gathered from a reputed company for the purpose of this study.

4.1 Dynamic tube hydroforming model

The dynamic tube hydroforming model was constructed by using the MSL tube hydroforming model and augmenting the S curve learning model to it.

4.1.1 Tube hydroforming model

Tube hydroforming is a metal forming process in which a work piece is deformed by a pressurized liquid (usually water based) into complex shapes in a die cavity, with added compressive axial forces applied.

A process based cost model was developed to understand and analyze the economics of manufacturing for tube hydroforming by the Materials Systems Lab at MIT. The process based cost model for tube hydroforming is a comprehensive model capable of evaluating all the different sub-processes which might be involved in tube hydroforming; starting from de-coiling and slitting of coil to roll forming, bending, annealing, pre-forming, hydroforming, and finishing of the final part (Constantine 2001).

The same model structure has been used in this study, but the learning model has been applied only to the hydroforming sub process of tube hydroforming. This is because the data collected pertains to only this sub process.

4.1.2 Incorporating S curve learning model into hydroforming model

The learning curve model has been used to represent the process parameters in form of S curves. The S curves for the learning model has been generated from the data collected for tube hydroforming. The data primarily captures the cycle time and downtime for the hydroforming step as a function of time and volume. The cycle time and downtime of the hydroforming step has been modeled as S curve and passed into the hydroforming model to get cost as a function of volume and time.

4.1.2.1 Determination of S curves from the data

To determine the S curve for a process variable, at least four parameters (max value, min value, alpha and beta) are required to be defined. Looking at a given set of data the maximum value and long term saturation or the minimum value can be determined by simple inspection. But determination of alpha α and beta β requires some kind of regression analysis over the data. The method which was used to determine α and β for this analysis is shown with cycle time as an example, and this method could be extended to determine α and β for any process variable.

Analysis to determine α and β for cycle time:

$$CT = CT_{\min} + \left[\frac{1}{1+\exp\left(\alpha' V + \beta\right)} \right] * (CT_{\max} - CT_{\min})$$

$$\exp\left(\alpha' V + \beta\right) = \frac{(CT_{\max} - CT_{\min})}{(CT - CT_{\min})} - 1 \qquad (4.1)$$

$$\left(\alpha' V + \beta\right) = \ln\left(\frac{CT_{\max} - CT}{CT - CT_{\min}} \right) \qquad (4.2)$$

$$\left(\alpha' V + \beta\right) = K(V) \qquad (4.3)$$

$$\text{where, } K(V) = \ln\left(\frac{CT_{\max} - CT}{CT - CT_{\min}} \right)$$

Linear regression analysis can be carried out over equation (4.3) to determine α and β for the given set of data. For the present work the linear regression was done using the least square analysis.

The sets of data obtained for cycle time and downtime are shown in Figure 14 and Figure 15, respectively. The data was collected on weekly basis for a single hydroforming line. The analysis was carried out on the data set to determine the maximum value, minimum value and values of α and β for given process variable and the results have been tabulated below.

For cycle time data:

CTmax	1.32	α	1.24E-06
CTmin	0.63	β	0.283

For downtime data:

DTmax	0.49	α	2.02E-07
DTmin	0.03	β	0.59

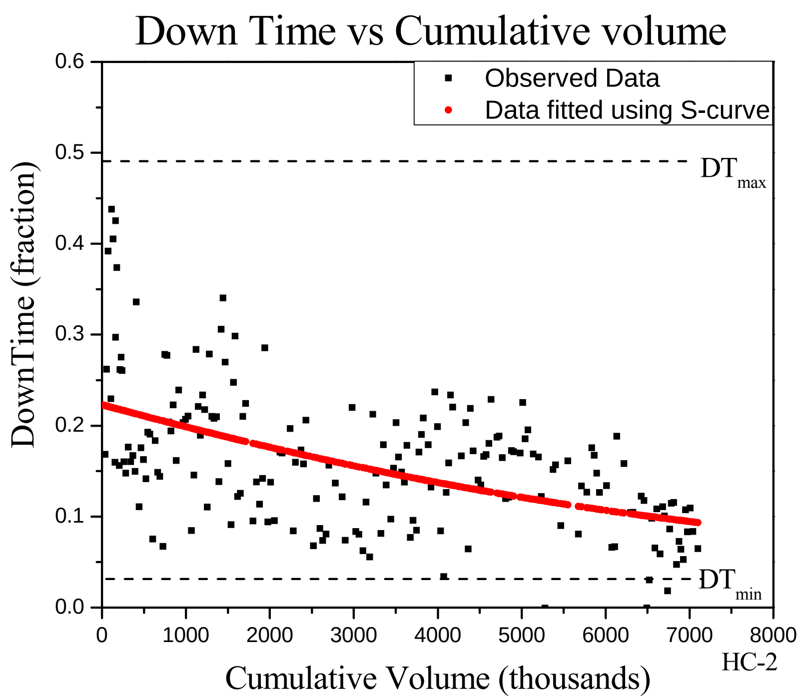

Figure 14: Down time vs. cumulative volume

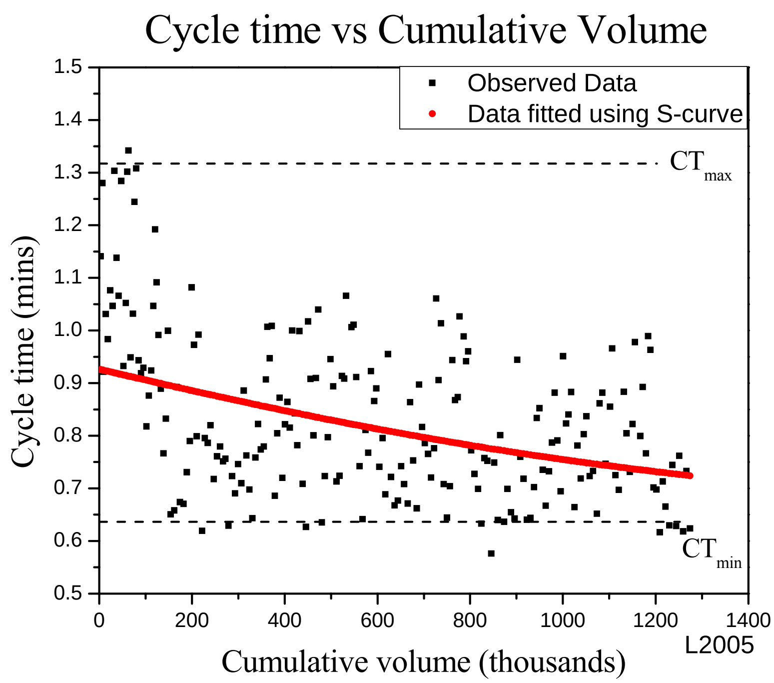

Figure 15: Cycle time vs. cumulative volume

The data fitted S curves shown in Figure 14 and Figure 15 looks more like a linear curve but its functional form is that of an S curve.

The data collection for the hydroforming line was started some years after the process fully came into commercial application. This could be a reason why the initial transient is missing and only the linear portion is seen. The saturation value of each of the process is shown in form of dotted line and would be achieved in future years. Since both the initial transient as well as the saturation portion of the S curve is missing, it looks more like a linear curve.

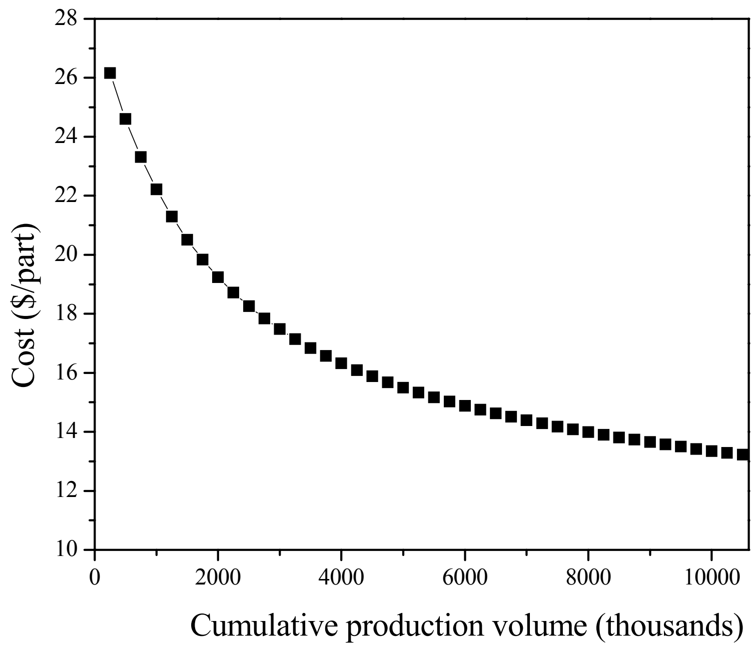

Figure 16: Total cost for tube hydroforming as a function of volume

The S curves obtained using the learning rates (α and β) were passed into the process based cost model for tube hydroforming, which was run for a part which was 1.5m long, weighed about 2.8 kilogram and had 8 bends. The final cost which was obtained as a function of cumulative volume (

Figure 16) included the cost of the raw material and the processing cost (labor, equipment and tools) on a per part basis. For the list of general inputs and assumptions, see appendix A.

The total cost over time can also be further broken down into its elemental costs (tool, equipment, labor and material) (Figure 17). This gives insight into how each of the elemental costs evolves to bring down the cost with production volume. The cost of labor and equipment goes down with time, but the cost of tooling and material has remained constant. It is pretty intuitive that cost of material remained constant because the material cost is unaffected by the improvements in cycle time and downtime. The cost of material is only affected by the reject rate and for the case study above the reject rates was constant throughout the analysis.

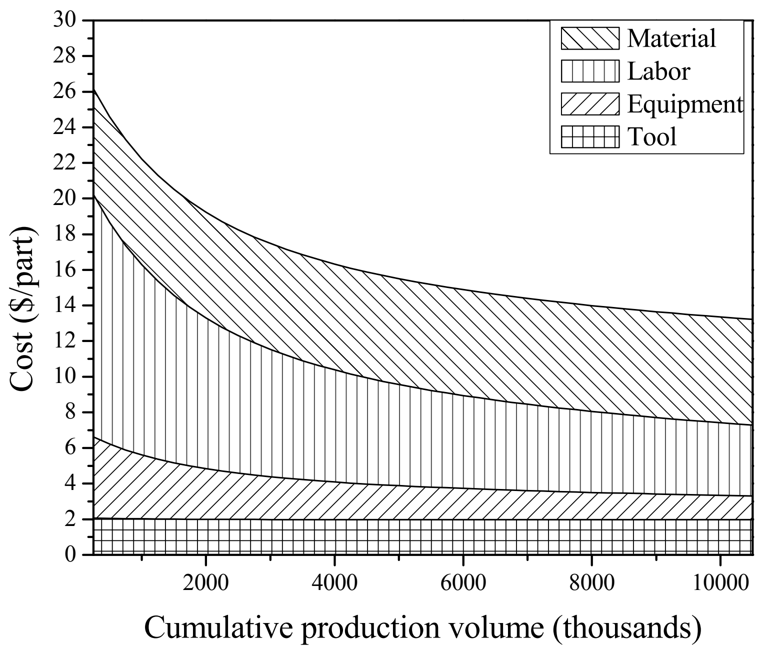

Figure 17: Cost evolution for tube hydroforming on elemental cost basis

The tools for a process are generally dedicated; hence the tool cost per part will remain constant if the production volume is constant. In the above case it was assumed that the production volume for the hydroforming process is constant, hence tool cost showed no improvement with time. The tooling costs are not affected by learning and show improvements only by economies of scale.

4.2 Identifying critical learning levers

In the previous section time series production data for a tube hydroformed component was used to estimate its cost evolution as a function of cumulative volume. The process based cost modeling approach along with learning curves can also be used to understand how these trends would be affected by changes in the learning rate for these same process parameters. In the case study of tube hydroforming; cycle time and downtime were passed to the cost model as a function of cumulative volume. For the analysis carried out in this section the learning curve pertaining to cycle time and downtime would be used from the previous study, the data for reject rate has been hypothetically created assuming a fast learning rate. The learning curves for all the process variables are listed in appendix A. The ways in which each of these variables changed with cumulative volume were systematically altered and the resulting affects on the cost evolution were noted. Understanding these relationships could help production managers, engineers and researchers to target their efforts towards improvements in those factors which have the largest and fastest impacts on cost.

Before looking into this issue it is important to understand the concept of scope of improvement for a process. Scope of improvement communicates the room for improvement in the parameter under consideration. Scope for improvement is high if the process parameter can be improved by a large extent and it is low if not much improvement can be brought to the process by any means. For a new technology, it is sometimes difficult to predict the scope of improvement a priori, but knowledge and an in depth understanding of the process facilitate the estimation of the scope in a more logical manner.

For the purposes of this study, several assumptions were made for the scope of learning. High scope means that the specified parameter can be improved by 50%; while low scope means that the parameter cannot be improved (assumed for this study). The combined cost/learning model was run for different learning scope scenarios to determine the effects of improvement in each process variable on the cost evolution. Table **1** shows how the different combinations of learning scope that were explored. In the first scenario, all three major process variables, cycle time, downtime and reject rate, had high scopes of learning. The next scenarios consider having high scope for only one variable. These analyses indicate the relative performance of each of the three variables. The final scenario considers a low scope for all variables and is representative of a process for which very little or no learning is possible i any of these process variables

Table 1 : Effect of scope on cost evolution

Scenario	Scope of Cycle Time	Scope of Reject	Scope of Down Time	Remark
1	High	High	High	High potential to observe the effect of learning
2	High	Low	Low	Observe effect of cycle time learning over other learning
3	Low	High	Low	Observe effect of reject learning over other learning
4	Low	Low	High	Observe effect of down time learning over other learning
5	Low	Low	Low	No effect of learning

4.2.1 Case study for identifying critical learning levers

For the case study some initial and final values of cycle time, down time and reject have been chosen (Table 2). The improvements in the process parameters are assumed to take place due to learning at a fast rate (Chapter 3.2.2.2, and Appendix A).

Table 2: Initial and final values for the process parameter

	Cycle Time	Down Time	Reject rate
Initial	2.8 min	57%	10%
Final value	1.4 min	28%	5%

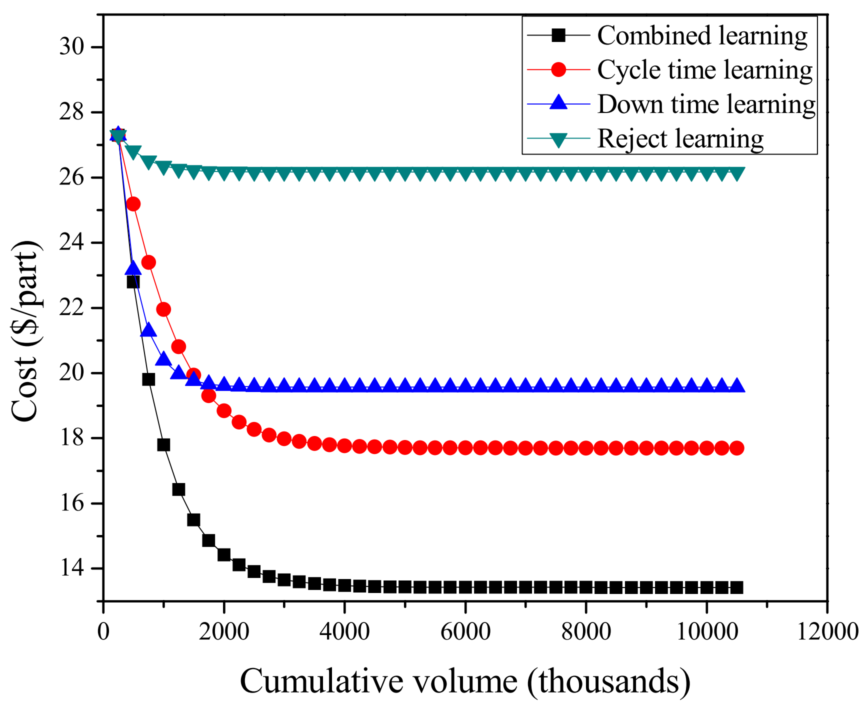

Figure 18: Effect of learning for different process variables on cost evolution

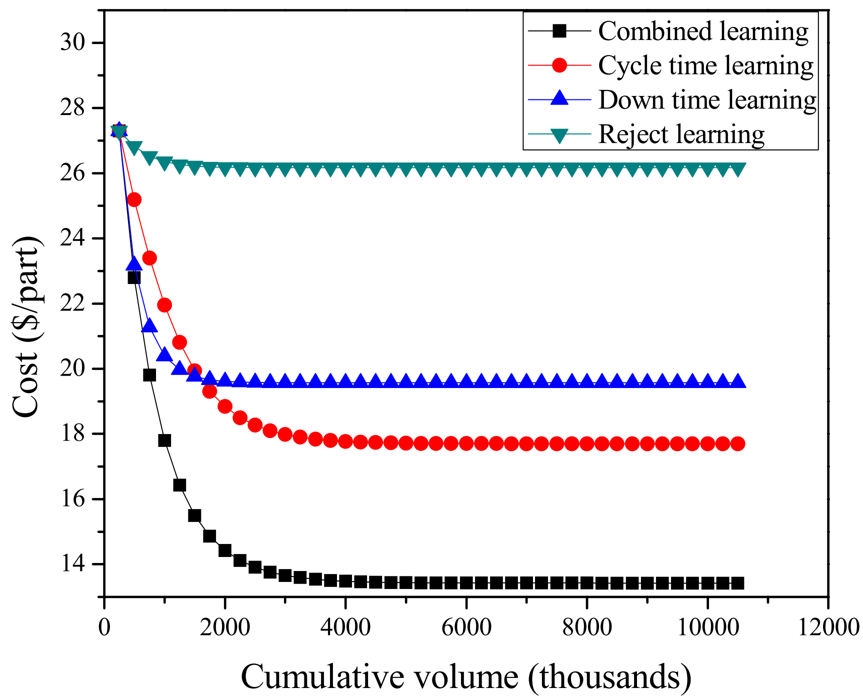

Figure 18) shows that with combined learning the cost reduces by almost half the initial value. Since this incorporates high scopes of learning for all variables, it represents the maximum reduction in cost that is possible for this process (assuming only these process variables are subject to improvement over time). Looking at each parameter individually indicates that the cost reduction associated with cycle time learning is the greatest in the long run.

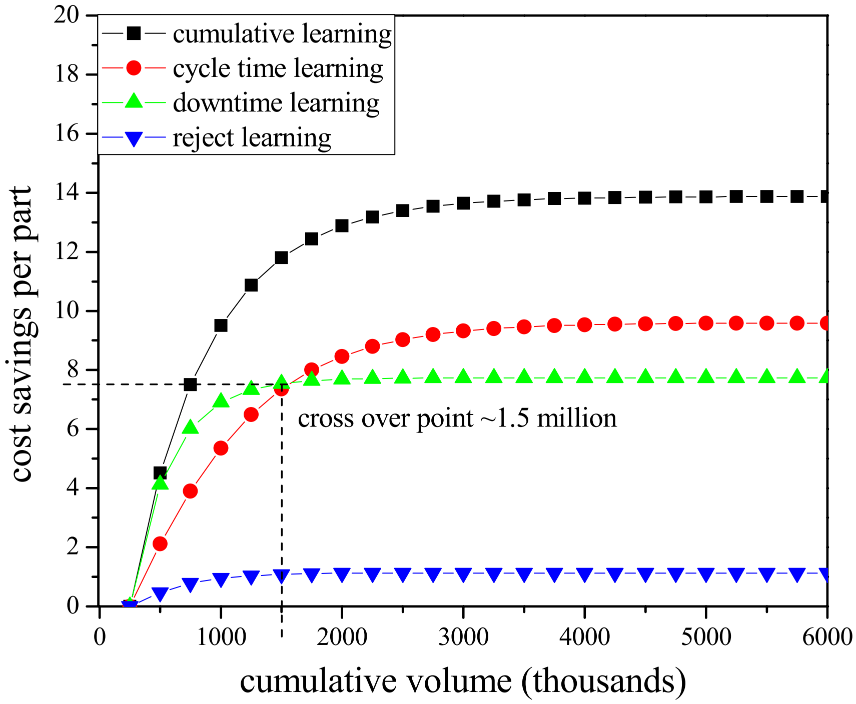

Figure 19: Cost saving per part pertaining to improvements in different parameters

Figure 19 above shows the cost savings per part which can be achieved with learning. It shows that the saving per part produced associated with downtime learning is higher that cycle time learning up to a cumulative volume of 1.5 million. This would give an impression that if a plant plans to produce more than 1.5 million parts then it should prioritize cycle time improvement rather than downtime improvement. In reality, to answer this problem one needs to look at the cumulative cost saving achieved by the plants over cumulative production volume before deciding which learning to prioritize. The cumulative cost saving was calculated as a function of cumulative volume (Figure 20). The graph shows that the cumulative saving achieved by cycle time learning surpasses that of downtime learning only after 3 million parts. Thus cycle time learning should be given higher priority only if the plant plans to produce more than 3 million parts and not 1.5 million parts, in the long run.

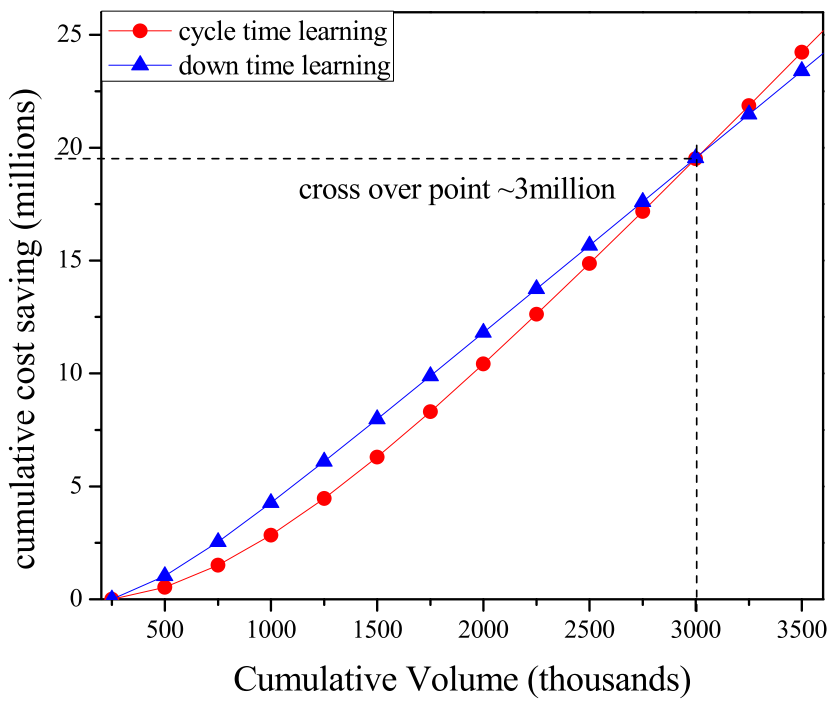

Figure 20: Cumulative cost saving for cycle time and down time learning

5. Process Variable Learning Cost Model Taxonomy

The previous chapter presented a case study using a time dependent or dynamic process based cost model. The incorporation of learning curves for key process variables resulted in a model which could estimate the cost reductions achievable as a result of learning as well as the rates at which the costs are reduced. It also identified the major drivers responsible for the cost reduction and the timing of the influence of each driver. However, the analysis was performed on an existing technology, tubular hydroforming, and relied on a considerable amount of time series data for each of the major process variables as well as a detailed model of the tubular hydroforming process as it is used today. Unfortunately, collecting this amount of detailed data for new processes and technologies is difficult at best and is often impossible. At early stages of the technology development, there is often only a basic understanding of how the manufacturing processes will work and no time series data indicating the influence of learning on key parameters. A practical method to generate time dependent cost estimates for new technologies must recognize the limited availability of data.

Historical approaches to time based cost estimation used learning curves which directly related costs to time or cumulative production volume for existing technologies (see discussion in chapter 1). These curves were then applied to new technologies in similar industries to create a cost versus time trajectory. Unfortunately, the application of learning curves across all products and processes within an industry can often give misleading results. The problem was that within an industry, processes could be quite different. Furthermore, even if the technologies had some similarities to previous processes, they may only share some characteristics and could still be substantially different with regard to key process variables and therefore costs.

The problem is to find some middle ground between the traditional simple cost learning curve approach and the data intensive complete process based cost modeling approach. A compromise can be found by generating cost evolution curves for major classes of processes and within each of these for the different ways in which each key process variable will change with learning. A classification scheme or taxonomy can be developed and cost evolution curves generated for each element in that scheme. New process technologies would then need only to be matched to its classification. Each classification would have a basic process based cost model and learning curves for the key variables which could be applied to the new technology to understand its cost trajectory over time. Practical application of generalized learning curves to the process variables requires these curves to be dimensionless so that they only need to be matched based on issues related to learning such as its scope and rate and not based on magnitude.

A detailed discussion of a classification scheme or taxonomy as well as an approach to the use of dimensionless learning curves is presented in this chapter. Specific scenarios within the taxonomy are explored to show the ways in which learning impacts different classes of processes. Finally, the tube hydroforming case is revisited using the taxonomy learning curves and compared with the results obtained from the detailed analysis in chapter 4.

5.1 Taxonomy Categories

The first step in building this framework is to determine which process characteristics might influence cost trends. Clearly this should include characteristics directly related to the time/learning dependent process variables considered in the combined learning/cost model, but must also include factors that affect the static portion of the process based cost model.

5.1.1 Determination of Taxonomy Dimensions

For each of the variables modeled with s-curves, a classification is needed with regard to the amount of improvement possible (scope) and the rate at which that learning occurs. The ways in which these variables impact cost is also dependent on the nature of the process.

An initial approach to this classification includes two key concepts. First, products with different levels of materials intensity are likely to be impacted by learning in different ways. This is because learning will have little impact on the amount spent on the material, having only an indirect effect through the reduction in the amount of material waste. Consequently, those products that have a high percentage of their cost arising from materials are unlikely to see large cost reductions with learning. However, products with a high percent of their costs arising from other factors have more room for cost reductions from learning. Second, processes which are capital intensive are likely to be impacted by learning differently than processes which are labor intensive. As discussed in chapter 1 of this thesis, previous studies of learning curves have often shown that labor intensive industries are more greatly impacted by learning than capital intensive industries (Adler and Clark 1991).

5.1.2 Taxonomy Dimensions Used in This Study

For this study, three process variables were considered to be directly impacted by learning; cycle time, downtime and reject rate. While clearly other variables also under improvements due to learning, these three were thought to have the greatest impact. For each of these variables, there are two elements which impact cost reductions; scope of learning and rate of learning. In addition, this study considered two more categories related to the product and process; level of material intensity and level of capital (versus labor) intensity. In all, this leads to eight dimensions for the categorization scheme.

1. Capital vs. labor intensity of the process

2. Material intensity of the product

3. Learning rate for cycle time

4. Learning rate for downtime

5. Learning rate for reject rate

6. Scope of improvement in cycle time

7. Scope of improvement in downtime

8. Scope of improvement in reject rate

5.1.3 Definitions of Taxonomy Categories

Having eight category dimensions means that there will be quite a large number of total categories by which a user would define a new technology or process. If only two options exist for each category, there are already $2^8 = 256$ individual categories as shown in Figure 21 below .

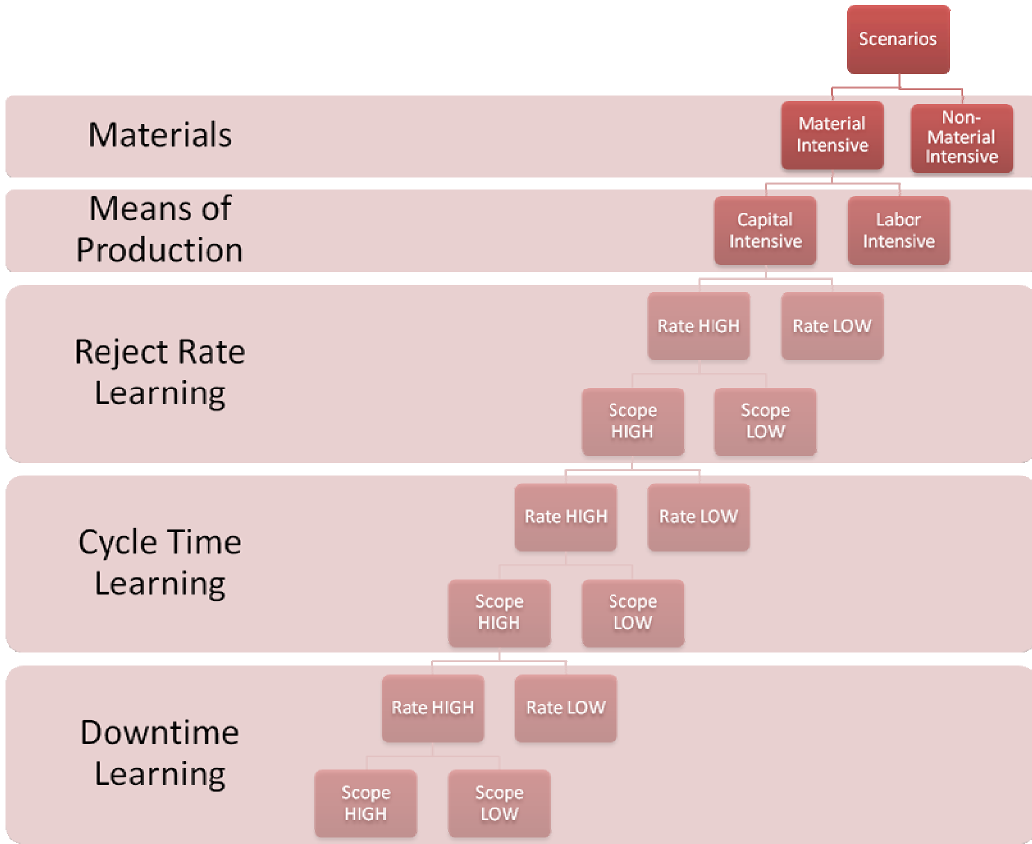

Figure 21 : Illustration of the framework based on the classification levers

In reality, across each of the eight dimensions a continuum of categories is possible. For example, the process can have not only a very high or very low level of capital intensity, but can take on all values in between. However, constructing a cost framework with that level of granularity is both impractical and of little use to the end user. It is impractical because the number of categories grows exponentially. It is of little use because it would be impossible to specify the levels of each of the eight categories with such precision for a new process or technology. A more reasonable approach is to use two to three categories for each dimension. For demonstration purposes for this study, this was limited to just 2 categories per dimension.

The categorization scheme also requires a definition of each category within each characteristic dimension. To fully develop the cost evolution results for each category, a precise definition of the process variables associated with that category is needed. When applying these categories to new technologies, a precise match is not necessary, but rather it is important to find the category which most closely resembles the expectations with regard to the new technology in that particular dimension.

5.1.3.1 Capital (vs. Labor) Intensity

Two categories in this space were considered in the taxonomy, capital intensive processes and labor intensive processes. A process is defined to be capital intensive if the payment on capital per year is more than twice the annual cost of labor. Currently, the capital cost includes the cost of equipment and tooling, whereas the labor cost includes the amount of money spent on labor and their benefits.

A process is defined as labor intensive if the annual cost of labor is more than twice the capital cost incurred over a year's period.

The capital cost, as already stated includes the cost of equipment and tool but resource allocated between capital and tool depends upon the process which is being looked at. The cost walk down for tool and equipment is different from each other; equipment cost improves with learning in the process parameters whereas tooling cost improves only with economies of scale. Thus different combinations of equipment and tool will lead to different capital cost walk downs. But for this analysis the ratio of resource allocation between equipment and tool has been assumed to be constant.

5.1.3.2 Material Intensity

Again two categories were selected for this study; material intensive and non-material intensive products. A process is defined as material intensive if the cost of material per unit is greater than two-thirds of the total per part production cost.

A process is defined as non-material intensive if the cost of material per unit is less than 5% of the total per part production cost.

It is worth noting that with learning and improvement in process the ratio of capital, labor and material changes. To account for this change in the present analysis the ratios are calculated at the point where the process is completely learnt (saturated portion of s-curves). There is no hard and fast rule that the calculations need to done using the data points at the end of the curve and can be done using data at any point of the curve, but in that case the ratios used for defining the taxonomy rule might change accordingly.

5.1.3.3 Learning Rates for Cycle Time, Down Time and Reject Rate

For each of the three process variables, two categories for learning rates were used; slow and fast learning. The learning rate provides a measure of how rapidly improvement takes place for each process variable. Except in some very special functional forms, the rate of improvement is not constant and therefore the learning rate cannot be represented by a single value. The s-curves used in this study are based on four parameters, two of which describe the rate of improvement, α and β (the other two describe the learning scope). The value of α defines the slope of the learning curve whereas the value of β defines the initial transient in the learning curve. A more complete discussion of these concepts has already been provided in section 3.3.2.

It is difficult to envision the shape and position of the learning curve simply by looking at the values for α and β. Instead, to define the categories for fast and slow learning rates, two points on a dimensionless learning curve for each category were selected, and the resulting values for α and β, were calculated. The same definitions used in section 3.3.2 were also used in this categorization scheme. Recall that fast learning was defined as experiencing a 5% improvement after just 0.1% of the normalized cumulative volume and a 95% improvement after just 50% of the normalized cumulative volume. In contrast, slow learning meant that it would require 0.1% of the cumulative volume before achieving a 5% improvement and a full 100% of the normalized cumulative volume before achieving a 95% improvement.

The concept of dimensionless s-curves and normalized cumulative volume is used here so that the definitions of slow and fast can be made once and then applied to each of the process variables using the appropriate scaling factors. A more complete treatment of these concepts was given in section 3.3.2.

The resulting values for α and β are:

Fast Learning: $\alpha = 11.801$ and $\beta = -2.956$

Slow Learning: $\alpha = 5.948$ and $\beta = -3.004$

These values were applied to each of the three process variables that are considered to experience learning; cycle time, downtime and reject rate. The method of applying the learning rates to a dimensionless s curve has already been discussed in chapter 3. Cycle time is the amount of time, in minutes, to produce a single part or product. It is assumed that with learning the cycle time improves; that is lesser time is required to produce a part. Downtime is the time when the line is not producing. With learning and improvement in process understanding, the downtime is assumed to decrease. Reject rate is the percent of the parts produced which cannot be sold because they do not meet the expected standards.

5.1.3.4 Scope of improvement in Cycle Time, Down Time and Reject Rate

Scope of improvement communicates the room for improvement in the parameter under consideration. Scope for improvement is high if the process parameter can be improved by a large extent and is low if not much improvement can be brought to the process by any means.

For the purposes of this study, two categories for learning scope for each of the three process variables were considered. High scope was defined as having a 50% improvement in the long term over initial value, while low scope was defined as having no improvement. For example, a process with an initial cycle time of 2 minutes would have high scope for learning in cycle time if eventually it could be reduced to just 1 minute

Scope of improvement is an important concept which should be treated in conjunction with the rate of learning. Learning rate is relatively unimportant under conditions with low or no scope for learning since the opportunities for improvement are minimal. On the other hand, even a slow learning rate might have a dramatic effect if there is an extremely high scope of improvement.

5.2 Analysis of the Taxonomic Scenarios

The combined learning curve/technical cost model was run for all 256 taxonomy categories to produce cost evolution curves for each case. In reality, this involved modeling just four product/process combinations using each of the different learning scenarios. The four product/process combinations are:

1. Material Intensive & Labor Intensive (ML)
2. Material Intensive & Capital Intensive (MC)
3. Non-material Intensive & Labor Intensive (NML)
4. Non-material Intensive & Capital Intensive (NMC)

64 learning categories were applied to each of these; slow and fast learning rate and high and low scope for each of the three process variables under consideration.

5.2.1 Description of the Baseline Process Model

Analysis of the baseline scenarios used a generic process based cost model following the principles outlined in chapter 3.2. This was a generic model in the sense that the process specific details contained in the 'process model' portion of a conventional PBCM were replaced by inputs. To simulate the various learning scenarios, the cycle time, down time and reject rate inputs were linked to s-curves that gave the value of these inputs as a function of cumulative volume. The s-curve parameters, α and β, were varied to model the slow and fast learning rate scenarios; and the minimum and maximum values were varied to model the high and low learning scopes for each variable. Process parameter inputs related to capital/labor intensity and material intensity were calculated to simulate the four product/process scenarios described in the previous section. The remaining model inputs, such as interest rate, energy cost, wage, etc. were held constant. A complete list of process inputs are given in appendix B.

5.2.1.1 Calculating Capital and Labor Intensive Scenario Inputs

The relative importance of the impact of capital, labor and materials on cost is the result of the interplay of a subset of cost model variables as well as the key process parameters modeled by s-curves. The other major variables that influence the capital cost are the investments in tools and equipment, the interest rate, equipment life and the annual production volume. Unit labor costs are primarily influenced by the number of workers per line and the wage. Material costs are influenced by the amount of material needed to produce the part and the unit price of the materials.

Typical values for several of these variables (interest rate, equipment life, production volume, wage and material price) were assumed in order to perform the analysis. In addition, the initial unit cost of the product was assumed to be $100 for all scenarios. This provided a single basis for comparison for all scenarios. By applying each product/process scenario definition, the ratio of capital to labor costs and the ratio of material to capital plus labor costs, the remaining model inputs can be found. Table 3 shows the inputs for equipment investment, workers per line and part weight for each product/process scenario and the resulting long term cost breakdown.

Table 3: Model inputs for different industry scenarios

	MC	ML	NMC	NML
Investment	$1.56M	$0.52M	$1.84M	$0.62M
Workers/Line	2	6	4	7
Unit Material Cost	$66.67	$66.67	$3.75	$3.75
Unit Labor Cost	$8.33	$25	$24	$72.25
Unit Capital Cost	$25	$8.33	$72.25	$24
Total Unit Cost	$100	$100	$100	$100
Material Intensity	Yes	Yes	No	No
Capital Intensity	Yes	No	Yes	No

5.2.2 Impact of Learning on Different Types of Processes

All 64 learning scenarios were explored for the four process/product scenarios. Several are highlighted to best explore the impact of learning in each process variable on the cost evolution trajectory. Four main scenarios (Table 4) are investigated; one with all learning rates and scopes high, the other three have high learning rates and scopes for just one variable. In addition, there is a variant on the all high learning scenario that incorporates the concept of growing demand or annual production volume. Generally in this study, the production volume was held constant so that the effect of learning could be studied in isolation, without the effect of economies of scale. However, it is also interesting to understand how economies of scale affect the cost evolution along with the learning curves. A scenario (scenario 1') was chosen with 20% growth in annual production, to investigate the combined effect of learning and economies of scale.

Table 4 : Scenarios based on the scope levers (rate of learning is high in all these scenarios)

Scenario	Scope of Cycle Time	Scope of Reject	Scope of Down Time
1	High	High	High
1’	High[iii]	High	High
2	High	Low	Low
3	Low	High	Low
4	Low	Low	High

5.2.2.1 Scenario 1: High Learning Rate & Scope for All Variables

Scenario one has both high scope as well as high learning rates; the scenario can be further broken down into growth and no growth scenarios respectively. In the no growth scenario, the annual production volume is held constant at 54,000 parts annually which yields about 1.1 million parts over the observed period of twenty years. For the growth scenario, the production volume started at 4,000 parts per year and a growth rate of 20% annually was applied. This also yielded about 1.1 million parts over the 20 year observation period.

Annual production volume = 54,000

Growth Rate = 0% (Growth rate has been put to zero to study the effect of learning without the effect of economies of scale).

Figure 22 shows the cost evolution results for the four product/process scenarios for scenario 1. In all cases, the initial cost per part is $100, but the cost reduction paths are considerably different for each since the learning factors have very different impacts on the different sources of cost.

[iii] Scenario 1’ represents the scenario with 20% growth rate to understand the affect of economies of scales apart from learning on the cost evolution

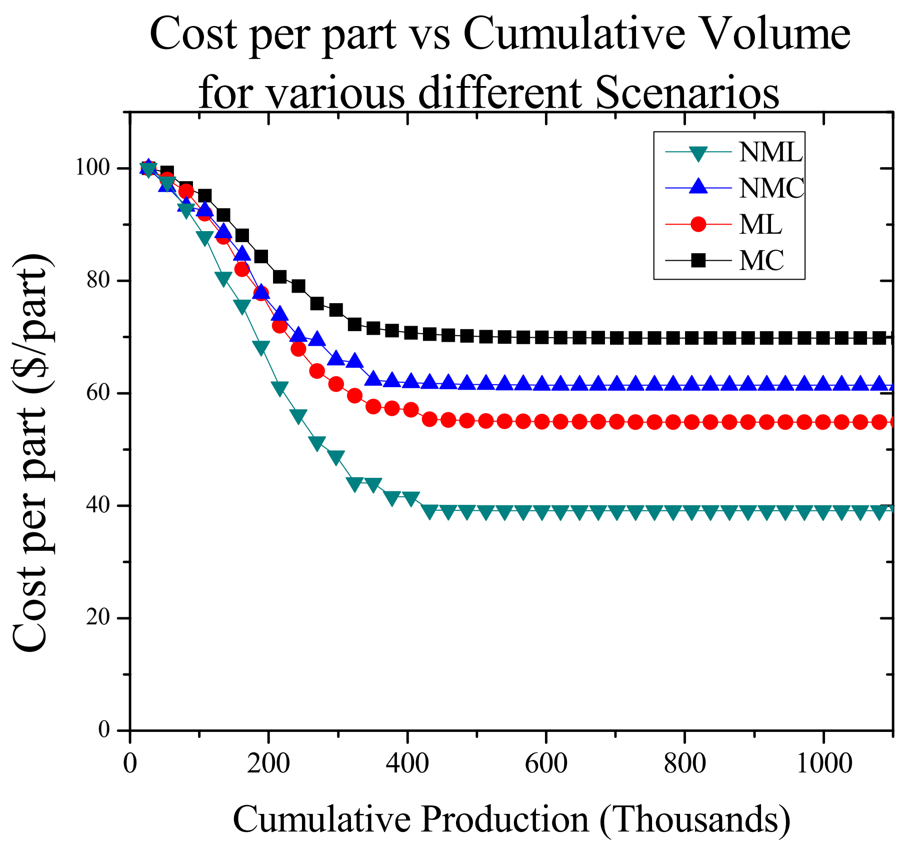

Figure 22 : Cost per part vs. cumulative volume for no growth scenario for material and Capital intensive (MC), Material and Labor intensive (ML), Non-material and Capital intensive (NMC) and Non-material and Labor intensive (NML) industries.

The preliminary analysis shows that cost per part reduction for non-material, labor intensive products is the highest and is the lowest for material, capital intensive products. The other two scenarios fall in between. The cost has been further broken down with respect to material, equipment, tools and labor to gain a better understanding of why learning affects these industries differently.

Figure 23 shows the cost break down on a per part basis for the different industries with respect to labor, material, equipment, and tool cost. It can be inferred from Figure 23 that there is no learning with respect to tools. Learning does not happen with tools because the tools can only be used to produce the part of interest and therefore are treated as dedicated investments. Consequently, any improvement in the process will not lead to better utilization of tools. Per part tool costs would only change if the investment in tools changes (no learning is considered in this respect) or if the production volume increased to the point where additional tool sets were needed. Since, the production volume is held constant in this scenario, the tooling cost per part produced will remain constant over the observation period

Per part equipment costs are reduced with learning because improvement in cycle time, down time and reject rates all impact the time needed for production. Since equipment is treated as a non-dedicated investment (time the equipment is not used to produce the part of interest can be used to produce other parts), its costs are spread across the set of products made on that equipment according to the percent of time used to produce each part. The learning induced reduction in production time therefore leads to a lower allocation of the equipment costs.

There is a direct impact of cycle time improvement on production time, but improved downtime and reject rates have similar impacts. Improvement in reject rate means that there are fewer unusable parts and therefore the fewer additional process cycles need be run in order to make up for the rejected parts. Improvement in downtime means the equipment can run for a longer time each day and therefore the fraction of time the equipment is used to produce this particular product is also reduced. The result is that less of the equipment cost is allocated to the part of interest.

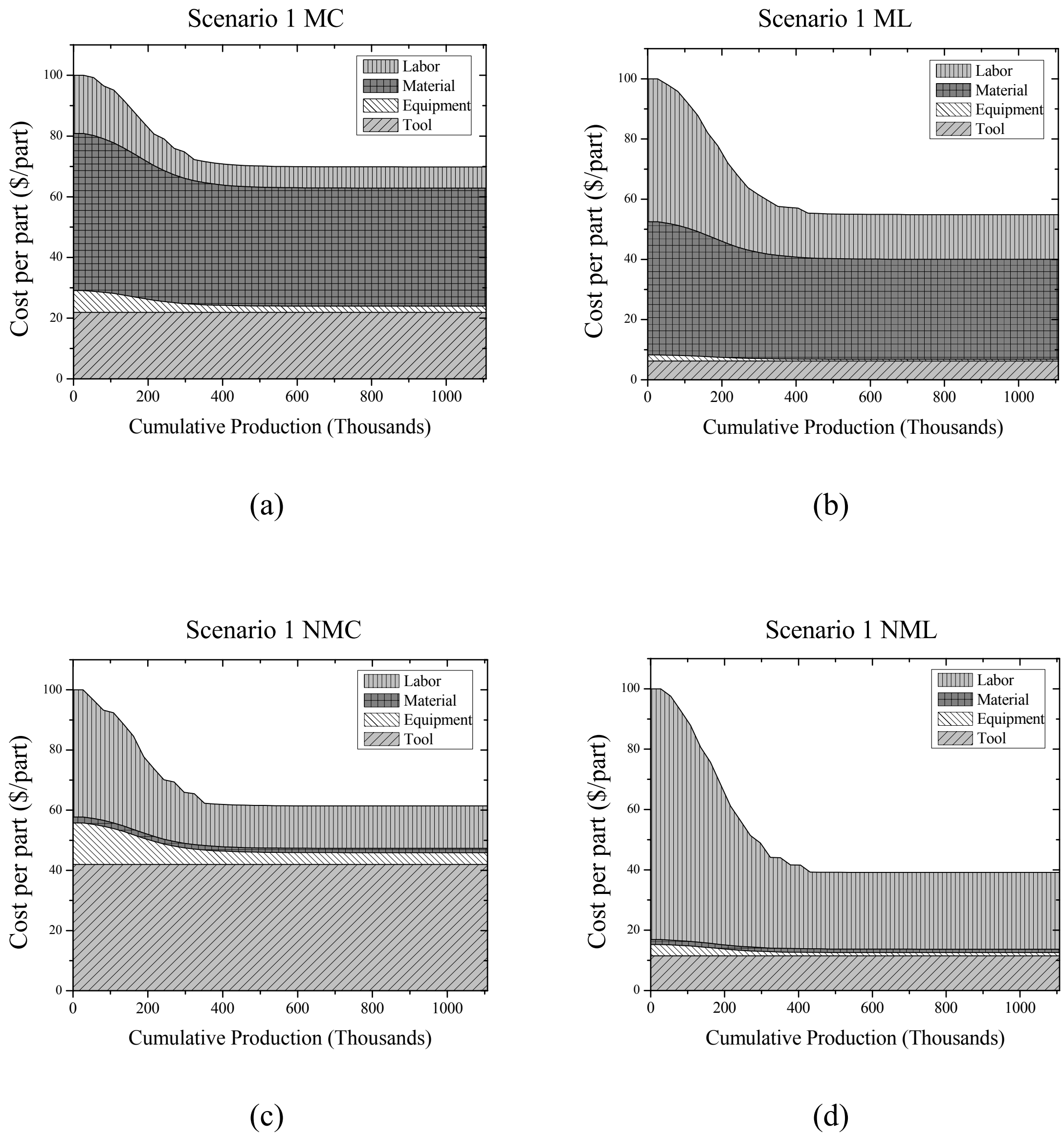

Figure 23 : Cost per part break down with respect to labor, material, equipment and tool for (a) material and Capital intensive (MC); (b) Material and Labor intensive (ML); (c) Non-material and Capital intensive (NMC) and (d) Non-material and Labor intensive (NML) industries

The effect of learning on labor cost is similar to the impact on equipment cost. A constant number of workers per production line is assumed. Consequently, the reductions in production time that come with learning result in a lower labor hour content for the part.

The material cost is a direct function of the number of parts produced, both good parts and those that have to be rejected. As a result, improvements in reject rates reduce the per part material cost, but the other learning factors, cycle time and downtime, do not affect this cost.

The reduction in equipment and labor cost is brought about by the improvement in all the three learning factors, cycle time, down time and reject rate, whereas the improvement in material cost is only the result of improvements in reject rate, and there is no cost reduction for tooling. Figure 24 shows this trend; equipment and labor cost show the greatest improvement, followed by material cost, then tool cost.

	Labor and Equipment	Material	Tools
Learning Factors	Cycle Time Down Time Reject Rate	Reject Rate	None

Figure 24: Effect of learning on labor, equipment, material and tool (no growth scenario)

These cost reduction patterns can be used to understand the different impacts that learning has on the different product/process scenarios. For the material and capital intensive (MC) scenario, Figure 23 (a), the major components of the per part cost are the material and tooling costs. (Note that in these scenarios most of the capital investment was directed towards tooling rather than equipment). Since there is no learning induced reduction in tool cost and limited improvement in material costs, there is on a small overall cost improvement. On the other hand, for the non-material, labor intensive scenario (NML) Figure 23 (d), component costs are driven primarily by the labor cost. Since learning has a significant effect on labor costs, the component cost for this scenario are substantially reduced through learning. For the non-material, capital intensive scenario, (NMC) Figure 23 (c), labor and equipment contribute roughly half of the initial cost. While there are significant reductions in labor and equipment costs, the other half is governed by tool cost. This limits the scope of improvement of this process. Finally, for the material, labor intensive scenario, (ML) Figure 23 (b), the majority of cost is attributed to material and labor. Since material is a large fraction of cost and its improvement is due only to learning based improvements in reject rates, the overall improvement of the material, labor intensive scenario (ML) is less than that of the non-material, capital intensive, scenario (NMC).

5.2.2.2 Scenario 1': High Learning Rate & Scope for All Variables with Growing Annual Production Volume

This scenario is the same as the previous, but the issue of production volume growth over time is superimposed. Annual production volume is initially 4000 and increases by 20% per year until it reaches 1.1 million cumulative production by the end of the 20 year period of interest in this study. This was done to investigate the impact of economies of scale along with learning in cycle time, downtime and reject rate. For new technologies, learning is rarely observed on its own, but rather is usually seen in conjunction with increasing product demand and therefore the improvements due to economies of scale.

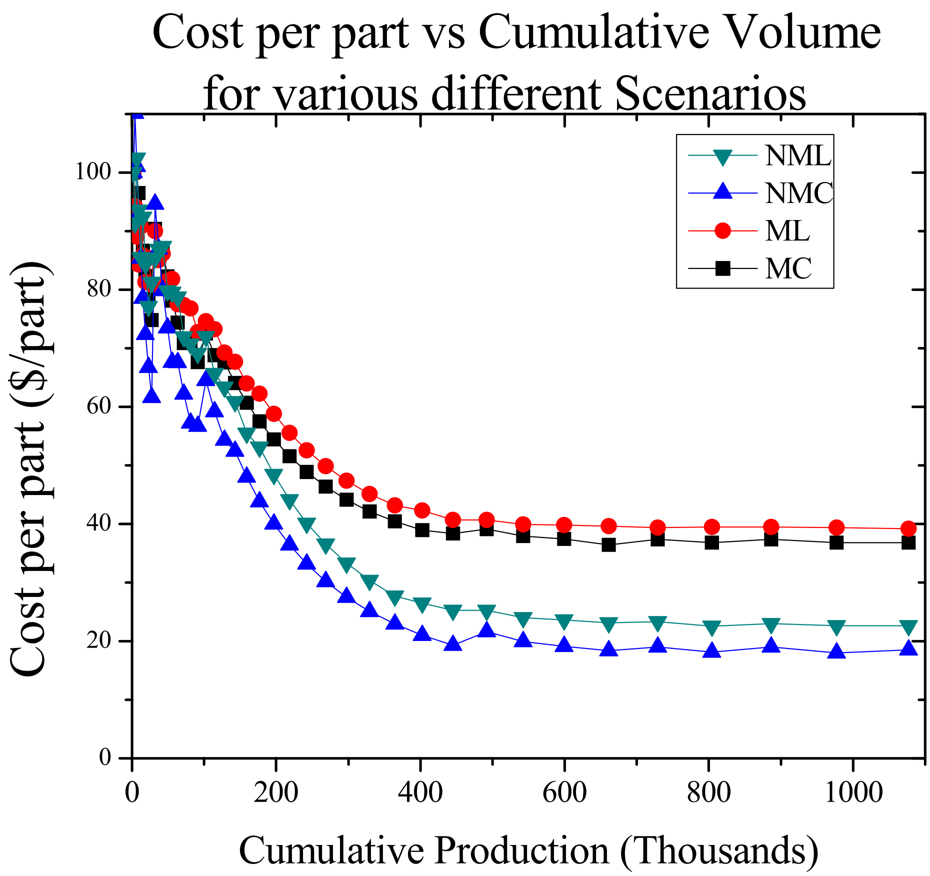

Figure 25: Cost per part vs. cumulative volume for 20% growth scenario for material and Capital intensive (MC), Material and Labor intensive (ML), Non-material and Capital intensive (NMC) and Non-material and Labor intensive (NML) industries.

Figure 25 shows the different cost evolution trajectories for the four different product/process scenarios. The preliminary analysis shows that cost per part reduction for the non-material, capital intensive scenario is the highest and is the lowest for material, labor intensive scenario. The other two situations fall in between the two. This is different than in the no growth scenario presented in the previous section. The capital intensive scenarios now show far greater cost reductions than in the previous, no growth analysis.

The costs have been further broken down with respect to material, equipment, tools and labor to better understand the reasons for the greater impact on capital intensive processes in this scenario.

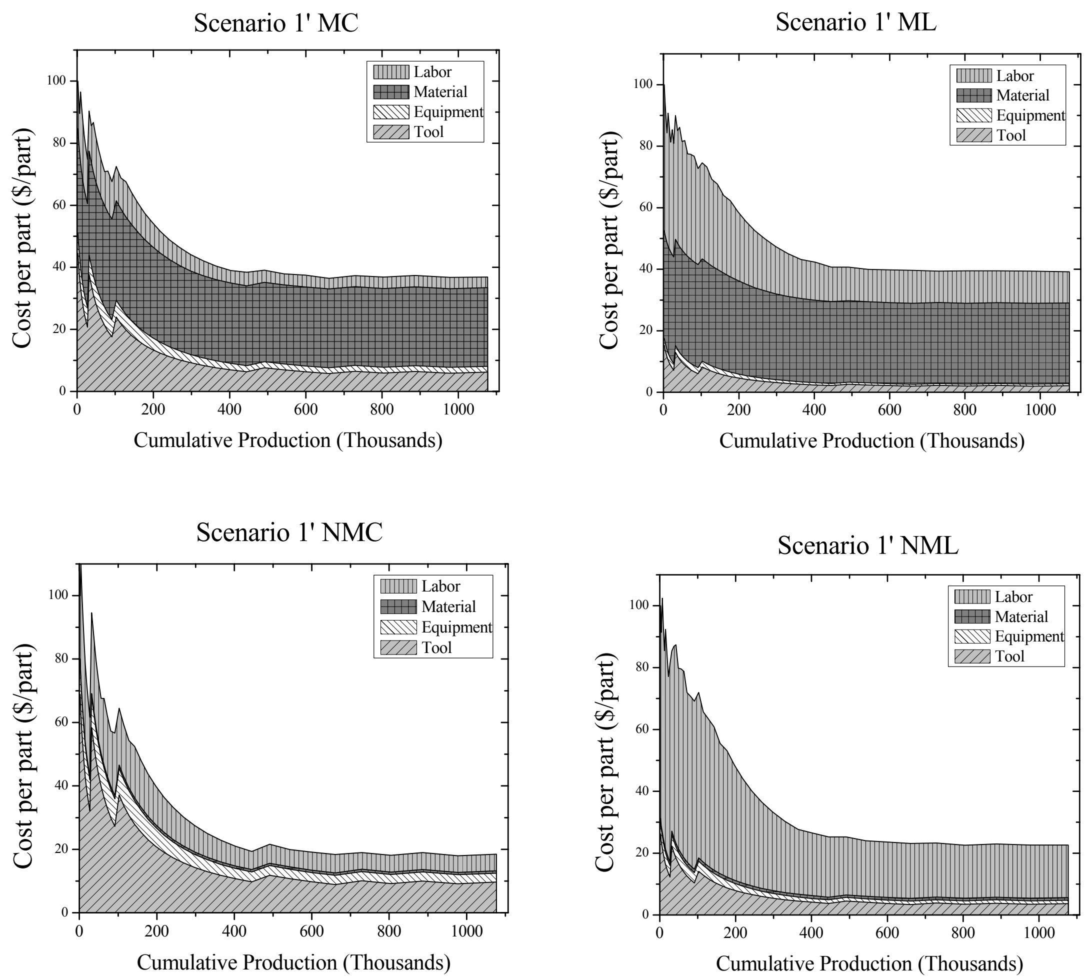

Figure 26: Cost per part break down with respect to labor, material, equipment and tool for (a) material and Capital intensive (MC); (b) Material and Labor intensive (ML); (c) Non-material and Capital intensive (NMC) and (d) Non-material and Labor intensive (NML) industries

Figure 26 shows the cost breakdown on a per part basis for different process/product scenarios. The main difference with the previous no growth scenario (Figure 22 and Figure 23), is that in this case, the cost of tooling decreases with volume. This is because the set of tools are dedicated to the production of this part. Increases in production volume means the cost of tools can be distributed over larger number of parts. Thus, economies of scale, rather than learning play a major role in reducing the tooling cost over time.

The behavior of equipment, labor and material follow the same trend as previous scenario. The cost of equipment and labor, like in the no growth scenario, depends on learning in cycle time, downtime and reject. The cost of material depends only on the improvement in reject rates (Figure 27). Tools are not affected by any of the operation parameters. However, tool costs improve due to economies of scale as indicated in this scenario with 20% growth.

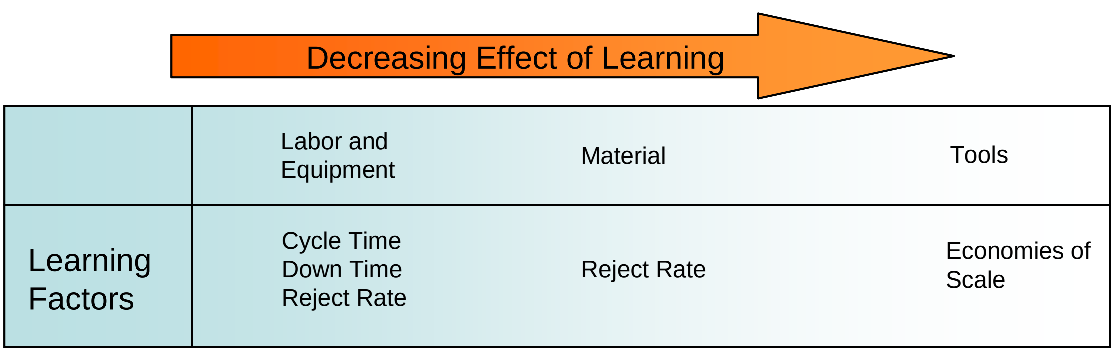

Figure 27: Effect of learning on labor, equipment, material and tool for growth scenario

The improvement in labor, equipment, material and tools is brought about by the improvement in cycle time, down time, reject and economies of scale. It is evident that the fraction of improvement in labor and equipment shall always be greater than material since it depends on three factors compared to material which depends on one. It is difficult to compare the impact of reduction in tooling costs to the other improvements since the mechanism behind these improvements are quite different, tooling cost reductions due to economies of scale while the others are due to learning induced process improvements.

An interesting result to note (Figure 26) is that the cost reduction followed by material, labor intensive industry (ML) is very similar to material, capital intensive industry (MC). Similarly, the cost reduction followed by non-material, labor intensive industry (NML) is very similar to cost reduction followed by non-material, capital intensive industry (NMC). This result implies that the cost evolution trajectory followed in this scenario is dependent on whether the process is material intensive or not rather than the capital labor ratio. This result is very different from the commonly held belief that labor intensive industry should learn differently from capital intensive industry (Hartley 1965; Adler and Clark 1991).

In this analysis, it was assumed that the number of workers required to run the production lines are constant. Hence, the number of workers required maps one to one with the number of production lines. Since the allocation of the equipment and labor costs both scale with operating time, they will experience the same impact from learning. It could be argued that this method of accounting for the labor cost might neglects "learning by doing". However, the perspective used for this work has been different from the previous learning literature and explicitly considers learning only through improvements in cycle time, reject rate and downtime. Learning by doing is considered only as an indirect effect on these variables. The improvement in cycle time occurs partly as a result of improvement in labor skills achieved in the learning by doing sense. The workers have, over a period of time, learned to run the lines in better fashion. Additional impacts of learning by doing could effect the number of workers needed to operate a given production system, thus further enhancing this effect. While not explicitly modeled in this study, the impact of a reduction in workers per production line over time could easily be included by including a time dependent relationship for this variable as well.

5.2.2.3 Scenarios 2, 3 & 4: High Learning Rate & Scope for One Variable Only

Scenarios 2, 3 and 4 deals with the situation where the scope of learning and the learning rate are high for cycle time reject rate and down time, respectively. The cost evolutions for these scenarios are shown in Figure 28-31, for each of the four process/product scenarios.

For material intensive industry Figure 28 and Figure 29, the reject learning rate was the primary driver in bringing down the cost. This was evident because the material constituted 67% of the total product cost for material intensive industries. With learning in reject rates the cost of material improves because lesser number of rejects was produced. Reject learning is also instrumental in bringing down the cost of labor and equipment, because lesser number of rejects leads to higher equipment and labor utilization. But the reduction in equipment and labor cost is an indirect effect of reject learning and its impact in bringing down the cost is lower as compared to material cost which is a major contributor in this case and is directly affected by reject rate learning.

The cycle time was the second most important driver followed by down time in both the cases. This is because cycle time and down time does not affect the material cost which is the major cost contributor in this case.

Cycle time and down time learning only affect the labor and equipment cost, and they showed a greater impact in labor intensive industry because a greater fraction of cost was associated with labor and equipment cost compared to capital industry. In case of capital intensive industry a high fraction of cost was tied to tools which showed no learning thus reducing the impact of cycle time and down time learning.

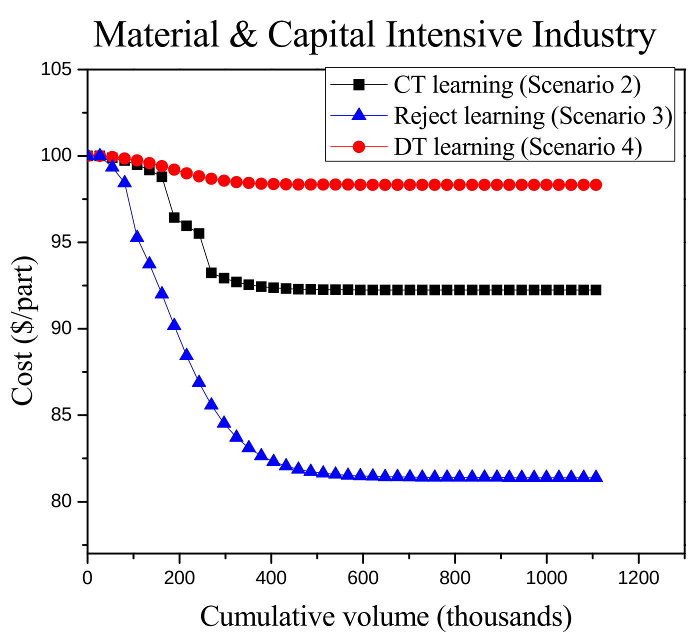

Figure 28 : Cost evolution for Scenarios 2, 3 and 4 for material, capital intensive industry

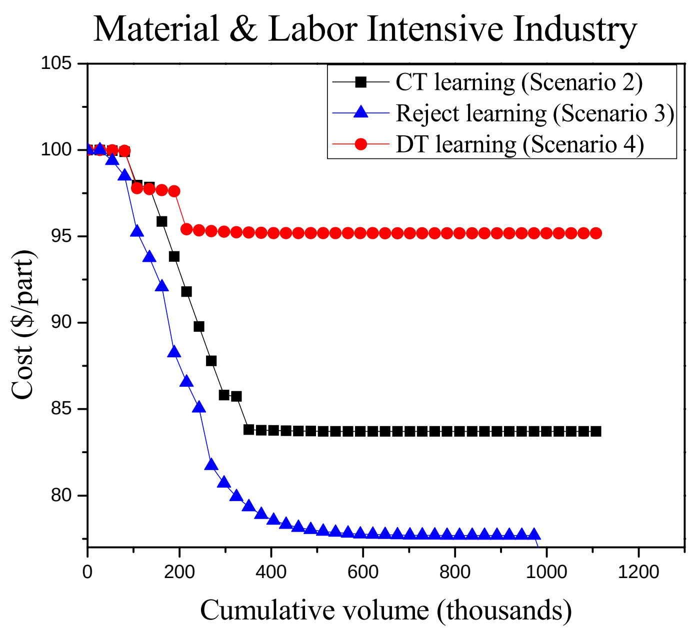

Figure 29: Cost evolution for Scenarios 2, 3 and 4 for material, labor intensive industry

For non material intensive industry Figure 30 and

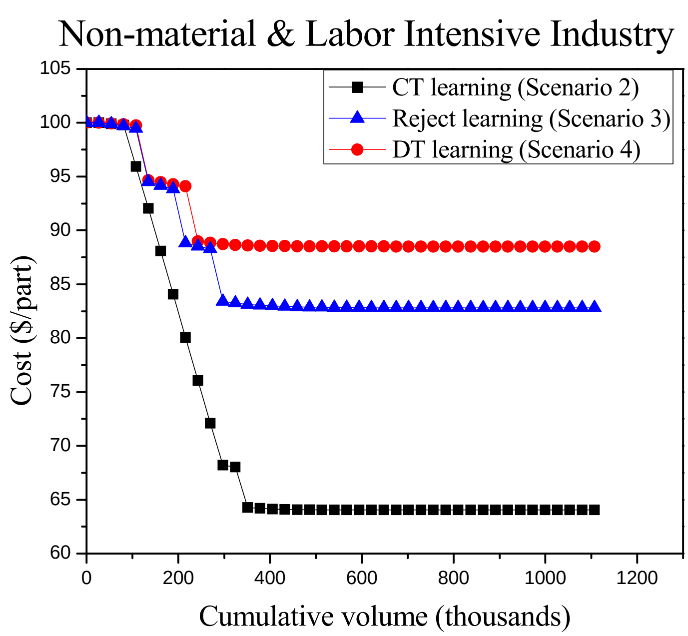

Figure **31**, cycle time was the primary driver in cost reduction because capital and labor accounted for the major cost of part produced (96%), and both of them are directly impacted by the improvements in cycle time. Again the improvement with cycle time learning is lower for capital intensive industry because tools accounted for a major portion of the cost and showed no improvement with learning.

Reject rate was the second most important driver followed by downtime, because reject rate learning lead to improvement in material, equipment and labor cost, whereas the down time lead to improvements only in labor and equipment cost.

Even though learning in reject rate leads to improvement in material, equipment and labor cost its impact is lesser than cycle time learning which leads to improvement in just

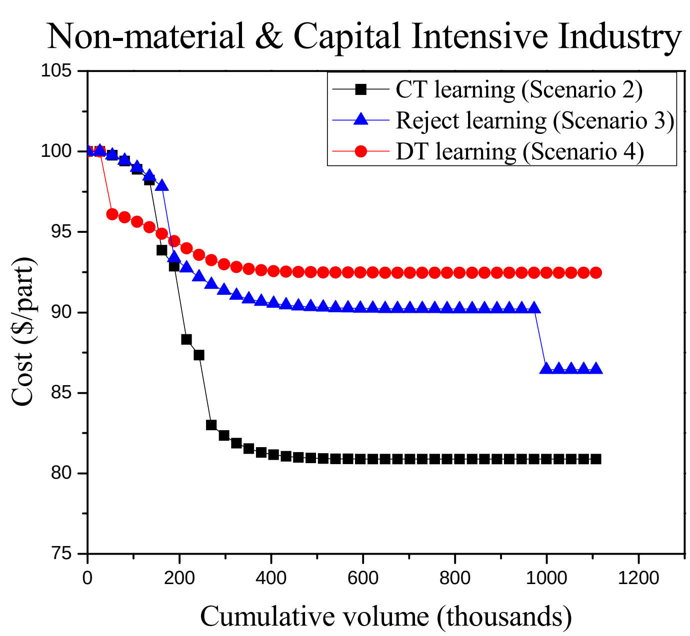

Figure 30 : Cost evolution for Scenarios 2, 3 and 4 for Non-material, capital intensive industry

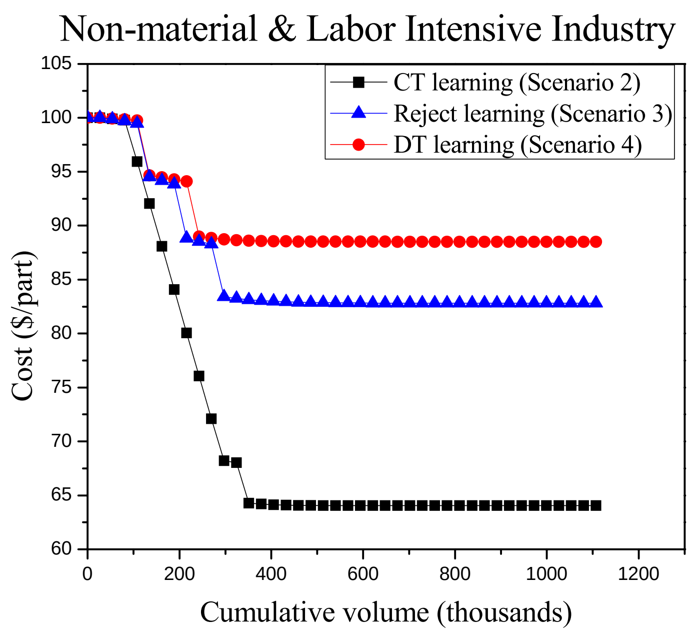

Figure **31**: Cost evolution for Scenarios 2, 3 and 4 for non-material, labor intensive industry

equipment and labor cost, because cycle time directly affects the equipment and labor cost which constitute a big portion of the total cost (96%) whereas reject and down time learning have an indirect and much lower impact on the equipment and labor cost. A detailed analysis of cost breakdown for scenario 2, 3 and 4 is given in Appendix C

5.3 Using the Taxonomy Model to Calculate Cost Evolution

Recall that the initial approach to this classification included two key concepts. First, was to determine the level of materials intensity (material cost per part) and the capital investment required compared to labor cost and, second was to decide the scope and learning rate for the process variables (cycle time, down time and reject rates). For evaluating a new technology the material and capital/labor intensity has to be decided, based on the definition of material, capital and labor intensity (chapter 5.1.3). It might be difficult to decide the parameters a priori for a new technology, but knowledge about the sub processes can help in making a more informative decision. The level of granularity for the model is limited to making binary choices (high/low) for material, capital/labor and, scope and learning rate for the process variables which makes it easier to make a decision.

Once all the eight parameters are decided the corresponding scenario can be chosen from the taxonomic classification model. The model gives the trend for the cost evolution for the chosen scenario. The output given by the model is normalized on $100 per part basis and requires to be rescaled to the technology/product of interest. This is done by multiplying the taxonomy model output with a factor which makes the initial cost output of the model equal to that for the new product/technology of interest.

Similarly the normalized cumulative volume in the taxonomy model output has to be converted back to cumulative volume. This is done by multiplying the normalized cumulative volume axis by equivalent volume of the product/technology of interest.

5.4 Comparing the Taxonomy and Detailed Cost Modeling Approach Using the Tubular Hydroforming Case

In the previous section it was seen how taxonomic classification could be used to probe into the cost walk down of a technology which is very new and which has a very little available knowledge base. To validate the approach of taxonomic classification we can compare the cost evolution for tube hydroforming (Figure 16) with the scenario which fits best with the hydroforming technology.

In the hydroforming analysis following trends was observed for the levers:

- Non material intensive [10%]
- Capital intensive [67%]
- CT (slow learning, high scope)
- DT (fast learning, high scope)
- Reject (no scope)
- Equivalent volume (V_{eq})= 12.3 million parts

The trend observed above matched with one of the taxonomic classifications. The output given by the taxonomy model was normalized with respect to both cumulative volume and cost. The rescaling in cumulative volume was done by multiplying it with the volume equivalent of the hydroforming process (12.3 million)[iv].

The output given by the taxonomic classification corresponds to the starting point of a new technology whereas the data collected for hydroforming corresponded to a period eight years down the line. Hence both the data sets were offset by a period of eight years. During this period of time around 2 million parts had been produced using the hydroforming technology. The results from the hydroforming analysis had to be shifted by 2 million parts to take care of the temporal lag which was present.

The rescaling of the cost from the taxonomic output ($100 basis) had to be done with respect to the cost of the 2 millionth part, because the cost of the 2 millionth part in the taxonomic model corresponded to the first data point of the hydroforming data set. The

[iv] For calculation of equivalent volume refer to chapter 3.2.1.3

cost of first part in the hydroforming data set was \$26.10 which was equivalent to the cost of the 2 millionth part of the taxonomic model which was \$92.97

To carry out the rescaling of the taxonomy model it was multiplied by a factor of $\frac{26.1}{92.97} = 0.28$. After this rescaling the data points for the 2 millionth parts matched each other because they correspond to the same hydroformed part.

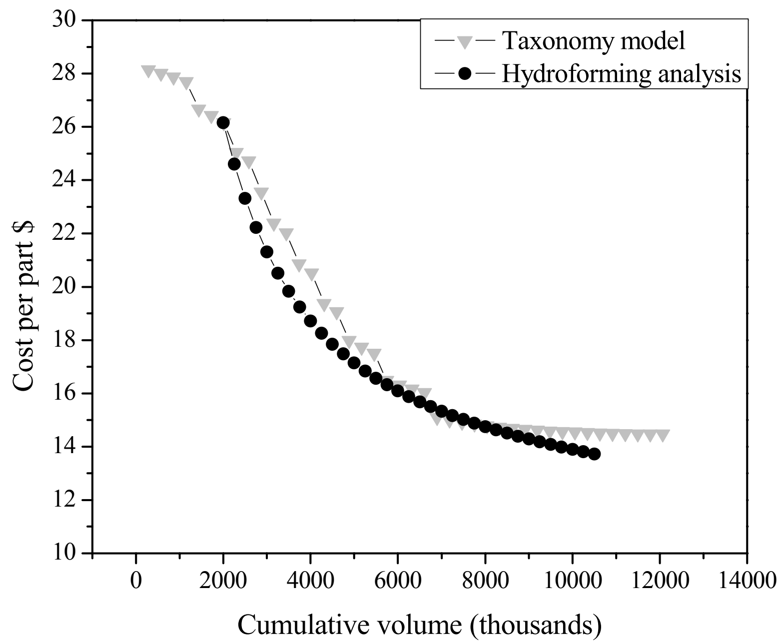

Figure 32 : Comparison of cost evolution between hydroforming data and taxonomic scenario

Figure 32 compares the result from the taxonomy model and the hydroforming model after incorporating the time lag. The taxonomy model gives an output for the hydroforming technology since its inception where as the hydroforming model data set gives the cost output since the data set was collected (8 years, which roughly corresponds to 2 million parts). The comparison between the hydroforming analysis and taxonomic classification shows that the classification method developed was able to predict the trends pretty accurately.

6. Conclusion

For several decades, the concept of experience based improvements in efficiency and effectiveness and mathematical implementation in the form of learning or experience curves have been used to characterize and project the cost walk down for various industries. In the past couple of decades, this work and the application of learning curves to firm decision-making has been expanded to comprehend not only improvements in labor requirements to broader, firm-wide drivers for cost.

In the past, most of the work done looked at evolution of cost at a very macro level by using log linear curves and relating cost to cumulative volume. The strength of this method was that it was analytically inexpensive to use since it was not very data intensive. And it also matched well with some of the industry cases. But the weakness of the method lay in the fact that since it took an aggregate approach it neglected the underlying technology involved in the process. This made the method look technology blind, which implied that there was no element of causation present in the analysis.

In the present work, a different perspective was taken on the application of learning behaviors to the inform early-stage technology selection decisions. Fundamentally, this different perspective was to move from analyzing the aggregate, resultant consequence of manufacture in the form of price or cost, to the perspective of the cost-driving activities at the level of the manufacturing line. Instead of using the learning curves to predict total cost with time, they were used within a generative cost model to look at the direct implications of some key operational levers like cycle time, down time and rejects on that same measure of performance – cost. Process based cost modeling was used to convolute these parameters defined by S curves, to determine cost as a function of volume. Even with the approach proposed in this thesis, the learning curves are based on historic data and speculation, however, by moving from aggregate to operational behavior the speculations are focused around tangible technological and operational characteristic. This allows technical and physical knowledge to be applied to the question of future evolution. Hopefully, negating some of uncertainty and definitely allowing for focused debate.

Tube hydroforming data was used as a case study to establish the feasibility of this approach. The positive aspect of this case study was that it demonstrated the method's ability to tackle the problem at a more causal level probing into the drivers which eventually leads to cost reduction. It gives the line engineers a better picture of understanding the mechanism of cost reduction, arming them with the tool to direct effective cost reduction for a given technology. The case study has successfully shown methods to identify the drivers of improvement, empowering them to prioritize particular drivers over other.

While the model-based learning evaluation is powerful it requires detailed information about processing characteristics. Information that may be difficult to acquire for novel technologies or ones produced outside of the firm making a selection decision. In response to this need, the final section of the thesis proposes a structured method to guide the selection of probable learning behaviors for a technology under evaluation. In the final part a taxonomical classification was developed which aimed to address very nascent technologies with little or no historic data present. The classification was based on eight characteristics – process attributes of material and capital and learning characteristics around downtime, rejects, and cycle time. By exercising this process-based learning model against discretized values of these characteristics a catalog of non-dimensionalized learning behaviors was developed. If thoroughly populated, any given technology should be represented by one of the cost behaviors within the catalog. By correlating this behavior with characteristics of the technology a feasible set of cost evolution behaviors can be selected methodically. The hydroforming cost evolution was compared to one of the taxonomic scenarios and it was observed that the evolution trend matched well. The study suggests that it may be possible to successfully identify expected cost evolution trends for technologies based on limited available knowledge about those technologies. If this result can be demonstrated by application to other cases, this approach would provide a powerful tool to improve the early-stage technology decisions made across industries today.

7. Future Work

The idea of looking at cost evolution at manufacturing level using S curves has produced very promising outcomes. There were few shortcomings which can be addressed and improved in future course of work.

As discussed in chapter 4, the manufacturing parameters were limited to cycle time, down time and reject rate. It was assumed that these levers would be in a position to capture major evolution trends, since their impact factor is high. It would be a good idea to introduce some other parameters like engineering scrap, equipment and tool cost, which are also subject to improvement over time. In chapter 5, the taxonomic classification was based on material cost, and capital versus labor cost. The capital cost was assumed to be distributed between equipment and tool in a fixed proportion. The ratio between equipment and tool varies across the industry and a new lever (equipment versus tool cost) can be introduced to account for this observation.

In chapter 4, the learning rates, scope, material and capital were assumed to be binary in nature. They were either high or low in value. But in practice there might be situations where these might fall some where in the grey area. It would be a good idea to introduce three levels (fast, medium and slow) to define the levers. There is no hard rule to keep the level down to three; it is very possible to introduce 5 levels (fast, fast-med, medium, med-slow and slow). But with too many levels it would be even difficult for the experts to speculate the appropriate levels.

It should also be kept in mind that linear increase in levers results in exponential increase in the number of possible scenario combinations. There are two kinds of levers, process levers and learning levers. Material Intensive, Capital/Labor, Equipment/Tool will fall into the first kind since these levers are used to define the industry and they are not related to learning. Levers like cycle time, down time, reject rate, engineering scrap fall into the category where learning is involved.

In calculating the number of scenarios, the levers which are not affected by learning have just 3 states, for each of them. So if there are ‘m’ non learning levers then there are 3^m cases possible. For levers which are affected by learning, it is important to specify both scope as well as rate of learning. There are 3 states possible for each of scope and learning rate. So for ‘n’ learning levers there are $(3.3)^n$ possible cases.

Calculating the number scenarios with the new set of proposed levers:

Number of Scenario=$3^m.(3.3)^n$

m : Number of levers which are not affected by learning
n : Number of levers which are affected by learning

For the above case m=3 (material, capital/labor, equipment/tool)

Table 5: Scenario possible for given number of learning levers

n	Possible scenarios
1	243
2	2,187
3	19,683
4	177,147
5	1,594,323
6	14,348,907
7	1.29E+08
8	1.16E+09
9	1.05E+10
10	9.41E+10

Table 5 shows how the possible scenario combination scales up with the number of variables. After some point a tradeoff has to be decided between the number of scenarios in taxonomic classification and the granularity of the analysis. With n=5, there would be approximately 1.5 million scenarios which would be really large. The level of granularity for future analysis should be decided after looking into these numbers.

The taxonomic classification carried out in chapter 5, was based on 5 levers in which 2 were non learning viz. (material, capital versus labor). The combination of these 2 levers leads to 4 primary classification. The hydroforming analysis fell into one of these category (Capital intensive, material non intensive) and the data for the analysis was used to verify the taxonomic classification. In future data should be gathered for the remaining 3 major classification and should be verified against the taxonomic classification.

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Appendix A

Modeling assumptions for hydroforming model

Annual Production Volume	500,000	Units
Low Volume Production	0	[0=No,1=Yes]
Batch Size	5,000	parts/batch
Product Life	2	Years
Multiple parts hydroformed simultaneously?	0	[0=No,1=Yes]
Number of parts hydroformed simultaneously?	2	parts
Multiple parts contained in each hydroforming?	1	[0=No,1=Yes]
Number of parts contained in each hydroforming	3	parts
Exogenous Variables		
Days/year (Plant Operation)	240	days/yr
Hours/Day	16	hr/day
Wage Rate (Including Benefits)	40	$/(person*hr)
Interest	10%	
Equipment Life	20	yrs
Building Life	25	yrs
Building Cost	1500	$/m^2
Fixed Overhead Rate	35%	
Electricity Unit Cost	0.1	$/kWhr
Indirect workers/Direct Worker	0.2	

Material Information: Dual Phase 600		
Material Price	0.65	$/kg
Scrap Price	0.1	$/kg
Material Density	7860	kg/m^3
Material Specific Heat	460	J/kgK
Material Yield Strength	300	MPa
Material Flow Stress at 20% Strain	450	MPa
Anneal Temperature	600	°C

PART DATA		
Part Length	1.5	m
Pre-Hydroforming Tube Diameter	0.09700	m
Wall Thickness	0.00075	m
Number of bends	8	
Outer dimensions of bent tube:		
Length (Usually the largest dimension of the bent part)	5	m
Width (Usually the second largest dimension of the bent part)	0.3	m
Height (Usually the diameter of the pipe.)	0.05	m
Stacking Dimension (1=Length, 2=Width, 3=Height)	3	

Input for learning curves (Hydroforming)

Process	1	Hydroforming		TYPE	1	
LEARNING CURVE EFFECT						
				CYCLE TIME		
Cycle Time	1-Fast	3	LC_CT_Tog_1	Maximum Time(min)	2.798	LC_CT_Max_1
	2-Medium			Minimum Time(min)	0.8543	LC_CT_Min_1
	3-Slow					
				UNPLANNED A %		
DownTime	1-Fast	2	LC_DT_Tog_1	Maximum Time(min)	57%	LC_DT_Max_1
	2-Medium			Minimum Time(min)	4%	LC_DT_Min_1
	3-Slow					
				REJECT		
Reject	1-Fast	1	LC_REJ_Tog_1	Maximum Reject%	5	LC_REJ_Max_1
	2-Medium			Minimum Reject%	1	LC_REJ_Min_1
	3-Slow					
				TOOL		
Tool	1-Fast	2	LC_TOOL_Tog_1	Max Tool Cost	150000	LC_TOOL_Max_1
	2-Medium			Min Tool Cost	150000	LC_TOOL_Min_1
	3-Slow					
				EQUIPMENT		
Equipment	1-Fast	2	LC_EQP_Tog_1	Max Equipment Cost	6000000	LC_EQP_Max_1
	2-Medium			Min Equipment Cost	6000000	LC_EQP_Min_1
	3-Slow					

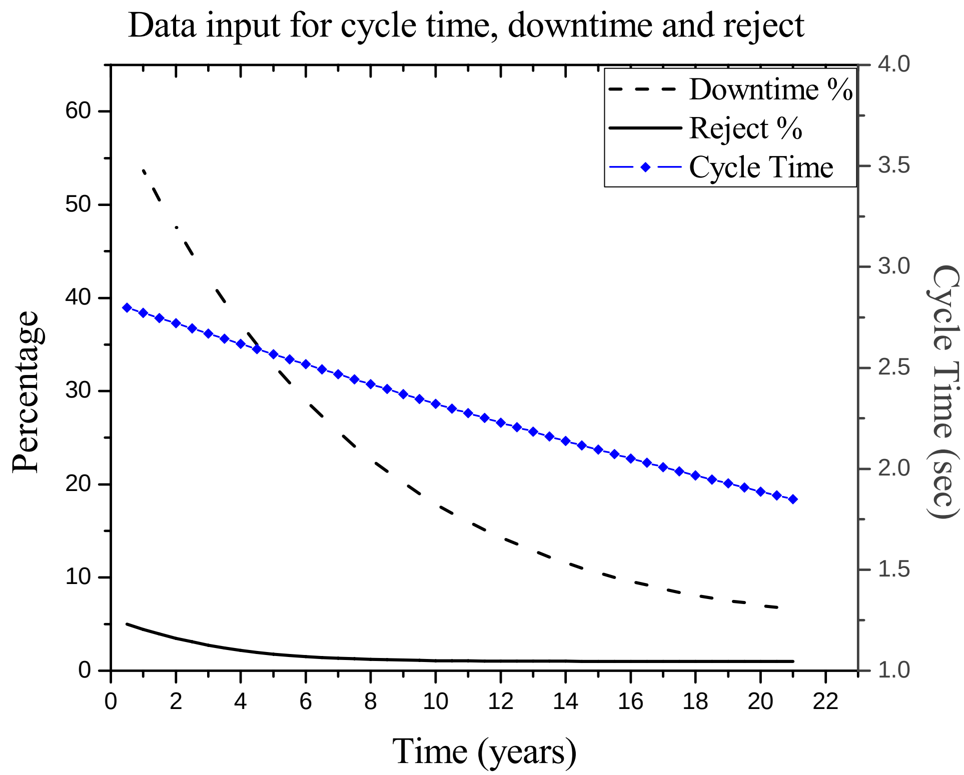


Figure 33**:** Evolution of cycle time, down time and reject with time for tube hydroforming analysis (generated using the S-curves)

Appendix B

Modeling assumptions for the baseline taxonomy model

Model Output Controls		
Number of readings per year	2	number/yr
Projected production per year	54,000	number
Dedicated	N	Y/N
Exogenous Variables		
Number of working days/yr	240	days
Labor Wage	30	$/hr
Interest Rate	12.0%	percent
Building Unit Cost	400	$/sq.m
Building Area used	4,231	sq.m
Building Life	40	yrs
Cost of Tool	461,522	$
Number of parts produced by a single tool	1,000,000	number
Time to amortize the tool (yrs)	11	yrs
Cost of Equipment	153,841	$
Lifetime of the equipment (in yrs)	11	yrs
Cycles the equipment can last	1,000,000	yrs
Average Power consumption	1	kW
Idle Space	0	sq. m
Unit Energy Cost	0.1	$/kW-hr

Material Input A		
Material not in the list [1=TRUE, 0=FALSE]	0	
Material Used	41	number
	Some Material	
Part Weight	2.1	kg
Growth	0%	
Growth Toggle	0	[0=Fixed,1=Var]
Length of shift	8	hr
Number of Labor/unit	6.6	

Number of Shifts@8 hrs/shift	2	
Indirect workers/Direct Worker	0.2	
Wage Rate (Indirect)	40	$/hr
Maintenance	0.01	hr/operation hr

PLANT UTILIZATION		
Total time the plant is available	24	hrs
Time Slot for manufacture of A and B	16	hrs
Time for analyzed part manufacture A and B	11.2	hrs
Average plant utilization	70%	percent
Break paid/unpaid	0.8	hrs
MATERIAL INPUT B		
Cycle Time	10	min
Maintenance	0.02	fraction
Reject Rate	0.06	fraction
Downtime	0.04	fraction
Volume equivalent	1,156,320	

Scenario Toggle	193
Material Intensive (0=No, 1=Yes)	0
Capital or Labor Intensive [C/L]	L
CT Scope [1=High, 2=Low]	1
CT learning [1=Fast, 2=Slow]	1
DT Scope [1=High, 2=Low]	1
DT learning [1=Fast, 2=Slow]	1
Reject Scope [1=High, 2=Low]	1
Reject learning [1=Fast, 2=Slow]	1

LEARNING CURVE EFFECT for A						
				CYCLE TIME		
Cycle Time	1-Fast	1	**CT_TOG**	Maximum Time(min)	**10**	**CT_MAX**
	2-Medium			Minimum Time(min)	**5**	**CT_MIN**
	3-Slow					
				UNPLANNED A %		
DownTime	1-Fast	1	**DT_TOG**	Maximum Time(min)	**30%**	**DT_MAX**
	2-Medium			Minimum Time(min)	**12%**	**DT_MIN**
	3-Slow					
				REJECT		
Reject	1-Fast	1	**REJ_TOG**	Maximum Reject%	**40**	**REJ_MAX**
	2-Medium			Minimum Reject%	**16**	**REJ_MIN**
	3-Slow					

Appendix C

Detailed Analysis of Taxonomic Scenarios 2, 3 and 4

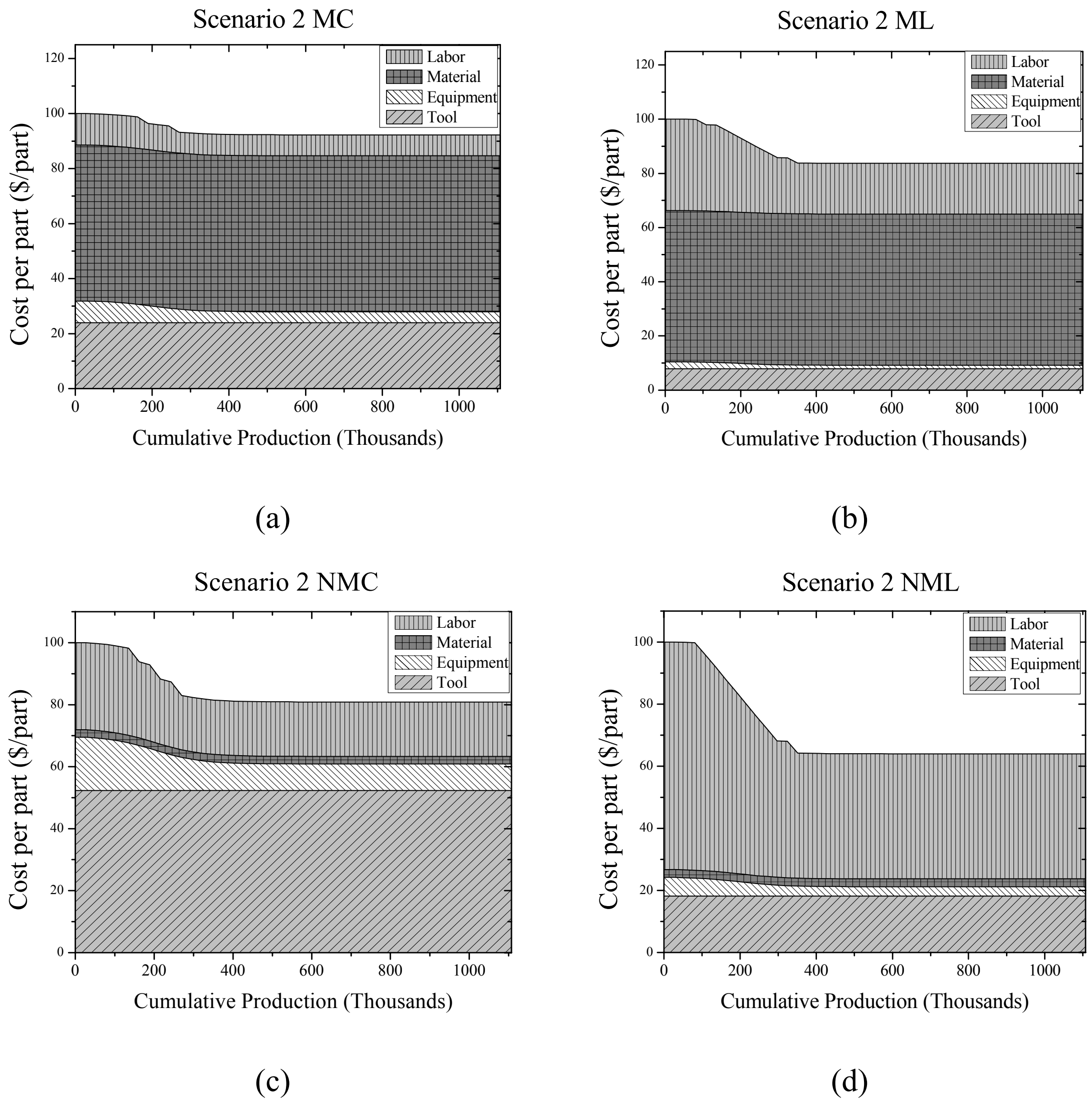
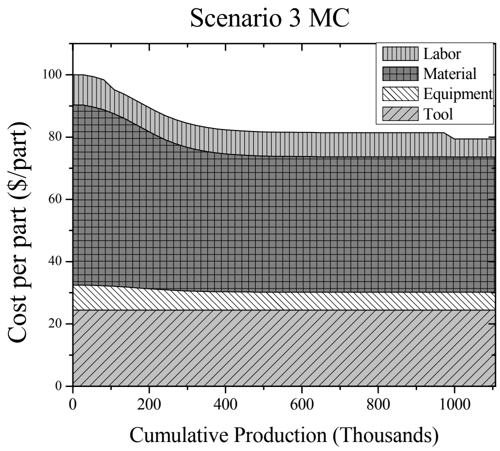
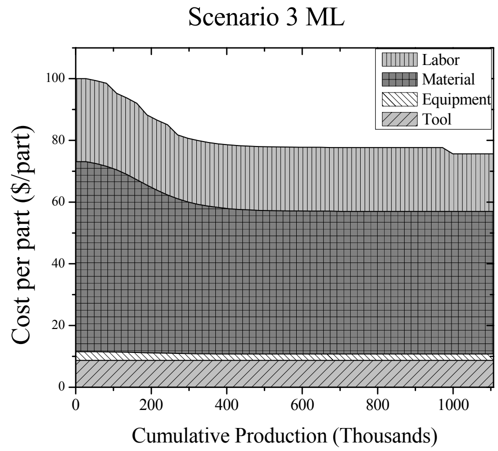


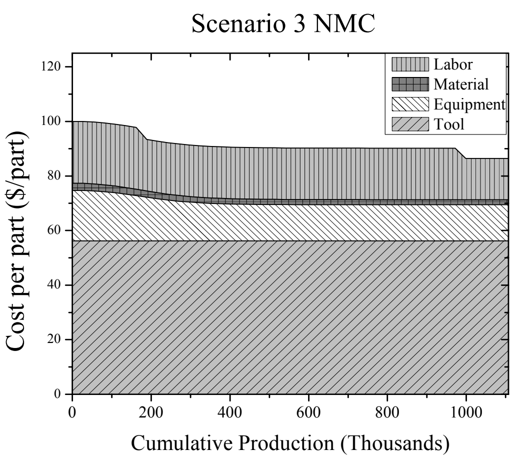
Figure 34: Cost per part break down with respect to labor, material, equipment and tool for (a) material and Capital intensive (MC); (b) Material and Labor intensive (ML); (c) Non-material and Capital intensive (NMC) and (d) Non-material and Labor intensive (NML) industries for scenario 2 (only cycle time learning present)



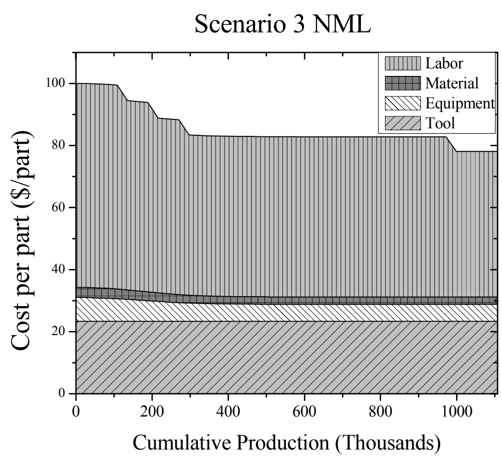
(a)



(b)



(c)



(d)

Figure 35: Cost per part break down with respect to labor, material, equipment and tool for (a) material and Capital intensive (MC); (b) Material and Labor intensive (ML); (c) Non-material and Capital intensive (NMC) and (d) Non-material and Labor intensive (NML) industries for scenario 3 (only reject learning present)

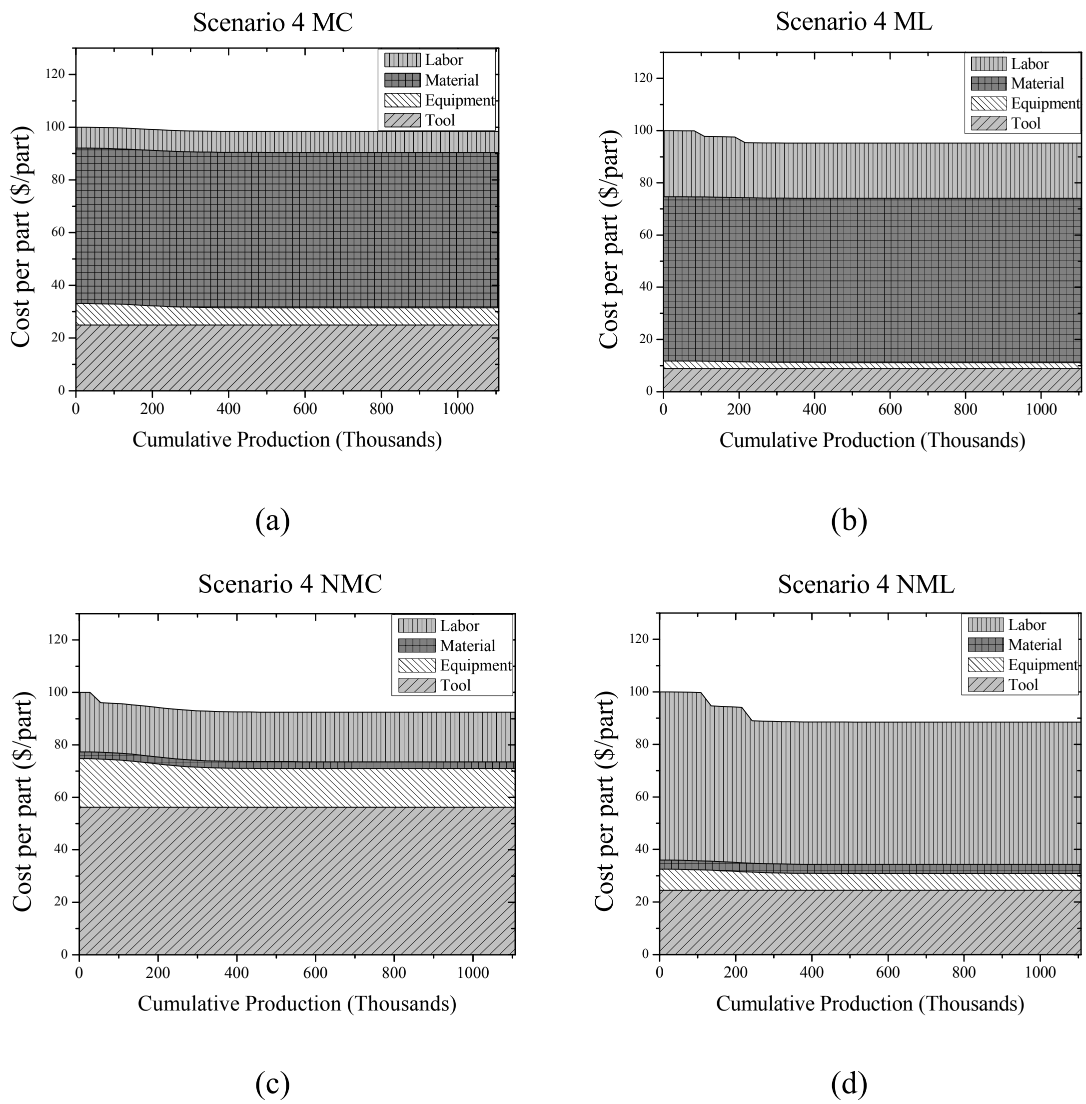


Figure 36: Cost per part break down with respect to labor, material, equipment and tool for (a) material and Capital intensive (MC); (b) Material and Labor intensive (ML); (c) Non-material and Capital intensive (NMC) and (d) Non-material and Labor intensive (NML) industries for scenario 4 (only down time learning present)