Evaluating Manufacturing Flexibility Driven by Learning

by
Marie-Claude Nadeau

B.Eng. Electrical Engineering
McGill University, 2007

Submitted to the Engineering Systems Division
in partial fulfillment of the requirements for the degree of

Master of Science in Technology and Policy

at the
Massachusetts Institute of Technology
June 2009

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ABSTRACT

A defining feature of modern industry is operating in a context of nearly continuous technological change. Nevertheless, industrial decision-makers must select technologies and implement production strategies even in the face of known-to-be-incomplete information and environmental uncertainties. Further complicating the picture, the performance, including the economic performance, associated with novel technology options is likely to change over time. To address this problem, two approaches are possible: improving the quality of currently available information, and implementing flexible production strategies. The present work characterizes how the former approach impacts the valuation of the latter.

First, a dynamic approach integrating learning curves and process-based cost modeling is used to examine learning in manufacturing, thus allowing decision-makers to incorporate information about expected technology evolution into their economic evaluations of technology. The approach is applied to an automotive assembly process, and quantifies the cost impacts of learning improvements in manufacturing time, downtime, and defect rates. Analyses can be used to focus learning activities on primary learning operational drivers, and to forecast cost improvements for a novel process.

Flexibility strategies are often focused on capital-intensive processes, while labor-intensive processes are thought to be inherently flexible. The existence of learning effects, however, implies that labor flexibility has costs and, potentially, benefits in the context of uncertainty. A simple automotive assembly case is used here to illustrate the impact of manufacturing learning on labor flexibility and its economic value. A framework using cash-flow and decision tree models is introduced to quantify the costs and benefits of acquiring worker flexibility, and improve information available for strategic decision-making in labor-intensive systems. The front-end characterization of the technical drivers of learning provides insight into how the value of flexibility can be impacted at the operational level, enabling managers to prioritize improvements and minimize the costs of flexibility.

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Acknowledgement

I would like to thank all my MIT, TPP and MSL colleagues who supported me and made my stay in Cambridge over the last two years absolutely unforgettable.

In particular, I would like to thank Randy for his constant and extraordinary support, dedication, and availability. His brilliant insights and feedback on this thesis work and any other academic or non-academic problems have taught me more than I would have thought possible on rigorous thought and analysis, framing and motivation, and effective communication. Because of him, I feel much better prepared to take on my future career. I also want to thank Rich for all his help, support, and input, especially in the days when cost modeling seemed to be having the better of me. His knowledge and understanding of a number of subjects, but particularly of the automotive industry, is always impressive and incredibly useful. To Frank, I would like to say thank you for all the hard questions, to which I owe my now compulsive tendency to actually try to fully understand what I am going to say before I say it. Finally, I would like to thank Jeremy for guiding me through the hardships of data acquisition, and taking the time to teach me how to do research when I was just the new student on the block. I would also like to thank all of the MSL staff and students whom I worked with every day – Randy, Rich, Frank, Jeremy, Terra, Jeff, Elsa, Gabby, Tommy, Yingxia, Sup, Elisa, Anna, Susan, Trisha, Nate, Boma, Tracey – for the endless laughter, and for making all of those research meetings and presentations so tremendously enjoyable.

I would also like to thank my sponsors, General Motors, and in particular Dr. Patrick Spicer, for all his support, input, and patience. His curiosity and dedication are truly amazing.

To all my MIT and TPP colleagues – thank you for making my journey at MIT such an interesting one. I learned so much from all of you. I would especially like to thank Valerie, Michel, Stephan, Ben, Anya, Lauren, Guillaume, Laurent, Alex (from the other side of town), Rebecca, Ashleigh, Garth, and Ellie for all the friendship, support, insightful conversations, and really good times.

Finally, I would like to thank my parents, Jacinthe and Luc, siblings, Loulou and Martin, and friends Marc-André, Mélisande, Gosia, and Marc, for their constant love and support throughout the years. Behind every thesis is a great family.

Table of Contents

List of Figures

List of Tables

1 Introduction

Across almost every sector of the economy, a defining feature of modern industry is operating in a context of nearly continuous technological change. This implies that decision-makers have to operate in a highly uncertain environment, where external conditions, such as product demand and material prices, are in constant flux. Results of a business decision can therefore be uncertain even in cases of mature technology implementation. Nevertheless, despite this context, industrial decision-makers must still select and implement technologies – whether they be novel materials, processes, or architectures – even in the face of known-to-be-incomplete information. Further complicating the picture, the performance, including the economic performance, associated with novel technology options is likely to change over time. Changes can emerge due to a number of mechanisms, including, for example, economies of scale, and changes in the factor prices associated with the technology. Moreover, evolution in performance can occur through gains in productivity that develop over time, or the learning effect.

As a consequence of uncertainty in both future economic environment and technology performance, current financial data likely will not accurately reflect the future economics of a technology, and making decisions on this current data can be misleading. To address this issue, decision-makers can adopt two distinct approaches, or a combination of them: (a) improving the quality and quantity of the information currently available to them; and (b) implementing flexible business strategies to reduce the negative impacts of uncertainty or enable improvements as uncertainties are resolved. On the one hand, the first approach raises critical questions for technology decision-makers: How can one estimate the future economics of a novel technology? How can one determine which strategies will be most effective for driving down the costs of a particular technology? On the other hand, the second approach raises another important issue: How can one estimate the costs and benefits of flexible strategies under conditions of external uncertainty?

Moreover, these issues bring about the question of interaction between the two approaches, i.e. how can improved information or understanding about the future economics of a technology impact the evaluation of flexible strategies, and thus strategic decision-making? How can operational strategies to improve the cost of a particular technology also improve or degrade the value of flexibility strategies?

This thesis attempts to partly answer these questions by particularly focusing on learning effects in manufacturing and their impact on the value of flexibility in a labor-intensive system. First, an analytical framework is used that allows decision-makers to incorporate information about expected technology evolution into their economic evaluations of technology. This is accomplished through the use of process-based cost modeling (PBCM), a modeling approach that deconstructs the determinants of manufacturing economics. As such, PBCM provides a convenient and powerful framework within which to study the impact of learning on major underlying cost drivers and, therefore, on overall cost evolution. In particular, this document explores the value of a dynamic PBCM approach by examining the effect of learning on process parameters such as manufacturing time, downtime, and defect rate on cost evolution. This approach provides a technical-level understanding of how cost evolution depends on product or process characteristics. In particular, results demonstrate that the scope and timing of cost learning behavior varies across processes depending on their technical and financial characteristics, as well as across cost elements within individual processes. These observations suggest that the proposed approach has the potential not only to improve future cost estimates and technology selection, but also to direct action in order to facilitate learning by targeting the most effective drivers, and to achieve the highest available cost reductions in a timely manner.

Second, an approach is presented which uses the previously described characterization of learning effects to evaluate flexibility strategies for a manufacturing process. This approach characterizes the impact of cost learning on the value of flexibility, particularly in a labor-intensive process. Evaluation of flexibility strategies is often focused around capital-intensive processes, partly because labor-intensive processes are widely thought to be inherently flexible. The existence of learning effects, however, implies that labor flexibility is not inherent or immediate; that is, workers are not able to produce any new product immediately at optimal cost or performance, and this flexibility only comes about via cumulative experience. Acquiring this experience has costs; yet, because it leads to increased flexibility, it can be seen to have potential benefits in the context of uncertainty. The framework introduced here integrates the dynamic PBCM characterization of learning effects with simple cash-flow and decision tree models, in order to quantify the costs and benefits of acquiring worker flexibility through cumulative experience. This aims to improve information available for strategic decision-making in labor-intensive systems. A stylized automotive assembly case is explored to illustrate the impact of manufacturing learning on labor flexibility and its economic value. Specifically, flexible and non-flexible product-to-plant allocation schemes are evaluated in the context of demand uncertainty for a novel technology. Results show that considering learning effects can: (i) provide a structured approach for the evaluation of labor functional flexibility; (ii) increase the value of this flexibility; and (iii) change economically preferred strategic flexibility decisions in terms of product-to-plant allocation. By linking this analysis to the front-end characterization of the technical drivers of learning, insight is gained as to how the value of flexibility can be impacted at the operational level, enabling managers to prioritize improvements, minimize the costs of flexibility, and maximize the positive uncertainty mitigation effects of flexible labor strategies.

The balance of this document proceeds by first presenting a review of past publications on the two major subjects of interest in this thesis: learning in manufacturing; and flexibility in manufacturing, with a special focus on worker flexibility. A methodology is then presented to complement this past work, by integrating a dynamic process-based cost modeling approach to learning with cash-flow and decision tree modeling tools for flexibility valuation. The method is used in the context of a case study on automotive general assembly. First, learning effects are examined from the perspective of the cost impact of individual cost drivers (manufacturing time, downtime, and defect rate) and differentiated impact on various elements with the process' cost structure (labor, energy, overhead, equipment, tooling, building, and maintenance costs).

The cost learning characterization obtained for automotive assembly is then integrated into a cash-flow model, and combined with a decision tree model of demand uncertainty for two novel automotive products. These models are used to evaluate a number of flexible and non-flexible decision scenarios pertaining to the allocation of these products to two individual plants. Economically preferred decisions as well as the value of flexibility are compared under varying operating conditions, and the consideration of learning effects in decision-making is shown to increase the perceived value of flexibility.

2 Literature Review

The present work occurs at the intersection of two literatures in the realm of manufacturing: specifically, it attempts to both extend and further the connection between learning curve theory, and the valuation of flexibility. This chapter presents an overview of the previous work on each subject, as well as how they have been linked in the past.

2.1 Manufacturing Learning

Learning curve theory is based on the observation that the amount of input required to produce a unit output level diminishes as production progresses. This theory is usually attributed to T.P. Wright, who introduced a mathematical model (2.1) describing a learning curve in 1936 (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 attributed to the increased proficiency, or learning, of the manufacturing workers on the line as they performed various repetitive tasks. Wright described the learning effect using an exponential function of the form:

$$h_V = aV^{-b} \tag{2.1}$$

where h_V is the number of labor hours required to produce the V^{th} unit; a is the number of labor hours required to produce the first unit, hence $a = h_1$; V is the cumulative number of units produced; and b is a parameter describing the learning behavior.

Numerous studies in a variety of sectors and industries have led to the recognition of the wide applicability of the learning effect. Among other industries, the behavior has been documented in the manufacturing of aircrafts (Hartley 1965; Argote and Epple 1990), automobiles, apparel, and large musical instruments (Baloff 1971) metal products (Dudley 1972), steam turbine generators (Sultan 1974), chemicals (Lieberman 1984; Sinclair, Klepper et al. 2000), radar equipment (Preston and Keachie 1964), ships (Argote, Beckman et al. 1990), and rayon (Jarmin 1994). Learning curves have also been applied to the cost of power plants (Zimmerman 1982) and in the construction industry

(Tan and Elias 2000). Most recent areas of application include the semiconductor industry (Dick 1991; Gruber 1992; Grochowski and Hoyt 1996; Hatch and Mowery 1998; Chung 2001), fuel cells (Tsuchiya and Kobayashi 2004), ethanol production (Goldemberg, Coelho et al. 2004), as well as carbon capture and sequestration (Riahi, Rubin et al. 2004).

The learning effect has also been shown to occur for aspects of manufacturing other than labor time input or labor costs. Boston Consulting Group (Henderson 1972) added a new dimension to the concept in late the 1960s when it demonstrated that learning curves can also characterize administrative, capital and marketing costs. Of particular note to the work presented here, learning behaviors have been shown to occur in operational characteristics such as nuclear power plant reliability (Joskow and Rozanski 1979); surgery success rates (Kelsey 1984); semiconductor chip yield (Chung 2001); yield, speed of production, and processing capability (Terwiesch and E. Bohn 2001); and the amount of rework needed after a manufacturing process (Jaber and Guiffrida 2008).

Although learning effects have been demonstrated in a large number of contexts, high variations in learning rates have also been observed across different products and organizations. Gruber (Gruber 1992) has shown that variations in learning occurred within a single semiconductor manufacturing company across chip types, even if the chips were considered very similar. Variations have also been observed across organizations producing the same product (Argote, Beckman et al. 1990; Argote and Epple 1990), and across shifts within the same organization (Epple, Argote et al. 1991). Understanding the sources of these variations, and thus the underlying mechanisms that drive learning, has been the object of significant work. The importance of understanding the underlying mechanisms of learning is based on the observation that the learning process is not guaranteed; rather, it is an opportunity for management action to produce improvements (Day and Montgomery 1983; Dutton and Thomas 1984; Terwiesch and E. Bohn 2001). This view of the learning effect as actionable has been adopted by many in the context of developing firm operational strategies. Spence (Spence 1981), for example, developed a model of competitive interaction and industry evolution, concluding that a firm can achieve higher profits in the long run by increasing current production in order to move down the learning curve faster than its competitors. Argote has particularly focused on the organizational mechanisms responsible for learning and knowledge management (Argote 1993; Argote, McEvily et al. 2003). Lapre et al. (Lapre, Mukherjee et al. 2000) have shown that quality improvement activities can positively impact learning when they lead to acquiring both know-why and know-how; Hatch and Dyer (Hatch and Dyer 2004) also show that investment in human capital can lead to accelerated learning. Terwiesch and Xu (Terwiesch and Xu 2004) have examined how learning effort and process change can be traded-off in order to optimize a desired outcome. While these studies have provided powerful insights into strategies to improve learning, they have focused on higher level industrial and organizational performance and strategies. In doing so, these studies have not attempted to prioritize the different types of sources of learning that could occur at the operational level. To explore the possibility of gaining that insight, this paper will couple the concepts of a learning effect within a detailed generative cost model.

Others have explored the coupling of learning and more detailed models. Womer (Womer 1979) in particular, emphasized the importance of integrating production functions with learning models, and production functions integrating a learning curve parameter have been used in a number of empirical studies (Preston and Keachie 1964; Rapping 1965; Argote, Beckman et al. 1990). In another paper, Day and Montgomery (Day and Montgomery 1983) characterized their 'experience curve' as comprising the effects of learning, technological advances, and scale economies. They also noted that different learning curves can be applied to different cost types, among which they distinguished value-added and controllable costs, and observed that this approach could yield a total cost learning curve that can be significantly different from the result obtained if a single curve is applied directly. Nadler and Smith (Nadler and Smith 1963) developed a method which decomposes a manufacturing process into a number of individual operations, and applies a learning curve to each of them. The total learning function for a product is then the time-weighted combination of these individual learning curves. Most recently, Terwiesch and Bohn (Terwiesch and E. Bohn 2001) examine how learning should be focused on yield or production rate improvement, depending on the economic conditions that prevail in the system.

To-date, across this literature, no study has explored the differentiated effects of learning across various operational characteristics, how those effects combine and translate into aggregate financial behavior, or the trade-offs that exist in emphasizing specific elements of operational learning. This research will use the method introduced by Kar (Kar 2007) to demonstrate that by developing insight at the operational level, it may be possible to both characterize the potential for cost learning of a specific technology based on that technology's financial and process characteristics and to prioritize the efforts of an operational manager to maximize the economic impact of learning activities. The former should improve technology selection decision-making; the latter should improve operational decisions.

2.2 Manufacturing Flexibility

2.2.1 General framework

Flexibility in engineering systems has been the focus of a large body of literature in recent years, and its strategic importance in the context of an uncertain environment has been widely recognized (de Neufville, de Weck et al. 2004; Saleh 2008). It can be generally defined as "the ability to change or react with little penalty in time, effort, cost or performance" (Upton 1994). The abstract nature of the concept has led to a number of researchers generating frameworks, taxonomies, and definitions for various types of flexibility. Most recently, Saleh (Saleh 2008) provided a multi-disciplinary review of the subject. Multiple studies have also focused specifically on flexibility in manufacturing systems (see for example (Sethi and Sethi 1990; Hyun and Ahn 1992; Gerwin 1993; Upton 1994; Beach, Muhlemann et al. 2000; Gerwin 2005; Saleh 2008)).

An especially comprehensive taxonomy of manufacturing flexibility is provided by Hyun and Ahn (Hyun and Ahn 1992), and is summarized in Table 1. Their systems view focuses on the relationship between overall system flexibility and the flexibility of its components, and specifically hardware and software components, in the case of manufacturing flexibility. Their environment-associated view characterizes the components of flexibility by the interactions they have with internal and external environmental uncertainties. Finally, what they term the decision-hierarchical view defines the type of flexibility by the time span which is associated with a flexibility decision.

Systems view	*Machine*	Ability to replace tools with low setup; to process a wide range of products
	Routing	Ability to vary machine visitation sequence in case of breakdown
	Control	Ability to change the ordering of operations
	Worker	Ability of workers to operate various machines or to alter working methods
Environment-associated view	*Expansion*	Ability to handle increases in capacity
	Product	Ability to handle non-standard orders; to make design changes
	Mix	Adaptability of the system to changes in product mix
	Volume	Ability to accelerate production to meet demand profitably
	Program	Ability to handle contingencies during operation
Decision-hierarchical view	*Long-term (strategic)*	Ability to reposition in a market, change strategy, introduce new products
	Mid-term (tactical)	Ability to operate at varying rates, accept varying parts, monitor the manufacturing process, convert the plant to other uses
	Short-term (operational)	Ability to reset and readjust between known production tasks, to admit variations in sequencing, scheduling

Table 1: Classification and definition of various types of flexibility (Hyun and Ahn 1992)

Particularly relevant to the present work is *worker* flexibility and its potential impact on *mix* flexibility, which is also appears as *process* flexibility (Sethi and Sethi 1990), or *product mix* flexibility (Saleh 2008) in the literature.

Sethi and Sethi regard machine, material handling and operation flexibilities as contributing to process flexibility; they also note its dependence on a multi-skilled workforce. However, the concept of worker flexibility is notably absent from their formal classification. Their survey is not a unique case. Although the importance of multi-skilled labor is sometimes recognized in passing (for instance, in (Sethi and Sethi 1990; Upton 1994; Saleh 2008)), labor flexibility is not identified in most of the general categorizations referred to above. In fact, labor is often thought of as inherently flexible, with the implementation of flexibility strategies being seen as making manufacturing technology more human-like (see (Simon 1977), cited in (Sethi and Sethi 1990)). Nonetheless, the issue of worker flexibility has been the object of a somewhat distinct body of literature, which will be treated in 2.2.2.

Another common feature of many flexibility overview studies is the observation that flexibility is a proactive strategy (Gerwin 1993), one that should be acted upon by managers both at the strategic and operational levels (de Neufville, de Weck et al. 2004). Sethi and Sethi (Sethi and Sethi 1990), for example, systematically identify the general means by which each type of flexibility can be achieved. However, in recent work, identifying methods for delivering, operationalizing and embedding flexibility into engineering systems is still often recognized as one of the main challenges and academic gaps in flexibility literature (Upton 1994; Gerwin 2005; Saleh 2008).

2.2.2 Worker flexibility

In the last decades, worker flexibility has been widely identified as an issue of strategic importance for firms in a number of industries (Atkinson 1985; Blyton 1996; Esping-Andersen 1999), although some studies have suggested that its value is not universal (Valverde, Tregaskis et al. 2000; Hoyt and Matuszek 2001). Labor flexibility can be implemented at many levels, some of which are described in Table 2. The present work will focus on *functional* flexibility, and will generally refer to it simply as labor or worker flexibility.

Numerical flexibility	Ability to adjust the number of workers employed
Temporal flexibility	Ability to employ workers with varying work terms
Financial flexibility	Ability to adjust worker pay to reflect performance
Functional flexibility	Ability of workers to perform multiple different tasks

Table 2: Description of various types of worker or labor flexibility (Blyton 1996)

In the manufacturing literature, functional flexibility has probably received the most attention. Hyun and Ahn (Hyun and Ahn 1992) identified it as the differentiating factor between Japanese firms' success and American firms' failure at implementing and operating flexible manufacturing systems (FMS). Blyton (Blyton 1996) points out that advantages of functional flexibility are more than performance-related, and include increased job satisfaction and earnings potential for workers. In an empirical study, Zhang and Vonderembse (Zhang, Vonderembse et al. 2003) also established a positive statistical link between labor flexibility as a flexible competence, flexible capacities such as mix and volume flexibilities, and customer satisfaction. This link between worker and mix flexibilities will be explored in more detail in the present work.

Much of the work on worker flexibility in manufacturing systems was done in the context of modeling and analyzing dual resource constrained (DRC) systems. In DRC job shops, both machines and labor impose constraints on production, and their allocation scheme impacts system performance. The literature on the subject recognizes the relevance of worker flexibility as a mitigation strategy in the face of many types of uncertain environments. While some do it at the qualitative level (Atkinson 1985; Blyton 1996), others explicitly model or quantify the impact of uncertainty. Some researchers focused on the performance of cross-training policies under internal uncertainties occurring at the operational level, such as variations in job arrival rates (Malhotra, Fry et al. 1993; Fry, Kher et al. 1995; Felan and Fry 2001), individual machine processing times, and absenteeism (Bokhorst, Slomp et al. 2004). Jordan and Inman also consider large uncertainties in task arrival rates in their study of chained cross-training (Jordan, Inman et al. 2004). Yue et al. (Yue, Slomp et al. 2008) examine the impact of variations in a part's expected life cycle. Others examined a wider range of uncertainties. Malhotra and Ritzman (Malhotra and Ritzman 1990) compared the impacts of machine and labor flexibilities in a DRC shop under various uncertainties, including unreliable vendors, yield loss, inaccurate records, equipment failure, demand variability, and missing components. Ramasesh and Jayakumar (Ramasesh and Jayakumar 1991) measure a group of flexibilities, including labor flexibility, with respect to variations in product mix and worker skills.

Most work on labor flexibility identifies training, or cross-training, as a requirement for the acquisition of a multi-skilled workforce. Carrillo and Gaimon (Carrillo and Gaimon 2004) recognize the importance of knowledge management for process change, particularly focusing on the fact that the increase in capabilities resulting from learning and training is itself associated with much uncertainty. Furthermore, some analyses use learning curve theory to quantify the performance drawbacks associated with training during the acquisition of worker flexibility. The vast majority of DRC studies incorporating learning curves use a log-linear model (Felan and Fry 2001), sometimes combined with models to account for labor attrition rates (Malhotra, Fry et al. 1993; Fry, Kher et al. 1995), or forgetting (Yue, Slomp et al. 2008). The specific use of learning curves for the measurement of the performance cost of flexibility will be discussed in 2.2.3 below.

2.2.3 Measurement and valuation

Establishing adequate, generalized measures of flexibility has been another challenge of flexibility literature. In this section, two sorts of approaches to the measurement of flexibility will be reviewed: non-financial, or performance-based, approaches; and financial, or value-based, approaches. Both approaches comprise multiple specific implementations suggested in the literature.

Non-financial measures of flexibility have been reviewed by a number of researchers.

Gerwin (Gerwin 1993) enumerates the most common: the number of options available; entropy; the range in defining characteristics of the output; impact on a given performance criterion; and qualitative scales. The physical units of these measures are mostly dependent on the type of flexibility one considers. Moreover, as Ramasesh and Jayakumar (Ramasesh and Jayakumar 1991) point out, they are *local* measures, in that they look to specific aspects or dimensions of flexibility without regard for possible interactions or trade-offs. Gerwin's later study (Gerwin 2005) also suggests numerous measures which are particular to the type of flexibility. The same observation applies to the survey done by Sethi and Sethi (Sethi and Sethi 1990), which presents a large number of possible measurements that are all specific the type of flexibility considered. For instance, non-financial measures of process (i.e. mix) flexibility reviewed include the number of part types the system can produce, the range of certain part characteristics, the changeover time required, and the ratio of total output to waiting costs of parts. More recently, in an empirical study, Koste et al. (Koste, Malhotra et al. 2004) reviewed 24 scales for measuring six different flexibility dimensions, and proposed that the scales within each dimension could be grouped into factors representing "scope" and "achievability" of flexibility responses.

Most research specific to worker flexibility has adopted performance-based measurement approaches. In DRC literature, mean flow time, or an equivalent, is often the metric of choice (Malhotra, Fry et al. 1993; Fry, Kher et al. 1995; Bokhorst, Slomp et al. 2004; Jordan, Inman et al. 2004; Yue, Slomp et al. 2008). This is the amount of time required for a job to finish processing all operations. It can be accompanied by mean tardiness (Malhotra, Fry et al. 1993; Fry, Kher et al. 1995; Felan and Fry 2001), which is the average amount of time a job is completed after its due date, and is sometimes viewed as a proxy for customer satisfaction (Malhotra and Ritzman 1990). Standard deviation in workload is also used as a proxy for worker satisfaction by Bokhorst and Slomp (Bokhorst, Slomp et al. 2004). Other performance-based measures include total inventory (Malhotra and Ritzman 1990; Felan and Fry 2001), and percent time spent on learning (Malhotra, Fry et al. 1993).

Many performance-based metrics used in the DRC literature are taken as proxies for the cost of worker flexibility. In the context of evaluating the impact of labor attrition on flexibility, Fry et al. (Fry, Kher et al. 1995) use the mean number of worker transfers and direct labour variance in this way. Felan and Fry (Felan and Fry 2001) apply criteria of operating variance and transfer variance as a measure indicative of cost. Fry et al. (Fry, Kher et al. 1995) also suggest it is possible to determine the performance cost of worker flexibility directly from the applicable learning curve model. As illustrated in Figure 1, the total lost performance is then equal to the area under the learning curve and above the standard processing time. That is, the cost in processing time is given by:

$$\int_{1}^{V_{tot}} \left(t(V) - t_{std} \right) dV \qquad (2.2)$$

where V is the cumulative production volume; V_{tot} is the total volume produced over the lifetime of the product; $t(V)$ is the unit processing time at a cumulative volume of V, or learning curve; and t_{std} is the standard unit processing time. The form used for $t(V)$ is most frequently Wright's log-linear model. However, the analysis and discussion of the impact of learning on flexibility is often limited, as the learning rate is either fixed arbitrarily, or given at most two discrete values.

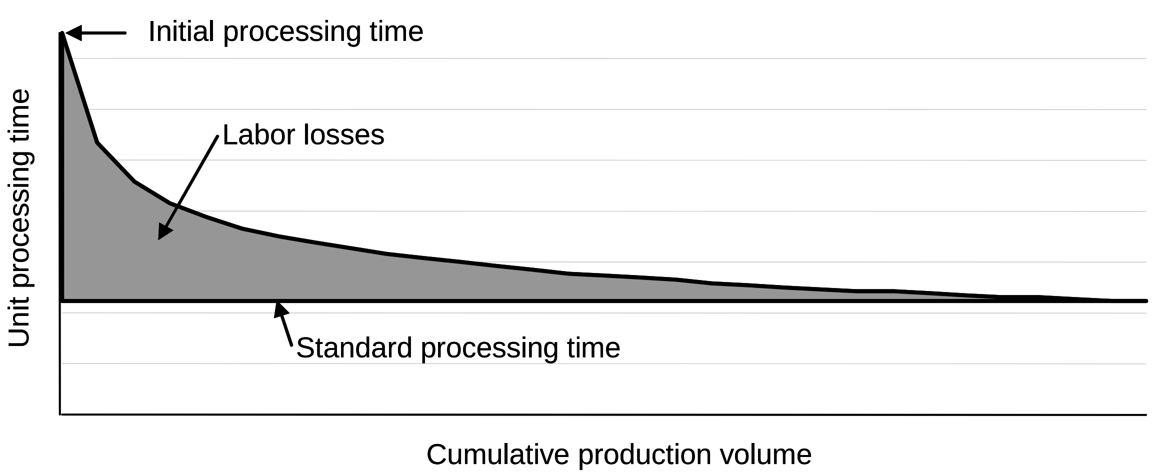

Figure 1: Performance cost of acquiring worker flexibility, determined from a learning curve (Fry, Kher et al. 1995)

In the general flexibility literature, value-based approaches to the measurement of flexibility have been widely discussed. Financial measures have multiple advantages. They are applicable to any type of flexibility, and allow their simultaneous measurement along multiple dimensions (Ramasesh and Jayakumar 1991), including both costs and benefits. Many have also noted that for the purpose of measurement, flexibility should not be isolated from the environment in which the manufacturing system functions (Ramasesh and Jayakumar 1991), since flexibility is the systems ability to respond to that environment. In particular, any measure of flexibility should take into account the level of uncertainty present in the environment and management objectives, in addition to any properties or configurations of the system (Gupta 1993). Value-based approaches also have limitations - for example, they are often only applicable to problems with comparable time horizons (Ramasesh and Jayakumar 1991). They still find a large number of proponents, however, since a universal measure has yet to be identified (Saleh 2008). A large number of models using value-based criteria have been introduced for the evaluation of flexibility; for example, stochastic models applied to the valuation of product flexibility include the ones presented by Fine and Freund (Fine and Freund 1990), and Gupta (Gupta 1993).

Borison (Borison 2005) provides a good review of flexibility valuation methods, and classifies them into four categories: classic, subjective, marketed asset disclaimer (MAD), revised classic, and integrated approaches. They are summarized in Table 3.

Approach	Tools	
Classic	Classic option pricing tools from finance theory	Assumes existence of a replicating portfolio; inputs determined from market data
Subjective	Classic option pricing tools from finance theory	Assumes existence of a replicating portfolio; inputs determined from subjective estimates
MAD	Cash-flow model; Monte Carlo simulation; binomial lattice	No replicating portfolio assumption; simulation and C-F model used to obtain a distribution of NPV to populate lattice
Revised classic	Classic option pricing tools; cash-flow model and decision tree	Distinguishes two investment types. If risks are public, apply classic approach. If risks are private, apply decision analysis.
Integrated	Classic option pricing tools; cash-flow model and decision tree	Distinguishes two types of risk within private investments. For public risks, calculate risk-neutral probabilities; for private risks, estimate probabilities subjectively.

Table 3: Real options/flexibility valuation approaches (Borison 2005)

It is also useful to note that within the domain of value-based approaches, many metrics can be used as a measurement of flexibility. Some are based on expected costs (Fine and Freund 1990), or revenues (Jaikumar 1984; Gupta 1993). Cardin et al. (Cardin, de Neufville et al.) use a combination of expected net present value (NPV), and what they term Value-At-Risk and Gain (VARG) charts, which are effectively cumulative probability distributions of NPV. Their approach thus considers both the value and the risk associated with flexibility. Similarly, Ramasesh and Jayakumar (Ramasesh and Jayakumar 1991) take into account both value and risk by constructing a metric equal to the expected NPV divided by the standard deviation.

Most literature on the value of flexibility and real options focuses on capital-intensive systems, with high upfront costs for the acquisition of flexibility. Of the studies mentioned above, only Ramasesh and Jayakumar's work (Ramasesh and Jayakumar 1991) includes labor flexibility in its evaluation. To do this, they apply rules to labor resources which are akin to the rules for machine resources: each worker's productivity is associated with a probability distribution, and their capabilities are binary – i.e. they are labeled as able or unable to process a given product. The cost of flexibility is uniquely represented for all flexibilities by a fixed cost that is added when a new product is introduced on the line.

The existence of learning implies that worker flexibility has unique features which distinguish it from its technological counterparts: for example, that productivity may increase over time instead of being randomly distributed; that the flexibility or inflexibility of labor resources may not be discrete characteristics since even inflexible labor may be able to produce multiple products, simply at higher cost; and that the cost of acquiring flexibility is not only fixed and paid upfront, but is instead spread out and decreases over time. Indeed, from the studies on learning effects presented above, the cost of acquiring flexibility can be viewed as the cost of the extra input required to produce the first units of output – i.e. the area between the learning curve and the standard or optimal cost level. In accordance with Wright's learning model, this additional input requirement decreases (at a decreasing rate) with cumulative experience.

The research presented here seeks to further the work on the valuation of worker flexibility by strengthening the link between value and manufacturing learning. Learning curve theory provides a framework that enables a more specific understanding and quantification of the costs and benefits of acquiring worker flexibility. It also provides insight into how this value can be impacted. The former could improve the value of decision-making with respect to worker flexibility, while the latter could improve the ability of operational managers to minimize its cost.

3 Problem Statement

3.1 Gap analysis

The present research attempts to complement past work on worker flexibility by proposing two extensions, as well a strengthening of the link between manufacturing learning and flexibility.

Table 4 summarizes the features which are included in six studies on worker flexibility. The table highlights that none of the work ties manufacturing learning to its operational drivers. Moreover, no single study examines the full spectrum or chain of events, from operational drivers of learning to economic value of labor flexibility; and in fact, none establishes the link between learning and value. Furthermore, the impact of learning rates on worker flexibility deserves more attention, as it has only been briefly addressed in the studies shown here.

Features included	(Atkinson 1985)	(Ramasesh and Jayakumar	(Fry, Kher et al. 1995)	(Bokhorst, Slomp et al.	(Jordan, Inman et al. 2004)	(Yue, Slomp et al. 2008)
Describes operational drivers of learning						
Quantifies and connects learning to worker flexibility			✓			✓
Identifies worker flexibility as uncertainty mitigation strategy	✓	✓	✓	✓	✓	✓
Measures worker flexibility			✓	✓	✓	✓
Values flexibility economic costs and benefits		✓				

Table 4: Features included in studies on worker flexibility

The present work will provide an analysis following the full path from operational parameter improvement, to manufacturing cost learning, to worker flexibility, and to economic value. This will introduce a framework to better quantify the costs and benefits of acquiring worker flexibility, and improve the information available for strategic decision-making in contexts involving non-capital intensive, labor intensive manufacturing systems. Furthermore, the front-end characterization of the technical drivers of learning will provide insight into how the value of this flexibility can be impacted at the operational level, thus helping manager prioritize improvements in order to minimize the costs of flexibility.

3.2 Research Questions

In providing an analysis of the impact of learning on the value of flexibility, this thesis seeks to answer the following questions:

1. What is the economic impact of learning effects on a labor-intensive process like general assembly?

2. What is the impact of learning effects on the value of flexibility, and more specifically the value of labor functional flexibility?

3. Can considering learning effects change strategic-level decisions with respect to flexibility?

Answering the first question involves characterizing learning effects in general assembly at the operational level, and linking this characterization to the process' economic performance. By considering this economic performance in the context of an uncertain environment, a framework is created which enables the evaluation of learning-driven flexibility. Here, specifically, the value of labor flexibility driven by learning is quantified under uncertain product demand, and is compared to an evaluation of flexibility which would be done without consideration of learning effects.

In either case, the evaluation can be assumed to lead to a strategic business decision as to whether flexibility is implemented in the system. The decisions considered in later chapters relate to product-to-plant allocation, where the most economically favorable (lowest cost) allocation decision is preferred. The third question therefore looks at whether the differences in flexibility evaluation that stem from considering or neglecting learning effects will lead to changes such that different decisions become economically preferable.

As a whole, these three questions and this document trace the path from the operational characterization of learning effects to strategic decision-making, via a framework that quantifies and focuses on the system's economic performance. The economic lens is useful here as a common metric for connecting the various aspects of the problem, such as learning effects, process performance, labor flexibility, and strategic decision-making. The specific tools employed for this purpose are discussed in the next chapter.

4 Methodology

The method presented in this document links manufacturing learning at the operational level to the value of labor flexibility and related strategic decisions. As depicted in Figure 2, it is composed of four individual tools, which are described in more details in this chapter. First, Wright's learning model is used to characterize learning effects at the operational level. This characterization is integrated with a process-based cost model (PBCM), which uses knowledge of the manufacturing process to produce estimates of cost learning as production progresses. The learning model and PBCM form the dynamic PBCM portion of the method.

The characterization of cost learning obtained is then used in a cash-flow model to characterize the financial performance of a set of product-to-plant allocation decisions. This financial performance is evaluated against a number of demand scenarios which are defined in a decision tree. The valuation of flexibility is done by comparing the expected value of non-flexible decisions with the expected value of flexible decisions. The cash-flow and decision tree models therefore constitute the real options or flexibility valuation portion of the method.

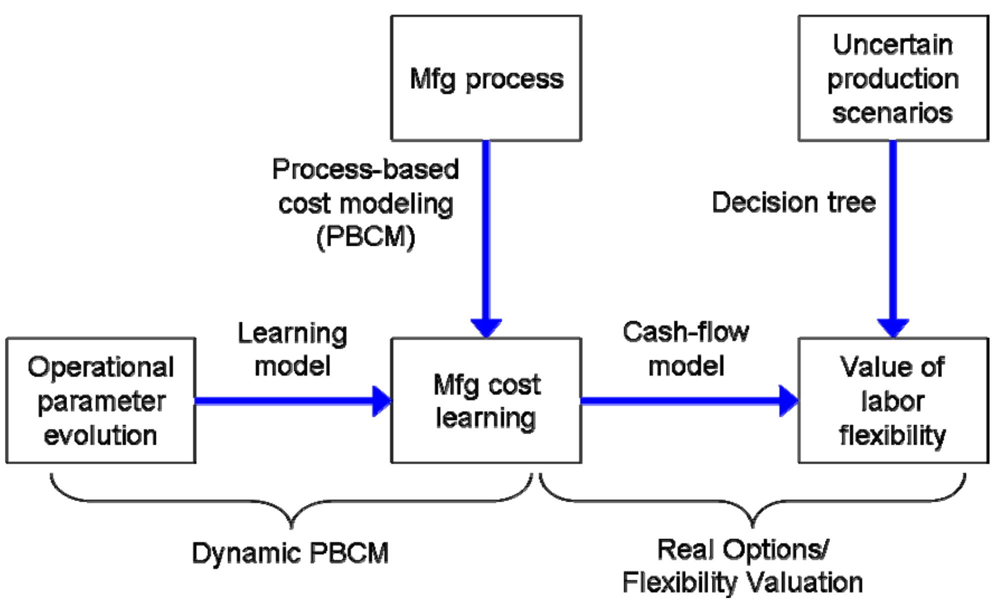

Figure 2: Schematic overview of methodology

4.1 Process-Based Cost Modeling for General Assembly

The impact of process parameters on production cost has been characterized in a static fashion previously through the use of a number of generative costing methods. This study will extend this by integrating learning effects into a specific modeling method, process-based cost modeling (PBCM), which analytically derives from technical and operational drivers to estimate the total cost of production (Field, Kirchain et al. 2007). A static PBCM framework will be presented here, and the model implementation specific to general assembly will be described.

4.1.1 Static process-based cost modeling framework

The PBCM framework introduced by Field et al. (Field, Kirchain et al. 2007) is represented in Figure 3. It postulates that cost can be regarded as a function of technical factors, such as cycle time, downtime, reject rate, equipment and tooling requirements, or the material used.

$$Cost = f(cycletime, downtime, reject, equipment, tools, material, etc.) \qquad (4.1)$$

Understanding the effect of these underlying technical cost drivers can provide insight for managers and engineers as to what process improvements are most critical to lower production costs (Fuchs, Bruce et al. 2006). It also allows them to better predict manufacturing costs for new technologies or designs, since it incorporates knowledge of technical, often more tangible, information about the products and processes, and does not rely wholly on historical data. Figure 3 shows the break-down of the overall cost model into three interconnected sub-models that describe the process, operational and financial aspects of production.

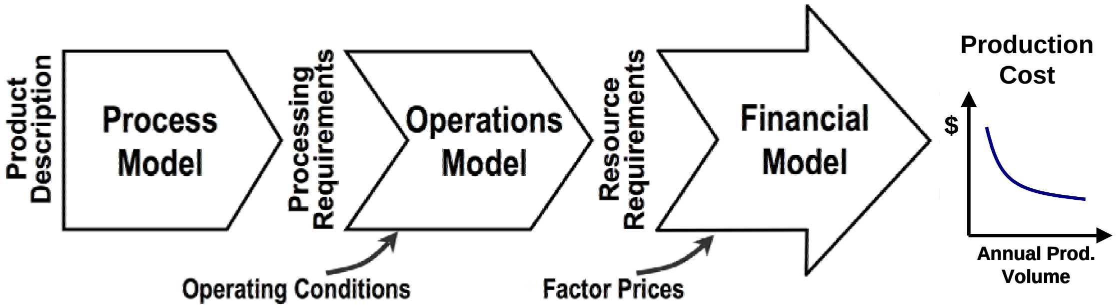

Figure 3: Process-based cost modeling framework (Field, Kirchain et al. 2007)

The process model is based on engineering, technological and scientific principles. It relates final product or part characteristics such as size, shape, and material to the technical parameters of the process required to produce it. These parameters can include cycle time (the total processing time required for a single part); equipment capacity, such as press tonnage and size; and tooling requirements. The process model also characterizes the relationships and constraints between various processing variables: for example, increases in downtime and reject rates can limit the technical feasibility of reductions in cycle time.

Processing requirements are passed on to the operational sub-model along with production operating conditions, which take into account the production shift schedule, working hours, and production volume. These inputs are translated into the total amount of equipment, labor, floor space, energy, and other resources needed to achieve the desired product output.

The financial sub-model applies factor prices to the resource requirements determined by the operations model, and allocates costs over time and across products, in order to output a unit production cost. This figure can be broken down in terms of fixed and variable costs or into individual contributions from labor, equipment, tooling, and material costs. Although this cost is not time-dependent or cumulative volume-dependent, the underlying relationships implemented by the model enable the analysis of variations in production costs as operating and processing parameters change. Such sensitivity analyses allow identification of primary cost drivers which can be targeted for improvement.

4.1.2 Description of the static general assembly PBCM

Production cost figures used in later analyses are generated by a detailed process-based cost model of automotive general assembly. This section contains a high-level overview of the model's characteristics. The calculations described assume that the assembly plant is dedicated to the production of a single type of car; small additions to the model will be proposed in later sections to account for multiple vehicle production. It is also relevant to note here that, for the most part, the assembly plant described by the model is assumed to have a single assembly line. Scaling with production volume happens in a serial fashion; that is, as production volume increases, the time spent at each station on the line (the cycle time) decreases, and the number of stations in series on this line increases.

Although the description is made at the level of the entire assembly process, the actual model implementation allows the user to divide the plant into multiple sub-processes, or groups (indexed on *g*), each of which can be assigned distinct operational variables. The concept of groups is illustrated below in Figure 5. The total process cost is simply the sum of the individual group costs, i.e.:

$$C_{total} = \sum_{g} C_{total,g} \tag{4.2}$$

This partitioning of the process allows for more resolution in model results, and enables taking into account inefficiencies that occur in a realistic plant where assembly is not single continuous process due to physical precedence and facility layout related constraints. For simplicity and clarity of presentation, group indices will be omitted from most of the description, and subsequent analyses are to compute the resource requirements and costs per group. Variables relating to content, as well as conveyor costs, station space, and wage rates, are implemented as group-specific parameters.

It is also worth noting that the model as described excludes material costs (i.e., the cost of the components which are assembled into a vehicle), which, in the case of automotive general assembly, can be so high as to cloud the analysis of the assembly process itself. Implicitly, this approach assumes that material costs are independent from process changes that are being investigated. This assumption is largely reasonable, since in automotive assembly entire cars are rarely rejected and scrapped. Instead, outgoing products undergo a rework process to eliminate unacceptable defects. Future work should explore if assembly process changes have significant effects on rework or component reject rates.

4.1.2.1 Operations sub-model

The general assembly cost model is first based on processing requirements of the product – more specifically, its work content ($t_{content}$), which represents the value-added time required to assemble the components within one group. Value-added time is defined by most automotive firms as the time operators spend directly modifying the vehicle; by contrast, it excludes any time spent walking, reaching for parts, scanning bar codes, etc. Note that in the actual model implementation, work content can be specified at the group level.

Work content is used to compute the unit manufacturing time (t_{mfg}), which is the total operating time required to produce a single vehicle:

$$t_{mfg} = \frac{t_{content}}{ValueAdded \cdot LineEff} + t_{rework} \tag{4.3}$$

*ValueAdde*d is the average percentage of value added time vs. non-value added time for the process. *LineEff* is a percentage value accounting for the average efficiency in line balancing, as well as for the addition of buffer stations and carriers. Inefficiencies in line balancing occur because many tasks are indivisible, and therefore the cycle time available at a single station can rarely be occupied fully by active work. Moreover, inefficiencies in station counts are added buffer stations and carriers, which are used for various purposes, such as preparing for future reordering of tasks, or protecting against a full-line stoppage due to a short single station breakdown. The parameter *rework* is the amount of time required to rework defective products. This amount of time depends on the number of defects found per vehicle (*defects*), and the average time needed per defect repair (t_{repair}):

$$t_{rework} = defects \cdot t_{repair} \tag{4.4}$$

The unit manufacturing time can be used to compute the number of simultaneous operations (*ops*) (illustrated in Figure 5 below) that the line must be divided into in order to produce the target annual volume V:

$$ops = \frac{t_{mfg} \cdot V}{t_{avail}} \tag{4.5}$$

where t_{avail} is the annual amount of time available per operation; and V is the production volume. The plant available time is represented in Figure 4. Note that in this figure, it is assumed that there are no "other parts", and that idle time is zero.

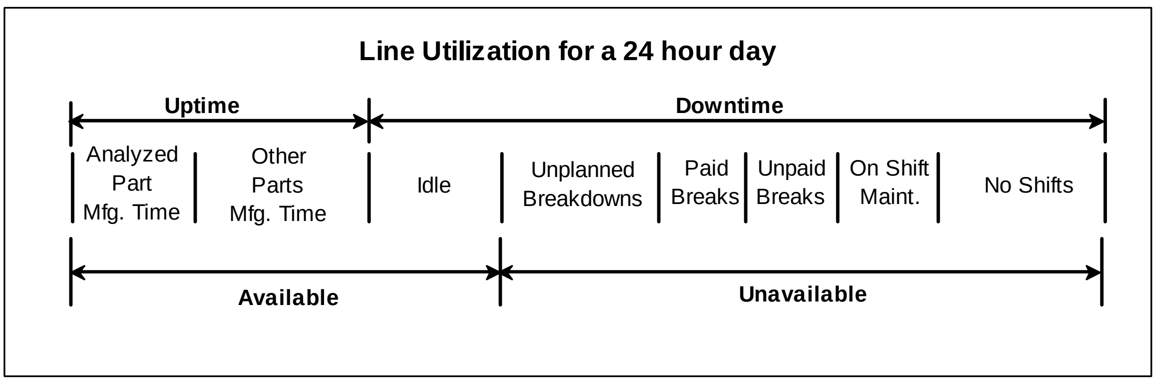

Figure 4: Available operation time based on a 24 hour day clock (Fuchs, Bruce et al. 2006)

It is therefore defined as:

$$t_{avail} = days \cdot (24 - t_{NS} - t_{UD} - t_{PB} - t_{UB} - t_{OSM}) \tag{4.6}$$

where *days* is the number of days of plant operation during the year; t_{NS} is the daily time during which no shift is held; t_{UD} is the time when unplanned breakdowns (unplanned downtime) occur; t_{PB} accounts for paid breaks; t_{UB} accounts for unpaid breaks; and t_{OSM} accounts for on-shift maintenance.

From the number of operations in (4.5), simple factors are used to compute the number of direct operators (L_{op}) and the number of workstations required in the plant:

$$L_{op} = ops \cdot OperatorDensity \tag{4.7}$$

$$stations = \lceil ops \cdot StationDensity \rceil \tag{4.8}$$

where *OperatorDensity* is the average number of operators required per operation, and *StationDensity* is the inverse of the average number of operations per workstation. Both of these concepts are represented in Figure 5.

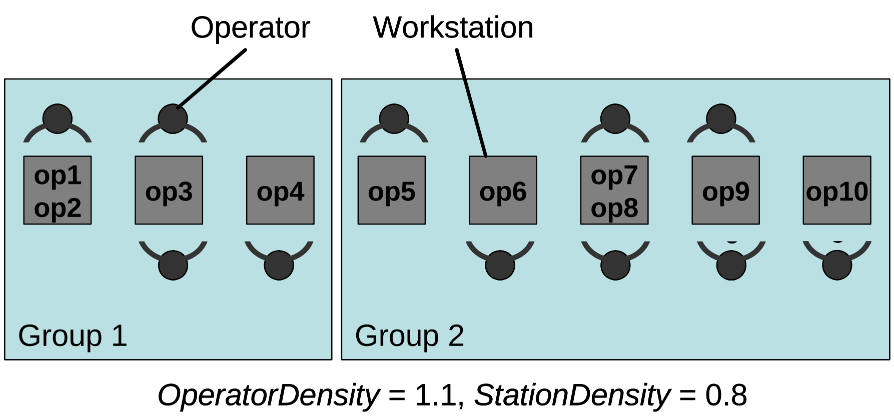

Figure 5: Schematic representation of the concepts of groups, stations, operations and operators

The total number of direct workers (direct labor, L_{dir}) for the plant is calculated from the number of operators by adding on a proportionate number of team leaders and absentee replacement workers:

$$L_{dir} = L_{op} \cdot (1 + LeadRatio + AbsRatio) \tag{4.9}$$

Indirect labor (L_{ind}) is also modeled to be proportional to direct labor. The model differentiates between indirect workers dedicated to material handling (L_{mat}), and those doing quality checks and repairs (L_{qual}). The latter depends on the amount of rework needed. The number of indirect workers is given by:

$$L_{ind} = L_{mat} + L_{qual} \tag{4.10}$$

where:

$$L_{mat} = L_{dir} \cdot MatRatio \tag{4.11}$$

$$L_{qual} = L_{dir} \cdot QualRatio \cdot \frac{t_{rework}}{t_{mfg}} \tag{4.12}$$

In addition to labor requirements, the model computes building requirements with respect plant area. Total plant area (A_{plant}) is composed of areas for process ($A_{process}$), material storage (A_{mat}), and general plant facilities (A_{gen}) like offices and cafeterias:

$$A_{plant} = A_{process} + A_{mat} + A_{gen} \tag{4.13}$$

The process area is occupied mainly by workstations, and it is given by:

$$A_{process} = stations \cdot A_{station} \tag{4.14}$$

where $A_{station}$ is the average area per workstations, which includes space for conveyors, operators, line-side material storage, and aisles. The material storage area has a fixed portion ($A_{mat\text{-}fixed}$) – representing space which is used to package components, unload deliveries, carry components between storage spaces and the assembly line, etc. – and a portion that scales proportionally to the process area:

$$A_{mat} = A_{mat-fixed} + A_{process} \cdot MatAreaRatio \tag{4.15}$$

General plant area, on the other hand, scales with labor:

$$A_{gen} = (L_{dir} + L_{ind}) \cdot GenAreaRatio \tag{4.16}$$

Finally, the energy requirement for the plant takes into account the power needed to operate equipment, conveyors, and the facility itself:

$$energy = \left(E_{equip} + E_{conv} \cdot stations + E_{build} \cdot A_{plant} \right) \cdot t_{mfg} \cdot V \tag{4.17}$$

where E_{equip} is the total power requirement of all equipment in the plant; E_{conv} is the average power requirement of the assembly line conveyor for one workstation, and E_{build} is the power consumption per unit area of the facility.

4.1.2.2 Financial sub-model

The next part of the PBCM constitutes the financial model, and applies factor prices to the resource requirements described above. It also allocates cost over time and production to compute a unit cost per part produced. The annual costs in the model presented here are divided into seven categories:

$$C_{total} = C_{labor} + C_{overhead} + C_{energy} + C_{building} + C_{equipment} + C_{conveyor} + C_{maintenance} \tag{4.18}$$

First, the annual labor cost is obtained by applying the appropriate hourly wage (p_{dir}) to the number of paid direct person-hours:

$$C_{labor} = L_{dir} \cdot t_{paid} \cdot p_{dir} \tag{4.19}$$

where t_{paid} is the annual paid time, as per Figure 4. That is,

$$t_{paid} = days \cdot (24 - t_{NS} - t_{UB}) \tag{4.20}$$

Similarly, the overhead cost is given by the cost of indirect labor:

$$C_{overhead} = L_{ind} \cdot t_{paid} \cdot p_{ind} \tag{4.21}$$

where p_{ind} is the indirect labor wage rate.

The energy cost is obtained by scaling energy consumption by a unit energy price p_{energy}:

$$C_{energy} = energy \cdot p_{energy} \tag{4.22}$$

Building, equipment, and conveyors are considered to be capital investments. In order to incorporate these investments into a unit cost, the financial model distributes them across time by determining a series of annual payments which are financially equivalent to the initial investment. The distribution is done over the useful life of the building, equipment or conveyor in question, and applies a common discount rate. The capital recovery factor CRF_i (where the index i is used to represent building, equipment, or conveyor) used to determine annual payments is therefore:

$$CRF_i = \frac{r(1+r)^{L_i}}{(1+r)^{L_i} - 1} \tag{4.23}$$

where r is the annual discount rate and L_i is the useful life in number of years.

The model considers that building investment scales with the area of the plant using a factor investment per unit area (CAP_{build}), i.e.:

$$C_{building} = A_{plant} \cdot CAP_{build} \cdot CRF_{build} \tag{4.24}$$

In a similar manner, conveyor investment scales with the number of workstations in the plant, where CAP_{conv}:

$$C_{conveyor} = stations \cdot CAP_{conv} \cdot CRF_{conv} \tag{4.25}$$

Equipment investment varies within the model in a step-wise manner with line-speed and, therefore, production volume. This represents the fact that a set of equipment may only be appropriate for a particular range of line speeds, and changes in the equipment selection may be required at other line speeds. The equipment cost is therefore:

$$C_{equipment} = CAP_{equip,V} \cdot CRF_{equip} \tag{4.26}$$

where $CAP_{equip,V}$ is the capital investment for the set of equipment required at volume V.

Finally, the cost of maintenance for the facility, the equipment and the conveyors is computed as a proportion of each initial investment (represented as $MaintRatio_i$), in addition to wages paid to specialized labor dedicated to the maintenance and repair of equipment and conveyors:

$$C_{maintenance} = t_{paid} \cdot p_{maint} \cdot (L_{equip} + L_{conv} \cdot stations) + \sum_i MaintRatio_i \cdot CAP_i \tag{4.27}$$

Here, L_{equip} is the number of workers dedicated to equipment maintenance, and L_{conv} is the number of workers required for conveyor maintenance per workstation.

Finally, these annual costs can be used to compute a unit cost per part (U):

$$U_{total} = \frac{C_{total}}{V_{net}} \tag{4.28}$$

The production cost obtained from the PBCM can be examined in a number of different ways. Individual cost categories and sub-processes can be compared to identify primary cost drivers. Sensitivity analyses on various process parameters can also be performed to further characterize their impact on system and cost behavior. A detailed level of sensitivity analysis is possible because the model derives cost from technical information defined at the process level, rather than using statistical methods to determine cost directly from the part description. This makes it a powerful tool to understand the effects and interactions of the different technical parameters which impact manufacturing cost.

4.2 Dynamic PBCM: Incorporating Learning Curves

In this section, a method will be presented for expanding the use of PBCMs to address the question of cost evolution with time, and particularly through learning.

4.2.1 Dynamic PBCM Framework

Because the PBCM considers a number of technical or process parameters in its cost calculation, it is possible to investigate the impact on cost if these vary over time through learning by doing. As mentioned in a previous section, learning effects have been observed directly for operational characteristics such as yield and speed of production. In the framework presented here and illustrated in Figure 6, this effect is incorporated by applying a learning curve to certain processing requirements such that they, as well as the resulting cost, effectively vary with cumulative volume.

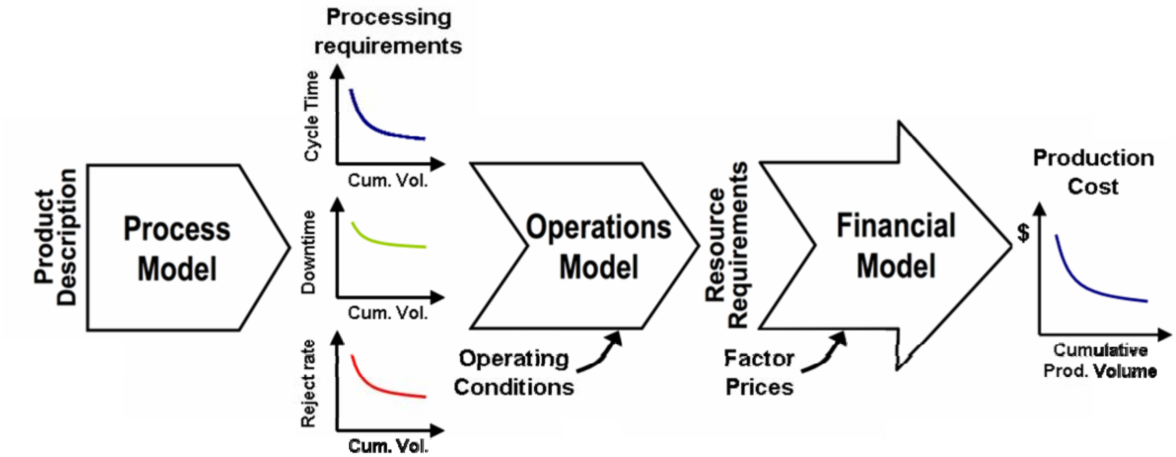

Figure 6: Modified framework for a dynamic PBCM incorporating learning effects

The parameters chosen here to investigate learning effects are manufacturing time (t_{mfg}), unplanned downtime or breakdowns (t_{UD}), and the defect rate (*defects*). Learning effects have been observed in previous literature for operational variables which are either equivalent or comparable in nature, such as speed of production, plant reliability, and yield. In addition, these are parameters for which the data collected show distinct improvement over time. They are not meant to form an exhaustive list of the parameters included in the model which are impacted by learning. Rather, they represent a few examples of such characteristics, chosen in the interest of focusing and simplifying the analysis.

4.2.2 Learning Curve Functional Form

The functional form of the learning curve has been debated by many researchers and practitioners. However, Wright's learning model, which consists of a log linear curve varying with cumulative volume, is by far the most commonly used (for examples of its application, see (Henderson 1972; Lieberman 1987; Argote and Epple 1990; Riahi, Rubin et al. 2004). It is also the basis for the learning curve functional form adopted in the present work.

The learning model proposed by Wright uses cumulative production volume as the only factor responsible for learning and cost reduction. Many later studies have indeed identified cumulative volume as the best proxy for learning. Rapping (Rapping 1965), in a World War II shipbuilding study, statistically tested cumulative production and calendar time as explanatory variables for learning. He found that although the two parameters were statistically significant when used individually, cumulative volume "survived" calendar time when both included in the model. Lieberman (Lieberman 1984) observed similar trends after he analyzed the three-year price change of thirty-seven chemical products. He examined several candidate explanatory variables for 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. Statistical tests revealed that cumulative industry output was the single best proxy for learning. Cost reductions were also statistically linked to cumulative investment and scale economies, although the latter had a much weaker effect. Stobaugh and Townsend (Stobaugh and Townsend 1975) came to similar findings when studying the price change over time of eighty-two petrochemical products as a function of number of competitors, product standardization, experience and static scale economies. They concluded that for a petrochemical's market of three or more competitors, experience has a stronger effect on price than the other three factors.

Wright's learning curve has a log linear shape defined by two parameters: a, which determines the initial value of the function at a volume of 1, and b, which defines the learning rate. Other learning curve geometries have been applied and discussed in the literature, and were reviewed by Yelle (Yelle 1979). Wright's model was used for this paper, not only because it is the most widely applied, but also because it provided the best fit when statistically tested against available data for the current study. Conceptual weaknesses of the log linear model include the lack of initial transient and final saturation phases, which are sometimes observed in learning behaviour. It is also counter-intuitive that any process parameter could improve indefinitely, rather than eventually reaching a best value or approaching it asymptotically. However, the initial transient phase described by other models was absent from the data used in this study. The steep slope which is displayed by the log linear curve at very low cumulative volumes was not representative of the data either, but it is possible to remove it by setting a maximum value to which the parameter is limited, as in Figure 7. In addition, the lack of a final saturation phase and the indefinite parameter improvement issues can be addressed by setting a minimum value for each parameter beyond which the curve becomes flat and learning no longer occurs. Similar cut-offs have been suggested for learning models of various functional forms (see (Kar 2007)).

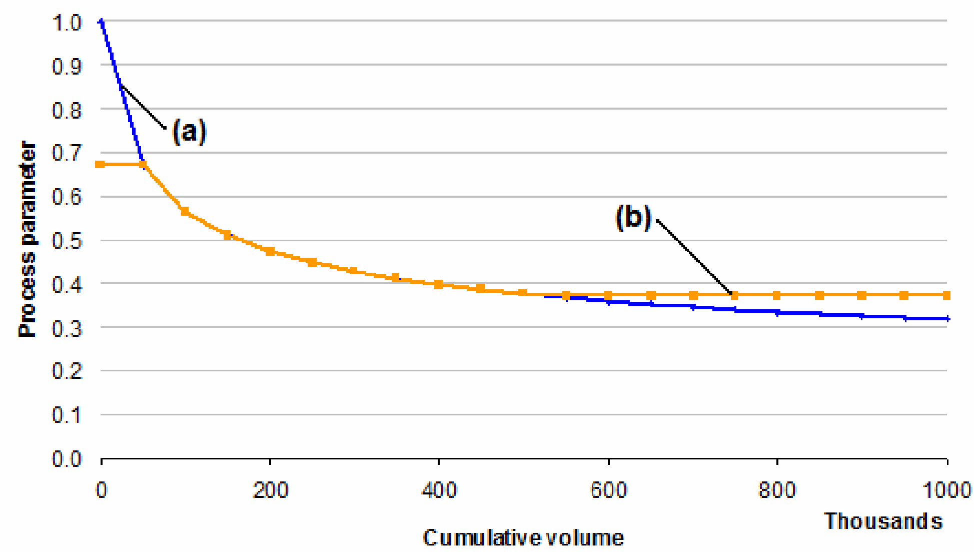

Figure 7: (a) Log linear curve without saturation; (b) Log linear curve with maximum and minimum saturation levels

The modified log linear curve shown in Figure 7(b) was applied to the three process parameters mentioned above in order to produce a dynamic process-based cost model, which outputs cost as a function of cumulative production volume.

4.2.3 Learning Curve Definition and Application

Parameters a and b for the log linear portion of the learning curve were determined via least-squares regression for Wright's model in the form:

$$\ln(Y_t) = \ln(a) + b * \ln(V_t) \tag{4.29}$$

where Y_t is the value of the process parameter for which learning occurs, at time t (in months); and V_t is the cumulative volume produced at time t. The sets of data used for these regression analyses represented monthly average values for cycle time, unplanned downtime, and reject rates observed in a tube hydroforming process over several years.

It is possible to apply the same learning pattern (as defined by a and b) to multiple process parameters which take various ranges of values. This can be done by setting the maximum and minimum saturation levels as described above, and normalizing the learning curve output. For a maximum parameter value of Y_{max} and minimum of Y_{min}, the normalized curve is:

$$Y_t^* = \frac{\min(\max(aV_t^{-b}, Y_{\min}), Y_{\max}) - Y_{\min}}{Y_{\max} - Y_{\min}} \tag{4.30}$$

where Y_t^* is the normalized learning curve output, with $0 < Y_t^* < 1$. In this model, the parameter b defines the learning rate, or timing. A high value of b indicates fast learning with respect to cumulative volume. The values of Y_{max} and Y_{min} determine the learning scope, or the magnitude of the improvement that can be achieved. Scope can be defined as $(Y_{max}-Y_{min})/Y_{max}$.

4.3 Valuation of Learning-Driven Flexibility

As discussed in section 2.2.3, many approaches have been proposed for the valuation of flexibility. In his review, Borison suggests (Borison 2005) an integrated approach distinguishing between public and private risks within private investments (see Table 3). Risks considered here pertain to demand for a particular product, and will be considered private. Therefore, following his approach, the valuation method used will combine a cash flow model with decision tree analysis, using subjectively estimated probabilities. As these probabilities are hypothetical, sensitivity analyses will be performed to determine their impact on decision-making. The cash flow model presented here will incorporate learning effects in order to value labor flexibility.

4.3.1 Cash-flow model

The cash-flow model is used here to compute the present value of costs under a given scenario of future demand.

4.3.1.1 Net Present Value of Costs

The costs are computed at the level of individual products (indexed in p) within specific plants (indexed in q), and summed. In other words, the net present value of the cost of production for an entire system comprising multiple products and plants is:

$$NPV_{tot} = \sum_p \sum_q NPV_{pq} \tag{4.31}$$

The following equations are applied for every pq combination individually. However, for simplicity, these indices will be omitted from most of the model description.

The model is based on unit costs assuming that the capital investments are amortized as in section 4.1.2.2. Unit cost figures are calculated at every time period s = 0, 1, 2, …, s_{max}, where periods are spaced by a constant time step Δ, in years. The time elapsed since the beginning of production is therefore:

$$t = \Delta \cdot s \tag{4.32}$$

Every period is associated with a given demand volume V_s, which is a fraction of the corresponding annual production volume AV_s:

$$V_s = \Delta \cdot AV_s \tag{4.33}$$

Since revenues are excluded from the model, at every time period, the period's cash flow is equal to the cost of producing this volume:

$$CF_s = C_s \cdot V_s \tag{4.34}$$

where CF_s is the cash flow (cost of production) for period s; and C_s is the unit cost of the product, in the considered plant, at period s. The determination of this unit cost incorporates learning effects as well as the more traditional concept of flexibility up-charges. This will be discussed in the following section. Following (4.34), the net present value of the production costs (for a particular product in a specific plant) at time 0 is:

$$NPV = \sum_{i=0}^{s_{\max}} \frac{CF_i}{(1+r)^{\Delta \cdot i}} \tag{4.35}$$

where r is the annual discount rate. Similarly, the net present value of future costs can be determined at any period s:

$$NPV_s = \sum_{i=s}^{s_{\max}} \frac{CF_i}{(1+r)^{\Delta \cdot (i-s)}} \tag{4.36}$$

The NPV at period s is used to evaluate decisions that are not made initially, but can instead be delayed to that period. Note that because the model only considers costs, lower values of NPV will be preferred for the purpose of decision-making.

4.3.1.2 Unit cost with learning and up-charges

A product's actual unit cost C_s depends on the level of learning which has been achieved:

$$C_s = Y_t^* \cdot (C_{\max,s} - C_{\min,s}) + C_{\min,s} \tag{4.37}$$

The normalized learning fraction Y_t^* is calculated as in (4.30), for given learning curve parameters a, b, Y_{min} and Y_{max}, and with $V_t = CV_s$, which is the cumulative volume at each period and determines the current position on the learning curve:

$$CV_s = \sum_{i=0}^{s} V_i \tag{4.38}$$

Cmin,s and Cmax,s are the minimum and maximum saturation levels of the learning curve, and are related by the scope of learning improvement possible for the product of interest:

$$C_{\min,s} = C_{\max,s} \cdot (1 - Scope) \tag{4.39}$$

The maximum unit cost is composed of operational and capital expenditure portions:

$$C_{\max,s} = C_{cap,s} + C_{op,s} \tag{4.40}$$

Each portion takes into consideration a base cost figure, as well as any potential flexibility up-charges:

$$C_{cap,s} = B_{cap} \cdot (1 + Flex_s \cdot CapUp + Flex_{init} CapInit) \tag{4.41}$$

$$C_{op,s} = B_{op} \cdot (1 + Flex_s \cdot OpUp + Flex_{init} \cdot OpInit) \tag{4.42}$$

B_{cap} and B_{op} are the base unit cost figures attributable to capital expenditure and operational expenditure, respectively. Flexs and Flexinit are binary variables indicating whether a plant is flexible (able to produce multiple products) or inflexible. $Flex_{init}$ is non-zero only if the given plant is initially flexible, i.e. at period 0:

$$Flex_{init} = \max(0, \min(1, n_0 - 1)) \tag{4.43}$$

where n_0 is the number of values of p for which V_{pq0} is non-zero, where V_{pq0} is the volume of a product p in plant q at period 0. In the case where the plant is initially flexible and $Flex_{init} = 1$, the initial capital and operational up-charges (*CapInit* and *OpInit*) are applied to the base cost. *CapInit* represents the initial flexibility upcharge on capital expenditures; it accounts for any additional equipment or building space which is required to accommodate more than a single product. *OpInit* represents the initial flexibility upcharge on operational expenditures; it accounts for any inefficiency in operations that is inherent to the production of multiple products, even without considering learning effects.

$Flex_s$, on the other hand, indicates whether a plant has become flexible after its initial start-up:

$$Flex_s = \min(0, \max(1, N_s - 1)) - Flex_{init} \tag{4.44}$$

where N_s is the maximum n, the number of values of p for which V_{pqs} is non-zero, in any period before period s. That is,

$$N_s = \max(n_0, n_1, ..., n_s) \tag{4.45}$$

If $Flex_s = 1$, on-going capital and operational expenditure up-charges (*CapUp* and *OpUp*) are applied. These up-charges are not necessarily equal to *CapInit* and *OpInit*, because introducing flexibility in a plant after it is built may have a different cost than implementing if from the start.

Finally, the sum of the capital and operational portions of the base cost form the total base cost, which is effectively the initial (maximum) unit cost of the product in a non-flexible plant:

$$C_0 = C_{\max,0} = B_{cap} + B_{op} = B, \quad \text{if } n_0 = 1 \tag{4.46}$$

In order to differentiate capital-intensive from non capital-intensive products, it is also useful to define:

$$CapEx = \frac{B_{cap}}{B} \tag{4.47}$$

where *CapEx* is the percentage weight of capital expenditures in the unit cost.

4.3.2 Decision Tree Model

The decision tree models the uncertainty in future demand for the various products considered, and evaluates the production decisions which can be made in this context using the cash flow model described above.

4.3.2.1 Demand scenarios

The decision tree model considers that demand for individual products (D_p) evolves in stages. More specifically, the model in this work uses binary stages, where at each stage the demand is changed to a high (up, indexed in *u*) or low (down, indexed in *d*) value. Shifts to high and low values from any state are associated with probabilities P_u and P_d, where:

$$P_u + P_d = 1 \tag{4.48}$$

Figure 8 illustrates how demand for product *p* progresses at each stage through the binary tree. It is important to note that stages for the demand scenarios are not necessarily equivalent to the time periods used in the cash flow model. Indeed, a single demand stage can encompass multiple time periods, during which demand remains constant.

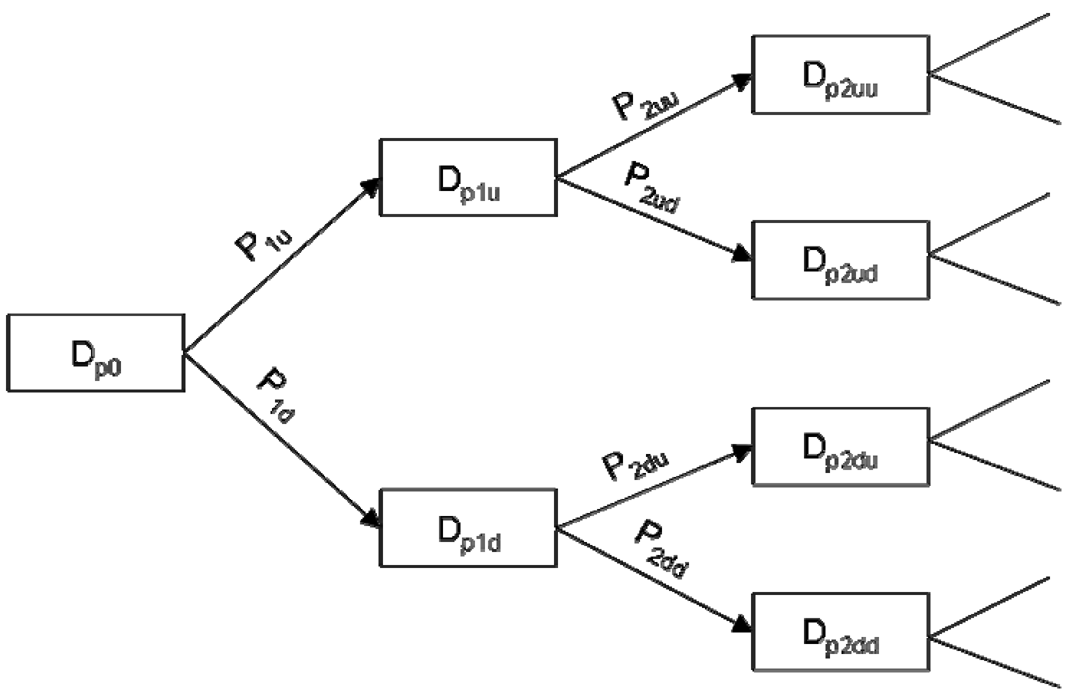

Figure 8: Schematic tree of demand scenarios and associated probabilities

Each shift in demand also corresponds to a decision point, when the production allocation scheme can be modified.

4.3.2.2 *Allocation decisions*

The decision occurring at every stage consists of allocating the required volume of each product to specific plants. This can be viewed as implementing a product-to-plant allocation matrix such as the one represented in Figure 9, where V_{pq} is the production volume of product *p* in plant *q* for a particular stage.

		Plant			
		1	2	…	q
Product	1	V_{11}	V_{12}	…	
	2	V_{21}	…		
	…	…			
	p				V_{pq}

Figure 9: Schematic of a generic product-to-plant allocation matrix

At every stage, the allocation scheme must meet a number of constraints. First, the demand for every product must be met, i.e.:

$$V_p = \sum_q V_{pq} = D_p \quad \forall p \tag{4.49}$$

In addition, the production of each plant cannot exceed that plant's capacity (cap_q) for products 1 through p, i.e.:

$$V_q = \sum_p V_{pq} \le cap_q \quad \forall q \tag{4.50}$$

4.3.2.3 *Valuation*

The allocation decision is can made at every stage in order to minimize the expected NPV of costs at the current time period. For example, at the 0th stage, the expected NPV ($ENPV_0$) will be evaluated for a number of allocation matrices, and the lowest ENPV plan will be implemented until the next decision point. For the tree in Figure 8, the ENPV at stage 0 is:

$$
\begin{aligned}
ENPV_0 &= P_{1u} \cdot P_{2uu} \cdot NPV_0(D_0, D_{1u}, D_{2uu}) + P_{1u} \cdot P_{2ud} \cdot NPV_0(D_0, D_{1u}, D_{2ud}) \\
&+ P_{1d} \cdot P_{2du} \cdot NPV_0(D_0, D_{1d}, D_{2du}) + P_{1d} \cdot P_{2dd} \cdot NPV_0(D_0, D_{1d}, D_{2dd}) \\
&= \sum_{i \in (u,d)} \sum_{j \in (u,d)} P_{1i} \cdot P_{2ij} \cdot NPV_0(D_0, D_{1i}, D_{2ij})
\end{aligned} \tag{4.51}
$$

where $NPV_0(X)$ values are given by the cash flow model from 4.3.1 for the demand scenario described by X; stage 1 outcomes are indexed in i; and stage 2 outcomes are indexed in j. For future stages, the allocation decision may depend on which demand state actually materializes. For example, for a 1st stage decision occurring at time period s, if the demand is high, the allocation decision will be made to minimize:

$$
ENPV_{1u} = P_{2uu} \cdot NPV_s(D_{1u}, D_{2uu}) + P_{2ud} \cdot NPV_s(D_{1u}, D_{2ud}) \tag{4.52}
$$

A similar procedure applies if the demand at stage 1 is low.

An important note to make about this valuation method is that it takes into account the fact that unit costs are path dependent when learning is considered. For example, even if $D_{2ud} = D_{2du}$, the unit cost applicable in that state would depend on the demand levels and allocation decisions which were in effect in the previous state, and on whether any cost learning has occurred. Many flexibility valuation methods – binomial lattices, for instance – make assumptions of path independence which are not applicable when learning is involved. If learning is ignored, however, the method used here becomes path independent. This can be done by initially setting unit costs to their optimal value (C_{min}), the learning scope (*Scope*) to zero, and learning rates (b) to zero. Unit costs then cease to be a function of previous production volume, and simply depend on whether the plant is flexible in its current state.

This method ultimately provides a set of optimal (expected cost-minimizing) decisions to be implemented. The set of decisions chosen under path dependent conditions can be compared to the baseline decision set, which is optimal when no learning is considered (i.e. for the path independent approach), to determine whether the inclusion of learning effects in the analysis has the potential to change allocation decisions. Of particular interest here is the question as to whether more flexibility is introduced (i.e. more plants are allocated multiple products) when learning effects are considered with the path dependent approach. The value of this flexibility can then be computed as the difference in ENPV of costs between the baseline, path independent decision set, and the new, path dependent, optimal decision set.

5 Learning in General Assembly

In the following chapter, the dynamic PBCM approach described above is used to characterize and evaluate learning in the context of an automotive general assembly plant. First, the shape of the learning curve is determined for each process parameter examined. The chosen learning patterns are then incorporated in the PBCM, allowing the analysis of their individual and combined impacts on unit cost.

5.1 Learning curve parameters

Two and a half years of monthly data on production volume, hours worked, and defect rates for an automotive assembly production line were used to determine learning curve parameters via least-squares regression, as described in section 4.2.3. The fitted curves are shown in Figure 10 and Figure 11.

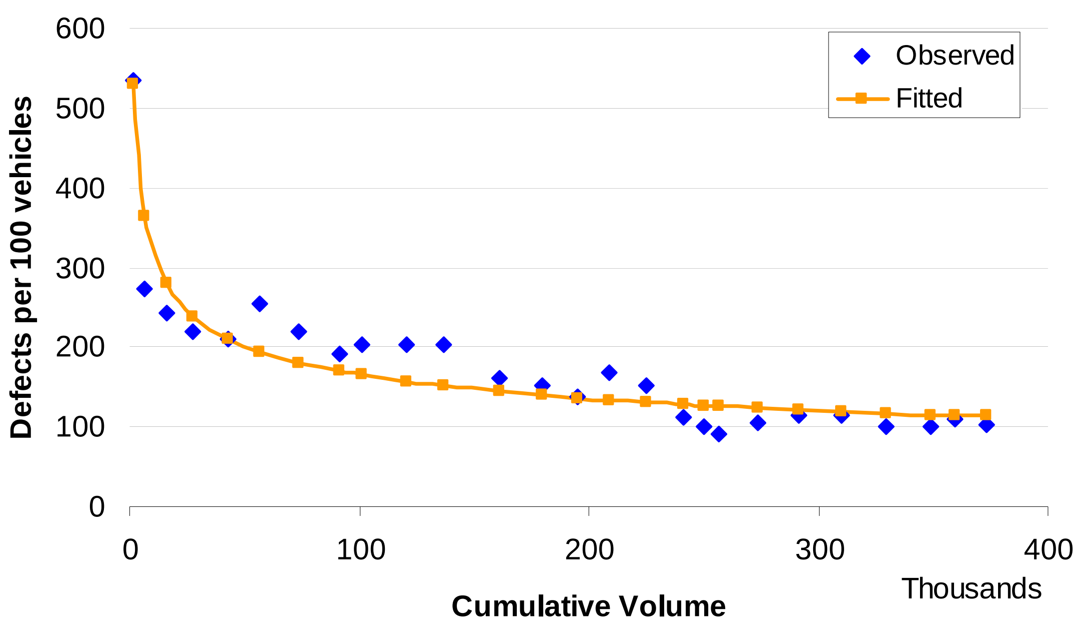

Figure 10: Log linear regression of defect rate data vs. cumulative volume

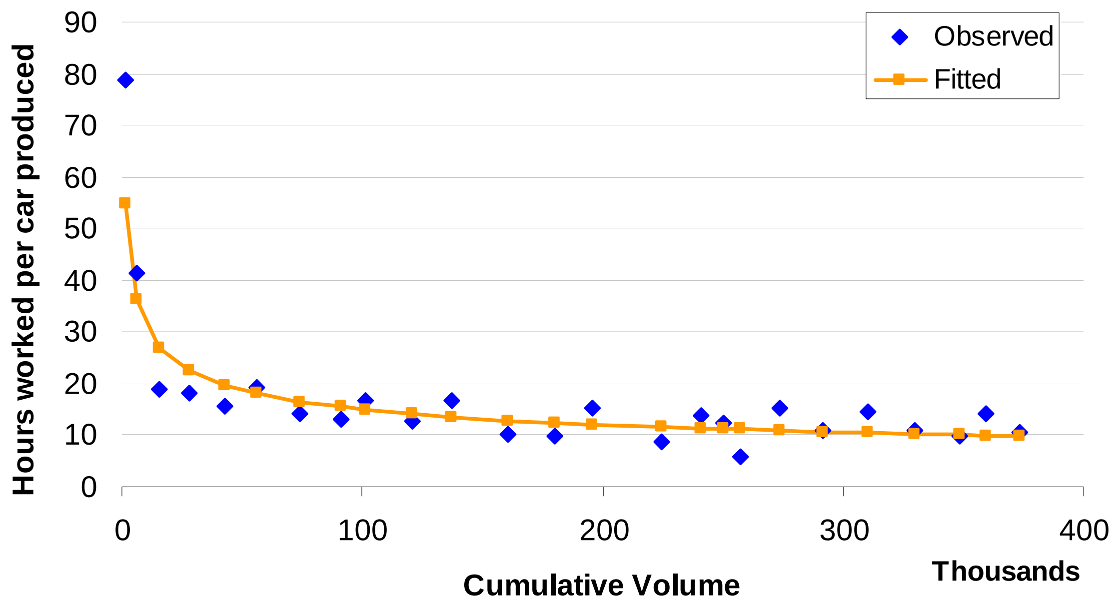

Figure 11: Log-linear regression of hours worked per car vs. cumulative volume

Resulting model parameters a and b for each of the two data sets, as well as the adjusted R^2 statistic for both regression analyses, are summarized in Table 5.

	a	***b***	**Adjusted R^2**
Defect rate	4494.2	0.2869	0.8126
Hours worked	593.4	0.3196	0.7338

Table 5: Summary of log linear learning curve parameters

No data were available to directly perform a regression on downtime or manufacturing time; however, the data on the number of hours worked effectively includes downtime as well as production uptime. Therefore, for the purposes of this study, it was assumed that both the manufacturing time and the downtime parameters experienced the same learning pattern that was determined by the regression on hours worked data, after normalization of the learning curve. The maximum and minimum saturation levels used to normalize each process parameter's learning curve are shown in Table 6. Minimum values were based on best practice estimates obtained from discussions with experts in the field, while scope and corresponding maximum values were determined from the regressed data.

Process parameter	***Y_{max}***	***Y_{min}***	**Scope**
Manufacturing time (t_{mfg})	27.3	4.9	82%
Unplanned downtime (t_{UD})	4.5	0.8	82%
Defect rate (*defects*)	530	110	79%

Table 6: Summary of process parameter maximum and minimum saturation levels

The learning patterns were inserted into the general assembly process-based cost model described in section 4.1.2, resulting in a cost figure which varied with cumulative production volume. Other inputs to the cost model were chosen to reflect the operating conditions of a high-volume North American automotive plant.

5.2 Dynamic PBCM Results

Model output suggests that the unit cost of a vehicle would experience more than a 80% reduction over a cumulative production of approximately 400,000 units, when learning effects in the three process parameters mentioned above are combined. Because learning is applied at the operational level in the PBCM, contributions to cost improvement from learning in individual process parameters can be isolated as in Figure 12.

It is interesting to note that the combined learning effect is not simply the sum of the learning effects from each of the individual parameters. While individual cost savings sum up to over $5,600 after 400,000 vehicles produced, the combined learning only generates a unit cost saving of $4,500 over the same period. The underlying relationships of the dynamic PBCM allow the user to examine this combined learning effect while taking into account the fact that improvements in a certain parameter may undercut improvements in others, leading to less cost learning than would sometimes be expected from a direct cost analysis. This occurs because the learning effect within the cost model is often multiplicative instead of additive; for example, t_{mfg} and t_{UD} are effectively divided in (4.5). With a multiplicative effect, a 10% improvement in one parameter along with a 20% improvement in another will lead to a total improvement of:

$$1-(1-0.1)(1-0.2)=0.28 \tag{5.1}$$

Thus the cost would be reduced by 28% instead of an additive 10% + 20% = 30%, as could be expected at first glance.

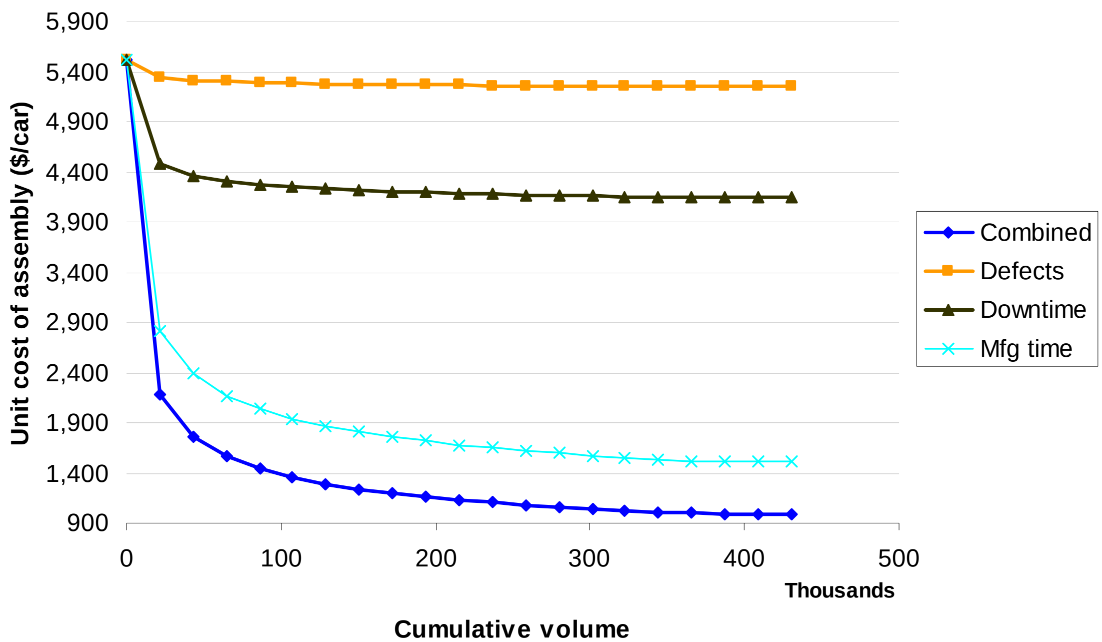

Figure 12: Total cost improvement through learning with increasing cumulative production volume, by process parameter

The analysis represented in Figure 12 would indicate that for the assembly process the majority of the cost improvement comes from learning on manufacturing time. This suggests that this is the metric that managers and engineers should focus on improving in order to gain maximum cost impact. Manufacturing time learning has a larger impact despite relatively similar scope of learning to the other two parameters. This can partly be explained by the fact that manufacturing time has more influence on actual production time than downtime or rework time: while downtime takes up approximately 5-10%, and rework time requires 10-20%, of a plant's operating time, manufacturing time determines the use of approximately 70-85% of available time.

The use of a process-based cost model also enables the analysis of the process' cost structure. Figure 13 shows that labor and overhead constitute the major part of unit assembly cost, but that this proportion diminishes as learning increases. As expected, Figure 14 shows that learning has the most impact these same cost elements. However, while reductions in time requirements have a direct impact on how much labor is needed, it also improves utilization of non-dedicated resources such as equipment and building. As the time required to produce the desired volume is reduced, these resources can be used for other production, and the portion of their cost allocated to the product of interest is reduced.

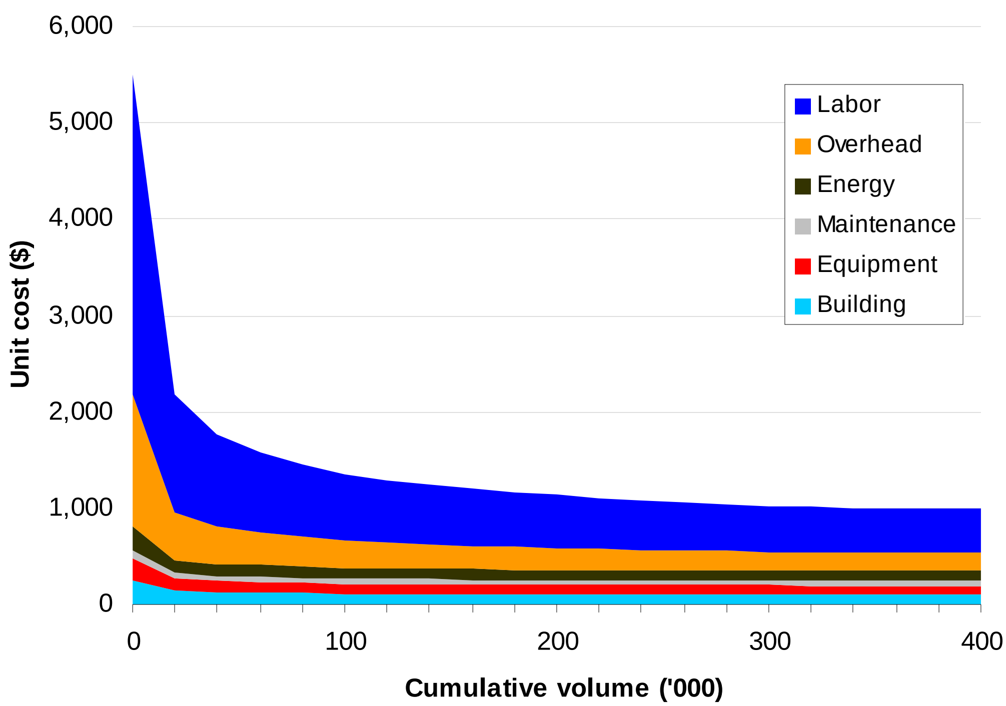

Figure 13: Unit cost variation with cumulative production, by cost category

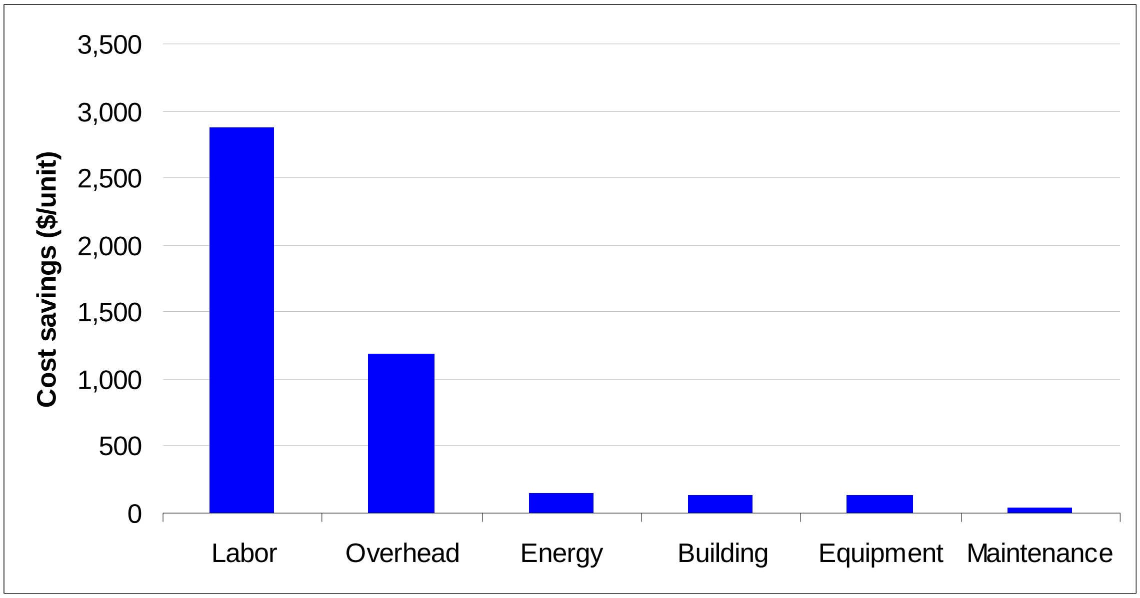

Figure 14: Cost improvement from learning, by cost category

In a case where the plant considered is dedicated to a single product, the equipment time and building area that become available as learning progresses will not be used to produce another vehicle. The cost allocated to the first product due to initial investment therefore remains constant across time. The resulting cost learning curve for a dedicated plant is shown in Figure 15; the cost savings due to learning are reduced from $4,500 to $4,200 over a cumulative volume of 400,000 cars.

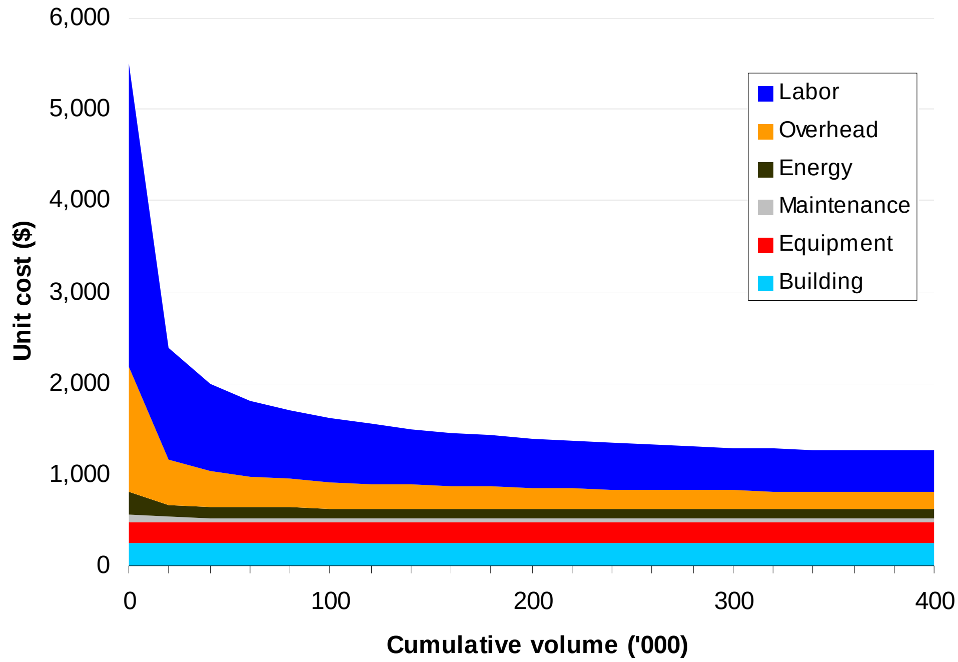

Figure 15: Unit cost learning by cost category for a dedicated assembly plant

5.3 Cost learning characterization

The total cost learning rate for the process can be characterized by the same log-linear model by using regression analysis as in 4.2.3, for the modeled unit cost curves. The learning model parameters obtained are reported in Table 7, for both dedicated and non-dedicated plants.

	a	***b***	**Adjusted R^2**
Non-dedicated plant	6290.9	0.1374	0.9262
Dedicated plant	6067.8	0.1177	0.9445

Table 7: Total unit cost learning curve parameters

It is also possible to analyze the sensitivity of the overall cost learning rate to operational parameters by varying the underlying learning rates. Figure 16 shows cost learning curves for various rates of learning applied to manufacturing time and downtime. The rates of learning were obtained via regression for each of these curves, and are plotted in Figure 17.

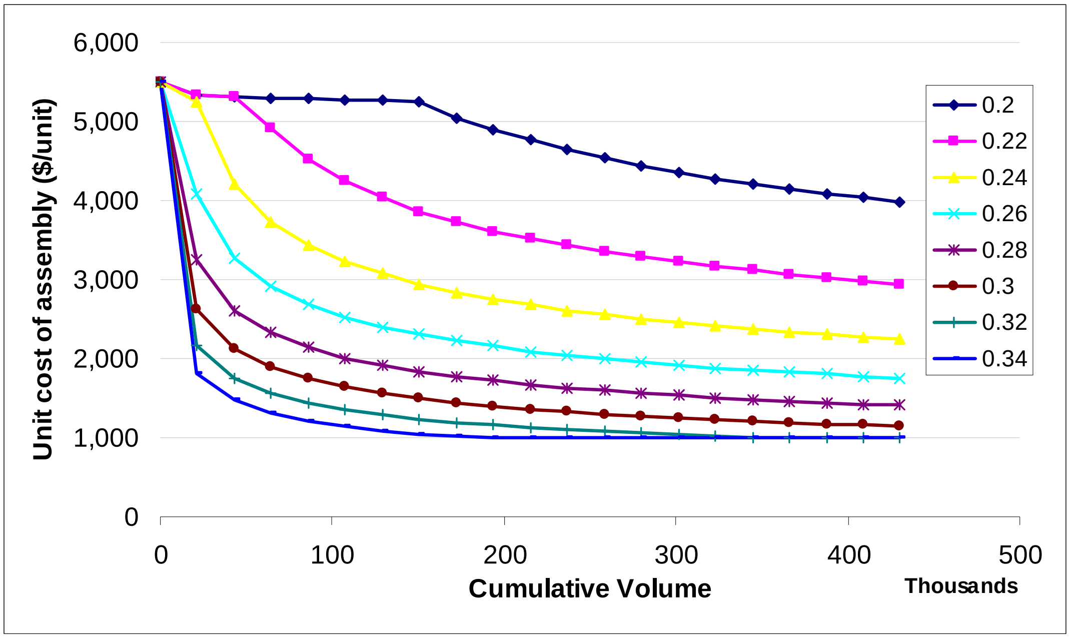

Figure 16: Cost learning curves at varying learning rates for manufacturing time and downtime

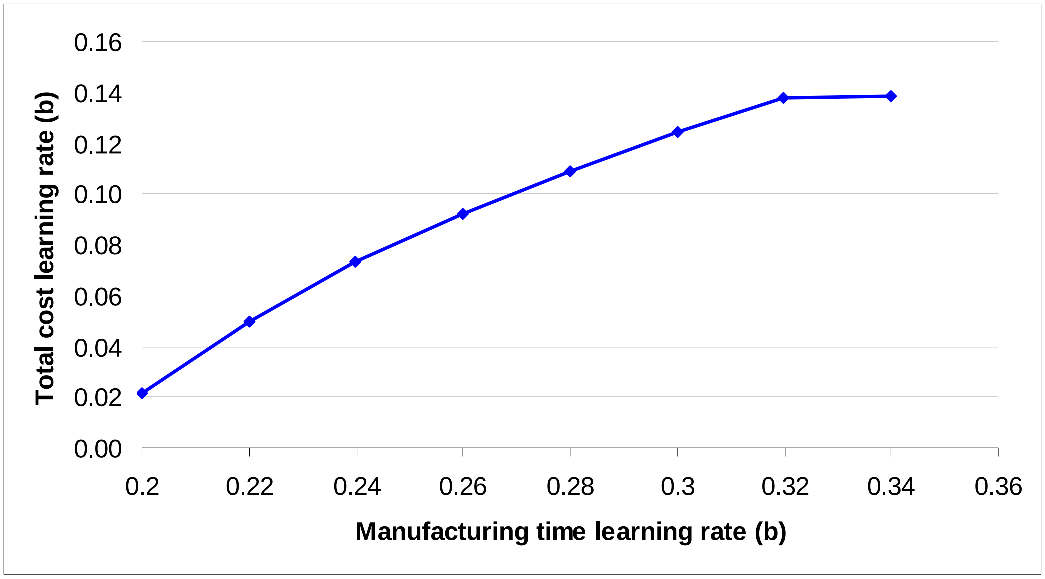

Figure 17: Sensitivity of modeled cost learning to manufacturing time and downtime learning rates

The total cost learning rates obtained range from $b = 0.02$ to $b = 0.14$. Although the learning rate which will be used in the analyses of the next section will be the base value of $b = 0.137$ obtained earlier, sensitivity analyses will also examine the impact of varying the learning rate within such a range. In particular, the impact of the learning rate on the value of labor functional flexibility will be investigated.

6 The Impact of Learning-Driven Flexibility

As noted in previous literature (Fry, Kher et al. 1995; Yue, Slomp et al. 2008), the existence of the learning effect in manufacturing implies that labor, as well as other operational expenditure-related resources, are not inherently functionally flexible; that is, they are not able to produce any new product immediately at optimal cost or performance. However, the learning effect also implies that this full flexibility can be acquired through experience, at the price of producing an initial output at higher-than-optimal cost, or lower-than-optimal performance. As with any type of flexibility, it is expected that the cost of acquiring it can be partly or entirely offset by benefits in the face of uncertainty.

The following stylized case study on automotive general assembly attempts to define conditions under which the benefits of acquiring labor flexibility through learning can outweigh its cost. Because learning is not usually considered when valuing flexibility, conditions where learning-driven flexibility positively impacts economic outcomes are equivalent to conditions under which consideration of learning effects may also change traditional flexibility decisions. Here, the evaluation of learning-driven flexibility is done entirely from a production cost perspective; that is, a situation where benefits outweigh costs is considered to translate into expected direct cost savings due to flexibility (as opposed to increased revenue or profit). Future work could attempt to characterize potential revenue-side benefits of worker flexibility. The figures presented here thus likely represent conservative estimates of the value of worker flexibility.

This chapter therefore attempts to demonstrate three points: (a) taking learning effects into account can lead to changes in product-to-plant allocation decisions; (b) these decision changes can involve increasing worker flexibility when considering uncertainty; and (c) learning theory can be used in conjunction with other tools to quantify the value of this increased flexibility.

6.1 Case assumptions and scenario definition

This case study considers two automotive general assembly plants (plant 1 and plant 2), and three products: two novel vehicles (product A and product B) needing to be produced in those two plants, and a third vehicle with mature technology (product Z) which can be produced at minimum cost in either plant. The case is meant to represent a situation where an older product Z has been produced in those two plants for some time, and it is to be replaced by one of two technologies, product A or B. The decision to be made is whether to introduce product A and B in separate plants, or to have the plants each produce all three products A, B and Z. At the time when the allocation decision must be made, it is uncertain which of technology A or B will take off and eventually dominate the market segment.

The decision must take into account the fact that producing all products in a single plant will result in somewhat higher capital investments (a flexibility up-charge), although this up-charge is reduced if flexibility is implemented when initially retooling the factory. If considering learning effects, a plant producing all three products will also increase costs because in such an allocation scenario, the production volume of each product in individual plants is reduced, which slows the accumulation of experience and thus, the cost learning process. The case presented here assumes that no learning transfer occurs between distinct plants or products – thus dividing the production volume of a single product between different plants has a slowing effect on learning.

Although products and scenarios are hypothetical, cost figures and learning parameters used are the ones derived as described in chapter 0.

6.1.1 Cash-flow model inputs

The cash-flow model is described in section 4.3.1, and key inputs are summarized in Table 8. The figures reported are base values, and most will be subject to sensitivity and what-if scenario analyses in subsequent sections.

Input	Symbol	Value	Unit
Time period length	Δ	0.125	years
Number of periods	s_{max}	48	time periods
Discount rate	r	15%	%/year
CapEx initial flexibility up-charge	*CapInit*	5%	% of CapEx
CapEx on-going flexibility up-charge	*CapUp*	10%	% of CapEx
OpEx flexibility up-charges		0%	% of unit cost
Capital expenditure weight	*CapEx*	20%	% of unit cost
Product A and B base cost	*B*	5,500	$/unit
Product A and B learning scope	*Scope*	82%	% of unit cost
Learning curve parameters	a	6291	$/unit
	b	0.137	
	Y_{max}	6291	$/unit
	Y_{min}	1059	$/unit

Table 8: Key cash-flow model inputs

Note that a capital expenditure weight (*CapEx*) of 20% corresponds to approximately a $200 million capital investment per plant (for an annual production volume of 200,000 vehicles).

6.1.2 Demand scenario

For the baseline demand scenario, let Product B start with a lower demand than product A ($D_{A0} > D_{B0}$), but have a stronger potential for growth. It may eventually dominate almost the entire market segment, making product A disappear almost entirely. The total demand for both products is considered to be constant (D_{total}) at every stage of production, that is:

$$D_{As} + D_{Bs} = D_{total} \tag{6.1}$$

for all time periods s. The demand for product Z is not represented; it is assumed to be large enough so that any available production time in plants 1 or 2 can be occupied by the production of product Z. Moreover, only the costs for products A and B will be considered in subsequent calculations.

This type of scenario is examined here because it appears to be the most interesting from the point of view of flexibility implementation. A scenario where a product's demand would initially be low and only possibly stay low or decrease would have little implications for the functional flexibility of the plants considered – only one plant would be required to make the product. Conversely, a scenario where the demand starts high and has the possibility to remain high or increase further would also only require that both plants analyzed be able to produce it. A third possibility, where demand would initially be high but have the possibility to decrease, is effectively the converse scenario of Product B in the base case described above – i.e. the product with high, but possibly decreasing, demand is Product A.

The proportion of demand for B is the parameter which will define the demand scenario at every stage in the decision tree. This fraction will be labelled D_F, such that:

$$D_{Fs} = \frac{D_{Bs}}{D_{total}} \tag{6.2}$$

The decision tree used will take on the form depicted in Figure 8, with three demand stages (including the 0^{th} stage), and where the absolute demand variable D_p is replaced with the variable ratio D_F.

Defining demand scenarios in this manner has a number of advantages. First, it simplifies scenario definition by reducing the characterization of both products' demand to a single variable. Second, while requiring that production volume equal demand may be somewhat unrealistic (as demand often exceeds initial production for novel products), this simplifying assumption, along with the premise of a constant total demand and production volume, allows economies of scale to reasonably be neglected. And third, if both products are assumed to be sold at the same price, this approach can be viewed as providing constant revenue, such that any impact on costs is directly reflected in profits.

Unless indicated otherwise, the total demand value used in the following analyses will be D_{total} = 400,000 units. The demand volume is distributed between the two plants, each having a capacity of 200,000 units for A and/or B. This level of demand is effectively a high volume scenario for modern automobile general assembly.

The base scenario values used for both demand and probabilities at every stage are exhibited in their tree format in Figure 18. Demand stages have a length of two years, for a total time analyzed of six years, which is roughly the life cycle of most vehicle models in today's market.

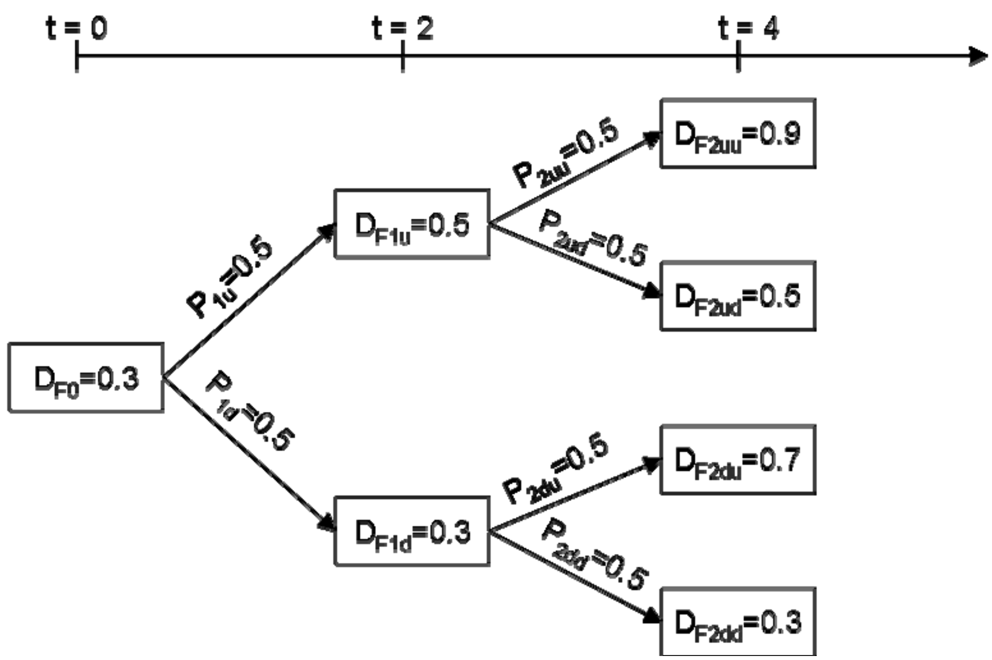

Figure 18: Decision tree with base demand and probability values

6.1.3 Allocation decision sets

Decision variables consist of the production volumes of each product which is assigned to each plant – effectively filling out a 2x2 allocation matrix as in Table 9 – at stages 0 (t=0), 1 (t=2), and 2 (t=4). These decisions also happen independently for high and low demand states. As noted in section 4.3.2.2, the production volumes must meet all demand, and plant capacities cannot be exceeded.

		Plant	
		1	2
Product	A	V_{A1}	V_{A2}
	B	V_{B1}	V_{B2}

Table 9: Two-by-two generic allocation matrix

6.1.3.1 Characterizing allocation decisions

Because there are a large number of allocation decisions possible, it is useful to characterize and categorize them more broadly. First, a plant will be categorized as flexible at a particular point in time if it was allocated both products A and B in the past – i.e. plant q is flexible at period s if cumulative volumes $CV_{Aqs} > 0$ and $CV_{Bq} > 0$. Hence, at any point after a period where $D_F \neq 0.5$, at least one plant will need to be flexible in order to have accommodated all demand. This notion of flexibility refers mainly to worker functional flexibility as discussed previously, meaning that for a plant to be flexible, workers must be given the opportunity to learn how to make both products. Note that in fact, full flexibility (i.e. optimal cost for both products) will not be achieved as soon as the second product is assigned to the plant because of the time required for learning. However, this terminology will be used to simplify characterization of decisions with respect to plant flexibility.

Further, an allocation scheme will be categorized as flexible if *both* plants 1 and 2 are flexible, i.e. if $CV_{pq} > 0$ for all p and q. This will necessarily happen if the value of D_F

goes from below 0.5 to above 0.5, or vice versa. For example, if D_F is initially 0.3, it is possible to have a partially flexible allocation as in Table 10 (where plant 1 is non-flexible and plant 2 is flexible). If from this demand level, D_F then shifts to 0.7, at least a portion of plant 1 will need to be used for the production of vehicle B – thus necessarily making plant 1 flexible, since it had also been allocated vehicle A in the past ($CV_{A1} > 0$).

Product		Plant 1	Plant 2
	A	*200*	*80*
	B	-	*120*

Table 10: Non-flexible allocation matrix for D_F=0.3 (units in thousands)

However, an allocation decision can also be termed "flexibility-forcing", which will be used to describe allocations that result in the implementation of flexibility prior to the impetus from immediate external demand requirements. For example, for an initial D_F value of 0.3, a flexibility-forcing decision would allocate both products to both plants, as in Table 11.

Product		Plant 1	Plant 2
	A	*140*	*140*
	B	*60*	*60*

Table 11: Flexibility-forcing allocation matrix for an initial D_F=0.3 (units in thousands)

In addition, a flexibility-forcing allocation decision will be characterized in terms of "how much" flexibility if forces – specifically, the minimum demand portion of the low-volume product which is allocated to what would normally be the non-flexible plant. This fraction will be labeled F, with $0 \leq F \leq 0.5$; and it can be understood as a kind of flexibility index which accounts for the fact that full flexibility (here, $F = 0.5$) is not required, nor is it, as will be shown later, always optimal. For cases where $D_F < 0.5$ (i.e. product B has lower volume than A) and plant 1 is designated as the normally non-flexible plant, the volume of B allocated to plant 1 is determined by:

$$V_{B1} = D_{total} \cdot D_F \cdot F \tag{6.3}$$

In Table 11, for instance, 50% of the lower-volume product B is allocated to plant 1 (alternatively, plant 2), which could have been non-flexible under the allocation scheme shown in Table 10; hence, $F = 0.5$. For $F = 0$, the allocation scheme is not flexibility-forcing. The base value for F used in most analyses will be 0.05; Table 12 illustrates the allocation matrix for $D_F = 0.3$ and $F = 0.05$.

	Plant	
Product	1	2
A	*194*	*86*
B	*6*	*114*

Table 12: Flexibility-forcing allocation matrix for D_F=0.3 and F=0.1 (units in thousands)

6.1.3.2 Allocation decision scenarios

Using the categorization described above, it is possible to define a finite number of decision scenarios, which represent the sets of allocation decisions made at each stage. More specifically, at each stage, the allocation can either be flexibility-forcing, or not. Then, for every set of inputs analyzed, the decision scenario with the least ENPV of costs is chosen.

Although specific costs and benefits associated with flexible allocation will be discussed in later sections, it is expected that flexibility-forcing allocation decisions would introduce an extra cost – if only in terms of additional or more sophisticated equipment required to accommodate the additional product type – which is only offset by benefits if external demand can potentially require flexibility in the future. For this reason, no flexibility-forcing decisions are expected to be made at stage 2 (t = 4) of the decision tree, when demand for the following two years is assumed to remain constant.

Flexibility-forcing decisions are therefore reasonable only at stages 0 and 1, and they are what will define the set of decision scenarios evaluated. This set is described in Table 13 in terms of the decision type made at every stage.

Scenario	Stage 0	Stage 1(high)	Stage 1(low)
I	F = 0	F = 0	F = 0
II	F = 0	F > 0	F = 0
III	F = 0	F > 0	F > 0
IV	F > 0	F > 0	F > 0

Table 13: Definition of decision scenarios - allocation type corresponding to every stage

Scenario I corresponds an allocation scheme which will only be flexible if required by the evolution of demand – i.e. it will never be flexibility-forcing. Scenario II does not initially force flexibility, but does so if demand shifts to its "up" state in stage 1. Potential benefits of this scenario include the opportunity to resolve part of the demand uncertainty (will demand increase or decrease in year 2?) before making a costly flexibility-forcing decision. Decision scenario III forces flexibility in both states of stage 1; although it does not involve the benefits of resolving uncertainty, its potential benefit lies in the delaying of the flexibility decision, meaning that its costs are reduced after accounting for time value of money. Finally, scenario IV forces flexibility immediately from stage 0, allowing benefits to incur if, for example, flexible allocation is required by demand in stage 1.

6.2 Base Case Analysis

The following analysis is done with the input values listed above (except for learning parameters which are modified for the no-learning decision) to determine whether the consideration of learning would change the decision made in this specific context, and how much value this change in decision could bring.

6.2.1 Decision without learning

In order to evaluate the implications of considering learning in flexibility decision-making, it is necessary to construct a benchmark evaluation using a more conventional approach. For this purpose, the four decision scenarios will be evaluated for a context where both vehicles can already be produced at their optimal costs in either plant. To model this, the base cost for both products is modified to:

$$B^* = B \cdot (1 - Scope) \tag{6.4}$$

Thus, the base cost is initialized at the minimum value on the learning curve; and the scope of learning (*Scope*) is set to 0%.

The resulting expected net present values of the production costs for each decision scenario are reported in Table 14.

Decision scenario	ENPV ($million)
I	1,617.1
II	1,620.5
III	1,624.0
IV	1,623.2

Table 14: ENPV by decision scenario without considering learning effects

From these figures, scenario I is the decision with the least expected cost, and would be implemented. Thus, no flexibility would be introduced as long as external demand did not immediately require it.

The extra costs incurred for scenarios II-IV are uniquely due to flexibility up-charges. For scenario II, on-going up-charges are applied only in the case of the high state for stage 1.

For scenario III, on-going up-charges are applied regardless of the state at stage 1. In scenario IV, up-charges are also applied regardless of the evolution of demand; the expected cost is reduced because initial up-charges are defined lower (by half) than on-going up-charges

6.2.2 Decision with learning

By setting B and Scope back to their original values (see Table 8), the same decision scenarios are modeled while taking learning into account. The resulting ENPVs are shown in Table 15.

Decision scenario	ENPV ($million)
I	2,014.0
II	2,012.3
III	2,013.9
IV	2,016.4

Table 15: ENPV by decision scenario, with learning effects

First, from these results, considering learning effects has increased the ENPVs in general by approximately $400 million. This is because in the previous section’s results, unit costs were assumed to be at their optimal (i.e. minimum) level from the start, while in the latter results, unit costs are initially much higher than this optimal value.

Second, it is interesting to notice that the lowest cost decision has now changed to scenario II. Furthermore, this decision change involves an increase in flexibility: from no flexibility-forcing allocation, the decision has moved to a potential flexibility-forcing situation if demand increases after 2 years.

Lastly, by comparing the figures obtained for each scenario, it is possible to determine the value of having considered learning for this decision, which is also the value of introducing flexibility. If the decision is made without taking into account learning effects, scenario I is chosen. Considering that learning effects will materialize even if decision-makers do not incorporate them into their analysis, the actual expected costs for this decision is \$2,014 million. Therefore, considering learning effects and choosing scenario II yields a cost saving of:

$$\$2,014,000,000 - \$2,012,300,000 = \$1,700,000 \qquad (6.5)$$

This \$1,700,000 can also be viewed as the value of the flexibility introduced by scenario II. The value can be compared with the expected additional capital investment required to implement the flexibility, i.e. the amount of the capital up-charge incurred at $t = 2$ with probability $p = 0.5$. For a base capital investment of approximately \$200 million, the expected additional investment for flexibility is:

$$Flex\_Investment = \frac{Invest \cdot CapUp \cdot p}{(1+r)^t} = \frac{(\$200M)(10\%)(0.5)}{(1+0.15)^2} = \$7,56M \qquad (6.6)$$

The return on investment for the implementation of flexibility here is therefore:

$$ROI = \frac{\$1.7M}{\$7.56M} = 22.4\% \qquad (6.7)$$

6.2.3 Conceptual definition of learning-driven costs and benefits of flexibility

As is exemplified by the difference in ENPV between sections 6.2.1 and 6.2.2, the consideration of learning reveals a significant amount of cost which is simply ignored otherwise. In the previous base case example, this difference is approximately \$400 million. This cost is well illustrated by a curve similar to Figure 1, which is reproduced here in a slightly modified form (Figure 19):

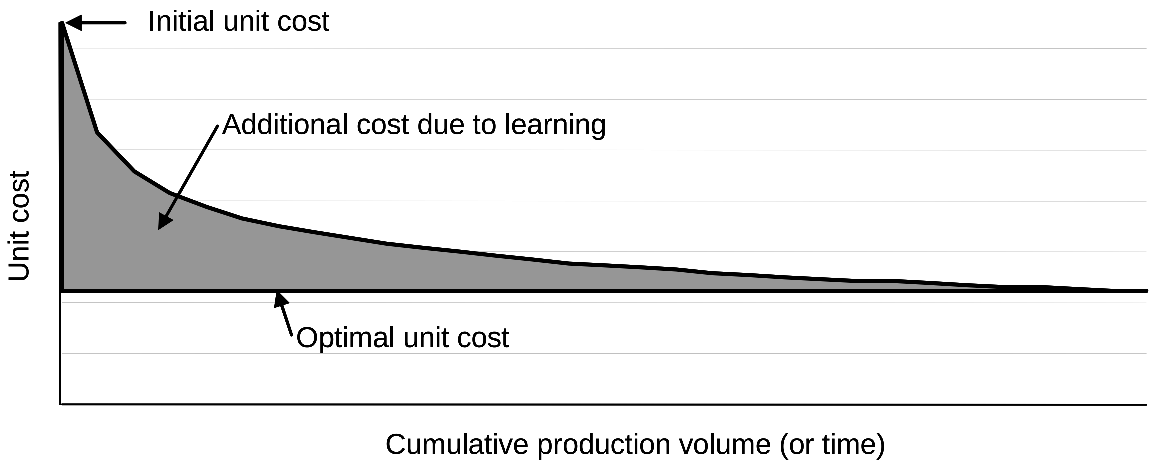

Figure 19: Conceptual representation of the additional cost from considering learning effects

The shaded area represents the additional cost considered, which is effectively:

$$NPV_{add} = \sum_{s} \frac{(C_s - C_{opt}) \cdot V_s}{(1 + \Delta \cdot r)^s} \tag{6.8}$$

where NPV_{add} is the additional NPV from considering learning; C_s is the unit cost in period s; C_{opt} is the optimal unit cost; V_s is the period production volume; Δ is the length of each period in years (although Δ used here is less than a year); and r is the yearly discount rate. In addition, C_s varies with cumulative volume (here according to Wright's log-linear model) such that:

$$NPV_{add} = \sum_{s} \frac{\left(a \cdot (\sum_{i=0}^{s} V_i)^{-b} - C_{opt} \right) \cdot V_s}{(1 + \Delta \cdot r)^s} \tag{6.9}$$

This cost is incurred for any new product, regardless of whether flexibility is implemented in the plant. However, introducing flexibility increases this cost by reducing the volume of each product in a plant, which slows the learning process. This additional cost is illustrated in Figure 20.

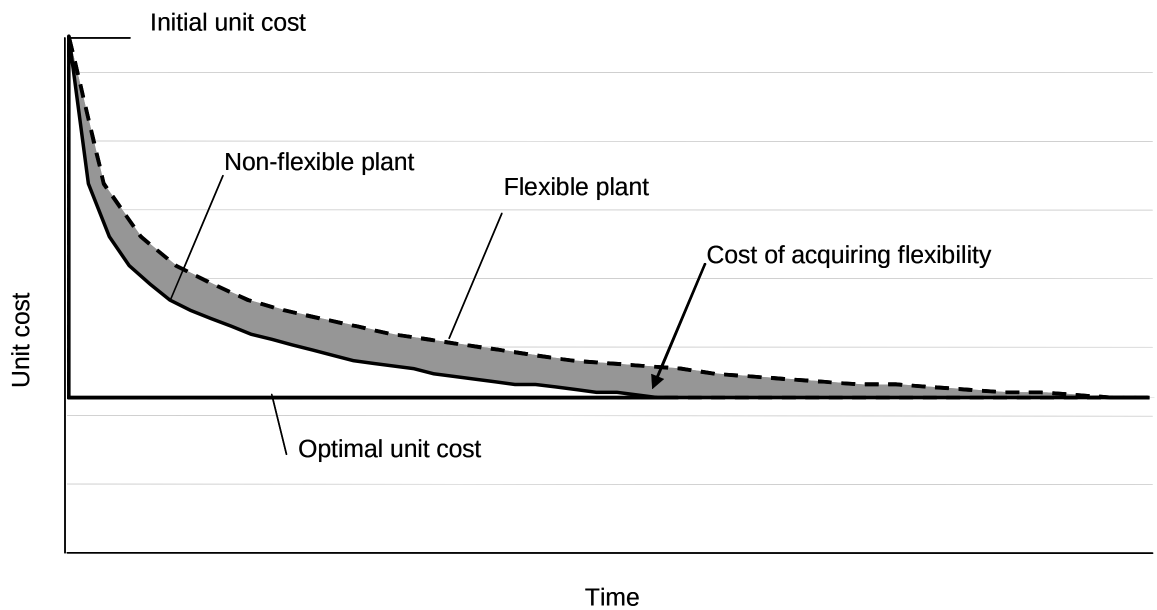

Figure 20: Conceptual representation of the cost of labor functional flexibility driven by learning

Mathematically, the additional NPV of costs incurred due to labor functional flexibility can be represented as:

$$NPV_{flex} = \sum_{s} \frac{a \cdot \left(\left(\sum_{i=0}^{s} V_i \cdot (1-F) \right)^{-b} - (\sum_{i=0}^{s} V_i)^{-b} \right) \cdot V_s}{(1+\Delta \cdot r)^s} \quad (6.10)$$

where F is the flexibility-forcing parameter defined in section 6.1.3, or the portion of the volume which is moved out of the plant. NPV_{flex} can be compared to an option price, or the cost incurred to acquire functional flexibility in a given plant.

The benefits of flexibility, in terms of cost savings (i.e. for an assumption of constant revenue), occur solely if the plant is required to become flexible in the long run. In that case, having acquired flexibility early on removes any learning costs which would be paid to start producing the product in the plant of interest. Essentially, if full learning has occurred before flexibility becomes required, the option strike price is zero, and the product can be produced at no additional cost (Figure 21(a)). On the other hand, if the additional product has not been introduced in the second plant, when flexibility becomes required by demand, learning costs are incurred. These costs are represented by the dark shaded area in Figure 21(b), and can be mathematically represented as in (6.9). It is important to note that these costs are discounted because they occur later in time; and in a scenario where demand is uncertain, their expected value is also reduced by the probability that the flexibility will never be required in the considered plant.

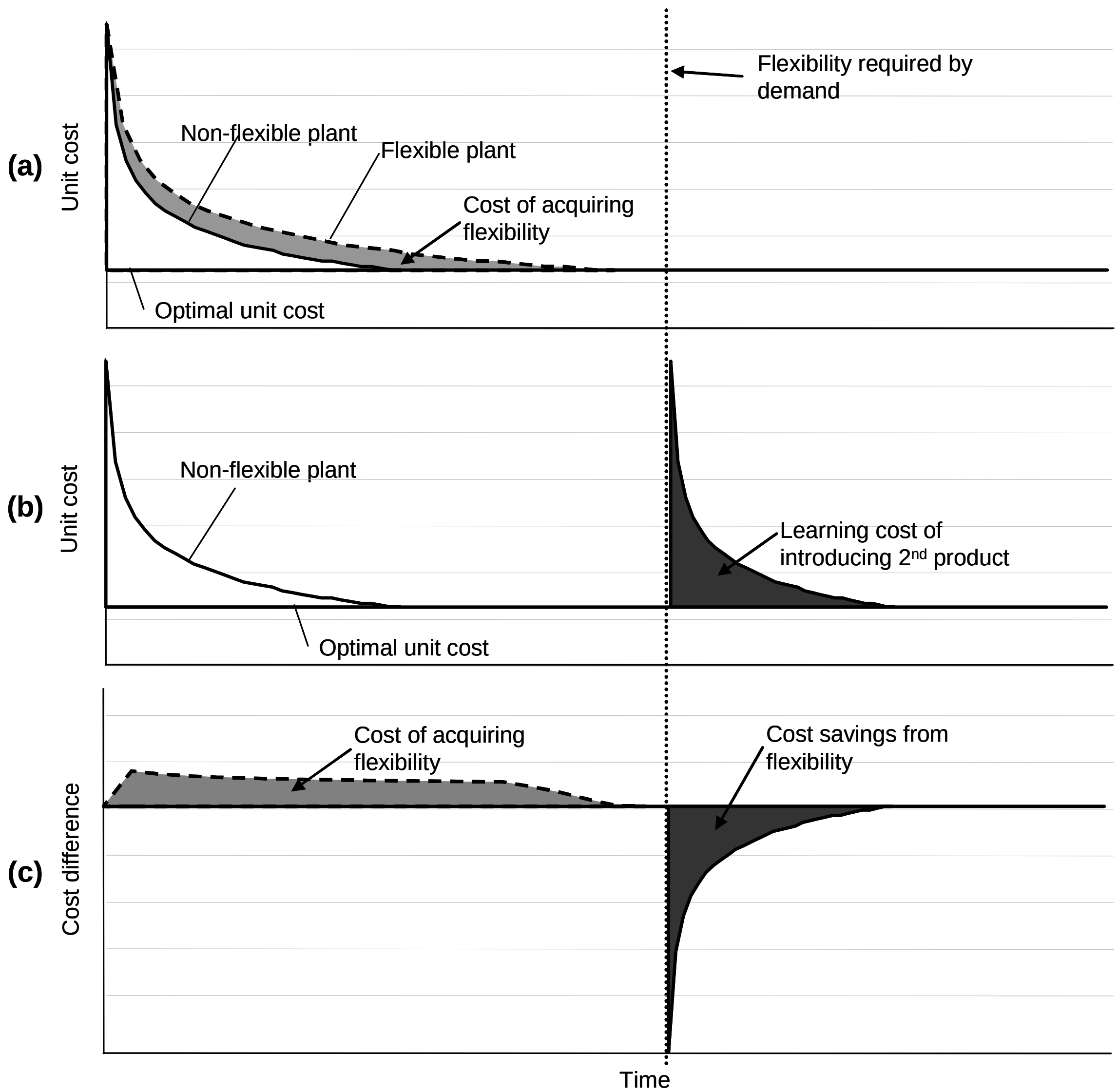

Figure 21: Conceptual representation of the costs and potential cost savings from flexibility: (a) cost of flexibility-forcing approach over time; (b) cost of non-flexibility-forcing approach over time; (c) cost difference between (a) and (b)

The difference between the expected costs of the two approaches yields the value of flexibility forcing. This difference is conceptually plotted against time in Figure 21(c), which displays the trade-off between the additional learning costs incurred now from flexibility-forcing, and potential (uncertain) cost savings occurring the future.

6.3 Influence of learning on the value of flexibility

In this section, the value of flexibility when learning effects are considered is compared to the perceived value of this flexibility when learning effects are ignored, and unit costs are assumed to immediately reach their steady-state, optimal value.

6.3.1 Value of flexibility without learning

Although the general assembly process is labor-intensive, it also involves capital investments, which grow with the number of products being produced in each plant. In the cash-flow model, this effect is captured by the capital expenditure up-charge parameters (*CapInit* and *CapUp*) that increase the capital expenditure portion of unit cost when a plant is made flexible. As mentioned before, the two distinct parameters are used to reflect the fact that building flexibility features into a new plant (greenfield) is often less expensive than retrofitting them into an already existing plant (brownfield). For this reason, it is most likely that *CapInit* < *CapUp*.

If the ratio *CapUp*/*CapInit* is large enough, it is therefore possible that a decision based on the perceived cost calculated without consideration of learning would involve flexibility-forcing at stage 0. This would be done in order to protect against potential demand scenarios where flexibility would be required later on, and the large *CapUp* cost would need to be incurred. Although this decision would not involve any consideration of labor flexibility, under certain conditions of the stylized case study, the flexibility embodied in decision scenario IV would have a positive perceived value. This is illustrated in Figure 22, where after *CapUp* surpasses a certain threshold, decision IV becomes preferred and the value of flexibility starts increasing linearly. In this figure, *CapInit* is held at 5%, and learning is eliminated, i.e. unit costs are set at their optimal level as in Eq. (6.4) and scope is reduced to 0%.

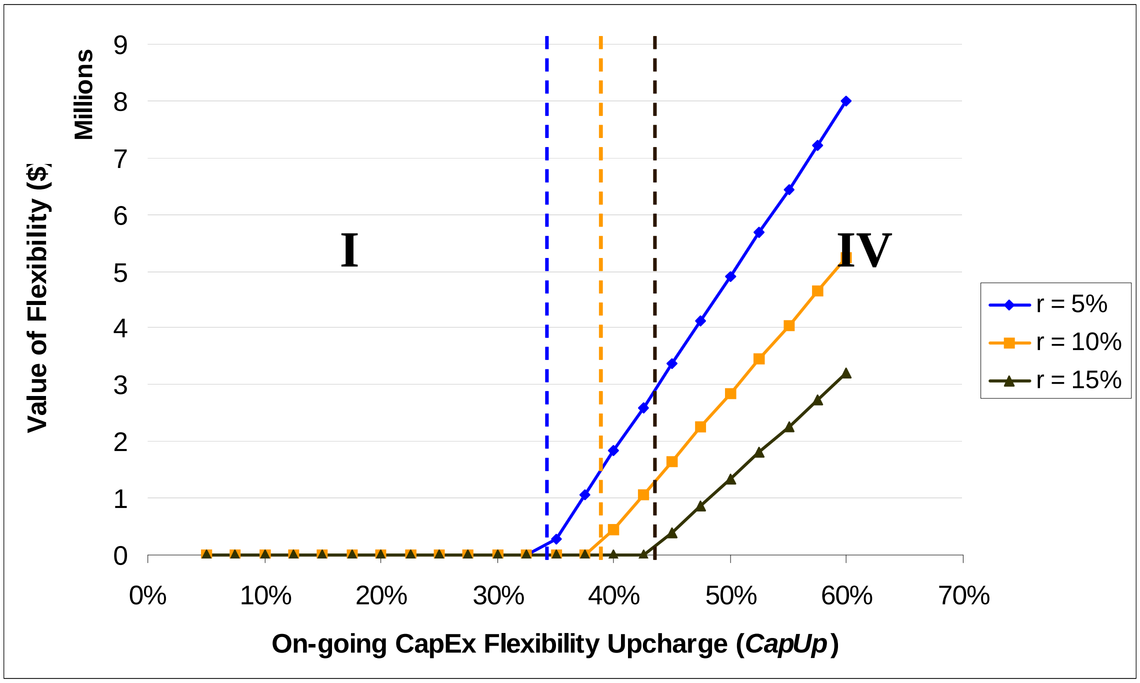

Figure 22: The value of flexibility without consideration of learning, for varying on-going capital expenditure up-charge and discount rate. *CapInit* is held constant at its 5% base case value.

As expected, the value of flexibility increases as *CapUp* increases with respect to *CapInit*. In addition, the value increases with decreasing discount rates, since at large discount rates, the present value of later costs incurred from the on-going up-charge is effectively reduced. Note also that in this no-learning case, decision scenarios II and III do not add value: the value of the on-going up-charge is the same whether the flexibility is implemented in stage 1 or 2, and flexibility-forcing in stage 1 would simply bring costs forward, thus reducing the beneficial discounting effect. The advantage of flexibility-forcing, without learning, only appears at stage 0, when the up-charge is less.

6.3.2 No-learning vs. learning comparison

If the same analysis is performed by varying CapUp while taking into account the base case learning parameters, the results shown in Figure 23 are obtained.

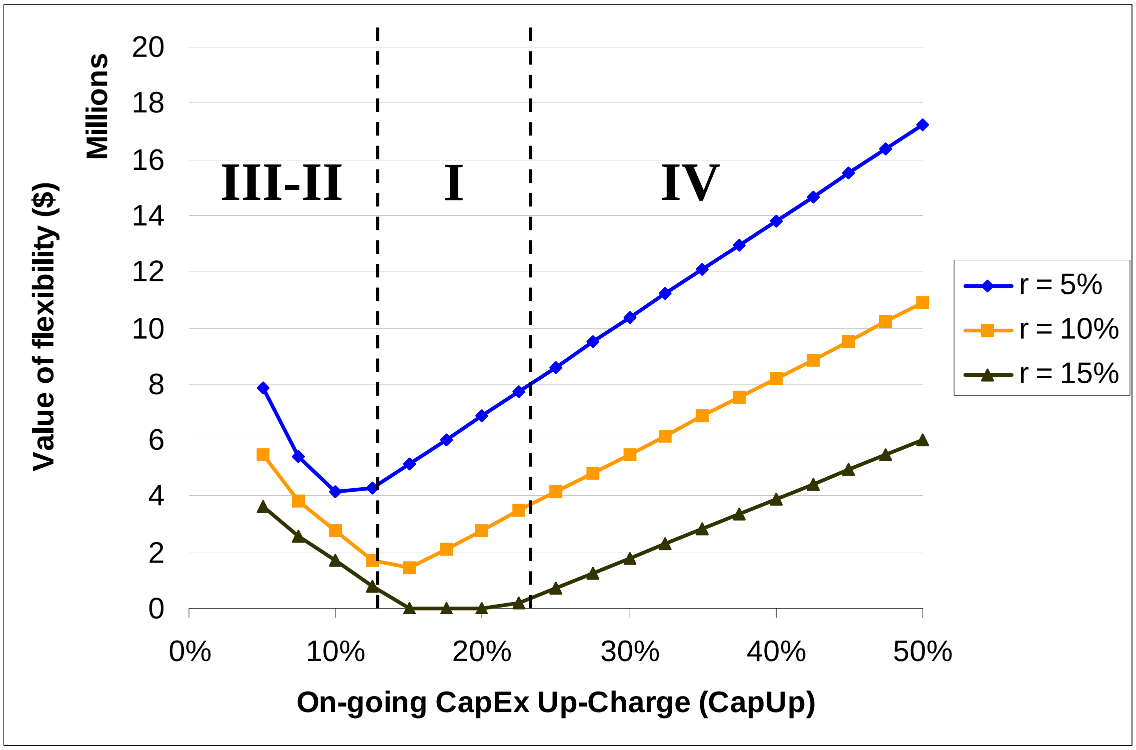

Figure 23: The value of flexibility when considering learning effects, for varying *CapUp* and discount rate. *CapInit* is held constant at 5%.

As for the no-learning case, large *CapUp* values lead to decision IV, where flexibility is forced initially at stage 0 and the lower *CapInit* up-charge is incurred. For some values of *CapUp* and r, decision I is still preferred. However, unlike in Figure 22, at lower values of *CapUp*, decisions III and II become valuable: benefits from learning early, but still delaying the extra cost, start outweighing the additional up-charge incurred by not initially forcing flexibility.

The difference between the two sets of results presented above indicates the additional value of flexibility which is captured by considering learning effects. This increase in value is plotted against the on-going flexibility up-charge in Figure 24. It is non-zero for almost all values of CapUp and discount rates considered, and it continues increasing even in regions where flexibility has a non-zero value without learning effects. This indicates that even in cases where the on-going capital up-charge justifies the implementation of flexibility in itself, considering learning effects still increases its value faster as the capital up-charge increases.

This added value of functional labor flexibility is present regardless of whether the process considered is labor- or capital-intensive. However, the importance of this value relative to the value conferred simply from additional capital investment requirements would be less for a process with high capital expenditures, and thus high CapEx up-charges for flexibility implementation.

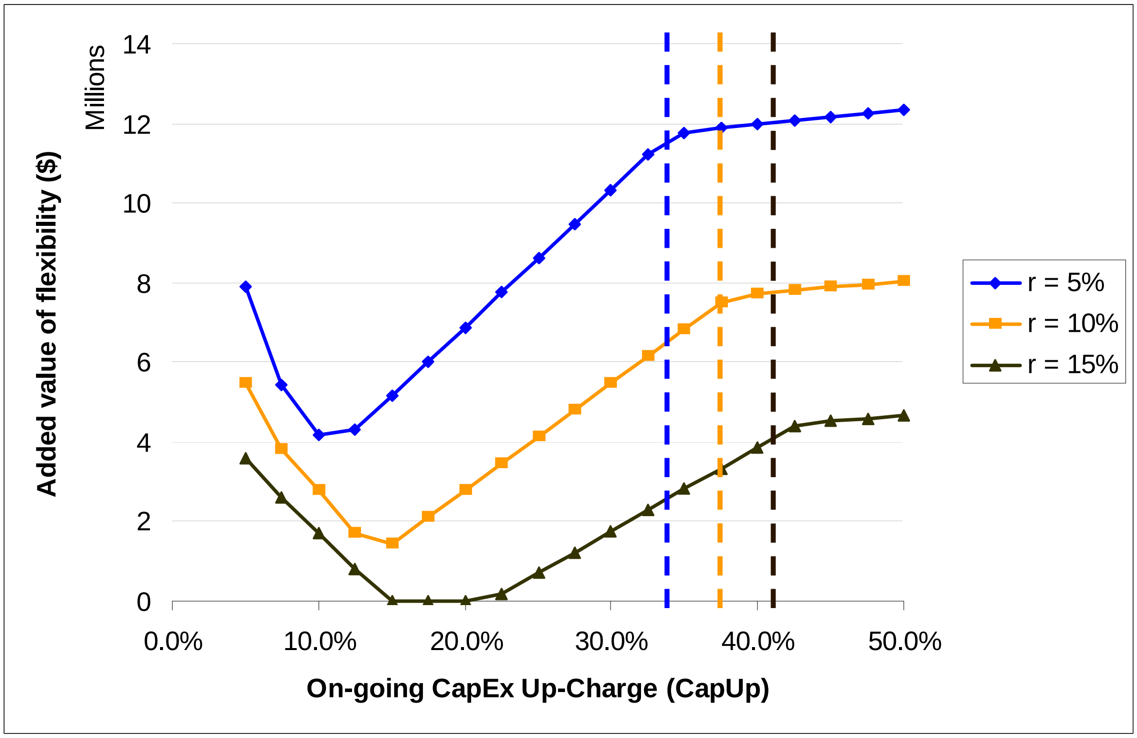

Figure 24: Added value of flexibility from learning effects vs. *CapUp* and discount rate. Flexibility has a non-zero perceived value without learning effects in the areas to the right of the dotted lines.

For the right-most area of the graph where decision scenario IV is preferred, the investment required for the implementation of flexibility (which occurs initially at stage 0) is given by:

$$Flex\_Investment = Invest \cdot CapInit = (\$200M)(5\%) = \$10M \tag{6.11}$$

Therefore, in such cases, the return on investment (at a discount rate of 15%) of functional labor flexibility – isolated from capital flexibility – is:

$$ROI = \frac{\$4.5M}{\$10M} = 45\% \tag{6.12}$$

6.4 Sensitivity Analyses on Base Case

From the base case presented above, a number of parameters can be varied to examine how decisions and their value would change depending on the operating conditions.

6.4.1 Sensitivity to *F* parameter

The value of *F* indicates how much of the volume of B is shifted to the second plant in flexibility-forcing situations. Effectively, it reflects how much flexibility is imposed by decisions II, III and IV, and impacts how much value can be added by this flexibility, as exhibited in Figure 25.

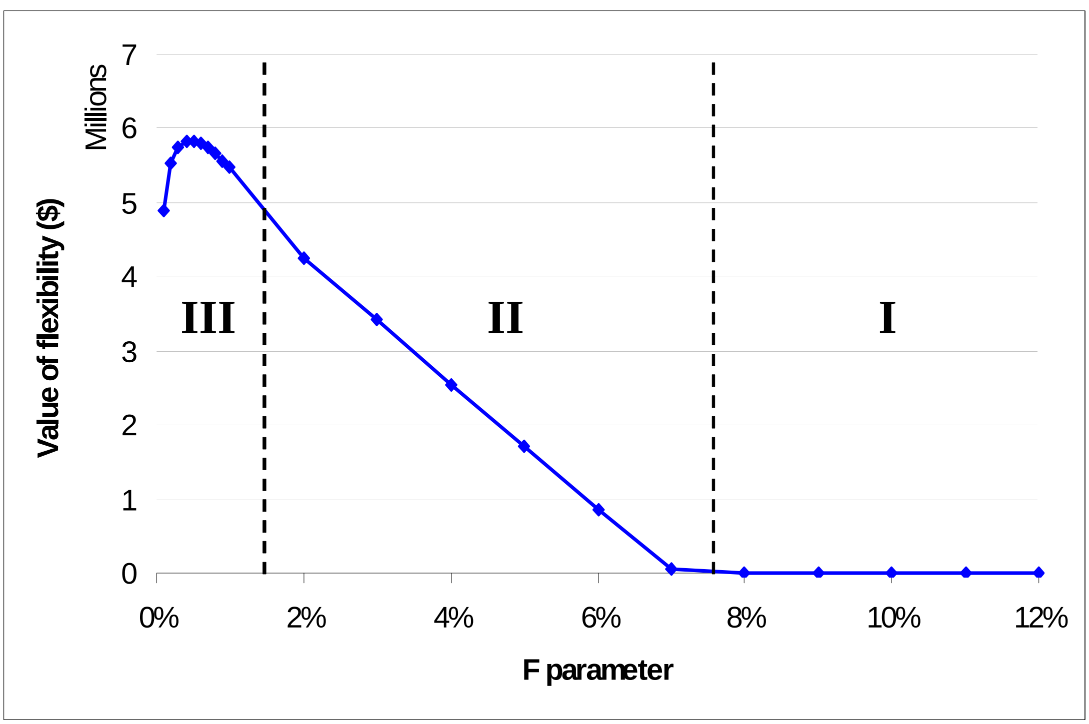

Figure 25: Sensitivity of the value of flexibility and optimal decision scenario to *F*

These results show that the chosen value for F not only affects the value of flexibility, but also changes the preferred decision. More interestingly, the curve in Figure 25 has a maximum value, here around 0.5%, indicating that there is an optimal value for F which maximizes the value of flexibility, and thus minimizes the expected NPV of costs. This indicates that full flexibility (represented by $F = 0.5$) is not always the optimal solution even when the presence of some flexibility is preferred. Because the F parameter is effectively set by the decision-maker, this is a direct lever which can be used to maximize the value of a flexible strategy.

6.4.2 Sensitivity to learning parameters

The learning parameters (rate and scope) used in the cash flow model can be expected to have a significant influence on the value of flexibility, which here is driven almost solely by learning effects. The parameters used in the base case analysis were derived from observed data, but sensitivity analysis showed that overall learning can vary significantly with variations in learning at the operational level (see section 5.3). The sensitivity of the value of flexibility to learning parameters is therefore examined here.

6.4.2.1 Sensitivity to learning rate

Figure 26 shows that there is a threshold learning rate below which no flexibility-forcing occurs, and flexibility has a value of zero. However, once that threshold is reached, results show that faster learning increases the value of flexibility. Although the increase is not linear, the approximate slope between $b = 0.13$ and $b = 0.15$ indicates a \$1.7 million increase in value for an increase of 0.01 in learning rate.

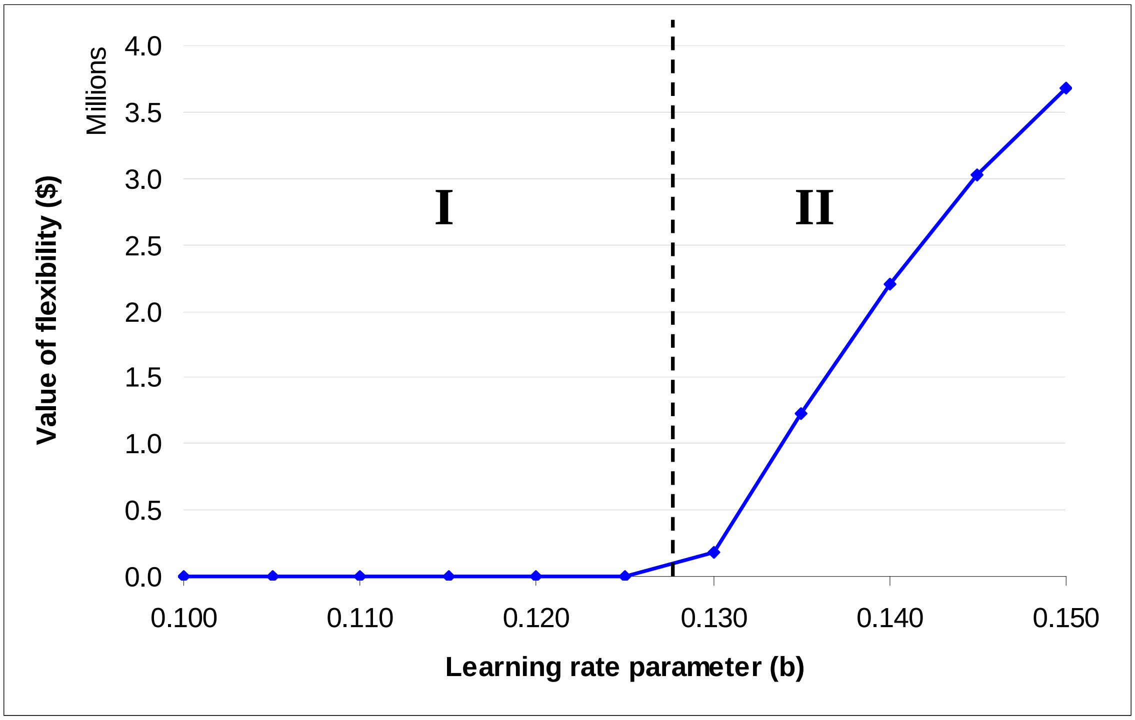

Figure 26: Sensitivity of flexibility value and decision to learning rate

Because, as mentioned above, learning rate is a parameter which can be impacted at the operational level, it can also be seen as a lever to be used by managers and engineers to increase the value of flexibility. As illustrated in Figure 17, a 0.01 increase in overall cost learning rate would approximately require a 0.01 increase in the learning rate for manufacturing time.

6.4.2.2 Sensitivity to learning scope

Figure 27 shows how the value of flexibility and the preferred decision scenario change with varying learning scope. As for the learning rate, there is a threshold scope below which flexibility does not add value. Beyond that threshold, the value appears to increase almost exponentially as scope increases.

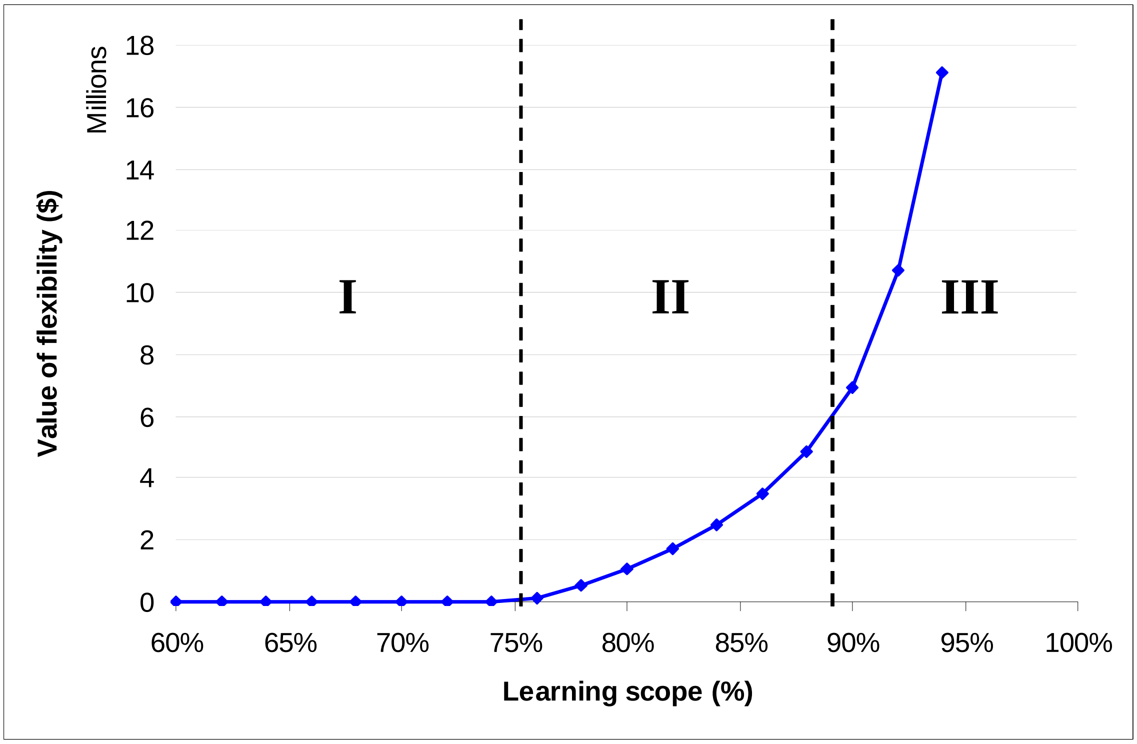

Figure 27: Sensitivity of flexibility value and decision to learning scope

Learning scope is strongly tied to the process' cost structure (as shown in Appendix 1), suggesting that a learning-driven flexibility would have more value for a labor-intensive process than for a capital- or material-intensive process. Scope is also restricted by physical and operational limitations (e.g. physical limits to the speed of the equipment employed, minimum achievable rework rate). However, this sensitivity analysis indicates any improvements that could be made to augment this scope by improving the lower bounds of certain parameters at the operational level would have a significant positive impact on the ultimate value of flexible decisions.

6.4.3 Sensitivity to cash-flow model parameters

It can be expected that some parameters used in the cash-flow model will have a significant effect on the evaluation of flexibility. In particular, sensitivity analyses to discount rate and up-charge parameters are included here.

6.4.3.1 *Sensitivity to discount rate*

As the discount rate increases, benefits of flexibility that occur later in time have less value in the present. Therefore, as expected, the value of flexibility decreases with discount rate as in Figure 28.

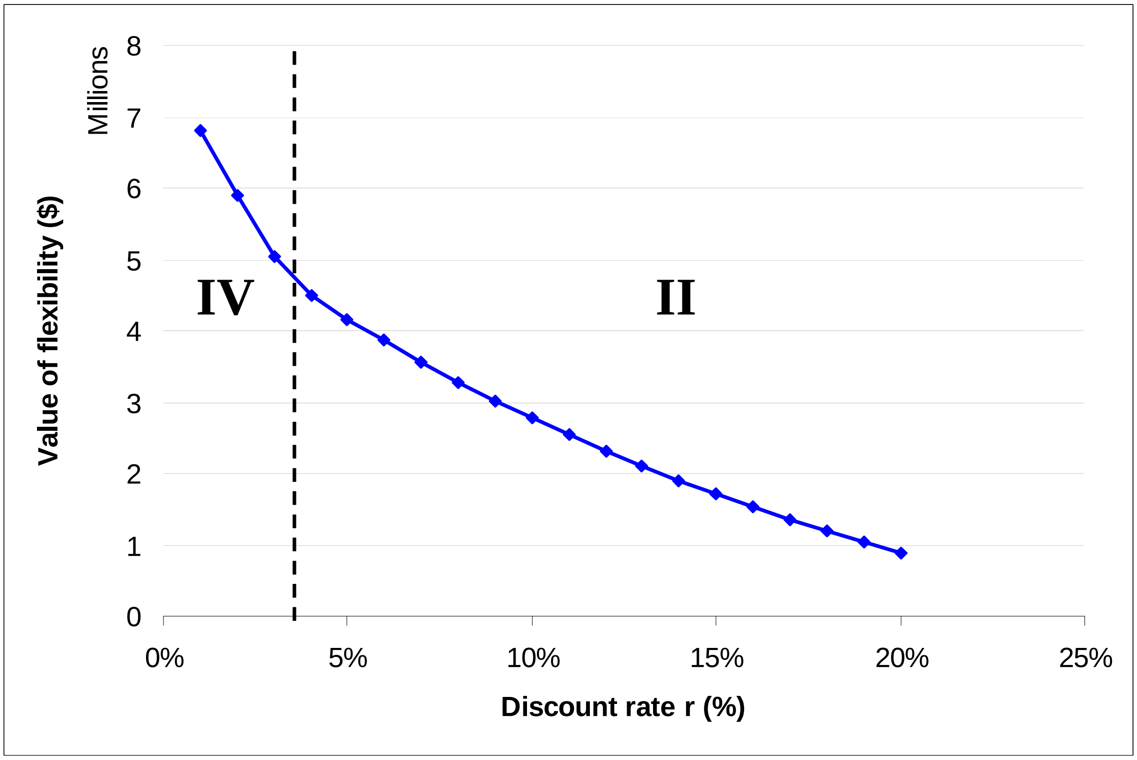

Figure 28: Sensitivity of flexibility value and decision to discount rate

Within the range of discount rates considered, the value never reaches zero, and flexibility-forcing always occurs. The decision switches to the full flexibility option at very low discount rates. Although a fairly common figure, the 15% rate used in the base case can be considered somewhat high for the automotive industry. As shown here, using a rate of 5% would more than double the value of flexibility compared to the base case.

6.4.3.2 Sensitivity to capital flexibility up-charge

Section 6.3.2 explored the sensitivity of the value of flexibility to the ratio of on-going to initial capital flexibility up-charges. The plot in Figure 29 shows how the value of flexibility and the associated decision varies with the initial capital flexibility up-charge, while the *CapUp/CapInit* ratio remains constant at 2.

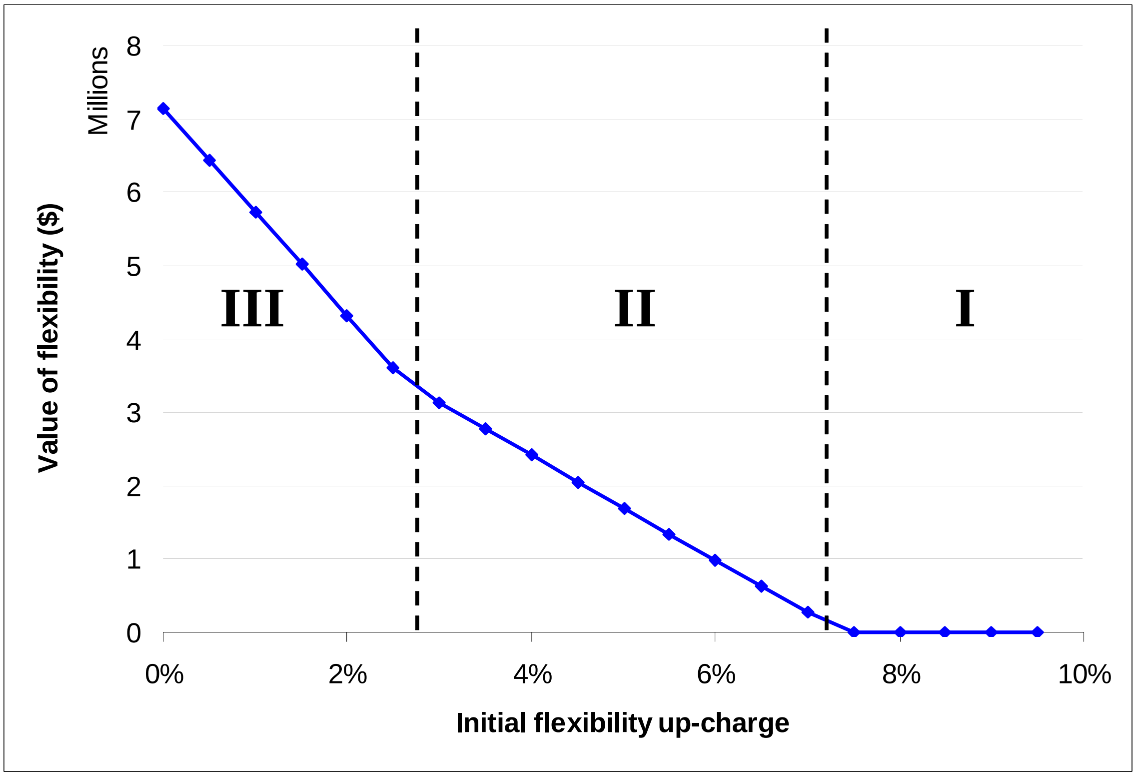

Figure 29: Sensitivity of flexibility value and decision to initial flexibility up-charge (*CapInit*)

As the initial up-charge increases, the cost of flexibility increases as well, thus decreasing the value of flexibility-forcing decisions. Beyond a certain up-charge threshold, introducing flexibility does not add any value and decision scenario I is chosen.

6.5 Variations in demand scenarios

Because the value of flexibility is by definition context-dependent, it is interesting to examine the impact of the level of uncertainty on decision-making and the outcome of the valuation approach presented. To do this, this section uses a two-parameter characterization of demand uncertainty and examines the sensitivity of flexibility value to these parameters.

6.5.1 Parameter definition

In order to reduce the number of degrees of freedom in defining demand uncertainty, as represented by the decision tree in Figure 18, this section will characterize the demand scenarios using a simple two parameter model comparable to a binomial lattice. The resulting simplified tree is shown in Figure 30.

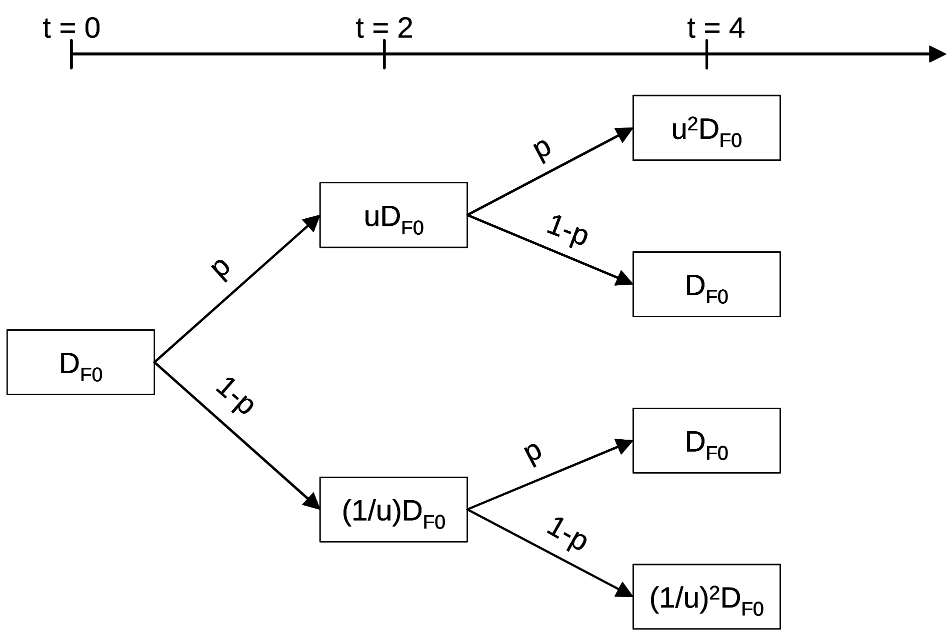

Figure 30: Simplified decision tree using *u* and *p* parameters

The parameter p represents the probability of an upward transition (at any stage), while the probability of a downward transition is simply its converse, $1-p$. At every upward transition, the demand level from the previous stage is multiplied by the parameter u to obtain the next period's demand level (note that it cannot exceed 100%). Demand is divided by u for downward transitions. In this way, u characterizes the volatility of demand, such that:

$$u = e^{\sigma\sqrt{t}} \tag{6.13}$$

where σ is the annual standard deviation (volatility) of demand; and t is the length of a period in years.

The values used as a starting point for the main parameters are reported in Table 16.

Parameter	**Value**
D_{F0}	0.3
p	0.5
u	1.65
t	2
σ	35%

Table 16: Simplified decision tree parameter values

6.5.2 Sensitivity to *u* and *p* parameters

The sensitivity of the value of flexibility and related decisions to u and p parameters is examined here for a number of discrete levels of initial demand.

Figure 31 shows how the value of flexibility varies with u and p parameters for a starting demand level of D_{F0} = 0.2. Below a threshold u and p value, flexibility does not add value, and decision scenario I is preferred. Passed this threshold, decision II becomes preferred, and the value of flexibility increases as either u or p increases. Because the flexibility introduced in the case study effectively only becomes useful if demand increases, it can be expected that its value would increase as the probability of an upward trend in demand increases. In addition, as with most types of flexibility, value could be expected to increase as uncertainty increases, which occurs here along the u (volatility) axis.

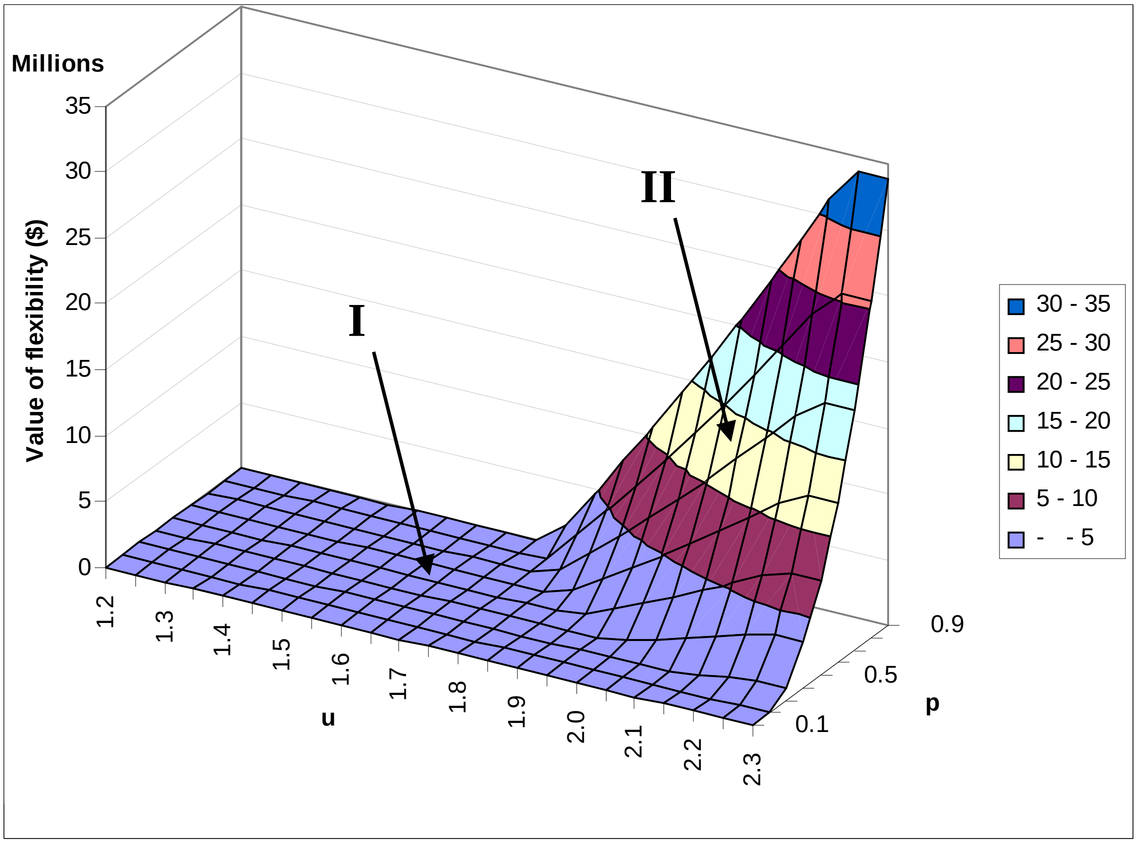

Figure 31: Sensitivity of flexibility value and decision to *u* and *p* parameters, for D_{F0} = 0.2

The graph in Figure 32 displays the same analysis done with a starting demand level of 0.25. At this demand level, there are two distinct zones where flexibility has a non-zero value. In the first zone, decision II is the preferred scenario, and a similar behavior to the previous analysis is observed, where the value increases with increasing *p* and *u*. Decision II ceases to be preferred when *u* reaches a value of 2.0, however, because then the "high" value for demand at stage 1 surpasses 0.5, and flexibility-forcing at that stage is no longer valuable (it is automatic). Therefore, at *u* = 2, the value of flexibility drops to zero.

Beyond this point, at high enough *u* and *p* values, there is a second zone where decision IV starts being preferred, and the value of flexibility once again increases with *u* and *p*.

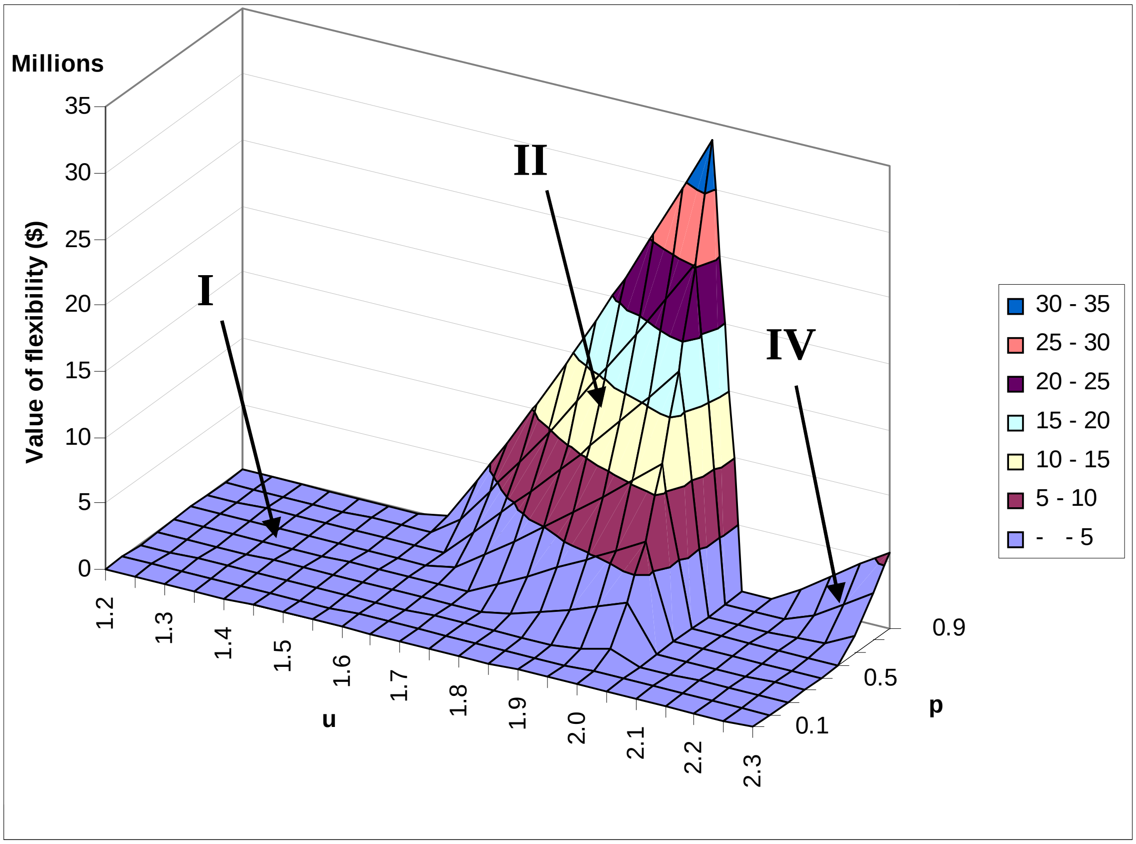

Figure 32: Sensitivity of flexibility value and decision to *u* and *p* parameters, with D_{F0} = 0.25

The same effects can be observed in the analysis from Figure 33. The zone favorable to decision II ends beyond u = 1.65, and the zone where decision IV is preferred is larger. Overall, the area where flexibility has a non-zero value has also grown in size. As a general trend, the height of the peak for decision II is decreasing with increasing initial demand, while the height of the decision IV zone is increasing with initial demand. As initial demand grows, more values of the multiplying factor u lead to flexibility being required by demand in subsequent periods; thus the advantage of delaying flexibility-forcing is reduced, and the benefit of early flexibility-forcing are enhanced.

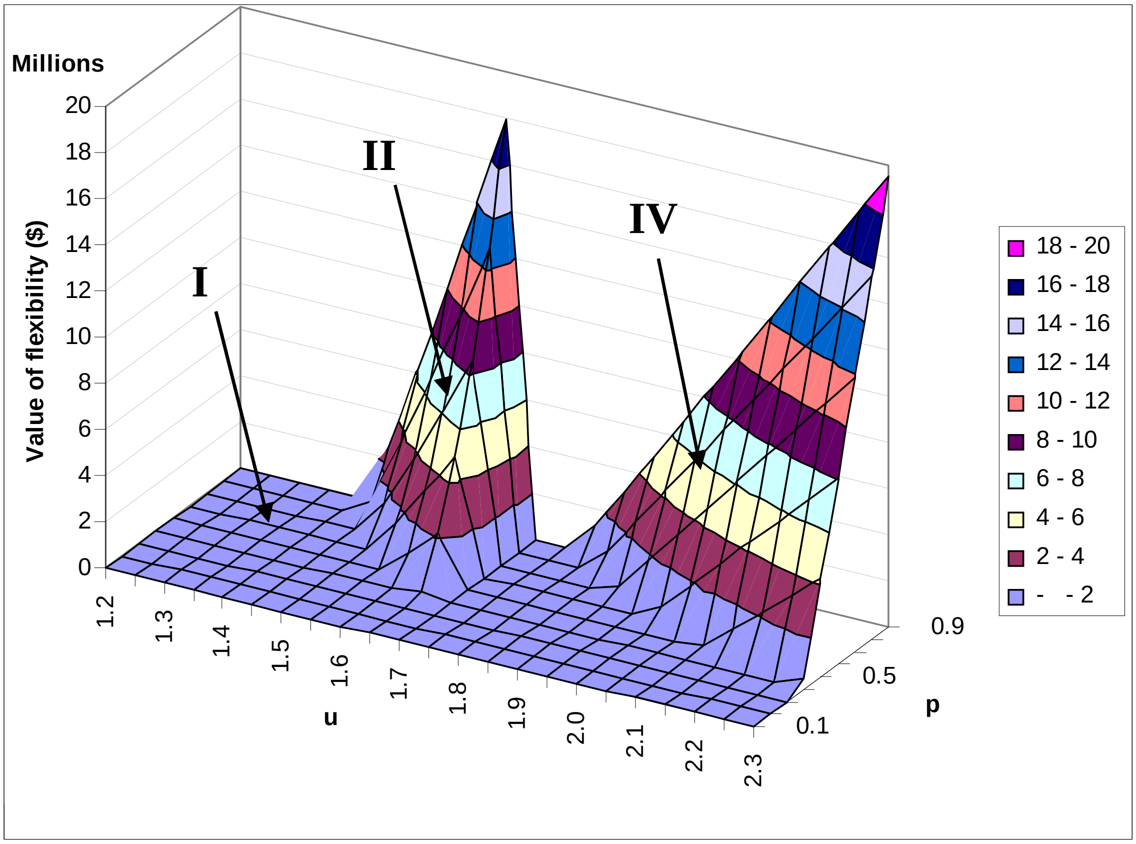

Figure 33: Sensitivity of flexibility value and decision to *u* and *p* parameters, with D_{F0} = 0.3

This trend continues as initial demand level is increased to 0.35 (shown in Figure 34). With an initial demand level of 0.4, the zone where decision II is preferred has all but disappeared, and decision IV is preferred for the majority of the values of u and p considered (Figure 35). Within the range of parameter values considered, the value of flexibility reaches a peak of $48 million.

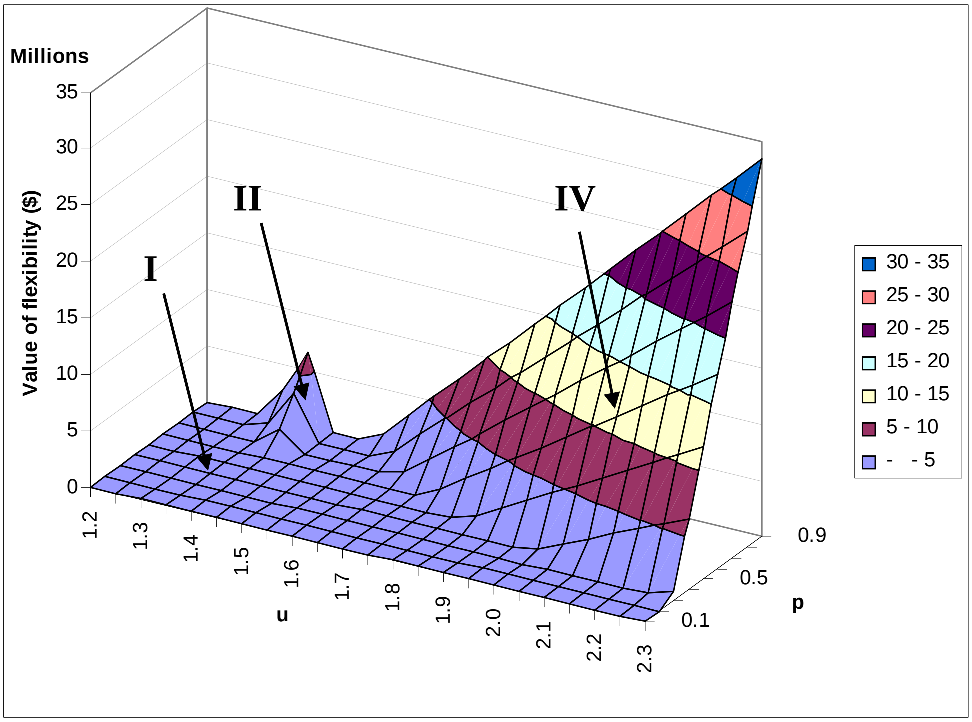

Figure 34: Sensitivity of flexibility value and decision to *u* and *p* parameters, with D_{F0} = 0.35

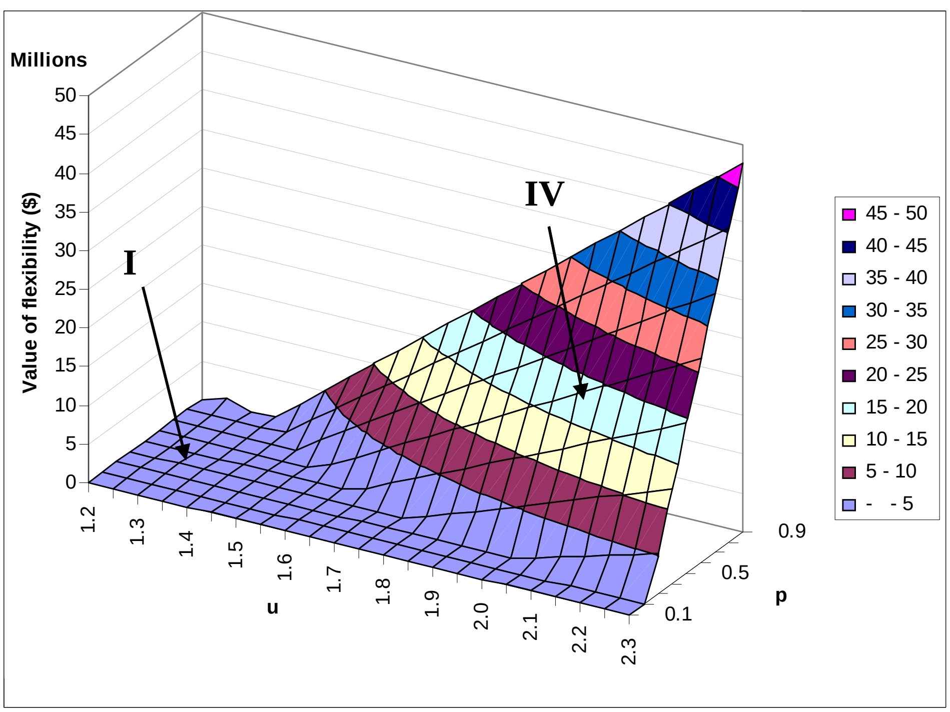

Figure 35: Sensitivity of flexibility value and decision to *u* and *p* parameters, with D_{F0} = 0.4

6.6 Case variation: Product A as a mature technology

In the base case analysis and the variations considered above, both products A and B are considered new technologies, and undergo learning as they are introduced in a plant. This is representative of a scenario where two competing technologies are introduced in a market, and it is uncertain which of the two will dominate the market segment when the technology and consumer preferences have stabilized.

Another interesting case variation to consider is for a single new technology being introduced in production. Here, for example, with product B being the new, up-and-coming technology, product A would be a mature technology for which learning does not need to occur in either plant 1 or 2.

6.6.1 Sensitivity analyses with a mature product A

In this section, the sensitivity analyses conducted in section 6.4 above are re-examined with the unit cost of product A initially set at its optimal value, and no learning scope. The same base case parameters apply in all other instances, and learning parameters are left at their previous values for product B.

6.6.1.1 Sensitivity to F parameter

The value of flexibility for this new case is plotted against the *F*-parameter in Figure 36. Dotted lines and roman numerals indicate decision changes for the new case only. First, it can be noticed that the value of flexibility when A is mature either exceeds or equals the value in the base case. Because product A does not experience learning effects, the reduction in its individual plant production volume which occurs when flexibility-forcing is implemented does not increase product A's unit cost. The overall costs of flexibility-forcing are thus reduced. In addition, the optimal value for *F* has also shifted from 0.5% to 0.3%, with a peak value of approximately $7 million.

In addition to changes in value figures, the decisions made in this new case are also modified. At low *F* values, decision IV is now preferred over decision III. The transition point from a flexible decision (II) to a non-flexible decision (I) has also shifted, from an *F* of 7% to an *F* of 9%.

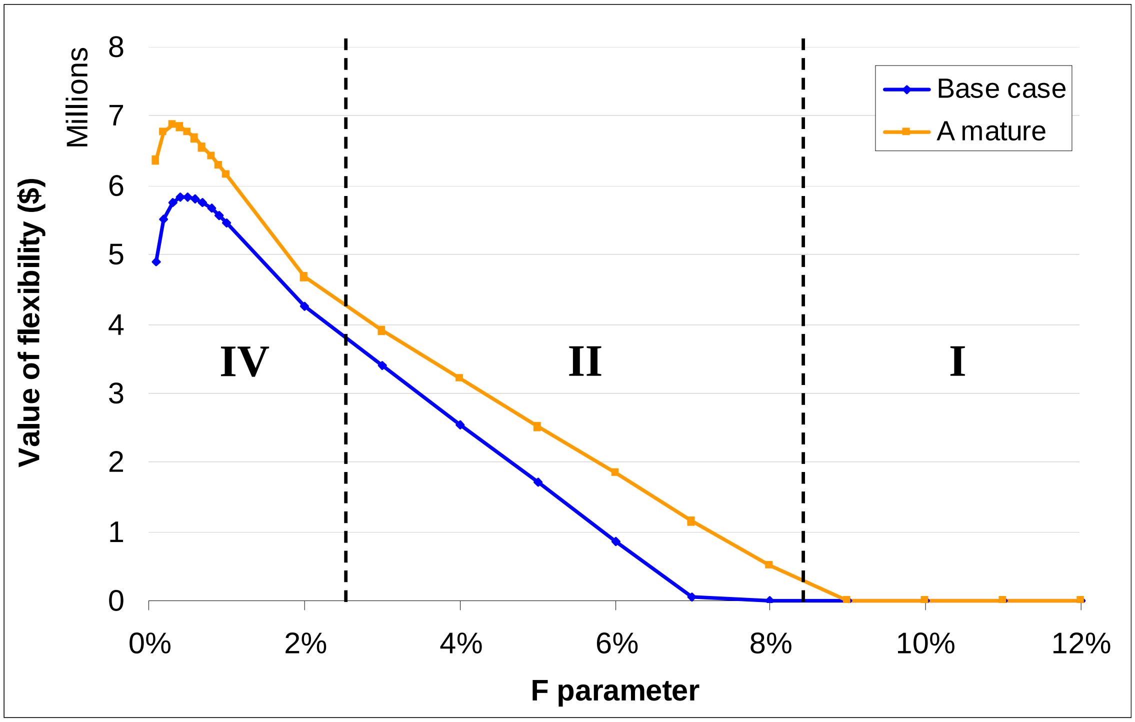

Figure 36: Sensitivity of flexibility value and decision to F parameter, with a mature product A

6.6.1.2 Sensitivity to learning parameters

Figure 37 and Figure 38 show the variation of the value of flexibility with learning rate (parameter *b*) and learning scope. As expected, once again having a mature product A increases the value of the flexibility introduced for product B. Moreover, this new context significantly shifts the learning rate at which the transition to flexibility occurs – from 0.125 to 0.095. In this case, flexibility is worthwhile even for much slower learning rates than the one considered in the base case.

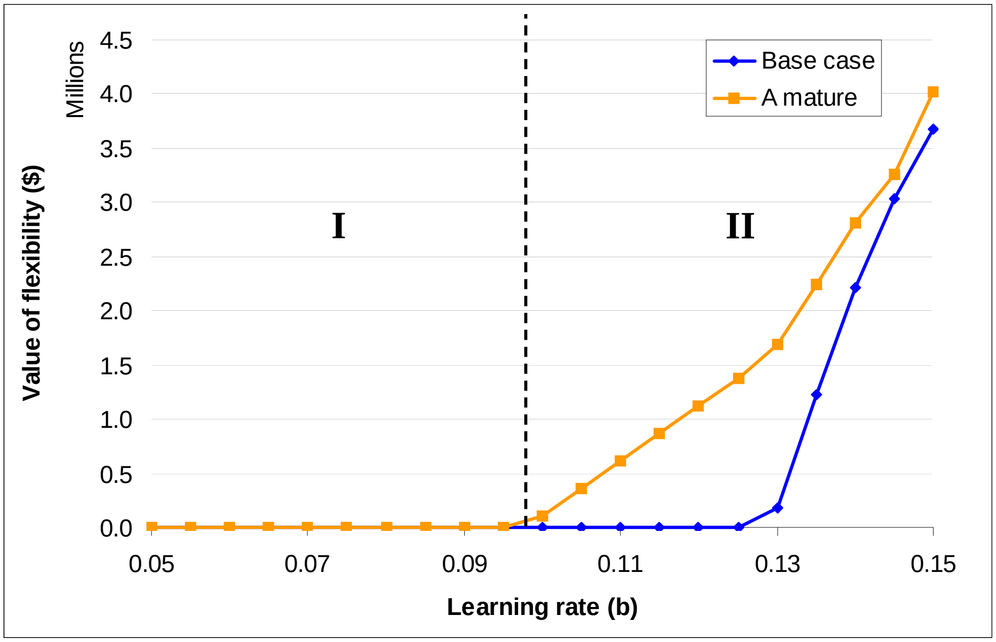

Figure 37: Sensitivity of flexibility value and decision to learning rate, with a mature product A

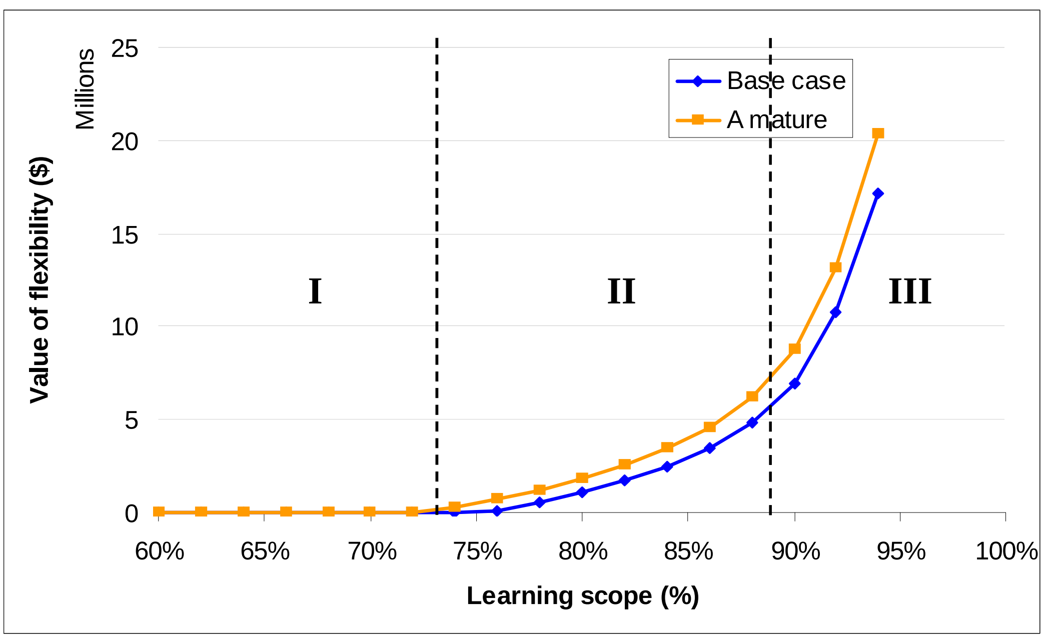

Figure 38: Sensitivity of flexibility value and decision to learning scope, with a mature product A

6.6.1.3 Sensitivity to cash-flow model parameters

FiguresFigure 39Figure 40 andFigure 41 show the variation in the value of flexibility with discount rate, initial flexibility up-charge, and the ratio of ongoing to initial flexibility up-charges, respectively. All three graphs display an increase in value for the case where A is a mature product. Furthermore, decision shifts occur in all three analyses. The discount rate where the decision switches from IV to II is shifted from 4% to 10%, meaning that at a reasonable discount rate of 5% for the automotive industry, decision IV would now be preferred. For the second analysis, the threshold initial up-charge also moved, from 9% to 11%. For the third analysis, decision I is completely eliminated, and flexibility has a non-zero value for all the ratios of on-going to initial up-charge considered.

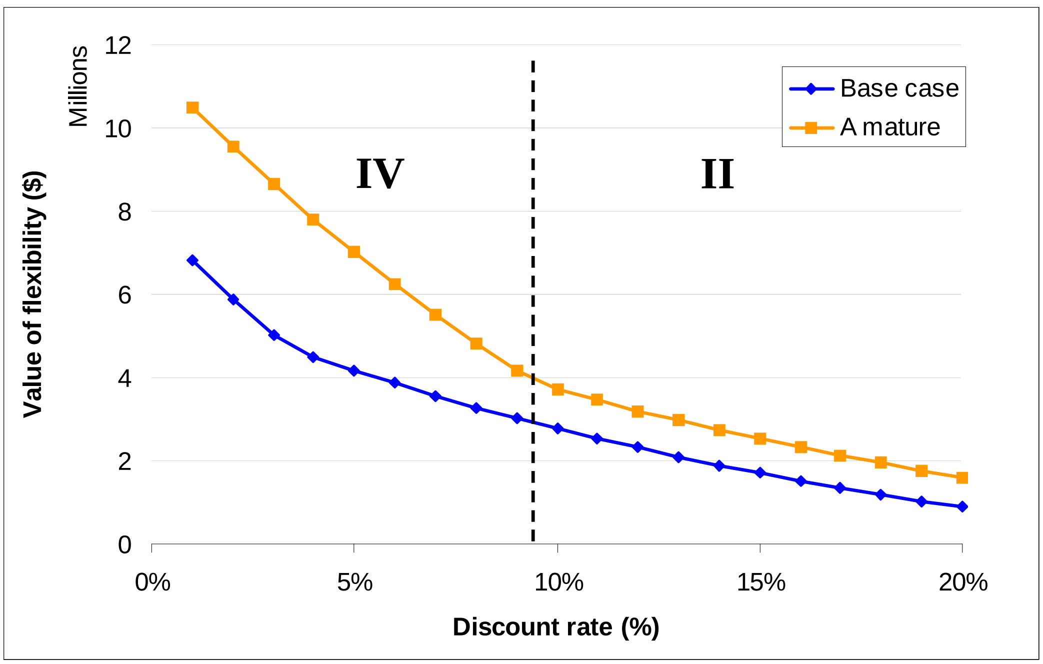

Figure 39: Sensitivity of flexibility value and decision to discount rate, with a mature product A

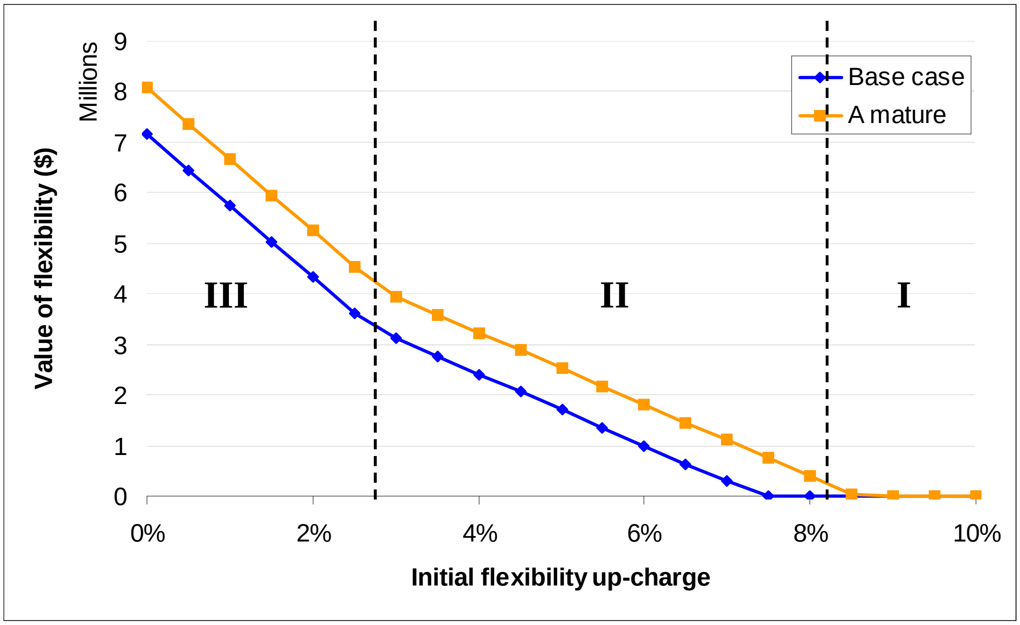

Figure 40: Sensitivity of flexibility value and decision to initial flexibility up-charge, with a mature product A

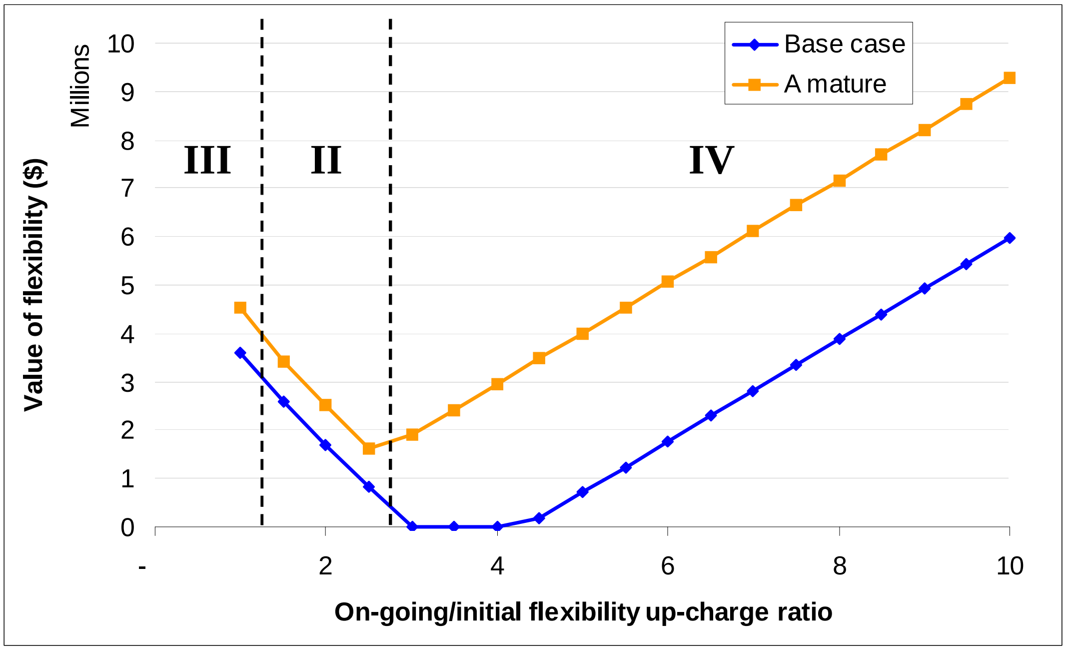

Figure 41: Sensitivity of flexibility value and decision to the ratio of on-going vs. initial flexibility up-charge, with a mature product A

6.6.2 An upper-bound estimate

Using the understanding acquired from the multiple sensitivity analyses presented above, it is interesting to finally conduct an analysis to determine an approximate upper bound for the value of flexibility driven by learning, in the case of automotive assembly. To do this, some of the parameter values were revised to reflect less conservative assumptions. Product A was also assumed to be a mature technology. The revised values are reported in Table 17.

Input	Symbol	Value
Discount rate	r	5%
CapEx on-going flexibility up-charge	$CapUp$	15%
Learning rate	b	0.14
Learning scope	$Scope$	85%
F-parameter	F	1%
Probability of "up" transition	p	0.75
Volatility parameter	u	1.7

Table 17: Revised inputs for upper bound estimate

Decision scenario	ENPV ($million)
I	2,400.4
II	2,400.4
III	2,406.1
IV	2,350.7

Table 18: Expected NPV of costs by decision scenario, for upper-bound case

The resulting expected NPV of costs for each decision scenario are reported in Table 18.

The preferred decision in this case is decision IV, and the expected value of flexibility driven by learning is approximately $50 million.

Because this value may appear small compared to total costs of production, it may be useful to also look at it in terms of its return on investment. The investment necessary to implement this flexibility at stage 0 (for decision scenario IV), represented by the initial capital up-charge, is approximately $10 million, as indicated previously in section 6.3.2. The expected ROI (expected NPV divided by initial investment) in this case is approximately 500%.

Additionally, it is possible to consider the extra operational cost incurred because of flexibility-forcing (as explained in section 6.2.3) during the initial stage as part of the initial investment or price of the flexibility. This extra cost is plotted against time in Figure 42, and its present value is $4.5 million.

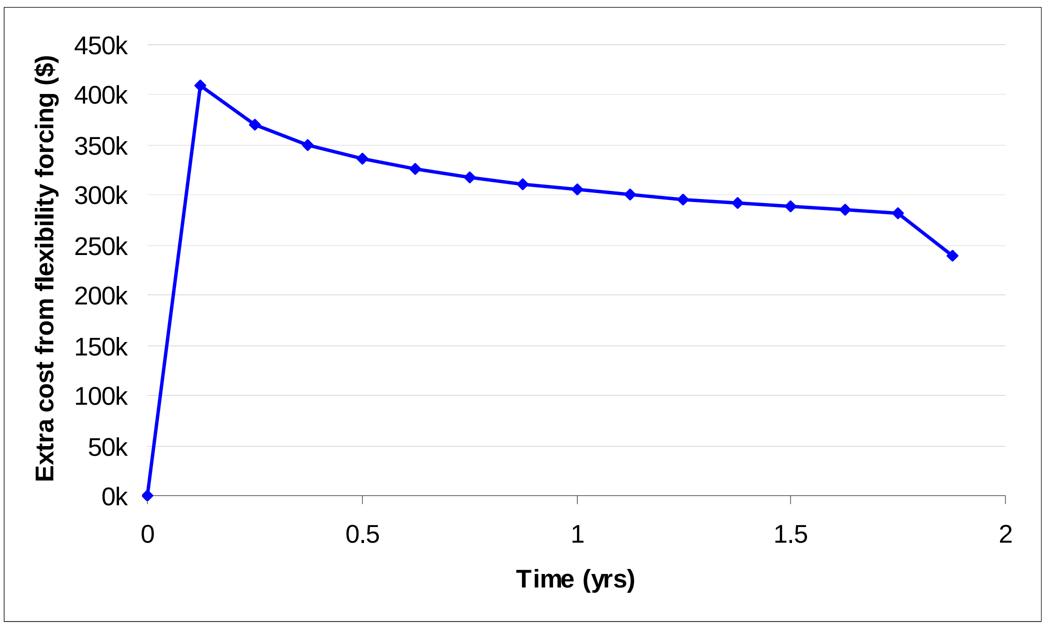

Figure 42: Additional costs from flexibility-forcing incurred in stage 0, without up-charge

A more conservative value for the return on investment would therefore be:

$$ROI = \frac{\$50M}{\$10M + \$4.5M} = 345\% \quad (6.14)$$

The investment in flexibility can thus be highly justified by its potential return.

7 Conclusion

In a context of constant technological change, firms can address uncertainty in two ways, or a combination of them, when making a technology implementation decision: by (a) improving the quality and quantity of current information about that decision (i.e. reducing the uncertainty); and (b) implementing flexible business strategies that allow the firm to adapt to future uncertain events. The former approach implies taking into account the future evolution of a novel technology's performance, including economic performance. To do this, decision-makers need tools to both estimate this future performance, and to identify the most effective ways to positively impact it. Learning theory provides a useful framework to examine the gains in productivity that accrue over time with increased experience. Moreover, process-based cost modeling leverages technical knowledge about a process to provide a static evaluation of economic performance, and the identification of primary operational cost drivers. By coupling PBCM with learning theory, it is possible to model the dynamic cost behaviour and overall performance of a process as experience increases, and to identify the main operational drivers of cost learning.

The second approach involves evaluating feasible technology decisions under conditions of external uncertainty, such as demand or price uncertainty, and using the best currently available information. A cash flow model is an appropriate tool for financial evaluation of business decisions, and combining it with a decision tree model allows one to capture the effects of external uncertainty on future financial performance, as well as potential future modifications to any initial technology implementation decisions. Furthermore, by combining a dynamic process-based cost modeling approach with cash-flow and decision tree modeling, it is possible to investigate the potential impact of approach (a) on approach (b). More specifically, one can examine how improving current information on future financial performance through learning theory can change strategic decision-making with regards to flexibility.

By incorporating dynamic learning effects into a static process-based cost model, it is possible to characterize the cost evolution attributable to learning both in terms of its operational drivers, and its implication across various cost elements. For the detailed case investigated in this paper – automotive general assembly, labor costs were found to be the cost elements most substantially reduced by learning. Additionally, manufacturing time learning was found to be the main driver of the cost savings in assembly. This characterization should be valuable to the operational manager in identifying strategies and focusing his or her learning efforts to most effectively drive down the cost of the novel technology at hand. It should also provide insight for the technology decision-maker to better estimate the future economics of this novel technology, and therefore improve performance targets and technology selection.

The results indicate that the cost savings attributable to learning are not distributed evenly across all cost elements of a process. By comparing three processes – general assembly, tube hydroforming, and copper wire drawing – it was possible to illustrate that this distribution depends on the technical and financial particularities of the system analyzed. Explicitly considering the particular cost structure and operational conditions of a process provides insight into the primary drivers of cost learning. This type of insight can be used by managers and engineers to focus learning activities and specifically target the most effective operational drivers, in order to facilitate learning and extract the most value and cost savings from these activities.

In addition to information on the drivers of learning-derived cost savings, the dynamic PBCM method should enable decision-makers to more accurately project the economic impact of learning for a specific novel technology. Ultimately, any projection of this sort requires some method to estimate future change. Whether this can rely upon statistical extrapolation or must be based solely on expert elicitation, the estimate should be improved by incorporating technical-level understanding of operational and technological characteristics. This is true because operational and technical information about an emerging product or technology is often better known or at least easy to estimate in advance than financial parameters. As a consequence, the method presented here provides a particularly useful tool to structure projections in cost learning for a newly-developed process.

Considering learning effects in the evaluation of product-to-plant allocation in automotive general assembly was shown to have a large impact on the expected cost of production. In cases shown above, expected costs when including learning effects were approximately 25% higher than perceived costs when learning was ignored. In addition, these expected costs varied depending on the level of flexibility introduced by the allocation decision. Thus, the structured characterization of learning effects provided insight into the valuation of flexibility in a case on automotive assembly, for which costs are dominated by labor. The value of flexibility estimated when considering learning effects surpassed the value found when only considering traditional flexibility costs, such as up-charges on capital expenditure. Conceptually, this increase in the value of flexibility can be attributed to recognizing the additional value that derives from improving labor functional flexibility – i.e. the ability of labor to produce multiple products – which can be attained through cumulative experience, and which is typically excluded from real options assessments.

The value of labor functional flexibility driven by learning effects was found to vary depending on a number of operational and financial conditions. Depending on these conditions, increases in the value of flexibility were also found to change economically-based strategic decisions with respect to product-to-plant allocation. In particular, in situations where an evaluation that does not consider learning would yield a non-flexible decision, explicit consideration of learning effects led to flexibility-forcing decisions which decreased costs by up to \$50 million, for a prior investment of only \$10 million, plus \$4.5 million in additional operating costs. This value increases with decreasing discount rate, increasing learning scope and learning rate, increasing volatility, and increasing probability of upward shifts in demand. It also increases as the difference between the investment for on-going vs. initial implementation of flexibility increases. Furthermore, the value can be maximized by choosing an optimal level of flexibility, i.e. by allocating an optimal amount of production to a second flexible facility. The method presented can therefore be a useful tool for decision-makers to consider learning in their assessment of technology and flexibility choices, and for improving the value of such strategic decisions.

Because the method presented allows the analyst to look at sensitivity of the value of labor flexibility and its associated decisions to various operating conditions, it is also helpful for investigating the potential impact of changes in these conditions. In particular, the full path traced from learning effects in operational parameters to the valuation of labor flexibility allows operational managers and engineers to estimate the impact of improving learning, at the operational level, on the financial value of strategic decisions regarding flexibility. Results also indicate that combining the concepts of learning effects with labor flexibility reveals an added value of flexibility in cases where this value would generally be overlooked.

8 Future work

Many aspects of the work presented here would deserve further attention in order to reduce the number of simplifying assumptions and increase the impact of the conclusions. For instance, a major area which was not examined here is the revenue-side impact of learning effects and worker flexibility. By allowing total production volume to vary and to not equal market demand, a reasonable hypothesis could be that worker flexibility driven by learning would allow the capturing of high demand peaks, thus increasing the overall value of flexibility. Furthermore, by considering the interaction between multiple firms producing competing products, it could be possible to observe a competitive advantage to labor flexibility. For example, the ability to produce new products faster or at lower cost could yield an advantage to a firm with labor flexibility, over a competitor who does not take learning effects into account in his decision-making.

Other simplifying assumptions that were made about the learning effects considered could be investigated in future work. While cross-parameter cost effects were considered, cross-learning effects between different products and plants were ignored, as well as forgetting effects. These effects have been shown to be significant in previous literature, and could be hypothesized to have an impact on the results presented here. Furthermore, the manner in which learning is assumed to occur is through accrued experience only; investigation of the trade-offs involved in training and other knowledge management tools could yield interesting results. In addition, although the functional form chosen for the learning model is the most widely used in literature, other functional forms have been introduced which could lead to different insights into the value of learning-driven flexibility.

Finally, in order to make the case study more realistic and the conclusions more concrete, it would be useful for future work to improve on data quality and quantity, both in terms characterizing learning effects for actual novel technologies, and in terms of representing real products, plants, and allocation decisions for flexibility valuation. Acquiring data for case studies in other industries would also be useful to validate general conclusions in non-automotive settings. In particular, examining less complex products or industries could lead to a clearer observation of learning effects, and stronger conclusions on the value of flexibility.

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Appendix 1: Differences in Learning Effects between Processes and Technologies

The cost of automotive is dominated by labor costs, both direct and indirect. Two other cases are analyzed below to illustrate the variations in learning effects that occur when the cost elements for a technology are distributed differently. The first alternative example is of a tube hydroforming process, for which cost is mainly driven by fixed costs, such as tooling, equipment, and building. The second is a copper wire drawing process, the cost of which is strongly dependent on raw materials use. For this analysis, a simplified and more generic process-based cost model was used, and is described in section 0.

Generic cost model description

Production costs reported for the case studies presented here are the result of a simple process-based cost model. First, each product is assumed to be produced through a process, each completed in cycle time *CT*. Given an overall target net volume V_{net} and reject rates *rej* for the process as operating parameters, the gross number of parts V_{gross} made by the process is:

$$V_{gross} = \frac{V_{net}}{1 - rej} \tag{9.1}$$

The total operating time *t* required in a year for the production of V_{net} defect-free parts is therefore:

$$t = CT * V_{gross} \tag{9.2}$$

The operating time, or uptime, of a production line is considered to be 24 hours per day on days when the plant is open, less the time when the line is either idle due to lack of demand, or unavailable for production:

$$UT = DPY * (24 - NS - UD - PB - UB) - Idle \tag{9.3}$$

where *UT* is line uptime per year; *DPY* is the number of days of plant operation per year; *NS* is amount of time per day when no shifts are run; *UD* represents unplanned downtime and breakdowns; *PB* is time for paid breaks; *UB* is time for unpaid breaks; and *Idle* is the time during the year when the plant is available, but not running, for example due to lack of demand. Given the uptime of a single line and the operating time requirements to produce a target volume, the integer number of production lines (*nl*) needed is:

$$nl = \left\lceil \frac{t}{UT} \right\rceil \tag{9.4}$$

It is also possible to compute the annual amount of paid time (*APT*) required from workers in the plant, considering that they receive wages for paid breaks, unplanned downtime, as well as when the plant is idle.

$$APT = (24 - NS - UB) * nl \tag{9.5}$$

The next part of the PBCM constitutes the financial model, and applies factor prices to the resource requirements described above. It also allocates cost over time and production to compute a unit cost per part produced. The annual costs in the model presented here are divided into seven categories:

$$C_{total} = C_{material} + C_{labor} + C_{overhead} + C_{energy} + C_{building} + C_{equipment} + C_{tooling} \tag{9.6}$$

Material cost is the product of the number of parts entering production (n_s), the weight of the part *w*, and the price per unit mass *p*. Parts rejected during processing constitute scrap which can be sold at a price p_{scrap}.

$$C_{material} = n_s wp - (n_s - n_0) wp_{scrap} \tag{9.7}$$

Labor cost is the product of the paid time required to produce the target volume, and the labor wage rate p_{wage}. Because the model assumes that other parts or products may be produced in the plant when it is available but not used to produce the part of interest, the labor time attributed to the production of this part is not necessarily equal to the total annual paid time of the plant. Instead, this annual paid time is multiplied by the fraction of the available plant time (*UT* + *Idle*) which is actually used to produce the part.

$$C_{labor} = APT * p_{wage} * \frac{t}{UT} \tag{9.8}$$

The overhead cost in this model is meant to capture the indirect labor required to maintain production, which is modeled using a ratio of the number of indirect workers required for each direct worker (*ind*). Indirect workers are paid at a wage rate p_{ind}; the cost of overhead is thus:

$$C_{overhead} = APT * ind * p_{ind} * \frac{t}{UT} \tag{9.9}$$

The energy cost is proportional to the average energy consumed by the process, which is modeled as a power requirement E multiplied by the operating time of the process:

$$C_{energy} = E * t * p_{energy} \tag{9.10}$$

Building, tooling and equipment are considered to be capital investments. In order to incorporate these investments into a unit cost, the financial model distributes them across time by determining a series of annual payments which are financially equivalent to the initial investment. The distribution is done over the useful life of the building, equipment or tool in question, and applies a common discount rate. The capital recovery factor CRF_j (where the index j is used to represent either building, equipment, or tooling) used to determine annual payments is therefore:

$$CRF_j = \frac{r(1+r)^{L_j}}{(1+r)^{L_j} - 1} \tag{9.11}$$

where r is the annual discount rate and L_j is the useful life in number of years.

The annual building cost is computed given an initial building capital investment $CAP_{building}$:

$$C_{building} = CRF_{building} * \frac{t}{UT} * CAP_{building} \tag{9.12}$$

The equipment in the plant is assumed to be non-dedicated and shared across other parts produced; therefore, the cost of equipment can be multiplied by the fraction of available plant time used to produce the part of interest. Equipment capital investment is the sum of the equipment capital required for each line ($CAP_{equipment}$), multiplied by the number of lines in the plant. The annual equipment cost is:

$$C_{equipment} = CRF_{equipment} * nl * \frac{t}{UT} * CAP_{equipment} \tag{9.13}$$

Tooling, on the other hand, is assumed to be dedicated to a certain part. The entire tooling capital investment is therefore attributed to the part considered by the model:

$$C_{tooling} = CRF_{tooling} * nl * CAP_{tooling} \tag{9.14}$$

Finally, these annual costs can be used to compute a unit cost per part (U):

$$U_{total} = \frac{C_{total}}{V_{net}} \tag{9.15}$$

The production cost obtained from the PBCM can be examined in a number of different ways. Individual cost categories and sub-processes can be compared to identify primary cost drivers. Sensitivity analyses on various process parameters can also be performed to further characterize their impact on system and cost behavior. A detailed level of sensitivity analysis is possible because the model derives cost from technical information defined at the process level, rather than using statistical methods to determine cost directly from the part description. This makes it a powerful tool to understand the effects and interactions of the different technical parameters which impact manufacturing cost.

Comparison of learning between technologies

The cost model input data were modified to reflect the individual characteristics of the three processes (see Table 19). Note that in the case of copper wire drawing, a unit of output is considered to be 1 kilometre of wire. These values were developed through input from experts in these two respective industries. Although indicative of current operations, these values are not reflective of any given firm.

Key inputs	**Hydroform**	**Assembly**	**Copper wire**
Production volume (units/year)	500,000	200,000	400,000
Interest rate (%/year)	12%	12%	12%
Workers per line	3	500	1
Indirect/direct worker ratio	0.2	0.5	0.2
Power consumption (kWh/line)	240	40,000	70
Part weight (kg)	2.8	-	7
Material price ($/kg)	0.65	-	3.30
Scrap price ($/kg)	0.10	-	1.00
Equipment investment ($/line)	$4.5M	$15M	$1.5M
Tooling investment ($/line)	$1.7M	$75M	$1.5M
Building area per line (m^2)	2,200	95,000	2,500

Table 19: Key cost model inputs

Learning was modeled for three parameters: *CT*, *UD* and *rej*. Monthly data on cycle time and downtime for a single hydroforming line was used to determine the learning parameters, which are reported in Table 20.

Process parameter	***a***	***b***	Significance on F-statistic
Cycle time (*CT*)	2.829	0.093	1.077E-6
Unplanned downtime (*UD*)	0.562	0.177	0.0044

Table 20: Learning curve parameters from tube hydroforming data

No data were available to perform a regression on reject rate improvement. For the purposes of this study, it was assumed that the reject rate parameter experienced the same learning pattern as unplanned downtime, after normalization of the learning curve. The maximum and minimum saturation levels used to normalize each process parameter's learning curve for the tube hydroforming process are shown in Table 21. Values for cycle time and unplanned downtime are based on the collected data, while reject rate maximum and minimum values are assumptions based on estimates by hydroforming process experts from the same firm at which data was collected.

Process parameter	Y_{max}	Y_{min}	Scope
Cycle time (*CT*)	1.160	0.764	34%
Unplanned downtime (*UD*)	0.103	0.047	54%
Reject rate (*rej*)	0.200	0.100	50%

Table 21: Learning scope parameters for tube hydroforming

	Initial cost ($/unit)			Final cost ($/unit)		
Cost element	**Hydroforming**	**Assembly**	**Wire**	**Hydroforming**	**Assembly**	**Wire**
Material	2.19	-	27.85	1.98	-	25.54
Labor	3.43	897.13	0.74	1.89	582.76	0.41
Energy	0.58	94.70	0.11	0.34	65.86	0.06
Overhead	0.69	299.04	0.15	0.38	194.25	0.08
Tooling	8.05	41.61	2.08	8.05	41.61	2.08
Equipment	4.49	85.76	1.27	2.48	55.71	0.71
Building	3.19	119.40	1.99	1.76	77.56	1.10
Total	22.61	1,537.63	34.18	16.87	1,017.75	29.98

Table 22: Initial and learning improved costs for each tube hydroforming, general assembly, and copper wire drawing processes, by cost category

Initial cost figures and learning-improved costs (after 1.25 million parts produced) are shown by cost element in Table 22. Results, as displayed in Figure 43, show that learning impacts on individual cost elements differ significantly across the three processes. For the tube hydroforming process, reductions in equipment cost accounts for 35% of the total cost reduction attributable to learning, with reductions in labor and building costs each accounting for 25%, respectively. In contrast, for the case of general assembly, 60% of cost reduction due to learning occurs in the direct labor category. When indirect (overhead) labor is included the learning-related savings attributable to labor climbs to over 80%. For copper wire drawing, 55% of the cost savings occur in materials expenses. However, when considering cost elements individually, it appears that the scope of learning in material cost (from $27.85 to $25.54, an 8% decrease) is lesser than the scope of learning in labor cost (from $0.74 to $0.41, a 45% decrease). This is because all three learning parameters considered have an impact on labor costs, while material cost is only affected by reject rate learning. Moreover, the impact of reject rate improvement on material cost is mitigated by the possibility of selling material scrap at a reasonable price. Nevertheless, due to the dominance in materials cost for this process, learning there remains the most critical for cost reduction.

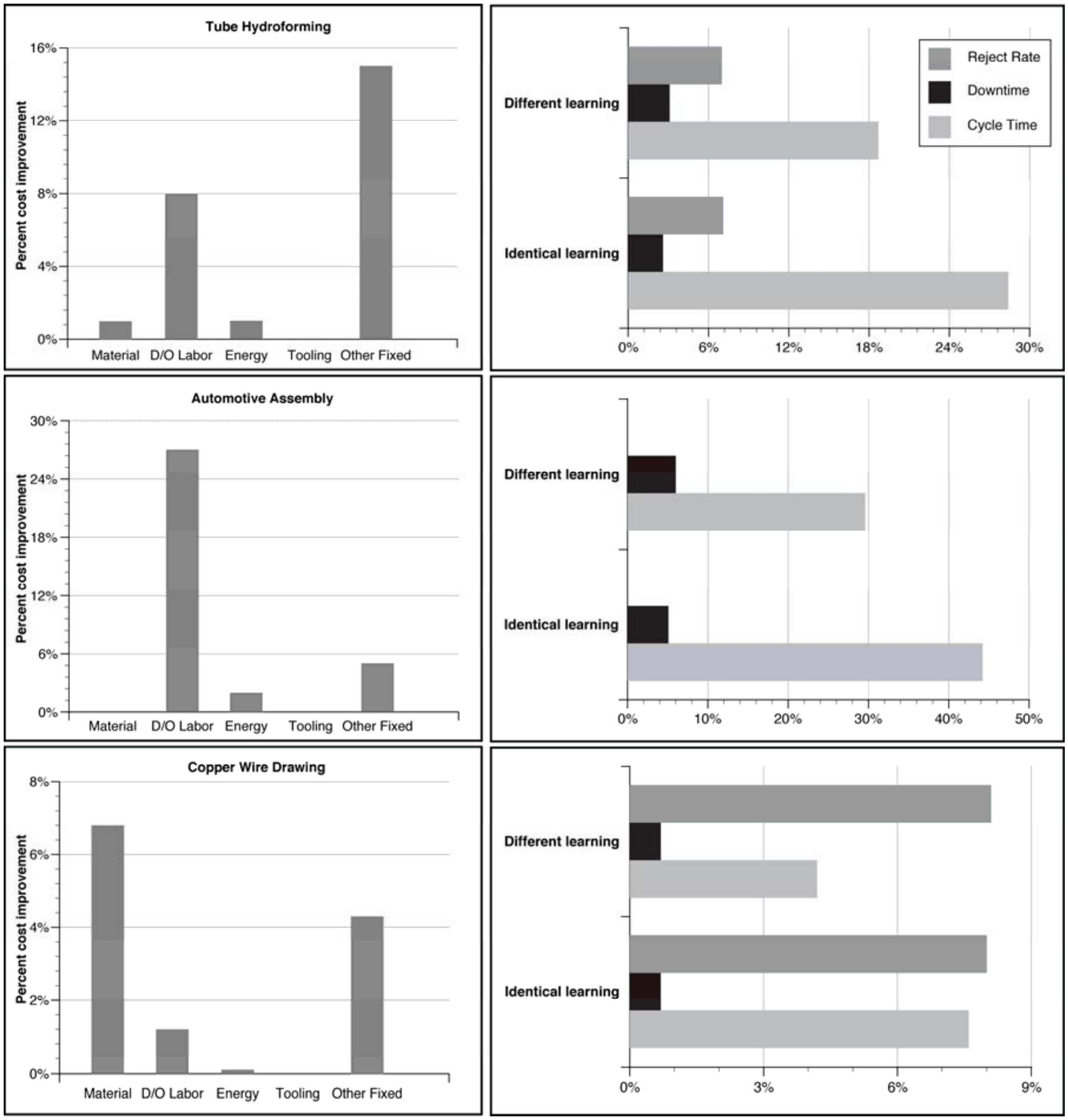

Figure 43: Left - Percent of initial cost saved through learning by cost element for (a) hydroforming; (b) general assembly; and (c) copper wire drawing processes. Right - Cost improvement by operational parameter, for identical and differing learning rates and scopes.

Modeling results also revealed that main cost learning drivers can differ from one technology to the next. While in the case of tube hydroforming, cycle time learning was the main driver for cost improvement, Figure 43 shows that reject rate learning is the main source of cost savings for copper wire drawing. Cycle time is the main learning driver for general assembly.

Differences in cost structure and operational conditions for each process translate into not only differences in the underlying drivers of learning benefits, but also to distinct overall cost learning behaviors. Figure 44 shows the resultant aggregate learning behaviour that derives from the operational characteristics listed in Table 19. Clearly, all three processes exhibit dramatically different aggregate behaviour despite being based around identical operational characteristic learning rates and scopes. Table 23 reports parameters from fitted log-linear curves for each process' total cost, representing their implicit aggregate learning rates.

Learning curve	***a***	***b***	**Significance on F-statistic**
Tube hydroforming	48.62	0.0769	2.64E-18
Automotive assembly	4837.71	0.1161	1.05E-45
Copper wire drawing	46.49	0.0320	1.21E-21

Table 23: Log-linear model parameters for implicit aggregate cost learning of each process

Learning in general assembly only appears slower on a time scale due to a lower production volume, but has a more significant impact on cost than for hydroforming or copper production after about 18 months.

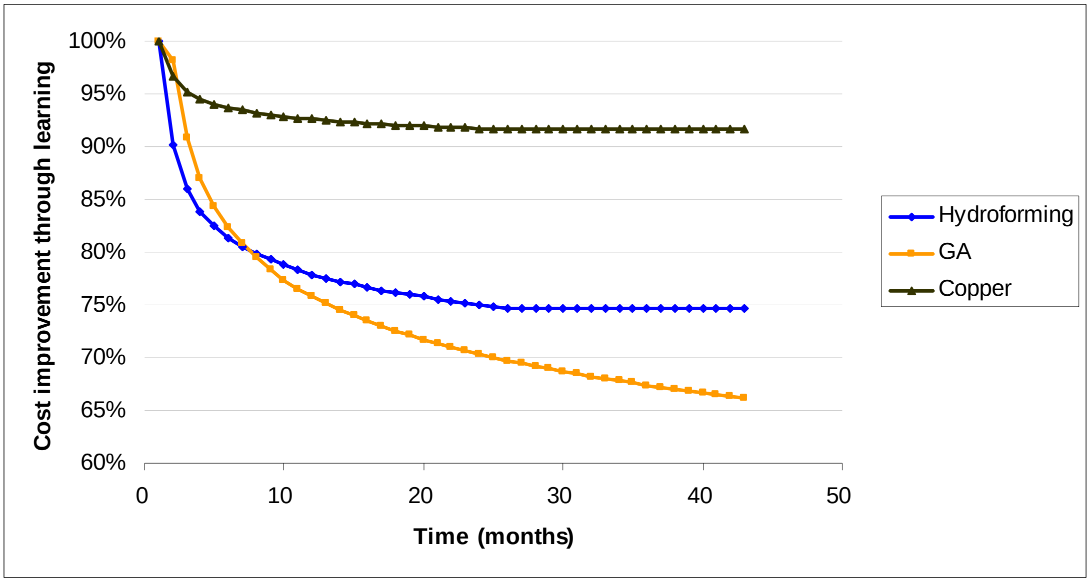

Figure 44: Cost learning curves for tube hydroforming, car general assembly, and copper wire drawing processes