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TECHNOLOGY DECISIONS IN NEW PRODUCT DEVELOPMENT

by

AMIR SANAYEI

DISSERTATION

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

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MAJOR: INDUSTRIAL ENGINEERING

Approved By:

Advisor

Date

DEDICATION

To Dad, Mom and Brother.

Thank you for your endless support and encouragement.

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I would like to express my sincere gratitude to my advisor Prof. Leslie Monplaisir, who has been so supportive during my Ph.D. study and research at Wayne State University. His patience, motivation, enthusiasm and immense knowledge on New Product Development have guided me through all the time of my research and the completion of this thesis.

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CHAPTER 1. INTRODUCTION

In the current business environment, companies can achieve competitive advantage through superior manufacturing, but sustaining a competitive advantage over time requires generating new products and processes. Companies must also consider which technologies to use when developing new product processes. Evaluating emerging technologies enables businesses to either continue on a technology growth curve or to replace existing technology to keep ahead of competitors and retain a desirable market share. However, financial constraints may limit a company's technological choices. The selection of proper technology is one of the most important and strategic tasks that should be taken in the early stages of new product development. Selecting the right technologies to incorporate in new products is a particularly challenging aspect of new product definition and development. While newer advanced technologies may offer improved performance, they also make the product development process more risky and challenging [Krishnan and Bhattacharya, 2002]. A company can waste its competitive advantage by investing in the wrong alternatives at the wrong time or by investing too much in the right ones; however, selecting the right technology could enhance a company's competitive advantages. Technology selection has a great impact on product success factors: product performance, unit product cost and product time to market. Figure 1.1 shows relationships among technology selection, new product development, and product success factors schematically.

The increasing number of technological advances and their complexity can make it difficult to choose the proper one. Furthermore, the uncertain nature of the competitive business environment and new technology alternatives make the technology selection problem more

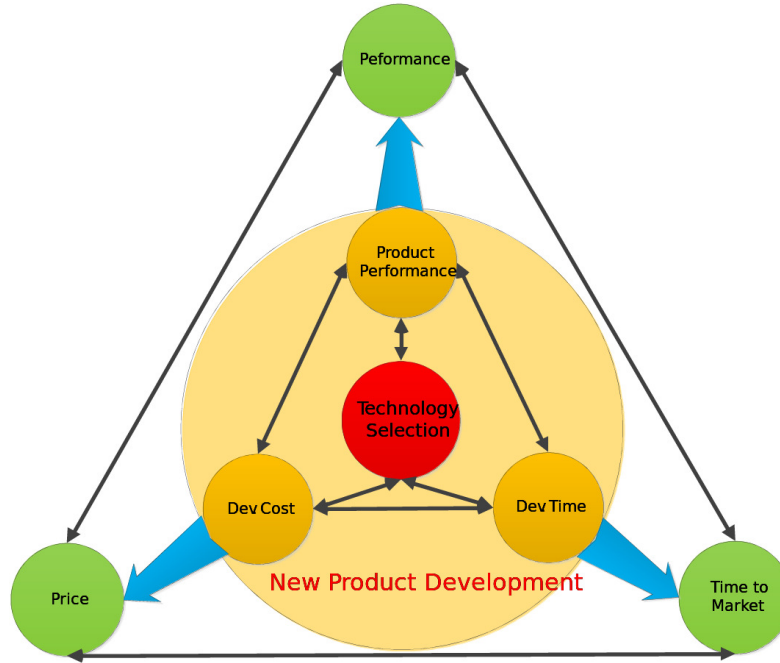


Figure 1.1: Technology selection and product success factors

complex. In addition, limited financial resources and time constraints increase the complexity of the problem. Technology selection has a significant impact on technological capability and technology management capability, which, in turn, have a significant positive impact on innovation success, which then has a significant impact on organizational performance [Hao and Yu, 2011].

The risk associated with a technology can be positive in terms of opportunity or it can be negative in the shape of a threat perceived with a technology alternative. The technology selection processes in the literature have mostly considered opportunities related to a technology and have not included the threats associated with a technology alternative while considering it for strategic selection Farooq and O'Brien [2012].

Technology selection literature related to current research relies on three fields: R&D Project selection, New Product Development, and Marketing:

1) R&D project selection literature aims to maximize a firm's benefit from a project or portfolio of projects over time. Little or no attention is given to the product development process. The relationship between time to market and market share is usually not addressed. The fixed targets of projects' performance are often assumed to be exogenously given. The impact of the unit cost on the product development process is ignored.

2) Marketing literature emphasizes the diffusion of new products and the effects of cannibalization. The trade-off between product performance and unit cost of the product has also been examined in the marketing literature while product development related issues are usually ignored.

3) The focus of New Product Development literature is on product configuration and performance. Technology development and related issues are usually ignored. Furthermore, product life cycle profit has not garnered much consideration.

Figure 1.2 graphically represent the relationship between the existing literature.

Although authors have developed many tools and methods have been developed to address the problem of technology selection, little attention has been devoted to the modeling of this problem under uncertainty and studying trade-offs between time, cost performance, and uncertainty. Additionally, in many works it is implicitly assumed that all the information regarding technology alternatives is available at the time of decision making, ignoring the flow of information that can be learned from development process. In many real cases, all technology alternatives are not at the same level of readiness, and additional alternatives may need to be developed. Furthermore, in existing methods, trade-offs among important product success factors during the technology development process such as performance, development time, and cost are ignored. Existing methods are unable to simultaneously

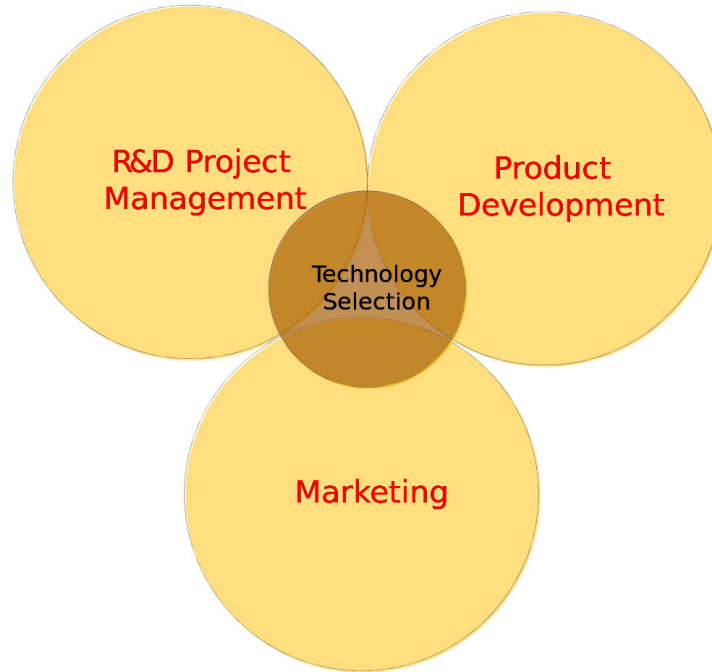


Figure 1.2: Technology selection and related literature

consider and model the impacts of time-to-market and utilization of available resources. Furthermore, many existing works have a very narrow point of view of the product life cycle that technology selection impacts and consider only the product definition phase of new product development.

In chapter 2, We model the technology selection problem of a firm that is defining its new product in the presence of technological uncertainty. The firm faces two options: (i) a proven technology which is known to be viable and (ii) a prospective technology with higher performance to price results whose viability is not fully proven. At each review stage, the firm has two options: select and commit to any technology alternatives or postpone the decision to the next review stage in order to gather more information. Delays in making technology decisions are likely to increase NPD cycle time by shifting forward downstream activities and ultimately may impose an increased development cost and profit loss for the

firm. Our Analysis describes the optimal strategies for this problem and investigates the impact of uncertainty and time trade-offs on the technology selection problem in NPD. In chapter 3, we extend the model to compare two uncertain technologies at the same time. We model technology selection while considering life cycle demand uncertainty in chapter 4. Finally, in chapter 5 we draw some conclusions.

CHAPTER 2. SINGLE UNCERTAIN TECHNOLOGY

2.1 Introduction

By increasing attention on market leadership in the current business environment, new product development (NPD) has a greater role in creating and retaining competitive advantages for firms. Firms are developing new products with higher performance by using advantages of new, emerging technologies. Although new technologies offer higher performance, their unproven and uncertain nature are likely to make NPD projects more risky by increasing the development cost and cycle time. In such environments, it is crucial for firms to manage uncertainty in technological decisions.

Product specification such as performance levels and features is being defined during the early stages of the NPD. The outcome of product definition provides a crucial input for subsequent downstream detailed design and prototyping activities [Krishnan and Bhattacharya, 2002]. Selecting the technology that offers the product its ability to perform at the level set in its specifications is one of the key decisions made during the product definition phase. The product development team is frequently faced with the choice of more than one technological option [Krishnan and Bhattacharya, 2002].

Having the option to postpone the product definitions during the NPD process gives the PD team more flexibility to deal with the technology selection decision. However it is obvious that delaying that decision may result in increasing NPD cycle time. In such an environment firms are constantly trying to make trade-off between the pressure to introduce new products faster against the cost and performance Cohen et al. [1996]. While delaying the introduction

of new products allows development teams to incorporate improved technologies, it might also result in a significant loss of market opportunities.

Deferring technology decisions may mean shifting subsequent downstream design activities forward which can increase the development cycle time and decrease product revenue by imposing additional costs. Reduction of NPD cycle time and improvements in product performance have been a strategic objective for many technology-driven firms [Cohen et al., 1996]. After finalizing product definition, including the technology choice, any change in design would be very costly and may result in a delayed launch. To reduce the effects of design changes, sometimes it is recommended that specifications be frozen early in the development process [Cooper, 2011]. Indeed, there are some studies in the literature that discuss the postponement of finalizing the product definition such as [Bhattacharya et al., 1998, Krishnan and Bhattacharya, 2002].

Krishnan and Bhattacharya [2002] argue the *pizza-bin* approach in which the products are developed from "on-the-shelf" proven technologies, whose feasibility must be completely proven before product development commences. The *pizza-bin* approach aims to reduce the risk inherent in the Product Development (PD) process. However, by refusing to consider promising prospective technologies that are not yet fully proven, a firm may not get the chance to commercialize new technologies ahead of competitors and thereby differentiate its products.

Krishnan and Bhattacharya [2002] described a case study at Dell Company where the Product Development (PD) team was under intense pressure to develop a new portable computer since the firm's earlier product had failed and was abandoned in the market because of quality. Based on market studies, battery life is considered a differentiating feature in

product success in the market place. There were two alternative battery technologies available: (i) a nickel-metal-hydride (NiHi) battery which was widely used by most PC firms and (ii) a lithium ion (LIon) battery. NiHi technology was proven but the battery could not last more than three hours and it would recharge only to a fraction of the full level. Although LIon battery technology was under development, it offered a significantly higher battery density (or higher battery life per unit weight) than the NiHi batteries. However, the LIon technology was not yet completely proven for usage in portable computers, especially given that there were some cases of over-charging and explosion. Although an alternative circuit was designed to prevent the overcharging problem and was coupled with extensive testing of the new enhancement, the final outcome was uncertain in terms of the viability. Choosing either technology would significantly affect the product performance and more importantly product design and downstream activities. In such situations, the firm faced a challenging decision of technology selection under uncertainty.

Generally in such situations, by postponing the technology decision and getting more information from lab reports and field tests, technology uncertainty can be resolved or at least reduced and companies can get a clearer idea about the viability of the new technology. This helps the firm make better technology decisions; however, postponing such a decision in the NPD process may result in delays in product launch, losing market share and significant profit loss.

In this paper, we review related literature in section 2.2 and formulate the technology selection problem under uncertainty as a dynamic sequential decision making problem in section 2.3. The model is analyzed in section 2.4. Some managerial insights are proposed in section 2.5. Finally, section 2.6 includes concluding remarks.

2.2 Literature Review

The Problem of technology selection has attracted the attention of numerous authors during the last 3 decades. Different techniques including different multiple criteria decision making (MCDM) methods have been applied to this problem. The Analytical Hierarchy Process (AHP) is used by many authors in this field. Kim et al. [2010] proposed a dual AHP technique to prioritize emerging technologies. A 2-step model is proposed by Hsu et al. [2010]. At the first stage they utilized the Fuzzy Delphi Method to obtain the critical factors of the technology by interviewing experts. In the second stage, the Fuzzy AHP is applied to find the weighted significance of each criterion as the measurable indices of the technology. Chen et al. [2006] applied fuzzy AHP to new product portfolio selection in the TFT-LCD2 technological environment. The Analytical network process (ANP) is also used by Mulebeke and Zheng [2006] for software selection in product development. Kang et al. [2012] presented an integrated model using interpretive structural modeling (ISM) and fuzzy analytic network process (FANP) to evaluate available technologies for NPD. The ISM is used to understand the interrelationships among the factors, and the FANP is used to facilitate the evaluation process of decision makers with interrelated factors. Farooq and O'Brien [2012] described a framework for manufacturing technology selection using AHP and a Strategic Assessment Model to integrate the supply chain into the decision making process. Jiang et al. [2011] used AHP to propose a framework for re-manufacturing technology portfolio selection. Chuang et al. [2009] suggested an operational strategy for the selection of new production technology that integrates the market trends, competitive and operational strategies, as well as manufacturing attributes by using the relationship matrix in the QFD method. Also different

mathematical programming methods have been addressed to solve this problem. Singh et al. [1990] applied binary programming for multi-stage production systems technology selection. Ahmed and Sahinidis [2008] proposed a multi-period investment problem for selection, acquisition, and allocation of alternative manufacturing technology choices to meet the demand of a number of product families over a long range planning horizon by using a linear programming (LP) relaxation solution for solving the problem. Khouja [1995] applied Data Envelopment Analysis (DEA) as the first step of a 2-step model to identify the technology with the best performance. Then a MADM method was used in the second phase to select the best technology. Later, Baker and Talluri [1997] discussed the methodology proposed by Khouja [1995] and suggested a more robust analysis based on the cross efficiencies in DEA. Bhaskaran and Ramachandran [2011] developed a two stage conceptual model to study how a firm could incorporate the presence of a strategic competitor in making technology selection and investment decisions regarding new products. They concentrated on a competitor's impact on technology selection, pricing and timing of new product.

Almost all these methods rely on a very subjective criteria evaluation process that strongly depends on expert opinion and intuition. Thus, the process is not effective if there is lack of visibility and traceability in the decision making process. In that sense, the firm can't be confident that resources are being optimized to maximize the benefits. Furthermore, almost all the works cited above ignore the fact that information regarding new technology may not be available at the beginning or may become available throughout the process. In other words they do not consider the possibility of postponing the technology decision in order to gather more information and assume -implicitly or explicitly- that, the right timing for the decision is known. Additionally, the methods cited are not able to dynamically

take into account technology uncertainty and cost, time, and demand dynamics with their trade-offs.

Our research is aligned with previous literature in technology uncertainty and information acquisition. McCardle [1985] modeled the adoption of new technology when its profitability was rarely known at the beginning. He assumed that companies collect sequential information in order to estimate the profitability of the technology. Kornish and Keeney [2008] studied annual influenza vaccine composition decision making which must happen in the spring to allow time for vaccine production before the fall flu season begins. They model the dynamic decision problem in which the decision can be made at the present time or postponed to gather more information, which tightens the time for producing the vaccine. Krishnan and Bhattacharya [2002] formulated a model of a firm that must define its products in the presence of technology uncertainty and investigate the problem of technology selection and commitment under uncertainty. They consider two technology alternatives, a prospective technology with an uncertain outcome and a proven alternative with a certain outcome in terms of viability. In their model, product launch time is assumed to be fixed, so in case of delay (because of technology failure), the firm will incur profit loss, while our model is more comprehensive and uses a general opportunity cost function which analyzes the trade-off between cost, time and risk.

Our research may relate to the research stream on R&D project management such as Huchzermeier and Loch [2001], Santiago and Vakili [2005], Wang and Yang [2012] in which real option analysis is applied to manage the uncertainty and identify proper managerial actions. They assumed that based on managerial actions such as amount of investment, performance of the R&D project can be increased or decreased. However in this research we

concentrate on identifying the conditions and timing for new technology to be considered for new products based on a stream of new information.

Our research is also related to new product development cycle time and time-to-market literature. Cohen et al. [1996] investigated new product launch time and target performance level by using a logit model to capture consumer behavior in a competitive market. They indicated how optimal time-to-market and its implied product performance targets vary with exogenous factors such as the size of the potential market, the presence of existing and new products, profit margins, the length of the window of opportunity, the firm's speed of product improvement, and competitors product performance. In this research, we investigate the optimal choice and timing for technology decisions which have a great impact on product performance and are influenced by competitive market situations.

2.3 Model Formulation

In this section we develop a model to capture the nature of the technology selection problem in NPD under presence of uncertainty. We focus on a firm that is aiming to develop a new product. Like Krishnan and Bhattacharya [2002] we assume that there are two technology alternatives available: *proven* (denoted by pv) and *prospective* (denoted by ps) technology. However, our model and analysis can be easily extended to more than two alternatives. A proven technology is defined as the one which already has been used in previous, similar products and the firm has 100% confidence level about its viability, based on laboratory tests, manufacturing feasibility studies, or track record of the technology. On the other hand, a prospective technology is the one which has not been utilized by the firm in similar products and the firm has a lower confidence level about its viability than the proven

technology in the beginning of the development process [Krishnan and Bhattacharya, 2002].

It is assumed that by introducing the product with *ps* technology, the firm can gain a higher profit compared to a situation that *pv* technology is used in new product. If the *pv* alternative is chosen, the firm will gain a profit of m . But if the firm decides to choose the *ps* alternative, an initial investment cost of I has to be made. In case the outcome turns out viable, the firm will gain a profit of M where $M \geq m$. Otherwise if this alternative is not viable, by incurring a reversion cost of F , the design has to be reverted to the one based on *pv* technology. For the product being considered, the PD process is being reviewed at discrete periodic time intervals. The development team's estimate of the viability of *ps* technology at each review stage n is described by the parameter v_n . Expected profit from *pv* and *ps* technology alternatives at each review stage n can be expressed as following equations:

$$m^{pv} = m \tag{2.1}$$

$$m^{ps}(v_n) = v_n \times M + (1 - v_n) \times (m - F) - I \tag{2.2}$$

Equation (2.1) shows that the expected value of profit from *pv* technology is constant and equal to m . The equation (2.2) expresses the expected profit of selecting *ps* alternative. In order to select a *ps* alternative, an initial investment cost of I has to be made. The outcome will be viable by probability of v_n , and then the firm will gain a profit of M . Otherwise if this alternative is not viable by probability of $1 - v_n$, by incurring a reversion cost F , the design has to be reverted to the one based on *pv* technology in which firm will gain a profit of $m - F$. The expected profit from choosing *ps* alternative depends on its estimated viability, the higher the v_n the higher the expected profit. However in equation (2.1), since

the out come of *pv* technology is known, the expected profit of choosing the *pv* alternative does not rely on any chance factor.

We assume that the firm is not following the *pizza-bin* approach in which *ps* technologies are rejected by the firm outright before the PD process begins. The firm should decide to consider either *pv* or *ps* technology alternatives. Comparing expected profit equations (2.1) and (2.2) we can obtain the break-even point v_{thr} in order to consider *ps* technology by setting $m_n^{ps} \geq m_n^{pv}$ or :

$$v_n \geq v_{thr} = \frac{F + I}{M - m + F} \quad (2.3)$$

While the equation (2.3) is neither necessary nor sufficient for the firm to consider the *ps* technology, it could be argued that a rational firm gives serious consideration to the *ps* technology when its expected profit exceeds profit from *pv* technology [Krishnan and Bhattacharya, 2002]. In that sense, the above equation can be considered as proxy for the "threshold" value of viability above which the *ps* technology is likely to be considered. Necessary and sufficient conditions depend on subsequent information which will be modeled later.

Also the firm has the option to postpone the technology decision. At each review stage, the firm decides to commit to either *pv* or *ps* alternatives or to postpone this decision to the next stage. Figure 2.3 shows the sequential decision making process of the described technology selection model.

Deferring the technology decision shifts all downstream design activities forward. This may lead to an increasing development cost and profit loss by increasing the NPD cycle

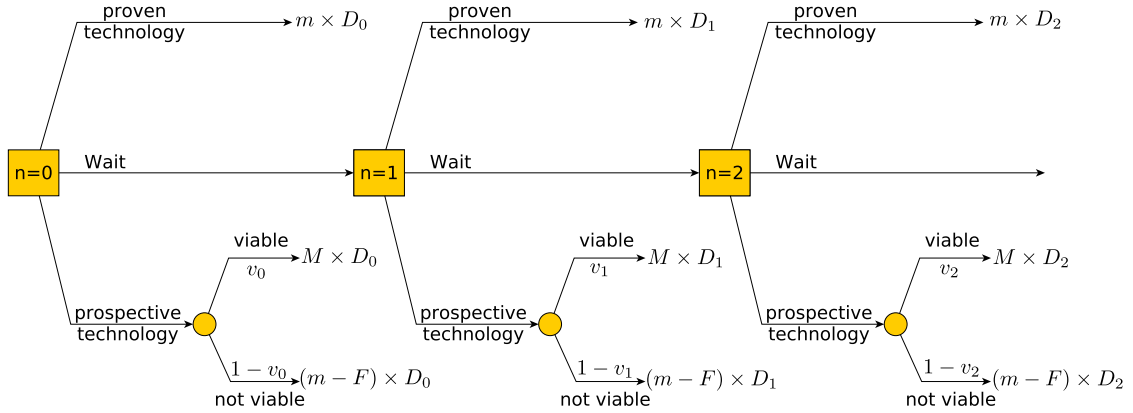


Figure 2.3: Decision Tree for Technology Selection Model.

At each review stage, the firm has three options: **(i)** reject the *ps* technology; **(ii)** commit to the *ps* technology; **(iii)** and postpone this decision to the next stage. In the case of committing to *ps* technology, the outcome could be either viable or not. If it is not viable, the design has to be reverted to *pv* technology.

time. By postponing the decision at each stage n , the firm incurs an opportunity cost which is assumed to be a portion of the product's expected profit. By committing to either *ps* or *pv* technologies at stage n , the expected payoff is obtained by multiplying profit to the opportunity cost ratio of D_n as equation (2.4) in which d_i is the opportunity cost of delaying the decision at stage i and is assumed to be a proportion of the product's expected profit.

$$D_n = 1 - \sum_{i=0}^n d_i \quad (2.4)$$

The expected payoff of choosing *pv* and *ps* alternatives at review stage n can be expressed as equations (2.5 - 2.6). D_n indicates the portion of the total profit that the firm can obtain if it postpones the decision till stage n .

$$\pi_n^{pv} = m^{pv} \times D_n \quad (2.5)$$

$$\pi_n^{ps} = m^{ps}(v_n) \times D_n \quad (2.6)$$

The firm cannot postpone the technology decision indefinitely; it finally reaches a point that the penalty of delaying the decision is equal to the profit of the NPD project. This fact is depicted by equation (2.7) where N is the latest possible review stage that the firm can still make a profit by postponing the decision by that point. It implies the fact that by delaying the technology decision, profit from both alternatives is decreasing and finally reaches the point where it becomes zero. The impact of the opportunity cost will be discussed in more detail in section 2.4.

$$\sum_{i=0}^N d_i = 1 \quad (2.7)$$

At each review stage, the firm can benefit from the real time information regarding the viability of the technologies from laboratory and field tests. We assume that the firm starts with a prior estimate for viability of ps technology and updates this prior estimate by receiving signals from the field tests in a Bayesian manner. It is common in the literature to assume that there is prior and posterior distribution from conjugate distributions [Krishnan and Bhattacharya, 2002, McCardle, 1985]. Considering the nature of the parameters, similar to Krishnan and Bhattacharya [2002] we assumed that the prior estimate of viability of ps technology follows *Beta* distribution (between 0 and 1 with parameters α and β), and signals are from *Binomial* distribution. A favorable (unfavorable) signal indicates success (failure) of the technology in the testing. At each review stage $n + 1$, the viability of ps technology, v_{n+1} , can be estimated by having viability of the previous period v_n as follows:

$$v_{n+1} = \frac{(\alpha + \beta + \sum_{i=1}^n S_i)v_n + S_{n+1}^+}{\alpha + \beta + \sum_{i=1}^{n+1} S_i} \quad (2.8)$$

Where S_i^+ and S_i indicate the number of positive signals and total number of signals received at review stage i .

It is assumed that the firm is risk averse and decides based on expected value of profit. At each review stage, the firm will commit the most profitable alternative and select between pv or ps technology, or it will wait and continue gathering information and postpone the decision if the expected payoff of at next stage is higher :

$$R_n(v_n) = \max \begin{cases} \pi_n^{pv} & \text{Select } pv \\ \pi_n^{ps}(v_n) & \text{Select } ps \\ E[R_{n+1}(v_{n+1})|v_n, s_{n+1}] & \text{Wait} \end{cases} \quad (2.9)$$

Payoff at review stage N will be zero and directly results from the equation (2.7). This is depicted in equation (2.10):

$$R_N(v_N) = 0 \quad (2.10)$$

Note that this boundary condition implies that launching product after a certain deadline has no value. Expected value of payoff at the next stage or the expected value of waiting can be obtained by the following equation:

$$E[R_{n+1}(v_{n+1})|v_n, S_{n+1}] = \sum_{S_{n+1}^+=0}^{S_{n+1}} p(S_{n+1}^+|v_n, S_{n+1})R_{n+1}(v_{n+1}|v_n, S_{n+1}, S_{n+1}^+) \quad (2.11)$$

The probability part can be written as:

$$p(s_{n+1}^+|v_n, S_{n+1}) = \binom{S_{n+1}}{s_{n+1}^+} (v_n)^{s_{n+1}^+} (1 - v_n)^{(S_{n+1} - s_{n+1}^+)} \quad (2.12)$$

By having equations (2.9 - 2.12), we can formulate the technology selection problem as sequential stochastic dynamic programming. The dynamic programming equation for the optimal value is the maximum of the values of the three possible choices: commit to ps technology, reject ps technology or defer to until the next period then choose optimally.

2.4 Model Analysis

In this section we will investigate the optimal conditions in which the firm would select each choice and obtain some general properties of the technology selection problem described in the previous section. For readability and continuity proofs are proposed in the appendix.

Lemma 2.1. *The expected profit at next review stage is equal to the current estimate of profit.*

Lemma 2.1 implies the fact that at each stage all available information incorporated in

the current forecast includes the previous stage forecast plus the information that has been received since the last review stage. Note that the forecast of payoff at the current stage is not necessarily equal to that of the previous stage; however, on average, the two are equal.

Proposition 2.1. *If $\sum_{i=0}^n d_i = 0$, then it is optimal to delay technology decision by review stage n .*

Proposition 2.1 states that as long as there is no opportunity cost, it is optimal to delay the decision. Intuitively the firm would not commit the technology unless the firm is confident about its profitability otherwise it will prefer to postpone this decision at least to the next stage. By delaying the decision, the firm hopes that the uncertainty will resolve itself due to receiving more information. However, this may impose an opportunity cost to the firm. In a sense if a firm does not incur any penalty, it seems reasonable to delay technology decisions as much as possible in a hope to get a better estimation of the profit at the next stages and increase the chance of selecting the best technology. This implies that it is optimal to delay technology decisions as long as there is no cost.

Investigating equation (2.2), reveals that the revenue of ps technology is increasing by v_n , which intuitively make sense; The higher possibility of success, the higher the expected revenue. This fact is stated in Lemma 2.2.

Lemma 2.2. *Next stage expected profit is increasing in current estimate of profit.*

Intuitively we expect that favorable or unfavorable news tends to persist in the next stage. This fact is stated in Lemma 2.3 which indicates that the higher forecast in current stage implies higher forecast at the next stage.

Lemma 2.3. *The Expected payoff is increasing in previous estimate of viability.*

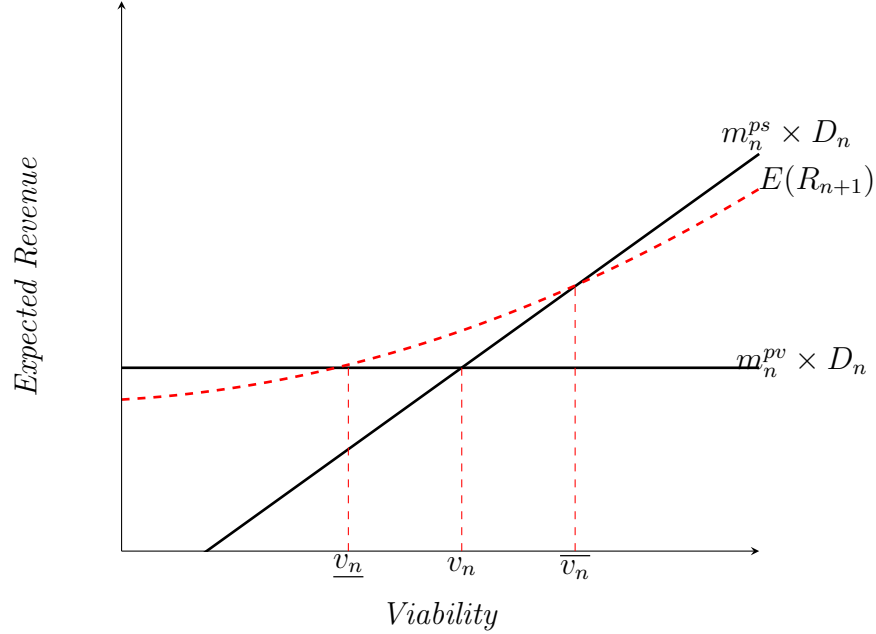


Figure 2.4: Expected revenue of selecting pv , ps and postponing the decision

At each review stage n , the lower threshold \underline{v}_n , is the intersection of the next stage revenue ($E(R_{n+1})$) with current estimated profit from pv technology (m_n^{pv}). While the upper threshold \bar{v}_n , is the intersection of the next stage revenue ($E(R_{n+1})$) with current estimated profit from ps technology (m_n^{ps})

The firm will not postpone the decision, unless it is possible that new information will be received later to alter the decision. It is obvious that paying the penalty by delaying the decision and receiving the information which will not change the outcome. In order to wait, firm's estimate must be able to crossover the break-even point, either from profitable to unprofitable or vice-versa. In other words, we will not choose to wait unless the new information could cause a crossover or move the estimate to the next waiting stage.

Proposition 2.2. *At each time period n there exist a pair of numbers \underline{v}_n and \bar{v}_n such that if $\underline{v}_n \leq v_n \leq \bar{v}_n$, it is optimal to wait until the next stage, if $v_n \leq \underline{v}_n$ it is optimal to choose pv technology, and if $v_n \geq \bar{v}_n$, it is optimal to choose the ps technology.*

Proposition 2.2 states that at each stage there are lower and upper thresholds that having estimated viability between these thresholds may be changed at the next stage by receiving

new information. These thresholds are shown in Figure (2.4), where the expected profit of the next stage intersects expected profit of the current stage. By having the current estimate of viability between two intersection points, it is possible that the next stage's estimated value of profit would be improved. This implies that the more information a firm has, the more confident it should be about its estimate. Suppose that the firm is at stage n with viability estimate of v_n and $v_n \geq \bar{v}_n$. It seems intuitive that if the firm had more information with the same estimate, it would also find considering ps technology optimal.

Proposition 2.3. *The expected value of the waiting is non-increasing in n .*

Proposition 2.3 shows that the firm's average expected profit decreases as the amount of information already collected increases. Increasing n decreases the riskiness (in the sense of second order stochastic dominance) of posterior distribution. As the firm acquires more information, it tightens its posterior distribution. This fact is stated in Proposition 2.4 and shown in Figure (2.5). Expected profit at the stage $n + 2$ will be less than expected profit at stage $n + 1$, and then it will intersect the current estimate of the profit at \underline{v}_{n+1} and \overline{v}_{n+1} where $\underline{v}_n \leq \underline{v}_{n+1}$ and $\overline{v}_{n+1} \leq \overline{v}_n$.

Proposition 2.4. *At each time period n the lower threshold \underline{v}_n and upper threshold \overline{v}_n are respectively decreasing and increasing in n .*

Results from proposition 2.2 and 2.4 are summarized in Figure (2.6). Receiving positive signals causes an increase in viability and a move upward while receiving negative signals causes a decrease in viability and move downwards. The firm starts with an estimate of viability (v_0). As the firm continues to test and acquire more information, it moves rightward in the direction of increasing information in Figure (2.6). It stops and considers the ps

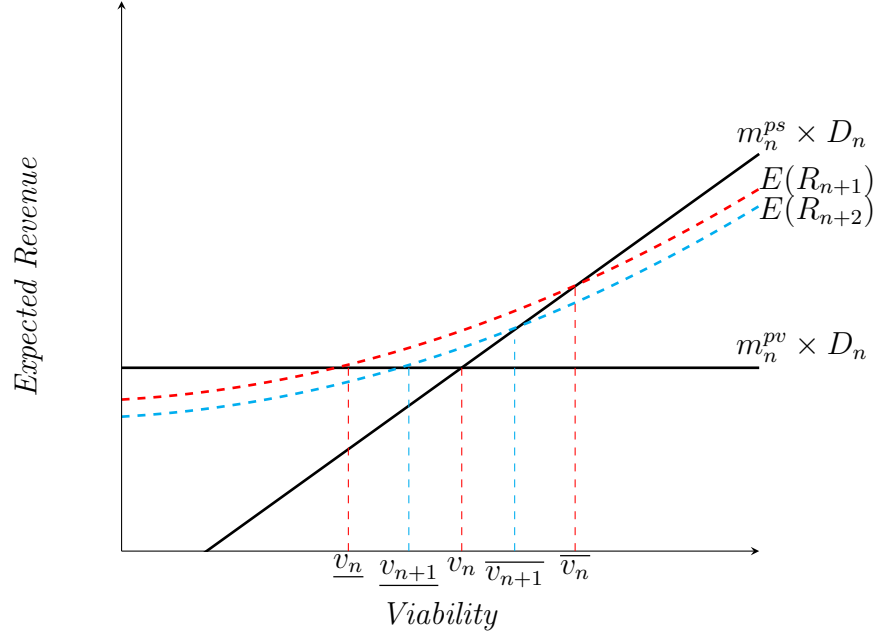


Figure 2.5: Illustration of tightening thresholds

At each stage n , imposed extra opportunity cost, $E(R_{n+2})$ will be lower than $E(R_{n+1})$ which results in increasing the lower threshold ($v_{n+1} \geq v_n$) and decreasing in upper threshold ($\bar{v}_{n+1} \leq \bar{v}_n$)

technology if its estimate of viability is high (region A). On the other hand, it stops and rejects the ps technology if its estimate of profitability is low (region C). The firm continues to research and collect information when the estimate is neither high nor low (region B). For a given amount of information, if the firm's estimate of viability is such that the firm stops collecting information and adopts the innovation, then with more information and the same estimate the firm would also stop and adopt: greater precision, as represented by more information, does not change the adoption decision. The same holds true if the firm were to reject the innovation, giving rise to the conic shape of region B.

Proposition 2.5. *For every period n , by multiplying payoff from pv and ps technologies by a_{pv} and a_{ps} respectively, the lower and upper thresholds:*

- (i) will not change if $\frac{a_{ps}}{a_{pv}} = 1$

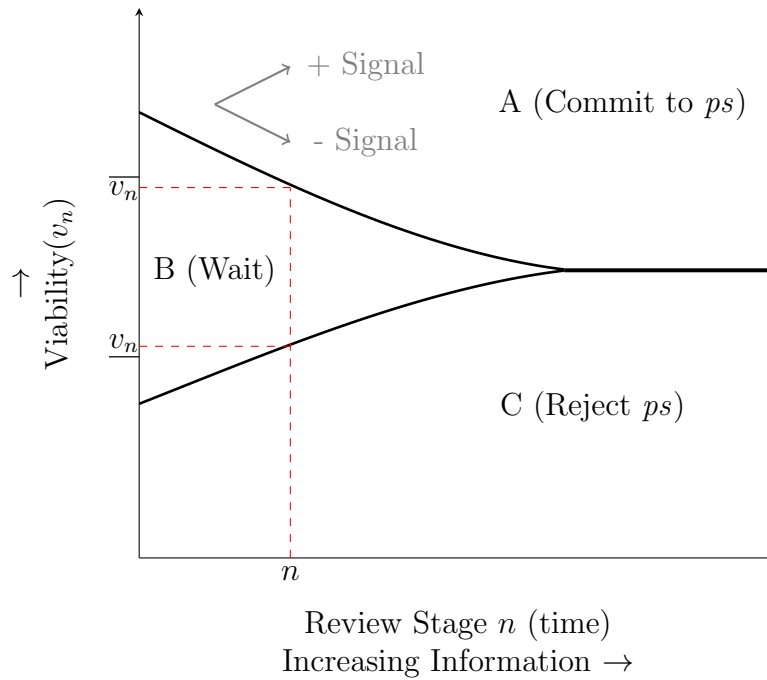


Figure 2.6: Illustration of Optimal Strategy Structure: Commit, Reject and Wait Regions

The firm starts with viability estimation of v_0 at the beginning. It moves forward by testing and gathering more information during the time period. Receiving positive signals causes an increase in estimation of viability of the next stage while receiving negative signals causes a decrease in that which is causing movement up or down respectively. As long as we stay at the waiting stage)it is optimal to postpone the technology decision. However, once we pass the upper threshold, it would be optimal to commit to ps technology. The firm will reject ps technology if it enters the rejection region.

(ii) will decrease if $\frac{a_{ps}}{a_{pv}} > 1$

(iii) will increase if $\frac{a_{ps}}{a_{pv}} < 1$

Proposition 2.5 describes the optimal strategy by changing the revenues for all review stages. The first part essentially says that a can be cancelled out in the comparisons. Also, such a change does not affect the balance between the commit, reject and wait strategies because ultimately the wait strategy depends on the relative attractiveness of the two technologies. This logic leads to a more general result: if both revenues are proportional to the same parameters, then changes in that parameter do not affect the optimal decisions. The intuition for the second result is as follows: by proportionally increasing the revenue from the ps technology compared to pv technology, the firm is willing to consider it even if its viability ratio seems relatively lower than before. Similarly for the third case, if the revenue from the ps technology proportionally decreases, the firm is more reluctant to consider it. In fact, in this situation the firm needs more confidence to consider ps technology since its related revenue is decreased. Like the first case, we can generalize the results from the second the third cases: if both revenues are proportional to the same parameters, then increasing the ratio of that parameter in ps and pv technology will decrease the thresholds while decreasing that ratio will increase the thresholds.

The generalized results are very insightful. The payoff from both alternatives is proportional to parameters such as market size, market share and price. These parameters can be changed for both alternatives with similar or different ratios based on different market situations. In that sense, the proposition 2.5 gives us a useful method to investigate the optimal strategy.

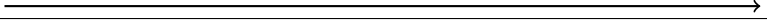
Proposition 2.6. *The optimal payoff will increase by changing the opportunity cost function for each stage review i from d_i to d'_i , if for every $n \leq N$ we have $\sum_{i=0}^n d'_i \leq \sum_{i=0}^n d_i$.*

Proposition 2.6 states that accumulating the opportunity cost to the end side of the product life cycle, increases the firm's revenue. In other words, shifting the opportunity cost toward the end of the product's life cycle provides more opportunity to the firm to research and develop new and prospective technologies with losing profit. In the opposite situation, when competitive products are already on the market and the opportunity cost is high or very high even at early stages of NPD, delaying the technology decision is very costly. In such situations firms usually find committing pv technology as an optimal solution.

2.5 Managerial Insights

The current practice of industry is to reject ps technology early in the product development cycle mainly to alleviate the uncertainty associated with such technology. However, our model clearly demonstrates that such a strategy should not be adopted early in the PD cycle as it's better to postpone the decision to a later stage where the decision to choose ps can be attractive. The expected revenue from ps technology can be significant, providing the company with the ability to be competitive in the marketplace and differentiate its products. It is obvious that by increasing the profitability of the ps technology or decreasing the chance of reversion (failure), the firm is more likely to consider the ps technology. Other factors that impact the firm's choice are the amount of initial investment and the relative difference between profitability of ps and pv technologies. Our model shows that lowering the amount of investment or widening the difference between profitability of ps and pv technologies will make the firm more willing to consider the ps technology. These are important considera-

Table 2.1: Optimal decisions on early and late NPD stages (Single Uncertain Technology)

Viability	Decision		
	Early Stages		Late Stages
High	Wait	Commit to ps	Commit to ps
Moderate	Wait	Wait	Reject ps
Low	Reject ps	Reject ps	Reject ps
Increasing Information 			

tions that should be made by product development organizations in deciding whether to take the risk and launch a ps rather than reverting to pv technology where potential profitability may be lower.

In our model, it is recommended that pursuing the ps technology is reversible for any reason. If the ps technology is not viable, the firm can revert to back up plan (pv technology) at any time during the PD process. We recognize that a company will incur development costs that are lost when reverting to pv but will mitigate the high investment cost for ps and potential marketplace failure. Considering ps technology does not necessary mean that the new product should be based on that technology. Basically our analytical results provide a framework for NPD sequential decision making process in order to identify the timing and conditions in which a ps technology should be considered. An Optimal strategy for decision making is depicted in Figure (2.6). The firm starts with an estimate of viability (v_0). Testing and gathering information causes it to move rightward, while favourable signals cause an upward shift and unfavourable signals cause a downward shift. The firm continues to test and collect more information as long as it remains in the waiting stage and rejects the ps technology by reaching into rejection area (Figure 2.6).

Table 2.1 summarizes some of the findings of the model. In early stages of NPD, rejecting or committing to ps technology may not be an optimal choice. By testing and increasing

information, if the viability for ps technology increases to or remains relatively high, the firm would prefer ps technology. But if in the firm's estimation the viability of ps the technology remains or becomes either low or moderate, the firm would finally have to reject ps technology.

The function D_n is a decreasing function and can be considered as a proportion of product life cycle demand that will be covered if the decision is made at time n . This helps us understand the impact of the life-cycle demand on the firm's technology decisions. For instance, any delay in the launch of the product would mean a proportional loss in demand and revenues. If, for example, the firm introduces the product n units of time into the life cycle, it would lose the proportion of gross revenues represented by $\sum_{i=0}^n d_i$.

Our results enable us to analyze different market situations and their impact on an optimal solution. The revenue from both alternatives is often proportional to the same parameters such as market size and market share. Our analysis provides an insight to investigate how changing different parameters for both alternatives one at a time or simultaneously could affect the firm's optimal choice.

If the product life cycle demand is relatively accumulated to the end side of the life cycle, it gives more chance for the ps technology to be considered. In that situation the waiting stage is relatively grater than the one in which the demand is mostly accumulated at the beginning of the life cycle. Intuitively if the firm is expecting more demand on early product life cycle, it would prefer to introduce the product with pv technology and less chance will be given to the ps technology. The opposite case is when the firm expects more demand will happen at the latter part of the product life cycle, when the firm feels more freedom to test new ideas and consider ps technology.

2.6 Conclusion

We modeled the technology selection problem in NPD as a sequential decision making problem. This model can be used by the management team deciding not only whether to consider a new technology but also to explore the timing of the decision. The decision can be postponed, and by delaying the decision, we can increase the precision of our estimation. However, delaying the decision is costly. Our model finds the optimal trade off between current precision and potential future information that may change the decision.

The proposed model is suitable for different sequential selection problems in NPD involving uncertainty such as concept selection, feature selection, etc. We made a number of assumptions that need to be relaxed in future work. First for the purpose of simplicity we assumed that only two alternative technologies are available: ps and pv . Having more than one uncertain technology will add to the complexity. Second, The penalty function D is assumed to be deterministic, which may not be the case in practice, especially when this function is representing the product life cycle demand.

CHAPTER 3. DUAL UNCERTAIN TECHNOLOGIES

3.1 Introduction

In the current business environment with the increasing attention on market leadership, new product development (NPD) plays a key role in creating and retaining competitive advantages for the firms. Rapid improvements in underlying technologies enable firms to develop new generations of products with higher performance. While offering higher performance, the unproven and uncertain nature of new technologies may increase product development cost and time. In such environments, it is crucial for firms to manage uncertainty and choose the right technology at the right time.

One of the key decisions made during the early stages of NPD is the selection of the right technology/architecture that offers the product its ability to perform at the level set in its specifications. The outcome provides a crucial input for subsequent downstream detail design and prototyping activities [Krishnan and Bhattacharya, 2002, Bhattacharya et al., 1998].

Frequently, the firm is faced with the choice of more than one technological option. It can either commit to any technology option or it can postpone this decision to the next stage. Deferring product technology decision may increase NPD cycle time and ultimately impose extra development cost and profit loss to the firm by shifting subsequent downstream design activities forward. However after finalizing product definition, any changes to the design would increase NPD cost and cycle time. To reduce the effects of design changes, sometimes it is recommended that specifications be frozen early in the development process

[Cooper, 2011]. However there are some studies in the literature such as [Krishnan and Bhattacharya, 2002, Bhattacharya et al., 1998] that discuss the effects of postponing the final product definition. Having the option to postpone the product definitions during the NPD process gives more flexibility to the PD team to deal with technology selection decision. In such an environment firms are constantly trying to make trade-offs between the pressure to introduce new products faster against the cost and performance [Cohen et al., 1996]. While delaying the introduction of new products allows development teams to incorporate improved technologies, it might also result in a significant loss of market opportunities Bhattacharya et al. [1998].

In such situations, the firm faces a challenging decision to make trade-offs between product performance and time-to-market under uncertainty. By postponing the technology decision and gathering more information from lab reports and field tests, technical uncertainty could be resolved or at least reduced and firms could get a clearer image about the viability of the new technology. This helps firms make better technology decisions; however, delaying such decisions in the NPD process may result in increased NPD cycle time, losing market share and significant profit loss. In this paper, after reviewing related literature in section 3.2, we propose a dynamic programming model for technology decisions in the NPD process in section 3.3 which is analyzed in section 3.4. Some managerial insights are proposed in section 3.5. Finally section 3.6 includes concluding remarks.

3.2 Literature Review

Many authors have examined the technology selection process during the last 3 decades. Moreover, this process is influenced by several evaluation factors. Different multi-attribute

decision making (MADM) methods have been applied and various techniques such as Analytical Hierarchy Process (AHP) [Chen et al., 2006, Hsu et al., 2010, Jiang et al., 2011], Analytical Network Process (ANP) [Kang et al., 2012, Mulebeke and Zheng, 2006], Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [Khalili-Damghani et al., 2012, Oztaysi, 2014], and Multi Attribute Utility Theory (MAUT) [Frank et al., 2013] have also been used.

In addition to multiple factors, the uncertainty involved in the technology selection problem imposes more complexity. In order to deal with the inherent uncertainty, many authors used "fuzzy logic" in combination with other techniques. Tavana et al. [2013] proposes a data envelopment analysis (DEA) model in which the vagueness of the objective functions is modeled by means of multi-objective fuzzy linear programming. The ambiguity of the input and output data is modeled using fuzzy sets. All these methods rely on a criteria evaluation process which is very subjective and strongly depends on expert opinion and intuition. Thus, if there is lack of visibility and traceability in the decision making process, the process is not effective. In addition, most of the research cited above ignored the impact of new information on technology decision. In other words they do not consider new information may become available throughout the process or it is possible to postpone the technology decision in order to gather more information. They assume -implicitly or explicitly- that the correct timing for the decision is known. Furthermore these techniques are not able to dynamically consider technology uncertainty and cost, time, and demand dynamics with their trade-offs.

Our research aligns with previous literature in technology uncertainty and information acquisition. McCardle [1985] modeled the technology adoption problem when its profitability was rarely known at the beginning. In his model, the firm is collecting sequential information

in order to estimate the profitability of the technology. Kornish and Keeney [2008] modeled annual influenza vaccine composition decision making as a dynamic decision problem in which the decision can be made now or postponed to gather more information which tightens the time for producing the vaccine. Krishnan and Bhattacharya [2002] studied a firm that must define its products in the presence of technology uncertainty. They consider single uncertain alternative at a time while in our model the outcome for all alternatives can be uncertain. In their work, product launch time is assumed to be known while in our model by considering a general opportunity cost function, we analyze the trade-off between development cost, time and risk.

Our research may seem related to the research stream on R&D project management using Real Options such as [Huchzermeier and Loch, 2001, Santiago and Vakili, 2005, Wang and Yang, 2012]. The main assumption is that managerial actions such as continue or stop investment on NPD projects can increase or decrease the performance of the project so by identifying the optimum managerial actions, the uncertainty can be managed. However, in this research we concentrate on identifying the conditions and timing to consider new technology for new product based on stream of new information.

Our research is also related to new product development cycle time and time-to-market literature. Cohen et al. [1996] investigated new product launch time and target performance level. They analyzed optimal time-to-market and its implied product performance targets. Although they considered exogenous factors such as the size of the potential market, the presence of existing and new products, profit margins and speed of product improvement, they did not consider new information which becomes available throughout the process.

3.3 Model Formulation

In this section we model the technology selection problem in NPD in presence of uncertainty as a sequential decision making problem. We focus on a firm that is aiming to develop a new product whose attractiveness to customers is due to its performance. The product's performance is highly dependent of its underlying *core technologies* (For example, in a portable computer, the core technologies include the microprocessor technology, battery technology, display technology, memory technology, etc.) Here we concentrate on selecting one core technology that most affects the attractiveness of a product or is its specific differentiating feature. There could be several technology alternatives available but for simplicity we consider two unproven technology alternatives denoted by $k = 1, 2$. However, our model and analysis can be extended to the case that there are more than two technologies.

The firm is not 100% confident about the outcome of both alternatives in terms of viability. There is a backup plan in case the technology fails: the design can revert to a proven viable outcome. It is assumed that introducing the product with original design can gain a higher payoff compared to the backup plan. By choosing alternative k , after investing initial investment of I^k , the firm will receive a payoff of M^k if the technology is viable, otherwise the design has to be reverted to the backup plan in which by incurring a reversion cost of F^k , the firm will gain a payoff of m_k . The initial investment is incurred after the firm decides to commit to a technology alternative.

For the product being considered, the PD process is being reviewed at discrete periodic intervals. The development team's estimate of viability for alternative k at review stage n is shown by parameter v_n^k . Expected profit from selecting alternative k at the review stage

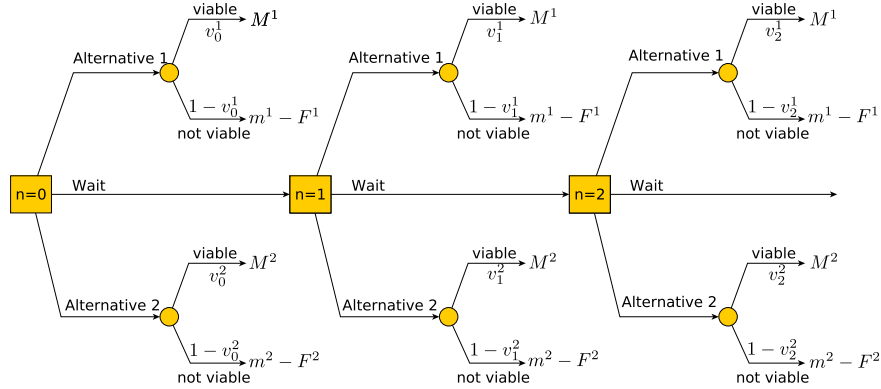


Figure 3.7: Decision Tree for Technology Selection Model.

At each review stage, the firm has three options: (i) commit to the first alternative and reject the other; (ii) commit to the second alternative and reject the first one; or (iii) postpone this decision to the next stage in order to acquire more information. In case of committing to each alternative, the outcome could be either viable or not. If it is not viable, the design has to be reverted to the backup plan.

n can be expressed by the following equations:

$$P_n^k = v_n^k \times M^k + (1 - v_n^k) \times (m - F^k) - I^k \quad (3.1)$$

Equation (3.1) shows that at each review stage n , by choosing alternative k , An initial investment of I has to be made and then the firm will get a payoff of M^k with probability of v_n^k . If the design fails with a probability of $1 - v_n^k$, by incurring a reversion cost of F^k , the firm will get payoff m^k from the backup plan.

At each review stage, the firm either decides to commit to any available alternatives or to postpone this decision to the next stage. Figure 3.7 shows the sequential decision making process of the described model.

Deferring the technology decision shifts all downstream design activities forward. This may result in increasing NPD cost and cycle time, which could lead to significant profit and market share loss. By postponing the decision at each stage n , firm incurs an opportunity cost

which is assumed to be a portion of product's expected profit. By making the commitment decision at each stage n the expected payoff is obtained by multiplying of profit to the ratio of D_n which can be expressed by equation (3.2) where d_i is the opportunity cost of delaying the decision at stage i and it is assumed to be a proportion of product's expected profit. D_n is a decreasing function in time and implies the fact that by postponing the commitment decision, payoff decreases because imposed opportunity cost.

$$D_n = 1 - \sum_{i=0}^n d_i \quad (3.2)$$

The firm cannot postpone the technology decision indefinitely as it will reach a point that the penalty of delaying the decision is equal to the profit of the NPD project. This fact is depicted by equation (3.3) where N is the latest possible review stage that the firm can still make a profit by postponing the decision. It implies that by delaying the technology decision, profit from both alternatives are decreasing and finally reach a point that becomes zero. The impact of the opportunity cost will be discussed with more details in section 3.4.

$$\sum_{i=0}^N d_i = 1 \quad (3.3)$$

D_n can be interpreted as the portion of the total profit that the firm can obtain if the decision is postponed by until stage n . The expected payoff of choosing alternative k at the review stage n can be expressed as equation (3.4).

$$\pi_n^k = P_n^k \times D_n \quad (3.4)$$

In equation (3.4) we consider the same opportunity cost function for both alternatives. The impact of having different opportunity cost functions will be discussed in section 3.4.

At each review stage, the firm can benefit from the real time information available regarding the viability of the alternatives from laboratory and field tests. We assume that the firm starts with a prior estimate of v_n^k for the viability of each alternative k and updates this prior estimate by receiving signals from the field tests in a Bayesian manner. It is common in the literature to assume that the prior and posterior distribution from conjugate distributions [Krishnan and Bhattacharya, 2002, McCardle, 1985]. Considering the nature of the parameters, similar to Krishnan and Bhattacharya [2002] we assumed that the prior estimate of viability follows *Beta* distribution (between 0 and 1 with parameters α^k and β^k for each alternative k), and signals are from *Binomial* distribution. A favorable (unfavorable) signal indicates success (failure) of the technology during testing. At each review stage $n + 1$, the viability of alternative k , v_{n+1}^k , can be estimated by having viability of the previous period v_n^k as follows:

$$v_{n+1}^k = \frac{(\alpha^k + \beta^k + \sum_{i=0}^{n-1} S_i^k)v_n^k + S_n^{k+}}{\alpha^k + \beta^k + \sum_{i=0}^n S_i^k} \quad (3.5)$$

Where s_i^{k+} and s_i^k indicate the number of positive signals and total number of signals received at review stage i for alternative k .

It is assumed that the firm is risk averse and decides based on expected value of profit. Meaning that at each review stage, firm will commit the most profitable alternative or continue gathering information and postpone the decision to the next review :

$$R_n(v_n^1, v_n^2) = \max \begin{cases} \pi_n^1(v_n^1) & \text{Alternative 1} \\ \pi_n^2(v_n^2) & \text{Alternative 2} \\ E[R_{n+1}(v_{n+1}^1, v_{n+1}^2) | v_n^1, v_n^2, s_{n+1}^1, s_{n+1}^2] & \text{Wait} \end{cases} \quad (3.6)$$

In equation 3.6, R_n represents the optimal payoff from committing to optimal solution where v_n^1, v_n^2 are respectively the viability estimates of alternative 1 and 2 and s_n^1, s_n^2 are respectively the number of received signals from testing alternative 1 and 2.

Payoff at review stage N will be zero and directly results from the equation (3.3). This is depicted in equation (3.7):

$$R_N(V_N) = 0 \quad (3.7)$$

Note that this boundary condition implies that launching product after a certain deadline has no value. Expected value of postponing the decision by next stage can be obtained by equation 3.8 where s_{n+1}^{1+} and s_{n+1}^{2+} respectively represent the number of positive signals for alternatives 1 and 2 at next review stage.

$$E[R_{n+1}(v_{n+1}^1, v_{n+1}^2) | v_n^1, v_n^2, s_{n+1}^1, s_{n+1}^2] = \sum_{s_{n+1}^{1+}=0}^{s_{n+1}^1} \sum_{s_{n+1}^{2+}=0}^{s_{n+1}^2} p(s_{n+1}^{1+}, s_{n+1}^{2+} | v_n^1, v_n^2, s_{n+1}^1, s_{n+1}^2) \times R_{n+1}(v_{n+1}^1, v_{n+1}^2 | v_n^1, v_n^2, s_{n+1}^1, s_{n+1}^2, s_{n+1}^{1+}, s_{n+1}^{2+}) \quad (3.8)$$

where the probability part can be rewritten as:

$$p(s_{n+1}^{1+}, s_{n+1}^{2+} | v_n^1, v_n^2, s_{n+1}^1, s_{n+1}^2) = \begin{aligned} & \binom{s_{n+1}^1}{s_{n+1}^{1+}} (v_n)^{s_{n+1}^{1+}} (1 - v_n)^{(s_{n+1}^1 - s_{n+1}^{1+})} \\ & \times \binom{s_{n+1}^2}{s_{n+1}^{2+}} (v_n)^{s_{n+1}^{2+}} (1 - v_n)^{(s_{n+1}^2 - s_{n+1}^{2+})} \end{aligned} \quad (3.9)$$

By having equations (3.6 - 3.9), we can formulate the technology selection problem as sequential stochastic dynamic programming. The dynamic programming equation for the optimal value is the maximum of the values of the three possible choices: commit to one of the alternatives and reject the other alternative or defer the decision until the next period then choose optimally.

3.4 Model Analysis

In this section we will investigate the optimal conditions under which the firm would select each choice and obtain some general properties of the technology selection model described in previous section. For readability and continuity, proofs are proposed in appendix.

3.4.1 Threshold Policies

At each time period, the firm has three options: (i) Select technology 1; (ii) Select technology 2 or (iii) to postpone the technology decision to the next stage. In this section we will investigate the optimal conditions under which the firm would select each choice.

Lemma 3.1. *The expected profit at next review stage is equal to the current estimate of profit.*

Lemma 3.1 implies the fact that on average there are no anticipated changes on our estimation of profitability in the next stage. Note that forecast of revenue at current stage is

not necessarily equal to that of previous stage, however on average it would be equal to. At each stage all available information incorporated in current forecast which includes previous forecast plus the information that has been received since last review stage.

Proposition 3.1. *If $\sum_{i=0}^n d_i = 0$, for every review stage $i \leq n$ it is optimal to delay technology decision by review stage n .*

Proposition 3.1 states that as long as there is no opportunity cost, it is optimal to delay the decision. This implies the fact that having an option to choose between alternatives which provide more value and flexibility without paying extra cost is always better than the case that there is no option. In such situations it seems rational to keep this option as long as possible. Intuitively the firm would not commit to any alternative unless it is confident about its profitability; otherwise, the firm will prefer to postpone this decision at least to the next stage. By delaying the decision, firm hopes that the uncertainty will resolve by receiving more information, but this also imposes an opportunity cost to the firm. In a sense while we do not incur any cost, it seems reasonable to delay our decision as much as possible in a hope to get a better estimation of the profit at the next stages in order to increase chance of selecting the best technology. This implies that it is optimal to delay technology decision as long as there is no cost for doing so.

Intuitively we expect that favorable or unfavorable news tends to persist in the next stage. This fact is stated in Lemma 3.2 which indicates that the higher forecast in current stage implies higher forecast at the next stage.

Lemma 3.2. *Next stage expected profit is increasing in current estimate of profit.*

By increasing v_n^k we expect that profitability of the technology will increase. The higher

possibility of success, the higher expected revenue. This fact is stated in Lemma 3.3.

Lemma 3.3. *The Expected profit is increasing in previous estimate of viability.*

Lemma 3.3 implies that by increasing current estimate of profitability we expect it would increase at next stage. It relies on the fact on every stage we update our estimation of viability based on Bayesian manner in which the probability of receiving a positive signal at next stage is equal to our estimation of viability at current stage. Note that although at each stage, the expected value of next stage is equal to estimation of current stage. However, after realizing the signal, depending on whether it is positive or negative, the realized estimation of the next stage will be different.

At each stage, the firm will not postpone the decision unless it is possible that new information will be received later to alter the decision. In fact at each decision stage, the firm is seeking a balance between confidence and opportunity cost. It is obvious: Why pay the penalty to delay the decision to receive the information which will not change the outcome? Equation 3.6 reveals under the optimal strategy, in order to postpone the decision, firm's estimate must be able to crossover the break-even point, either from alternative 1 to 2 or vice-verse. In other words, we will not choose to wait unless the new information could cause a crossover or move the estimate to the next waiting stage. If the firm sees that the benefit from collecting information is less than its cost, it will decide to stop and make technology commitment choice. Once the decision to stop is made, the firm will commit to the most profitable technology.

For a dynamic program of equations (3.6 - 3.8), similar to Kornish and Keeney [2008] and McCardle [1985], we can identify optimal solution at time n for every settings of P_n^1 and

P_n^2 . These actions can be shown by three regions; for each point inside each region, different optimal action is required. Proposition 3.2 states the existence of such regions and their boundaries formally.

Proposition 3.2. *At each review stage n , for every P_n^2 , there exist a pair of numbers \underline{P}_n^1 and \bar{P}_n^1 ($\underline{P}_n^1 \leq \bar{P}_n^1$) such that if $\underline{P}_n^1 \leq P_n^1 \leq \bar{P}_n^1$, it is optimal to continue. If $P_n^1 \geq \bar{P}_n^1$ it is optimal to select technology 1. If $P_n^1 \leq \underline{P}_n^1$ is optimal to select technology 2.*

Proposition 3.2 shows that at period n for any value of P_n^2 there exists two thresholds for P_n^1 , such that if P_n^1 is less than lower threshold \underline{P}_n^1 , it is optimal to choose technology 2. If P_n^1 lies between two thresholds, $\underline{P}_n^1 \leq P_n^1 \leq \bar{P}_n^1$ it is optimal to continue collecting more information and delay the technology decision. Finally having $P_n^1 > \bar{P}_n^1$ give sufficient condition that selecting technology 1 would be optimal.

Thresholds described in proposition 3.2 are increasing by in P_n^2 . This fact is stated in proposition 3.3.

Proposition 3.3. *Thresholds \underline{P}_n^1 and \bar{P}_n^1 are increasing in P_n^2*

Figure 3.8 shows a two-dimensional representation of the optimal solution for a review stage n . The solution has a threshold structure that depends on the relative levels of P_n^1 and P_n^2 . If one had to commit to either technology 1 or technology 2, the optimal strategy would be select technology 1 if P_n^1 is high enough than P_n^2 and vice versa. If the values of the P_n^1 and P_n^2 are relatively close so that none of them can be preferred in a sense that there is a possibility that next information can change the outcome in favor of the other alternative, it would be optimal to postpone the decision. The threshold for “high enough” of P_n^1 (P_n^2) is an increasing function of P_n^2 (P_n^1).

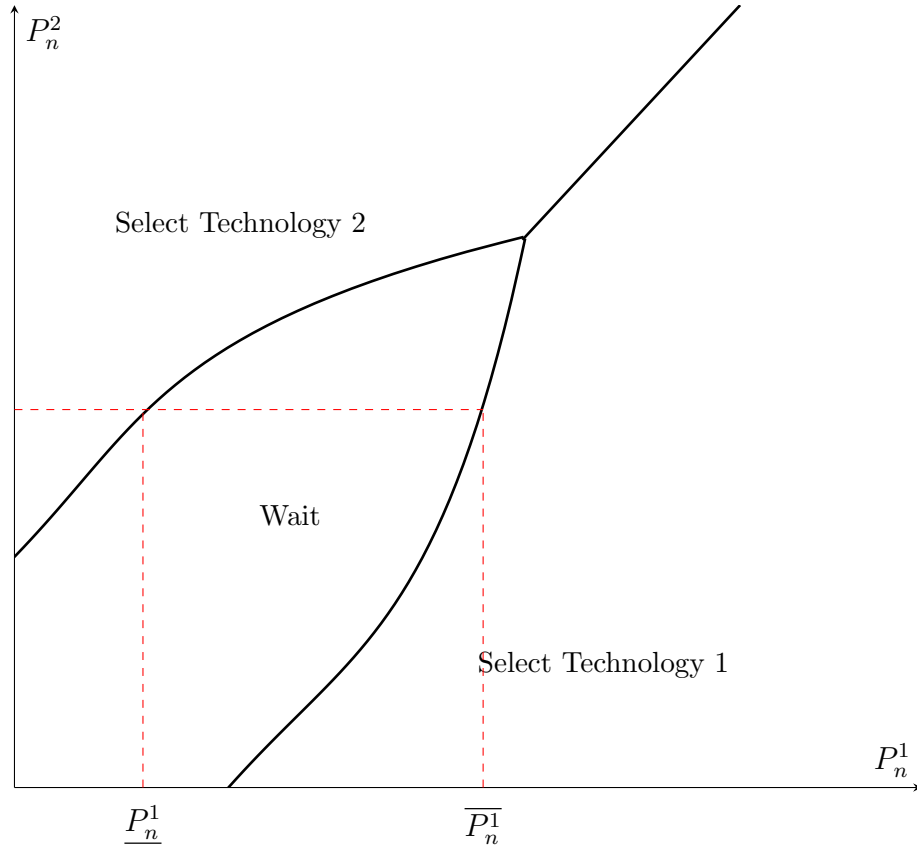


Figure 3.8: Two dimensional representation of optimal decision region at review stage n . Optimal regions for selecting technology 1, technology 2 and waiting area at stage review n : If the relative levels of payoff are low and close to each other, it is optimal to wait. If the expected payoff from technology 1 is relatively higher than expected payoff of the technology 2, firm will choose technology 1 and vice versa.

Proposition 3.4. *The expected value of the waiting is non-increasing in n .*

As a result of this proposition 3.4, we can conclude that waiting area is shrinking as n increases. It seems intuitive that the firm will not continue collecting information indefinitely and finally will decide at a certain point before the deadline so the waiting stage decreases over the time. This fact is shown in figure 3.9.

3.4.2 Changing Profitability

In this section we investigate how relatively changing opportunity cost and other parameters of profitability would affect technology choice.

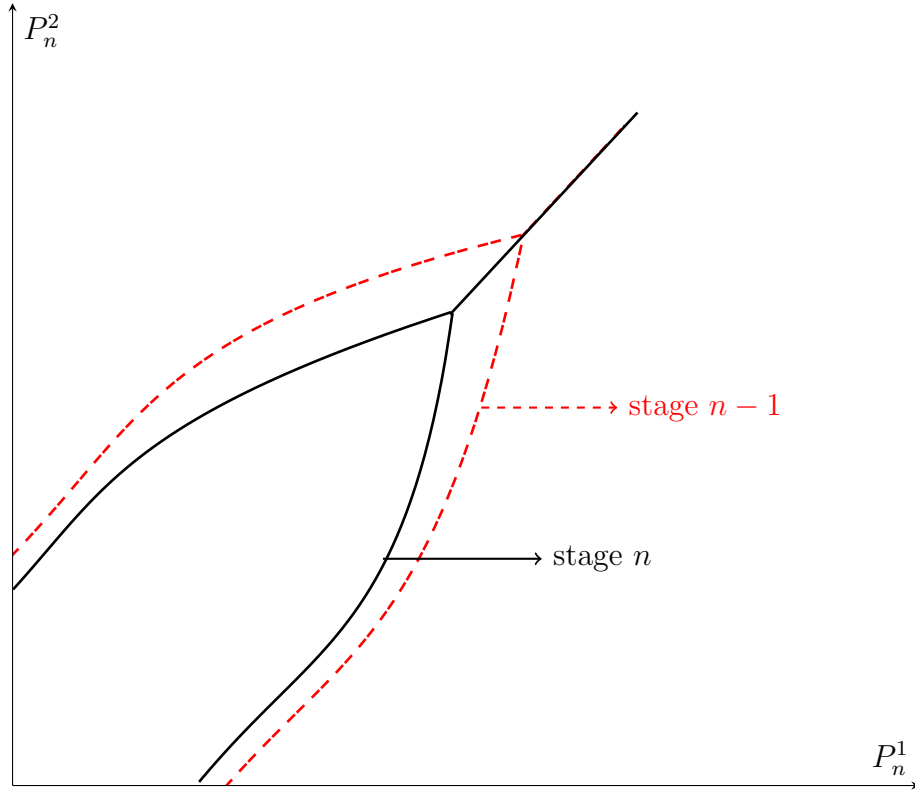


Figure 3.9: Comparing of optimal decision regions at review stage n and $n - 1$
Optimal regions for waiting is shrinking by increasing n .

Proposition 3.5. For each review period n , by multiplying payoff from technology 1 and technology 2 by a_1 and a_1 respectively, the thresholds \underline{P}_n^1 and \overline{P}_n^1

- will not change if $a_2 = a_1$;
- will decrease if $a_2 < a_1$;
- will increase if $a_2 > a_1$

Proposition 3.5 describes the optimal strategy by changing the payoffs for all review stages. The first part essentially says that a can be canceled out in the comparisons. Also, such a change does not affect the balance between the commit, reject and wait strategies because ultimately the wait strategy depends on the relative attractiveness of the two tech-

nologies. This logic leads to a more general result: if both payoffs are proportional to the same parameters, then changes in that parameter do not affect the optimal decisions. The intuition for the second result is as follows: by proportionally increasing the payoff from the second technology compared to first one, the firm is more willing to consider the second technology even if its viability ratio seems relatively lower than before. Similarly for the third case, if the payoff from the second technology proportionally decreases, the firm will be more reluctant to consider it. In fact, in this situation firm needs more confidence to consider first technology since its related payoff is decreased. The profit from technology 1 has to be relatively higher in order to be considered by the firm. Similar to the first case, we can generalize the results from the second and the third cases: if both payoffs are proportional to the same parameters, then increasing that parameter in one of the technologies will increase the thresholds of profitability for the other one.

The generalized results are very insightful. The payoff from both alternatives is proportional to parameters such as market size, market share and price. These parameters can be changed for both alternatives with same or different ratios based on different market situations. In that sense, proposition 3.5 give us a useful to investigate the optimal strategy. Figure 3.10 shows how optimal strategy can be affected by altering such parameters.

Proposition 3.6. *The optimal payoff will increase by changing the opportunity cost function for each stage review i from d_i to d'_i , if for every $n \leq N$ we have $\sum_{i=0}^n d'_i \leq \sum_{i=0}^n d_i$.*

Proposition 3.6 states that accumulating the opportunity cost to the end stage of the product life cycle, increases firm's revenue. In other words, shifting the opportunity cost toward the end of the product's life cycle provides more opportunity to the firm to research and

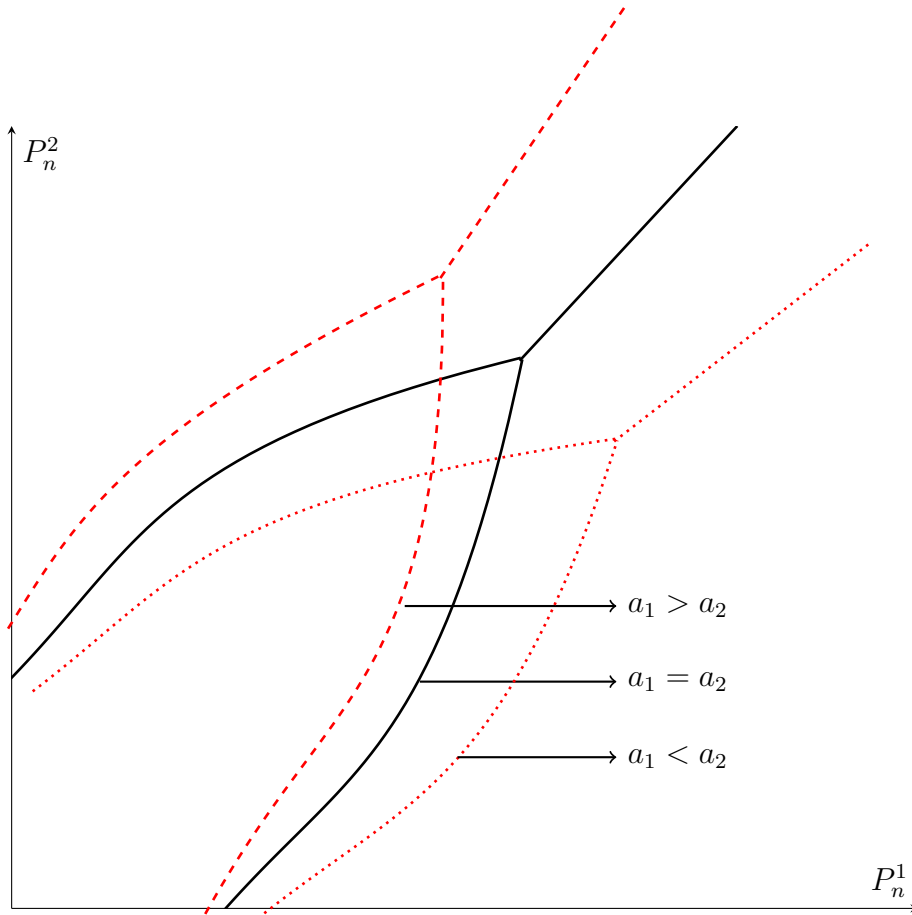


Figure 3.10: Effects of changing profit from each technology on optimal choice
 By multiplying revenue from technology 1 and technology 2 by a_1 and a_2 respectively, the thresholds \underline{P}_n^1 and \overline{P}_n^1 will not change if $a_1 = a_2$; will increase if $a_2 > a_1$ and will decrease if $a_2 < a_1$.

develop new and prospective technologies without losing profit. Conversely, when competitive products are already on the market and opportunity cost is high or very high, delaying the technology decision is very costly even at early stages of NPD.

3.4.3 Single Unproven Technology

We analyzed the technology selection model when the firm has to choose between two unproven alternatives. A special case of this problem is when the firm is facing only one new unproven technology and a backup plan. In such situations, PD team is trying to answer whether to commit to the new technology or to reject it. In this all lemmas and proposition

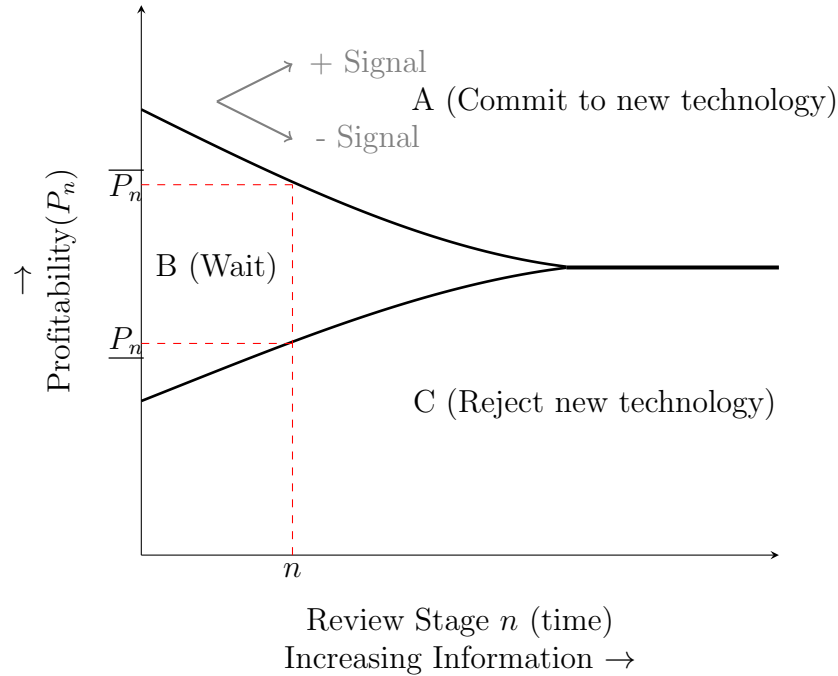


Figure 3.11: Illustration of optimal policy regions in single new technology settings
 Commit, Reject and Wait Regions; Firm starts with profitability estimation of P_0 at the beginning. It moves forward by testing and gathering more information during the time. Receiving positive signals cause an increase in estimation of profitability while receiving negative signals causes a decrease in that which causes moving up or down respectively. As long as we stay at the waiting stage, it is optimal to postpone the technology decision. However, once we pass the upper threshold, it would be optimal to commit to the new technology. Firm would reject the new technology if estimation enters rejection region.

stated earlier will still be valid with only difference that we reduced one dimension of uncertainty. Figure 3.11 shows the threshold policy in such situation. After choosing among competing unproven technologies, analysis can be followed for the remaining technology in single technology settings.

3.5 Managerial Insights

Our analytical results provide a framework for the NPD sequential decision making process in order to identify the timing and conditions in new, prospective technology should be considered. Optimal strategy for decision making at each stage is depicted in figure (3.8).

The firm starts with an estimate of profitability for each technology alternative. If the

Table 3.2: Optimal decisions on early and late NPD stages (Dual Uncertain Technologies)

Profitability		Decision	
T1	T2	Early Stages	Late Stages
Low	Low	Reject both	Reject both
Low	Medium	Wait	Reject T1 Continue analysis with T2
Low	High	Reject T1 Continue analysis with T2	Reject T1
Medium	Low	Wait	Reject T2 Continue analysis with T1
Medium	Medium	Wait	Reject the lower one Continue analysis with the other
Medium	High	Wait	Reject T1
High	Low	Wait	Reject T2
High	Medium	Wait	Reject T2
High	High	Wait	Reject the lower one Continue analysis with the other

relative levels of profitability are low and close to each other inside the waiting area, it is optimal to wait. If the profitability of each alternative is relatively higher than the other one and fits in the selection area, that technology will be selected. In order to select optimally, the same approach will continue at next stage in which the waiting area will be shrunk (figure 3.9). If any technology alternative is selected, the analysis will be continued to commit or reject that technology (figure 3.11).

Table 3.2 summarize some of the finding of the model. In early stages of NPD, rejecting or committing the technology may not be an optimal choice unless the profitability is too low. By testing and increasing information, if the profitability of the technology increases or remains relatively high, firm would prefer to consider that technology. But if in firm's estimation the profitability remains or becomes either low or moderate, firm would ultimately have to reject that technology. By rejecting one alternative, analysis will continue on to the remaining alternatives, to decide either to commit to that technology or choose the backup plan.

The current practice of industry is to reject unproven technology early in the product development cycle mainly to alleviate the uncertainty associated with such technology. However, our model clearly demonstrates that such a strategy should not be adopted early in the PD cycle and it is better to postpone the decision to a later stage when enough information has been collected. At that point, the decision to choose new technology could have a significant payoff due to the company's ability to be competitive in the marketplace by differentiating its products.

It is obvious that by increasing the profitability of the technology or decreasing the chance of reversion (failure), the firm is more likely to consider that technology. Other factors that impact the firm's choice are the amount of initial investment and the relative difference between profitability of two technologies. Our model shows that lowering the amount of investment or increasing the difference between profitability of two technologies will make firm more willing to consider the technology with the payoff relatively higher than the other one. After rejecting one of two unproven technologies, the remaining one can be analyzed in single technology settings mentioned in section 3.4.3. In that situation, the difference between profitability of the technology and its backup plan and the initial investment would also be important considerations made by product development teams in deciding whether to take the risk and launch the new product with new technology rather than rejecting it where potential profitability can be lower.

In our model, it is recommended that pursuing the unproven technology is reversible, for any reason. If the technology is not viable, the firm can revert to back up plan (proven technology) at any time during the PD process. We recognize that a company will incur development costs that are lost when reverting to the proven technology but will mitigate the

high investment cost and potential marketplace failure. Considering unproven technology does not necessary mean that the new product should be based on that technology.

The function D_n is a decreasing function and can be considered as proportion of product life cycle demand that will be covered if the decision is made at time n . This helps us understand the impact of the life-cycle demand on the firm's technology decisions. For instance, any delay in the launch of the product would mean a proportional loss in demand and payoffs. If, for example, the firm introduces the product n units of time into the life cycle, it would lose the proportion of gross payoffs represented by $\sum_{i=0}^n d_i$.

Our results enable us to analyze different market situation's impact on optimal solutions. The revenue from both alternatives is often proportional to same parameters such as market size and market share. Our analysis provides an insight to investigate how changing different parameters for both alternatives one at a time or simultaneously could affect the firm's optimal choice.

If the product life cycle demand is relatively accumulated to the end side of the life cycle, it gives more chance to the unproven technology to be considered. In that situation the waiting stage is relatively greater than the one in which the demand is mostly accumulated to the beginning of the life cycle. Intuitively if the firm is expecting more demand early in the product life cycle, it would prefer to introduce the product with proven technology and less opportunity will be given to the unproven technology. The opposite case is when the firm expects more demand will happen later during the product life cycle, so the firm feels more freedom to test new ideas and consider unproven technology.

3.6 Conclusions

We modeled the technology selection problem in NPD as a sequential decision making problem. This model can be used by the management facing the decision of not only whether or not consider a new technology but also the timing of the decision. The decision can be postponed, and by delaying the decision we can increase the precision of our estimation. However, delaying the decision is costly. Our model finds the optimal trade off between current precision and potential future information that may change our decision.

The proposed model is suitable for different sequential selection problems in NPD involving uncertainty such as concept selection, feature selection, etc. For future work, some of the assumptions that we made can be relaxed such as the penalty function D assumed to be determined, which may not be the case in practice especially when this function is representing the product life cycle demand.

CHAPTER 4. TECHNOLOGY AND MARKET UNCERTAINTY

4.1 Introduction

New product development plays a crucial role in creating and retaining competitive advantages for the firms. Companies can achieve competitive advantage through superior manufacturing, but sustaining a competitive advantage over time requires developing new products and processes [Terziovski and Sohal, 2000]. NPD processes face many uncertainties from different sources. Two major sources of uncertainty are technical and market uncertainty.

Enhancing new products with new prospective technologies might enable the firms to develop more attractive products with higher performance per cost ratio in order to keep ahead of competitors and retain a desirable market share. New underlying technologies usually offer higher performance or less manufacturing cost, leading to an increase in product market share and profit margin. New prospective technologies may offer higher levels of flexibility to launch different generations of the product in responding to the market demand changes during the product life cycle. This flexibility is more valuable when future demand and customer needs are uncertain and subject to significant changes, especially if the product development process suffers from long delays [Hommes and Renzi, 2014].

Technology selection is considered during very early stages of the product development in which the specifications of the new product are defined based on customer, company, market and functional viewpoints. The outcome gives a vital input for all subsequent downstream design and prototyping activities [Krishnan and Bhattacharya, 2002]. Once the product

specifications are finalized and technology decisions are made, further changes impose a substantial increase in development cycle time and cost depending on the contribution and interaction of the technology to the whole design. To minimize the effects of design changes, it is often recommended that specifications including technology decisions be frozen early in NPD process [Cooper, 2011]. However there are some studies that discuss postponement of finalizing product specification and definition which provide more flexibility for the PD team to deal with technological and market uncertainty [Bhattacharya et al., 1998]. By delaying the technology decision, the more time spent on new technology validation, the more data can be collected, and more accurately the outcome of the new technology can be predicted. Although this precision provides more confidence for the firm in reducing risk of making improper decisions and, therefore, increases expected profit, postponing the technology decisions may lead to defer downstream activities which can result in delays in time to market and significant profit loss.

Another major source of the uncertainty in NPD is market uncertainty. Market demand and structure are not precisely known at the early stages of product development and firm has to rely on forecast that may prove to be completely inaccurate at the later stages of the product life cycle. In order to develop a successful product, PD team should be able to reduce the impact of such uncertainties by incorporating proper techniques. Due to critical impact of early product development decisions on all downstream activities, such techniques should be considered very early in the product development process.

This research proposes a framework to manage the new product technology decisions in order to incorporate managerial flexibility into NPD projects to decrease technical and market risks, while increasing potential market value. In our framework, the outcome of the

new technology is uncertain in terms of viability. At each review stage, management has the option to either commit to any available alternative or to postpone this decision to the next review stage. Postponing the technology decision provides more opportunity to acquire more information that helps to resolve the uncertainty regarding the outcome of the new technology. However, it may simultaneously cause increasing product development cost and cycle time and consequently significant profit loss. In proposed model, a Bayesian manner is used to update firm's perception for the technology's viability based on received information on each review stage. The Monte Carlo simulation is used to evaluate the market uncertainty. An illustrative example is presented to choose the battery pack control system in hybrid and electric vehicles.

The remainder of this paper is divided into the following sections. After reviewing related literature in section 4.2 , the assumptions and theoretical basis of the model as well as some of its properties are given in section 4.3. The proposed framework to analyze technology decisions in NPD process is presented in section 4.4 . An illustrative example is presented in section 4.5 to choose the battery pack control system in hybrid and electric vehicles. Some managerial insights and conclusion are included in the final section.

4.2 Literature Review

In the last decade, technology selection problem has attracted much attention in the literature. Since several criteria impact this problem, researchers often considered it as a Multi-Criteria Decision Making (MCDM) problem and applied variety of MCDM techniques to deal with it. Kim et al. [2010] developed a method based on Analytical Hierarchy Process (AHP) technique to prioritize emerging technologies. Hsu et al. [2010] presented a 2-step

model based on AHP in which at the first stage the Fuzzy Delphi Method is used to obtain the critical factors of the technology by interviewing experts. Then in the second stage, the Fuzzy AHP is applied to find the importance weight of each criterion as the measurable indices of the technologies. Farooq and O'Brien [2012] described a framework for manufacturing technology selection using AHP and Strategic Assessment Model to integrate supply chain into decision making process. Jiang et al. [2011] presented a framework for re-manufacturing technology portfolio selection based on AHP. Chuang et al. [2009] discussed an operational strategy for the selection of a new production technology that integrates the market trends, competitive and operational strategies, as well as manufacturing attributes by using Quality Function Deployment (QFD) method. Kang et al. [2012] developed an hybrid model based on fuzzy ANP to evaluate available technologies for NPD.

Several publications have proposed using optimization techniques to deal with this problem. Khouja [1995] applied Data Envelopment Analysis (DEA) as the first step of a 2-step model to identify the technology with the best performance. Then a multi-attribute decision making (MADM) method was used in the second phase to select the best technology. The proposed model is illustrated using robot selection. Later, Baker and Talluri [1997] discussed the methodology proposed by Khouja [1995] and suggested a more robust analysis based on the cross-efficiencies in DEA.

Although many tools and methods have been developed to address the technology selection problem, most of the previous studies do not consider technical uncertainty. In these models it is usually assumed (implicitly or explicitly) that all needed data is available at the time of the technology decision. The design evaluation process, which is very common in NPD process, is often ignored. In that sense, decisions cannot be dynamically adapted

as new information is available. The main drawback of previously proposed models is that they ignored the impact of time in their decision making process. Decision timing has several impacts in technology selection problem. By postponing the decision making, the firm can get more information, which results in making better decisions with less uncertainty. However since technology selection lies on critical path of NPD projects, any delay in that may cause delay in downstream activities and finally a delay in launch and market loss. Generally, proposed models often are unable to effectively quantify and take into account trade-offs between crucial technology selection factors such as uncertainty, cost, time to market, performance and market demand.

The most interesting approach to this problem has been proposed by Krishnan and Bhattacharya [2002] . They investigated the technology selection problem under the uncertainty. To minimize the impact of uncertainty, they pursued parallel paths that allowed the firm to concurrently develop its products while the technology was being validated. They obtained a threshold for uncertainty and showed that this threshold was impacted by product development cost and demand dynamics. However, their model is unable to consider demand and market uncertainty. Bhaskaran and Ramachandran [2011] developed a model to study technology selection problem in the presence of a strategic competitor and investment decisions regarding new products. They mainly concentrated on competitor's impact on new product's technology choice.

Our research is related to previous studies dealing with the time to market in the literature. Cohen et al. [1996] investigated new product launch time and target performance level by using a logit model to capture consumer behavior in a competitive market. In their model, a single launch environment and two-stage product development process (product de-

sign and development process) were assumed. They indicated how optimal time-to-market and its implied product performance targets vary with exogenous factors such as the size of the potential market, the presence of existing and new products, profit margins, the length of the window of opportunity, the firm's speed of product improvement, and competitor's product performance.

Our research is also relevant to previous works on the information acquisition literature. Although the basics of our model for acquisition of information is similar to McCardle [1985] and Ulu and Smith [2009], we developed and modified our model in NPD environment with specific attention to life cycle demand uncertainty.

4.3 Model Conceptualization and Formulation

We focus on technology selection problem during the early stages of the NPD process in a firm that is facing multiple technology alternatives to develop its new product. Technology alternatives may vary in confidence and readiness level. In particular, two types: proven and prospective technologies are available. Proven technology (*pv*) has been used in previous products or systems ($TRL^* = 9$) which the firm has 100 % confidence in its reliability and success. On the other hand, prospective technology has not been employed in any other product or similar system previously ($TRL < 9$) and there is a chance that the design will fail because of reliability issues. However prospective technology (*ps*) potentially offers higher levels of performance and flexibility for possible product generations and promises a higher payoff during the product life cycle with the amount of this payoff depending on the market situation.

*Technology Readiness Levels (TRL) are a method of estimating technology maturity. TRL are based on a scale from 1 to 9 with 9 being the most mature technology [Technology readiness level, 2015].

It is assumed that selected technology has a vital impact on product performance and life cycle demand as well as product design and, consequently, all downstream PD activities. In such situations technology selection task lies in critical path of the NPD process where completion of all detailed design activities relies on it. By employing ps in the product, the firm can gain higher profit compare to pv . If the firm commits to pv , it will gain a profit of m . However by employing ps alternative, firm can gain a higher profit of $M > m$ if the design turns out to be viable. Otherwise the firm has to revert the design to employ pv and will incur a reversion cost of F .

4.3.1 Validating Process

Design is periodically being reviewed at discrete time intervals and the PD team estimates the viability of ps alternative. At each review stage n we define the viability estimate by v_n . At each review stage, the firm has the option to commit to either alternative or postpone this decision to the next review stage. Figure 4.12 illustrates the sequential decision making process of the described selection model. At each stage n , the firm spends a continuation cost of c_n to continue collecting more information and postpones the decision to the next. Furthermore, firm incurs an additional development cost of d_n in order to continue development of the ps alternative at each stage n .

We show the expected payoff from committing to pv and ps alternatives at review stage n respectively by π_n^{pv} and π_n^{ps} as following equations:

$$\pi_n^{pv} = m - C_n \tag{4.1}$$

$$\pi_n^{ps}(v_n) = v_n M + (1 - v_n)(m - F) - C_n - D_n \quad (4.2)$$

Equation 4.1 express that payoff from pv is not variant to v_n . In equation 4.1, C_n represents the accumulated continuation cost that is imposed until stage n and is expressed in equation 4.3. Equation 4.2 states the fact that expected payoff from ps alternative is a function of v_n . Firm can gain profit of M if ps is viable with probability of v_n . If the design is not viable, with probability of $(1 - v_n)$, by reverting the design to pv and incurring reversion cost of F gains a profit of $(m - F)$.

$$C_n = \sum_{i=0}^n c_i \quad (4.3)$$

By setting $\pi_n^{ps}(v_n) \geq \pi_n^{pv}$ we can obtain a break-even point v_{thr} to consider ps alternative as follows:

$$v_n \geq v^{thr} = \frac{F}{M - m + F} \quad (4.4)$$

While the equation 4.4 is neither necessary nor sufficient for the firm to consider the ps technology, it could be argued that a rational firm will give serious consideration to the ps technology when its expected profit exceeds profit from pv technology [Krishnan and Bhattacharya, 2002]. In that sense, the above equation can be considered as proxy for "*threshold*" value of viability above which the ps technology is likely to be considered. Necessary and sufficient conditions depend on subsequent information received and will be modeled later.

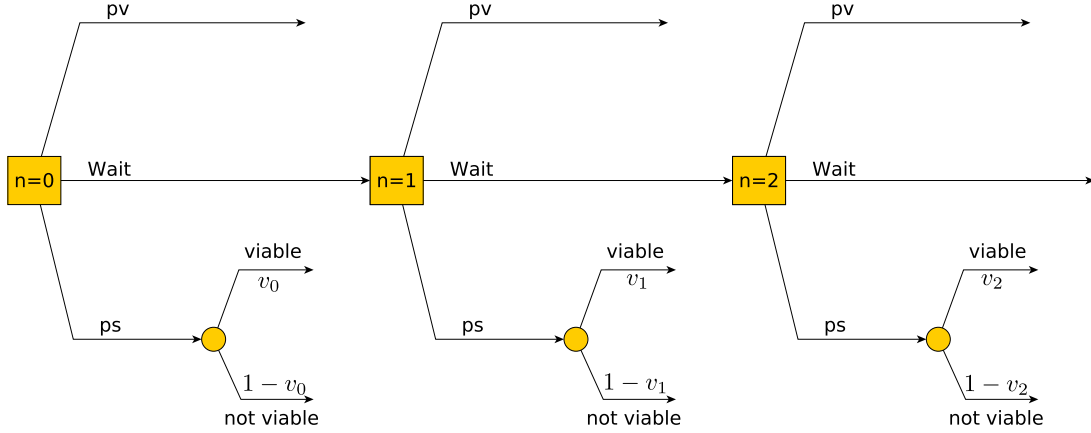


Figure 4.12: Decision Tree for Technology Selection Model.

At each review stage, firm has three options: **(i)** reject the *ps* technology; **(ii)** commit to the *ps* technology; **(iii)** and postpone this decision to the next stage. In case of committing to *ps* technology, the outcome could be either viable or not. If it is not viable, the design has to be reverted to *pv* technology.

4.3.2 Learning Process

PD team can benefit from the real time information available regarding the viability estimation of the *ps* from laboratory and field tests. We assume that the firm starts with a prior estimate for viability of *ps* technology and updates this estimate by receiving signals in a Bayesian manner. It is common in the literature to assume the prior and posterior distribution from conjugate distributions [Krishnan and Bhattacharya, 2002, McCardle, 1985]. Considering the nature of the parameters, similar to Krishnan and Bhattacharya [2002] we assumed that the prior estimate of viability of *ps* technology follows *Beta* distribution (between 0 and 1 with parameters α and β), and signals are 1 and 0. A favorable (unfavorable) signal indicates success (failure) of the technology in the testings. At each review stage $n + 1$, the viability of *ps* technology, v_{n+1} , can be estimated by having viability of the previous period v_n as follows:

$$v_{n+1} = \frac{(\alpha + \beta + n)v_n + s}{\alpha + \beta + n + 1} \quad (4.5)$$

Where $s = 1$ and $s = 0$ indicate receiving positive (favorable) and negative (unfavorable) signals respectively at review stage i .

It is assumed that the firm is risk averse and decides based on expected value of profit. At each review stage, firm will commit the most profitable alternative and either select between pv or ps technology, or will wait and continue gathering information and postpone the decision if the expected payoff of at next stage is higher :

$$R_n(v_n) = \max \begin{cases} \pi_n^{pv} & \text{Select } pv \\ \pi_n^{ps}(v_n) & \text{Select } ps \\ E[R_{n+1}] & \text{Wait} \end{cases} \quad (4.6)$$

Expected value of payoff at next stage or in another words expected value of waiting can be obtained by following equation:

$$E[R_{n+1}] = v_n R_{n+1}(v_n^+) + (1 - v_n) R_{n+1}(v_n^-) \quad (4.7)$$

Where v_n^+ and v_n^- represent v_{n+1} in case of receiving positive ($s = 1$) and negative signals ($s = 0$) respectively.

4.3.3 Market Uncertainty and flexibility

The technology has a great impact on providing flexibility to support and launch different generations of the product when responding to market demand changes during the product

life cycle. Therefore, the provided flexibility has a crucial role on firm's technology choice. In such situations, the flexibility value directly affects profit from both pv and ps alternatives. The value of this flexibility is highly dependent on future market demand that is often very uncertain, as is the way that the firm will exercise this flexibility option. Firms often prefer exercising the flexibility option when higher demands for specific generations of the product are observed. We use Monte Carlo simulation to evaluate market uncertainty and flexibility, which will be discussed in more details later.

4.3.4 Model Analysis

Defining the problem as structure explained in section 4.3 benefits some properties that will be discussed in this section. For readability and continuity proofs are presented in the appendix.

Proposition 4.1. *The expected value of the receiving new information is non-increasing in n .*

Proposition 4.1 shows that the firm's average expected profit decreases as the amount of information already collected increases. Increasing n decreases the riskiness (in sense of second order stochastic dominance) of posterior distribution. As the firm acquires more information, it tightens its posterior distribution.

As a result of proposition 4.1, since value of new information is decreasing, firm will not continue gathering information indefinitely and will reach a point that waiting value is zero or negative. After this point, postponing the decision will not be an option anymore. Firm has to choose either alternative. This fact is stated in proposition 4.6

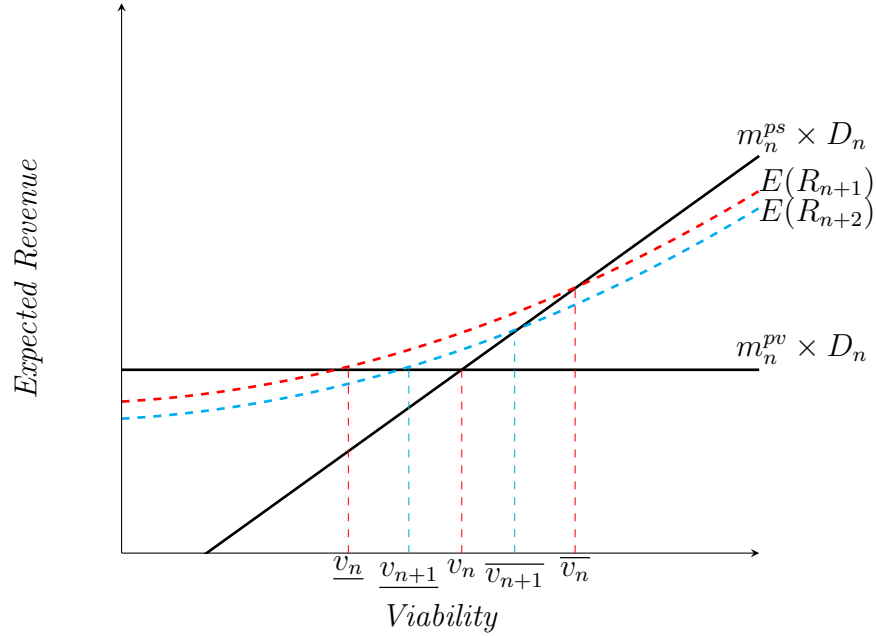


Figure 4.13: Illustration of tightening thresholds

At each stage n , imposed extra opportunity cost, $E(R_{n+2})$ will be lower than $E(R_{n+1})$ which results in increasing the lower threshold ($v_{n+1} \geq v_n$) and decreasing in upper threshold ($\bar{v}_{n+1} \leq \bar{v}_n$)

Proposition 4.2. *There is a finite N which firm will not continue collecting information after that stage N .*

Proposition 4.3. *At each time period n there exist a pair of numbers \underline{v}_n and \bar{v}_n such that if $\underline{v}_n \leq v_n \leq \bar{v}_n$, it is optimal to wait until the next stage, if $v_n \leq \underline{v}_n$ it is optimal to choose pv technology, and if $v_n \geq \bar{v}_n$, it is optimal to choose the ps technology.*

Proposition 4.3 states that at each stage there are lower and upper thresholds that have estimated viability between thresholds that may be changed at the next stage by receiving new information. These thresholds are shown in Figure (4.13) where the expected profit of the next stage intersects expected profit of current stage. By having the current estimate of viability between two intersection points, it is possible that next stage estimated value of profit would be improved. This implies that the more information a firm has, the more

confident it should be about its estimate. Suppose that the firm is at stage n with viability estimate of v_n and $v_n \geq \bar{v}_n$, it seems intuitive that if the firm had more information with the same estimate, it would also find optimal ps technology.

Proposition 4.4. *At each time period n the lower threshold \underline{v}_n and upper threshold \bar{v}_n are respectively decreasing and increasing in n .*

Results from proposition 4.3 and 4.4 can be summarized in Figure (4.14). Receiving positive signals cause increase in viability and move upward while receiving negative signals cause decrease in viability and move downwards. The firm starts with an estimate of viability (v_0). As the firm continues to test and acquire more information, it moves rightward in the direction of increasing information in Figure (4.14). It stops and considers the ps technology if its estimate of viability is high (region A). On the other hand, it stops and rejects the ps technology if its estimate of profitability is low (region C). The firm continues to research and collect information when the estimate is neither high nor low (region B). For a given amount of information, if the firm's estimate of viability is such that the firm stops collecting information and adopts the innovation, then with more information and the same estimate the firm would also stop and adopt. Greater precision, as represented by more information, does not change the adoption decision. The same holds true if the firm were to reject the innovation, giving rise to the conic shape of region B.

4.4 Proposed Framework

This paper develops a technology management procedure during the early stages of product development that systematically identifies technical and life cycle uncertainties and determines the appropriate management actions in order to minimize effect on downstream

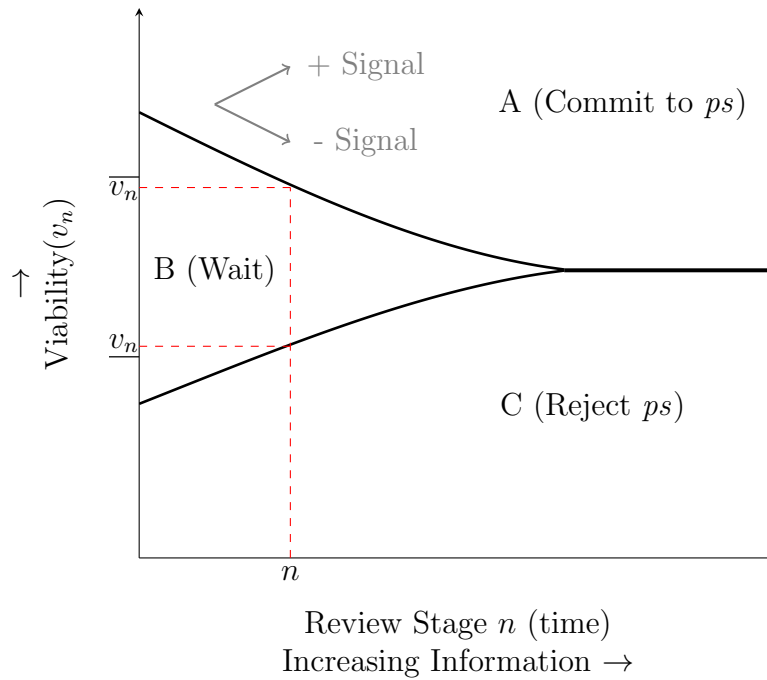


Figure 4.14: Illustration of Optimal Strategy Structure: Commit, Reject and Wait Regions

Firm starts with viability estimation of v_0 at the beginning. It moves forward by testing and gathering more information during the time. Receiving positive signals causes an increase in estimation of viability of the next stage while receiving negative signals causes a decrease in that which is causing movement up or down respectively. As long as we stay at the waiting stage, it is optimal to postpone the technology decision. However, once we pass the upper threshold, it would be optimal to commit to ps technology. Firm would reject ps technology if it enters rejection region.

activities and maximize return and management flexibility to respond to market uncertainties. The management actions can be adopted in response to new information during the early stages of NPD. This framework is based on the model that is presented in section 4.2. It takes the advantages of using the real options concept to provide a quantitative approach to evaluate the flexibility as well as Bayesian learning process to acquire new information regarding technical uncertainty as they become available during design validation. At each design review stage, management can decide to commit to any available technology alternative or to postpone this decision to the next stage. Market structure and demand uncertainties are modeled using Monte Carlo simulation technique. Although here we use the term technology, we generally mean a new innovation. The developed procedure can be adopted and applied for selection of any innovation such as technology, new design concept and new product architecture. The proposed framework is divided into 4 phases: (1) identifying technology alternatives, (2) recognizing critical risk and uncertainties, (3) evaluating market structure and flexibility, (4) technology decision process.

4.4.1 Recognizing critical risks and uncertainties

NPD process suffers from different risks and uncertainties during product life cycle. These risks rise from different sources of uncertainties such as technical, future competitive market demand and structure, and varying customer needs. Identifying these uncertainties will help the firm and PD team to get better image of the future and be able to propose effective product concepts to overcome risks.

4.4.2 Identifying technology alternatives

In this phase, after defining new product goals, PD team identifies all possible technology alternatives that can be embedded in a new product in order to satisfy customer requirements and gain the desired market share. Flexibility to overcome future market uncertainties should be considered. Technologies can be either proposed by a supplier or developed by the firm's R&D team. Technology alternatives are mainly divided into two groups: (1) proven technology (TRL=9) which already has been used in previous systems and products (2) prospective technologies (TRL<9) in which there is considerable doubt about their reliability and performance despite their higher expected performance and flexibility.

4.4.3 Evaluating market structure and flexibility

After identifying future market uncertainties and available technology alternatives this section examines how different technology alternatives and their offered performance and flexibility could impact market structure, demand, and the product's payoff. To reach this aim, demand and market structure forecast models should be built to generate different scenarios. Then the concept of real options approach is applied to find the returns from both proven technology (m) and prospective technology (M) in each scenario. Flexibility evaluation process starts with traditional business case model. Usually a business case model uses point forecasts to determine the Net Present Value (NPV). Building a model requires a full understanding of market possibilities and technical details. By acknowledging uncertainty, the second phase is to run NPV simulation over a distribution of input variables to generate different market scenarios to assess the profitability of each technology alternative.

4.4.4 Technology decision process

This phase aims to systematically evaluate technical risk and adopt management actions step by step as more information becomes available during the NPD process. The technology selection model and its properties presented in section 4.3 provide the theoretical basis for this phase. Market returns for proven technology (m) and prospective technology (M) are evaluated in a previous phase.

Prior distribution for viability rates of prospective technology is acquired based on expert opinions and benchmark data. Then the lower and upper thresholds are calculated for each review period. The estimation of viability is updated at every review stage that we receive a signal. If new estimation is inside thresholds, we continue collecting information; otherwise, we have to reject T2 if our estimations is below the lower threshold. If the estimation is above the threshold, consideration of the prospective technology is recommended.

4.5 Illustrative Example

Previously, the auto industry had concentrated on process innovation and developing reliable vehicles based on standardized platforms. However, recent trends on vehicle electrification and developments in battery technology have pushed this industry into a new disruptive innovation phase which creates opportunities and uncertainties for automotive manufactures [Hommes and Renzi, 2014]. Different types of electrified vehicles are currently on the market or companies are planning to introduce vehicles such as full hybrid (FHEV), plug-in hybrid (PHEV), and battery electric vehicles (BEV) to the market. The future market demand for these types of vehicles is very uncertain and highly affected by different trends such as gasoline prices, consumer preferences, economic, and global social trends which are

very hard to predict [Hommes and Renzi, 2014].

Different types of electrified vehicles have varying battery requirements. In addition, batteries require a control system for temperature, voltage, and current to avoid risky situations that may lead to explosion. Predicting battery technology over the next 10 years is unlikely to yield accurate results. Batteries and hybrid drive systems continue to improve, both incrementally (process improvements) and disruptively (Nickel Metal Hydride batteries transitioning to Lithium-ion batteries). Lithium-ion is the state-of-the-art. They have begun to appear in electrified vehicles (e.g. the 2012 Nissan Leaf BEV and 2013 Ford Fusion Hybrid), with new challenges in the control of the technology. The level of risk and control requirements for Lithium-ion differs from Nickel Metal Hydride, and future chemistry may add extra requirements, including other promising energy storage technologies on the horizon [Hommes and Renzi, 2014]. The rapid development of battery technology and the variable power requirements of different vehicle types as well as future market demand create uncertainties surrounding vehicle design, battery pack system and battery control technology.

In such situations, two concept/technology, T1 and T2, are proposed for battery control system by the firm's PD team in order to incorporate flexibility in design. Among those T1 is the baseline concept in current production vehicles (proven technology). T2 is the potential solution with embedded options that enable the design to switch among the different electrified vehicle types and hence provide flexibility to adapt to the future battery technology and market uncertainties. However, there is considerable doubt about the success of T2 regarding their performance and reliability (prospective technology).

After identifying market uncertainties, future market predictive models are built and used

to evaluate different alternatives for battery control system by aid of Monte Carlo simulation. Some more details are provided by Hommes and Renzi [2014]. Then returns from T1 (m) and T2 (M) are identified. Prior distribution for viability rates of T1 is acquired based on expert opinions and benchmark data. Then the lower and upper thresholds are calculated for each time period. As we update our estimation of viability at every review stage, we follow the decision process described at section 4.4.4.

For example, assuming a prior distribution $Beta(3, 1)$ for success rate yields to estimation of 0.75 for θ . If in the next review positive information comes, based on Bayesian approach, our estimation would be 0.79. In such case, firm would stop collecting information and select prospective technology. Otherwise, if the firm receives negative information, the estimate of success will drop to 0.63 where the firm would prefer to continue collecting information and postpone the technology decision at least to the next review. Fig 4.15 shows how such strategy can be applied to reduce the number of possible scenarios. It can be seen that after 6 stages, there is active node. This is because, by increasing time, the continuation area become tighter Therefore, less likely estimated viability rate, fits inside the interval. Finally after 6 stages, there is no chance that viability rate lies between intervals. The maximum number of stages that is needed to reach stop decision in any scenario depends on prior distribution of viability rate and also market uncertainty. Following such a strategy will limit the number of possible technical uncertainty scenarios and provide a guideline for management to make an optimal decision regarding new technology.

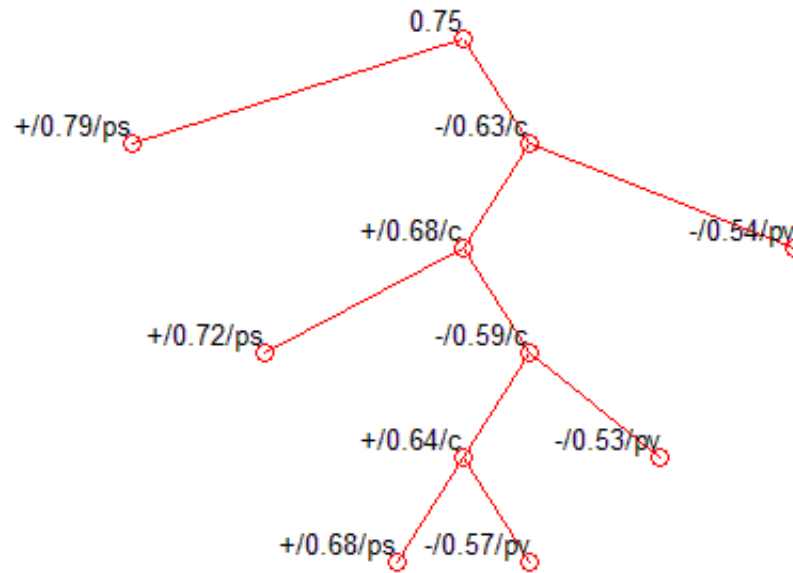


Figure 4.15: Sequence of technology decisions under technical uncertainty

At each node, left numbers shows the signal is either positive or negative. Middle number indicates the updated viability estimation and finally the right hand side number shows the optimum decision where c indicates "continue", ps and pv are indicating selection of prospective and proven technology respectively.

4.6 Conclusion

New product technology has a vital role on a new product's success. New prospective technologies offer higher levels of payoff, but because of inherent uncertainty, firms are struggling to choose between prospective and proven technologies. Furthermore, technology selection problem lies in NPD project's critical path and is a prerequisite of all downstream activities. Any delay in selecting technology would cause delay in launch and significant profit loss. However, by spending more time on testing new technology and collecting more information, firm can decide more precisely. Therefore, decision timing and its trade-off between performance/reliability, cost and market payoff is very important in technology selection problem and it has not been paid enough attention in the literature.

We proposed a decision framework that not only enables us to consider technical uncertainty in the technology selection problem but also enable us to consider market uncertainty. Our framework enables the decision maker while testing the design to either decide about the technology now or to postpone it until later. If decision to stop is made, decision maker can either accept the prospective technology or reject it and commit to proven one. We start formulating the problem by expressing firm's payoff function based on new technology success (survival) rate. During the time, by receiving more information we dynamically update our perception based on Bayesian approach.

We showed that at each stage, there is a threshold for uncertainty that is decreasing as time increases. Our analysis points out that it may be optimum to reject or accept the technology immediately. If the precision of firm's estimate is low, it is optimal for the firm to gather information about prospective technology. We found lower and upper bounds at each stage and constructed a skewed funnel shape continuation area. If our estimation of success rate lies inside the funnel, it is optimum to postpone the technology decision; otherwise, if it lies under or above the funnel, we respectively reject or accept the prospective technology.

The above analysis has assumed a risk-neutral firm. In practice, firms are risk averse and may be reluctant to consider unproven technology. The risk-averse firm's objective is to maximize the certainty equivalent of its expected profit, which would be lower than the profit anticipated by the risk-neutral firm. The effect of risk aversion is, in general, to lead the firm to choose the pv technology because of its lower uncertainty.

In our analysis we assume that for every prospective technology we have one backup proven technology that we can revert to in case of failure. In practice this assumption is often true. To mitigate risk, firms usually consider a backup for unproven technologies.

However, we can consider multiple options in case of failure of prospective technology rather than reverting to a proven one. This can be considered an extension of this work.

We used term "technology" generally to refer any type of innovation. Other than technology, our framework can be used for evaluating and selecting any innovative design or architecture during the NPD process.

CHAPTER 5. CONCLUSION

We modeled the technology selection problem in NPD as a sequential decision making problem. This model can be used by the management facing the decision of not only whether or not consider a new technology but also the timing of the decision. The decision can be postponed, and by delaying the decision, we can increase the precision of our estimation. However, delaying the decision is costly. Our model finds the optimal trade off between current precision and potential future information which may change our decision. In chapter 2, we assumed a situation where only one of the technologies is uncertain. However, in chapter 3 we relaxed this assumption and considered two uncertain technologies. In both models we penalized delaying the technology decision by missing a percentage of total possible achievable profit. However in chapter 4, by modeling the same problem we penalized the delay by an independent cost function and considered uncertainty in life cycle demand. The first two models are proper when product life cycle is short and by delaying the decision we lose a portion of a life cycle demand. However, in the third model by considering independent delay cost, it is more suitable for long life cycle products.

APPENDIX

Lemma 2.1. *The expected profit at next review stage is equal to the current estimate of profit.*

Proof. Proof has two cases, in case of *pv* technology, for every review stage n , the expected profit is constant and equals to m in other word we have $m_{n+1}^{pv} = m_n^{pv} = m$. For *ps* technology, it shows that $E(m_{n+1}^{ps}|v_n, S_{n+1}) = m_n^{ps}$. We can rewrite equation (2.2) as:

$$m_{n+1}^{ps} = v_{n+1}(M - m + F) + m - F - I \quad (.1)$$

in which m_{n+1}^{ps} is a linear function of which of v_{n+1} . In order to prove we need to show that

$E(v_{n+1}|v_n, S_{n+1}) = v_n$. Considering equation 2.8, LHS can be rewritten as $\sum_{S_{n+1}^+ = 0}^{S_{n+1}} \binom{S_{n+1}}{S_{n+1}^+} v_n^{S_{n+1}^+} (1 - v_n)^{(S_{n+1} - S_{n+1}^+)}$ $\frac{(\alpha + \beta + \sum_{i=1}^n S_i)v_n + S_{n+1}^+}{\alpha + \beta + \sum_{i=1}^{n+1} S_i}$ which can be proved that is equal to v_n . The proof can be

obtained by simple induction. □

Proposition 2.1. *If $\sum_{i=0}^n d_i = 0$, then it is optimal to delay technology decision by review stage n .*

Proof. I shows that $R_n = E[R_{n+1}(v_{n+1})|v_n, S_n]$ for every stage $i \leq n$. We have $\sum_{i=0}^n d_i = 0$ then $D_i = 1, \forall i \leq n$. Then Based on equations 2.5 and 2.6, there is no penalty of delaying the decision to the next stage. Thus to show that $R_n = E[R_{n+1}]$, it suffices to have $m_n^{ps} = E(m_{n+1}^{ps})$ which holds based on Lemma 2.1. □

Lemma 2.2 . *Next stage expected profit is increasing in current estimate of profit.*

Proof. For pv technology we need to show that m_{n+1}^{pv} is increasing in m_n^{pv} where we have $m_{n+1}^{pv} = m_n^{pv} = m$, thus the proof is obvious. For ps technology we need to show that m_{n+1}^{ps} is increasing in m_n^{ps} . By substituting v_{n+1} from equation 2.8 in equation .1 we have:

$$m_{n+1}^{ps} = \frac{(\alpha + \beta + \sum_{i=1}^n S_i)v_n + S_{n+1}^+}{\alpha + \beta + \sum_{i=1}^{n+1} S_i} \times [(M - m + F) + m - F - I] \quad (.2)$$

By simplifying, RHS can be written as an increasing function of m_n^{ps} . □

Lemma 2.3. *The Expected payoff is increasing in previous estimate of viability.*

Proof. For pv technology m_n^{pv} is constant. For ps technology, we need to show that m_{n+1}^{ps} is increasing in v_n . Recall equation .2 it is obvious that RHS is an increasing function of v_n . □

Proposition 2.2. *At each time period n there exist a pair of numbers \underline{v}_n and \overline{v}_n such that if $\underline{v}_n \leq v_n \leq \overline{v}_n$, it is optimal to wait to the next stage, if $v_n \leq \underline{v}_n$ it is optimal to choose pv technology, and if $v_n \geq \overline{v}_n$, it is optimal to choose the ps technology.*

Proof. We start with the upper bound for v_n . We show that there is a threshold \overline{v}_n such that for every $v_n \geq \overline{v}_n$, it is optimal to select ps technology. For this purpose we need to show that if v_n is such that it is optimal to select ps technology, it would remain optimum to choose ps technology for any larger values of v_n . It shows that $R_n \leq m_n^{ps} \times D_n$ will be valid by increasing v_n . It is equivalent to show that $R_n - m_n^{ps} \times D_n$ is decreasing in v_n . To prove we follow induction: 1) For $n = N - 1$, $\max\{m \times D_{N-1}, m_{N-1}^{ps} \times D_{N-1}, 0\} - m_{N-1}^{ps} \times D_{N-1}$. In which first argument of max expression is constant, the second argument of max as well as the second term are the same and increasing in v_N , so the whole expression is

constant in v_N . 2) We assume that $R_n - m_n^{ps} \times D_n$ or $\max\{m \times D_n, m_n^{ps} \times D_n, E[R_{n+1}]\} - m_n^{ps} \times D_n$ is decreasing in v_n . 3) Show that $R_{n-1} - m_{n-1}^{ps} \times D_{n-1}$ is decreasing in v_n or $\max\{m \times D_{n-1}, m_{n-1}^{ps} \times D_{n-1}, E[R_n]\} - m_{n-1}^{ps} \times D_{n-1}$ is decreasing in v_n . If the first two arguments of the max expression yields, the claim is true. For the third argument we need to show that $E[R_n] - m_{n-1}^{ps} \times D_{n-1}$ is decreasing in v_n . By adding and subtracting $E[m_n^{ps} \times D_n]$ we can get $E[R_n] - m_{n-1}^{ps} \times D_{n-1} + E[m_n^{ps} \times D_n] - E[m_n^{ps} \times D_n]$ then this expression can be rewritten as $E[R_n - m_n^{ps} \times D_n] + E[m_n^{ps} \times D_n] - m_{n-1}^{ps} \times D_{n-1}$. The first expectation is decreasing in v_n based on induction hypothesis. It will be also decreasing in v_{n-1} . Now we show that $E[m_n^{ps} \times D_n] - m_{n-1}^{ps} \times D_{n-1}$ is decreasing in v_n . By using Lemma 2.1 we have $m_n^{ps} \times D_n - m_{n-1}^{ps} \times D_{n-1}$ which can be rewritten as $m_{n-1}^{ps}(D_n - D_{n-1})$. Hence $D_n - D_{n-1} \leq 0$ thus the expression is obviously decreasing in v_{n-1} . In order to prove existence of the lower thresholds, we show that there is a lower bound v_n such that for any $v_n \leq \underline{v}_n$, it is optimal to select pv technology. For this purpose, we show that once \underline{v}_n is in a level that it is optimal to select pv technology, it remains optimal for every $v_n \leq \underline{v}_n$. It shows that $R_n - m \times D_n$ is increasing in v_n . The second term is invariant to v_n , so it shows that R_n is increasing in v_n . In order to prove we follow by induction. 1) For $n = N - 1$ we have $R_{N-1} = \max\{m \times D_{N-1}, m_{N-1}^{ps} \times D_{N-1}, 0\}$ which is increasing in v_n . 2) We assume that R_n is increasing in v_n . 3) Show that R_{n-1} is increasing in v_n . We have $R_{n-1} = \max\{m \times D_{n-1}, m_n^{ps} \times D_{n-1}, E[R_n]\}$. The claim holds if first two arguments yields. The third argument is also increasing in v_n based on induction hypothesis and Lemma 2.2 and 2.3.

□

Proposition 2.3. *The expected value of the waiting is non-increasing in n .*

Proof. We follow the induction, for $n = N - 1$, we have $R_{N-1} = \max\{m \times D_{N-1}, m_{N-1}^{ps} \times D_{N-1}, 0\} \geq R_N$. We assume for $n = k$ we have $R_k \geq R_{k+1}$, and show it holds for $n = k - 1$.

We need to show $R_{k-1} \geq R_k$.

$$R_{k-1} = \max \begin{cases} m \times D_{k-1} \\ m_{n-1}^{ps} \times D_{k-1} \\ E(R_k) \end{cases} \quad (.3)$$

$$R_k = \max \begin{cases} m \times D_k \\ m_n^{ps} \times D_k \\ E(R_{k+1}) \end{cases} \quad (.4)$$

Comparing equation (.3) and (.4), $D_{k-1} > D_k$, based on Lemma 2.1, $E(m_n^{ps}) = m_{n-1}^{ps}$ and based on induction hypothesis we can conclude that $R_{k-1} \geq R_k$ \square

Proposition 2.4. *At each time period n the lower threshold \underline{v}_n and upper threshold \overline{v}_n are respectively decreasing and increasing in n .*

Proof. We start with the upper threshold, \overline{v}_n which is the maximum of two v_n s obtained from solving of the following two equations:

$$m \times D_n = m_n^{ps}(v_n) \times D_n \quad (.5)$$

$$m_n^{ps}(v_n) \times D_n = E[R_{n+1}] \quad (.6)$$

In equation (.5), right-hand side (RHS) and left-hand side (LHS) are increasing in n with the same rate, thus v_n obtained from this equation is constant in n . LHS of equation (.6) is decreasing in n based on Proposition 2.3, thus v_n obtained from solving this equation is also decreasing in n . Thus the maximum of v_n s obtained from equation .5 and .6 is decreasing in n .

Similarly, lower threshold is the minimum of two v_n s obtained from solving equations (.5) and (.8).

$$m \times D_n = m_n^{ps}(v_n) \times D_n \quad (.7)$$

$$m \times D_n = E[R_{n+1}] \quad (.8)$$

Obtained v_n from equation (.7) is constant in n . In equation (.8), RHS can be rewritten as $E(\max\{m \times D_{n-1}, a \times v_{n+1} + b, E(R + 2)\})$, where a and b are slope and intercept parts in $m_n^{ps}(v_n)$. Obtained v_n from equation (.8), will have coefficient of D_n/D_{n+1} which can be proved by induction that it is increasing in n . Then the minimum of the two v_n s obtaining from equations (.5) and (.8) are increasing in n . \square

Proposition 2.5. *For every period n , by multiplying payoff from pv and ps technologies by a_{pv} and a_{ps} respectively, the lower and upper thresholds:*

(i) *will not change if $\frac{a_{ps}}{a_{pv}} = 1$*

(ii) will decrease if $\frac{a_{ps}}{a_{pv}} > 1$

(iii) will increase if $\frac{a_{ps}}{a_{pv}} < 1$

Proof. Proof has 3 cases:

(i) $\frac{a_{ps}}{a_{pv}} = 1$

In order to prove we need to show that the optimal strategy We proceed by induction. If $n = N - 1$ we have $R'_{N-1} = \max\{a \times mD_{N-1}, a \times m_{N-1}^{ps}D_{N-1}, 0\}$ which can be rewritten as $R'_1 = a \times \max\{mD_{N-1}, m_{N-1}^{ps}D_{N-1}, 0\}$ it is obvious that multiplying the demand by a has no effect on selected argument inside the maximum expression. It is clear that $R'_{N-1} = aR_{N-1}$

Now we assume that the claim holds for period n and we have $R'_n = aR_n$. We show that it holds for $n - 1$ For period $n-1$, we have

$$R'_{n-1} = \max \begin{cases} a \times mD_{n-1} \\ a \times m_{n-1}^{ps}D_{n-1} \\ E[R'_{n-1}] \end{cases} = a \times \max \begin{cases} mD_{n-1} \\ m_{n-1}^{ps}D_{n-1} \\ E[R_n] \end{cases}$$

It is obvious that selected argument of maximum expression is not affected by multiplying $a > 0$ which can be concluded that $R'_n = aR_n$.

(ii) $\frac{a_{ps}}{a_{pv}} > 1$

We show that by multiplying ps technology by $a \geq 1$ will decrease lower and upper thresholds.

We start with the upper threshold, for every stage n , \bar{v}_n which is the maximum of two v_n s obtained from solving of the following two equations:

$$m \times D_n = a \times m_n^{ps}(v_n) \times D_n \quad (.9)$$

$$a \times m_n^{ps}(v_n) \times D_n = E[R'_{n+1}] \quad (.10)$$

Where R'_{n+1} shows the expected profit from waiting with prospective technology's revenue multiplied by $a \geq 1$. in first equation, RHS is increasing in a but not the LHS, then v_n obtained from this equation will be decreasing in a . In second equation both sides are increasing in a , however increasing rate of RHS is higher than LHS, thus v_n obtained from this equation is also decreasing in a . Both v_n are decreasing thus their maximum \bar{v}_n .

Similarly, lower threshold is the minimum of two v_n s obtained from solving equations (.11) and (.12).

$$m \times D_n = a \times m_n^{ps}(v_n) \times D_n \quad (.11)$$

$$m \times D_n = E[R'_{n+1}] \quad (.12)$$

In both equations, RHS is increasing in a , but not the LHS, thus v_n obtained from these equations are decreasing in a as well as their maximum \underline{v}_n .

$$(iii) \frac{a_{ps}}{a_{pv}} < 1$$

Similar to case 2, we can prove that lower (\underline{v}_n) and upper (\bar{v}_n) thresholds will increase in

a .

□

Proposition 2.6 *The optimal payoff will increase by changing the opportunity cost function for each stage review i from d_i to d'_i , if for every $n \leq N$ we have $\sum_{i=0}^n d'_i \leq \sum_{i=0}^n d_i$.*

Proof. Let's show the value of the optimal decision with demand D' at time period n by R'_n .

Having $\sum_{i=0}^n d'_i \leq \sum_{i=0}^n d_i, \forall n$ or $D'_n \geq D_n$.

We need to show that $R'_n \geq R_n, \forall n$. We proceed by induction:

For $n = N-1$ we have $R_{N-1} = \max\{mD_{N-1}, m_{N-1}^{ps}D_{N-1}, 0\}$, $R'_{N-1} = \max\{mD'_{N-1}, m_{N-1}^{ps}D'_{N-1}, 0\}$

which is obviously $R'_{N-1} \geq R_{N-1}$.

We assume that for period n we have $R'_n \geq R_n$. We prove that it holds for $n-1$. We have:

$$R_{n-1} = \max \begin{cases} mD_{n-1} \\ m_n^{ps} D_{n-1} \\ E(R_n) \end{cases} \quad (.13)$$

$$R'_{n-1} = \max \begin{cases} mD'_{n-1} \\ m_n^{ps} D'_{n-1} \\ E(R'_n) \end{cases} \quad (.14)$$

Comparing equation (.13) and equation (.14) reveals that if the first two argument inside max expression yields, it is obvious that $R'_{n-1} \geq R_{n-1}$. The third argument holds $E(R'_n) \geq E(R_n)$ holds because of the induction hypothesis, thus $R'_n \geq R_n$. \square

Lemma 3.1 *The expected profit at next review stage is equal to the current estimate of profit.*

Proof. To prove we need to show that $E[P_{n+1}^k] = P_n^k$. From equation 3.1, we have

$$P_n^k = p_n^k(M^k - m + F^k) + m - F^k - I^k \quad (.15)$$

Thus it suffices to prove that $E[p_{n+1}^k] = p_n^k$. By substituting from equation 3.5, LHS can be rewritten as $\sum_{S_{n+1}^+ = 0}^{S_{n+1}} \binom{S_{n+1}}{S_{n+1}^+} (v_n^k)^{S_{n+1}^+} (1 - v_n^k)^{(S_{n+1} - S_{n+1}^+)} \frac{(\alpha^k + \beta^k + \sum_{i=1}^n S_i^k) p_n^k + S_{n+1}^{k+}}{\alpha^k + \beta^k + \sum_{i=1}^{n+1} S_i^k}$. Which can be proved that equals to p_n^k by induction. \square

Proposition 3.1 *If $\sum_{i=0}^n d_i = 0$, then it is optimal to delay technology decision by review stage n .*

Proof. I shows that $R_i = E[R_{i+1}]$ for every stage $i \leq n$. We have $\sum_{i=0}^n d_i = 0$ then $D_i = 1, \forall i \leq n$. Then Based on equation 3.4 , there is no penalty of delaying the decision to the next stage. Thus to show that $R_n = E[R_{n+1}]$, it suffices to have $P_n^k = E(P_{n+1}^k)$ which holds based on Lemma 3.1. \square

Lemma 3.2 *Next stage expected profit is increasing in current estimate of profit.*

Proof. We need to show that P_{n+1}^k is increasing in P_n^k . By substituting p_{n+1}^k from equation 3.5 in equation .15 we have

$$P_{n+1}^k = \frac{(\alpha^k + \beta^k + \sum_{i=1}^n S_i^k) P_n^k + S_{n+1}^{k+}}{\alpha^k + \beta^k + \sum_{i=1}^{n+1} S_i^k} \times (M^k - m + F^k) + m - F - I \quad (.16)$$

By simplifying, RHS can be written as an increasing function of P_n^k . \square

Lemma 3.3 *The Expected payoff is increasing in previous estimate of viability.*

Proof. We need to show that m_{n+1}^k is increasing in p_n^k . Recall equation .16 it is obvious that RHS is an increasing function of p_n^k . \square

Proposition 3.2 *At each review stage n , for every P_n^2 , there exist a pair of numbers \underline{P}_n^1 and \bar{P}_n^1 ($\underline{P}_n^1 \leq \bar{P}_n^1$) such that if $\underline{P}_n^1 \leq P_n^1 \leq \bar{P}_n^1$, it is optimal to continue. If $P_n^1 \geq \bar{P}_n^1$ it is optimal to select technology 1. If $P_n^1 \leq \underline{P}_n^1$ is optimal to select technology 2.*

Proof. We start first with the upper bound for P_n^1 . We need to show that there is a threshold \underline{P}_n^1 as a function of P_n^2 such that for every $P_n^1 \geq \underline{P}_n^1$ it is optimal to commit to technology 1. In order to show this we need to show if P_n^1 is such that selecting technology 1 is optimal, it would remain optimal any larger values of P_n^1 . It shows that $R_n \leq P_n^1 D_n$ will be valid by increasing P_n^1 or show that $R_n - P_n^1 D_n$ is decreasing in P_n^1 . To prove we follow by induction. 1) For $n = N - 1$, $\max\{P_{N-1}^1 D_{N-1}, P_{N-1}^2 D_{N-1}, 0\} - P_{N-1}^1 D_{N-1}$ is decreasing in P_{N-1}^1 . 2) We assume that $R_n - P_n^1 D_n$ is decreasing in P_n^1 . 3) show that $R_{n-1} - P_{n-1}^1 D_{n-1}$ is decreasing in P_{n-1}^1 or $\max\{P_{n-1}^1 D_{n-1}, P_{n-1}^2 D_{n-1}, E[R_n]\} - P_{n-1}^1 D_{n-1}$ is decreasing in P_{n-1}^1 . If the first two arguments of the max expression yields, the claim is true. For the third argument we need to show that $E[R_n] - P_{n-1}^1 D_{n-1}$ is decreasing in P_{n-1}^1 . By adding and subtracting $E[P_n^1 D_n]$ we can get $E[R_n] - P_{n-1}^1 D_{n-1} + E[P_n^1 D_n] - E[P_n^1 D_n]$ then this expression can be rewritten as $E[R_n - P_{n-1}^1 D_n] + E[P_n^1 D_n] - P_{n-1}^1 D_{n-1}$. The first expectation is decreasing in P_n^1 based on induction hypothesis. It will be also decreasing in P_{n-1}^1 .

Now we show that $E[P_n^1 D_n] - P_{n-1}^1 D_{n-1}$ is decreasing in P_{n-1}^1 . By using Lemma 3.1 we have $E[P_n^1 D_n] = P_{n-1}^1 D_n$. By substituting the expression can be rewritten as $P_{n-1}^1 D_n - P_{n-1}^1 D_{n-1}$. We have $D_n - D_{n-1} \leq 0$ so the expression is decreasing in P_{n-1}^1 and P_n^1 .

In order to prove existence of the lower thresholds, we show that there is a lower bound

\underline{P}_n^1 such that for any $P_n^1 \leq \underline{P}_n^1$, it is optimal to select technology 2. For this purpose, we show that once P_n^1 is in a level that it is optimal to select technology 2, it remains optimal for every $P_n^1 < \underline{P}_n^1$. It shows that $R_n - P_n^2 D_n$ is increasing in P_n^1 . The second term is invariant to P_n^1 , so it shows that R_n is increasing in P_n^1 . In order to prove we follow by induction.

1) For $n = N - 1$ we have $R_1 = \max\{P_{N-1}^1 D_{N-1}, P_{N-1}^2 D_{N-1}, 0\}$ which is increasing in P_{N-1}^1 . 2) We assume that R_{n-1} is increasing in P_{n-1}^1 . 3) Show that R_n is increasing in P_n^1 . $R_n = \max\{P_n^1 D_{n-1}, P_n^2 D_{n-1}, E[R_{n-1}]\}$. The claim holds if first two arguments yields. The third argument is also increasing in P_n^1 based on induction hypothesis and Lemma 3.1. \square

Proposition 3.3 *Thresholds \underline{P}_n^1 and \bar{P}_n^1 are increasing in P_n^2*

Proof. We first show that thresholds are increasing. We start with the upper threshold. \bar{P}_n^1 is the maximum of two P_n^1 s obtained from solving of the following two equations:

$$P_n^1 D_n = P_n^2 D_n \quad (.17)$$

$$P_n^1 D_n = E[R_{n-1}] \quad (.18)$$

In eq. (.17), right-hand side (RHS) is increasing in P_n^2 , thus P_n^1 obtained from this equation is increasing in P_n^2 . RHS of eq. (.18) is also increasing in P_n^2 , thus P_n^1 obtained from solving this equation is also increasing in P_n^2 . Both P_n^1 s are increasing, their maximum (\bar{P}_n^1) is increasing in P_n^2 .

Similarly, lower threshold is the minimum of two P_n^1 s obtained from solving equations (.17) and (.20).

$$P_n^1 D_n = P_n^2 D_n \quad (.19)$$

$$P_n^2 D_n = E[R_{n-1}] \quad (.20)$$

P_n^1 obtained from eq. (.19) is increasing in P_n^2 with increasing rate of $P_n^2 D_n$. In eq. (.20) both sides are increasing in P_n^2 but LHS increasing rate is higher than right-hand side (RHS). LHS increases with the rate of D_n for one unit increase in P_n^2 while RHS increases by at most rate of $(\sum_{k=1}^{n-1} d_k)$. Both P_n^1 points are increasing in P_n^2 so the minimum of them. \square

Proposition 3.4 *The expected value of the waiting is non-increasing in n .*

Proof. We follow the induction, for $n = N - 1$, we have $R_{N-1} = \max\{P_{N-1}^1 \times D_{N-1}, P_{N-1}^2 \times D_{N-1}, 0\} \geq R_N$. We assume for n we have $R_n \geq R_{n+1}$, and show it holds for $n - 1$. We need to show $R_{n-1} \geq R_n$.

$$R_{n-1} = \max \begin{cases} P_{n-1}^1 \times D_{n-1} \\ P_{n-1}^2 \times D_{n-1} \\ E(R_n) \end{cases} \quad (.21)$$

$$R_n = \max \begin{cases} P_n^1 \times D_n \\ P_n^2 \times D_n \\ E(R_{n+1}) \end{cases} \quad (.22)$$

Comparing equation (.21) and (.22), $D_{n-1} > D_n$, based on Lemma 3.1, $E(P_n^k) = P_{n-1}^k$

and based on induction hypothesis we can conclude that $R_{n-1} \geq R_n$ □

Proposition 3.5 *For each review period n , by multiplying payoff from technology 1 and technology 2 by a_1 and a_2 respectively, the thresholds \underline{P}_n^1 and \overline{P}_n^1*

- *will not change if $a_1 = a_2$;*
- *will decrease if $a_2 < a_1$;*
- *will increase if $a_2 > a_1$*

Proof. Proof has 3 cases:

(i) $a_1 = a_2$

In order to prove we need to show that the optimal strategy is not changing. We proceed by induction. If $n = N - 1$ we have $R'_{N-1} = \max\{a \times P_{N-1}^1 D_{N-1}, a \times P_{N-1}^2 D_{N-1}, 0\}$ which can be rewritten as $R'_1 = a \times \max\{P_{N-1}^1 D_{N-1}, P_{N-1}^2 D_{N-1}, 0\}$ it is obvious that multiplying the demand by a has no effect on selected argument inside the maximum expression. It is clear that $R'_{N-1} = aR_{N-1}$

Now we assume that the claim holds for period n and we have $R'_n = aR_n$. We show that it holds for $n - 1$ For period $n-1$, we have

$$R'_{n-1} = \max \begin{cases} a \times P_{n-1}^1 D_{n-1} \\ a \times P_{n-1}^2 D_{n-1} \\ E[R'_n] \end{cases} = a \times \max \begin{cases} P_{n-1}^1 D_{n-1} \\ P_{n-1}^2 D_{n-1} \\ E[R_n] \end{cases}$$

It is obvious that selected argument of maximum expression is not affected by multiplying $a > 0$ which can be concluded that $R'_n = aR_n$.

(ii) $a_1 > a_2$

Let $a = \frac{a_1}{a_2}$. We show that by multiplying 1 technology by $a \geq 1$ will decrease lower and upper thresholds.

We start with the upper threshold, for every stage n , \overline{P}_n^1 which is the maximum of two P_n^1 s obtained from solving of the following two equations:

$$P_n^1 \times D_n = a \times P_n^2(v_n) \times D_n \quad (.23)$$

$$a \times P_n^1(v_n) \times D_n = E[R'_{n+1}] \quad (.24)$$

Where R'_{n+1} shows the expected profit from waiting with prospective technology's revenue multiplied by $a \geq 1$. in first equation, RHS is increasing in a but not the LHS, then P_n^1 obtained from this equation will be decreasing in a . In second equation both sides are increasing in a , however increasing rate of RHS is higher than LHS, thus P_n^1 obtained from this equation is also decreasing in a . Both P_n^1 are decreasing thus their maximum \overline{P}_n^1 .

Similarly, lower threshold is the minimum of two P_n^1 s obtained from solving equations (.25) and (.26).

$$m_n^1 \times D_n = a \times m_n^2(v_n) \times D_n \quad (.25)$$

$$m_n^1 \times D_n = E[R'_{n+1}] \quad (.26)$$

In both equations, RHS is increasing in a , but not the LHS, thus P_n^1 obtained from these

equations are decreasing by multiplying in $a > 1$ as well as their maximum \underline{P}_n^1 .

(iii) $a_1 < a_2 < 1$

Let $a = \frac{a_1}{a_2}$. Similar to case 2, we can prove that lower (\underline{P}_n^1) and upper (\overline{P}_n^1) thresholds will increase by multiplying in $a < 1$. \square

Proposition 3.6 *The optimal payoff will increase by changing the opportunity cost function for each stage review i from d_i to d'_i , if for every $n \leq N$ we have $\sum_{i=0}^n d'_i \leq \sum_{i=0}^n d_i$.*

Proof. Let's show the value of the optimal decision for new opportunity cost of D' at time period n by R'_n . Having $\sum_{i=0}^n d'_i \leq \sum_{i=1}^n d_i, \forall n$ or $D'_n \geq D_n$.

We need to show that $R'_n \geq R_n, \forall n$. We proceed by induction:

For $n = N-1$ we have $R_{N-1} = \max\{m_{N-1}^1 D_{N-1}, m_{N-1}^2 D_{N-1}, 0\}$, $R'_{N-1} = \max\{m_{N-1}^1 D'_{N-1}, m_{N-1}^2 D'_{N-1}, 0\}$

which is obviously $R'_{N-1} \geq R_{N-1}$.

We assume that for period n we have $R'_n \geq R_n$. We prove that it holds for $n-1$. We have:

$$R_{n-1} = \max \begin{cases} m_n^1 D_{n-1} \\ m_n^2 D_{n-1} \\ E(R_n) \end{cases} \quad (.27)$$

$$R'_{n-1} = \max \begin{cases} m_n^1 D'_{n-1} \\ m_n^2 D'_{n-1} \\ E(R'_n) \end{cases} \quad (.28)$$

Comparing equation (.27) and equation (.28) reveals that if the first two argument inside max expression yields, it is obvious that $R'_{n-1} \geq R_{n-1}$. The third argument holds $E(R'_n) \geq E(R_n)$ holds because of the induction hypothesis, thus $R'_n \geq R_n$. \square

Proposition 4.1 *The expected value of the receiving new information is non-increasing in n .*

Proof. It shows that $\Delta = E[R_{n+1}] - R_n$ is constant or decreasing in n . Based on value of R_{n+1} and received signal, we have four cases:

i) Receive a positive signal and π_{n+1}^{pv} is selected. For this case we should have $v_n^+ \leq v^{thr}$ which implies $v_n \leq v^{thr}$ then we have $R_n = \pi_n^{pv}$. So $\Delta = -c_{n+1}$ which is a negative constant value.

ii) Receive a negative signal and π_{n+1}^{ps} is selected. For this case we should have $v_n^- \geq v^{thr}$ which implies $v_n \geq v^{thr}$ then we have $R_n = \pi_n^{ps}$. So $\Delta = -c_{n+1}$ which is a negative constant value.

iii) Receive a positive signal and π_{n+1}^{ps} is selected. For this case we should have $v_n^+ \geq v^{thr}$. In such situation R_n can either π_n^{pv} or π_n^{ps} . We have $\Delta = \pi_{n+1}^{ps}(v_n^+) - \max(\pi_n^{pv}, \pi_n^{ps}(v_n))$. From equation 4.5 we see that v_{n+1} is decreasing in n then $\pi_{n+1}^{ps}(v_{n+1})$ which is a linear function of v_{n+1} will be decreasing in n . If the first argument of max expression selected, which is a constant value, the result will be decreasing in n . If the second argument form

max expression is selected, we have $\Delta = \pi_{n+1}^{ps}(v_n^+) - \pi_n^{ps}(v_n)$ which can be written as:

$$\Delta = (M - m + F)(v_n^+ - v_n) - c_{n+1} \quad (.29)$$

It shows that $v_n^+ - v_n$ is decreasing in n . Substituting from equation 4.5 we have $v_n^+ - v_n = \frac{1-v_n}{\alpha+\beta+n+1}$ which is decreasing in n .

iv) Receive a positive signal and π_{n+1}^{pv} is selected. We will have $\Delta = \pi_{n+1}^{pv} - \max(\pi_n^{pv}, \pi_n^{ps}(v_n))$.

Either first or second argument from max expression selected, the result would be non-increasing in n . □

Proposition 4.2 *There is a finite N which firm will not continue collecting information after that stage N .*

Proof. We need to show that the value of collecting extra information is less than zero. In proposition 4.1, the value of extra information is negative in both case 1 and 2. For cases 3, and 4, the value is decreasing in n . By setting $N \geq \frac{M-m+F}{C_{n+1}}$ we can make sure that value always be negative. □

Proposition 4.3 *At each time period n there exist a pair of numbers \underline{v}_n and \bar{v}_n such that if $\underline{v}_n \leq v_n \leq \bar{v}_n$, it is optimal to wait until the next stage, if $v_n \leq \underline{v}_n$ it is optimal to choose pv technology, and if $v_n \geq \bar{v}_n$, it is optimal to choose the ps technology.*

Proof. We start with the upper bound for v_n . We show that there is a threshold \bar{v}_n such that for every $v_n \geq \bar{v}_n$, it is optimal to select ps technology. For this purpose we need to show that if v_n is such that it is optimal to select ps technology, it would remain optimum

to choose ps technology for any larger values of v_n . It shows that $R_n \leq \pi_n^{ps}$ will be valid by increasing v_n . It is equivalent to show that $R_n - \pi_n^{ps}$ is decreasing in v_n . To prove we follow induction: 1) For $n = N - 1$, $\max\{\pi_{N-1}^{pv}, \pi_{N-1}^{ps}, 0\} - \pi_{N-1}^{ps}$. In which first argument of max expression is constant, the second argument of max as well as the second term are the same and increasing in v_{N-1} , so the whole expression is constant in v_{N-1} and V_N . 2) We assume that $R_n - \pi_n^{ps}$ or $\max\{\pi_n^{pv}, \pi_n^{ps}, E[R_{n+1}]\} - \pi_n^{ps}$ is decreasing in v_n . 3) Show that $R_{n-1} - \pi_{n-1}^{ps}$ is decreasing in v_n or $\max\{\pi_n^{pv}, \pi_{n-1}^{ps}, E[R_n]\} - \pi_{n-1}^{ps}$ is decreasing in v_n . If the first two arguments of the max expression yields, the claim is true. For the third argument we need to show that $E[R_n] - \pi_{n-1}^{ps}$ is decreasing in v_n . By adding and subtracting $E[\pi_n^{ps}]$ we can get $E[R_n] - \pi_{n-1}^{ps} + E[\pi_n^{ps}] - E[\pi_n^{ps}]$ then this expression can be rewritten as $E[R_n - \pi_n^{ps}] + E[\pi_n^{ps}] - \pi_{n-1}^{ps}$. The first expectation is decreasing in v_n based on induction hypothesis.

Now we show that $E[\pi_n^{ps}] - \pi_{n-1}^{ps}$ is decreasing in v_n . We have

$$E[\pi_n^{ps}(v_n)] = v_{n-1}\pi_{n-1}^{ps}(v_{n-1}^+) + (1 - v_{n-1})\pi_{n-1}^{ps}(v_{n-1}^-) - C_n \quad (.30)$$

in equation .30, RHS can be written as $(M - m + F)[v_{n-1}(v_{n-1}^+ - v_{n-1}^-) + v_{n-1}^-] - m - F - C_n$ where $v_{n-1}(v_{n-1}^+ - v_{n-1}^-) + v_{n-1}^-$ can be simplified to v_{n-1} . we have $\pi_n^{ps}(v_{n-1}) = (M - m + F)v_{n-1} - m - F - C_{n-1}$ Thus equation .30 can be rewritten as:

$$E[\pi_n^{ps}(v_n)] = \pi_{n-1}^{ps}(v_n - 1) - c_n \quad (.31)$$

So $E[\pi_n^{ps}] - \pi_{n-1}^{ps}$ is decreasing in v_n

In order to prove existence of the lower thresholds, we show that there is a lower bound v_n such that for any $v_n \leq \underline{v}_n$, it is optimal to select pv technology. For this purpose, we show that once \underline{v}_n is in a level that it is optimal to select pv technology, it remains optimal for every $v_n \leq \underline{v}_n$. It shows that $R_n - \pi_n^{pv}$ is increasing in v_n . The second term is invariant to v_n , so it shows that R_n is increasing in v_n . In order to prove we follow by induction. 1) For $n = N - 1$ we have $R_{N-1} = \max\{\pi_n^{pv}, \pi_{N-1}^{ps}, 0\}$ which is increasing in v_n . 2) We assume that R_n is increasing in v_n . 3) Show that R_{n-1} is increasing in v_n . We have $R_{n-1} = \max\{\pi_n^{pv}, \pi_n^{ps}, E[R_n]\}$. The claim holds if first two arguments yields. The third argument is also increasing in v_n based on induction hypothesis. \square

Lemma .1. *The expected optimal payoff is non-increasing in review stage n*

Proof. According to proposition 4.2, if $n \geq N$ we have $R_n = R_{n+1}$. To prove for $n < N$ we follow the induction. We have $R_{N-1} = \max(m - C_{N-1}, \pi_{N-1}^{ps}(v_{N-1}) - C_{N-1}, E[R_N])$ and $R_N = \max(m - C_N, \pi_N^{ps}(v_N) - C_N)$. We can see that $R_{N-1} \geq R_N$. Now we assume that we have $R_n \geq R_{n+1}$, we prove that it is true for $R_{n-1} \geq R_n$. We have $R_{n-1} = \max(m - C_{n-1}, \pi_{n-1}^{ps}(v_{n-1}) - C_{n-1}, E[R_n])$ and $R_n = \max(m - C_n, \pi_n^{ps}(v_n) - C_n, E[R_{n+1}])$. To prove, it shows that $E[R_n] \geq E[R_{n+1}]$ which is true based on assumption. \square

Proposition 4.4 *At each time period n the lower threshold \underline{v}_n and upper threshold \bar{v}_n are respectively decreasing and increasing in n .*

Proof. Based on Lemma .1, if it is optimal to make decision at with estimate v_n at time n , it would be optimal to make decision with the same estimate at time $n + 1$ which completes the proof. \square

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ABSTRACT**TECHNOLOGY DECISIONS IN NEW PRODUCT DEVELOPMENT**

by

AMIR SANAYEI**May 2016****Advisor:** Dr. Leslie Monplaisir**Major:** Industrial Engineering**Degree:** Doctor of Philosophy

Selecting the right technology is one of the most important and challenging decisions in new product development (NPD) process that can greatly affect all downstream design activities which have a great impact on product success in the market place. Although new technologies may bring more competitive advantage by offering higher performance to price, they also make the NPD process more risky and challenging. We model the technology selection problem of a firm that is defining its new product in the presence of the technology uncertainty. At each review stage, firm has the options: select and commit to any technology alternatives or postpone this decision to the next review stage in order to gather more information. Delays in making technology decisions are likely to increase NPD cycle time by shifting forward downstream activities and ultimately may impose an increased development cost and profit loss for the firm. Our Analysis describes the optimal strategies for this problem and investigate the impact of technological and market uncertainty as well as time trade-offs on technology selection problem in NPD.

AUTOBIOGRAPHICAL STATEMENT

AMIR SANAYEI

Education

- *Ph.D. in Industrial Engineering*, Wayne State University (May 2016)
- *M.S. in Computer Science*, Wayne State University (May 2016)
- *M.S. in Industrial Engineering*, Iran University Science and Technology (Sep 2006)
- *B.S. in Industrial Engineering*, Iran University Science and Technology (Sep 2003)

Selected Publications

1. SANAYEI, AMIR, S. FARID MOUSAVI, AND ALIREZA YAZDANKHAH. "Group decision making process for supplier selection with VIKOR under fuzzy environment." *Expert Systems with Applications* 37.1 (2010): 24-30.
2. SANAYEI, AMIR, ET AL. "An integrated group decision-making process for supplier selection and order allocation using multi-attribute utility theory and linear programming." *Journal of the Franklin Institute* 345.7 (2008): 731-747.
3. SAREMI, MAHMOUD, S. FARID MOUSAVI, AND AMIR SANAYEI. "TQM consultant selection in SMEs with TOPSIS under fuzzy environment." *Expert Systems with Applications* 36.2 (2009): 2742-2749.
4. SANAYEI, AMIR, AND LESLIE F. MONPLAISIR. "Integrating product life cycle issues in technology selection." *Technology Management for Emerging Technologies (PICMET)*, 2012 Proceedings of PICMET'12:.. IEEE, 2012.
5. SANAYEI, AMIR, AND LESLIE F. MONPLAISIR. "Integrating product life cycle issues in technology selection." *Technology Management for Emerging Technologies (PICMET)*, 2012 Proceedings of PICMET'12:.. IEEE, 2012.
6. SANAYEI, AMIR, AND LESLIE F. MONPLAISIR. "New Product Development and Technology Decisions under Uncertainty" Submitted to *IEEE Transactions on Engineering Management*.
7. SANAYEI, AMIR, AND LESLIE F. MONPLAISIR. "New Product Technology Decisions: Considering Technical Uncertainty and Development Cycle Time" Submitted to *International Journal of Production Economics*.
8. SANAYEI, AMIR, AND LESLIE F. MONPLAISIR. "Technology Selection in New Product Development: Technical and Market Uncertainty" Submitted to *Expert Systems with Applications*.