Resource Allocation and New Product Development Portfolio Management

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1.1. Introduction

Developing the "right" new products is critical to firm success and is often cited as the key to a sustained competitive advantage. Managers often set ambitious goals for future revenue generated from new products. Statements such as "*innovate or die*" overflow the popular business press and confirm the importance of successful new product development (NPD).

Any company that engages in NPD faces the important problem of allocating resources between innovation initiatives in a portfolio. Companies that make poor choices with respect to their NPD portfolio run the risk of losing their competitive advantage. Examples abound in practice: DuPont experienced trouble because the company diverted the majority of its estimated $2 billion yearly R&D budget to improving established business lines (Barrett, 2003). Drug maker AstraZeneca revealed the decision to restructure its portfolio to include more incremental projects (Pilling, 2000). Kodak is investing resources in revolutionary new technologies to catch up in the digital photography market, despite the fact that the company was synonymous with photography for the better part of the twentieth century (Schoenberger, 2003). These cases underscore the reality that effective resource allocation and NPD portfolio management profoundly impact firm success. The NPD portfolio practically determines the firm's strategy for the medium and long-term future, and is the responsibility of the senior managers of the firm (Roussel et al. 1991, Cooper et al. 1997). When managers make resource allocation and NPD portfolio decisions they take an implementation step that links innovation strategy with reality. This step embodies a difficult choice: allocate resources to the development of fundamentally new technologies, products, and markets that are naturally more risky investments or improve existing technologies, extend product lines, and entrench existing market position without excessive risk. Of course, the problem is exacerbated by the fact that the former investments have the lure of potentially high payoffs while the latter often result in smaller payoffs (Tushman and O'Reilly, 1996).

From the dawn of Operations Research in the early 1950s, to the emergence of managerial frameworks (such as the BCG matrix) in the 1970s, through today, the problem of developing the "right" new products has motivated academics and practitioners to propose a number of solutions. Several tools and theories have been developed by different constituencies, resulting in an interesting dichotomy: a collection of rigorous analytical efforts with minimal adoption and minimal practical impact (Loch et al. 2001, Shane and Ulrich 2004), and a variety of managerial frameworks grounded in individual case studies with widespread impact but little theoretical foundation. In either case, managerial guidelines are limited to a generic notion of "balance" among different value determinants due to the lack of understanding about fundamental problem drivers. Hence, senior managers, R&D managers, and project managers are forced to make resource allocation decisions based primarily on intuition or heuristic rules.

Recent data verify that the overall impact of NPD portfolio methods and research remains largely in doubt. A study conducted by the Product Development Management Association (PDMA) reveals an interesting result: between 1994 and 2004 development cycle times have significantly improved. A portion of this effect is a due to overall improvement in the management of the product development process. However, the percentage of resources allocated to minor product changes and small improvements also increased significantly during the same period of time. Hence, there is evidence that firms are increasingly focused on incremental NPD efforts. The bad news is that high performing firms emphasize diverse portfolios that include "cutting edge", "new to the market", or "new to the world" initiatives in addition to incremental efforts (Adams and Boike, 2004). Figure 1 illustrates these results.

Collectively these facts indicate that a deeper understanding of NPD portfolio management is necessary. The purpose of this chapter is to provide a theoretical framework that can be used to study resource allocation and NPD portfolio management. We begin in §2 with an important underlying premise: NPD portfolio management is a complex problem. This discussion sets the stage for §3 in which we provide a theoretical framework for resource allocation and NPD portfolio management. In §4 we associate our framework with existing literature that addresses different levels of decision making with respect to the NPD portfolio. We summarize the current state of knowledge and highlight some important open questions in §5.

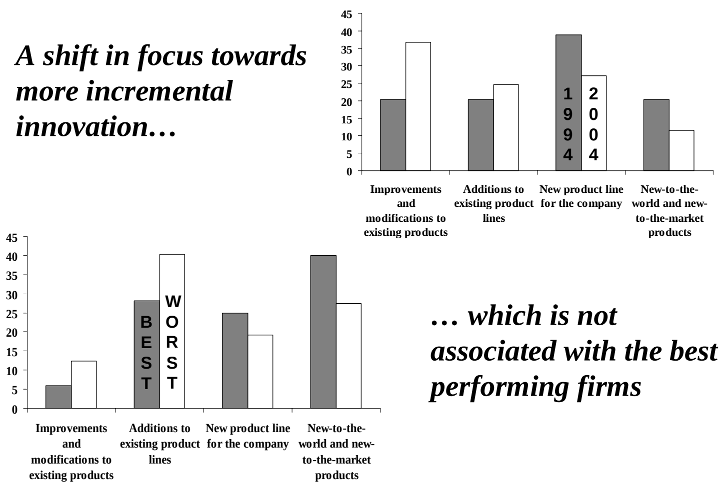

Figure 1: Product Development Institute Report, 2004

1.2. What makes NPD portfolio management so difficult?

NPD portfolio management is concerned with methods and tools that ensure effective resource allocation among an ensemble of innovation efforts. The NPD portfolio determines the minor improvements, new product introductions, or radical breakthrough developments associated with the product mix of a company. In doing so, the NPD portfolio influences the balance between market segments and the time to market profile for each innovation effort. The essential feature that defines the NPD portfolio problem is that projects should be viewed together rather than in isolation. The portfolio view necessarily gives rise to several considerations:

- *Strategic alignment*. The NPD portfolio allows a firm to operationalize and implement strategy over time. This point implies that the NPD portfolio problem entails a large component of ambiguity and complexity, since the determinants of firm success and their interactions are rarely known. Moreover, successful NPD portfolio management rests upon the ability to effectively communicate firm strategy and cascade it down to an implementable NPD program or project level (Loch and Tapper 2003).
- *Resource scarcity*. Scarce resources often critically constrain the NPD portfolio problem. It is common practice to pursue many projects in parallel in order to

achieve broader product lines (mass customization) and higher market share (e.g., Reinertsen 1997, Ulrich and Eppinger 2003, Cusumano and Nobeoka 1998). In multi-project environments, scarce resources render the resource allocation decision a critical factor for success (Adler et al. 1995). Scarcity may involve the total R&D budget, testing equipment availability (analogous to bottleneck machines in production scheduling), or specialists with unique areas of expertise. In several contexts, project managers need to "queue" for access to these specialized resources.

- *Project interactions*. Companies often develop multiple products and services in closely related market segments. Hence, the new products that are developed exhibit synergies or incompatibilities in their technical aspects. Similarly, on the market side, products may substitute or complement one another. Interactions between success determinants play a critical role in the resource allocation decision, since interactions proxy decision complexity.
- *Outcome uncertainty*. NPD projects are characterized by lack of precise knowledge regarding their outcomes. Hence, management faces uncertainty along the dimensions of the potential market value and technical output of any given project. NPD managers face risks related to the overall functionality of the product (technical risk) and to the adoption of the product from the end customers (market risk). Moreover the type of uncertainty determines the ability to "optimize." Pich et al. (2003) discuss such a typology within the context of project management.
- Dynamic nature of the problem. Decision makers must allocate resources over time and NPD programs evolve over time. Therefore, managers must take into account future values and risks when allocating resources to a promising idea. However, it is often difficult to quantify the potential of promising ideas or precisely measure the risks involved. Furthermore, the various innovation initiatives in a portfolio do not typically evolve at the same pace.

The five sources of decision complexity outlined above highlight the difficulties associated with NPD portfolio management. Moreover, they illustrate that resource allocation and NPD portfolio decisions, like several other NPD decisions, are not necessarily centralized decisions; rather, they span across different levels of management. As the locus of decision-making moves from strategic to tactical and operational, resource allocation decisions are driven by more tangible and specific project metrics. However, they are constrained by significantly less flexibility (Anderson and Joglekar 2005). In this chapter we will not delve into the issues of product line design and competitive product positioning, since there are other chapters in this book that focus on such decisions. Rather, we will consider a general framework for resource allocation and NPD portfolio management, and we will link decisions to different organizational levels.

1.3. A Theoretical Framework for NPD Portfolio Management

In this section we present a general model of resource allocation and NPD portfolio management. We use the model as a foundation upon which we build, and we discuss how the drivers of the resource allocation decision change depending on the organizational level at which the decision takes place (from senior management, to the NPD program level, and finally the individual project level). Once the differences are presented we introduce the associated literature and we overview the findings.

Figure 2 depicts the resource allocation decision and illustrates the different elements of the decision. A number of NPD programs must be funded by a pool of resources (the budget) in every period. The NPD programs are targeted at different, but not necessarily independent products that serve customer markets. Each product delivers an uncertain payoff at each period in time. The possibility of technical synergies and/or incompatibilities between program outcomes complicates the decision further.

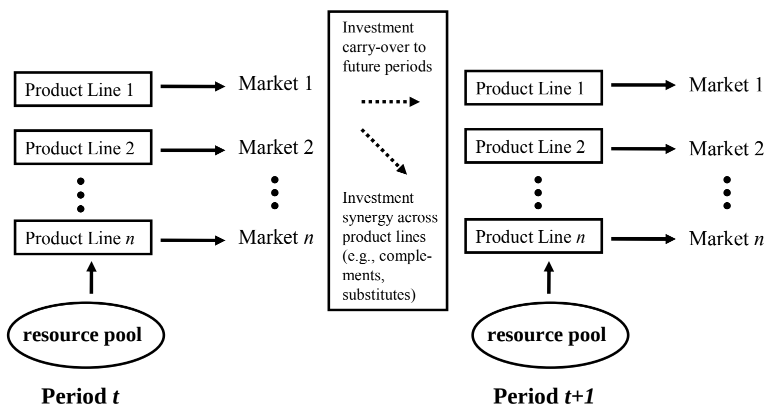

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Figure 2: The dynamic portfolio selection decision(s).

We begin by considering that the firm's product portfolio is comprised of n distinct products. Each product is defined as a configuration of technology and market attributes. Management decides to develop and introduce products that employ specific technologies and target various customer needs. Therefore, managers must specify the product attributes such as core technology utilized and aesthetic design elements in addition to market related variables such as price or distribution channel. Formally, each product is a vector

$$\vec{y}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,M(i)})$$

where $i=1,2,...,n$ is the number of products in the portfolio, $M(i)$ denotes the number of attributes that define product i, and $x_{i,j}$ is the j-th attribute that defines product i (e.g. whether a microchip has wireless capabilities or not). The firm operates in an environment where $M(i) \leq M$ and M defines the complete space of known and unknown product attributes. Thus, we allow for situations in which decision-makers are not aware of the existence of some product attributes that influence performance. Note at this point that a subset of the attributes are deliberate choices of management while others may not be (e.g. some technologies are used simply because of the absence of better alternatives or a particular distribution channel may be used because of prior experiences). The configuration of technology and market attributes determines product performance (sales or revenue) and the portfolio of products determines firm performance. We assume that each product i generates revenue $V(\vec{y}_i, \vec{y}_{-i})$ where $\vec{y}_{-i}$ represents all products in the firm's portfolio other than product i. Decision makers may have precise knowledge of how the attributes contribute to the overall performance, or not. Therefore, the mapping from $\vec{y}_i$ to $V_i(\bullet)$ may be known precisely, or not. The reasons for $V_i(\bullet)$ being unknown lie in the extent of decision maker's information processing capabilities and the interactions among the $x_{i,j}$ that define each product. Limited information processing capability leads to bounded rationality and a large number of interactions defines very complex $V_i(\bullet)$ functions.

On a periodic basis (e.g. quarterly or semi-annually), the firm conducts portfolio review meetings. The focus of the portfolio review meetings are the NPD programs that address the improvements or changes for each product or product line. We consider each NPD program to be a collection of projects that drive improvement and/or innovation in a single product line. In our formal representation, an NPD program drives a transition from configuration $\vec{y}_i$ to a new configuration $\vec{y}'_i$. Note that such a transition may not necessarily be the result of one individual project. It could rather be the outcome of several ongoing parallel efforts. In addition, note that NPD programs determine the innovation strategy of the firm. Innovation may be more or less incremental or radical depending on the number of attributes that are actually altered in a transition from $\vec{y}_i$ to $\vec{y}'_i$. Thus, innovation acquires a "spatial" (Schumpeterian) quality, reflecting the notion of how different the innovation effort is compared to the existing configuration. Two distinct effects must be addressed here:

1. Depending on the magnitude of innovation pursued, as denoted by the number of attribute changes in the product configuration $\vec{\delta}_i = \vec{y}'_i - \vec{y}_i$ and its Euclidean distance $\Delta_i = \left|\vec{\delta}_i\right|$, the risk for obtaining a configuration that results in superior performance depends on the distance of search. For any set of configurations with the same distance Δ_i, the likelihood that configuration $\vec{y}_i + \vec{\delta}_i$ results in higher performance compared to $\vec{y}_i$ is a decreasing function of Δ_i. Formally, $\Pr\{V(\vec{y}'_i) \geq V(\vec{y}_i)\}$ is a decreasing function of

Δ_i. This represents the fact that radical innovation is more risky than incremental innovation due to the distance of search.

2. The resources required to explore a transition from $\vec{y}_i$ to $\vec{y}'_i$ also depend on the distance of search. Formally $C_i(\Delta_i)$, is an increasing function of Δ_i. This observation implies that for the same amount of resources allocated to an NPD program, either few very innovative or multiple incremental innovation configurations can be explored.

Finally, the portfolio decision involves the solution of a complicated dynamic problem:

$$J_t(\vec{y}_1, \vec{y}_2, ..., \vec{y}_n) = \max_{\vec{y}'_j \in \Omega, j=1,2,...,n} \{-\sum_i C_i(|\vec{y}'_i - \vec{y}_i|) + \sum_i V_i(\vec{y}'_i) + J_{t+1}(\vec{y}'_1, \vec{y}'_2, ..., \vec{y}'_n)\}$$

subject to the budget constraint on a period basis: $\sum_i C_i(|\vec{y}'_i - \vec{y}_i|) \le B_t$. The equation to be maximized consists of the total resource expenditure for changing each product, the immediate revenue generated by each new product configuration, and the value of the portfolio in period *t+1* and beyond.

The general description above gives rise to several immediate questions regarding (i) the potential solution space and the degree of available knowledge regarding that space (i.e., "*what are the maximization levers available to management?"*), (ii) the level of knowledge regarding the performance functions $V_i(\bullet)$, as well as the interdependencies across the performance determinants $x_{i,j}$ (i.e., "*how do decisions change the performance value obtained?*"), and (iii) how strict is the resource constraint (i.e., "*does management have flexibility with respect to resource allocation or does management operate within the confines of a strict budget?*").

In this chapter we posit that a hierarchical perspective on the resource allocation and NPD portfolio management problem is appropriate. We argue that depending on the level of decision making within the organization, and on the unit of analysis (be it a choice within single project versus the investment in an NPD program or even the composition of the entire NPD portfolio) the resource allocation decision faces distinct challenges. Our thesis here relates to an already growing body of research on NPD decisions across different levels in the organization - a "hierarchical planning approach" - and the emerging knowledge gaps therein (see also chapters 11, and 12 in this book).

Figure 3 introduces the main decisions, variables, and challenges encountered at different organizational levels. Across different organizational levels the decisions relate to (i) the degree of knowledge regarding the solution space, (ii) the degree of knowledge regarding the underlying performance structure, and (iii) resource availability (and flexibility). The notion of "degree of knowledge" captures full, partial, or lack of knowledge and maps directly into deterministic, foreseeable uncertainty, or ambiguous situations (Pich et al. 2003).

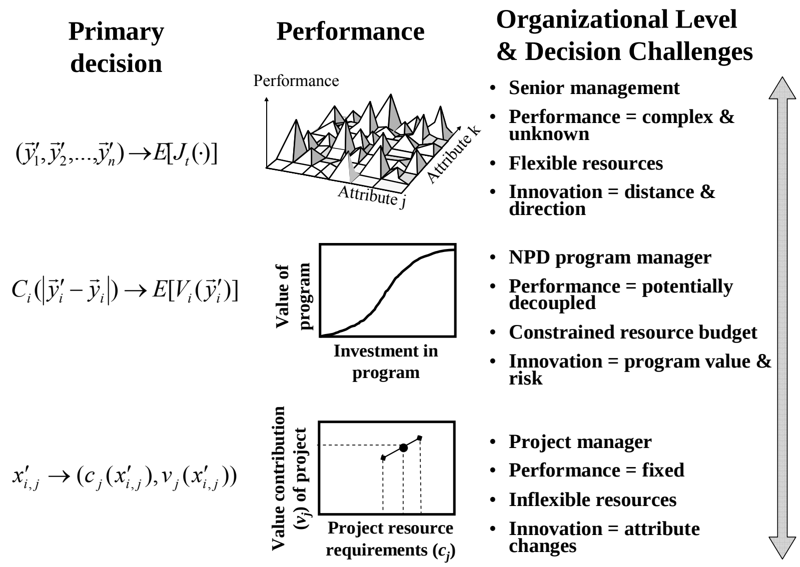

Figure 3: NPD portfolio selection in the organization

At the level of senior management the decision involves several dimensions that include target markets (e.g. industrial or consumer), basic technologies (e.g. process specifications), revolutionary technologies (e.g. hybrid engines), strategic considerations of the organization (e.g. generalists versus niche players), and external influences (e.g. regulations from antitrust committees) among others. Therefore, individual product performances are no longer seen as independent, rather they are highly coupled due to the interactions across different performance determinants. In addition, uncertainty, ambiguity (Pich et al. 2003), and bounded rationality (Simon, 1982) are confounded disallowing the use of standard risk assessment models. Although the decision is highly complex, an interesting consideration is that resource allocation is flexible at this level of decision making, and the decision objective transforms from one of constrained optimization to a search for the best NPD portfolio. Given these observations, the maximization aspect introduced in our previous theoretical framework is overly limited and managers reside on methods and tools that aim to decipher potential trade-offs and shed some light on the decision process (e.g. market potential versus competitive position for each product line).

The NPD program level addresses a collection of focused innovation efforts (projects) aimed towards the improvement of a product or product line. At this level, several dimensions introduced previously become clearer without rendering the decision extremely easier. Given the innovation goal (e.g. "need to radically change this product line" versus "need to advance performance to the next stage"), the NPD program team performs within the boundaries of a specific search strategy. Therefore the NPD manager faces a specific return on investment curve, where the magnitude of performance change is positively correlated with the degree of innovation, but so is the risk of the endeavor.

Eventually, the NPD program manager must select how to invest a specific budget (thus resource availability becomes an issue) across projects with potentially different returns on investment and different risk profiles. However, as the focus becomes more specific (e.g. a specific product line), management has better understanding of the $V_i(\bullet)$ functions and can appropriately value the innovation outcome.

Finally, at the individual NPD project level, priorities are well established. In this case, different solutions that address specific product attributes (or a small subset of attributes) are designed and tested (e.g. the drop-down menu design team for a software company has to account for their strictly defined budget as well as the dictated performance goals). Performance determinants at this operational level are well understood and the residual risk lies in the exact resource requirements necessary to make a solution work. The flexibility associated with decisions at this level is limited but there is ample opportunity for optimization. Unfortunately, due to inflexible project characteristics and the combinatoric nature of the selection problem, optimization is not always guaranteed to work. Once again, managers must reside on heuristics that trade-off higher project performance with capacity utilization ("knapsack" problems).

Thus far we have established a hierarchical framework for resource allocation and NPD portfolio management. For the remainder of this chapter we attempt to highlight different insights obtained from the literature and how they relate to the framework presented in this chapter.

1.4. Existing Literature

This section offers a literature review of the resource allocation and NPD portfolio management problem. We summarize the research undertaken, and we categorize it along two dimensions: the unit of analysis (firm portfolio, versus R&D program, versus individual projects) and the timing considerations of a static versus a dynamic analysis (Figure 4).

Figure 4 exhibits upfront an interesting finding. The inverse relationship between the amount of theoretical work performed and the level of analysis. Hence, at the strategic (firm) level of decision making the amount of work is significantly less than the work in the "tactical" level of project selection. The work at the latter level, as attested by our summarizing Figure needs to be classified in sub areas. Even more interestingly, the tactical work has not managed to make a substantial impact to the upper levels of the managerial community reflecting the misalignment between the complex reality of the decision and the introduced simplifications of the modeling abstraction. The latter observation, has first been recorded by Souder (1973), and Schmidt and Freeland (1992); and iterated by Loch et al. (2001), Kavadias and Loch

(2003) and very recently by Shane and Ulrich (2004) in their review paper for the fiftieth anniversary of technology management and product development research in *Management Science*[1]. Below, we discuss the main findings and limitations of the previous work in the different groups. Our focus is to link them back to the overall framework we have established.

	Static	Dynamic
Firm level	• Roussel et al. (1991) • Wheelwright and Clark (1992) • Ali et al. (1993) • Adler et al. (1995) • Cooper et al. (1997) • Comstock and Sjolseth (1999)	• Balasubramanian et al. (2004) • Girotra et al. (2005) • Pisano and Gino (2005) • Chao and Kavadias (2006)
R&D program level	• Analytical Hierarchy Process models, Liberatore (1987) • Jones (1999) • Fridgerisdottir and Akella (2005)	• Chikte (1977) • Nobeoka and Cusumano (1997) • Loch and Kavadias (2002) • Ding and Eliashberg (2002) • Blanford (2004) • Setter and Tishler (2005) • Chao et al. (2006) • Bhattacharya and Kavadias (2007)
Project level	• Mathematical Programming Formulation Models, Fox, Baker and Bryant 1984, Loch et al. 2001 • Multi-criteria decision making tools, Brenner 1994 • Net Present Value (NPV) analysis, Hess (1993), Sharpe and Kellin (1998) • Break-Even Times (BET), House and Price (1991)	• Multi-Armed Bandit (MAB) models, Gittins and Jones 1972, Whittle 1980, Asawa and Teneketzis 1996 • Dynamic Scheduling Models, Smith 1956, Harrison 1975, Wein 1992, Van Mieghem 2000, Kavadias and Loch 2003 • Optimal admission models, Stidham 1985, Kleywegt and Papastavrou 1998, Lewis et al. 1999 • Economic models, Weitzmann 1979, Fox and Baker 1985, Vishwanath 1992

Figure 4: Overview of portfolio selection literature

1.4.1. NPD Portfolio Management at the Strategic Level

The NPD portfolio problem has attracted strategy and management research interest, reflecting its importance for senior management. Because of the complexity of the decision at this level of decision making, as we argued in our general framework, the literature has mainly grown to a set of "best practices" recorded through case studies. Yet recently, several theoretical studies have tried to open the "black box" of the $V_i(\vec{y}_i)$ product performance functions. We start off by presenting the former group, which has shaped managerial decision making in a significant way. We then proceed to discuss further the recent studies.

Roussel et al. (1991) popularized the importance of portfolio selection for top management in organizations. Cooper et al. (1997) and Liberatore and Titus (1983) carried out a large survey of top management decision making concerning their NPD

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[1] "*A substantial body of research has focused on which innovation projects to pursue... surveys have shown that these models have found very little use in practice... If 50 years of research on an area has generated very little managerial impact, perhaps it is time for new approaches*" (Shane and Ulrich 2004, p.136)

portfolios. Also, Wheelwright and Clark (1992a) recognized the importance of portfolio selection for strategic decision making. Most of these studies confirm a general trend: top management tend to complement their routine financial project evaluations with *ad hoc* tools, in particular resource allocation balances over ``strategic buckets'', and the comparison across market competition and newness and/or technological risk Wheelwright and Clark 1992a, Cooper et al. 1997). We depict some representative, and often used[2], managerial tools in Figure 5.

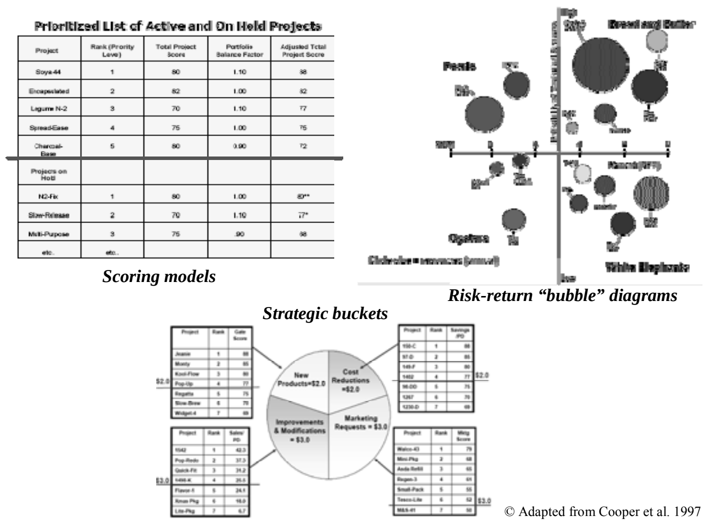

Figure 5: Qualitative portfolio selection tools

In *scoring models* (upper left of Figure 5), various projects are ranked with respect to a weighted average of their performance on multiple criteria as the latter ones are defined by management. The *n* best projects, according to their overall score, “make it” to the portfolio. The upper right classification tool, a *risk-return “bubble diagram”* categorizes the different R&D programs or projects along their technology risk and their potential return (as indicated by the net present value). The objective for top management is to achieve balance between the overall risk and the return of the portfolio. An efficient frontier could characterize the best returns that are being obtained at given risk levels. This tool is widely used in practice (see, e.g., Cooper et al. 1997). Finally, the division of resources into different “strategic buckets” as illustrated in the bottom of Figure 5 aims to balance resource allocation across efforts of different innovation levels given that long term programs with very risky outcomes would always be undermined when compared financially with short term, “quick cash” initiatives. Different case studies have argued for the determinants of the bucket sizes (Cooper et al. 1997), but the only one that has managed to achieve an abstract approach to this issue has been Wheelwright and Clark (1992a). They identify the

2 See for example Taggart and Baxter 1992, Braunstein and Salsamendi 1994, Foster 1996, Groenveld 1997, Stillman 1997, Comstock and Sjolseth 1999, Tritle et al. 2000.

(manufacturing or sales) process change versus the extent of product change as the classification factors. Their idea is that a large change in either of these two dimensions increases risk, which must be balanced in order to achieve better "planning, staffing, and guiding of individual projects" (Wheelwright and Clark 1992a).

The main insight of these studies is the notion of ***balance*** across the different dimensions/factors that determine the product performance and subsequently the overall portfolio performance. At the same time, the very same issue becomes their limitation. These tools have the ability to generate only *ad hoc* rules of thumb: thus, they help management to "think through" the factors that help out in the decision, but they lack additional theoretical or empirical basis for further recommendations. Still, we need to recognize the fact that these methods have been heavily used in practice, because they facilitate useful discussions in managerial meetings (Loch 1996, describes the challenges that arise in such a setting). Hence, this line of work, albeit descriptive or based on a few examples, has aimed at addressing the central challenge of the top management decision: its complexity. All the previously cited tools, encompass efforts for understanding the implications of multi-period effects, of market variables, technology factors and "external" performance determinants, as well as their interactions. Due to the lack of a theoretical focus, these methods are obliged to stay at a very aggregate level, without really assessing the exact balance that management should keep in the portfolio. However, their result is essential, since they illustrate that further work should be performed in analyzing in detail the trade-offs between the various performance determinants, the $x_{i,j}$ attributes of our general model.

As a response to the difficulty of assessing all potential factors a relatively new approach has promoted the idea that generic criteria, such as risk, return or any type of score, are not sufficient. Rather, the NPD activities should be explicitly linked to the goals of the business strategy (e.g., Kaplan and Norton 1996, Wheelwright and Clark 1992b, Comstock and Sjolseth 1999). The R&D strategy must be "cascaded" down to the individual activities instead of allocating a given budget according to (generic or customized) scores (Loch and Tapper 2002).

A few normative studies have tried to uncover potential trade-offs at that level. Ali et al. (1993) model an R&D race between two firms that choose among two different products. They show the effect that competition has on project choice, given heterogeneous firm capabilities to innovate (i.e. time and resource effectiveness). Although, their approach is static, they highlight the importance of the "external" factors and identify the fact that for different conditions different strategies are suggested, a notion closer to the performance "landscape" advocated by our framework.

Two studies (Adler et al. 1995, Gino and Pisano 2005) emphasize the capacity choices on portfolio success. They both view the R&D department of a firm as a manufacturing shop floor where different "servers" process each project before it is completed. Issues of internal delays due to congestion arise, revealing the latent technical interactions across innovation efforts that shall be considered when defining the portfolio. Gino and Pisano (2005) also argue for the behavioral component in the decision of which projects should be admitted in each stage. In a pioneering empirical effort, Girotra et al. (2007) try to draw a systematic link between the portfolio choices and the overall value of the firm. They conduct an event study in the pharmaceutical industry, and they show that project failure without the appropriate build-up of "back-up" alternative compounds may result in high company value loss. We believe that such studies are of crucial importance in order to really uncover the performance drivers and apply optimization techniques to product portfolio management. Along similar premises Balasubramanian et al. (2004) analyze the changes in the product portfolio breadth over time within several high-tech industries, as a response to environmental factors like market opportunities and uncertainty. Although their work focuses on R&D program choices we classify it here due to the firm level data and the effort to once more quantify the trade-offs between performance determinants.

Chao and Kavadias (2006) introduce a theoretical framework that relies upon similar premises as the general model presented in this chapter. They explore factors that shift the proposed balance in the NPD portfolio, and they attempt to offer a theoretical basis for the strategic buckets tool presented above. Their findings show that the amount of interactions among the performance drivers is a major determinant of the portfolio balance. Thus, highly coupled marketing and technology performance attributes prompt for the existence of buckets, i.e. the "protection" of resources aimed at risky and radical innovation efforts. They also show the pro-incrementalism effect of environmental turbulence (likelihood that structural features of $V_i(\bullet)$ may change) and competition (likelihood of survival in the future).

1.4.2. Resource Allocation and NPD Programs

The decision of how to allocate resources among NPD programs necessarily operates under a set of constraints: (i) the type of innovation balance as defined at the strategic level, and (ii) the limited available resources, which can be flexibly assigned. Hence, studies at that level of analysis entail the flexibility of varying investment because different individual projects may be started or stopped within the program. At the same time, due to the focus on one product line the complexity is reduced and due to the proximity to the specialists (the R&D program manager and his/her project managers) there is finer understanding of the underlying performance structure. Thus, as we have argued, the value can be better estimated given a specific configuration $\vec{y}'_i$ and the issue is the investment in different projects that could gradually - over time - capture the potential value.

The need for a hierarchical analysis, investment-wise, has been advocated by Liberatore and Titus (1983). It allows the break down of the difficulty associated with the combinatoric nature of the problem at the single-project level. At the same time, it encompasses the same notion as the strategic buckets. Resources are divided based on a hierarchy of criteria. Hence first a division based upon the upper level criteria is done and then each subset of resources is allocated across individual projects.

Some empirical studies suggest the formation of "within a product line" development strategies (Nobeoka and Cusumano 1997, Jones 1999). They highlight the importance of product line management for firm performance, and they focus on the value of platforms[3]. These studies offer empirical evidence from the automotive and the telecommunications industries. Along similar lines Setter and Tishler (2005) try to estimate the technology investment curves with the defense industry context, and Blanford and Weyant (2005) analyze the technology investments in climate change prevention initiatives.

There have not been many studies in a dynamic context, where the presence of uncertainty lead to allocation changes in the optimal allocation over time. Chikte (1977), models parallel development activities and corresponding resource allocation strategies. He assumes that investment in an innovation effort impacts its likelihood of success. He analyzes general structural properties without any attempt to outline some managerial decision rules.

In the same category, there is extensive literature on the dynamic financial portfolio investments (e.g., Merton 1969, Constantinides and Malliaris 1995, Samuelson 1969). These financial models generally assume linear returns (e.g., number of stocks multiplied by stochastically changing prices). Instead, the returns from NPD investments are non-linear in the amount of resources (e.g., Arthur 1994, Brooks 1975).

Loch and Kavadias (2002) have developed a dynamic allocation model that addresses part of the previous challenges. Hence, they focus on R&D program investments, and account for the carry over feature of the investment, that is the fact that investments within the product line may build up gradually over time. They assume knowledge of the potential value and of the interactions across product lines rendering the applicability of the model limited in cases of radical innovation efforts were both the value and the potential interactions are unknown. They show that the investment should follow a "marginal benefit" logic where management should try to invest the next dollar to the program with the highest *overall* marginal benefit (that is the benefit in the current and the subsequent periods). Along similar lines, Ding and Eliashberg (2002) analyze the number of parallel efforts in each different stage within an R&D program (they assume that all efforts aim at obtaining the same goal), in order to ensure success. Their main insight prompts for overinvestment in each stage due to the individual project potential failures. Fridgeirsdottir and Akella (2005) explore the capacity optimization decisions given the congestion effects that may arise within an NPD program[4]. Their insight links idea arrival rates to a capacity *ex-ante* division, a notion that approximates the hierarchical suggestions by Liberatore and Titus (1983). Recently, Blanford (2004) analyzes the resource allocation dynamically between two innovation endeavors, an incremental one and a radical risky one. Chao et al. (2006) build along the same notion, and they consider the problem of dynamic investment in NPD programs under the assumptions that the overall budget depends on how cash is generated over time, and that resource availability may be constrained at different

[3] We should note here that the notion of a platform and its derivative products, aligns very well with the definition of an R&D program. The key concept here is the fact that all these efforts revolve around a specific configuration $\vec{y}_i$ or its close "neighbors."

[4] They assume that all undertaken projects are of the same "type," i.e. same processing rate with different categories of payoffs

points in time as the programs evolve. Under this situation, they analyze how the investment in incremental or revolutionary NPD programs depends on the level of autonomy given to decision makers. Also Bhattacharya and Kavadias (2007) explore how the R&D resources can be allocated over time on different product development efforts given that these rely upon different underlying technologies. They look at the effects of learning that some technologies may exhibit in conjunction to their time of "arrival," on the optimal allocation of resources.

1.4.3. NPD Portfolio Selection at the Tactical Level

At the tactical level of decision making, a fixed budget must be allocated among multiple ongoing projects, both statically (one-time) and dynamically (repeatedly, once per review period, or whenever a new project idea emerges). The fact that the single project may focus on a smaller subset of performance drivers (i.e. $x_{i,j}$) as dictated by the NPD program decisions, implies that the associated complexity is significantly reduced, resulting in more accurate value estimates and resource requirements. However, at the same time the rigidity of the resource requirements and the fixed outcome (value) lend a combinatoric nature to the problem and do not allow standardized solution processes. Thus, the majority of the proposed solutions reside on heuristic methods.

From a practice-oriented standpoint, such approaches encompass findings from the financial literature like net present value (NPV) analysis (Hess 1993, Sharpe and Keelin 1998) and break-even time (BET) (House and Price 1991) applied at the operational level of a single project. Each project is assigned an index (its financial value), and these indices are ranked to determine the *n* best candidates. Observe, however, that the resulting portfolio is not necessarily optimal[5]. Decision theorists have also proposed project ranking via a composite average score on multiple "qualitatively" assessed dimensions, choosing the n best candidates for the portfolio (Brenner 1994, Loch 2000). Similarly, the analytical hierarchy process (AHP, see Liberatore 1987, Saaty 1994, Hammonds et al. 1998, Henriksen and Traynor 1999) is a structured process of multi-criteria decision making. However, apart from the previously mentioned combinatoric nature due to capacity, the multi-dimensional decision making methods lack a significant determinant of project choice, namely interactions among projects, both on the technical and on the market side. The majority of the normative literature has treated the problem at hand through two different sets of lenses: either as a "knapsack problem[6]" or as a dynamic allocation of a critical resource across projects (dynamic scheduling literature).

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[5] The simpler counterexample is the following: consider two projects with requirements c_1, c_2 respectively. $c_1 + c_2 > B$, where B is the budget, $c_1 < c_2$, and $\frac{R_1}{c_1} >> \frac{R_2}{c_2}$, where R_1 are the respective project revenues. Although from an ROI perspective project 1 is better eventually project 2 is chosen. Similar arguments can be built for all such ranking methods.

[6] The *knapsack problem*, proposed by Operations Research theorists, considers a set of projects with specific resource requirements and value propositions and a fixed total budget (i.e. the knapsack). The objective is to maximize the value "put" into the knapsack

Along the first category, there have been many attempts to model the selection problem with different mathematical programming formulations. Hence, formulations such as knapsack have been examined in depth in Operations Research (OR) and they have utilized many variants of mixed-integer programming heuristics for their solutions. Several of these efforts were applied in specific companies (Beged-Dov 1965, Souder 1973, Fox et al. 1984, Czajkowski and Jones 1986 Schmidt and Freeland 1992, Benson et al. 1993, Belhe and Kusiak 1997, Loch et al. 2001, Dickinson et al. 2001).

Although mathematical programming is a sound methodology for optimization problems, and it has been successfully applied in several specific cases, it has not found widespread acceptance by practitioners (Cabral-Cardoso and Payne 1996, Gupta and Mandakovic 1992, Loch et al. 2001). This gap stems partly from the complexity and sophistication of the methods, which are difficult to understand and to adopt for people who are not trained in OR, and partly from the lack of transparency and from the sensitivity of the results to changes of the problem parameters (an example is demonstrated for a mixed-integer programming application in Loch et al. 2001). In addition, mathematical programming formulations in order to retain some level of analytical tractability they rarely account for dynamic decision making, such as the option to abandon some of the projects during development, or the fact that different projects start and end at different points in time. Recently, Beaujon et al. (2001) made the observation that project funding is not a "zero or one" decision, but that it can be continuously adjusted. Kavadias et al. (2006) rely upon the observation of Beaujon et al. (2001) but consider upper and lower limits of funding. They propose a heuristic method that relies upon a marginal benefit ranking. Still, the main message from this literature is the extreme difficulty to obtain wide diffusion due to the lack of managerial "buy-in."

With respect to the second stream of literature, several authors have explored the dynamic portfolio selection decision emphasizing optimal policies rather than algorithmic solutions. Reflecting the uncertainty in projects, this work mostly considers stochastic settings. This literature comprises four groups.

The largest group is the multi-armed bandit (MAB) problem literature, which has strongly influenced the scheduling literature in Operations Research (OR). It was first solved by Gittins and Jones (1972), and since then, many variants have been proposed and solved by other researchers. The general formulation concerns K projects proceeding in parallel, and a critical resource that should be devoted to only one project at a time. Gittins and Jones formulated the well-known *Gittins index*, a number that can be assigned to each project at each time t, and that characterizes the optimal policy. At any time t, it is

optimal to work on the project with the highest Gittins index, which depends only on each individual project's state (Bertsimas and Niño-Mora 1996, Whittle 1980, Ross 1982) and corresponds to the reward that would make the decision maker indifferent as to whether to continue the project or exchange it for that reward.

The MAB policy rests upon a number of assumptions, which make extensions to more realistic settings extremely hard to obtain reverting us back to algorithmic approximations. Gittins (1989) shows that, for differing general discount functions, there is no general index (pp. 27-29). Banks and Sundaram (1994), prove that the existence of switching costs across projects leads to the absence of a general index solution. The characteristics of NPD projects, challenge as well the basic premises of MAB, payoffs are earned only after the project outcomes are launched onto the market. Moreover, projects tend to be interdependent due to prioritization. The latter causes penalties due to delayed market launch[7]. Kavadias and Loch (2003) expand existing results to incorporate these characteristics of NPD, and provide a useful discussion on the limitations for policy extensions.

The second group of models approaches the project prioritization problem as a multiclass queueing system, where different classes of jobs (i.e. types of projects) share a common server. Each job class requires a stochastic time on the server and incurs a linear delay cost. The main result is the "$c\mu$ rule" (Smith 1956, Harrison 1975): give priority to the job with the highest delay cost divided by the expected processing time (marginal cost c, over time $\tau = \frac{1}{\mu}$). The rule is optimal for linear delay cost structures in various applications (Wein 1992, Ha 1997, Van Mieghem 2000)[8]. For non-linear delay costs, the "generalized $c\mu$ rule" (G-$c\mu$) has been shown to be asymptotically optimal in heavy traffic (Van Mieghem 1995).

The third group outlines optimal admission rules when a budget has to be allocated over time to several project ideas[9]. Kavadias and Loch (2004) present such an NPD setting (chapter 5; for an overview of the general problem, see Stidham 1985, Miller 1969). The NPD reality differs from manufacturing settings in two aspects: (i) The project attractiveness measure is continuous (there are uncountably many customer classes). (ii) The NPD system has a waiting buffer of size 1, from which the waiting project disappears when a new project idea arrives. In other words, the new idea is not turned away, but the old idea is superseded. This assumption represents project obsolescence, which is more important in NPD than in manufacturing. These model features lead to results that are consistent with recent literature (more available capacity lowers the threshold for acceptance, see, e.g., Stidham 1985, Lewis et al. 1999).

Finally, the stochastic and dynamic version of the knapsack model. Kleywegt and Papastavrou (1998) show that if all items are of the same size, a threshold policy is optimal, the value function is concave in the remaining amount of resource, and the threshold increases as the resource is depleted. Kleywegt and Papastavrou (2001) show that the results generalize to the case of stochastic resource requirements of the items, but only if the resource requirement distribution fulfills certain conditions (concavity), and the terminal value function is concave non-decreasing. Still, the NPD

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[7] Which violates the basic MAB assumption that a project's value function remains unchanged while it is not worked on.

[8] The $c\mu$ rule is a "continuous time" approximation of the Gittins index. Van Oyen et al. (1992) among others have pointed out the similarity between bandit policies and the $c\mu$ rule.

[9] The third and second groups of work share methodological foundations, but differ in the main research question: prioritization versus admission.

reality imposes additional constraints on the problem, such as the fact that the investment in a given project may not be a one shot decision but it progresses through milestones, where additional action may be taken.

1.5. Discussion and Conclusions

Management researchers and practitioners have proposed many methodologies for tackling the complexity of the portfolio selection problem. The literature review suggests that quantitative research efforts have been restrained at the tactical level of analysis and they have not been widely adopted in practice because of the complexity associated with the decision.

This chapter introduces a theoretical framework that outlines the main project decisions at the different organizational levels, and the challenges that accompany them. In that light we emphasize that as we move down the organizational hierarchy, resource allocation to different innovation efforts acquires a finer and better defined success measure (the effort output is easier to estimate or approximate) with a much tighter budget constraints and a finer search strategy for the solution(s). Within this context, we offer a comprehensive literature review, highlighting several of the previous research findings, and some of the lessons drawn for for researchers and practitioners. In this final section, we draw some general conclusions that we believe to be relevant for managers responsible for portfolio management and we identify a few open questions for the NPD portfolio selection problem.

1.5.1. Insights

- At the highest level, the context of making funding decisions is unstructured and messy; it depends on an uncertain future, actions by competitors, and a complexity of the overall “business problem” that defies orderly problem solving. This is the realm of strategy. Strategy should provide a structured business proposition within which the organization can perform targeted problem solving. Strategy should align the actions of the various players, and outline “categories” of different types of NPD and R\&D activities, each of which is homogenous enough to be managed consistently.
- It is within these categories (i.e. the different R&D programs that have a ``next generation'' scope, or ``a product line technical support'' objective) where we can hope to perform quantitative project selection. So the R&D program investment will depend on the potential return (e.g. ROI) as defined from the various project ideas, given the program objectives and goals.
- These “return” functions associated with each NPD program stem from three conceptually distinct activities within each program, where projects are

managed as an *ensemble*, and not individually: *idea screening*, *quantitative selection for funding*, and *ongoing prioritization*. Basic theoretical structures have been proposed for the distinct tasks, but unfortunately, there has been little work that approaches the various distinct stages as a unified coherent process (Ding and Eliashberg 2002, and Chan et al. 2006, are steps towards this direction).

In conclusion, our framework serves to accomplish two things: (a) characterize the portfolio problem through the *structure* of the optimization problem that the organization faces at its different decision making levels, and (b) establish a solid foundation, and add value by outlining the problem intuition to practicing managers.

1.5.2. Open Research Questions

The last point allows us to make the transition to the set of open ended research questions associated with NPD portfolio management decision. We summarize them in the following Figure.

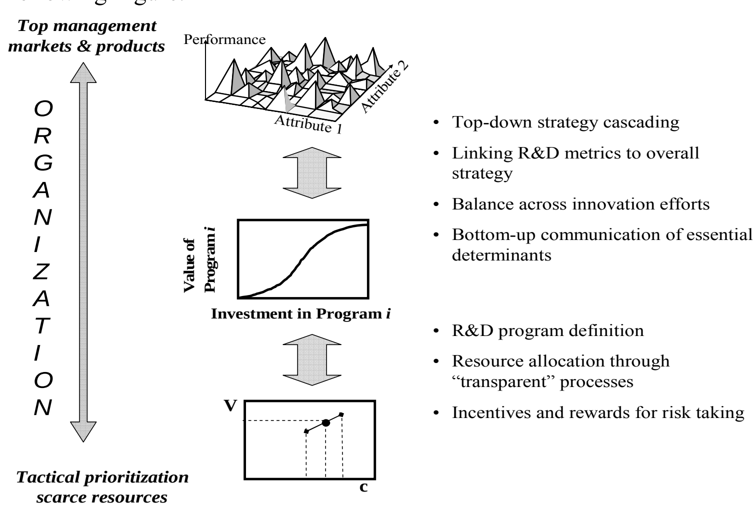

Figure 6: Management challenges in NPD portfolio decisions

Figure 6 illustrates that the research community should try to acquire a holistic view of the portfolio decision making process, where the fact that different parameters are defined at different levels of organization hierarchy is recognized. In addition:

1. We need to target finer methods that can shed light into the structure and measure of the cross interactions among profit determinants at a strategic level. A few models have tried to isolate specific influence factors, but we feel that research here is at an embryonic stage.

2. The research methodologies proposed need to identify the notion of organizational hierarchy and its impact on the decisions; the infamous quote that "*resources are allocated to the project manager that screams the loudest*"

signifies that project managers associate their career paths with specific activities of the portfolio and that they may "game" the system. Thus, we need to build additional intuition as to the incentive and motivation structures associated with R&D portfolio decisions. Moreover, Sosa (2005), in an insightful case study, highlights an additional dimension of importance: the organizational design. Its impact on portfolio decisions stems from the ability to exploit or explore. Thus, management needs to decide whether to invest on integrating or specialization capabilities.

3. The theoretical structures that look at isolated decisions of the R&D "funnel" (Wheelwright and Clark, 1992a) should be extended to allow for a **holistic** process view. In addition, we should note that since the overall portfolio value emerges from single project outputs, we ought to look for new methods that aggregate the individual project information into a total value.

4. Finally, additional empirical effort should assess the importance of different NPD portfolio strategies. R&D portfolio decisions are of vital importance to firm competitiveness, therefore portfolio data are extremely sensitive and often confidential. However, event studies (such as Girotra et al. 2007) offer a reasonable methodology for assessing the impact of portfolio decisions.

We believe that the NPD portfolio selection problem remains largely an open problem especially at its top management decision making. We also echo previous observations (Shane and Ulrich 2004) that call for new approaches and methods. Since the NPD project portfolio determines the medium to long term company future it is essential that we further understand the various steps for operationalizing such a complex decision.

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