

MANAGING NEW PRODUCT DEVELOPMENT PROJECTS
IN A COMPETITIVE MARKET

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Abstract

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New product development projects play a major role in the modern economy, especially for firms that compete in the most innovative industries. The speed-to-market for new products in these industries is often regarded as a key source of competitive advantage since the first entry has the opportunity to build barriers to deter new entries and/or enjoy monopoly status for a period of time. Shortening the development time to market, however, typically requires higher development costs that may offset, or even outweigh, any anticipated first-mover advantages.

The objective of this dissertation is to study the implications of speed-to-market in the context of project management when the project return depends in large part on the time of product introduction to the market relative to that of the competitor. Specifically, we analyze the decision process of a risk neutral firm that wants to maximize the expected profit of

a new product development project in a market with potential rivals and a product that can only be marginally differentiated. In the model, expected profit is determined by the timing of the product's entry into the market as well as the firm's management of allocated resources.

We formulate a continuous time-cost trade-off project management model under competition. Our model assumes that the market entry time of the competitor is a random variable following a general distribution. We consider both deterministic and stochastic activity durations, both static and dynamic project scheduling policies, and consider two types of payment schemes that reflect most new product markets.

In the model for deterministic activity durations, we present analytical results for the static resource allocation policy which offer various managerial insights that help managers better understand the trade-offs and impact of competition on project management strategy. When resource allocation decisions can be made dynamically we develop a heuristic procedure that facilitates managers decision making process to increase or decrease allocated resources to some tasks, or to terminate the project altogether, at various states of the development project. For projects with stochastic activity durations, we develop heuristic scheduling/compression strategies to maximize the expected profit while guaranteeing feasibility of the scheduling solution.

Contents

List of Tables	iv
List of Figures	vi
1 Introduction	1
1.1 Overview	1
1.2 New Product Development Projects	4
1.3 The Importance of Speed to Market	6
1.4 The Cost of New Product Development	10
1.5 Managing New Development Projects Under Competition	13
1.6 Scope of Dissertation	15
1.6.1 Market Definition	16
1.6.2 Fixed Return Market Competition	16
1.6.3 Variable Return Market Competition	17
1.7 Additional Related Literature	18
1.8 Contributions of this Research	23
1.9 Organization of this Dissertation	24
2 Basic Trade-offs in Projects	26
2.1 Definitions and Assumptions	26
2.2 The Continuous Time-Cost Trade-off Model for Deterministic Activity Durations	29
2.3 Competition Model	32
2.4 Chapter Summary	37
3 New Product Development Projects with Competition: Fixed Payment Market and Deterministic Activity Durations	38

3.1	Assumptions and Notations	42
3.2	Static Resource Allocation Policy	44
3.2.1	Competition interval includes the solution interval ($a \leq S^{min}$ and $S^{base} \leq b$)	45
3.2.2	Competition interval overlaps with the solution interval	48
3.2.3	Solution interval includes the competition interval	50
3.3	Dynamic Resource Allocation Policy	51
3.3.1	Serial Project Network	52
3.3.2	General Project Network	62
3.3.3	Numerical Study	67
3.4	Chapter Summary	73
4	New Product Development Projects with Competition: Variable Payment Market and Deterministic Activity Durations	75
4.1	Assumptions and Notations	79
4.2	Static Resource Allocation Policy	80
4.2.1	Competition interval includes the solution interval, ($a \leq S^{min}$ and $S^{base} \leq b$)	81
4.2.2	Competition interval overlaps the solution interval	85
4.2.3	Solution interval includes the competition interval ($S^{min} \leq a$ and $b \leq S^{base}$)	89
4.3	Dynamic Resource Allocation Policy	89
4.3.1	Serial Project Network	89
4.3.2	General Project Network	93
4.3.3	Numerical Study	93
4.4	Chapter Summary	99
5	New Product Development Projects with Competition and Uncertain Ac-	

tivity Durations	101
5.1 Motivation to the Problem	101
5.2 Robust Optimization: Overview	108
5.2.1 Robust Optimization: Methodology	110
5.2.2 The Adjustable and Non-adjustable Formulations	111
5.2.3 The Affinely Adjustable Robust Counterpart (AARC)	112
5.2.4 Application to A Stochastic Time-Cost Trade-off Problem	114
5.2.5 Competition Model with Robust Optimization	124
5.3 Fixed Payment Problem with Uncertain Project Activity Durations	126
5.3.1 Static Recourse Policy	127
5.3.2 Dynamic Recourse Policy	131
5.4 Variable Payment Problem with Uncertain Project Activity Durations	142
5.4.1 Static Recourse Policy	143
5.4.2 Dynamic Recourse Policy	149
5.5 Chapter Summary	156
6 Conclusions	158
6.1 Summary	158
6.2 Managerial Insights	162
6.3 Future Extensions	163
References	166

List of Tables

1	The Importance of Being First to the Market by Industry	10
2	Mean Elasticity of Cost with Respect to Time, Development and Commercialization Parts of the Innovation Process, Mansfield (1988)	11
3	Adjusted Average Development Spending per Drug, 1997-2011	12
4	Parameters for Fixed Payment Example	40
5	Parameters for Serial Two-stage Example	56
6	Probability for Selected Strategy	56
7	Expected Profit for Different Compression Strategies	59
8	Parameters for DAM Heuristic Example	65
9	Static Solutions	66
10	Possible Dynamic Solution Vectors	66
11	Parameters for 7-Activity Network: Fixed Payment	68
12	Numerical Result for 7-Activity Network: Fixed Payment	68
13	Parameters for 12-Activity Network: Fixed Payment	69
14	Numerical Result for 12-Activity Network: Fixed Payment	70
15	Parameters for 12-Activity Serial Network: Fixed Payment	71
16	Parameters for Variable Payment Example	77
17	Parameters for 7-Activity Network: Variable Payment	94
18	Numerical Result for 7-Activity Network: Variable Payment	94
19	Parameters for 12-Activity Network: Variable Payment	95
20	Numerical Result for 12-Activity Network: Variable Payment	96
21	Parameters for 12-Activity Serial Network: Variable Payment	97
22	Parameters for Example Project with Uncertain Activity Duration	102
23	Activity Start and Finish Times for No Compression Strategy	104
24	Parameters for Robust Scheduling Example	116

25	Parameters for Fixed Payment Robust Example	127
26	Parameters for Variable Payment Robust Example	143

List of Figures

1	Project Time, Cost, and Design Trade-offs	5
2	Scope of Dissertation	18
3	Total Project Cost versus Project Makespan	27
4	Example of AON Network	28
5	Direct project cost versus project duration	33
6	Solution Interval to the Competitive Model	35
7	Competition interval includes the solution interval	35
8	$S^{min} < a < S^{base}$ and $b > S^{base}$	36
9	$a < S^{min}$ and $S^{min} < b < S^{base}$	36
10	Solution Interval Includes the Competition Interval	36
11	Innovator Firm Wins the Competition	38
12	Innovator Firm Loses the Competition	39
13	Activity Network for Fixed Payment Example	39
14	Examples where $g(\cdot)$ is monotone non-decreasing over $[S^{min}, S^{base}]$	47
15	Decision Tree for Serial Network Project	55
16	4-Activity Serial Project Example	55
17	Decision Tree and Expected Profit: No Compression to Activity 2	58
18	Activity Network for DAM Heuristic-Fixed Payment Example	64
19	Expected Profit for Dynamic Policy 4	66
20	Value of Flexibility for 12-Activity Serial Network (Fixed Payment Model)	72
21	Innovator Firm Wins the Competition	75
22	Innovator Firm Loses the Competition	76
23	Activity Network for Variable Payment Example	76
24	Value of Flexibility for 12-Activity Serial Network (Variable Payment Model)	97
25	Example Project with Uncertain Activity Duration	102

26	Example Project for Robust Scheduling	116
27	Example Project for Fixed Payment Robust Example	127
28	Example Project for Variable Payment Robust Example	143

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Dedication

This thesis is dedicated to my parents for their love, endless support and encouragement.

1 Introduction

1.1 Overview

During the 1990s, the U.S. motion picture industry saw waves of “disaster films” due in large part to the advanced computer-generated imagery (CGI) technology that made it possible for movie studios to create high quality visual effect scenes. In 1998, two highly anticipated blockbuster films in this genre were scheduled to debut in theaters at almost the same time. One was the movie “Deep Impact” which was a Paramount and DreamWorks co-production, and the other movie was “Armageddon” that was released by Disney’s Touchstone Pictures.

To the general audience, the plots of the two films were strikingly similar. The story line of both movies revolved around the discovery of a massive extraterrestrial object on course to collide with Earth. Facing imminent extinction, NASA and Russian scientists created an elaborate plan to detonate a nuclear device deep inside the asteroid and avert the biggest catastrophe in Earth’s history.

The fact that two movies had near-identical blueprints was not a secret to either studio, and this significantly raised the stakes of the competition to complete the production and release the film to theaters first. In the end, the movie Deep Impact debuted first on May 5, 1998 and became a big box office hit. Domestically, it became the highest grossing film directed by a woman and held that record for a decade until Twilight claimed the record in 2008. In response to the situation, later in the same month Disney chairman Joe Roth decided to expand Armageddon’s budget by \$3 million to include additional special effects scenes. This additional footage, incorporated just two months prior to the film’s release, was specifically added for the television advertising campaign to differentiate the film from Deep Impact which was released just a few months before. From a management

point of view, this extra expense could have been saved had the order of release been reversed.

The sequence of events that took place in this movie example, as well as the ramifications that followed for the winning and losing companies are also evident in many other industries. In fact, among numerous elements that collectively define success of a new product development, the speed to market factor - a notion commonly known as first-mover advantage (FMA) - has long been regarded as a key source of competitive advantage since the first mover can build substantial entry barriers to the later entrants, or impose significant cost to the follower as the movie *Deep Impact* did to the movie *Armageddon*.

The concept of first-mover advantage was supported empirically across broad samples of businesses (Robinson and Fornell, 1985; Robinson and Min, 2002) and was particularly evident among innovative industries such as the pharmaceutical (Caves et al., 1991; Grabowski and Vernon, 1992). Huff and Robinson (1994) reported that the greatest market share awards typically arise for innovative firms who are both first to market and have a long lead time over later entrants. On the same notion, Urban et al. (1986) showed through empirical study across multiple product categories the reward and penalty associated with the order of market entry.

On the contrary, the cost to expedite a new product development project to the market can be very costly. Mansfield (1988) presented empirical evidence that it could cost as much as 10% of the total development cost to merely accelerate the time to market by 1%. In the motion picture industry example, the production cost of the movie *Armageddon* was reported to be already twice as much as that of the rival movie *Deep Impact*, making it even harder to justify more investment to speed up the project. The increasing cost of accelerating new product development is evident in almost all industries in the economy, namely pharmaceutical, automobile, software, etc. The two conflicting demands, one to speed up

the development process, and the other to minimize the development cost, create a unique dynamic that underlines the importance of managing new product development projects and stimulates researchers from operations management, strategic management, information systems, marketing, and other disciplines alike to understand the challenges and opportunities inherent in new product development projects.

The main goal of this dissertation is to analyze a new product development that is subject to market competition in the context of project management, and answer an important question: how a scheduling strategy would be impacted by different types of competition to the market. Specifically, we focus on products or services that can only be marginally differentiated, and assume that the market return depends on the time that the product is introduced to the market in relation to its competitor. We first define a new product development in the context of a complex project scheduling problem, and provide basic descriptions and challenges in a general project. Then, we illustrate a project with a network diagram consisting of a broad range of activities, precedence relationships between activities (dependencies), activity duration, and different type of resources required. The classical continuous time-cost trade-off optimization model for general scheduling problems, in the absence of market competition, is introduced as a base model to demonstrate its role in solving general project scheduling problems. We subsequently introduce two different types of competitions into the base model. For each type, the time to the market of the competitor is random, following a general probability distribution, and the market return of the project depends on the relative order and/or timing of market entry between the firm and its competitor. Then, we discuss how the new dynamic brought about by market competition further complicates the project management strategy that is already charged with multitudes of challenges such as resource allocation, scheduling of activities, and issues concerning the uncertainty in activity durations.

While the problem with deterministic activity duration could be solved using different linear and non-linear programming approaches, we develop analytical conditions that offer various managerial insights that underscore the impact of competition on project management strategy. Furthermore, we analyze a dynamic resource allocation policy where the compression decisions can be made sequentially at different stages during the project, and a firm has the option to terminate the project.

Finally, we extend our analysis to a case of uncertain activity duration under both market competition types. We assume that activity durations are uncertain following unknown probability distributions. We then review the principles of a robust optimization and its applicability to the basic stochastic time-cost trade-off problem, and subsequently introduce market competition of various types to the optimization model. The robust model requires only moderate information about the activity duration, and the solution is a scheduling policy that firm can apply dynamically as project progresses and more information regarding the project and competition states become available. Numerical studies are performed to demonstrate the implementation of the solution procedure.

1.2 New Product Development Projects

The Product Development and Management Association (PDMA) defines the Product Development Process as follows;

“A disciplined and defined set of tasks and steps that describe the normal means by which a company repetitively converts embryonic ideas into salable products or services”

In essence, any new product development is a project by definition as it is a temporary endeavor undertaken to create a unique product or service where the collection of tasks are,

for example, concept generation, product manufacturing and test, marketing plan creation and evaluation, and commercialization of a new product.

While projects can vary greatly, Klastorin (2010) stated that a common challenge in managing a project involves a series of trade-offs among goals for which the project owner or a firm must decide which goals are most important and which goals can be relaxed in order to achieve the overall success for the organization. The major four goals are cost, time, scope, and quality, which are represented in Figure 1 below:

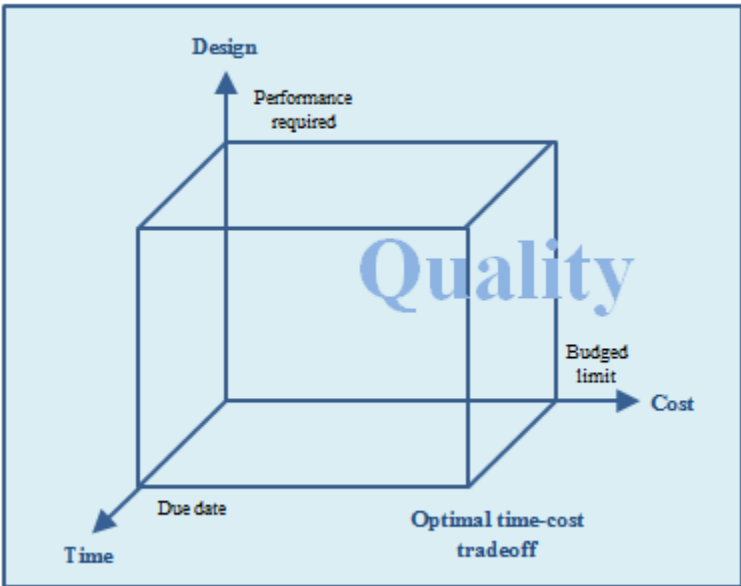


Figure 1: Project Time, Cost, and Design Trade-offs
Source: Project Management: Tools and Trade-offs, Klastorin (2010)

While all goals collectively determine the success in most projects, the primary focuses of this dissertation are on the time and cost dimensions, for which we study under different market competition environments.

1.3 The Importance of Speed to Market

Kerin et al. (1992) referenced a classic first mover advantage case in 1977 where Merrill Lynch launched the first Cash Management Account (CMA). The revolutionary new product combined an investment account, a transaction account, a debit card, and a credit line secured by the securities in the investment account. It was a major success and was later imitated by almost every securities firm. But by the time other brokerage firms entered the market in 1982, Merrill Lynch had sold 533,000 CMAs representing assets of \$ 32 billion. By 1989, it had 1.3 million CMAs with \$ 155 billion in assets-eight times the number of its nearest rival.

The competition to be first to the market for new products or services is commonplace in modern economies. The criticality of introducing the product or service before the competitors, however, appears to be a topic of debate since the market reward varies greatly across industries and depends on numerous factors. Lieberman (forthcoming) stated that the ambiguity and disagreement of the time of market birth, appropriate definition of market breadth, etc. can lead one observer to classify a given firm as the first mover, whereas another may view that firm either as a follower or as an entrant into a separate or precursor market. The issue can be compounded further by the taxonomy used in classifying new products, or the appropriate measures of success of a new product in a specific industry. Also, even when there is a consistent definition of new product and market, not every product that is first to market achieves the level of success anticipated, and some even experience complete failure for different reasons. Lieberman and Montgomery (1988) stated that the mechanisms that typically benefit the first-mover may be counterbalanced by various disadvantages. These first-mover disadvantages are, in effect, advantages enjoyed by late mover or fast follower firms in a form of (1) the ability to “free ride” on first-mover investments, (2) resolution of technological and market uncertainty, (3) technological discontinuities that provide “gateways” for new entry, and (4) various types of “incumbent inertia” that make it difficult for

the incumbent to adapt to environmental change. These phenomena can reduce, or even completely negate, the net advantage of the incumbent.

VanderWerf and Mahon (1997) performed a meta-analysis to investigate whether the prevalent notion of first mover advantage has been overstated due to the research methods used. They discover that when market share is used as a surrogate measure for success it is significantly more likely to find a first-mover advantage than tests using other measures such as profitability or survival rate of the first entrant. Suarez and Lanzolla (2005) discussed in their 2005 Harvard Business Review article that the importance of being first in the market depends greatly on the pace at which the category's technology is changing and the speed at which the market is evolving. When both the technology and the market changes are changing rapidly, it creates the worst conditions for the first mover to succeed.

On the contrary, the notion of first mover advantage is supported by many researchers, both empirically and analytically. Robinson and Min (2002) compared the survival rates for 167 first-entrant market pioneers versus 267 early followers for industrial goods businesses, and reported that 66% of the pioneers versus 48% of the early followers survived at least ten years. The main conclusion is that the pioneer's temporary monopoly over the early followers plus its first-mover advantages typically offset the survival risks associated with market and technological uncertainties.

Chen et al. (2005) emphasized the special significance of new product development speed in an unfamiliar, emerging, or fast-changing market. In 2000, an article on the Electrical Design News website (www.edn.com) also stated the following about the hi-tech and communication industry:

“Why are some companies valued at or acquired for hundreds of millions of dollars while

others cannot climb out of the purgatory of mere double-digit millions? The Cisco of the world know the answer: It's time-to-market. Smart companies rarely sacrifice time-to-market and never take it for granted. Time-to-market means life or death, and anything that can tip the scale in your favor is precious"

Suarez and Lanzolla (2005), in their 2005 article, also outlined several conditions and examples for first mover success. For example, Hoover in the vacuum cleaner industry, Sony and its success with the Walkman personal stereo in the early 1980's. A Pearson Education article also references the success of Sony in the late 20th century as follows:

"One of the most famous exemplars of first-mover advantage as a basis for corporate strategy is the Japanese electronics maker Sony. Set up by the legendary Ibuka Masaru in the ruins of Tokyo after the Second World War, Sony built not only its strategy but its entire corporate philosophy around Ibuka's idea of 'doing things that no one else is willing to do'. For Ibuka, as for his friend and successor Morita Akio, developing leading-edge products and getting them to market faster than the competition was not so much a strategy as a personal obsession, and is considered one of the cornerstones of Sony's rapid growth and continued success"

The first mover advantage is markedly amplified in certain industries, such as the pharmaceutical, where a legal monopoly status can be gained through patent protection, giving firms exclusive use of invented products or processes. Patents allow companies a certain period to recover the heavy costs of researching and developing products and technologies. In the U.S., drug patents give 20 years of protection, but since most patents are filed before clinical trials begin, the effective life of a drug patent tends to be between 7-12 years.

Beyond pharmaceutical products, a classic example that reinforces the patent-based le-

gal monopoly is Polaroid which for years held exclusive ownership of instant-film technology. Polaroid priced the product high enough to recoup, over time, the high cost of its technology development. Without competition, it enjoyed a monopolistic position in regard to pricing when it launched the products to the market.

In a technology-fueled business environment, a pioneer firm can also secure its advantage by exploiting the temporary monopoly status to set new industry standards. The extraordinary success of firms in the modern era such as Apple in the high-tech consumer electronics industry, and Amazon.com in the e-retail industry, are perhaps the best examples on this front. In 2009 Alliance Bernstein investment research attributed the success of Apple to its first mover advantage as follow:

“With the iPhone and its Apps Store, Apple has established a formidable smartphone ecosystem, which history suggests is very difficult to overcome...In fact, Apple has the potential to become a de-facto standard of sorts in the consumer smart phone market due in large part to its first mover advantage and tight software and hardware integration”

Acknowledging different perceptions among researchers and practitioners on the importance of being first to the market, we summarize the common set of products and markets that have been empirically studied to argue for and against the first mover advantage concept in Table 1. In this dissertation we do not attempt to prove or disprove the first mover advantage theory, rather we emphasize on market or industry that the first mover advantage is widely perceived important.

Not Important	Mixed Result	Important
Hotels	Chemical Products	Pharmaceutical
Medical Diagnostic Imaging Device	Printed Publishing	Financial/Money Products
Internet Startups	Automobiles	Mobile Telecommunication
		High Tech Computer Components

Table 1: The Importance of Being First to the Market by Industry

It is noteworthy to mention that, while non-commercial projects are outside the scope of this dissertation, they oftentimes culminate the importance of development speed and ramifications that ensue. In the military context, for example, the pinnacle of development competition was arguably the race to “split the atom” during World War II. Another profound example was the race to the moon in the 1960s between the U.S. Apollo project and The Soviet manned lunar project, albeit that The Soviet government publicly denied any participation in such competition. The landing on the moon by Apollo 11 on July 20, 1969 marked one of the greatest accomplishments in the history of space exploration by the U.S., and instantly propelled the status of the U.S. in the science and technology arena at the time.

1.4 The Cost of New Product Development

Given the high cost of developing new products and services, it has become critically important for firms to carefully manage these development projects and the trade-offs between development costs and speed to market. For example, Mansfield (1988) estimated that the direct costs to develop a new technological product are increased by as much as 8.8 percent in Japan and 3.6 percent in the U.S. to reduce the planned introduction date by approximately one percent. For some types of products (e.g., new machinery products), Mansfield estimated that the time-cost slope was as high as 15.7 percent in Japan and 7.4 percent in the U.S.

Industry and Nationality	Internal Technology		External Technology	
	Development	Commercialization	Development	Commercialization
All Industries Combined				
<i>Japan</i>	10.4	9.8	8.8	7.3
<i>United States</i>	6.2	4.0	3.6	3.7
Chemicals				
<i>Japan</i>	11.2	14.2	7.8	9.2
<i>United States</i>	2.7	2.5	2.8	3.1
Electrical & Instruments				
<i>Japan</i>	5.2	9.0	3.9	8.9
<i>United States</i>	4.3	3.3	5.7	4.8
Machinery				
<i>Japan</i>	15.7	7.7	14.3	4.7
<i>United States</i>	7.4	4.7	3.3	3.5

Table 2: Mean Elasticity of Cost with Respect to Time, Development and Commercialization Parts of the Innovation Process, Mansfield (1988)

Furthermore, the overall cost of research and development to push a new product to the market for many innovative industries can be very costly. Consider a case in the pharmaceutical industry for example, DiMasi et al. (2003, 2004) estimated the average cost of new drug development to be \$802 million per new drug, a number that continued to grow over the years. Adams and Brantner (2006, 2009) revisited the previous survey studies and suggested that the net revenue needed “to make investment in new drugs profitable” was over \$1 billion. In 2011, the InnoThink Center For Research in Biomedical Innovation reported that the average cost of bringing a new drug to market had grown to \$1.3 billion. Furthermore, a 2012 article reported by Forbes on the same subject revealed that when the actual spending is appropriately adjusted for relevant factors such as the failure rate and inflations, the average development cost per drug by a major pharmaceutical company would in fact range as high as \$4 billion to \$11 billion.

Company	R&D Spending Per Drug (\$ millions)
AstraZeneca	11,790.93
GlaxoSmithKline	8,170.81
Sanofi	7,909.26
Roche Holding AG	7,803.77
Pfizer Inc.	7,727.03
Johnson & Johnson	5,885.65
Eli Lilly & Co.	4,577.04
Abbott Laboratories	4,496.21
Merck & Co Inc	4,209.99
Bristol-Myers Squibb Co.	4,152.26
Novartis AG	3,983.13
Amgen Inc.	3,692.14

Table 3: Adjusted Average Development Spending per Drug, 1997-2011

Source: www.forbes.com

The soaring cost of new product development is not a phenomena observed only in pharmaceutical industry. In the video game marketplace with an annual revenue of 25-billion dollar as of 2011 (based on the Entertainment Software Association), the average development budget for a multi-platform next-generation game was approximated to be between \$18 and \$28 million in 2010. In addition, a study by entertainment analyst group M2 also estimated the development costs for single-platform projects at an average of \$10 million, with the development of high-profile games to cost \$40 million or higher.

A study by Purdue Pesticides Program in 2006 revealed that an average development project takes 9 years, the review of 140,000 compounds, and \$180 million to discover and develop a new pesticide product. In certain situations, the cost of development and level of complexity of the project can be so high that it is no longer feasible for firms to undertake the project by themselves. Collaboration between firms has therefore become a more common strategy in recent years and has spawned new challenges such as incentive mechanism (Bhaskaran and Krishnan, 2009; Erzurumlu et al., 2009). The persisting trend of growing development costs across various industries, and the seemingly conflicting goals to improve

the time to market yet prevent the development cost of a new product from growing out of control, underscore the criticality of managing the trade-offs in a new product development project.

1.5 Managing New Development Projects Under Competition

The importance of managing a new product development project is front and center for innovative companies to grow and prosper. Over the past few decades, literatures on managing innovations and product development decisions have been gaining attention continuously across various academic branches such as marketing, operations management, and engineering design. There exist numerous trade-offs that need managing in any project development. Ulrich and Krishnan (2001) provided a comprehensive review of research in product development which they define as “the transformation of a market opportunity into a product available for sale”.

Smith and Reinertsen (1998) identified four key objectives in NPD project management: project timeliness, product performance, development expense, and product cost. Among many objectives that typically receive special attention in project is the time-to-market of the product which is the focus of the dissertation. Stalk and Hout (1990) coined the term time-based competition to highlight the importance of quick time-to-market in today’s intensive competitive environment.

Scherer (1967) first discussed the problem of research and development resource allocation under competition. Kamien and Schwartz (1972) published a seminal paper that addressed the general matter of developing and introducing a new product in a competitive market. In their work, they develop a model that represents a firm facing increasing cost to shorten the development period, the reduction of profit opportunities, and the probability

of rival innovation and imitation which affect the potential rewards available to the firm. In their model it is assumed that product or service could only be marginally differentiated in design or quality from competitors' products and patent protection is either unavailable or ineffective for the innovator. The model also includes product pricing decision, and unlike other work based on game theory that assumed that the innovator firm had knowledge of the rival's cost structure, they only assume that the innovator firm has subjective knowledge of the distribution describing the rival's introduction time.

Reinganum (1972) considered a dynamic game theoretic approach to develop a theory of optimal resource allocation to research and development with n identical firms. From the model it is concluded that the increasing number of rivals results in an increase in each individual firm's Nash equilibrium rate of investment in a perfect patent protection competition.

More recent work includes Cohen et al. (1996) which focused on the trade-off between target performance and the time-to-market a new product, as well as integrating issues in operations and marketing. Their model considers a project as a multi-stage development with three main activities: Design, Process, and Market. The concept of speeds of improvement in the design and process stages is introduced and is the key factor for determining the optimal decisions regarding the stage duration and performance level of the product under development. Bayus (1997) analyzed the market, demand, and cost conditions associated with the optimal speed-to-market and product performance decisions. The main results suggest that fast development with low product performance levels is optimal for market with short product life cycle. Langerak and Hultink (2006) investigated sample data of 600 manufacturers of industrial products in the Netherlands. Two hypotheses are tested: 1. Development speed has an inverted U-shaped relationship with new product profitability, and 2. The development speed that maximizes new product profitability is lower for more innovative new products than for less innovative new products. The results were positive for

both hypotheses.

The problem of optimal strategy in new product development was also depicted by a Harvard Business School project management case study “Applied Materials” published in 1992, which partly inspired the work in this dissertation. At the time of the case, Applied Materials, a firm that specializes in designing and manufacturing equipment used in semiconductor wafer fabrication, was carrying out its new product development project when rumor surfaced that a competitor who was developing a product for the same market could potentially bring the product to the market first. Management was therefore pressed to determine whether to stay on course and risk losing the competition, or to accelerate the development, change incentive structures, and risk cost overrun and/or delivering a disappointing product.

1.6 Scope of Dissertation

In this dissertation, we build on the framework introduced by Kamien and Schwartz (1972) but extend it in a number of significant ways. Following their work, we focus on a profit-maximizing innovator firm that begins developing a new product or service and faces the threat of a rival firm that may enter the market with a competing product. However, we do not assume that the rival entry time is exponential, thereby negating one of their main findings. Instead, we represent the development process as a complex project that can be described by a network of tasks and precedence constraints (Elmaghraby, 1977) and assume that the rival entry time can be described by any general non-negative random variable. This approach allows us to model the development process as a stochastic programming problem that, in turn, provides optimal (or near optimal) solutions and managerial insights into both the static and dynamic resource allocation problems faced by the innovator firm.

1.6.1 Market Definition

We specifically focus on markets of product and service where only a small degree of product differentiation can be made (or equivalently the project scope is relatively inflexible), rendering the time to market the predominant factor that determines the profitability to a firm. In such a market environment, the first entrant who innovates the technology or service can either build substantial barriers to deter new entries and enjoy monopoly status for a certain period of time, or can legally obtain patents to effectively protect its innovation from imitators or later entrants.

We consider this problem an important extension of the standard project management literature that to the best of our knowledge has never been explicitly addressed before. The two types of market competition we investigate in this research are fixed and variable market returns.

1.6.2 Fixed Return Market Competition

We define a fixed return market competition as a type of competition where a firm enjoys a fixed large return if and only if it introduces the product to the market first regardless to how much or how little it wins. Otherwise, it receives a fixed small return. The time to the market of the competitor is random, following a general probability distribution. This represents an important class of new product development competition in many industries, e.g. products with perfect patent protection. With patent, the laws generally protect the inventor's rights for certain period of time (up to 20 years for pharmaceutical products in the U.S.). This protection enables the innovator to recover their investment costs, a form of reward that incentivizes firms to invent new and innovative solutions.

1.6.3 Variable Return Market Competition

We denote the second market structure as the variable payment case where the innovator firm earns a monopoly return rate for the time that it maintains a monopoly position until a rival firm enters the market. After a rival firm has entered the market, the innovator firm earns a normal return rate that is lower than the monopolist rate for the remaining duration of the product or service life cycle. This definition represents a class of product that is closely substitutable and can be imitated (imperfect patent protection). Similarly, we assume that the time to the market of the competitor is random, following a general probability distribution. The model could be extended to the case when normal return rate is a function of the number of firms in the market but this extension complicates the model while adding little additional insight.

In both cases, we assume that the selling price of the new product or service equals or exceeds the marginal production cost, and the amount of returns (fixed or variable) are independent of the number of firms or in the market and the exact time of entry. Note that if the market is purely competitive once a rival has entered, we would assume that the small return (fixed or variable) values equal zero. Within the analysis of fixed and variable market return, we also consider the following characteristics that are inherent in the project management problem;

- Activity durations
 - Deterministic
 - Stochastic
- Resource allocation policy
 - Static allocation
 - Dynamic allocation

When activity durations are assumed deterministic and the firm makes static resource allocation decisions, our goal is to develop a model that allows us to gain additional insights to the standard continuous time-cost trade-off problem. In the case of stochastic activity durations, our goal is to develop an efficient heuristic that helps a firm in the resource allocation and scheduling decisions of the new product development project.

The overview scope and section presented in this dissertation is summarized in Figure 2 below

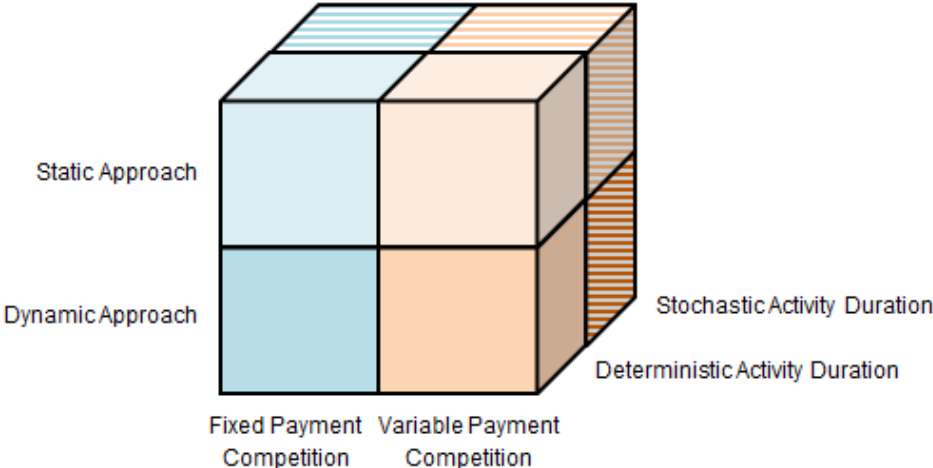


Figure 2: Scope of Dissertation

1.7 Additional Related Literature

While this research strictly analyzes the competition problem from a project management perspective, the problem is inspired by previous researches across broad disciplines such as marketing, economics, and strategic management.

On the concept of first-mover advantage of new product development, additional work related to the problem includes Datar et al. (1997), Huff and Robinson (1994), Robinson

et al. (1994), Robinson and Min (2002), Boulding and Christen (2003), Eggers and Grajek (2011), and Zheng (2010).

Literatures related to the problem of managing new product development includes an empirical analysis by Zirger and Maidique (1990) who studied high technology product innovation specifically in the electronics industry and report factors that differentiated successful from unsuccessful product development efforts. Schilling and Hill (1998) described strategies that have been shown to improve the process of new product development, and about which there is a great deal of consensus. Langerak and Hultink (2006) investigated the relationship between development speed and product profitability using a survey-based study of 233 manufacturers of industrial products in the Netherlands. Cohen et al. (1996) developed a modeling framework to analyze the implications of setting managerial priorities for time-to-market, product performance, and total development cost.

DeReyck and Leus (2008) analyzed R&D type project risks inherent to the product design could lead to termination before completion of the project. They examine, in the presence of failure risk, how project manager should schedule projects in order to maximize their expected net present value. Huchzermeier and Loch (2001) and Santiago and Vakili (2005) examined the value of flexibility, particularly the project termination option and corrective action option, in the context of R&D project. Reade and Lippman (2003) considered the problem of selecting a stopping time which determines when to exit an investment project when the project's cumulative profit up to time t is a Brownian motion with specific drift variance and develop a closed form probability threshold for which the firm should exit if its posterior probability of being in the high state is lower. Kwon and Lippman (2011) developed a sequential decision model to analyze a case where the firm undertakes a small-scale pilot project to learn, via Bayesian updating, about the project's profitability of new project before making two irreversible alternatives: exit and expansion.

Among limited papers in the project management domain that do not treat due date as an exogenous parameter, Baker and Bertrand (1981) discussed the topic of due date selection in the context of single machine scheduling where due date is discretionary or negotiable. Dumond and Mabert (1988) addressed the problem of establishing due dates for projects which require limited resources, in an environment where new projects arrive continuously and randomly over time. The due date setting procedures are tested via simulation and performance measures of project in terms of mean completion time, project mean lateness, project standard deviation of lateness, and total tardiness were reported. Gutierrez and Kouvelis (1991) developed a model to investigate the behavioral issues described as Parkinson's Law and study the effect of deadlines on the duration of project activities.

This research is also related to previous work by Dodin (2008); Dodin and Elimam (2001) who investigated the impact of treating the activity duration as a decision variable on the activities schedule, and the effects of introducing rewards (penalties) for early (late) completion as well as materials quantity discounts on the project schedule and cost. Crowston and Thompson (1967) developed a method for simultaneous planning, scheduling, and control of projects assuming an exogenous due date is given with fixed marginal reward and penalty per time period.

A wealth of literature work related to due date management in a job shop settings includes Karmarker (1987) who presented an extensive discussion of the role of due date assignments in the context of master production scheduling. Ragatz and Mabert (1984) provided a conceptual model of a due date management problem which, among other important variables, identifies a variety of due date assignment rules. Smith and Seidmann (1983) presented a comprehensive classification of due date selection procedures from which three major categories are derived: direct procedures (rules), heuristic procedures, and simulation.

More recent works that are closely related to our research include a working paper by Pinker et al. (Forthcoming) that studied the problem of scheduling a project to minimize the time between the adversary's awareness and reaction and the project's completion time, with a detailed example of nuclear weapons development project in motivating the problem. Shen et al. (2010) considered a two-stage stochastic optimization problem where a decision maker must trade off costs incurred in insuring arcs with expected penalties associated with late project completion times. Swinney et al. (2011) analyzed the competitive capacity investment timing decisions of firms entering new markets with high degree of demand uncertainty, and firms decide whether to invest in capacity early when uncertainty is high or late when uncertainty has been resolved, possibly at different costs. Kwon et al. (2010) studied different types of payment contract project owner offers to subcontractors and demonstrate conditions where a delayed payment contract, designed originally to reduce the project owner's financial risk, can in fact lower the its discounted revenue.

This research is also motivated by Klastorin and Mitchell (2013) who considered the problem of planning a complex project where there exists a possibility of disruptive event that may occur sometime during the project. They formulate a stochastic dynamic programming problem and demonstrate a number of implications to project manager. Williams et al. (1995) studied a large design and manufacture engineering project and emphasized the effect of design changes on the overall project cost.

Additional work related to the problem of project scheduling with stochastic activity durations include Cohen et al. (2007) who applied the robust optimization technique to a standard time-cost trade-off problem where the activity duration follows an unknown distribution, and they develop a similar heuristic to generate a compression policy which evolves with the realization of activity duration as time progress. Goh and Sim (2010, 2011), studied

a similar problem and introduced an advanced robust optimization tool where the project budget is limited. Herroelen and Leus (2005) reviewed the fundamental approaches for scheduling under uncertainty which includes reactive scheduling, stochastic project scheduling, fuzzy project scheduling, robust (proactive) scheduling and sensitivity analysis. They state the demand for more initiations in the study in project scheduling under uncertainty, and suggested the strong potential of sensitivity analysis in the context of project management.

Other related work includes the papers by Ben-Tal and Nemirovski (1998); Ben-Tal et al. (2004) who studied extensively the modeling methodology to solve a linear programming problems contaminated with uncertain data, and develop a novel procedure to replace the original problem with its robust counterpart (RC) and obtain the robust solutions of an uncertain linear programming problem via solving the corresponding explicitly stated convex robust counterpart program. Bertsimas and Sim (2004) proposed an approach that decreases the price of obtaining robust solution. They adjust the level of conservatism of the robust solutions in terms of probabilistic bounds of constraint violations which is a natural extension of the original work by Ben-Tal and Nemirovski (1998). Chen et al. (2008) proposed several new decision rules that improve upon linear decision rules technique used to obtain robust solution to uncertain linear programming problem, while keeping the approximate models computationally tractable. Finally, Beyer and Sendhoff (2007) surveyed the primary research both theoretical and applied, in the field of Robust Optimization (RO) and present some recent s that connect the robust optimization technique to adaptable models for multi-stage decision-making problems.

1.8 Contributions of this Research

In this dissertation we connect the concept of first mover advantage, speed to market of a new product development, and the project scheduling problem to analyze the impact that market competition imposes to the standard continuous time-cost project scheduling model.

We define different types of competition to the market, and show how project scheduling/compression strategy is affected by not only the level of competition but also the type of market payment scheme. We show also that the project profit depends largely on the time that a firm introduces its product/service to the market in relation to its competitor. We look at the case of both deterministic and stochastic activity duration project network in analyzing these problems.

We develop solutions and managerial insights for the deterministic time-cost trade-off model with market competition. Specifically, we reveal certain conditions where a firm is better off compressing beyond the base solution, compress the project to the minimum makespan, or when no compression beyond the base solution is warranted. Furthermore, when a firm can observe the competitor's development and resource allocation decisions can be made sequentially, we develop an algorithm for solving the expected profit maximization problem which also provides additional insight into the value of real options in project management.

Finally, we consider the project planning problem with uncertain activity duration under market competition. We examine the conceptual appeal and applicability of robust optimization techniques and propose a heuristic procedure that aids the resource allocation and scheduling decision process.

1.9 Organization of this Dissertation

The remainder of this dissertation is organized as follows. In Chapter 2 we introduce the basic model with deterministic project activity duration. The time-cost trade-off model which serves as a base model for deterministic activity duration project management problems is first described, then we introduce the general form of the competition models and demonstrate how the competition is incorporated into the base model.

In Chapter 3 we define the fixed payment model with deterministic project activity duration. For a static resource allocation policy we derive analytical results and discuss the effects that competition imposes on project scheduling strategy. For a dynamic resource allocation policy, we develop a heuristic procedure that facilitates manager's decision making process to increase or decrease allocated resources to some tasks, or to terminate the project altogether, at various states of the development project.

In Chapter 4 we define the variable payment model with deterministic project activity duration. Similar to chapter 3, we derive analytical results for a static resource allocation policy, and demonstrate in the dynamic resource allocation case how the heuristic procedure helps prescribe a strategy that optimizes the dynamic expected payoff of the project.

In Chapter 5 we analyze the original competition model in Chapters 3 and 4 with uncertain activity duration. We first discuss the challenges of solving for the exact solution to the problem, and introduce the concept of robust optimization and its applicability to our problem. We reiterate the two types of market payoff schemes, develop a heuristic procedure, and demonstrate the implementation of our proposed algorithm via several numerical project examples.

Finally, in Chapter 6 we summarize our findings and contributions for all problems, discuss further implications for scheduling strategy under competition, and conclude with our views of possible extensions to the problem.

2 Basic Trade-offs in Projects

The chapter proceeds as follows, section 2.1 describes the basic definitions, assumptions, and structures of a project. These notions will be utilized throughout this study. In section 2.2 we introduce the standard continuous time-cost trade-off model with deterministic activity duration for general project network. In section 2.3 the general form of a competition model is defined.

2.1 Definitions and Assumptions

Project Development Cost

Following standard project management assumptions (Klastorin, 2010), we assume that the development cost of a project is the sum of direct and indirect/overhead costs. We define direct cost as cost associated with an execution of activity, which comprises of fixed resource cost and activity compression cost. We assume that the direct cost is convex decreasing with project makespan (i.e. increasing with the size of compression), and it is incurred at the start time of an activity. The project also carries an indirect/overhead cost that associates with the project makespan, which we assume to be a fixed rate per time unit. That is, the overhead/indirect cost is a linear function of the project makespan (Cohen et al., 2007; Klastorin and Mitchell, 2013).

We assume that the new product development project does not have an inherent due date. Therefore, unlike many previous literatures in the field, we do not explicitly model the penalty cost. However, it will become clear that the price the firm has to pay (or reward to receive) for completing the development project late (or early) is a direct result of the firm's project completion time relative to that of the competitor.

The characteristic of total project cost is depicted in Figure 3.

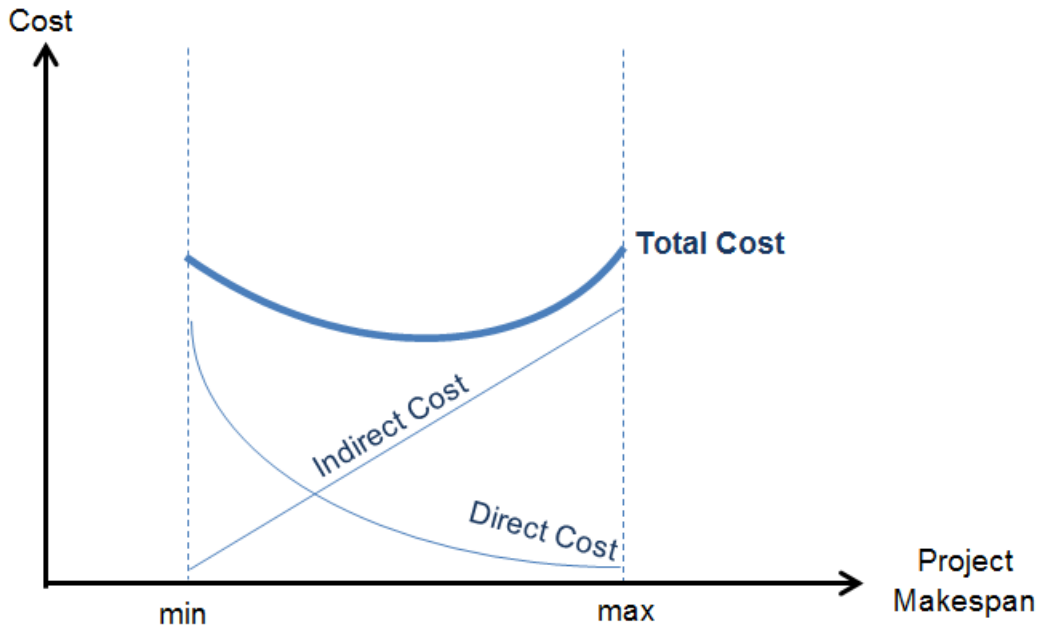


Figure 3: Total Project Cost versus Project Makespan

Project Network

A project network is an acyclic graph depicting the sequence in which a project’s activities are to be completed by showing terminal elements (start and finish nodes) and their dependencies or precedence relationships. The two most popular forms of project network are activity on node (AON) and activity on arc (AOA). The AON network uses nodes to represent activities and arcs to represent precedence relationships. The AOA network, in contrast, uses arcs to represent activities, and nodes to represent events or milestones. For comprehensive details of each network format we refer to Klastorin (2010). While both formats are used in project management literatures, the AON network appears to be the favorable choice for most commercial project management software.

In this dissertation we represent a development project by a directed acyclic activity-on-node (AON) graph $G = \{N, A, W\}$ consisting of a set of nodes $N = \{1, \dots, n\}$, a set of directed

arcs $A = \{(i, j) \mid i, j \in N\}$, where arcs (i, j) represent finish-to-start precedence relationships between activities i and j with zero lags, and a set of activity durations $W = \{t_i \mid i \in N\}$. Activities 1 and n denote the starting and ending milestones of the project, and by definition $t_1 = t_n = 0$. The direct cost function for activity $i, \forall i \in N$ is denoted as $C_i(\cdot)$ and the fixed overhead/indirect cost rate is C_o .

Figure 4 illustrates a simple example of an AON project network consisting of eleven activities (nine activities plus two milestone start and end activities), each activity is indicated by a node labeled 1, 2, 3, ..., 11 while arcs indicate the precedence relationships. Also, the two milestone start and end nodes take zero time and cost nothing to execute, but they must always be presented in the network since a project must start and end at a single node.

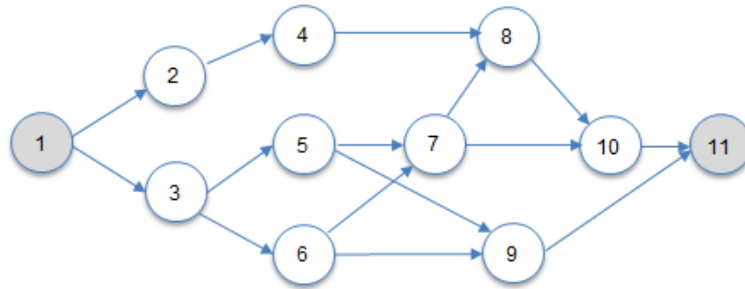


Figure 4: Example of AON Network

Additional Assumptions

- No resource constraint in the project
- Zero resource lead time
- Early start time for all activities
- All activity are independent
- All activities are non-preemptive

2.2 The Continuous Time-Cost Trade-off Model for Deterministic Activity Durations

Given the development cost and project network structure described previously, we introduce a model that describes the project scheduling problem facing a firm. For deterministic activity duration, the problem can be formulated as a standard continuous time-cost trade-off which has been studied extensively by a number of researchers including Elmaghraby (1977) and Klastorin (2010) which we shall review the fundamental concept of the model in this section.

The basic model assumes deterministic activity duration and a firm's goal is to minimize the total cost. Both the compression strategies and activity start times are decision variables. We define the solution to this model as a base solution for comparative analysis in the subsequent sections.

The following summarizes parameters and decision variables used for the time cost trade-off problem model:

Decision variables:

$$S = [S_1, S_2, \dots, S_n] = \text{activity start time}$$

$$y = [y_1, y_2, \dots, y_n] = \text{activity compression}$$

Parameters:

$C_i(y_i)$ = direct cost for activity i

$$= F_i + \gamma_i(y_i)$$

F_i = fixed resource cost associated with uncompressed task i

$\gamma_i(y_i)$ = additional cost of compressing task i by amount y_i

C_o = overhead/indirect cost per time period

\bar{y}_i = maximum compression for activity $i = 2, \dots, n - 1$

t_i = uncompressed activity duration for activity i

The optimization problem becomes;

$$\text{Minimize}_{S,y} \quad \sum_{i=1}^n C_i(y_i) + C_o S_n$$

subject to

$$S_j - S_i - t_i + y_i \geq 0, \quad \forall (i, j) \in A, \quad (1)$$

$$S_i \geq 0, \quad \forall i \in N, \quad (2)$$

$$0 \leq y_i \leq \bar{y}_i, \quad \forall i \in N \quad (3)$$

(P1)

Constraint (1) represents the precedence relationship between activities in the project. Constraint (2) ensures that all activity start times are non-negative, and the constraint (3) gives the range of allowable compression amount for each activity due to some technology limitation.

The optimization problem presented here is the standard time-cost trade-off problem (TCP), a convex programming problem that can be solved by standard software. Elmaghraby (1977) showed how the problem can also be solved as a network flow problem by replacing the functions $C_i(y_i)$ with a series of piece-wise linear approximations. We refer the solution to (P1) as the base solution, and denote the optimal makespan $S_n^* = S^{base}$. For a case where the benefit of makespan reduction is equivalent to the cost incurred to make a compression, we assume that a firm chooses to compress the project makespan.

2.3 Competition Model

We begin to introduce the competition into our analysis by assuming that the market entry time the competitor is a random variable following a general distribution, and the market return of the project depends on the order and timing of market entry. All decisions (activity start times, activity compression, project finish time) are made at the beginning of the project. We describe different types of competition and the corresponding return if a firm wins the competition, and provide managerial insights for project manager.

Note that if the competitor's market entry time is known priori, the problem reduces to a standard time-cost trade-off problem with due date, tardiness penalty, and/or early completion reward.

In order to incorporate market competition into the model, consider the basic deterministic model setup in section 2.2. Denote Z as the competitor's time to market, a non-negative random variable with general pdf, $Z \in \mathfrak{R}_{\geq 0}$. The distribution of Z is supported in a closed interval (e.g. $[a, b]; a < b$).

Denote $f(Z, S_n)$ as some market return function that depends on Z and S_n , and is monotone non-increasing with S_n . The general form of a time-cost trade-off with competition can be formulated as follows:

$$\begin{aligned} & \underset{S, y}{\text{Maximize}} && E(\pi) = f(Z, S_n) - \left(\sum_{i=1}^n C_i(y_i) + C_o S_n \right) \\ & \text{subject to} && (1)-(3) \end{aligned}$$

(P2)

Define τ as a target market introduction time (a decision variable). If we denote $\eta(\tau)$ as present value of the cheapest direct cost to enter the market at time S_n while preserving all precedence constraints. We can write the following:

$$\eta(\tau) = \text{Min}_{S,y} \sum_{i=1}^n C_i(y_i)$$

subject to (1)-(3) and $S_n = \tau$

Following previous research (Cohen et al., 2007; Mitchell and Klastorin, 2007), we approximate $\eta(\tau)$ to be a continuous convex decreasing function with τ , that is, $\frac{d\eta(\tau)}{d\tau} < 0$ and $\frac{d^2\eta(\tau)}{d\tau^2} > 0$. To simplify the notation, we let $\beta(\tau) = \frac{d\eta(\tau)}{d\tau}$. Given our assumptions about $\eta(S_n)$, it follows that $\beta(S_{min}) < \beta(S_{base})$.

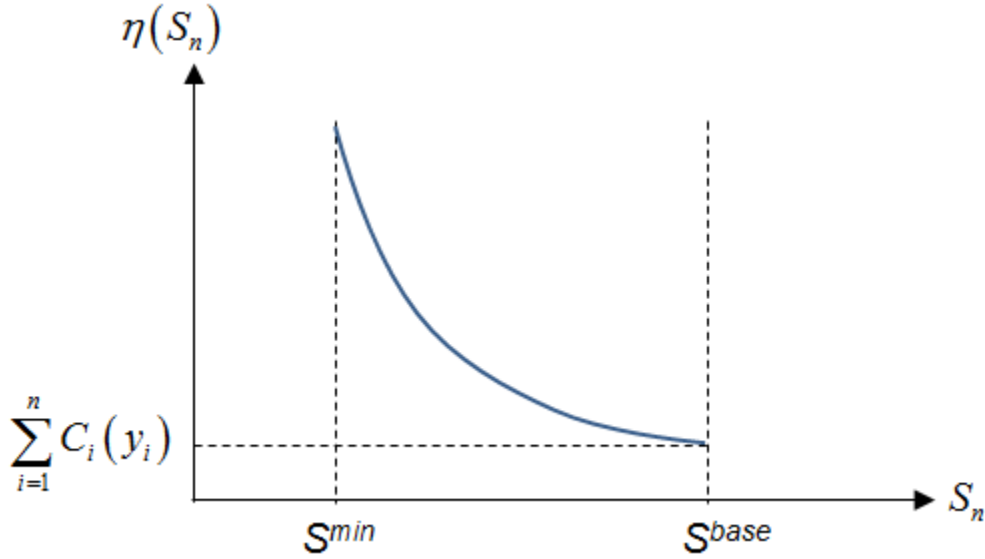


Figure 5: Direct project cost versus project duration

The objective function of (P2) can then be expressed as:

$$\text{Maximize}_{S_n} E(\pi) = f(Z, S_n) - (\eta(S_n) + C_o S_n)$$

We assume that a firm is risk neutral and it maximizes the expected profit. While (P2) could be solved using various non-linear programming techniques, we first attempt to develop analytical conditions that provide various managerial insights to underscore the impact of competition. In doing so, we first establish the upper and lower bounds of the optimal solution to the model with competition. This will also serve as a basis for the analyses in the later chapters.

Lemma 1. *In the presence of market competition, firm has no incentive to complete the project after time S^{base} , i.e. S^{base} constitutes an upper bound for the solution interval*

Proof. Consider the objective function

$$E(\pi) = f(Z, S_n) - (\eta(S_n) + C_o S_n)$$

Let S^B be a value such that $S^B \geq S^{base}$. By definition $f(Z, S^{base}) \geq f(Z, S^B)$, also by definition of S^{base} , $(\eta(S^{base}) + C_o S^{base}) \leq (\eta(S^B) + C_o S^B)$. It follows immediately that $E(\pi(S^{base})) \geq E(\pi(S^B))$

□

For the lower bound of the solution interval we can simply use the shortest possible project makespan of the project due to technological limitations. Let S^{min} denotes the shortest possible project makespan. S^{min} can be directly obtained by setting all activities to their shortest possible durations, and the critical path of the project would represent the value of S^{min} . Alternatively, let Ω denotes the largest real value. S^{min} can then be obtained by substituting C_o in (P1) with Ω and solve to optimality.

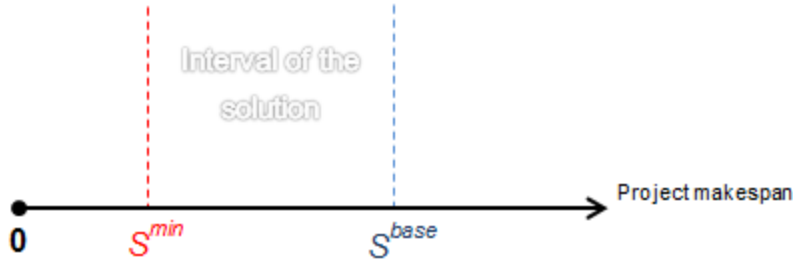


Figure 6: Solution Interval to the Competitive Model

To avoid trivial cases, we do not consider problems where $a > S^{base}$ or $b < S^{min}$. Such conditions imply that the firm will lose (or win) for certain. Furthermore, while possible, we do not consider a case with $S^{base} = S^{min}$. Any of the aforementioned conditions would render competition irrelevant. For clarity of our presentation, throughout chapter 3 and 4 we shall separate our analyses into three cases. Each case represents a unique type of overlap between solution interval and competition interval, which is illustrated in figures below;

- Case 1 Competition interval includes the solution interval ($a \leq S^{min}$ and $S^{base} \leq b$)

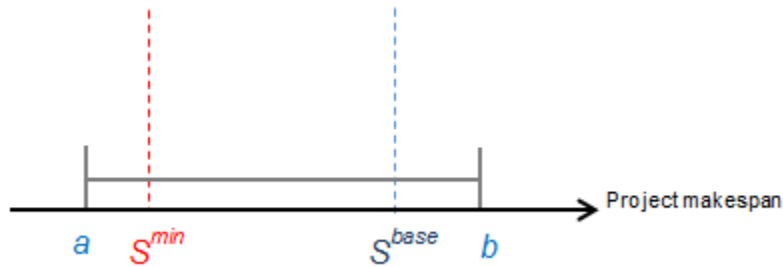


Figure 7: Competition interval includes the solution interval

- Case 2 Competition interval overlaps with the solution interval

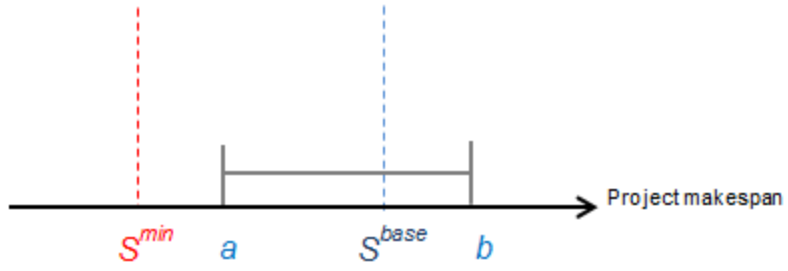


Figure 8: $S^{min} < a < S^{base}$ and $b > S^{base}$

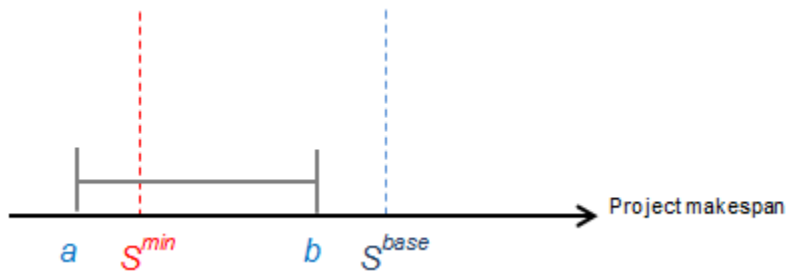


Figure 9: $a < S^{min}$ and $S^{min} < b < S^{base}$

- Case 3 Solution Interval Includes the Competition Interval ($S^{min} \leq a$ and $b \leq S^{base}$)



Figure 10: Solution Interval Includes the Competition Interval

2.4 Chapter Summary

In this chapter, we outline the general structure of a project, as well as the two most popular forms of describing and communicating information about a particular project. The conventional assumptions on project costs and constraints are introduced. Immediately from the definitions, we reveal the fundamental trade-off between direct and overhead/indirect costs faced by a project manager.

We then summarize parameters and decision variables involved in the basic problem, and establish the basic continuous time-cost trade-off model which has been studied extensively by a number of researchers. The model assumes deterministic activity duration, with activity compression and activity start times as decision variables. The three sets of constraints include: 1) Precedence relationship, 2) Non-negative start times, and 3) Maximum compression allowed.

With the presence of market competition, we characterize the general form of the optimization, assuming no information on the specific market payment function or the rival's entry time distribution. We define the direct cost as a function of target market entry time and establish the lower- and upper-bound of the solution interval. Finally, we illustrate different types of possible overlap between solution and competition intervals, which are proven key to our analyses as will be proven in the subsequent chapters.

3 New Product Development Projects with Competition: Fixed Payment Market and Deterministic Activity Durations

In this chapter, we focus on a case where the innovator firm gains a fixed amount of benefit if it introduces the product or service before a rival firm in the form of a single payment (e.g., present value of a patent), and it receives a fixed but smaller amount of market return otherwise. This model depicts a situation facing a profit-maximizing innovator firm that begins developing a new product or service and faces the threat of a rival firm that may enter the market with a competing product, and the net present value of patent protection (or penalty) can be accurately estimated.

The dynamic of the competition can be illustrated as follows: Figure 11 represents the case where the innovator firm enters the market first and wins the competition, while Figure 12 represents a case where the innovator firm loses the competition and receives a small market payment.

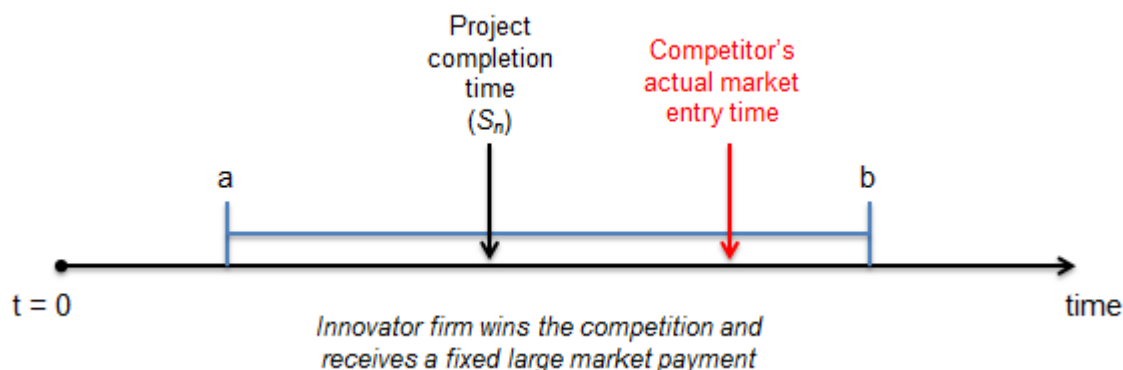


Figure 11: Innovator Firm Wins the Competition

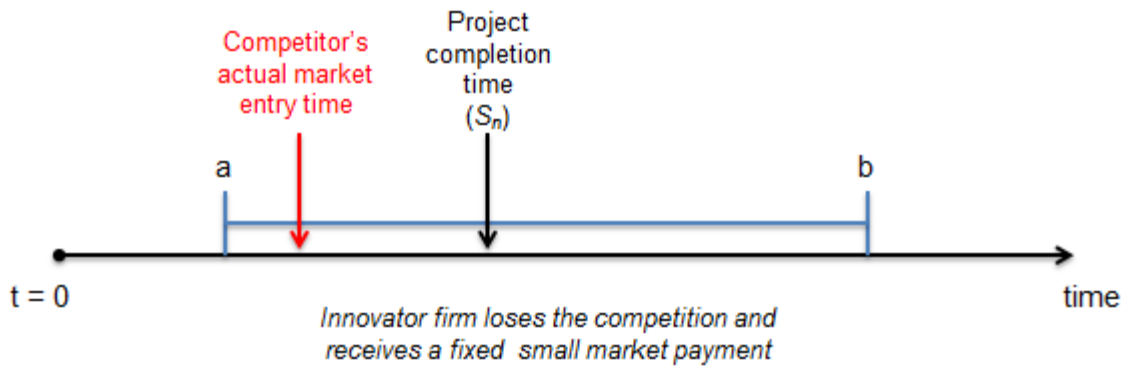


Figure 12: Innovator Firm Loses the Competition

To motivate the problem, consider a simple project example represented by the activity network shown in Figure 13 and that task detail given in Table 4.

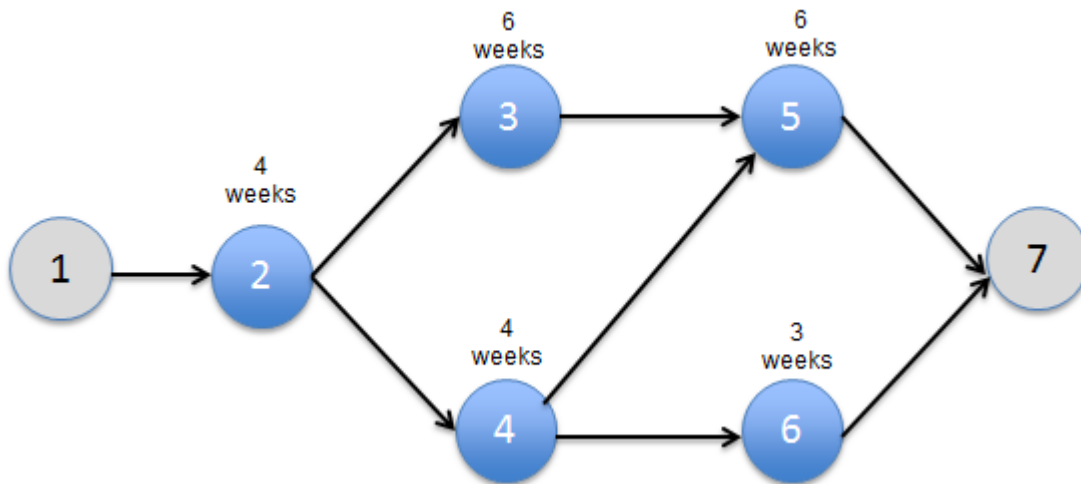


Figure 13: Activity Network for Fixed Payment Example

Activity	Uncompressed Activity Duration	Maximum Compression	Fixed Cost	Marginal Compression Cost (per Week)
1	0	0	0	0
2	4	1	1.0	3.5
3	6	3	2.5	2.5
4	4	2	1.5	2.0
5	6	3	2.0	3.1
6	3	2	3.0	3.1
7	0	0	0	0

Table 4: Parameters for Fixed Payment Example

In this example, the activity compression cost is assumed to be a linear function of the compression amount. In addition, assume that the innovator firm has a subjective estimation that the time when a competitor's product will initially be introduced is any time between 2 to 17 weeks from today (uniformly distributed), the indirect/overhead cost per week is \$1, and the market payment if a firm wins (loses) the competition is \$70 (\$20).

There are three possible paths, p_i , through this network:

$$p_1 : 1 \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 7$$

$$p_2 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow 7$$

$$p_3 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 7$$

If the innovator firm completely ignores, or is unaware of, the threat of the rival firm and believes it will receive the high market payment of \$70 for certain, the problem it faces simply reduces to the standard time-cost trade-off problem (P1) described in section 2.2.

Given such believe, the solution to the optimization above is straight forward. Since in this project example, no activity in the network is worth compressing, the optimal policy (minimum cost) to complete the project is to execute each activity at its normal duration. The project makespan, which is equal to the critical path (path p_1), is 16 weeks. The total

project cost is therefore \$26 (indirect cost of \$16 + direct cost of \$10). Therefore, if the firm naively disregard the threat from its rival or is unaware of the situation, it would expect a net profit of the project to be perceived $\$70 - \$26 = \$44$.

However, it can be easily shown that such evaluation is an inappropriate approach for the innovator firm. Should the firm plan to complete the project at week 16, there is a probability of as high as 0.93 (probability $0.93 = \frac{16 - 2}{17 - 2}$) that the rival would have already launched the product before and the firm would only receive the low market payoff of \$20. The expected market payoff based on the policy to complete the project at week 16 is $0.93(\$20) + 0.07(\$70) = \$23.3$ while the cost remains \$26. Therefore, the expected profit based on this policy is only $\$23.3 - \$26 = \$-2.7$. That is, the innovator firm would expect to lose \$2.7 should it plan to complete the project at week 16. Obviously, if presented with only two options: one to complete the project at week 16, and another not pursue the project altogether, the firm is better off with the latter option.

The simple example shown above underlines the impact of competition and how the awareness of the competition, or lack thereof, is crucial to the decision making process of an innovator. The methodology to appropriately incorporate the competition into the model shall be described in the next section. In essence, the innovator must modify the market return function in the general competitive model (P2) before solving for the optimal solution. Once the appropriate problem is setup, it can be shown in this example that the true optimal policy that produces maximum expected profit under competition is to compress activity 3 by two weeks, resulting in a project makespan of 14 weeks. The total project cost increases to \$29 (indirect cost \$14 and direct cost is \$15). When the innovator firm completes the project at week 14, the probability that the rival will enter the market first is reduced to 0.80 (probability $0.80 = \frac{14 - 2}{17 - 2}$). The expected market payoff based on the policy to complete the project at week 14 is $0.80(\$20) + 0.20(\$70) = \$30$. Therefore, the expected profit based

on this policy increases to $\$30 - \$29 = \$1$.

As stated in section 2.3, while the optimization problem could be solved directly using various techniques, in this chapter we will first focus on developing conditions that provide various managerial insights that facilitate the decision making process of project managers and underscore the impact of competition. We proceed to model the development process as a stochastic programming problem that, in turn, provides optimal (or near optimal) solutions and managerial insights into both the static and dynamic resource allocation problems faced by the innovator firm.

3.1 Assumptions and Notations

We first describe key characteristics and assumptions of a fixed return market competition as follow;

- Firm faces a competition to develop and introduce new product to the market
- The value of market returns for the new product or service can be approximated and are independent of the market entry time
- If a firm completes the development and introduces the product first to the market, it receives a fixed return M , and it receives m otherwise
- $M > m \geq 0$
- M is attained by a firm if it wins regardless to how much or how little it wins
- The innovator firm has a subjective estimate of the time when a competitor's product will initially be introduced. The market entry time of the competitor is a non-negative random variable following a general distribution

We define M to be larger than m to reflect a higher return for which only the firm first to market can enjoy. The high return can be attributed to various advantages the firm first in the market has. Examples of advantages of the first entry are plentiful in practice and literatures. For instance, patents protection in pharmaceutical industry gives legal protection to produce a patented product for certain period of time (Lieberman and Montgomery, 1988). Breshnahan (1985) also discussed Xerox's use of patents to deter new entries until challengers used anti-trust actions to force compulsory licensing. Also evident in commercial software products is the predatory pricing policies that would force any new entrants to operate at a loss.

Since the return of the project is uncertain, we assume that firm is risk neutral and it maximizes the expected profit of the project. Summarized below are parameters and variable introduced in addition to that presented in the base model;

Z = competitors market entry time, a non-negative random variable

a = lower bound of Z

b = upper bound of Z

$g(Z)$ = pdf of Z

M = large market return if firm enters the market before the competitor

m = small market return if firm enters the market after the competitor

$\Delta M = M - m =$ market return difference

3.2 Static Resource Allocation Policy

Under static policy, we assume that contracts have significantly long lead-times such that resource allocation decisions must be made at the beginning of the product development project (i.e., at time $t = 0$).

Based on the market characteristics described in section 3.1, we modify the market return function in the general competitive model (P2), the problem becomes;

$$\text{Maximize}_{S,y} \quad E(\pi) = \left[m \int_a^{S_n} g(Z) dZ + M \int_{S_n}^b g(Z) dZ \right] - \left(\sum_{i=1}^n C_i(y_i) + C_o S_n \right)$$

subject to (1)-(3)

(P3)

Similarly to (P2), when S_n is defined as the market entry time (a decision variable) and direct cost is represented by function $\eta(S_n)$, (P3) can be expressed as:

$$\text{Maximize}_{S_n} \quad E(\pi) = \left[m \int_a^{S_n} g(Z) dZ + M \int_{S_n}^b g(Z) dZ \right] - (\eta(S_n) + C_o S_n)$$

subject to (1)-(3)

3.2.1 Competition interval includes the solution interval ($a \leq S^{min}$ and $S^{base} \leq b$)

Lemma 2. *Under the fixed payment competition where $a \leq S^{min}$ and $S^{base} \leq b$, the firm must make additional compression beyond S^{base} .*

Proof. Since the direct cost is a function of S_n . The derivative of the objective function with respect to S_n by Leibnitz rule is

$$\begin{aligned} \frac{dE(\pi)}{dS_n} &= \left[m \frac{d}{dS_n} \int_a^{S_n} g(Z) dZ + M \frac{d}{dS_n} \int_{S_n}^b g(Z) dZ \right] - \frac{d\eta(S_n)}{dS_n} - C_o \\ &= (m - M) \cdot g(S_n) - C_o - \beta(S_n) \\ &= -\Delta M g(S_n) - C_o - \beta(S_n) \end{aligned}$$

$\beta(S_n)$ is convex decreasing with S_n , and we know that $\beta(S_n) = [\beta(S^{min}), \beta(S^{base})]$ for $S_n \in [S^{min}, S^{base}]$ where $\beta(S^{min}), \beta(S^{base})$ represent the highest and lowest marginal cost of project makespan compression beyond base solution respectively.

By definition of point S^{base} , we have $\beta(S^{base}) = -C_o$. Also, since we assume $M > m$ and term $g(\cdot) > 0$, term $-\Delta M g(S_n)$ is strictly negative.

Therefore, the derivative evaluated at point S^{base} can be written as:

$$\begin{aligned} \frac{dE(\pi(S^{base}))}{dS_n} &= -\Delta M g(S^{base}) - C_o - \beta(S_n) \\ &= -\Delta M g(S^{base}) < 0 \end{aligned}$$

Therefore, it follows that the optimal solution cannot be at point S^{base} when there is a

positive difference between the high and low market payoff. Hence, it is never optimal for an innovator firm to stay at the TCP solution S^{base} .

□

Lemma 3. *Under the fixed return competition where $a \leq S^{min}$, $g(S^{min}) \neq 0$, if $\Delta M < \frac{-\beta(S^{min}) - C_o}{g(S^{min})}$ then a firm will never compress the project makespan to S^{min} and the optimal solution is an interior point.*

Proof. Since the direct cost is a function of S_n . The derivative of the objective function with respect to S_n by Leibnitz rule is

$$\begin{aligned} \frac{dE(\pi)}{dS_n} &= \left[m \frac{d}{dS_n} \int_a^{S_n} g(Z) dZ + M \frac{d}{dS_n} \int_{S_n}^b g(Z) dZ \right] - \frac{d\eta(S_n)}{dS_n} - C_o \\ &= -\Delta M g(S_n) - C_o - \beta(S_n) \end{aligned}$$

Since $\eta(S_n)$ is convex decreasing with S_n , we know that $\beta(S_n) = [\beta(S^{min}), \beta(S^{base})]$ for $S_n \in [S^{min}, S^{base}]$ where $\beta(S^{min}), \beta(S^{base})$ represent the highest and lowest marginal cost of project makespan compression beyond base solution respectively.

When $-\Delta M g(S^{min}) - C_o - \beta(S^{min}) > 0$ or equivalently $\Delta M < \frac{-\beta(S^{min}) - C_o}{g(S^{min})}$ the optimal solution cannot be at point S^{min} since a higher expected profit can be obtained at some S_n ; $S^{min} < S_n \leq S^{base}$ (compressing to S^{min} is never justified). This result, together with result from Lemma 2, implies that the optimal solution must be an interior point in the interval $[S^{min}, S^{base}]$.

□

For special cases where $g(\cdot)$, is monotone non-decreasing over the interval $[S^{min}, S^{base}]$ as illustrated in the Figure 14 below:

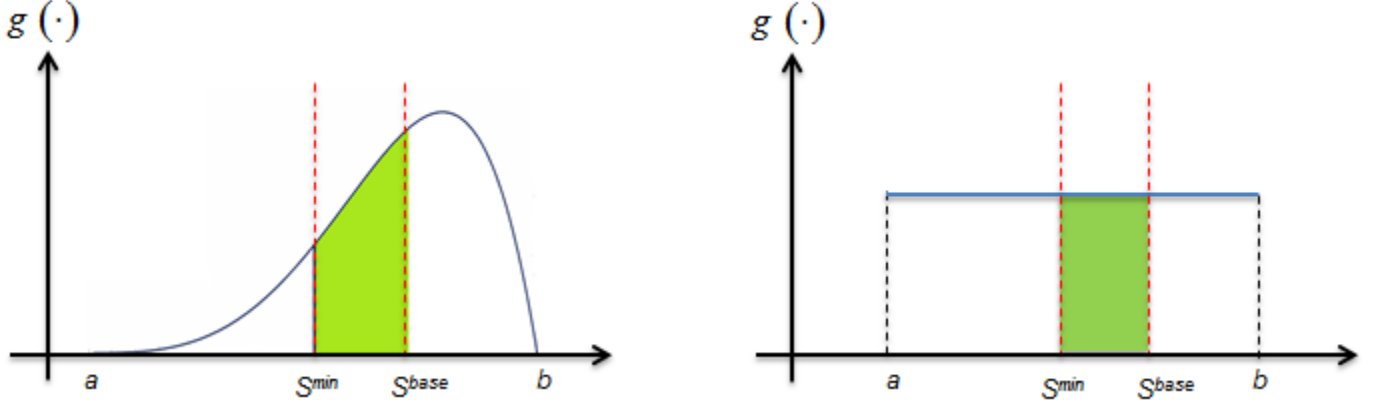


Figure 14: Examples where $g(\cdot)$ is monotone non-decreasing over $[S^{min}, S^{base}]$

We can describe condition which help firm decides on resource allocation as follows;

Proposition 1. *Under the fixed return market competition, if $g(\cdot)$ is monotone non-decreasing over the interval $[S^{min}, S^{base}]$, $g(S^{min}) \neq 0$, then S^{min} is optimal $\iff \Delta M \geq \frac{-\beta(S^{min}) - C_o}{g(S^{min})}$. Otherwise the optimal solution S_n^* is an interior point where $g(S_n^*) = \frac{C_o - \beta(S_n^*)}{\Delta M}$*

Proof. When $g(\cdot)$ is monotone non-decreasing over the interval $[S^{min}, S^{base}]$,

$$\begin{aligned} \frac{dE(\pi)}{dS_n} &= \left[m \frac{d}{dS_n} \int_a^{S_n} g(Z) dZ + M \frac{d}{dS_n} \int_{S_n}^b g(Z) dZ \right] - \frac{d\eta(S_n)}{dS_n} - C_o \\ &= (m - M) \cdot g(S_n) - C_o - \beta(S^{min}) \\ &= -\Delta M g(S_n) - C_o - \beta(S^{min}) \end{aligned}$$

Also,

$$\frac{d^2 E(\pi)}{dS_n^2} = -\Delta M g'(S_n) - \frac{d\beta(S_n)}{dS_n} < 0$$

That is, the expected profit function is concave over the interval $[S^{min}, S^{base}]$,

Hence S^{min} is the optimal solution $\iff -\Delta M g(S^{min}) - C_o - \beta(S^{min}) \leq 0$ (or equivalently $\Delta M \geq \frac{-\beta(S^{min}) - C_o}{g(S^{min})}$)

Otherwise, since we establish in Lemma 2 that the optimal solution cannot be at point S^{base} , the optimal solution has to be an interior point S_n^* that satisfies

$$g(S_n^*) = \frac{C_o - \beta(S_n^*)}{\Delta M}$$

□

In other words, given that $g(\cdot)$ is monotone non-decreasing over the interval $[S^{min}, S^{base}]$, firm can quickly determine (without explicitly solving the optimization problem) whether the optimal solution occurs at point S^{min} by comparing the reward of winning ΔM with thresholds defined by the marginal project makespan compression costs, overhead/indirect cost, and the pdf of market entry time of the competitor evaluated at point S^{min} , or it is an interior point by solving a simple equation.

3.2.2 Competition interval overlaps with the solution interval

For $S^{min} < a < S^{base}$ **and** $b > S^{base}$

Lemma 4. *Under the fixed return market competition where $S^{min} < a < S^{base}$, firm has no incentive to complete the project before time a , that is $S_n^* \geq a$*

Proof. Over the interval $[S^{min}, a]$, the expected profit function reduces to $\pi = M - (\eta(S_n) + C_o S_n)$ which is the case of no competition (P1). By definition, $\pi(a) \geq \pi(\xi); \forall \xi \in [S^{min}, a]$

□

This result implies that the solution interval is reduced from $[S^{min}, S^{base}]$ to $[a, S^{base}]$. Subsequently, by simply substituting S^{min} with a , all previous findings would apply.

For $a < S^{min}$ and $S^{min} < b < S^{base}$

Lemma 5. *Under the fixed return market competition where $S^{min} < b < S^{base}$, firm has no incentive to complete the project between time (b, S^{base})*

Proof. Over the interval $[b, S^{base}]$, the expected profit function reduces to $\pi = m - (\eta(S_n) + C_o S_n)$ which is the case of no competition (P1).

In this case, we have by definition that $\pi(S^{base}) = m - \eta(S^{base}) + C_o S^{base} \geq m - \eta(\xi) + C_o \xi \forall \xi \in [b, S^{base}]$

That is, the expected profit over the interval $[b, S^{base}]$ is always at the highest at point S^{base}

□

This result implies that the optimal solution must be a point in the interval $[S^{min}, b]$ or at point S^{base} . In other words, the optimal expected profit found in $[S^{min}, b]$ must be compared with the expected profit evaluated at point S^{base} .

Proposition 2. Under the fixed return market competition where $S^{min} < b < S^{base}$, firm will stay at S^{base} if $\Delta M < \frac{C_o(b - S^{base}) + \eta(b) - \eta(S^{base})}{1 - G(S^{min})}$

Proof. We know from Lemma 5 that the optimal solution will never occur in the interval (b, S^{base}) .

Now consider point S^{base} . The innovator firm's profit at point S^{base} is $m - \eta(S^{base}) - C_o S^{base}$. For any $S_n \in [S^{min}, b]$ we know that

$$E \{ \pi(S_n^*) \mid S_n^* \in [S^{min}, b] \} \leq m + \Delta M \bar{G}(S^{min}) - \eta(b) + C_o b$$

Therefore, firm obtains a greater profit by staying at point S^{base} if

$$m - \eta(S^{base}) - C_o S^{base} > m + \Delta M \bar{G}(S^{min}) - \eta(b) + C_o b$$

or equivalently,

$$\Delta M < \frac{C_o(b - S^{base}) + \eta(b) - \eta(S^{base})}{1 - G(S^{min})}$$

□

3.2.3 Solution interval includes the competition interval

When $S^{min} \leq a$ and $b \leq S^{base}$, it follows immediately from Lemma 4 that we can substitute S^{min} with a and the new solution interval becomes $[a, S^{base}]$. This result, together with Lemma 5, it can be deduced that the optimal solution must be a point in the interval $[a, b]$ or at point S^{base} .

3.3 Dynamic Resource Allocation Policy

When a firm has the flexibility of making a dynamic decision on the scheduling and compression strategy, e.g. updating the strategy as new information regarding the competition becomes available; superior results can be expected. Specifically in this context, the advantages of dynamic resource allocation policy over static policy stem from the flexibility to commit a particular decision only when required (not up front), as well as the option to abandon project. Elmaghraby (2005) illustrated through a simple problem example that the static optimization is inferior to dynamic resource allocation approach because it neglects the value of flexibility project manager may have.

However, for a project with general network, the problem of finding an optimal dynamic policy is NP-hard. Finding the optimal dynamic solutions/policies to the problem is usually not easy in complex project network with large number of activities since the decision-making process cannot be modeled according to a predefined sequence of stages. Consequently, it is generally difficult to apply stochastic dynamic programming (Bellman, 1957) to solve the problem.

In this section, we attempt to solve the dynamic resource allocation problem when project is subject to competition. We assume that resource allocation decisions are made just prior to starting any task, and zero lead-time for resource, but that resource allocations cannot be changed once a task has been started. Dynamic policies of this type are increasingly important in practice as many organizations try to increase the flexibility of their resource allocation systems through a Project Management Office (PMO) and related organizational structures. However, there have been only limited numbers of studies that compared the expected costs of static and dynamic policies in multistage stochastic models; given the significant costs associated with implementing flexible or agile project management, this

analysis has significant implications.

We initially consider a dynamic policy in a multi-stage serial network by formulating a stochastic dynamic programming model that represents a sequential decision making process of a firm under market competition. We consider a serial network for two reasons; first, many complex projects especially new product development projects are frequently viewed in practice as a series of stages separated by resource allocation review points (e.g., stage-gates). Second, a project with a sequential series of stages explains both the need and motivation behind the development of an effective heuristic algorithm for finding the optimal (or near optimal) solution when the project is represented by a general network. With respect to a general network, we shall introduce a simple but effective heuristic that can be implemented to large scale problem and returns near optimal solution.

3.3.1 Serial Project Network

For a special case of serial project network, we can formulate a stochastic dynamic programming and solve to optimal using a standard backward induction since all activities are executed in stages. It is obvious that any activity compression decision would reduce the project makespan by the same amount, a 1:1 relationship unique to a serial project network. The serial project under competition model also satisfies all conditions of stochastic dynamic programming with only one source of stochasticity which arises from the randomness of the competitor's market entry time. The serial project network, while relatively simple in structure, is particularly important in the context of this study because many new product developments can be characterized as serial project networks (Huchzermeier and Loch, 2001; Santiago and Vakili, 2005). Furthermore, the concept of serial project network is potentially useful in approximating any complex project with one dominant critical path.

We represent a new product development (NPD) project as a serial network with $k = 1, \dots, n - 1$ stages (ignoring the end milestone stage). At the end of any stage the state of the project is re-assessed (that is, whether or not a rival has entered the market) and the resource allocation decision is made for the next stage assuming zero lead-time. The makespan for the project and target product introduction time is $S_n = \sum_{i \in N} (t_i - y_i)$.

At any review point $i = 1, \dots, n - 1$ the maximum compression for i^{th} activity is limited by \bar{y}_i . Λ_i denotes the state for which competitor is not in the market, and Λ'_i denotes the state for which competitor is already in the market. Define $f(\Lambda_i)$ as the maximum expected profit from the i^{th} stage to the beginning of the final stage given that a rival has not entered the market prior to the start of the i^{th} stage and $f(\Lambda'_i)$ equals the expected profit given that a rival has entered the market prior to the start of the i^{th} stage. At the beginning of any stage $i = 1, \dots, n$, the recursive expression $f_i(\cdot)$ is defined as follows:

$$f_i(\Lambda_i) = \text{Max} \left(0, \text{Max}_{y_i} \left\{ -C_i(y_i) - C_o(t_i - y_i) + \left[f_{i+1}(\Lambda'_{i+1}) \frac{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^{\sum_{k=1}^i (t_k - y_k)} g(Z) dZ}{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^b g(Z) dZ} + f_{i+1}(\Lambda_{i+1}) \frac{\int_b^{\sum_{k=1}^i (t_k - y_k)} g(Z) dZ}{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^b g(Z) dZ} \right] \right\} \right) \quad (3.1)$$

$$f_i(\Lambda'_i) = \text{Max} \begin{cases} \text{Continue: } \text{Max}_{y_i} \{-C_i(y_i) - C_o(t_i - y_i) + f_{i+1}(\Lambda'_{i+1})\} \\ \text{Abandon: } 0 \end{cases} \quad (3.2)$$

And the boundary expression at the last review point

$$f_{n-1}(\Lambda_{n-1}) = \text{Max}_{y_{n-1}} \left(0, \text{Max}_{y_{n-1}} \left\{ -C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) + \left[m \cdot \frac{\int_{\sum_{k=1}^{n-2} (t_k - y_k)}^b g(Z) dZ}{\sum_{k=1}^{n-2} (t_k - y_k)} + M \cdot \frac{\int_{\sum_{k=1}^{n-1} (t_k - y_k)}^b g(Z) dZ}{\sum_{k=1}^{n-1} (t_k - y_k)} \right] \right\} \right) \quad (3.3)$$

$$f_n(\Lambda'_{n-1}) = \text{Max} \begin{cases} \text{Continue: } \text{Max}_{y_{n-1}} \{-C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) + m\} \\ \text{Abandon: } 0 \end{cases} \quad (3.4)$$

The stochastic dynamic programming above can be solved to optimality via standard backward induction. The sequential decision process in the context of serial project network can be represented by a decision tree in Figure 15 below.

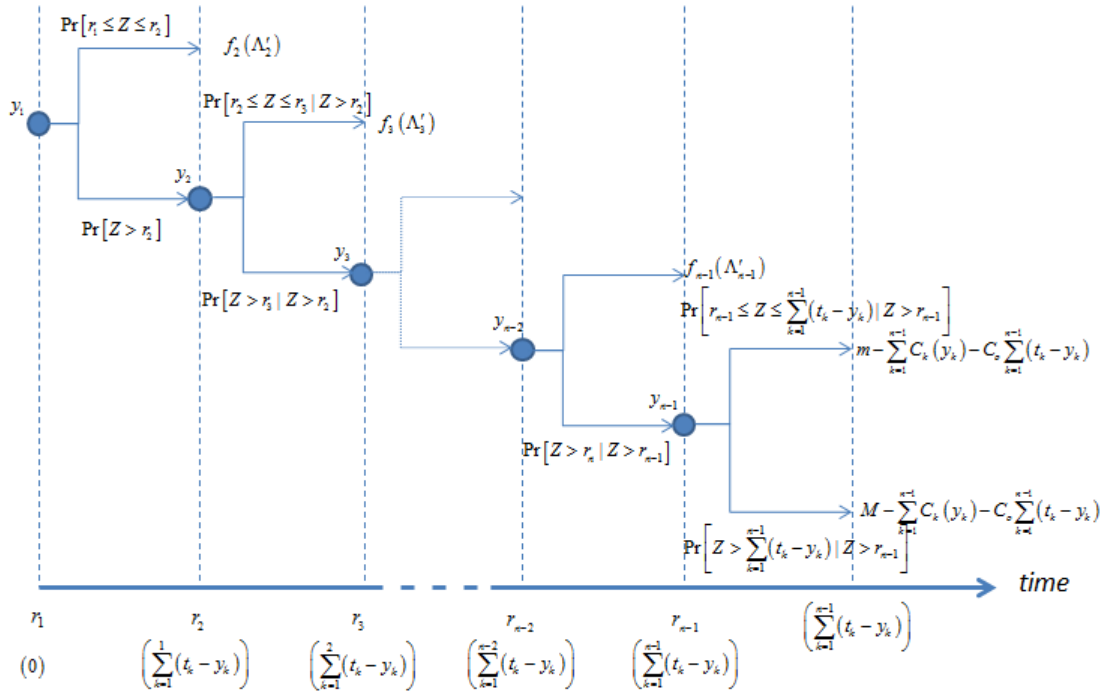


Figure 15: Decision Tree for Serial Network Project

To demonstrate the backward induction procedure, consider a simple 4-activity serial project as shown in Figure 16 where 1 and 4 are milestone start and end activities. Assume that the indirect/overhead cost is \$0.1 per week, and the high market payoff firm receives if/when it wins the competition to the market is \$20, and \$10 otherwise. In addition, assume that the competitor can enter the market at anytime between week zero and week 10. The activity parameters and compression costs are listed in Table 5.

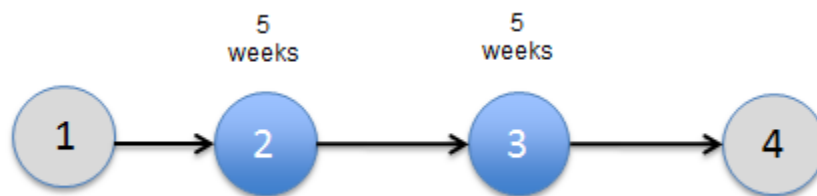


Figure 16: 4-Activity Serial Project Example

Activity	Uncompressed Activity Duration	Maximum Compression	Fixed Cost	Marginal Compression Cost (per Week)
1	0	0	0	0
2	5	3	2	1.0
3	5	3	2	1.2
4	0	0	0	0

Table 5: Parameters for Serial Two-stage Example

As stated previously, the stochastic dynamic programming here where uncertainty stems from the random state of the competition can be executed in sequential stages. Based on the Bellman formulation (Bellman, 1957) the optimal decision for the last stage can be determined, thereby allowing us to solve for the optimal decision in the previous stage(s), and such recursive relationship carries on until the optimal decision of the first stage is determined.

In the example project here, the completion of activity three marks the project finish time so we shall begin our analysis (note again that activity four is a milestone node). The time that stage three starts is clearly a function of the decisions (start time and compression) made for activity two. For simplicity, we assume that activity can be compressed by a discrete unit time with an incremental of one week. Table 6 below shows the start time of activity three given compression decision in activity two as well as the corresponding probability of project state;

Compression in Activity 2	Start Time of Activity 3	Prob that Rival Enters Before 3 Starts	Prob that Rival Enters After 3 Starts
0	5	0.50	0.50
1	4	0.40	0.60
2	3	0.30	0.70
3	2	0.20	0.80

Table 6: Probability for Selected Strategy

Consider the case where the decision for activity two is to make no compression, the start time of activity three would be at week 5. Given that the competitor enters the market before week 5 (a 0.50 probability), the firm would be solving the following optimization problem;

$$f_3(\Lambda'_3) = Max \begin{cases} \text{Continue: } \underset{y_3}{Max} \{-C_3(y_3) - C_o(t_3 - y_3) + m\} \\ \text{Abandon: } 0 \end{cases}$$

which is precisely equation (3.4). The continue option is clearly a TCP problem and the is a linear programming problem in this example. Since the firm has already lost to its competitor in this scenario, and since the compression cost of activity 3 is greater than the overhead/indirect cost, if the firm decides to continue at all it would do so by making no further compression. A simple calculation shows that the continue option yields a forward-looking profit of \$7.5 (\$7.5 = \$10 - \$0.5 - \$2) which is greater than 0 in the option to abandon, the firm will complete the project to earn the low market payment.

On the other hand, if competitor has not entered the market by week 5, the the firm would be solving the following optimization problem;

$$Max \left(0, \underset{y_3}{Max} \left\{ -C_3(y_3) - C_o(t_3 - y_3) + \left[m \cdot \frac{\int_5^{5+(t_3-y_3)} g(Z)dZ}{\int_5^{10} g(Z)dZ} + M \cdot \frac{\int_5^{5+(t_3-y_3)} g(Z)dZ}{\int_5^{10} g(Z)dZ} \right] \right\} \right) \quad (3.5)$$

which is equation (3.3). The optimal solution is then to compress activity 3 by 3 weeks, resulting in a project makespan of 7 weeks. Note that the compression is justified in this scenario because the project compression increases likelihood of receiving the high market payoff, and the net positive effect outweighs the compression cost.

Since the two scenarios above are mutually exhaustive, the expected project value given a strategy to make no compression in activity 2 can be depicted by a probability tree in Figure 17.

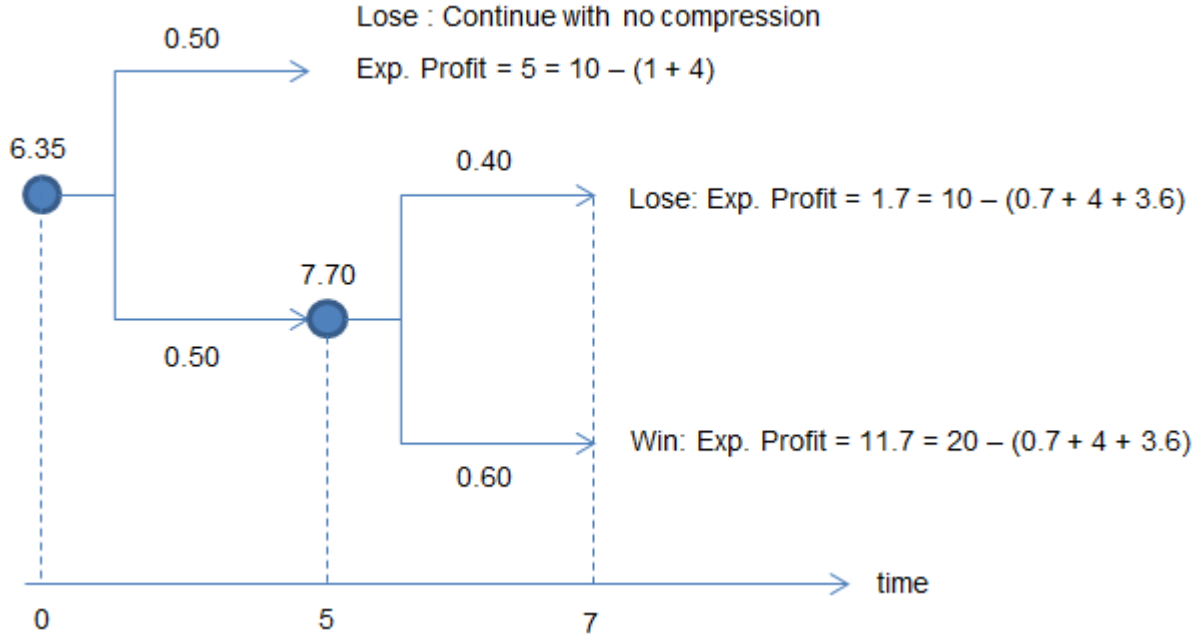


Figure 17: Decision Tree and Expected Profit: No Compression to Activity 2

And the expected profit can be calculated in a straight forward manner as follows;

$$E [Profit|y_2 = 0] = 0.50*\$5.0 + 0.5*\$7.70 = \$6.35$$

The same analysis can be performed for all other strategies in the same fashion, the complete result is shown in the Table 7 (In the table, denote y_2 and S_3 as the compression amount to activity 2 and the start time of activity 3 respectively).

y_2	S_3	Prob. rival enters before S_3	Max profit given rival enters before S_3	Prob. rival enters after S_3	Max profit given rival enters after S_3	Expected profit
0	5	0.50	5.00	0.50	7.70	6.35
1	4	0.40	4.10	0.60	7.47	6.12
2	3	0.30	3.20	0.70	7.04	5.88
3	2	0.20	2.30	0.80	6.50	5.66

Table 7: Expected Profit for Different Compression Strategies

It is evident from the example that the decision to make no compression for activity 2 yields the highest expected project value of \$6.35. Therefore, the complete policy which is best for the firm can be described as follows;

Optimal Policy:

1. Make zero compression to activity two
2. Check state of competition at week 5:
 - (a) If competitor has entered the market: make zero compression to activity three
 - (b) Otherwise compress activity three by 3 weeks to complete the project at week 7

The procedure shown in this example provides a general formulation that obtains an optimal solution and can be implemented to a serial project with any number of stages. One of the reasons for considering serial project is to develop insights that will later be proven useful in analyzing a general network project where activity is presumed non-preemptive. Also, notice that when competitor enters the market between any pair $(i - 1)^{th}$ and i^{th} review point, the optimization at the i^{th} review point (4.2) introduces a special structure to the problem which leads to the following result.

Proposition 3. *In a serial project network under the fixed return market competition when $m > \text{Min}_{y_{n-1}}[C_{n-1}(y_{n-1}) + C_o(t_{n-1} - y_{n-1})]$, there exists a unique review point k that, after which, a firm will always choose to complete the project regardless to the state of the competition*

Proof. Let the time of the i^{th} review point be at the beginning of the i^{th} activity in the serial network project with n activities. After solving (4.1)-(4.4) to optimality, the exact time of any i^{th} review point can be precisely determined.

Consider any review point k in the sequence $i = 2, \dots, k - 1, k, \dots, n - 1$. Suppose that the competitor enters the market between review point $k - 1$ and k , the optimization at the k^{th} review point is

$$f_k(\Lambda'_k) = \text{Max} \begin{cases} \text{Continue: } \text{Max}_{y_k} -C_k(y_k) - C_o(t_k - y_k) + f_{k+1}(\Lambda'_{k+1}) \\ \text{Abandon: } 0 \end{cases}$$

If the option of continue is chosen, it implies that the project will be completed since there is no benefit to continue the project and forgo m by abandoning at any future review points. Therefore, we can expand the expression for the continue option above to

$$f_k(\Lambda'_k) = \text{Max} \begin{cases} \text{Continue: } \text{Max}_{y_k} -C_k(y_k) - C_o(t_k - y_k) + \text{Max}_{y_{k+1}}(-C_{k+1}(y_{k+1}) - \\ C_o(t_{k+1} - y_{k+1}) - \dots + \text{Max}_{y_{n-1}}(-C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) \\ + m)) \dots) \\ \text{Abandon: } 0 \end{cases}$$

The nested problem in the continue option can be solved as a TCP problem where the project is truncated and begins at review point k (begin at activity k and end at activity n). Now, let $q(k), k = 2, 3, \dots, n - 1$ denotes the forward-looking maximum profit of this TCP problem that starts at review point k^{th} given that the competitor enters the market between review point $k - 1$ and k .

$$q(k) = \underset{y_k}{\text{Max}}(-C_k(y_k) - C_o(t_k - y_k) + \underset{y_{k+1}}{\text{Max}}(-C_{k+1}(y_{k+1}) - C_o(t_{k+1} - y_{k+1}) \\ - \dots + \underset{y_{n-1}}{\text{Max}}(-C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) + m) \dots))$$

If $m > \underset{y_{n-1}}{\text{Min}} [C_{n-1}(y_{n-1}) + C_o(t_{n-1} - y_{n-1})]$, (i.e. the small payment is larger than the total TCP cost to complete the $(n - 1)^{th}$ stage) there exists a review point $k = 2, 3, \dots, n - 1$ such that

$$q(k - 1) \leq 0 \leq q(k)$$

Then $f_k(\Lambda'_k) = q(k)$

That is, a firm is always better off completing the project to earn a fixed return of m if the project reaches the k^{th} review point even if they have already lost the competition.

In other words, if there exists at least one review point $k, k = 2, 3, \dots, n - 1$ where $q(k) \geq 0$, then the option to abandon the development project will never be exercised at or after the k^{th} review point because $0 \leq q(k) \leq q(k + 1)$, .

□

3.3.2 General Project Network

Given a general network G , the problem of finding an optimal dynamic policy is NP-hard (Garey and Johnson, 1979). Therefore, in this section we developed an effective heuristic methodology based on the stochastic dynamic programming approach used to solve the serial network case. We denote our heuristic as the Dynamic Approximation Method (DAM); the DAM algorithm has two phases but polynomial order complexity $O(n)$.

In the first phase, we solve a series of modified static fixed payment problems; that is, at time t_k (and iteration k), we maximize

$$E(\pi(\bar{S}, \bar{Y})) = \left[m \int_{\max(a, t_k)}^{S_n} g(Z) dZ + M \int_{S_n}^{S^{base}} g(Z) dZ \right] - \left(\sum_{i=1}^n C_i(y_i) + C_o S_n \right) - \varepsilon \sum_{j \in N} S_j$$

subject to constraints (1)-(3) where ε is a small positive constant. The last term guarantees that task starting times equal their early starting times (i.e., $S_j^* = ES_j$ for all $j \in N$); we use early starting times to reflect the time when resource allocation decisions would be implemented in a dynamic policy and to update the conditional probability that a rival has not entered the market prior to time ES_j . At each k^{th} iteration, we find a vector of task compression amounts, $\bar{Y}_k = (y_1^k, \dots, y_n^k)$.

We initially set $t_1 = 0$ (at iteration $k = 1$) and maximize (8) subject to (1)- (3) and find the resulting compression values $\bar{Y}_1 = (y_1^1, \dots, y_n^1)$. For iterations $k = 2, 3, \dots$, we set $t_k = \min\{ES_j > t_k | ES_j > a\}$ and $y_j^k = y_j^{k-1}$ for all tasks $j \in N$ when $ES_j < t_k$. We then maximize (8) subject to constraints (1)-(3) and calculate compression values $\bar{Y}_k = (y_1^k, \dots, y_n^k)$.

We continue this process until $t_k = S_n$; there will be at most n iterations.

In the second (backward) phase, we use the vectors $\bar{Y}_k = (y_1^k, \dots, y_n^k)$ to generate possible solutions for the dynamic policy case. We generate a maximum of n vectors of task compressions that form possible solutions to the dynamic policy; we denote these vectors of possible task compressions by $\pi^h = \{\theta_1^h, \theta_2^h, \theta_3^h, \dots, \theta_n^h\}$. To generate these vectors, we initially set all compression values to zero; i.e., $\pi^1 = 0, 0, \dots, 0$. For $h = 2, \dots$, the compression vectors are as follows:

$$\begin{aligned}\pi^2 &= \{0, 0, \dots, \max_k(y_n^k)\} \\ \pi^3 &= \{0, 0, \dots, \max_k(y_{n-1}^k), \max_k(y_n^k)\} \\ &\vdots \\ \pi^{n+1} &= \{\max_k(y_1^k), \dots, \max_k(y_{n-1}^k), \max_k(y_n^k)\}\end{aligned}$$

where tasks are ordered in ascending order by the latest starting times. In the case of a tie, we order the tasks randomly from among the set of tasks with the same late starting time.

We calculate the expected profit for each vector $\pi^h = \{\theta_1^h, \theta_2^h, \theta_3^h, \dots, \theta_n^h\}$ that provides a means of ranking these possible policies. We calculate the expected profit using a decision tree that represents alternative strategies if a rival firm enters the market between any task starting times that are calculated using task durations $t_j - \theta_j^h$. For example, given some compression vector $\pi^h = \{\theta_1^h, \theta_2^h, \theta_3^h, \dots, \theta_n^h\}$, consider sequential task (early) starting times S_{j-1} and S_j . The probability that a rival firm entered the market between time S_{j-1} and S_j (given that a rival firm had not entered prior to time S_{j-1}) is

$$\frac{\int_{S_{j-1}}^{S_j} g(Z)dZ}{\int_{S_{j-1}}^b g(Z)dZ}$$

If a rival firm has entered the market at any time, the innovator firm can continue the project (at reduced scope representing the minimum cost to complete the project) or can abandon the project (if no positive profit can be gained). These values are represented in the decision tree at appropriate decision nodes; the expected profit for each decision tree is calculated in typical backwards fashion. The implementation of the DAM algorithm is illustrated with the example project and parameters in Figure 18 and Table 8 below.

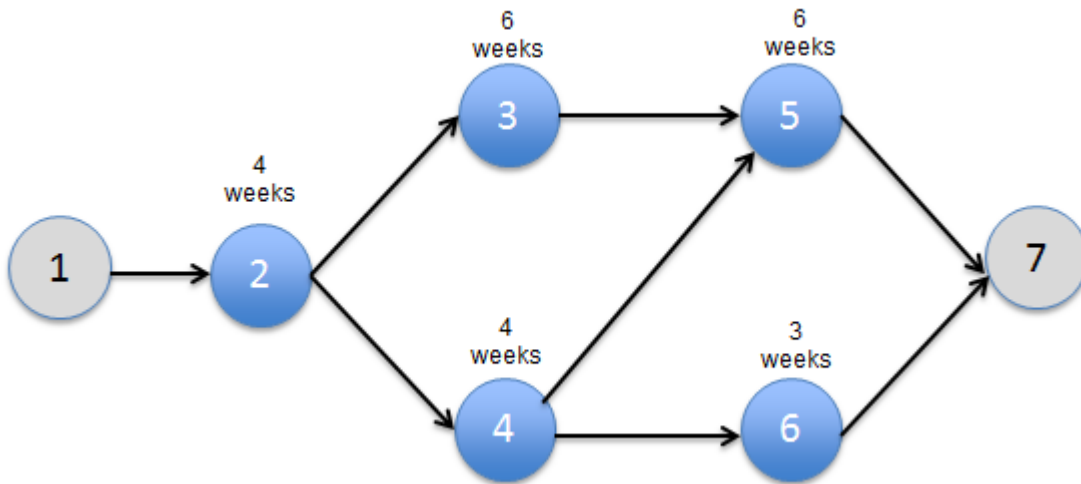


Figure 18: Activity Network for DAM Heuristic-Fixed Payment Example

Activity	Uncompressed Activity Duration	Maximum Compression	Fixed Cost	Marginal Compression Cost (per Week)
1	0	0	0	0
2	4	1	5	4.5
3	6	3	23	2.0
4	4	2	25	2.5
5	6	3	23	1.5
6	3	2	28	9.0
7	0	0	0	0

Table 8: Parameters for DAM Heuristic Example

We assume for this example that $M = \$160$, $m = \$110$ and $Z \sim U[2, 17]$. Without any additional compression, the project would take 15 weeks and cost \$15 in overhead/indirect costs and \$104 in (fixed) resource costs. The probability that a rival would enter the market first is 0.867 in which case the innovator firm would earn \$110 in revenue and incur a net loss of \$9. Solving the static policy (assuming that all resource decisions must be made at time $t = 0$), the innovator firm would compress task 3 by two weeks (to 4 weeks) and task 5 by three weeks (to a duration of 3 weeks) that would reduce the project makespan to ten weeks. The resulting expected profit is \$10.83; the probability that a rival firm would enter the market before the innovator firm is reduced to 0.533.

To investigate possible dynamic strategies, we use the optimal static solution with all tasks starting at their respective early start times. Assuming that resource allocations cannot be changed for ongoing tasks, the next opportunity (beyond $t = 0$) for reassessing resource allocations occurs at time $t = 3$. Thus, we fix the resource allocation for task 2 (that was set at time $t = 0$) at $y_2 = 0$, increase the lower bound on the pdf of Z to 3 (to reflect the conditional probability that no rival has entered the market prior to time $t = 3$) and resolve the static problem. This process is repeated for time $t = 6$. Since the makespan is reduced to nine weeks, this is the final opportunity for reassessing resource allocations. The three static solutions and resulting four possible dynamic strategies are indicated in Table 9 and

Table 10 below.

Static Solutions	Expected Profit	S_n	y_2	y_3	y_4	y_5	y_6
$t = 0$	\$10.83	10	0	2	0	3	0
$t = 3$	\$12.57	9	0	3	1	3	0
$t = 6$	\$20.36	9	0	3	1	3	0

Table 9: Static Solutions

Table 10: Possible Dynamic Solution Vectors

Solution	Expected Profit	y_2	y_3	y_4	y_5	y_6
1	-\$2.27	0	0	0	0	0
2	\$6.93	0	0	0	3	0
3	\$9.93	0	3	0	3	0
4	\$11.50	0	3	1	3	0
True Optimal	\$11.53	0	2	0	3	0

Each possible dynamic strategy is evaluated using a decision tree. Figure 19 below illustrates how the expected profit is evaluated for the fourth possible dynamic solution.

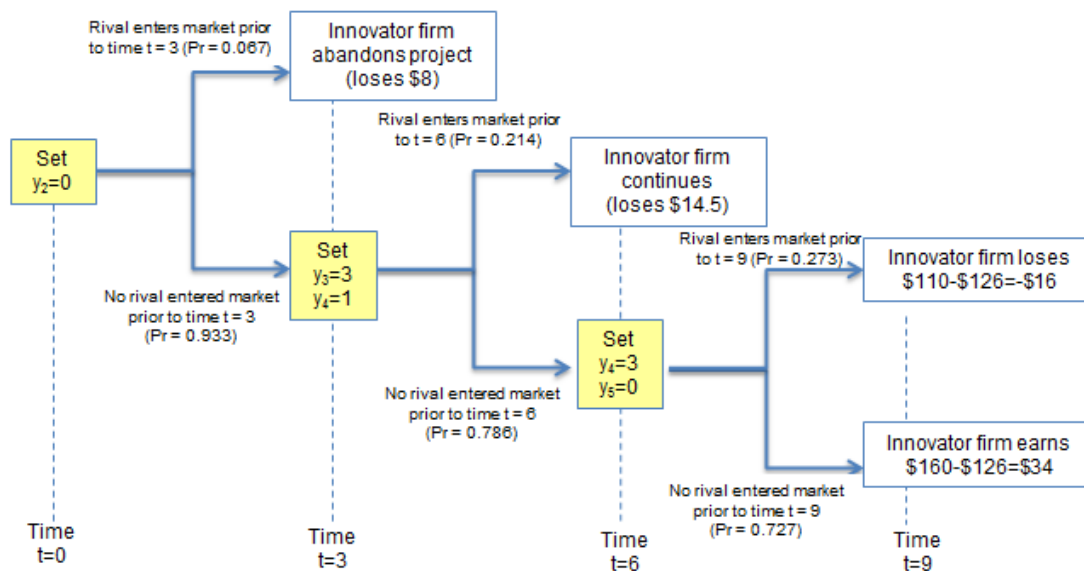


Figure 19: Expected Profit for Dynamic Policy 4

The decision tree in this case indicates that the innovator firm would abandon the project if a rival firm entered the market prior to time $t = 3$; to stay in the market at that point, the firm would lose \$14.50 while its abandon loss is only \$8. However, at time $t = 6$, the firm would stay in the market even if a rival firm has entered and thereby earn $m = \$110$ and incur a loss of \$14.50 which is significantly less than the loss it would incur if it abandoned the market at that point. Note that compression decisions change at the various review times depending on the state of the project, i.e. whether or not a rival has entered the market by that time.

Figure 19 also reveals that that if the innovator firm enters the market before its rival, it earns a profit of $\$160 - \$126 = \$34$. Finally, the dynamic strategy evaluated in Figure 19 results in an expected profit of \$11.50 (slightly lower than the true optimal solution of \$11.53) that results in a nine percent increase in expected profit over the optimal static policy. This is in fact the value of a flexibility or agile option.

3.3.3 Numerical Study

To test the efficacy of the DAM heuristic, we analyzed a series of randomly generated networks with seven and twelve activities (including milestone start and finish nodes), respectively. The networks were generated following Mitchell and Klastorin (2007) such that the network topology represented realistic projects. Parameters were set such that the solutions were non-trivial. In both cases, we compared the solution from the DAM heuristic to the optimal solution that was found by enumerating all possible solutions after discretizing the pdf $g(Z)$.

The parameters for the seven activity network, as well as the result, are presented in Table 11 and Table 12 below:

Attribute	Setup
Network topology	25 randomized topologies
Exit threshold for topology uniqueness	100 trials
Neighborhood size	U[2,7] (randomized)
Range of network connectivity	U[0.00,0.50] (randomized)
Uncompressed activity duration	[0 3 6 4 6 3 0]
Maximum activity compression	[0 1 3 2 3 2 0]
Overhead/Indirect cost	1.0
Compression cost (assumed linear)	[0 4.5 2.0 2.5 1.5 9.0 0]
Fixed cost	[0 5 23 25 23 28 0]
Low payoff (m)	\$110
High payoff (m)	\$150
Distribution of rival	U[2, 17]
Discretized size for optimal solution search	1.00

Table 11: Parameters for 7-Activity Network: Fixed Payment

Trial	Network Connectivity	Optimal Solution (Profit in \$)	DAM Solution (Profit in \$)	% Optimality Gap
1	0.40	-11.23	-11.23	0.00
2	0.04	0.00	0.00	0.00
3	0.40	11.03	11.03	0.00
4	0.21	10.93	10.93	0.00
5	0.17	25.33	25.33	0.00
6	0.19	24.03	24.03	0.00
7	0.13	23.93	23.93	0.00
8	0.28	23.93	23.93	0.00
9	0.00	13.00	13.00	0.00
10	0.46	13.27	13.27	0.00
11	0.44	11.53	11.50	0.29

Table 12: Numerical Result for 7-Activity Network: Fixed Payment

With 7 tasks, the DAM heuristic found the optimal solution in ten of eleven trials (91 percent); in the trial where it failed to find the optimal solution, the expected profit from the DAM heuristic was 0.29 percent lower than the optimal solution. The average and standard deviation of the optimality gap are 0.02% and 0.08% respectively. Note that the test exits after 100 trials as it can only find 11 unique network topologies.

Similar study is carried out for a 12-activity network. Parameters for the project, as well as the result, are presented in Table 13 and Table 14 below:

Attribute	Setup
Network topology	25 randomized topologies
Exit threshold for topology uniqueness	100 trials
Neighborhood size	U[2,12] (randomized)
Range of network connectivity	U[0.00,0.50] (randomized)
Uncompressed activity duration	[0 5 5 10 7 6 11 6 5 4 6 0]
Maximum activity compression	[0 1 2 3 3 0 3 2 2 2 1 0]
Overhead/Indirect cost	8.5
Compression cost (assumed linear)	[0 10 5 6 4 5 5 15 5 10 10 0]
Fixed cost	[0 40 30 40 40 30 60 30 20 20 0]
Low payoff (m)	\$500
High payoff (m)	\$1,000
Distribution of rival	U[10, 40]
Discretized size for optimal solution search	1.00

Table 13: Parameters for 12-Activity Network: Fixed Payment

Trial	Network Connectivity	Optimal Solution (Profit in \$)	DAM Solution (Profit in \$)	% Optimality Gap
1	0.49	-316.18	-332.9	5.30
2	0.20	43.97	43.97	0.00
3	0.10	343.58	343.58	0.00
4	0.05	20.17	20.17	0.00
5	0.33	366.85	366.85	0.00
6	0.31	173.15	173.15	0.00
7	0.13	87.08	86.03	1.20
8	0.19	206.85	206.85	0.00
9	0.26	-77.37	-77.37	0.00
10	0.05	172.3	172.3	0.00
11	0.18	213.93	213.93	0.00
12	0.28	356.18	356.18	0.00
13	0.20	15.43	15.43	0.000001
14	0.23	62.45	62.45	0.00
15	0.32	-18.52	-18.52	0.000001
16	0.32	209.32	209.32	0.00
17	0.37	48.83	48.83	0.00
18	0.34	290.58	290.58	0.00
19	0.43	54.45	54.45	0.00
20	0.27	-98.53	-98.53	0.00
21	0.16	-38.85	-38.85	0.00
22	0.22	37.22	37.22	0.00
23	0.25	19.43	19.43	0.00
24	0.18	72.13	72.13	0.00
25	0.34	162.28	162.28	0.00

Table 14: Numerical Result for 12-Activity Network: Fixed Payment

With 12 tasks, the DAM heuristic found the optimal solution in 21 of 25 trials (84 percent); in the trials where it failed to find the optimal solution, the largest optimality gap was 5.30 percent. The average and standard deviation of the optimality gap are 0.26% and 0.02% respectively.

To analyze the possible benefits of a flexible strategy, we performed a number of numerical experiments using n-stage serial projects. We used serial projects for two reasons: (1) many new product development projects are viewed as serial projects with sequential stages

separated by stage-gates where resource allocation decisions are re-assessed, and (2) we are able to efficiently find optimal solutions for serial dynamic policies as described in sections 2 and 3 for the fixed and variable payment problems. Table 15 summarizes the parameters used for the experiment.

Attribute	Setup
Network topology	12 activities, serialized
Uncompressed duration for stage j (t_j)	$t_j \sim U[3, 7]$ (randomized)
Maximum compression for stage j (\bar{y}_j)	$\bar{y}_j = 0.5 * t_j$
Overhead/Indirect cost	1.0
Compression cost for stage j	$U[2, 6]$ (randomized)
Fixed cost for stage j	$U[8, 16]$ (randomized)

Table 15: Parameters for 12-Activity Serial Network: Fixed Payment

For each randomly generated project, we calculated the optimal time-cost trade-off cost without competition (denoted by TCP) and set the low market payment $m = X(TCP)$ where X ranges from 0.8 to 1.5 in increments of 0.1. The value of high market payment M was set at a low value (equal to $2.0 m$), medium value (equal to $2.2 m$), and high value (equal to $2.4 m$). The time for a rival to enter the market, Z , was generated from a uniform distribution $Z \sim U[a, b]$, where $a \sim U[0, S^{min}]$ and $b = S^{base} + S^{min} - a$.

Results for the fixed payment model with 12 serialized activities project are indicated in Figure 20; we found similar patterns for networks with varying numbers of stages.

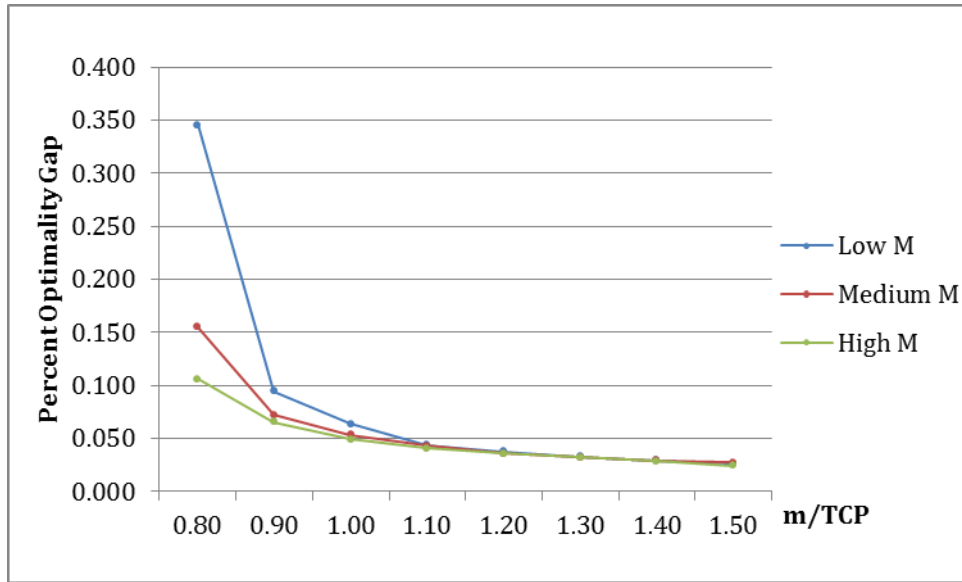


Figure 20: Value of Flexibility for 12-Activity Serial Network (Fixed Payment Model)

The graph in Figure 20 indicates the relative value of flexibility for the fixed payment model. The y-axis indicates the percent of optimality gap (the percent savings between the optimal dynamic and optimal static policies) and the x-axis represents the ratio of small market payment to the minimum TCP cost of the project. The results show that the value of flexibility increases significantly as the value of m decreases relative to the optimal TCP profit. Note that $m/TCP \geq 1.00$ implies that the option to abandon the project would never be exercised. All graphs in Figure 20 supports this concept as the value of flexibility drops sharply when the ratio m/TCP approaches one. These observations match our intuition that the value of flexibility is high when it is likely that a firm will need to adjust its strategy in the future stages.

3.4 Chapter Summary

In this chapter, we provide the definition of fixed market competition where the firm that wins the development race earns a high and fixed lump sum payment regardless of how much or little it wins, whereas the losing firm receives a smaller fixed payment. When the market is purely competitive, we can assume that the smaller return value equals zero. This class of competition reflects a development of product or service where patent protection can be filed and net present value of the product can be accurately estimated. The difference between high and low market returns can also be viewed as a price of losing the competition.

We pose the question to project managers how the resource allocation and project scheduling should be planned when faced with this competitive environment. In the static case, we assume that contracts concerning resources have long lead-times such that all decisions must be made at the beginning of the project. For this case, we show that there exist conditions where the optimal solution for a profit-maximizing firm would be to compress the project makespan to its minimum, or to completely ignore the competition and minimize its own project cost.

We also study the dynamic case where the firm does not have to commit to any resource or scheduling upfront and all decisions can be made just prior to the start of each activity; this method introduces the value of flexibility and real option which is becoming increasingly important in practice. We show that for a strictly serial project network, if the small fixed payment is sufficiently high, there exists a time after which the option to abandon the project will never be exercised. We define this time in the development project as the point of no abandonment (PNA).

For general project networks, we develop a dynamic approximation method (DAM)

heuristic to help project managers make sequential resource allocation decisions in order to maximize the expected profit of the project under competition. The DAM heuristic is tested using a 7- and 12-activity network. The results reveal that the heuristic achieves the optimal solution more than 80% of the time. In addition, the optimality gap is reasonably small (less than 10%) for instances where the solution is sub-optimal. Lastly, the result from our experiment with a 12-activity serial network shows how the options to abandon or adjust resource allocation decisions improve the expected profit of a project. This is precisely the value of flexibility built-in to the DAM heuristic we develop for the dynamic resource allocation case.

4 New Product Development Projects with Competition: Variable Payment Market and Deterministic Activity Durations

In this chapter, we consider a different form of market payment that a profit-maximizing innovator firm competes for. Similarly to the fixed market payment, the innovator firm begins developing a new product or service and faces the threat of a rival firm that may enter the market with a competing product. However, there is a finite life cycle for the product, and if the innovator firm enters the market first it earns a premium or monopoly profit for the time that it is in the market prior to entry by a rival firm, otherwise it receives a regular rate of market return.

To visually illustrate the dynamics of the competition, Figure 21 represents the case where the innovator firm enters the market first and its corresponding market reward, while Figure 22 represents a case where the innovator firm loses the competition and receives only the small market payment rate.

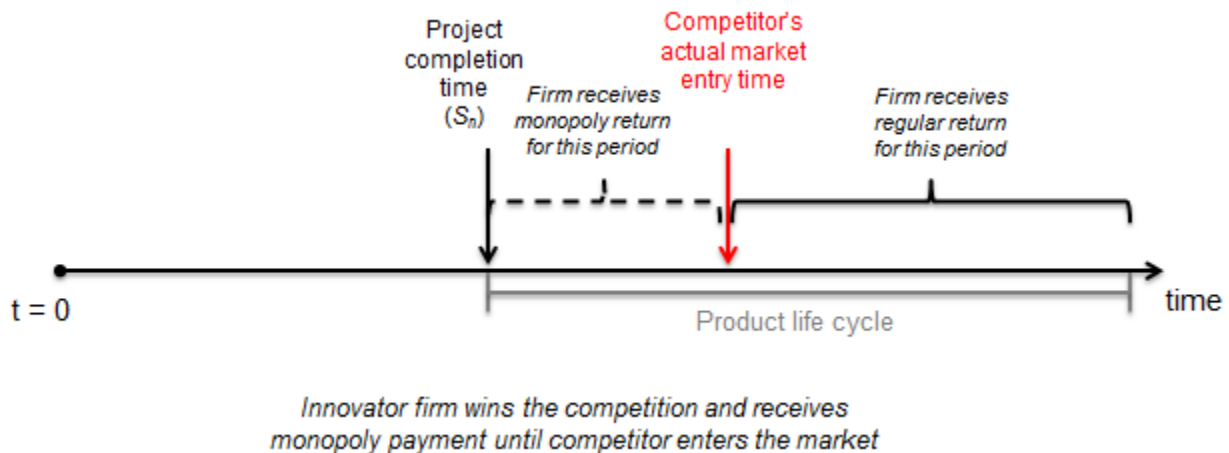


Figure 21: Innovator Firm Wins the Competition

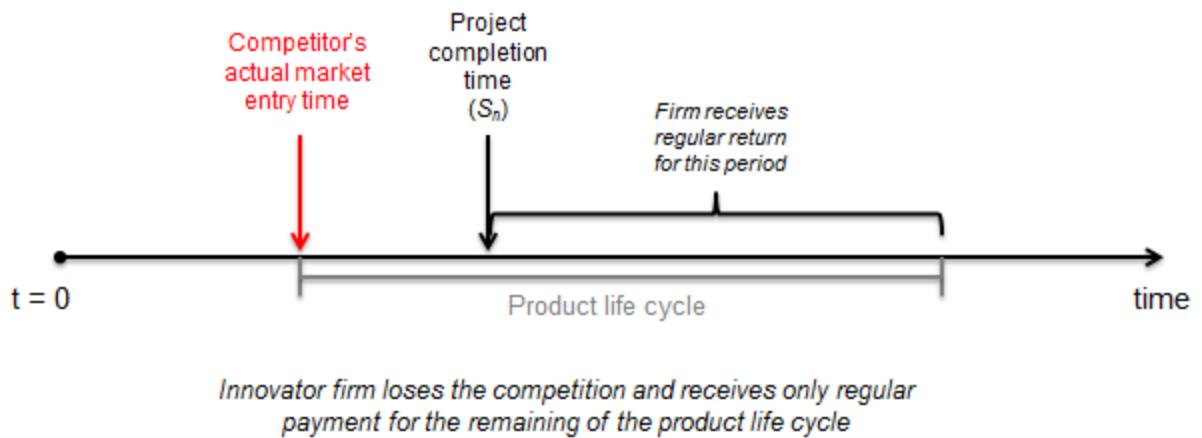


Figure 22: Innovator Firm Loses the Competition

As can be seen, the monopoly profit is a function of the lead time an innovator firm has over its competitor. Therefore, unlike in the fixed payment competition, an innovator firm may have to consider building sufficient lead time in optimizing its expected profit of the project.

To motivate the problem, we shall use the same project example illustrated in section 3.0. The project is represented by the activity network shown in Figure 23 and the activity parameters given in Table 16

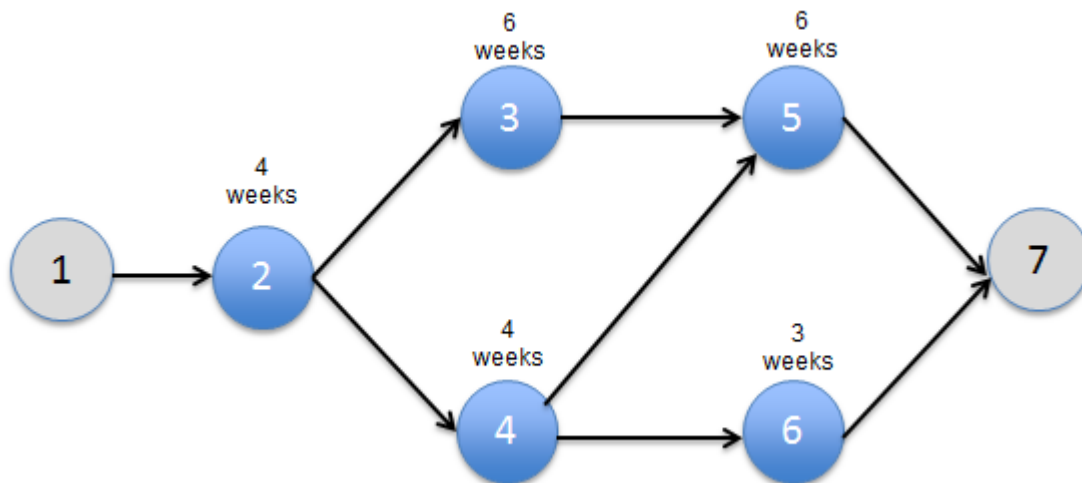


Figure 23: Activity Network for Variable Payment Example

Activity	Uncompressed Activity Duration	Maximum Compression	Fixed Cost	Marginal Compression Cost (per Week)
1	0	0	0	0
2	4	2	1.0	3.5
3	6	3	2.5	2.5
4	4	2	1.5	2.0
5	6	3	2.0	3.1
6	3	1	3.0	3.1
7	0	0	0	0

Table 16: Parameters for Variable Payment Example

The possible paths through the network, p_i , remain to be:

$$p_1 : 1 \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 7$$

$$p_2 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow 7$$

$$p_3 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 7$$

We maintain the assumptions that activity compression cost is a linear function of the compression amount, the innovator firm has a subjective estimation that the time when a competitor's product will initially be introduced could be any time between week 2 and week 17, and the indirect/overhead cost per week is \$1. In contrast, we assume that if an innovator firm wins, for every week it holds a monopolist status, it enjoys \$7. Otherwise, the innovator firm earns only \$2 per week. We assume that the product or service has life cycle of 15 weeks, and the life cycle begins when either the innovator firm or its rival enters the market. Under this circumstance, the amount that an innovator firm can earn clearly varies based on the competition outcome.

If the innovator firm completely ignores the threat of the rival firm and believes it will receive full monopoly market return over the life cycle of the product for certain, the problem it faces reduces to the standard time-cost trade-off problem (P1) described in section 2.2.

Given such believe, the solution to the optimization above is straight forward since the market payment is guaranteed to be \$105 ($105 = 7 \cdot 15$) there is no incentive to compress any activity in the network since all marginal compression cost is greater than the indirect/overhead cost of \$1. The optimal policy (minimum cost) is to execute each activity at its normal duration. The project makespan, which is equal to the critical path (path p_1), is 16 weeks. The total project cost is therefore \$26 (indirect cost of \$16 + direct cost of \$10) and the net profit of the project would be perceived as $\$105 - \$26 = \$79$.

Similarly to the case in section 3.0, it can be shown that such strategy is sub-optimal for the innovator firm. Should the firm plan to complete the project at week 16, the expected market payoff when accounted for the competition appropriately can be expressed as follow:

$$\begin{aligned}
 \text{Expected Payment} &= \int_{S_n}^b [Tr + \Delta R(z - S_n)] g(z) dz + \int_a^{S_n} [r(T + z - S_n)] g(z) dz \\
 &\text{for } S_n = 16 \\
 &= Tr + (R - r) \int_{16}^{17} (z - 16) g(z) dz + \int_2^{16} r(z - 16) g(z) dz \\
 &= 20 + (7 - 2) \int_{16}^{17} (z - 16) g(z) dz + 2 \int_2^{16} (z - 16) g(z) dz \\
 &= 30 + 5 \left(\frac{1}{15} \right) \left(\frac{z^2}{2} - 16z \right) \Big|_{16}^{17} + 2 \left(\frac{1}{15} \right) \left(\frac{z^2}{2} - 16z \right) \Big|_2^{16} \\
 &= 23.63
 \end{aligned}$$

Since we establish that the cost is \$26 given this policy, the net expected profit would be $\$23.63 - \$26 = \$-2.37$. That is, the innovator firm would expect to lose \$2.37 should it plan to complete the project at week 16. The firm is clearly better off not pursuing the project

in this case, hence the strategy to complete the project at week 16 cannot be optimal. In fact, when applying the appropriate approach (to be shown in the subsequent section) it can be shown in this this example problem that the optimal market entry time should be set at week 10 for the innovator firm.

4.1 Assumptions and Notations

We assume in this model a finite product life cycle to avoid trivial cases. The expected life span of the product or service under development is denoted by T ; we assume that the product life begins when the first firm - either the innovator firm or a rival firm - enters the market. We assume that the product life cycle is large enough such that either firm cannot completely avoid each other in the market. That is, $T > \max(b - S^{min}, S^{base} - a)$.

We let R denote the linear rate of premium return that the innovator firm earns per time period while having a monopoly status in the market, and r denote the linear rate of regular return when rival firms are in the market. We assume that both R and r are independent of the market entry times (although this could be relaxed in our models). Clark (1989) discussed product development models of this type for the automotive industry and noted that “each day of delay in market introduction costs an automobile firm at least \$1 million in lost profits”

Summarized below are key characteristics and assumptions of a variable return market competition:

- Firm faces a competition to develop and introduce new product or service to the market
- If a firm introduces the product to the market first, it enjoys a monopoly status in the

market until the competitor enters. As a monopolist, a firm receives a linear market return rate of R . After a competitor enters the market, the return rate becomes r

- If a firm introduces the product to the market after the competitor, a firm receives a linear market regular rate of r
- $R > r \geq 0$
- R and r is independent of market entry time
- Finite product life cycle $T > \max(b - S^{min}, S^{base} - a)$
- T is independent of market entry time
- The market entry of a firm does not affect the competitor's action

Based on the description above, the variable return market competition essentially depicts a market where the bulk of positive return maybe accumulated during the monopoly period because the innovator firm is the sole provider of the product or service in the market. Since we assume that the product or service cannot be differentiated effectively, the regular return is lower (can be zero) when products of both the firm and its competitor are available in the market. This describes a competition in products that can be imitated, or with imperfect patent protection.

4.2 Static Resource Allocation Policy

In a static resource allocation policy, all decisions (activity start time, market introduction time, compression) must be made at time zero. The stream of revenue earned by the innovator firm depends on whether or not it is first to enter the market. That is, if the innovator firm enters first, the revenue is equal to $Tr + \Delta R(Z - S_n)$ during the monopoly period

$(Z < S_n)$, but equal to $r(T + Z - S_n)$ (i.e. $Z \geq S_n$) where $\Delta R = R - r$.

The problem for static resource allocation model of the variable payment can be expressed as follows:

$$\text{Maximize}_{S,y} E(\pi) = \int_{S_n}^b [Tr + \Delta R(Z - S_n)] g(Z) dZ + \int_a^{S_n} [r(T + Z - S_n)] g(Z) dZ - \eta(S_n) - C_o S_n$$

subject to (1)-(3)

(P4)

Using the expected profit expression above, we can derive conditions which provide several managerial insights to the problem.

4.2.1 Competition interval includes the solution interval, ($a \leq S^{min}$ and $S^{base} \leq b$)

Lemma 6. *Under the variable return market competition where $a \leq S^{min}$ and $S^{base} \leq b$, a firm must make additional compression beyond the case solution S^{base} .*

Proof. The derivative of the objective function with respect to S_n by Leibniz rule is

$$\begin{aligned}
\frac{dE(\pi)}{dS_n} &= \frac{d}{dS_n} \int_{S_n}^b [Tr + \Delta R(Z - S_n)] g(Z) dZ + \frac{d}{dS_n} \int_a^{S_n} [r(T + Z - S_n)] g(Z) dZ - C_o - \frac{d\eta(S_n)}{dS_n} \\
&= -Trg(S_n) - \Delta R\bar{G}(S_n) + Trg(S_n) - r(S_n) - C_o - \beta(S_n) \\
&= -\Delta R\bar{G}(S_n) - rG(S_n) - C_o - \beta(S_n) \\
&= -\Delta R + RG(S_n) - 2rG(S_n) - C_o - \beta(S_n) \\
&= -\Delta R(1 - G(S_n)) - rG(S_n) - C_o - \beta(S_n)
\end{aligned}$$

Since $\beta(S_n)$ is convex decreasing with S_n , we know that $\beta(S_n) = [\beta(S^{min}), \beta(S^{base})]$ for $S_n \in [S^{min}, S^{base}]$ where $\beta(S^{min}), \beta(S^{base})$ represent the highest and lowest marginal cost of project makespan compression beyond base solution respectively.

By definition of point S^{base} , we have $\beta(S^{base}) = -C_o$, therefore the derivative at point S^{base} is:

$$\begin{aligned}
\frac{dE(\pi(S^{base}))}{dS_n} &= -\Delta R(1 - G(S^{base})) - rG(S^{base}) - C_o + C_o \\
&= -\Delta R(1 - G(S^{base})) - rG(S^{base})
\end{aligned}$$

Since we assume that $R > r$ ($\Delta R > 0$),

$$\frac{dE(\pi(S^{base}))}{dS_n} = -\Delta R(1 - G(S^{base})) - rG(S^{base}) < 0$$

Clearly, since the slope is strictly negative at point S^{base} , the optimal solution cannot be at point S^{base} since a higher expected profit can be obtained at some S_n ; $S^{min} \leq S_n < S^{base}$ (additional compression is required)

□

Therefore, it follows that the optimal solution cannot be at point S^{base} when there is a positive difference between the monopoly and regular rate of market payoff. Hence, it is never optimal for an innovator firm to stay at the base solution.

Lemma 7. *Under the variable return market competition, if $\Delta R < \frac{-\beta(S^{min}) - rG(S^{min}) - C_o}{1 - G(S^{min})}$ then a firm will never compress to the minimum project makespan S^{min} and the optimal solution is an interior point*

Proof. Given the derivative of the objective function with respect to S_n

$$\begin{aligned} \frac{dE(\pi)}{dS_n} &= \frac{d}{dS_n} \int_{S_n}^b [Tr + \Delta R(Z - S_n)] g(Z) dZ + \frac{d}{dS_n} \int_a^{S_n} [r(T + Z - S_n)] g(Z) dZ - C_o - \frac{d\eta(S_n)}{dS_n} \\ &= -\Delta R(1 - G(S_n)) - rG(S_n) - C_o - \beta(S_n) \end{aligned}$$

We know that $\beta(S_n) = [\beta(S^{min}), \beta(S^{base})]$ for $S_n \in [S^{min}, S^{base}]$ where $\beta(S^{min}), \beta(S^{base})$ represent the highest and lowest marginal cost of project makespan compression beyond base solution respectively.

Consider point S^{min} ; if $-\Delta R(1 - G(S^{min})) - rG(S^{min}) - C_o - \beta(S^{min}) > 0$ or equivalently $\Delta R < \frac{-\beta(S^{min}) - rG(S^{min}) - C_o}{1 - G(S^{min})}$ the optimal solution cannot be at point S^{min} since a higher expected profit can be obtained at some S_n ; $S^{min} < S_n < S^{base}$ (compressing to S^{min} is not justified). This result, together with result from the previous lemma, implies that the optimal solution must be an interior point in the interval $[S^{min}, S^{base}]$.

□

The structure of the expected profit function also provides an interesting result for a special case where $\Delta R \leq r$. This is described in the following proposition.

Proposition 4. *Under the variable return market competition, when $\Delta R \leq r$ the optimal solution occurs at point S^{min} if and only if $\Delta R \geq \frac{-\beta(S^{min}) - rG(S^{min}) - C_o}{1 - G(S^{min})}$ where $-\beta(S^{min})$ denotes the highest marginal project makespan compression cost beyond the base solution. Otherwise, the optimal solution is an interior point.*

Proof. Recall that the derivative of the objective function with respect to S_n is

$$\frac{dE(\pi)}{dS_n} = -\Delta R(1 - G(S_n)) - rG(S_n) - C_o - \beta(S_n)$$

The second derivative of the expected profit function becomes;

$$\frac{d^2 E(\pi)}{dS_n^2} = -\Delta R(-g(S_n)) - rg(S_n) - \frac{d^2 \beta(S_n)}{d^2 S_n}$$

By definition,

$$\frac{d^2 \beta(S_n)}{d^2 S_n} > 0$$

Thus, when $\Delta R \leq r$ we have

$$(\Delta R - r)(g(S_n)) - \frac{d^2 \beta(S_n)}{d^2 S_n} < 0$$

That is, the expected profit function is concave when $\Delta R \leq r$. Therefore, the solution is at the lower bound S^{min} if and only if $\Delta R \geq \frac{-\beta(S^{min}) - rG(S^{min}) - C_o}{1 - G(S^{min})}$.

Otherwise, there exists an interior inflection point S_n^* that solves

$$-\Delta R(1 - G(S_n^*)) - rG(S_n^*) - C_o - \beta(S_n^*) = 0$$

and S_n^* is the optimal solution by definition of concave function.

□

4.2.2 Competition interval overlaps the solution interval

For $S^{min} < a < S^{base}$ and $b > S^{base}$

Lemma 8. *Under the variable return market competition where $S^{min} < a < S^{base}$, the optimal solution can be in the interval $[S^{min}, a]$*

Proof. The derivative of the objective function with respect to S_n over $[S^{min}, a]$ is

$$\frac{dE(\pi)}{dS_n} = -\Delta R(1 - G(S_n)) - rG(S_n) - C_o - \beta(S_n)$$

But since $G(S_n) = 0 \quad \forall S_n \in [S^{min}, a]$, the first order condition reduces to

$$\frac{dE(\pi)}{dS_n} = -\Delta R - C_o - \beta(S_n)$$

For the optimal solution to occur only at a point greater than a (or $S_n^* > a$) like the result found in the fixed payment market model, the first order condition must be positive throughout the interval $[S^{min}, a]$. However, it is easy to show that such condition does not necessary hold when

$$\Delta R > -C_o - \beta(S_n),$$

Contradiction.

Hence, unlike the conclusion derived in the fixed market payoff model, the optimal solution for the variable payoff model can be in the interval $[S^{base}, a]$

□

For $a < S^{min}$ and $S^{min} < b < S^{base}$

Lemma 9. *Under the variable return market competition where $S^{min} < b < S^{base}$, the optimal solution can be in the interval $[b, S^{base})$*

Proof. The derivative of the objective function with respect to S_n over $[b, S^{base})$ is

$$\frac{dE(\pi)}{dS_n} = -\Delta R(1 - G(S_n)) - rG(S_n) - C_o - \beta(S_n)$$

But since $G(S_n) = 1 \quad \forall S_n \in [b, S^{base}]$, the first order condition reduces to

$$\frac{dE(\pi)}{dS_n} = -r - C_o - \beta(S_n)$$

Also,

$$\frac{d^2 E(\pi)}{dS_n^2} = -\frac{\beta(S_n)}{dS_n} < 0$$

That is, the expected profit is concave over the interval $[b, S^{base}]$. First, notice that the optimal solution cannot be at the upper boundary (point S^{base}) since

$$-r - C_o - \beta(S^{base}) < 0$$

However, if there exists a point $S_n^* \in [b, S^{base}]$ such that

$$-r - C_o - \beta(S_n^*) = 0$$

Then point S_n^* is an optimal solution.

□

The result above shows that, unlike the conclusion derived in section 3.2.2 for the fixed market payoff model with similar overlap between the competition and solution intervals, the optimal solution for the variable payment model can indeed occur in the interval $[b, S^{base})$

4.2.3 Solution interval includes the competition interval ($S^{min} \leq a$ and $b \leq S^{base}$)

It follows immediately from Lemma (9) that when $S^{min} \leq a$, the optimal solution can occur in the interval $[S^{min}, a]$. Also, when $b \leq S^{base}$ the optimal solution can occur in the interval $[b, S^{base}]$. Therefore, the only point in the solution interval that can never be an optimal point is S^{base} .

4.3 Dynamic Resource Allocation Policy

Similarly to the case in section 3.3, in a variable payment market, superior results (expected profit) is anticipated when firm has the flexibility of making a dynamic decision on the scheduling and compression strategy. The problem of finding an optimal dynamic policy for general network G is also NP-hard, hence we shall again begin the analysis by considering a multi-stage serial network first to obtain some managerial insights into the structure of the problem. Then we demonstrate how the heuristic procedure developed in section 3.4 can be implemented to large scale problem and returns near optimal solution in the same manner.

4.3.1 Serial Project Network

Similar to the fixed return competition, we maintain the same set of assumptions that sufficient resources are always available. At any review point $i = 1, \dots, n - 1$ the maximum compression for i^{th} activity is limited by \bar{y}_i . y_i is the compression decision at the i^{th} review point made to the i^{th} activity, and $C_i(y_i)$ represents the direct cost associated with such decision.

Define $f_i(\cdot)$ as the maximum expected project value from the i^{th} review point to the end of the project given certain project state. Similarly to the fixed return formulation, the

recursive expression can be expressed as

$$f_i(\Lambda_i) = \text{Max} \left(0, \text{Max}_{y_i} \left\{ -C_i(y_i) - C_o(t_i - y_i) + \left[f_{i+1}(\Lambda'_{i+1}) \frac{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^b g(Z) dZ}{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^b g(Z) dZ} + f_{i+1}(\Lambda_{i+1}) \frac{\int_{\sum_{k=1}^i (t_k - y_k)}^b g(Z) dZ}{\int_{\sum_{k=1}^{i-1} (t_k - y_k)}^b g(Z) dZ} \right] \right\} \right) \quad (4.1)$$

$$f_i(\Lambda'_i) = \text{Max} \begin{cases} \text{Continue:} & \text{Max}_{y_i} \{ -C_i(y_i) - C_o(t_i - y_i) + f_{i+1}(\Lambda'_{i+1}) \\ \text{Abandon:} & 0 \end{cases} \quad (4.2)$$

And the boundary expression at the last review point

$$f_{n-1}(\Lambda_{n-1}) = \text{Max} \left(0, \text{Max}_{y_{n-1}} \left\{ -C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) + \left[\frac{\int_{\sum_{k=1}^{n-2} (t_k - y_k)}^b (Tr + \Delta R(Z - \sum_{k=1}^{n-1} (t_k - y_k))) g(Z) dZ}{\int_{\sum_{k=1}^{n-2} (t_k - y_k)}^b g(Z) dZ} + \frac{\int_{\sum_{k=1}^{n-1} (t_k - y_k)}^b (r[T + Z - \sum_{k=1}^{n-1} (t_k - y_k)]) g(Z) dZ}{\int_{\sum_{k=1}^{n-2} (t_k - y_k)}^b g(Z) dZ} \right] \right\} \right) \quad (4.3)$$

$$f_{n-1}(\Lambda'_{n-1}) = \text{Max} \begin{cases} \text{Continue:} & \text{Max}_{y_{n-1}} \{ -C_{n-1}(y_{n-1} | \Lambda_{n-1}) - C_o(t_{n-1} - y_{n-1}) + r \left[T + Z - \sum_{k=1}^{n-1} (t_k - y_k) \right] \\ \text{Abandon:} & 0 \end{cases} \quad (4.4)$$

Note that if firm loses the competition, the ‘‘Continue’’ option again takes a form of

TCP problem although not identical to that found in the fixed market payment model. The stochastic dynamic programming above can also be solved to optimality via standard backward induction. The following proposition describes the point of no abandonment for a serial project network in the variable payment market.

Proposition 5. *In a serial project network under the variable return market competition, when $r > \min_{y_{n-1} \geq 0} \frac{C_{n-1}y_{n-1} + C_o(t_{n-1} - y_{n-1})}{T + a - S^{base}}$, there exists a point of no abandonment denoted by PNA such that, after which, a firm will always choose to complete the project regardless to the state of the competition*

Proof. Let the time of the i^{th} review point be at the beginning of the i^{th} activity in the serial network project with n activities. After solving (4.5)-(4.8) to optimality, the exact time of any i^{th} review point can be precisely determined.

Consider any review point k in the sequence $i = 2, \dots, k - 1, k, \dots, n - 1$. Suppose that the competitor enters the market between review point $k - 1$ and k , the optimization at the k^{th} review point is

$$f_k(\Lambda'_k) = \text{Max} \begin{cases} \text{Continue: } \text{Max}_{y_k} -C_k(y_k) - C_o(t_k - y_k) + f_{k+1}(\Lambda'_{k+1}) \\ \text{Abandon: } 0 \end{cases}$$

The option of continue can be expanded to the last stage:

$$f_k(\Lambda'_k) = \text{Max} \left\{ \begin{array}{l} \text{Continue: } \underset{y_k}{\text{Max}} -C_k(y_k) - C_o(t_k - y_k) + \underset{y_{k+1}}{\text{Max}}(-C_{k+1}(y_{k+1}) - \\ C_o(t_{k+1} - y_{k+1}) - \dots + \underset{y_{n-1}}{\text{Max}}(-C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) \\ + r \left[T + Z - \sum_{k=1}^{n-1} (t_k - y_k) \right]) \dots) \\ \text{Abandon: } 0 \end{array} \right.$$

But the nested optimization expression in the continue option above is simply a TCP problem where project network is truncated at k (begin at activity k and end at activity n).

Now, let $q(k)$, $k = 2, 3, \dots, n-1$ denotes the forward-looking maximum profit (ignoring all sunk costs incurred before the k^{th} review point) to complete the project from review point k given that the competitor enters the market between review point $k-1$ and k .

$$q(k) = \underset{y_k}{\text{Max}}(-C_k(y_k) - C_o(t_k - y_k) + \underset{y_{k+1}}{\text{Max}}(-C_{k+1}(y_{k+1}) - C_o(t_{k+1} - y_{k+1}) \\ - \dots + \underset{y_{n-1}}{\text{Max}}(-C_{n-1}(y_{n-1}) - C_o(t_{n-1} - y_{n-1}) + r \left[T + Z - \sum_{k=1}^{n-1} (t_k - y_k) \right]) \dots))$$

If $r > \min_{y_{n-1} \geq 0} \frac{C_{n-1}y_{n-1} + C_o(t_{n-1} - y_{n-1})}{T + a - S^{\text{base}}}$, (i.e. minimum payment is larger than the total TCP cost to complete the $(n-1)^{\text{th}}$ stage) there exists a review point $k = 2, 3, \dots, n-1$ such that

$$q(k-1) \leq 0 \leq q(k)$$

Then $f_k(\Lambda'_k) = q(k)$

That is, a firm is always better off completing the project to earn some market return if

the project reaches the k^{th} review point even if they have already lost the competition.

In other words, if there exists at least one review point $k, k = 2, 3, \dots, n-1$ where $q(k) \geq 0$, then the option to abandon the development project will never be considered at or after the k^{th} review point because $0 \leq q(k) \leq q(k+1), .$

□

4.3.2 General Project Network

To find the optimal or near optimal dynamic policy for the variable payment problem, we modified the Dynamic Approximation Methodology (DAM) algorithm described in the previous section. In this case, we initially solve a series of modified static problems by maximizing (P4) subject to same set of constraints.

The remaining process is essentially the same as the fixed payment problem; that is, we solved a series at most n static problems with updated values of t_k that were then used to formulate at most n compression vectors representing possible dynamic strategies. The vector with the maximum expected profit represented the optimal dynamic policy.

4.3.3 Numerical Study

We analyzed a series of randomly generated networks with seven and twelve activities (including dummy start and finish milestone activities), respectively. The networks were generated following Mitchell and Klastorin (2007) such that the network topology represented realistic projects.

The ranges of cost, product life cycle, and other parameters are set to generate non-trivial solutions. In all cases, we compared the solution obtained from the DAM heuristic to the

optimal solution that was found by enumerating all possible solutions after discretizing the compression decisions. Numerical tests indicate that the modified DAM algorithm is equally effective in the variable payment problem.

The parameters for the seven activity network, as well as the result, are presented in Table 17 and Table 18 below:

Attribute	Setup
Network topology	25 randomized topologies
Exit threshold for topology uniqueness	100 trials
Neighborhood size	$U[2, 7]$ (randomized)
Range of network connectivity	$U[0.00, 0.50]$ (randomized)
Uncompressed activity duration	[0 3 6 4 6 3 0]
Maximum activity compression	[0 1 3 2 3 2 0]
Overhead/Indirect cost	1.0
Compression cost (assumed linear)	[0 4.5 2.0 2.5 1.5 9.0 0]
Fixed cost	[0 5 23 25 23 28 0]
Low payment rate (r)	\$5
High payment rate (R)	\$7
Product life cycle	30
Distribution of rival	$U[2, 17]$
Discretized size for optimal solution search	1.00

Table 17: Parameters for 7-Activity Network: Variable Payment

Trial	Network Connectivity	Optimal Solution (Profit in \$)	DAM Solution (Profit in \$)	% Optimality Gap
1	0.21	20.10	19.10	4.98
2	0.15	20.13	20.13	0.00
3	0.41	33.00	23.93	0.00
4	0.31	32.63	32.63	0.00
5	0.47	8.40	8.40	0.00
6	0.11	26.10	26.10	0.00
7	0.17	21.90	21.90	0.00
8	0.31	34.50	23.93	0.00
9	0.01	20.10	20.10	0.00

Table 18: Numerical Result for 7-Activity Network: Variable Payment

With 7 tasks, the DAM heuristic found the optimal solution in eight of nine trials (89 percent); in the trial where it failed to find the optimal solution, the expected profit from the DAM heuristic was 4.98 percent lower than the optimal solution. The average and standard deviation of the optimality gap are 0.49% and 1.57% respectively. Note that the test exits after 100 trials as it can only find 9 unique network topologies.

Similar study is carried out on a 12-activity network. Parameters for the project, as well as the result, are presented in Table 19 and Table 20 below:

Attribute	Setup
Network topology	25 randomized topologies
Exit threshold for topology uniqueness	100 trials
Neighborhood size	$U[2, 12]$ (randomized)
Range of network connectivity	$U[0.00, 0.50]$ (randomized)
Uncompressed activity duration	[0 5 5 10 7 6 11 6 5 4 6 0]
Maximum activity compression	[0 1 2 3 3 0 3 2 2 2 1 0]
Overhead/Indirect cost	8.5
Compression cost (assumed linear)	[0 10 5 6 4 5 5 15 5 10 10 0]
Fixed cost	[0 40 30 40 40 30 60 30 20 20 0]
Low payment rate (r)	\$15
High payment rate (R)	\$25
Product life cycle	50
Distribution of rival	$U[10, 40]$
Discretized size for optimal solution search	1.00

Table 19: Parameters for 12-Activity Network: Variable Payment

Trial	Network Connectivity	Optimal Solution (Profit in \$)	DAM Solution (Profit in \$)	% Optimality Gap
1	0.36	299.42	299.42	0.00
2	0.11	71.42	71.42	0.00
3	0.35	-154	-154	0.00
4	0.01	357.42	316.67	11.4
5	0.02	-341	-341	0.00
6	0.21	0.42	0.42	0.00
7	0.19	-155.21	-157	0.00
8	0.26	68.42	68.41	0.00
9	0.06	204.42	204.42	0.00
10	0.48	147.42	141.67	3.90
11	0.48	-35.33	-35.33	0.00
12	0.01	-224.16	-226.06	0.84
13	0.09	-138.26	-141.61	2.42
14	0.33	-341	-341	0.00
15	0.05	-11.58	-11.58	0.00
16	0.41	239.75	239.75	0.00
17	0.42	-45.25	-45.25	0.00
18	0.44	-341	-341	0.00
19	0.25	-49.58	-49.58	0.00
20	0.24	62	62	0.00
21	0.3	-25.25	-25.25	0.00
22	0.24	238.42	238.42	0.00
23	0.05	378.67	352	7.04
24	0.15	290.67	290.67	0.00
25	0.25	-75.16	-75.16	0.00

Table 20: Numerical Result for 12-Activity Network: Variable Payment

With 12 tasks, the DAM heuristic found the optimal solution in 20 of 25 (80 percent); in the five networks where the optimal solution was not found, the average difference between the DAM heuristic and the optimal solution was 1.02 percent, and the standard deviation was 2.70 percent. The worst case optimality gap was a 11.4 percent.

To analyze the benefits of a dynamic strategy in the variable payment market, we performed a number of numerical experiments using n-stage serial projects. In these experiments, we used the same parameters used for the fixed payment model as shown in Table 21

below;

Attribute	Setup
Network topology	12 activities, serialized
Uncompressed duration for stage j (t_j)	$t_j \sim U[3, 7]$ (randomized)
Maximum compression for stage j (\bar{y}_j)	$\bar{y}_j = 0.5 * t_j$
Overhead/Indirect cost	1.0
Compression cost for stage j	$U[2, 6]$ (randomized)
Fixed cost for stage j	$U[8, 16]$ (randomized)

Table 21: Parameters for 12-Activity Serial Network: Variable Payment

For the product life cycle (T), we set $T = 1.25b$ and varied the value of the low market payment rate (r) from $(0.5TCP/T)$ to $(1.2TCP/T)$ in increments of 0.1. We set the high market payment rate (R) to three levels, $R = 2.75r$ (low value), $3.0r$ (medium value), and $3.25r$ (high value). The results for 12 serialized activities project for the variable payment model are indicated in Figure 24.

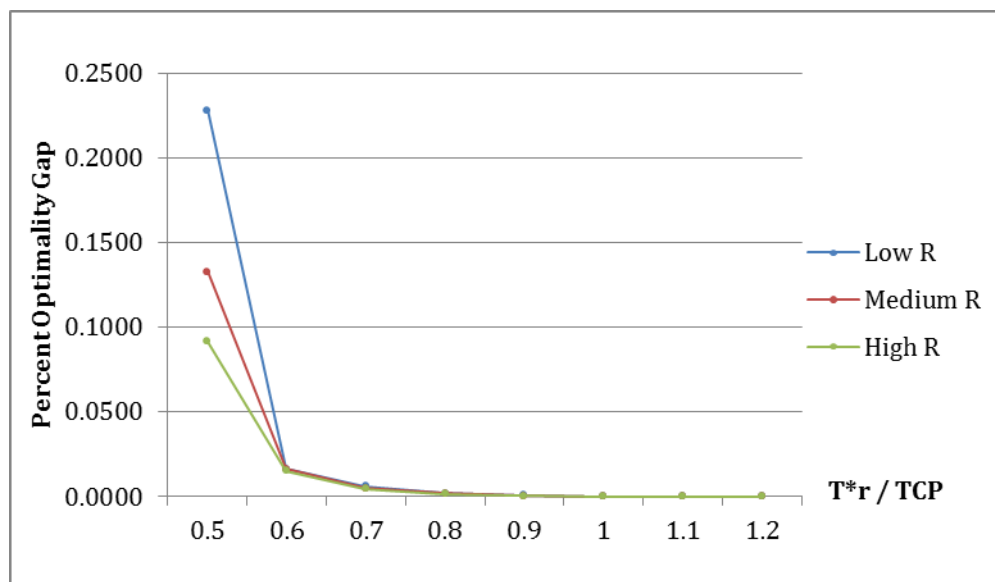


Figure 24: Value of Flexibility for 12-Activity Serial Network (Variable Payment Model)

Our numerical experiments for the variable payment problem indicate that the value of flexibility is relatively high when the ratio (Tr/TCP) is low and decreases with the ratio

(Tr/TCP) . However, once the ratio (Tr/TCP) exceeds 0.70, the benefits of a dynamic policy are reduced significantly. Again, we found that this pattern was consistent for varying numbers of stages.

4.4 Chapter Summary

In this chapter, we provide the definition of variable market competition which depicts a class of competition in which the product or service is closely substitutable and can be imitated (imperfect patent protection). The firm that wins the development race earns a high return rate during its monopoly period until the competitor enters the market where the return drops to a regular (lower) rate. When the market is purely competitive once a rival has entered, we can assume that the normal return rate equals zero.

In the static case, we assume that all decisions must be made at the beginning of the project. We develop various analytical results, and show that under no circumstance should a firm ignore the competition. We also compare and contrast with our findings in the fixed payment model developed in chapter 3.

For the dynamic case where all decisions can be made just prior to the start of each activity, we demonstrate that the “point of no abandonment (PNA)” concept developed in the fixed payment model also holds in the case of variable payment market with serial network project structure. That is, PNA exists when the smaller payment rate is sufficiently high. For general project networks, we show that the DAM heuristic is readily applicable with only minor modifications.

Our numerical studies on a 7- and 12-activity network reveal that the efficacy of the DAM heuristic is comparable to that of the fixed payment model. The rate of achieving the optimal solution is still at 80% or higher. The largest optimality gap found is 11.4%, compared to 10% found in the fixed payment case. The result from our experiment pertaining to the value of flexibility of the DAM heuristic for the variable payment model is also consistent with that obtained for the fixed market payment model. That is, the value of flexibility is

highest when the innovator firm faces fierce market competition (e.g. the value of T^*r is low).

5 New Product Development Projects with Competition and Uncertain Activity Durations

We begin this chapter with a discussion of uncertain activity durations in project management and the challenges they present to our analysis even in the absence of competition to the market. The analysis with uncertain activity durations is an important extension to the basic project planning problem, and it serves as a building block for our analysis in the subsequent sections where market competition is factored into the model. In section 5.1 we motivate the problem via a simple project example, and provide a brief overview on the history of work in the area of continuous time-cost trade-off under uncertain activity durations to review the advantages and disadvantages of methodologies that have been proposed in previous research. The review of the robust optimization methodology, how uncertainty in activity durations is incorporated into the formulation, and its appeal to the nature of our problem are discussed in section 5.2. A heuristic approach, built on the concept of robust optimization technique, is subsequently developed for our model. Finally, we show in section 5.3-5.4 how the heuristic can be implemented to the competition model through several numerical examples, as well as limitations and other challenges that we encounter.

5.1 Motivation to the Problem

In most real world projects, it is difficult to precisely determine the exact duration for an activity, or a set of activities, in a project network. Particularly in the context of new product development projects, it is possible that some or many activities may be performed for the first time, hence past information which is necessary to accurately estimate the activity durations may not be available.

To motivate the topic, consider the same project network example from Chapter 3. The durations of all activities, however, are now uncertain and can take any values in a given range. Implicit in this example, we assume that a firm is able to estimate the worst case (longest uncompressed activity duration) and best case (shortest uncompressed activity duration). The project is represented by the activity network shown in Figure 25 and activity details are provided in Table 22.

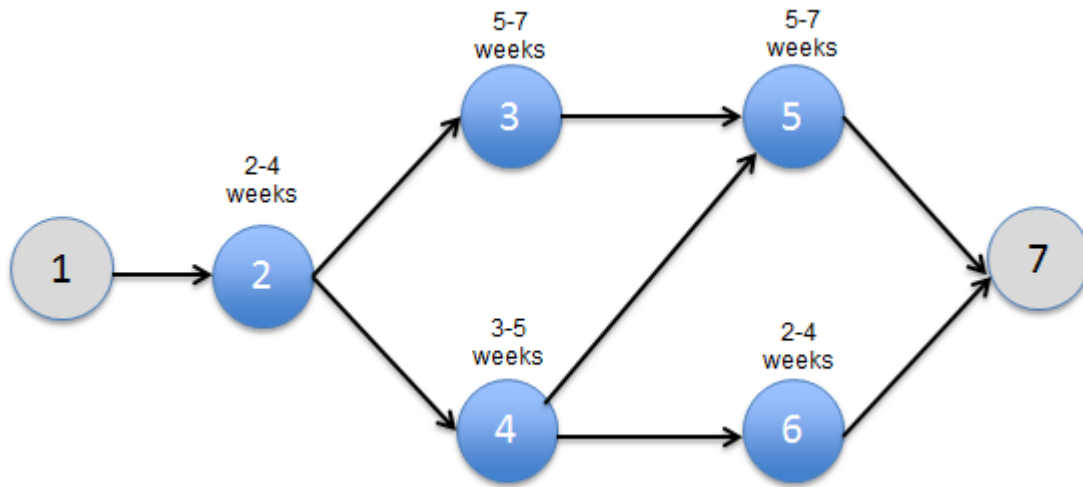


Figure 25: Example Project with Uncertain Activity Duration

Activity	Uncompressed Activity Duration Min - Max (week)	Minimum Compressed Duration (week)	Fixed Resource Cost	Marginal Compression Cost (per week)
1	0	0	0	0
2	2 - 4	1	4.0	3.5
3	5 - 7	3	4.0	2.5
4	3 - 5	2	3.0	2.0
5	5 - 7	3	2.0	3.1
6	2 - 4	1	3.0	3.1
7	0	0	0	0

Table 22: Parameters for Example Project with Uncertain Activity Duration

To illustrate the basic challenges introduced by the uncertain activity duration, consider

a simple case where there is no competition to the market. The three possible paths through the network, p_i , are:

$$p_1 : 1 \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 7$$

$$p_2 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow 7$$

$$p_3 : 1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 7$$

The length of each path, however, is uncertain. Depending on the actual uncompressed duration of the activities, any given path in this example has the potential to become the critical path of the project.

By inspection, it is easy to see that if maximum compressions are made to all activities and all activities take the shortest possible uncompressed durations, the project can be completed in as short as 7 weeks. On the contrary, if all activities take on their longest uncompressed durations and no compression is made to any activity, the project can take as long as 18 weeks to be completed.

If the innovator firm chooses to analyze the problem using the nominal activity durations as a surrogate measure, the problem will reduce to a deterministic equivalent as described in chapter 3. Given the cost parameters in this example, the optimal strategy would be to make no compression and execute all activities at their normal uncompressed duration. The start and end time for each activity, according to a no compression strategy, would subsequently be;

Activity	Start Time	Finish Time
1	0	0
2	0	3
3	3	9
4	3	7
5	9	13
6	7	10
7	10	10

Table 23: Activity Start and Finish Times for No Compression Strategy

Unfortunately, the approach outlined above is an oversimplification of the true problem. Given the uncertain nature of activity duration, it can be easily shown that the schedule prescribed in the table above can become infeasible, and is sub-optimal in most instances. For example, if the actual uncompressed duration for activity two turns out to be at its worst case of 4 weeks, activity three cannot begin at week 3 as planned, which subsequently impacts the start time of activity five, and so on. On the other hand, if for example activity two takes only 2 weeks to complete (best case scenario), activity three and four could technically start at week 2 but since the solution determines the start times for both activity three and four to be at week 3, the firm will not be able to capitalize on the favorable outcome of activity two.

The simple example above shows the obvious drawbacks of a solution drawn from an approximate deterministic equivalent of the true uncertain problem. Clearly, the issue will be compounded when competition to the market is incorporated to the model. Therefore it is our goal to develop in this chapter an efficient methodology to solve the resource allocation problem with market competition and activity durations are uncertain.

The general formulation of the continuous time-cost trade-off model for uncertain activity duration is in fact very similar to the standard problem for deterministic activity duration. Given the same cost structure and assumptions described in section 2.2, let \tilde{t}_i denotes the

uncompressed activity i duration (a random variable), and \dot{t}_i denotes the minimum duration required to complete activity i , the problem becomes;

$$\text{Minimize}_{S,y} \quad \sum_{i=1}^n C_i(y_i) + C_o S_n$$

subject to

$$S_j - S_i - \tilde{t}_i + y_i \geq 0, \quad \forall (i, j) \in A, \quad (4)$$

$$S_i \geq 0, \quad \forall i \in N, \quad (5)$$

$$0 \leq \dot{t}_i \leq \tilde{t}_i - y_i, \quad \forall i \in N \quad (6)$$

(P4)

The major difference between (P4) and the deterministic version (P1) lies in the precedence constraint where an uncertain activity duration \tilde{t}_i seen in (4) replaces the deterministic activity duration t_i seen in (1). This single modification, however, can add a considerable complication to the problem specifically for a complex network with large numbers of activity since the precedence relationship constraint must hold for all possible realization of \tilde{t}_i for all arc $(i, j) \in A$.

To tackle this challenge, numerous methods have been developed and proposed for the problem since the 1950's. The classic PERT system (Program Evaluation and Review Technique) is a well-known methodology developed by Malcolm et al. (1959) to address the complication of random activity duration in project scheduling problem. The approach assumes that project manager can estimate the most optimistic, most likely, and most pessimistic uncompressed duration for each activity, and each activity follows a beta distribution. These estimates are used to compute the expected value and standard deviation of each activity time in the project.

While the method is often implemented in practice due to the simplicity of the estimates, it is widely criticized by both practitioners and researchers alike. Among the notable issues is the significant problem with the determination of the project makespan using expected activity durations (Klastorin, 2010). Specifically, PERT model assumes that a path with the longest expected duration represents the critical path of the project. However, it is likely that some paths which are not critical based on PERT approach can become critical after the actual realization.

As the literature on uncertain activity duration project scheduling continues to grow, we observe two streams of heuristic procedures proposed for research in this domain: one that assumes known probability distribution for activity duration (Probabilistic Model), and the other that makes no assumption on the probability distribution (Non-probabilistic Model).

When activities in project have been processed in the past, it may be possible describe the activity durations by probability distributions. However, even with known probability distribution, the problem remains difficult to solve. Hagstrom (1988) proved that the problem of computing the cumulative distribution function or simply evaluating the average of the project duration is NP-hard, hence the relatively few publications on the stochastic time-cost trade-off problem. Elmaghraby (1977) concluded that the stochasticity of activity duration adds element of difficulty to the stochastic compression problem since the problem must be solved as a network problem without the benefit of a simplifying aggregate cost function. The topic of stochastic activity networks has been analyzed, also, by Martin (1965), Dodin (1985), Hagstrom (1990), and Sobel et al. (2009).

Johnson and Schou (1990) considered the application of simple heuristics to select activity for compression in a stochastic activity network. Gutjahr et al. (2000) introduced a stochas-

tic branch-and-bound approach to activity crashing in project management. Ke and Liu (2005) applied the chance-constraint programming and simulation based technique in minimizing total project cost under some completion time limits. Elmaghraby (2005) discussed the advantage of dynamic resource allocation in stochastic activity duration project with exponential distribution, and Mitchell and Klastorin (2007) proposed an effective methodology for the stochastic project compression problem where activities in the network follow a mixed of beta, exponential, and continuous uniform distributions.

In addition, when distribution of activity duration is known, it is possible to take advantage of simulation to estimate the expected values of any parameter of interest. Naylor et al. (1968), VanSlyke (1963), and Schonberger (1981) described the use of simulation, e.g. Monte Carlo Simulation, for determining the expected makespan and makespan distribution, and the approach can be a practical approach for many real-world projects.

For new product development environments where some activities could possibly be carried out for the first time, it is likely that parameters required in defining activity duration distributions cannot be accurately estimated. In project management literature when activity duration cannot be described probabilistically, two main principles are applied to aid the analysis of the standard time-cost trade-off model; fuzzy theory and robust optimization.

In the fuzzy set project scheduling literature, fuzzy numbers are used to model activity duration. The fuzzy set theory was first applied into the project scheduling problem by Prade (1979). For a comprehensive review on fuzzy time-cost trade-off problem and related problems, we refer to Herroelen and Leus (2005), Liu (2006), Ghazanfari et al. (2008, 2009), Ke et al. (2010), and Bhaskara et al. (2011).

The other alternative, robust optimization, is a methodology developed to handle op-

timization problems with uncertain data, which primarily applies to the activity duration in the context of project management. The concept has several appeals to the problem of planning new product development project under competition. First, it requires minimum information about the project activity duration from a project manager, and most importantly it does not demand any knowledge about activity distribution. This aspect is particularly attractive to many new product development project since some or many activities have limited data readily available to make an accurate estimation on activity distribution. Second, recent development of the methodology to address the issue of over conservatism allows the solution to adapt dynamically with new realization of information (e.g. actual activity duration) which reduces the optimality gap significantly while guaranteeing feasibility of the solution. In addition, although not part of this dissertation, robust optimization model is flexible enough to be formulated not only for risk-neutral but also for risk-taker or risk-averse firm (Bertsimas and Sim, 2004).

In the subsequent sections, it is our goal to develop a heuristic procedure based on the robust optimization concept to aid the resource allocation and scheduling decisions for project manager. The procedure shall provide solution that is adaptive (e.g. take advantage of new information) and practical to a general new product development project under market competition.

5.2 Robust Optimization: Overview

The characters of some or many activities in practical projects can be fluid and evolve as time progresses. While project manager may be able to prescribe estimations of activity durations, the actual realization can drift and vary within some finite uncertainly range. In the context of project management, when the problem of scheduling or resource allocation is formulated on the basis that all input data (e.g. activity duration) is known and fixed, the

corresponding solution may not be protected against uncertainty that firm faces in reality. In many cases, the actual data which differs from parameter input to the original optimization problem may render the solution completely meaningless.

Robust optimization is a methodology devised to operate under the uncertain environment of the optimization problem. The method was first introduced by Soyster (1973) who proposes a linear optimization model that prescribes a solution that is guaranteed feasible for all data in the uncertainty set. The solution to this original method, however, is considered very conservative. The theory was advanced further by Ben-Tal and Nemirovski (1998, 1999, 2000), Ghaoui et al. (1998), and Bertsimas and Sim (2004) to address the issue of over conservatism. For complete review of the robust optimization principle and applications we refer to Ben-Tal et al. (2009).

The focuses of the robust optimization development in the late 1990's have been on convex conic programming; specifically for linear programming (LP), second-order cone programming (SOCP), and semi-definite programming (SDP). For the linear models with uncertain parameters, the problem is referred to by various names, for instance "inexact linear programs", "uncertain linear programming", etc. Many practical optimization problems, however, are non-linear and non-convex. Recent efforts to generalize the robust optimization approach to a non-linear programming setting with parameter uncertainty includes Takeda et al. (2004), Zhang (2007), and Houska and Diehl (2009). The degrees of difficulty and complexity in such case depend greatly on the magnitude of parameter variations. In the context of project management, the magnitude of these parameter variations can be large, making the computation intractable for most non-linear models. Hence, in this dissertation, we restrict our focus to the well established linear and linear approximation versions of a more complex problem.

5.2.1 Robust Optimization: Methodology

At its general form, an uncertain linear programming problem is defined as a family of the following linear programming problem;

$$\text{Minimize}_x \{c^T x : Ax \leq b\}_{\varrho \equiv [A, b, c] \in \Upsilon} \tag{P5}$$

where A is a $m \times n$ matrix and the uncertain parameter ϱ vary in an uncertainty set $\Upsilon \subset \mathfrak{R}^{m \times n} \times \mathfrak{R}^m \times \mathfrak{R}^n$. The problem can also be presented as:

$$\begin{aligned} &\text{Minimize}_{\Gamma, x} \Gamma \\ &\text{subject to} \\ &c^T x \leq \Gamma \\ &Ax \leq b \quad \forall \varrho \equiv [A, b, c] \in \Upsilon \end{aligned} \tag{P6}$$

The robust optimization model presented here is shown to be solvable in polynomial time for a wide range of convex uncertainty set Υ . The optimal objective Γ^* and optimal solution x^* satisfy the constraints for all possible realizations of the uncertain data. Although the solution achieves the highest protection or level of robustness, the price paid to guarantee feasibility, however, can be significant because the solution to the model above is carried out before *any* of the uncertain data becomes known.

5.2.2 The Adjustable and Non-adjustable Formulations

While the solution to problem (P6) is often times too conservative in practice in a sense that it gives an objective function value that is much worse than what it could have been, if all solutions must be carried out prior to any realization of the uncertain data and a 100% feasibility must be guaranteed, then the solution to problem (P6) would represent the best solution that meet all the requirements. Although rare in practice, some actual problems are indeed best characterized in this fashion. For example, in the context of project management, if all tasks in a project demand special resources to execute, a firm may have to decide the level of all resources in advance before the project even begins. Under this circumstance, it is reasonable to assume that activity compression decisions, etc. must be made at the beginning of the product development. This unique environment justifies the use of standard robust optimization established by Soyster (1973) and is referred to as the “Non-adjustable” robust optimization formulation. This model is later advanced by Bertsimas and Sim (2004) for cases where a decision maker is willing to trade-off the level of robustness with a better objective value in the optimization problem. That is, a better objective function value can be obtained via a solution that is feasible with certain probability.

In contrast, for most projects, it is not likely that all decisions must be decided upfront. Hence, it stood to reason that some or many of the decision variables can and should be made later once more information related to such decision becomes available. This notion gave rise to a novel idea introduced by Ben-Tal et al. (2004, 2009) to improve the quality of the solution by formulating decision variables as “function” of previous realizations of the uncertain data. These decision variables are loosely referred to as “wait and see” decisions in robust optimization literature, and the modified problem is formally termed “Adjustable Robust Counterpart (ARC)”. The solution to ARC then becomes a “policy” rather than a fixed “solution”. The policy, in turn, provides a solution that evolves with the realization of the uncertain parameters. The adjustable aspect of the solution takes advantage of the

updated state of the problem as it prescribes a solution in a dynamic fashion, resulting in a higher quality of the solution.

At its most generic form, the Adjustable Robust Counterpart (ARC) formulation developed by Ben-Tal and Nemirovski is expressed as follow:

Minimize Γ
 Γ, r

subject to

$$v^T f(\varrho) + u^T r \leq \Gamma \quad \forall \varrho \in \Upsilon$$

$$Vf(\varrho) + Ur \leq b \quad \forall \varrho \in \Upsilon$$

(P7)

With this approach, $f(\varrho)$ is the adjustable decision vector that depends on the value of uncertain data ϱ , r represents decisions that must be made immediately (non-adjustable component). The original vector c and matrix A in (P6) are simply re-written in a form of $c = [v, u]$ and $A = [V, U]$ respectively to show elements associated with adjustable and non-adjustable part of the solution.

5.2.3 The Affinely Adjustable Robust Counterpart (AARC)

There are number of ways to formulate the “wait and see” decisions, some are more computationally demanding than the other. Ben-Tal et al. (2004) introduced the simple, yet novel approach called “Affinely Adjustable Robust Counterpart”. This approach, also known as “linear decision rule” is an attractive option as it is computationally tractable and is proven to be applicable to many large scale problems in project management (Cohen et al., 2007).

Consider the following case when we want to restrict the adjustable decision vector $f(\varrho)$ to be an affine function of the data:

$$f(\varrho) = \omega + W\varrho$$

Where W is a matrix and ω is a vector with appropriate dimensions, and both are decision variables to the problem. The intuition behind this formulation in the context of project management with due date is as follow: we let the exact decision (e.g. compression of an activity) be a function of the realizations (ϱ) of all activities that precedes it. That said, for a given activity, if activities that precede it are completed quickly, it may not be necessary to make a compression, and vice versa.

The affine function is designed in such way that it depicts this exact relationship between prior realizations and present decision. That is, the function will prescribe little or no compression when the precedence tasks complete early, and will prescribe higher amount of compression as the precedence tasks take longer to finish.

Substituting the affine function back to (P7) we get:

Minimize Γ
 Γ, r, ω, W

subject to

$$v^T(\omega + W\varrho) + u^T r \leq \Gamma \quad \forall \varrho \in \Upsilon$$

$$V(\omega + W\varrho) + Ur \leq b \quad \forall \varrho \in \Upsilon$$

(P8)

Problem (P8) is referred to as an Affinely Adjustable Robust Counterpart (AARC) model by Ben-Tal et al. (2004). The solution to each decision variable of (P8)(e.g. matrix W and vector ω), once substituted back in the affine function, will collectively define the policy function that a firm is searching for, namely the policy for “start time” or “compression amount” of an activity given its predecessors’ activity durations.

Recently, many researchers have introduced advanced linear and piece-wise linear decision rule and have shown that they yield superior results through extensive numerical studies. For comprehensive review, we refer to Chen et al. (2008); Goh and Sim (2010, 2011).

5.2.4 Application to A Stochastic Time-Cost Trade-off Problem

Cohen et al. (2007) was first to apply robust optimization, specifically with Affinely Adjustable Robust Counterpart formulation, to a standard time-cost trade-off project management problem. In their paper, activity durations follow an unknown distribution. Their model assumes various sources of stochasticity, namely the activity duration time and cost of executing an activity. The study was confined within the linear environment for tractability. Numerical studies have been performed on two types of uncertainty sets: Interval-type Uncertainty Set, and Ellipsoidal-Type Uncertainty Set, with a known due date and static objective of minimizing the total cost of the project. They develop a heuristic that generates a compression policy and evolves with the realization of activity duration as time progresses.

Goh and Sim (2010, 2011) presented an advanced robust optimization problem in project scheduling where the objective is to minimize the total project cost given a specific project due date and budget. Their model is among the few that allows for the incorporation of activity correlation.

The robust optimization model to be developed for our model differs in many respects from previous works. The key distinction is the incorporation of market competition into the model. Since our analysis throughout this dissertation revolves around competition to the market, the market payment is unknown in advance (i.e. both revenue and cost are uncertain in our analysis). Also, the development project in our model does not have an inherent due date. The price of being slow to the market is instead captured by the lost revenue/missed opportunity in the market.

As a building block for the work in this chapter, we shall first present a basic example of project with uncertain activity duration times with known information about the competition to illustrate how the concept of robust optimization can help firm plan on resource allocation.

Consider an example project with six activities illustrated in Figure 26. We assume that a firm is able to estimate the worst case (longest uncompressed activity duration) and best case (shortest uncompressed activity duration). Cost associated with compression of an activity is assumed linear. No assumption is made about the distribution of activity duration. For simplicity, assume that firm knows that rival will enter the market at week 14. If the innovator firms enters the market first, it receives \$60, and \$20 otherwise. The activity details, as well as their associated cost parameters, are given in Table 24.

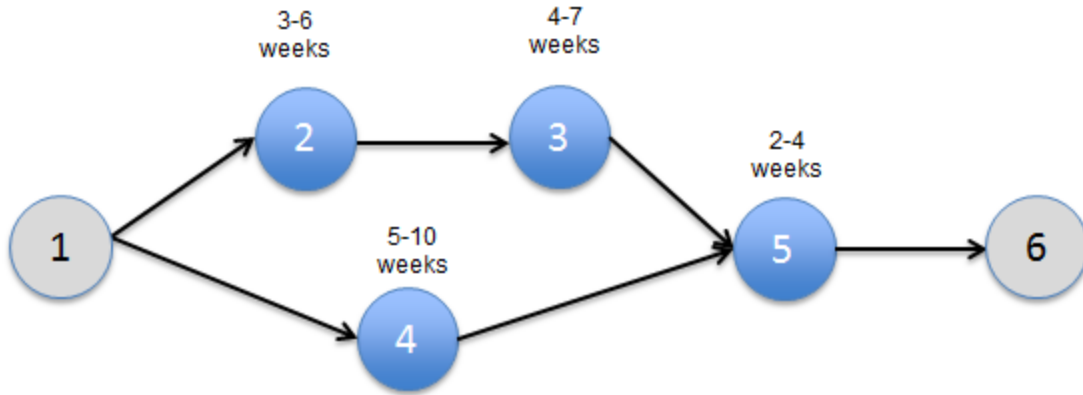


Figure 26: Example Project for Robust Scheduling

Activity	Uncompressed Activity Duration Min - Max (week)	Minimum Compressed Duration (week)	Fixed Resource Cost	Marginal Compression Cost (per week)
1	0	0	0	0
2	3 - 6	2	1.0	3.5
3	4 - 7	2	2.5	2.0
4	5 - 10	3	1.5	2.5
5	2 - 4	1	2.0	2.0
6	0	0	0	0

Table 24: Parameters for Robust Scheduling Example

The overhead/indirect cost is normalized to \$1/week, activities are non-preemptive and the firm cannot abandon the project.

For illustration, suppose a firm wants to ensure that it wins the competition (not necessary an optimal strategy), it must guarantee that its market entry time is on before week 14 even in the situation that all activities take on their longest uncompressed duration. Following the formulation of (P4), the first stochastic project problem is expressed as

Minimize $(b_2y_2 + b_3y_3 + b_4y_4 + b_5y_5 + C_oS_6)$
 S, y

subject to

$$S_3 - S_2 - \tilde{t}_2 + y_2 \geq 0 \quad (7)$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0 \quad (8)$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0 \quad (9)$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0 \quad (10)$$

$$S_1, S_2, S_3, S_4, S_5 \geq 0 \quad (11)$$

$$S_6 \leq 14 \quad (12)$$

$$0 \leq y_2 \leq \tilde{t}_2 - t_2 \quad (13)$$

$$0 \leq y_3 \leq \tilde{t}_3 - t_3 \quad (14)$$

$$0 \leq y_4 \leq \tilde{t}_4 - t_4 \quad (15)$$

$$0 \leq y_5 \leq \tilde{t}_5 - t_5 \quad (16)$$

$$y_1, y_6 = 0 \quad (17)$$

(P9)

where \tilde{t}_i denotes the duration of activity i (e.g. for this example $\tilde{t}_2 \in [3, 6]$) and t_i denotes the minimum duration required to complete activity i (e.g. for this example $t_2 = 2$).

The constraints (7)-(11) ensure that all precedence relationships are not violated, constraint (12) ensures that the market entry time is no later than week 14, and constraints (13)-(17) ensure that the compressed duration for any activity is no less than the minimum amount given in the problem.

We assume that the decision concerning start time and compression amount for any given activity is made based upon information of all its preceding activities in the network. Also, we assume that the actual activity duration is realized immediately after the task begins. It is clear in this example that all decisions associated with activities two and four must be determined at time zero, since their only predecessor activity is a milestone start node. On the other hand, decisions related to activities three and five can be postponed until needed. We shall first establish the affine function of uncertain data.

Let:

ψ_i = constant term for start time of activity i

ψ_i^j = coefficient of start time of activity i that corresponds to the duration of activity j 's

ϕ_i = constant term for compression amount of activity i

ϕ_i^j = coefficient of compression amount of activity i that corresponds to the duration of activity j 's

Now we define each decision variable as an affine function of all its preceding activity realization:

$$\begin{aligned}
S_2 &= \psi_2 \\
S_3 &= \psi_3 + \psi_3^2 \tilde{t}_2 \\
S_4 &= \psi_4 \\
S_5 &= \psi_5 + \psi_5^2 \tilde{t}_2 + \psi_5^3 \tilde{t}_3 + \psi_5^4 \tilde{t}_4 \\
S_6 &= \psi_6 + \psi_6^2 \tilde{t}_2 + \psi_6^3 \tilde{t}_3 + \psi_6^4 \tilde{t}_4 + \psi_6^5 \tilde{t}_5 \\
y_2 &= \phi_2 \\
y_3 &= \phi_3 + \phi_3^2 \tilde{t}_2 \\
y_4 &= \phi_4 \\
y_5 &= \phi_5 + \phi_5^2 \tilde{t}_2 + \phi_5^3 \tilde{t}_3 + \phi_5^4 \tilde{t}_4
\end{aligned}$$

Since \tilde{t}_i is a random variable, we must ensure that all constraints are never violated even in a least favorable scenario for the constraint.

The following illustration of formulation procedure follows Cohen et al. (2007). Consider, for example, constraint (7) of (P9):

$$S_3 - S_2 - \tilde{t}_2 + y_2 \geq 0$$

After substituting S_2, S_3, y_2 with their corresponding affine functions, we get

$$\psi_3 + \psi_3^2 \tilde{t}_2 - \psi_2 - \tilde{t}_2 + \phi_2 \geq 0$$

To guarantee robustness of this constraint, the lowest possible value of the left-hand side of the inequality must always be greater than or equal to the highest possible value of the

right-hand side. That is, we must show that for any possible value of \tilde{t}_2 :

$$\text{Minimize}_{\tilde{t}_2} \{ \psi_3 + \psi_3^2 \tilde{t}_2 - \psi_2 - \tilde{t}_2 + \phi_2 \} \geq 0$$

(P10)

Denote \bar{t}_i as a nominal duration of the random variable activity duration \tilde{t}_i , and ε_i as a deviation from the nominal duration for activity duration i . That is, $\tilde{t}_2 \in [\bar{t}_2 - \varepsilon_2, \bar{t}_2 + \varepsilon_2]$. Then, (P10) can be re-written as:

$$\psi_3 - \psi_2 + \phi_2 + (\psi_3^2 - 1)\bar{t}_2 - |(\psi_3^2 - 1)|\varepsilon_2 \geq 0$$

To eliminate the absolute term, we introduce a new variable $\tilde{\psi}_3^2$ and re-write the above in terms of the nominal value and deviation of activity duration as follows:

$$\begin{aligned} \psi_3 - \psi_2 + \phi_2 + (\psi_3^2 - 1)\bar{t}_2 - \tilde{\psi}_3^2 \varepsilon_2 &\geq 0 \\ \tilde{\psi}_3^2 &\geq (\psi_3^2 - 1) \geq -\tilde{\psi}_3^2 \end{aligned}$$

Such transformation shall be performed for all constraints. Once the process is completed, the problem (P9) can be solved for all ψ_i 's, ψ_i^j 's, ϕ_i 's, and ϕ_i^j 's. Substituting these values back to the affine function, we obtain the following:

$$S_2 = 0$$

$$S_3 = 0.75792 + 0.87368*\tilde{t}_2$$

$$S_4 = 0$$

$$S_5 = 8.7771 + 0.1104*\tilde{t}_2 + 0.22293*\tilde{t}_3$$

$$S_6 = \tilde{t}_5 + 10$$

$$y_2 = 0$$

$$y_3 = 0.66667*\tilde{t}_2 - 2$$

$$y_4 = 0$$

$$y_5 = 0.1104*\tilde{t}_2 + 0.22293*\tilde{t}_3 - 1.2229$$

As stated, for activity three and five the model returns a policy instead of fixed values for start time and compression decisions since neither activity must start immediately. To illustrate how the policy can be implemented, consider decisions that are required at time zero. These decisions include the start time and compression of activity two and four. Both activities do not have real activity preceding them, therefore, as expected, the model returns constant values as solutions for both activities at time zero (representing a “here and now” type of decision). The compression decisions for both activities are also set at zero, suggesting that a firm is better off to “wait and see” how well or poor these two activities turn out. Then, if one or both activities take longer than the firm had hoped for, firm can still compress future activities (three and five) to achieve the due date goal.

The start times and compression for activity three, in contrast, is a function of the duration of activity two (\tilde{t}_2). For illustration, if the uncompressed duration of activity two is 5 weeks, then:

The start time of activity three would be set at week $0.757792 + 0.87368*5 = 5.12$

The compression for activity three would be set to $0.6667*5 - 2 = 1.3335$ week

Similar argument and calculation can be made for the start time and compression decision for activity five.

To underline the notion of solution robustness, consider the compression policy of activity three above. Recall that the minimum compressed activity duration for activity three is 2 weeks. Since the duration of activity three is not known in advance, firm clearly should not plan to compress activity three by more than 2 weeks since if activity three takes on its shortest uncompressed duration of 4 weeks, any compression decision greater than 2 weeks would violate the minimum duration constraint.

Now if we turn our attention to the compression policy prescribed above, clearly the maximum compression on activity three occurs when activity two takes its longest duration of 6 weeks. In such scenario, which is the worst case, the policy would still prescribe only a compression of $0.6667*6 - 2 = 2.000$ week. This reaffirms the notion that the policy generated by the adjustable robust optimization model is guaranteed feasible even in the least favorable scenario for the constraint.

The project cost under the prescribed policy is also generated by the model since it is accounted for in the same fashion as other constraints during the problem formulation.

$$\text{Project Cost} = 1.5541*\tilde{t}_2 + 0.4459*\tilde{t}_3 + \tilde{t}_5 + 3.5542 + \text{Fixed resource costs}$$

While it appears that, except for the fixed resource cost term, no other cost (compres-

sion cost, indirect/overhead cost) is presented in the expression above, they are all in fact accounted for and are embedded in the coefficients terms. This is possible since we know deterministically how we would behave in the future given any possible set of realization. We can now easily calculate the project cost given activity duration, or show the range of costs from the best to the worst case scenarios.

In the best case scenario, all activities take on their shortest uncompressed duration and vice versa for the worst case scenario. Substituting the best case uncompressed durations for activity 2, 3, 4, and 5.

$$\tilde{t}_2 = 3$$

$$\tilde{t}_3 = 4$$

$$\tilde{t}_4 = 5$$

$$\tilde{t}_5 = 2$$

into the project cost expression, and substitute the fixed resource cost term with \$7, and immediately we obtain the project cost to be \$19.

Similarly, for the worst case:

$$\tilde{t}_2 = 6$$

$$\tilde{t}_3 = 7$$

$$\tilde{t}_4 = 10$$

$$\tilde{t}_5 = 4$$

and the project cost becomes \$27.

That is, the project cost could range from \$19 to \$27. Since a product launch on or before week 14 guarantees a revenue of \$60, the project cost range translates to a project

benefit of \$33 to \$41.

While the example here illustrates possible application of robust optimization technique to a project management under competition problem, the scope is somewhat limited due to various simplification assumptions made for the numerical demonstration (e.g. strategy is predicated on a policy to win the competition). In the next section, we shall outline our proposed heuristic to cope with the competition problem.

5.2.5 Competition Model with Robust Optimization

In this section we utilize the robust optimization concept to develop a heuristic procedure that prescribes resource allocation and scheduling policy for a firm that faces competition to the market and activity duration of the project is uncertain. Throughout the remaining sections of this dissertation, we assume that the innovator firm has a subjective estimate of the time when a competitor's will enter the market. Also, the firm is able to estimate the worst case uncompressed activity duration (longest duration) and best case uncompressed activity duration (shortest duration) for each activity in the project network. Firm is risk neutral and it maximizes the expected profit of the project. We assume that the actual activity duration is realized immediately after the task begins.

Recall that models established in chapter 3 for both fixed and variable payment markets are not restricted to any specific distribution of rival's market entry time. Hence it is possible that firm would face a non-linear optimization. In previous chapters, the non-linearity did not pose any significant challenges since we assume that activity duration for the project is deterministic. The non-linearity of the problem together with uncertain activity duration of the project network, however, can easily render the robust optimization approach intractable.

In this dissertation, when the problem is non-linear, we can develop a linear approximation (e.g. to the cost and/or payment function) to the problem. This approach is consistent with assumptions made in previous research in the field (Cohen et al., 2007).

The appeal of the proposed alternative are many folds: First and foremost is its simplicity as the method requires modest modification to the complex AARC formulation. Second, and most importantly, they allow us to leverage number of insights developed from previous models in chapter 3, including part of the DAM algorithm.

The solution policy generated by this heuristic procedure, according to most literature in robust optimization, is referred to as “fixed recourse” policy. At the highest level, the solution procedure to generate a fixed recourse resource allocation policy in an uncertain activity duration environment with competition to market involves the following steps:

Fixed Recourse Policy Generation

1. If the original problem is linear or piece-wise linear, proceed to step 2, otherwise formulate a linear approximation of the function
2. Formulate the corresponding AARC problem
3. Solve for the optimal solution policy

The implementation of the procedure above shall be demonstrated through examples in section 5.3 and 5.4. Specifically, a linear approximation step (which maybe required for some problems) will be shown in section 5.4.1.

5.3 Fixed Payment Problem with Uncertain Project Activity Durations

In this section we investigate the problem of managing new product development project with fixed market payment where firm faces both internal and external uncertainties. The uncertainty in activity durations of the project can be viewed as internal source of uncertainty, while the competition to the market is an external source of uncertainty added to the problem. Characters of the fixed payment market is defined previously in chapter 3.

Following the same organization, we shall first consider a case where the resource allocation “policy” has to be determined at time zero and cannot change. Note that even when policy is set before project starts, it is not equivalent to the static “solution” in a general sense because the policy still allows for some recourse actions given the activity realizations.

We maintain key characteristics and assumptions of a fixed payment market that the value of market return for the new product or service can be approximated and is independent of the market entry time. Also, if a firm completes the development and introduces the product first to the market, it receives a fixed return M , and it receives m otherwise ($M > m \geq 0$).

To demonstrate the implementation of the solution procedure, we introduce an example project shown in Figure 27. For the example project, we assume $M = \$80$ and $m = \$40$. The overhead/indirect cost is assumed \$1 per week. Lastly, we assume that the competitor is equally likely to enter the market at any point in time between week 4 and week 24. Other parameters are summarized in Table 25 below:

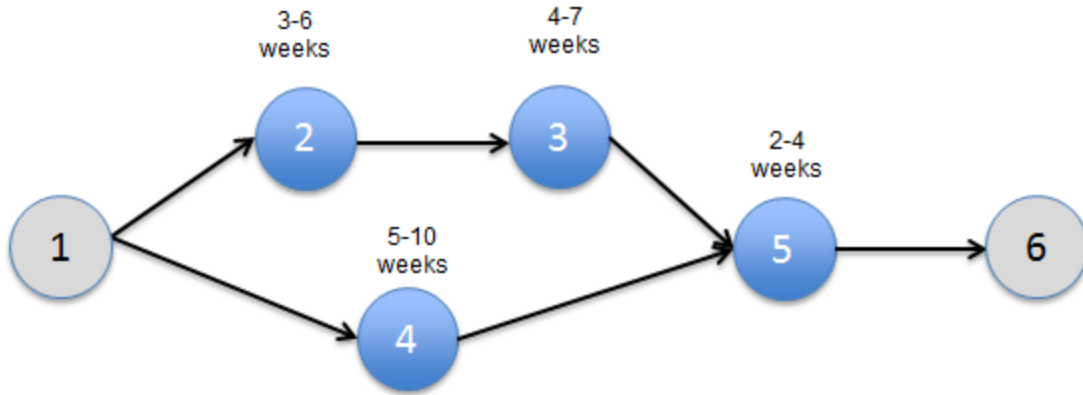


Figure 27: Example Project for Fixed Payment Robust Example

Activity	Uncompressed Activity Duration Min - Max (week)	Minimum Compressed Duration (week)	Fixed Resource Cost	Marginal Compression Cost (per week)
1	0	0	0	0
2	3 - 6	2	2.0	3.5
3	4 - 7	2	3.0	2.0
4	5 - 10	3	3.0	2.5
5	2 - 4	1	4.0	3.5
6	0	0	0	0

Table 25: Parameters for Fixed Payment Robust Example

In the end of this illustration, we shall also demonstrate how a policy can be evaluated given a certain realization instance.

5.3.1 Static Recourse Policy

In a static recourse scheme, a policy is generated only once at the beginning of the project (hence the name “Fixed Recourse Policy”). The actual start time and compression of activities may adapt to the realization of their preceding tasks.

Fixed Recourse Policy Generation

Step 1) If the original problem is linear, proceed to step 2

For this example, the problem can be expressed as:

$$\text{Maximize}_{S,y} E(\pi) = \Delta M \left(\frac{b - S_6}{b - a} \right) + m - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to (4)-(6)

Since the objective function is a piece-wise linear concave function, and all constraints are linear, the linear approximation process is not required (process will be illustrated in the later examples).

Step 2) Formulate the corresponding AARC problem

The problem can be formulated, following (P9), as:

$$\text{Maximize}_{S,y} E(\pi) = \Delta M \left(\frac{b - S_6}{b - a} \right) + m - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to

$$S_3 - S_2 - \tilde{t}_2 + y_2 \geq 0$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0$$

$$S_1, S_2, S_3, S_4, S_5, S_6 \geq 0,$$

$$0 \leq y_2 \leq \tilde{t}_2 - \dot{t}_2$$

$$0 \leq y_3 \leq \tilde{t}_3 - \dot{t}_3$$

$$0 \leq y_4 \leq \tilde{t}_4 - \dot{t}_4$$

$$0 \leq y_5 \leq \tilde{t}_5 - \dot{t}_5$$

$$y_1, y_6 = 0$$

(Note: In this example, $a = 4, b = 24$ and $\Delta M = 80 - 40 = 40$.)

Step 3) Solve for the optimal solution policy

Substituting all parameters in to the problem and we find the solution for this particular numerical example problem to be:

$$S_2 = 0$$

$$S_3 = 0.90682 + 0.84886*\tilde{t}_2$$

$$S_4 = 0$$

$$S_5 = 8.7419 + 0.07524*\tilde{t}_2 + 0.25809*\tilde{t}_3$$

$$S_6 = 0.07524*\tilde{t}_2 + 0.25809*\tilde{t}_3 + \tilde{t}_5 + 8.7419$$

$$y_2 = 0$$

$$y_3 = 0.66667*\tilde{t}_2 - 2$$

$$y_4 = 0$$

$$y_5 = 0$$

It is straight forward to evaluate the profit/loss of this given policy once the uncertainty concerning activity duration and competitor's market entry time are realized.

To illustrate one possible outcome when firm adopts this solution policy, suppose that the uncompressed activity duration (actual realization without compression) for activity two through five are 4, 4, 10, and 3 weeks respectively. Also, suppose that competitor enters at week 13 to (clearly this information is not known to the innovator firm at time zero), the policy would prescribe the following solution:

$$S_2 = 0$$

$$S_3 = 4.30226$$

$$S_4 = 0$$

$$S_5 = 10.07522$$

$$S_6 = 13.07522$$

$$y_2 = 0$$

$$y_3 = 0.66667$$

$$y_4 = 0$$

$$y_5 = 0$$

Furthermore, since the firm enters the market after its rival, the market payment is \$40. Therefore, the net profit for the project is

$$\begin{aligned} \text{Net Profit} &= \text{Market Payment} - \text{Overhead/Indirect Costs} - \text{Direct Costs} \\ &= 40 - 1 \cdot 13.07522 - (0.66667 \cdot 2 + 12) \\ &= 13.5914 \end{aligned}$$

That is, the fixed recourse policy would yield a positive return of \$13.5914 to the innovator firm on this specific instance of realization.

5.3.2 Dynamic Recourse Policy

When firm has the option to adjust its policy when new information about the competition becomes available, or to abandon the project altogether, superior result is naturally anticipated. However, in an uncertain activity duration environment the problem requires careful consideration as to how and when policy is updated. It is clear that firm does not know when

a given activity will be completed, hence review point which is set to be at the beginning of an activity becomes a random variable. For this reason, even if the precedence relationship is well defined, it is possible that in a general project network topology there exists a situation where a firm cannot predict which activity - among those that run in parallel - will start first. Hence not only the time of review point is unknown but also the order of it.

To compound the issue further, the firm also does not know in advance how many review points they should have for the entire project, as it is possible for a set of activities to complete simultaneously, for which case a firm will decide on resource allocations of those activities simultaneously (a reduction of review points). The collective effects mentioned above makes the optimal updating and revising of policy much harder to implement, and perhaps significantly more costly in practice. In order to take advantage of the firm's flexibility in updating the strategy while limiting the complexity of the implementation of such policy, we shall assume the following in our proposed heuristic:

- Firm sets a constant interval between two consecutive review points over the makespan of the project
- At each review point, firm cannot change the resource allocation to activity that has already begun (non-preemptive activity)

Given the set of assumptions above, we develop a dynamic Robust Approximation Method (RDAM) heuristic which can be described as follows:

Robust Dynamic Approximation Method (RDAM)

1. If project is completed, EXIT. Otherwise, update the state of the project and the state of the competition
2. Execute the **Fixed Recourse Policy Generation** for the updated problem
3. If the best case forward-looking expected profit is strictly negative, ABANDON. Otherwise, proceed to the next step
4. Overwrite the existing solution policy with a new solution policy for all activities that have not started. When the next review point is reached, go back to step 1)

The outline procedure above generally solves a series of AARC problem in a forward pass fashion until the project is complete. This is analogous to the first phase of the DAM algorithm introduced in chapter 3. In addition, the solution to each AARC problem can be obtained by the outline procedure described previously (“Fixed Recourse Policy Generation”). In essence, the heuristic introduced here is indeed a hybrid procedure between the DAM heuristic and Fixed Recourse Policy Generation procedure. As time progresses, the solution policy evolves with both the realization for the activity duration and the state of competition. The heuristic takes advantage of updated information on both activity duration and state of competition into its resource allocation and scheduling decisions.

However, it is important to note that unlike the deterministic activity duration model, here firm does not know exactly how many review points are required due to the uncertain

nature of the activity duration. As such, the result concerning the point of no abandonment (PNA) is negated. The generation of alternative policies obtained from a backward sweep (phase two of the DAM heuristic) through the network cannot be performed here for the same reason.

The analysis for the 6-activity project network is revisited here to demonstrate the implementation of the dynamic resource allocation algorithm. Assume that an innovator firm sets the time between two consecutive review points to be 5 weeks, the following numerical example demonstrates the procedure of RDAM.

Implementation of RDAM Heuristic

First Iteration: Week Zero

In the first iteration firm evaluates the situation at time zero so there is no information to update. At this point the problem is identical to the static problem described in section 5.2.1, thus the solution policy is as follow:

$$S_2 = 0$$

$$S_3 = 0.90682 + 0.84886*\tilde{t}_2$$

$$S_4 = 0$$

$$S_5 = 8.7419 + 0.07524*\tilde{t}_2 + 0.25809*\tilde{t}_3$$

$$S_6 = 0.07524*\tilde{t}_2 + 0.25809*\tilde{t}_3 + \tilde{t}_5 + 8.7419$$

$$y_2 = 0$$

$$y_3 = 0.66667*\tilde{t}_2 - 2$$

$$y_4 = 0$$

$$y_5 = 0$$

The forward-looking profit range is:

$$\text{Expected Profit} = 33.7743 - 1.55906*\tilde{t}_2 - 0.77427*\tilde{t}_3 - 3*\tilde{t}_5$$

The expected profit is positive under the best case outcome (shortest uncompressed duration) of activity 2, 3, and 5. In fact, the expected profit is positive even at the most unfavorable outcomes of the activity duration, so firm chooses to continue with the project.

The decision made to activity 2 and 4 must be implemented immediately as the two have no non-dummy predecessor. That is, activity 2 and 4 both start at time zero. Furthermore, no compression is made to either activity.

Notice that, if the uncompressed duration of activity 2 is less than 5 weeks, activity 3 which immediately follows activity 2 will begin before the next review time. In such case, innovator firm will make a compression to activity 3 corresponding the policy prescribed for activity 3 above.

Second Iteration: Week 5

At this point, the project is not completed, so we first update the project state. We assume here (for illustration purpose only) that the uncompressed activity durations for 2 and 4 are 4 and 10 weeks, respectively, and the competitor does not enter the market before week 5, so the firm is still in the race. The following summarizes decision variables that have been updated by information concerning the duration of activity 2 and 4 before this review point:

$$S_3 = 4.30226$$

$$S_5 = 10.07522$$

$$S_6 = 10.07522 + \tilde{t}_5$$

$$y_3 = 0.66667$$

Activity 3 has already started at week 4.30226 and it was decided that the compression

amount is 0.66667 weeks so activity 3 is no longer a decision variable at this review point. However, since activity 5 has not started at the beginning of this review point, we must solve the updated optimization problem to find a new policy for activity 5.

$$\text{Maximize}_{S,y} \quad E(\pi) = \Delta M \left(\frac{b - S_6}{b - a} \right) + m - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to

$$S_1, S_2, S_4 = 0$$

$$S_3 = 4.30226$$

$$\tilde{t}_2 = 4$$

$$\tilde{t}_3 = 4$$

$$\tilde{t}_4 = 10$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0$$

$$S_5, S_6 \geq 0,$$

$$y_1, y_2, y_4, y_6 = 0$$

$$y_3 = 0.66667$$

Note that the lower bound of the rival's market entry time distribution (a) is updated from 4 to 5 in the objective function in the same fashion described for the original DAM algorithm.

Solving the updated problem gives the following policy:

$$S_5 = 10.000$$

$$S_6 = 10.000 + \tilde{t}_5$$

$$y_5 = 0$$

We overwrite prior policy with the above policy. That is, firm will start activity 5 at week 10 (rather than at week 10.07522 prescribed by the original policy) with no compression.

The forward-looking profit range is:

$$\text{Expected Profit} = 45.806929 - 3.10526 \cdot \tilde{t}_5$$

Since the expected profit is positive even at the most unfavorable outcome of the activity 5 duration, firm chooses to continue with the project.

Third Iteration: Week 10

At this point, the project is not completed, so we first update the project state. Since we assume here (for illustration purpose only) that competitor does not enter the market before week 10, the firm is still in the race. Besides the competition status, there is no new information obtained regarding the activity duration. Since activity 5 has not started, we formulate the following problem.

$$\text{Maximize}_{S,y} \quad E(\pi) = \Delta M \left(\frac{b - S_6}{b - a} \right) + m - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to

$$S_1, S_2, S_4 = 0$$

$$S_3 = 4.333$$

$$\tilde{t}_2 = 4$$

$$\tilde{t}_3 = 4$$

$$\tilde{t}_4 = 10$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0$$

$$S_5, S_6 \geq 0,$$

$$y_1, y_2, y_4, y_6 = 0$$

$$y_3 = 0.6667$$

Note again that the lower bound of the rival's market entry time (a) is updated from 5 to 10 in the same fashion described for DAM algorithm in the deterministic model.

Solving the updated problem gives the following policy:

$$S_5 = 10.000$$

$$S_6 = 10.000 + \tilde{t}_5 - 1$$

$$y_5 = 1$$

Overwrite prior policy with the above solution policy. Again, with updated information, firm will now compress activity 5 by 1 week rather than no compression prescribed by policy generated at the last review point.

The forward-looking profit range is:

$$\text{Expected Profit} = 56.69104462 - 3.85714 \cdot \tilde{t}_5$$

Since the expected profit is positive even at the most unfavorable outcome of the activity 5 duration, firm chooses to continue with the project.

Fourth Iteration: Week 15

Project is completed, EXIT.

Similar to the demonstration in the previous section, it is straight forward to evaluate the profit/loss of the given policy. Since we assume here that the uncompressed activity duration of 5 is 3 weeks, the project is therefore completed at week 12. Since the firm completes and

enters the market before its rival (at week 13), the firm receives a high payment of \$60. The net profit for this specific scenario would be

$$\begin{aligned}\text{Net Profit} &= \text{Market Payment} - \text{Overhead/Indirect Costs} - \text{Direct Costs} \\ &= 80 - 1*12 - (0.6667*2 + 1*3.5 + 12) \\ &= 51.167\end{aligned}$$

That is, the dynamic robust approximation method would yield a positive return of \$51.167 to the innovator firm given this specific instance of realization (compared to \$13.5914 obtained by the fixed recourse policy).

Note that the solution obtained from DRAM does not *always* yield a higher profit than that of the fixed recourse policy. The DRAM algorithm may, for instance, prescribe a compression to activity that is optimal at the review time but this action could later be proven unnecessary if the competitor enters the market much later than anticipated.

5.4 Variable Payment Problem with Uncertain Project Activity Durations

In this section we turn our attention to the variable payment market using the concept of robust optimization discussed previously. One specific challenge that shall be addressed explicitly in this section is the non-linear nature of the optimization problem.

Following the same organization, we shall first consider a case where the resource allocation “policy” has to be determined at time zero and cannot change. Then we show how a dynamic policy generation approach is implemented.

We maintain the assumption that a product has finite life cycle denoted by T , $T > \max(b - S^{\min}, S^{\text{base}} - a)$; and the product life begins when the first firm - either the innovator firm or a rival firm - enters the market. The linear rate of premium return that the innovator firm earns per time period while being a monopolist in the market is denoted by R denote, and r otherwise. Both R and r are independent of the market entry times.

For the example project illustrated here, we assume $T = 30$, $R = \$2.0$ and $r = \$1.5$. Lastly, we assume that the competitor is equally likely to enter the market at any point in time between week 4 and week 24. The project network and other parameters are summarized in Figure 28 and Table 26.

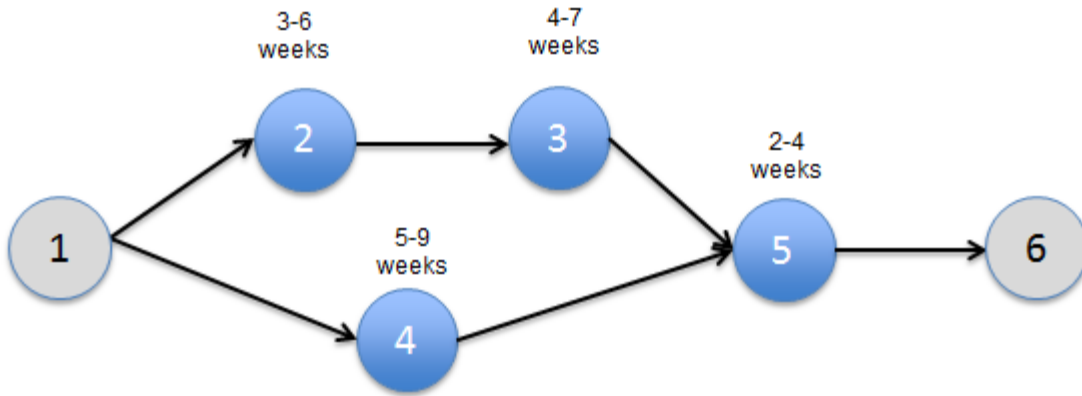


Figure 28: Example Project for Variable Payment Robust Example

Activity	Uncompressed Activity Duration Min - Max (week)	Minimum Compressed Duration (week)	Fixed Resource Cost	Marginal Compression Cost (per week)
1	0	0	0	0
2	3 - 6	2	2.0	2.0
3	4 - 7	2	2.5	2.0
4	5 - 9	3	1.5	2.5
5	2 - 4	1	2.0	2.0
6	0	0	0	0

Table 26: Parameters for Variable Payment Robust Example

Similar to the fixed payment example, at the end of this illustration, we shall also demonstrate how a policy can be evaluated given a certain realization instance.

5.4.1 Static Recourse Policy

Similar to the fixed payment market, the static recourse scheme generates a policy only once at the beginning of the project. However, we shall show here the case where problem is non-linear by nature and demonstrate the linear approximation method proposed earlier. The remaining of the solution procedure is implemented in the same way as that in the fixed

payment model.

Fixed Recourse Policy Generation

Step 1) If the original problem is linear, proceed to step 2, otherwise approximate the non-linear with linear function

Given the parameters of this example, the objective function of the problem can be expressed as follows:

$$E(\pi) = \int_{S_6}^b [Tr + \Delta R(z - S_6)] g(z) dz + \int_a^{S_6} [r(T + z - S_6)] g(z) dz - \eta(S_6) - C_o S_6$$

Clearly, the expected market payment given a chosen market entry time, which is represented by the two integral terms, is not linear with S_n . Therefore, we need to replace the non-linear expected payment function

$$\int_{S_6}^b [Tr + \Delta R(z - S_6)] g(z) dz + \int_a^{S_6} [r(T + z - S_6)] g(z) dz$$

(*)

with a linear approximation function.

In order to do so, we first consider the shortest and latest possible time to enter the market given the parameters of the network. By inspection, the values are found easily to

be 5 and 17 respectively, hence the approximation for expected market payment entry must be made over the range [5, 17].

Seven arbitrary points (5, 7, 9, 11, 13, 15, 17) are selected for the linear approximation purpose. Substituting these values for S_6 into (*), we get

Market entry time (S_6)	Expected market payment
5	49.475
7	48.275
9	46.875
11	45.275
13	43.475
15	41.475
17	39.275

Applying a linear regression to the data above to obtain the following:

$$\text{Expected market payment} = -0.85 * S_6 + 54.225$$

Step 2) Formulate the corresponding AARC problem

Given the linear approximation function for the market payment, the optimization problem can be expressed as:

$$\text{Minimize}_{S,y} \quad 54.225 - 0.85^* S_6 - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to

$$S_3 - S_2 - \tilde{t}_2 + y_2 \geq 0$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0$$

$$S_1, S_2, S_3, S_4, S_5, S_6 \geq 0,$$

$$0 \leq y_2 \leq \tilde{t}_2 - \dot{t}_2$$

$$0 \leq y_3 \leq \tilde{t}_3 - \dot{t}_3$$

$$0 \leq y_4 \leq \tilde{t}_4 - \dot{t}_4$$

$$0 \leq y_5 \leq \tilde{t}_5 - \dot{t}_5$$

$$y_1, y_6 = 0$$

Step 3) Solve for the optimal solution policy

The solution policy for this problem is found to be:

$$S_2 = 0$$

$$S_3 = 1.1980 + 0.80034*\tilde{t}_2$$

$$S_4 = 0$$

$$S_5 = 4.2844 + 0.61771*\tilde{t}_2 + 0.71563*\tilde{t}_3$$

$$S_6 = 4.2844 + 0.61771*\tilde{t}_2 + 0.71563*\tilde{t}_3 + \tilde{t}_5$$

$$y_2 = 0$$

$$y_3 = 0$$

$$y_4 = 0$$

$$y_5 = 0$$

To illustrate one possible outcome when firm adopts this solution policy, suppose that the uncompressed activity duration (actual realization without compression) for activity two through five are 6, 4, 9, and 2 weeks respectively. Also, suppose that competitor enters at week 14 (clearly this information is not known to the innovator firm at time zero).

First, given the realization, the policy would prescribe the following solution:

$$S_2 = 0$$

$$S_3 = 6$$

$$S_4 = 0$$

$$S_5 = 10.85318$$

$$S_6 = 12.85318$$

$$y_2 = 0$$

$$y_3 = 0$$

$$y_4 = 0$$

$$y_5 = 0$$

Furthermore, since the firm enters the market 1.14682 weeks before its rival, it receives a return rate of \$2.0 per week for the monopoly periods, then the rate changes to \$1.5 from week 14 to the end of the product life cycle (week 42.85318). Therefore, the net profit for the project is

$$\begin{aligned}\text{Net Profit} &= \text{Market Payment} - \text{Overhead/Indirect Costs} - \text{Direct Costs} \\ &= (1.14682*2 + 27.85318*1.5) - 1*12.85318 - 8 \\ &= 23.22023\end{aligned}$$

That is, the Fixed Recourse Policy Generation would yield a positive return of \$23.22023 to the innovator firm given this specific instance of realization.

5.4.2 Dynamic Recourse Policy

Similarly to the fixed payment model, superior result in terms of expected profit is anticipated in the variable payment model when firm has the option to adjust the policy or abandon the project. We continue to assume that firm sets a periodic review interval over the makespan of the project. At each review point, firm can only change the resource allocation policy to activity that has not already begun.

The following numerical example demonstrates how the robust dynamic approximation method heuristic (RDAM) is implemented in the variable payment market. Assume again that an innovator firm sets the time between two consecutive review points to be 5 weeks.

Implementation of RDAM Heuristic

First Iteration: Week Zero

The first iteration firm evaluates the situation at time zero so there is no information to update. The problem is identical to the static problem developed in section 5.3.1, thus the solution policy is as follow:

$$S_2 = 0$$

$$S_3 = 1.1980 + 0.80034*\tilde{t}_2$$

$$S_4 = 0$$

$$S_5 = 4.2844 + 0.61771*\tilde{t}_2 + 0.71563*\tilde{t}_3$$

$$S_6 = 4.2844 + 0.61771*\tilde{t}_2 + 0.71563*\tilde{t}_3 + \tilde{t}_5$$

$$y_2 = 0$$

$$y_3 = 0$$

$$y_4 = 0$$

$$y_5 = 0$$

The forward-looking profit range is:

$$\text{Expected Profit} = 38.29886 - 1.1428*\tilde{t}_2 - 1.32392*\tilde{t}_3 - 1.8500*\tilde{t}_5$$

Since the expected profit is positive even at the most unfavorable outcomes of the activity duration, firm chooses to continue with the project.

The decision made to activity two and four must be implemented immediately as the two activities have only a start milestone as their predecessor. That is, activity two and four both start at time zero.

Notice that, if the uncompressed duration for activity two is less than 4.7505 weeks, activity three which immediately follows activity two will begin before the next review time with no compression corresponding the solution policy above.

Second Iteration: Week 5

At this point, the project is not completed, so we first update project state. We assume that competitor does not enter the market before week 5, so the firm is still in the race. Also, for illustration purpose, we assume that the uncompressed duration of activity two and four are 6 and 9 weeks respectively. The following summarizes decision variables that have been updated by information concerning the duration of activity two and four before this review point:

$$S_3 = 6$$

$$S_5 = 10.85318$$

$$S_6 = 10.85318 + \tilde{t}_5$$

Activity 3 and 5 have not started at the beginning of this review point, so the policy must be updated. The fastest and latest possible time to enter the market given the parameters of the network are found easily to be 12 and 17 respectively. We must approximate the expected market payment entry over the range [12, 17].

Six arbitrary points (12, 13, 14, 15, 16, 17) are again selected for linear approximation purpose. Substituting these values for S_6 into (*) and we get

Market entry time (S_6)	Expected market payment
12	29.961
13	29.066
14	28.118
15	27.118
16	26.066
17	24.961

Applying a linear regression to the data above to obtain the following:

$$\text{Expected market payment} = -0.9993 * S_6 + 42.048$$

Given the linear approximation function for the market payment, the optimization problem can be expressed as:

$$\text{Minimize}_{S,y} \quad 42.048 - 0.9993 * S_6 - (b_2 y_2 + b_3 y_3 + b_4 y_4 + b_5 y_5 + C_o S_6)$$

subject to

$$S_1, S_2, S_4 = 0$$

$$S_3 - S_2 - \tilde{t}_2 + y_2 \geq 0$$

$$S_5 - S_3 - \tilde{t}_3 + y_3 \geq 0$$

$$S_5 - S_4 - \tilde{t}_4 + y_4 \geq 0$$

$$S_6 - S_5 - \tilde{t}_5 + y_5 \geq 0$$

$$S_2, S_3, S_5, S_6 \geq 0,$$

$$y_2, y_4, y_1, y_6 = 0$$

$$0 \leq y_3 \leq \tilde{t}_3 - t_3$$

$$0 \leq y_5 \leq \tilde{t}_5 - t_5$$

After the AARC transformation, the problem is solved and the new policy for activity three and five becomes:

$$S_3 = 6$$

$$S_5 = 5.57226 + \tilde{t}_3$$

$$S_6 = 5.20763 + 0.96471*\tilde{t}_3 + \tilde{t}_5$$

$$y_3 = 0.42732$$

$$y_5 = 0.365074 + 0.035291*\tilde{t}_3$$

The forward-looking profit range is:

$$\text{Expected Profit} = 34.54795202 - 2*\tilde{t}_3 - 2*\tilde{t}_5$$

Since the expected profit is positive even at the most unfavorable outcomes of the activity three and five, firm chooses to continue with the project and overwrite any prior policy with the above solution. The decision made to activity three must be implemented immediately.

Notice that the policy generated for activity five may or may not be adopted depending on whether activity five begins before or after the next review time at week 10.

Third Iteration: Week 10

At this point, the project is not completed, so we first update project state . We assume that competitor does not enter the market before week 10, so the firm is still in the race. Also, for illustration purpose, we assume that the uncompressed activity duration for activities three and five are 4 and 2 weeks respectively. The following summarizes decision

variables that have been updated by information:

$$S_5 = 9.57266$$

$$S_6 = 11.06647$$

$$y_5 = 0.506238$$

Clearly, because the uncompressed duration for activity three was only 4 weeks, activity five has already begun at week 9.57266 and the decision to make a compression of 0.506238 weeks to activity five has been implemented already. This leaves no other decision for the firm to make. Thus, the only action remaining is to wait until the next review point at week 15 to evaluate the profit/loss.

Fourth Iteration: Week 15

Project is completed, EXIT.

Since the firm enters the market before its rival, it receives a return rate of \$2.0 per week from week 11.06647 to week 14. Then the payment rate changes to \$1.5 from week 14 to the end of the product life cycle (week 41.06647). Similar to the demonstration in the previous section, it is straight forward to evaluate the profit/loss of the chosen policy. In this example, the net profit for the project is:

$$\begin{aligned}\text{Net Profit} &= \text{Market Payment} - \text{Overhead/Indirect Costs} - \text{Direct Costs} \\ &= (2.93353*2 + 27.06647*1.5) - 1*11.06647 - (0.42732*2.0 + 0.506238*2.0 + 8) \\ &= 25.533179\end{aligned}$$

That is, this dynamic robust approximation method, together with this exact set of realization, would yield a positive return of \$25.533179 to the innovator firm (compare to \$23.22023 obtained via the static policy).

5.5 Chapter Summary

In this chapter, we introduce the analysis of project management under competition with uncertain activity duration, which is an important extension of the basic project planning problem. We provide extensive discussion on uncertain activity duration in project management literature, and the challenges it presents to our analysis.

The history of work in the area of continuous time-cost trade-off under uncertain activity duration is explored. In the context of new product development environments, because some or many activities could possibly be carried out for the first time, it is likely that parameters required in defining activity duration distributions cannot be accurately estimated. The robust optimization methodology becomes our tool of choice since the method requires minimum information about the project activity duration from a project manager.

We first demonstrate how the approach to solve a stochastic project management problem using a deterministic equivalent will most likely lead to a sub-optimal, or even infeasible, solution. Then we introduce the general idea of solution robustness introduced by Soyster (1973) which was significantly advanced by Ben-Tal and Nemirovski (1998, 1999, 2000); Ben-Tal et al. (2004, 2009), among others. The implementation of robust optimization technique is demonstrated through a simple numerical example without market competition.

For a model with market competition, a heuristic approach, built on the concept of robust optimization techniques, is developed for our problem. The Robust Dynamic Approximation Method (RDAM) heuristic utilizes many aspects of the original (DAM) developed earlier in chapters 3 and 4.

Several numerical examples are introduced to demonstrate how the RDAM is imple-

mented. We show that, with modest modification efforts, the procedure is readily applicable to both fixed and variable payment models.

6 Conclusions

In this dissertation, we consider an important challenge in many new product development projects when an innovator firm faces competition to the market. This research offers numerous managerial insights, as well as methodologies for project managers to solve real-world projects for optimal or near optimal scheduling and resource allocation policies.

A brief summary of this dissertation and our findings are provided in section 6.1. In section 6.2 we discuss the managerial insights derived from this work and their implications on project management strategies. Finally, in section 6.3 we discuss the possible extensions of this research and future directions.

6.1 Summary

This dissertation extends the standard project management problem in many significant ways. First, we introduce the problem of a profit-maximizing innovator firm that begins developing a new product or service in presence of a rival firm that may enter the market with a competing product. To our knowledge, this is the first research to analyze the problem in the context of project management.

Second, we develop a time-cost trade-off model with competition to characterize analytically certain conditions a firm can use to determine the optimal strategy given information on project costs, market benefits, and the competitor's market entry time. Unlike conventional projects, the new product development project in our analysis does not come with an inherent due date. Rather, the reward (or penalty) for the project is a direct result of the firm's market entry time relative to that of the competitor. We assume that the competitor's market entry time can be described by any general non-negative random variable. This

approach allows us to model the development process as a stochastic programming problem that, in turn, provides optimal (or near optimal) solutions and managerial insights into both the static and dynamic resource allocation problems faced by the innovator firm.

We specifically examine markets of product and service where a small degree of product differentiation can be made (or equivalently the project scope is relatively inflexible), rendering the time to market the predominant factor that determines the profitability of a firm. In addition, a firm faces significant costs to accelerate the development time. In this market environment, a firm must balance two opposing desires: one to be first in the market, and another to minimize the development cost. We assume that the first entrant can either build substantial barriers to deter new entries and enjoy monopoly status for a certain period of time, or can legally obtain patents to effectively protect its innovation from imitators or later entrants. Products with these characteristics include many drug and chemical products, entertainment products (e.g., movies and games), as well as smart phones and other IT applications. We also assume, however, that shortening the development time to market, requires higher development costs. So the extra costs spent to accelerate the project may offset, or even outweigh, any anticipated first-mover advantages.

Two types of market structures are considered in our work; we denote the first structure as the fixed payment case where the innovator firm receives a fixed and high lump sum return when (and if) it enters the market before any rival firm. This payment can be viewed as the present value of a patent awarded to the first mover in a market. If a rival firm enters the market before the innovator firm, the latter firm earns a lesser fixed, lump sum amount. The second market structure is denoted as the variable payment case where the innovator firm earns a profit at a monopoly rate for the time that it maintains a monopoly position until a rival firm enters the market. After a rival firm has entered the market, the innovator firm earns a lower rate for the duration of the product or service life span. In both cases, we

assume that the selling price of the new product (or service) equals or exceeds the marginal production cost. If the market is purely competitive once a rival has entered, we would assume that the values of lower payment to be zero.

Both static and dynamic resource allocation policies are examined in this dissertation. Under static policies, we assume that contracts have significantly long lead-times such that resource allocation decisions must be made at the beginning of the product development project. In the dynamic case, we assume that resource allocation decisions are made prior to the start of each task (or revised at no cost) although resource allocation decisions cannot be changed for any ongoing task. The innovator firm also has an option to terminate the project at any time in the dynamic resource allocation policy.

In chapter 3, we provide the definition of fixed market competition and pose the question of how the resource allocation and project scheduling should be planned under this environment. We assume that activity duration is deterministic. For the static policy, we show analytically conditions that an innovator firm can use to determine the optimal resource allocation and scheduling policy. For the dynamic policy, under the assumption that activity relationship is strictly serial, we show that if the small fixed payment is higher than a certain threshold, there exists a point in a project where the option to abandon the project would never be used (point of no abandonment or PNA). For general project networks, due to the complexity of the problem, closed form and exact solutions are analytically and/or computationally intractable. We therefore develop a dynamic approximation method (DAM) heuristic procedure that helps a project manager through a decision making process of maximizing the expected profit of the project under competition and can be executed in a computationally feasible manner. We demonstrate the performance of our heuristic, as well as the value of flexibility embedded in the dynamic policy, through extensive numerical studies in the final section of chapter 3.

In chapter 4, we analyze the project management problem under variable market competition. Similar to the fixed payment in chapter 3, we are able to show analytically how the optimal resource allocation and scheduling policy can be determined given information about the project costs, market payments, and estimation of competitor's market entry time. We also compare and contrast with our findings in the fixed payment model developed in chapter 3. For the dynamic case where all decisions can be made just prior to the start of each activity, we demonstrate that the result of PNA developed in the fixed payment model is also valid in the case of the variable payment market with a serial network project structure. For general project networks, we show that the DAM heuristic is readily applicable with minor modifications and our numerical studies reveal that the efficacy of the heuristic is comparable to that of the fixed payment model.

Finally in chapter 5, we introduce the analysis of project management under competition with uncertain activity duration. Due to the complexity of the problem, it is our goal to develop a heuristic for approximating the solution. We propose the application of robust optimization methodology to our problem as it requires no information on the distribution of activity duration. This unique aspect has great appeal in the context of a new product development project since it is difficult to accurately describe distributions of activities with no (or limited) historical information. A Robust Dynamic Approximation Method (RDAM) built on the concept of robust optimization techniques is developed, and its implementation is demonstrated through example projects. The heuristic utilizes many aspects of the original (DAM) developed earlier in chapter 3 and 4. We also show that the procedure is readily applicable to both fixed and variable payment model.

6.2 Managerial Insights

One of the key managerial insights of our analysis is the influence of competition to the project management problem, and how it can be “quantified” so that the extent of its impact can be clearly communicated during the project planning phase.

Our analysis shows that there exist conditions where the innovator firm would want to compress the project makespan to the minimum. While such action may involve a large amount of upfront investment, we show that under the right circumstances, this decision can be justified by the increase in expected reward from the market. On the contrary, we also present conditions for which the innovator firm should never compress beyond the standard time-cost trade-off point (baseline solution). In these situations, although the extra cost may appear small, it may not be justified if the expected benefit gained through such a decision is smaller. It is important to note that when the innovator firm makes no extra compression beyond the baseline solution, it behaves as if there is no competition in the market.

We also compare and contrast results obtained from different market payment structures. For example, in chapter 4 we found that under no circumstance should the innovator firm behave as if there is no competition to the market, while such a strategy maybe optimal in the fixed market payment setting. These findings, underscore how important it is for the innovator firm to first and foremost assess and understand the competition landscape i which it is operating.

The comparison between cases with and without competition also offers explanation why sometimes we observe firms relentlessly attempt to eliminate competition through various means, e.g. corporate buyout, single consortium or cartel. For both market payment structures, we are able to quantify the maximum investment an innovator firm is willing to pay to

obtain the single developer status. The implications for the innovator firm are clear; when the difference in market payment is large, the innovator firm is willing to spend more to eliminate the competition. And not surprisingly, if the cost of eliminating competition is too high, the innovator firm will choose to compete.

The presence of competition also introduces a critical concept concerning the value of flexibility and options in project management. Our research clearly demonstrates how options to delay resource allocation decisions and/or to terminate the project play a crucial role in the decision making process for the innovator firm. With regard to the dynamic resource allocation policy, our results support the intuition that the value of flexibility is high when the innovator firm faces fierce competition in the market. For a market with a moderate or low level of competition, some options (e.g. to abandon) may never be exercised, hence the value of flexibility is less.

Through the formulation of the optimal dynamic resource allocation policy, we develop an insightful concept referred to as the “Point of No Abandonment (PNA)” which basically explains why the option to abandon the project may hold its value only for a period of time. Equally interesting is the fact that this finding offers an alternative explanation as to why the losing firm sometimes chooses to pursue and complete new product development projects even when there are only little benefits left to recoup.

6.3 Future Extensions

Many extensions of the problem we consider in this dissertation are relevant for future research. The first extension is the generalization of our model to a case with a non-stationary distribution of the rival’s market entry time. We assume throughout our study that the rival’s market entry time distribution does not change over time. In practice, an innovation

firm may be able to learn, through various signaling events, updated information surrounding the development of the competing firm. Our models could serve as building blocks to provide advanced insight into how and when an innovator firm may want to adjust its strategy in such circumstances.

Another direction involves possible information release of a new product development project prior to its introduction. In this dissertation, we assume that project secrecy is directly related to the innovator firm's effort (and associated expense) to restrain any information leaks. As noted in a recent article (Economist, 2011), some firms employ extraordinary efforts to protect their development efforts from potential rivals while other firms are much more transparent about their development efforts (Pinker et al., Forthcoming). Our models could provide insight into how and when an innovator firm may want to act in such circumstances.

Related to this is the incorporation of the game theoretic analysis into our model. Our model assumes asymmetric information flow where innovator firm has an estimate of the rival's market entry time, but the rival does not react to the innovator firm's optimal strategy. It would be insightful to analyze if some of our propositions continue to hold in the game theoretic approach. Another practical extension for the variable payment competition model is to consider different market return rates during the non-monopoly period. That is, the payment rate during the non-monopoly period is a function of whether or not a firm wins the competition. This generalization depicts an interesting dynamic in real-world competition where competing firms are not of equal size or strength. For example, if the innovator firm is smaller or less powerful than its rivals, the market payment rate during the non-monopoly period could be significantly lower, hence making it even more important to win the competition. On the contrary, if an innovator firm has already established its presence in the market via other products or services, the need to be first in the market may be of a lesser

degree.

Further analysis on the nature of project network and cost structures may also reveal more insights on the value of the DAM heuristic, albeit that a study in this direction can only be done numerically. Finally, another possible generalization is the modeling of uncertain development costs. For simplicity, in this dissertation we assume throughout that information concerning the overhead/indirect, fixed, and direct costs associated with all activities are known and fixed. The incorporation of uncertainty on both sides (cost and revenue) of the project should offer a complete view of a practical new product development project.

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Vita

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